Proyecto 2

1. Preparando los datos.

Los datos se descargan en Kaggle

In [353…
```python
#Preparando las bibliotecas a utilizar
import sys

import pandas as pd
import seaborn as sb
import numpy as np
import matplotlib as mpl
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.feature_selection import RFE
from sklearn.feature_selection import RFECV
from sklearn.svm import SVR
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from sklearn.linear_model import Ridge
sys.path.append("../PythonCode")
from modelo import estadisticas
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import LassoCV
from sklearn.linear_model import Lasso
```

In [354…
```python
#Leyendo los datos a utilizar
data = pd.read_csv('../Datos/train.csv')
test_data = pd.read_csv('../Datos/test.csv')
test_data.tail()
```

Out[354…

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	ScreenPorch	PoolArea	Poo
1454	2915	160	RM	21.0	1936	Pave	NaN	Reg	Lvl	AllPub	...	0	0	
1455	2916	160	RM	21.0	1894	Pave	NaN	Reg	Lvl	AllPub	...	0	0	
1456	2917	20	RL	160.0	20000	Pave	NaN	Reg	Lvl	AllPub	...	0	0	
1457	2918	85	RL	62.0	10441	Pave	NaN	Reg	Lvl	AllPub	...	0	0	
1458	2919	60	RL	74.0	9627	Pave	NaN	Reg	Lvl	AllPub	...	0	0	

5 rows × 80 columns

In [354…

Una vez leidos los datos se procede a dar un vistazo de las variables que contiene. En este caso vemos que se trata de una base de datos de **1460** registros y **80** variables. Además se identifica la variable objetivo como **SalePrice**, por lo que quedan **79** variables como posibles predictoras.

In [355…
```python
data.shape
```

Out[355…
```
(1460, 81)
```

In [356…
```python
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     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
```

De estas 79 variables hay algunas que en particular llaman mucho la atención, debido a la gran cantidad de valores con NAN. Estas son:

- Alley
- FireplaceQu
- PoolQC
- Fence
- MiscFeature

Estas deberán ser estudiadas a detalle antes de realizar los modelos.

Ahora vamos a separar las varibles según su tipo de dato. Vemos que los tres tipos presentes son:

- float64: variables continuas.
- int64: variables enteras (posiblemente son ordinales).
- object: variables cualitativas.

Se hace la unión de los datos de entrenamiento con los datos de test, esto debido a que se hace más fácil manejarlo de esta manera.

In [357…
```python
print("El test",test_data.shape)
y = data.SalePrice
#data = data.drop("SalePrice", axis = 1)
data = pd.concat([data, test_data], keys=["train", "test"])
#print(data.loc["train"])
```

```
El test (1459, 80)
```

In [358…
```python
#data = data.drop('Id', axis=1)
test_data = test_data.drop('Id', axis=1)
continuas = []
enteras = []
object = []
for feature in data.columns:
    if str(data[feature].dtype) == "float64":
        continuas.append(feature)
    elif str(data[feature].dtype) == "int64":
        enteras.append(feature)
    elif str(data[feature].dtype) == "object":
        object.append(feature)

print(continuas)
print(enteras)
print(object)
```

```
['LotFrontage', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalf
Bath', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'SalePrice']
['Id', 'MSSubClass', 'LotArea', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', '1stFlrSF', '2ndFlrS
F', 'LowQualFinSF', 'GrLivArea', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Firep
laces', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal', 'MoSol
d', 'YrSold']
['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhoo
d', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2n
d', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType
1', 'BsmtFinType2', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual', 'Functional', 'Fireplace
Qu', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
'SaleType', 'SaleCondition']
```

En este caso las tres variables continuas se verifican como continuas, incluida *GarageYrBlt*. Se clasifican las variables cualitativas en ordinales, nominales y dicotómicas.

In [359…
```python
continuas = continuas + ["LowQualFinSF",
                         "3SsnPorch","PoolArea","MiscVal","YrSold",
                         "FullBath","HalfBath","BedroomAbvGr",
           "KitchenAbvGr",
           "TotRmsAbvGrd",
                         ]

nominales = ["MSSubClass","MoSold",
             "MSZoning","Street","Alley","LotShape","LandContour",
             "Utilities", "LotConfig", "LandSlope", "Neighborhood",
             "Condition1", "Condition2","BldgType", "HouseStyle",
             "RoofStyle", "RoofMatl", "Exterior1st","Exterior2nd",
             "MasVnrType","Foundation","Heating", "Electrical",
             "Functional","GarageType","PavedDrive","Fence",
             "MiscFeature","SaleType","SaleCondition"
             ]
ordinal = ["OverallQual", "OverallCond",
           "Fireplaces",
           "ExterQual",
           "ExterCond",
           "BsmtQual",
           "BsmtCond",
           "BsmtExposure",
           "BsmtFinType2",
           "HeatingQC",
           "KitchenQual",
           "FireplaceQu",
           "GarageFinish",
           "GarageQual",
           "GarageCond",
           "PoolQC"]

dicotomicas = ["CentralAir",]
print(data.YearBuilt.nunique())
print(data.YearRemodAdd.nunique())
print(data.BsmtFinSF1.nunique())
print(data.BsmtFinSF2.nunique())

#Viendo por número de categorías
for x in  enteras:
    if data[x].nunique() < 50:
        print(x, data[x].nunique() )
print("********Object*********")
for x in  object:
    if data[x].nunique() < 50:
        print(x, data[x].nunique() )
print("********Features con 50 categorias o más*****")
for x in  enteras:
    if data[x].nunique() >= 50:
        print(x, data[x].nunique() )
        if x not in continuas:
            continuas.append(x)
            data[x] = pd.to_numeric(data[x])
continuas.remove("Id")
print("********Object*********")
for x in  object:
    if data[x].nunique() >= 50:
        print(x, data[x].nunique() )
        if x not in continuas:
            continuas.append(x)
#continuas.remove("SalePrice")

print("Continuas", len(continuas))
print("Dicotomicas", len(dicotomicas))
print("Nominales", len(nominales))
print("Ordinales", len(ordinal))
print("En total hay", len(continuas + dicotomicas + nominales + ordinal) , "features")
```

```
118
61
991
272
MSSubClass 16
OverallQual 10
OverallCond 9
LowQualFinSF 36
FullBath 5
HalfBath 3
BedroomAbvGr 8
KitchenAbvGr 4
TotRmsAbvGrd 14
Fireplaces 5
3SsnPorch 31
PoolArea 14
MiscVal 38
MoSold 12
YrSold 5
********Object*********
MSZoning 5
Street 2
Alley 2
LotShape 4
LandContour 4
Utilities 2
LotConfig 5
LandSlope 3
Neighborhood 25
Condition1 9
Condition2 8
BldgType 5
HouseStyle 8
RoofStyle 6
RoofMatl 8
Exterior1st 15
Exterior2nd 16
MasVnrType 4
ExterQual 4
ExterCond 5
Foundation 6
BsmtQual 4
BsmtCond 4
BsmtExposure 4
BsmtFinType1 6
BsmtFinType2 6
Heating 6
HeatingQC 5
CentralAir 2
Electrical 5
KitchenQual 4
Functional 7
FireplaceQu 5
GarageType 6
GarageFinish 3
GarageQual 5
GarageCond 5
PavedDrive 3
PoolQC 3
Fence 4
MiscFeature 4
SaleType 9
SaleCondition 6
********Features con 50 categorias o más*****
Id 2919
LotArea 1951
YearBuilt 118
YearRemodAdd 61
1stFlrSF 1083
2ndFlrSF 635
GrLivArea 1292
WoodDeckSF 379
OpenPorchSF 252
EnclosedPorch 183
ScreenPorch 121
********Object*********
Continuas 32
Dicotomicas 1
Nominales 30
Ordinales 16
En total hay 79 features
```

Ahora se revisa los tipos de las variables para ver si son congruentes con su categorización. Se convierten algunas variables enteras a cadena.

In [360…
```python
data[continuas].info()
data[dicotomicas].info()
data[nominales].info()
data[ordinal].info()

for x in nominales:
    if data[x].dtype != "object":
        data[x] = data[x].apply(str)

data["YearRemodAdd"] = data["YearRemodAdd"].apply(pd.to_numeric)
data["YrSold"] = data["YrSold"].apply(pd.to_numeric)

print("************Continuas")
data[continuas].info()
print("**********Dicotomicas")
data[dicotomicas].info()
print("**********Nominales")
data[nominales].info()
print("***********Ordinales")
data[ordinal].info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 32 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   LotFrontage    2433 non-null   float64
 1   MasVnrArea     2896 non-null   float64
 2   BsmtFinSF1     2918 non-null   float64
 3   BsmtFinSF2     2918 non-null   float64
 4   BsmtUnfSF      2918 non-null   float64
 5   TotalBsmtSF    2918 non-null   float64
 6   BsmtFullBath   2917 non-null   float64
 7   BsmtHalfBath   2917 non-null   float64
 8   GarageYrBlt    2760 non-null   float64
 9   GarageCars     2918 non-null   float64
 10  GarageArea     2918 non-null   float64
 11  SalePrice      1460 non-null   float64
 12  LowQualFinSF   2919 non-null   int64  
 13  3SsnPorch      2919 non-null   int64  
 14  PoolArea       2919 non-null   int64  
 15  MiscVal        2919 non-null   int64  
 16  YrSold         2919 non-null   int64  
 17  FullBath       2919 non-null   int64  
 18  HalfBath       2919 non-null   int64  
 19  BedroomAbvGr   2919 non-null   int64  
 20  KitchenAbvGr   2919 non-null   int64  
 21  TotRmsAbvGrd   2919 non-null   int64  
 22  LotArea        2919 non-null   int64  
 23  YearBuilt      2919 non-null   int64  
 24  YearRemodAdd   2919 non-null   int64  
 25  1stFlrSF       2919 non-null   int64  
 26  2ndFlrSF       2919 non-null   int64  
 27  GrLivArea      2919 non-null   int64  
 28  WoodDeckSF     2919 non-null   int64  
 29  OpenPorchSF    2919 non-null   int64  
 30  EnclosedPorch  2919 non-null   int64  
 31  ScreenPorch    2919 non-null   int64  
dtypes: float64(12), int64(20)
memory usage: 782.0+ KB
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   CentralAir  2919 non-null   object
dtypes: object(1)
memory usage: 75.1+ KB
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 30 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   MSSubClass     2919 non-null   int64 
 1   MoSold         2919 non-null   int64 
 2   MSZoning       2915 non-null   object
 3   Street         2919 non-null   object
 4   Alley          198 non-null    object
 5   LotShape       2919 non-null   object
 6   LandContour    2919 non-null   object
 7   Utilities      2917 non-null   object
 8   LotConfig      2919 non-null   object
 9   LandSlope      2919 non-null   object
 10  Neighborhood   2919 non-null   object
 11  Condition1     2919 non-null   object
 12  Condition2     2919 non-null   object
 13  BldgType       2919 non-null   object
 14  HouseStyle     2919 non-null   object
 15  RoofStyle      2919 non-null   object
 16  RoofMatl       2919 non-null   object
 17  Exterior1st    2918 non-null   object
 18  Exterior2nd    2918 non-null   object
 19  MasVnrType     2895 non-null   object
 20  Foundation     2919 non-null   object
 21  Heating        2919 non-null   object
 22  Electrical     2918 non-null   object
 23  Functional     2917 non-null   object
 24  GarageType     2762 non-null   object
 25  PavedDrive     2919 non-null   object
 26  Fence          571 non-null    object
 27  MiscFeature    105 non-null    object
 28  SaleType       2918 non-null   object
 29  SaleCondition  2919 non-null   object
dtypes: int64(2), object(28)
memory usage: 736.4+ KB
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 16 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   OverallQual   2919 non-null   int64 
 1   OverallCond   2919 non-null   int64 
 2   Fireplaces    2919 non-null   int64 
 3   ExterQual     2919 non-null   object
 4   ExterCond     2919 non-null   object
 5   BsmtQual      2838 non-null   object
 6   BsmtCond      2837 non-null   object
 7   BsmtExposure  2837 non-null   object
 8   BsmtFinType2  2839 non-null   object
 9   HeatingQC     2919 non-null   object
 10  KitchenQual   2918 non-null   object
 11  FireplaceQu   1499 non-null   object
 12  GarageFinish  2760 non-null   object
 13  GarageQual    2760 non-null   object
 14  GarageCond    2760 non-null   object
 15  PoolQC        10 non-null     object
dtypes: int64(3), object(13)
memory usage: 417.2+ KB
************Continuas
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 32 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   LotFrontage    2433 non-null   float64
 1   MasVnrArea     2896 non-null   float64
 2   BsmtFinSF1     2918 non-null   float64
 3   BsmtFinSF2     2918 non-null   float64
 4   BsmtUnfSF      2918 non-null   float64
 5   TotalBsmtSF    2918 non-null   float64
 6   BsmtFullBath   2917 non-null   float64
 7   BsmtHalfBath   2917 non-null   float64
 8   GarageYrBlt    2760 non-null   float64
 9   GarageCars     2918 non-null   float64
 10  GarageArea     2918 non-null   float64
 11  SalePrice      1460 non-null   float64
 12  LowQualFinSF   2919 non-null   int64  
 13  3SsnPorch      2919 non-null   int64  
 14  PoolArea       2919 non-null   int64  
 15  MiscVal        2919 non-null   int64  
 16  YrSold         2919 non-null   int64  
 17  FullBath       2919 non-null   int64  
 18  HalfBath       2919 non-null   int64  
 19  BedroomAbvGr   2919 non-null   int64  
 20  KitchenAbvGr   2919 non-null   int64  
 21  TotRmsAbvGrd   2919 non-null   int64  
 22  LotArea        2919 non-null   int64  
 23  YearBuilt      2919 non-null   int64  
 24  YearRemodAdd   2919 non-null   int64  
 25  1stFlrSF       2919 non-null   int64  
 26  2ndFlrSF       2919 non-null   int64  
 27  GrLivArea      2919 non-null   int64  
 28  WoodDeckSF     2919 non-null   int64  
 29  OpenPorchSF    2919 non-null   int64  
 30  EnclosedPorch  2919 non-null   int64  
 31  ScreenPorch    2919 non-null   int64  
dtypes: float64(12), int64(20)
memory usage: 782.0+ KB
**********Dicotomicas
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 1 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   CentralAir  2919 non-null   object
dtypes: object(1)
memory usage: 75.1+ KB
**********Nominales
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 30 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   MSSubClass     2919 non-null   object
 1   MoSold         2919 non-null   object
 2   MSZoning       2915 non-null   object
 3   Street         2919 non-null   object
 4   Alley          198 non-null    object
 5   LotShape       2919 non-null   object
 6   LandContour    2919 non-null   object
 7   Utilities      2917 non-null   object
 8   LotConfig      2919 non-null   object
 9   LandSlope      2919 non-null   object
 10  Neighborhood   2919 non-null   object
 11  Condition1     2919 non-null   object
 12  Condition2     2919 non-null   object
 13  BldgType       2919 non-null   object
 14  HouseStyle     2919 non-null   object
 15  RoofStyle      2919 non-null   object
 16  RoofMatl       2919 non-null   object
 17  Exterior1st    2918 non-null   object
 18  Exterior2nd    2918 non-null   object
 19  MasVnrType     2895 non-null   object
 20  Foundation     2919 non-null   object
 21  Heating        2919 non-null   object
 22  Electrical     2918 non-null   object
 23  Functional     2917 non-null   object
 24  GarageType     2762 non-null   object
 25  PavedDrive     2919 non-null   object
 26  Fence          571 non-null    object
 27  MiscFeature    105 non-null    object
 28  SaleType       2918 non-null   object
 29  SaleCondition  2919 non-null   object
dtypes: object(30)
memory usage: 736.4+ KB
***********Ordinales
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 16 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   OverallQual   2919 non-null   int64 
 1   OverallCond   2919 non-null   int64 
 2   Fireplaces    2919 non-null   int64 
 3   ExterQual     2919 non-null   object
 4   ExterCond     2919 non-null   object
 5   BsmtQual      2838 non-null   object
 6   BsmtCond      2837 non-null   object
 7   BsmtExposure  2837 non-null   object
 8   BsmtFinType2  2839 non-null   object
 9   HeatingQC     2919 non-null   object
 10  KitchenQual   2918 non-null   object
 11  FireplaceQu   1499 non-null   object
 12  GarageFinish  2760 non-null   object
 13  GarageQual    2760 non-null   object
 14  GarageCond    2760 non-null   object
 15  PoolQC        10 non-null     object
dtypes: int64(3), object(13)
memory usage: 417.2+ KB
```

Revisando las variables en busca de NA para comprender mejor la situación. Para ello primero vamos a calcular los porcentajes de NA en cada variable.

In [361…
```python
porcentajes = {}
for column in list(data.columns):
    porcentajes[column] = len(data[column][data[column].isna()==True]) / len(data[column]) *100
sorted(porcentajes.items(), key=lambda x:x[1])
```

Out[361…
```
[('Id', 0.0),
 ('MSSubClass', 0.0),
 ('LotArea', 0.0),
 ('Street', 0.0),
 ('LotShape', 0.0),
 ('LandContour', 0.0),
 ('LotConfig', 0.0),
 ('LandSlope', 0.0),
 ('Neighborhood', 0.0),
 ('Condition1', 0.0),
 ('Condition2', 0.0),
 ('BldgType', 0.0),
 ('HouseStyle', 0.0),
 ('OverallQual', 0.0),
 ('OverallCond', 0.0),
 ('YearBuilt', 0.0),
 ('YearRemodAdd', 0.0),
 ('RoofStyle', 0.0),
 ('RoofMatl', 0.0),
 ('ExterQual', 0.0),
 ('ExterCond', 0.0),
 ('Foundation', 0.0),
 ('Heating', 0.0),
 ('HeatingQC', 0.0),
 ('CentralAir', 0.0),
 ('1stFlrSF', 0.0),
 ('2ndFlrSF', 0.0),
 ('LowQualFinSF', 0.0),
 ('GrLivArea', 0.0),
 ('FullBath', 0.0),
 ('HalfBath', 0.0),
 ('BedroomAbvGr', 0.0),
 ('KitchenAbvGr', 0.0),
 ('TotRmsAbvGrd', 0.0),
 ('Fireplaces', 0.0),
 ('PavedDrive', 0.0),
 ('WoodDeckSF', 0.0),
 ('OpenPorchSF', 0.0),
 ('EnclosedPorch', 0.0),
 ('3SsnPorch', 0.0),
 ('ScreenPorch', 0.0),
 ('PoolArea', 0.0),
 ('MiscVal', 0.0),
 ('MoSold', 0.0),
 ('YrSold', 0.0),
 ('SaleCondition', 0.0),
 ('Exterior1st', 0.0342583076396026),
 ('Exterior2nd', 0.0342583076396026),
 ('BsmtFinSF1', 0.0342583076396026),
 ('BsmtFinSF2', 0.0342583076396026),
 ('BsmtUnfSF', 0.0342583076396026),
 ('TotalBsmtSF', 0.0342583076396026),
 ('Electrical', 0.0342583076396026),
 ('KitchenQual', 0.0342583076396026),
 ('GarageCars', 0.0342583076396026),
 ('GarageArea', 0.0342583076396026),
 ('SaleType', 0.0342583076396026),
 ('Utilities', 0.0685166152792052),
 ('BsmtFullBath', 0.0685166152792052),
 ('BsmtHalfBath', 0.0685166152792052),
 ('Functional', 0.0685166152792052),
 ('MSZoning', 0.1370332305584104),
 ('MasVnrArea', 0.7879410757108599),
 ('MasVnrType', 0.8221993833504625),
 ('BsmtFinType1', 2.7064063035286057),
 ('BsmtFinType2', 2.7406646111682083),
 ('BsmtQual', 2.774922918807811),
 ('BsmtCond', 2.8091812264474134),
 ('BsmtExposure', 2.8091812264474134),
 ('GarageType', 5.378554299417608),
 ('GarageYrBlt', 5.4470709146968135),
 ('GarageFinish', 5.4470709146968135),
 ('GarageQual', 5.4470709146968135),
 ('GarageCond', 5.4470709146968135),
 ('LotFrontage', 16.649537512846866),
 ('FireplaceQu', 48.646796848235695),
 ('SalePrice', 49.9828708461802),
 ('Fence', 80.4385063377869),
 ('Alley', 93.21685508735868),
 ('MiscFeature', 96.40287769784173),
 ('PoolQC', 99.65741692360398)]
```

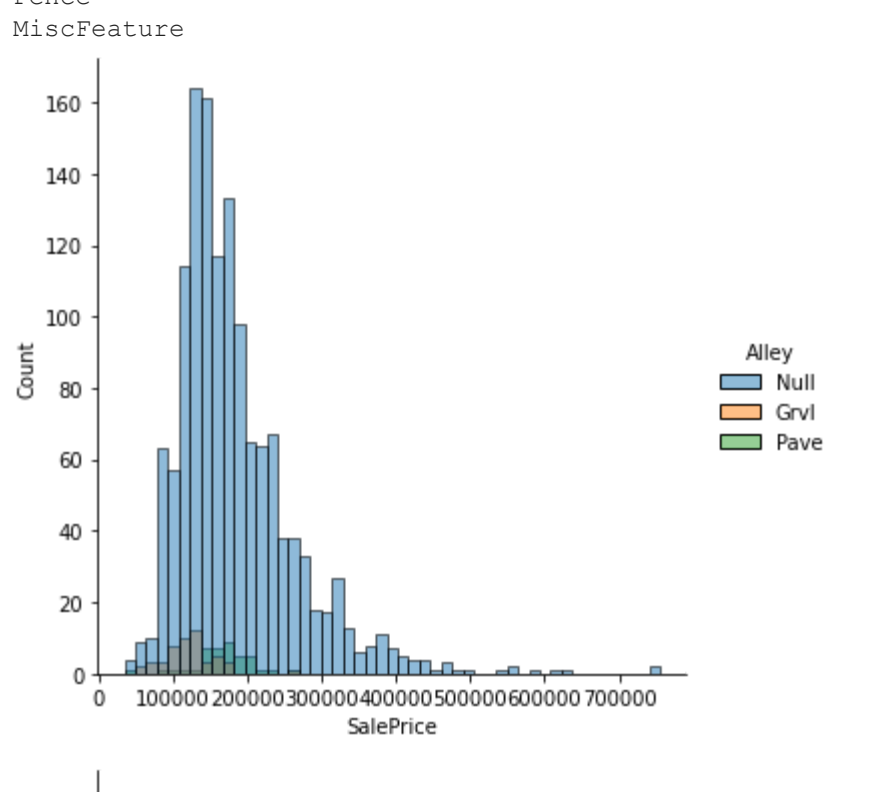
En este análisis se puede ver que hay columnas con 5.45% de datos con NAN y luego el número que les sigue es 16.65% (LotFrontAge). Hacemos un análisis junto con el diccionario de variables y vemos que:

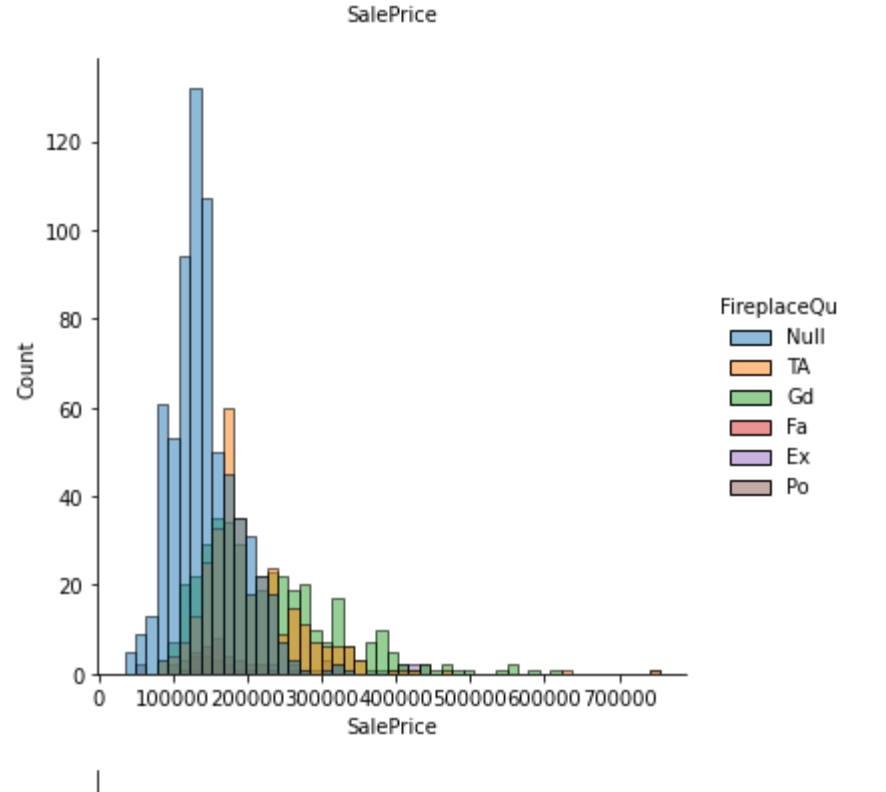
- LotFrontage: es una variable continua, al no haber dato no se puede inferir nada.
- FireplaceQu: es una variable ordinal. NA significa que la casa no tiene chimenea. En este caso esta variable podría ser recodificada.
- Fence: Fence quality, variable ordinal. NA significa que la casa no tiene cerca. Al igual que el caso anterior la variable podría ser recodificada.
- Alley: esta variable es nominal y el tipo de material del callejon. NA significa que la casa no tiene callejón aledaño. La variable puede ser recodificada.
- MiscFeature: esta variable describe comodidades extras del hogar. El NA indica que la casa no tiene extras de lujo. Esta variable también se podría recodificar.
- PoolQC: variable ordinal que describe la calidad de la piscina. NA se pone en caso la casa no tiene piscina. Esta variable es candidata a ser recodificada.

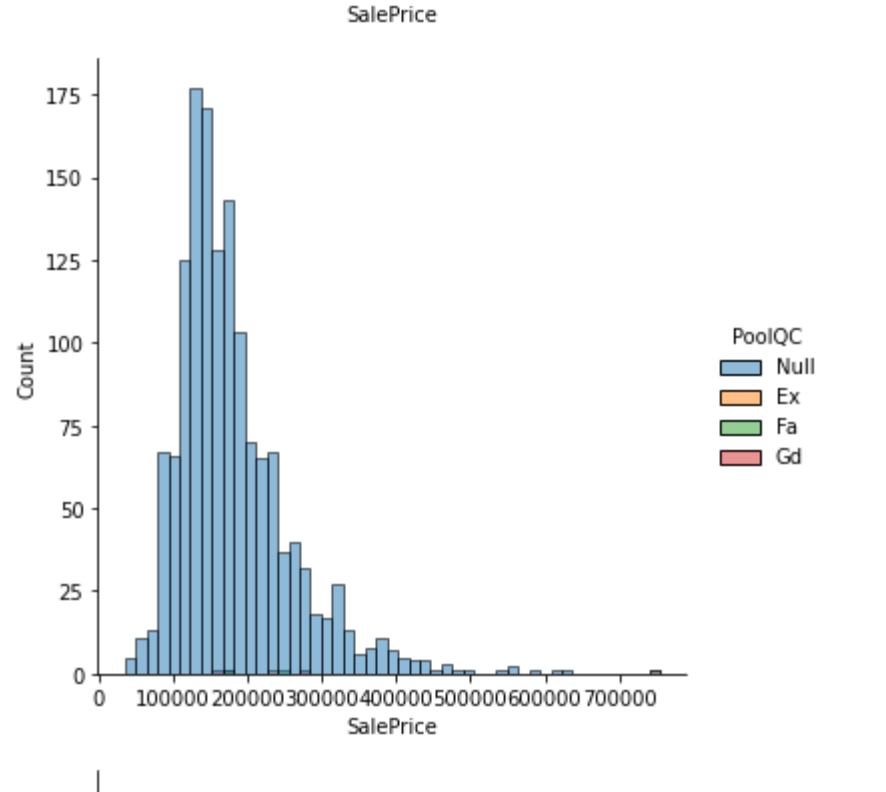
Con esto, resulta conveniente graficar estas variables para ver su comportamiento.

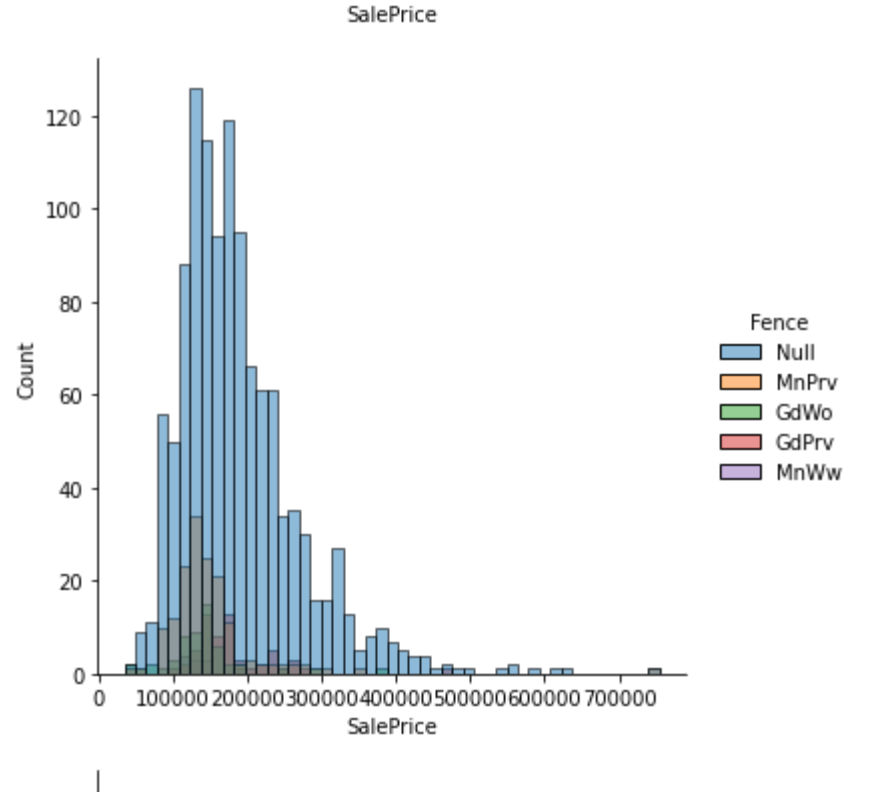
In [362…
```python
print(data.shape)
columnas_candidatas = []
for x in porcentajes:
    if porcentajes[x] >=10:
        columnas_candidatas.append(x)



columnas_candidatas = columnas_candidatas[1:]
print(columnas_candidatas)
training_recodificados = data.loc["train"].copy()
training_recodificados["SalePrice"] = y
columnas_candidatas.remove("SalePrice")
for col in columnas_candidatas:
    training_recodificados[col] = training_recodificados[col].fillna("Null")
    categorias = training_recodificados[col].value_counts().index.tolist()
    print(col)
    sb.displot(training_recodificados, x = "SalePrice", hue = col)
```

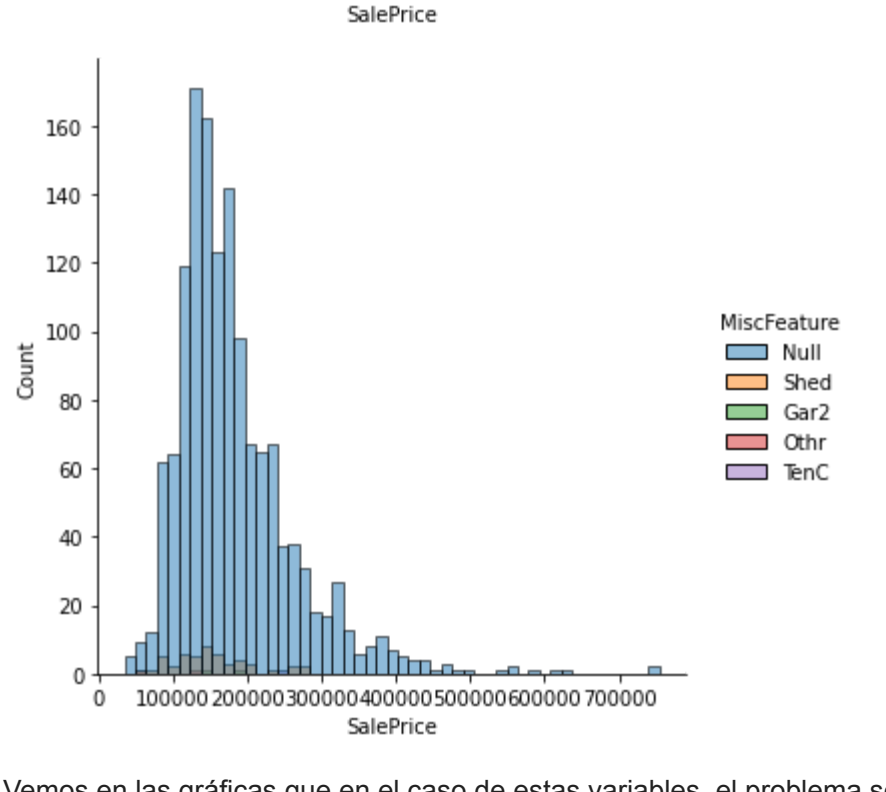
```
(2919, 81)
['Alley', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature', 'SalePrice']
Alley
FireplaceQu
PoolQC
Fence
MiscFeature
```







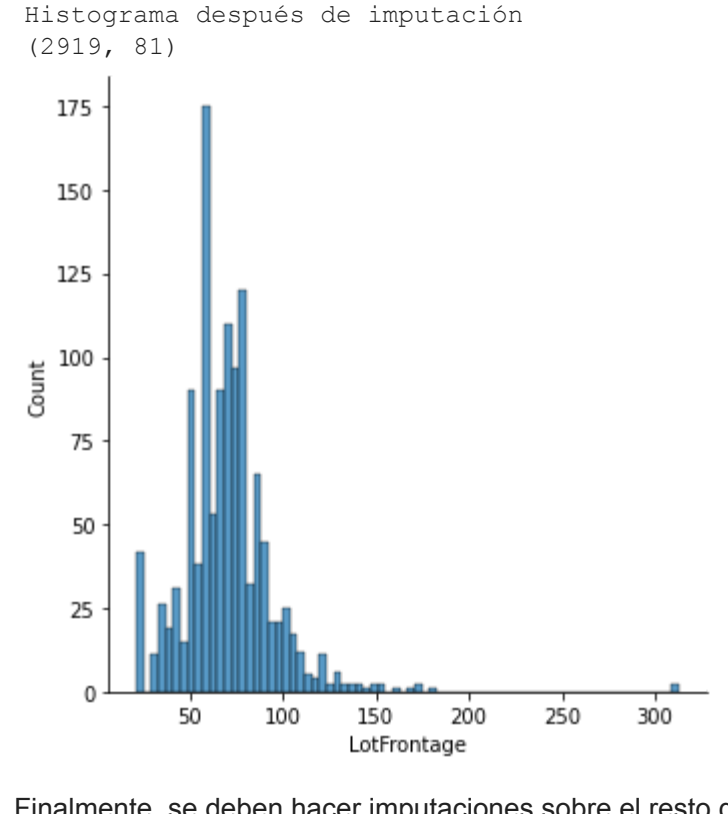




Vemos en las gráficas que en el caso de estas variables, el problema se arregla agregando una categoría más en lugar del NA. Esto debido a que se trata de variables descriptoras de calidad, así que cuando se encuentra un NA esto significa que la casa no tiene esa funcionalidad o ambiente, por lo que se se consignará de esa manera. Esto también conlleva a que estas variables que antes habían sido catalogadas como ordinales, ahora pasaran a ser variables nominales.

In [363…
```python
'''
training_recodificados.LotFrontage = np.where(data.LotFrontage.isnull(),1,0)
sb.displot(training_recodificados, x="SalePrice", hue="LotFrontage")
'''



imputer = SimpleImputer(missing_values= np.nan , strategy="mean")
imputer = imputer.fit(data[["LotFrontage"]])
data.LotFrontage = imputer.transform(data[["LotFrontage"]])
print("Histograma después de imputación")
sb.displot(training_recodificados, x = "LotFrontage")
print(data.shape)
```

```
Histograma después de imputación
(2919, 81)
```



Finalmente, se deben hacer imputaciones sobre el resto de las variables que tienen NANs y que no se pudieron arreglar mediante recodificación. Notemos que algunas de ellas son numéricas y otras son categóricas. De esa cuenta, en el caso de las numéricas, se imputarán usando como dato de imputación la media aritmética, mientras que para las categóricas se usará como dato de imputación el dato más frecuente.

In [364…

```python
print(features_imputacion)
#Haciendo imputación

for x in features_imputacion:
    try:
        imputer = SimpleImputer(missing_values= np.nan , strategy="mean")
        imputer = imputer.fit(data[[x]])
        data[[x]] = imputer.transform(data[[x]])
    except:
        imp = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
        imp.fit(data[[x]])
        data[[x]] = imp.transform(data[[x]])
    else:
        print("Un error ha ocurrido mientras se imputaba", x)
```

```
['MSZoning', 'Utilities', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'BsmtQual', 'BsmtCond', 'Bs
mtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Electrica
l', 'BsmtFullBath', 'BsmtHalfBath', 'KitchenQual', 'Functional', 'GarageType', 'GarageYrBlt', 'GarageFinish',
'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond', 'SaleType']
Un error ha ocurrido mientras se imputaba MasVnrArea
Un error ha ocurrido mientras se imputaba BsmtFinSF1
Un error ha ocurrido mientras se imputaba BsmtFinSF2
Un error ha ocurrido mientras se imputaba BsmtUnfSF
Un error ha ocurrido mientras se imputaba TotalBsmtSF
Un error ha ocurrido mientras se imputaba BsmtFullBath
Un error ha ocurrido mientras se imputaba BsmtHalfBath
Un error ha ocurrido mientras se imputaba GarageYrBlt
Un error ha ocurrido mientras se imputaba GarageCars
Un error ha ocurrido mientras se imputaba GarageArea
```

In [365…

```python
print(data.shape)
data.FireplaceQu = data.FireplaceQu.fillna("NF")
data.Fence =data.Fence.fillna("NFe")
data.Alley = data.Alley.fillna("NoAlley")
data.MiscFeature = data.MiscFeature.fillna("NoMiscFeature")
data.PoolQC = data.PoolQC.fillna("NoP")

print(data.shape)
```

```
(2919, 81)
(2919, 81)
```

Ahora se atienden las variables que tienen bajo porcentaje de NANs, haciendo imputaciones para el resto de las variables (cuyos porcentajes de NA fueron menor a 10%).

In [366…

```python
features_imputacion = []
for x in porcentajes:
    if porcentajes[x] <10 and porcentajes[x] >0:
        features_imputacion.append(x)
        print(x, porcentajes[x])
print(features_imputacion)

data.MasVnrType = data.MasVnrType.fillna("NoMasonry")
data.MasVnrArea =data.MasVnrArea.fillna(0)
data.BsmtQual = data.BsmtQual.fillna("NB") #Cambiar a nominal
data.BsmtCond = data.BsmtCond.fillna("NB") #Cambiar a nominal
data.BsmtExposure = data.BsmtExposure.fillna("NB") #Cambiar a nominales
data.BsmtFinType1 = data.BsmtFinType1.fillna("NB") #Cambiar a nominales
data.BsmtFinType2 = data.BsmtFinType2.fillna("NB") #Cambiar a nominal
#Con electrical el dato si está perdido, se sugiere perder esos registros
data.GarageType = data.GarageType.fillna("NG")
#Imputación
imputer = SimpleImputer(missing_values= np.nan , strategy="mean")
imputer = imputer.fit(data[["GarageYrBlt"]])
data.GarageYrBlt = imputer.transform(data[["GarageYrBlt"]])
#***
data.GarageFinish = data.GarageFinish.fillna("NG") #Cambiar a nominal si necesario
data.GarageQual = data.GarageQual.fillna("NG") #Cambiar a nominales
data.GarageCond = data.GarageCond.fillna("NG") #Cambiar a nominal



porcentajes = {}
for column in list(data.columns):
    porcentajes[column] = len(data[column][data[column].isna()==True]) / len(data[column]) *100
print(sorted(porcentajes.items(), key=lambda x:x[1]))
drop = []
print("Porcentaje vale", porcentajes)
for x in porcentajes.keys():
    if porcentajes[x] >0 and x!="SalePrice":
        drop.append(x)
        data.loc["train"].dropna( subset=[x] , inplace=True)
        print(x)
        print(data.shape)
```

```
MSZoning 0.1370332305584104
Utilities 0.0685166152792052
Exterior1st 0.0342583076396026
Exterior2nd 0.0342583076396026
MasVnrType 0.8221993833504625
MasVnrArea 0.7879410757108599
BsmtQual 2.774922918807811
BsmtCond 2.8091812264474134
BsmtExposure 2.8091812264474134
BsmtFinType1 2.7064063035286057
BsmtFinSF1 0.0342583076396026
BsmtFinType2 2.7406646111682083
BsmtFinSF2 0.0342583076396026
BsmtUnfSF 0.0342583076396026
TotalBsmtSF 0.0342583076396026
Electrical 0.0342583076396026
BsmtFullBath 0.0685166152792052
BsmtHalfBath 0.0685166152792052
KitchenQual 0.0342583076396026
Functional 0.0685166152792052
GarageType 5.378554299417608
GarageYrBlt 5.4470709146968135
GarageFinish 5.4470709146968135
GarageCars 0.0342583076396026
GarageArea 0.0342583076396026
GarageQual 5.4470709146968135
GarageCond 5.4470709146968135
SaleType 0.0342583076396026
['MSZoning', 'Utilities', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'BsmtQual', 'BsmtCond', 'Bs
mtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Electrica
l', 'BsmtFullBath', 'BsmtHalfBath', 'KitchenQual', 'Functional', 'GarageType', 'GarageYrBlt', 'GarageFinish',
'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond', 'SaleType']
[('Id', 0.0), ('MSSubClass', 0.0), ('MSZoning', 0.0), ('LotFrontage', 0.0), ('LotArea', 0.0), ('Street', 0.0),
('Alley', 0.0), ('LotShape', 0.0), ('LandContour', 0.0), ('Utilities', 0.0), ('LotConfig', 0.0), ('LandSlope',
0.0), ('Neighborhood', 0.0), ('Condition1', 0.0), ('Condition2', 0.0), ('BldgType', 0.0), ('HouseStyle', 0.0),
('OverallQual', 0.0), ('OverallCond', 0.0), ('YearBuilt', 0.0), ('YearRemodAdd', 0.0), ('RoofStyle', 0.0), ('Ro
ofMatl', 0.0), ('Exterior1st', 0.0), ('Exterior2nd', 0.0), ('MasVnrType', 0.0), ('MasVnrArea', 0.0), ('ExterQua
l', 0.0), ('ExterCond', 0.0), ('Foundation', 0.0), ('BsmtQual', 0.0), ('BsmtCond', 0.0), ('BsmtExposure', 0.0),
('BsmtFinType1', 0.0), ('BsmtFinSF1', 0.0), ('BsmtFinType2', 0.0), ('BsmtFinSF2', 0.0), ('BsmtUnfSF', 0.0), ('T
otalBsmtSF', 0.0), ('Heating', 0.0), ('HeatingQC', 0.0), ('CentralAir', 0.0), ('Electrical', 0.0), ('1stFlrSF',
0.0), ('2ndFlrSF', 0.0), ('LowQualFinSF', 0.0), ('GrLivArea', 0.0), ('BsmtFullBath', 0.0), ('BsmtHalfBath', 0.
0), ('FullBath', 0.0), ('HalfBath', 0.0), ('BedroomAbvGr', 0.0), ('KitchenAbvGr', 0.0), ('KitchenQual', 0.0),
('TotRmsAbvGrd', 0.0), ('Functional', 0.0), ('Fireplaces', 0.0), ('FireplaceQu', 0.0), ('GarageType', 0.0), ('G
arageYrBlt', 0.0), ('GarageFinish', 0.0), ('GarageCars', 0.0), ('GarageArea', 0.0), ('GarageQual', 0.0), ('Gara
geCond', 0.0), ('PavedDrive', 0.0), ('WoodDeckSF', 0.0), ('OpenPorchSF', 0.0), ('EnclosedPorch', 0.0), ('3SsnPo
rch', 0.0), ('ScreenPorch', 0.0), ('PoolArea', 0.0), ('PoolQC', 0.0), ('Fence', 0.0), ('MiscFeature', 0.0), ('M
iscVal', 0.0), ('MoSold', 0.0), ('YrSold', 0.0), ('SaleType', 0.0), ('SaleCondition', 0.0), ('SalePrice', 49.98
28708461802)]
Porcentaje vale {'Id': 0.0, 'MSSubClass': 0.0, 'MSZoning': 0.0, 'LotFrontage': 0.0, 'LotArea': 0.0, 'Street':
0.0, 'Alley': 0.0, 'LotShape': 0.0, 'LandContour': 0.0, 'Utilities': 0.0, 'LotConfig': 0.0, 'LandSlope': 0.0,
'Neighborhood': 0.0, 'Condition1': 0.0, 'Condition2': 0.0, 'BldgType': 0.0, 'HouseStyle': 0.0, 'OverallQual':
0.0, 'OverallCond': 0.0, 'YearBuilt': 0.0, 'YearRemodAdd': 0.0, 'RoofStyle': 0.0, 'RoofMatl': 0.0, 'Exterior1s
t': 0.0, 'Exterior2nd': 0.0, 'MasVnrType': 0.0, 'MasVnrArea': 0.0, 'ExterQual': 0.0, 'ExterCond': 0.0, 'Foundat
ion': 0.0, 'BsmtQual': 0.0, 'BsmtCond': 0.0, 'BsmtExposure': 0.0, 'BsmtFinType1': 0.0, 'BsmtFinSF1': 0.0, 'Bsmt
FinType2': 0.0, 'BsmtFinSF2': 0.0, 'BsmtUnfSF': 0.0, 'TotalBsmtSF': 0.0, 'Heating': 0.0, 'HeatingQC': 0.0, 'Cen
tralAir': 0.0, 'Electrical': 0.0, '1stFlrSF': 0.0, '2ndFlrSF': 0.0, 'LowQualFinSF': 0.0, 'GrLivArea': 0.0, 'Bsm
tFullBath': 0.0, 'BsmtHalfBath': 0.0, 'FullBath': 0.0, 'HalfBath': 0.0, 'BedroomAbvGr': 0.0, 'KitchenAbvGr': 0.
0, 'KitchenQual': 0.0, 'TotRmsAbvGrd': 0.0, 'Functional': 0.0, 'Fireplaces': 0.0, 'FireplaceQu': 0.0, 'GarageTy
pe': 0.0, 'GarageYrBlt': 0.0, 'GarageFinish': 0.0, 'GarageCars': 0.0, 'GarageArea': 0.0, 'GarageQual': 0.0, 'Ga
rageCond': 0.0, 'PavedDrive': 0.0, 'WoodDeckSF': 0.0, 'OpenPorchSF': 0.0, 'EnclosedPorch': 0.0, '3SsnPorch': 0.
0, 'ScreenPorch': 0.0, 'PoolArea': 0.0, 'PoolQC': 0.0, 'Fence': 0.0, 'MiscFeature': 0.0, 'MiscVal': 0.0, 'MoSol
d': 0.0, 'YrSold': 0.0, 'SaleType': 0.0, 'SaleCondition': 0.0, 'SalePrice': 49.9828708461802}
```

In [367…

```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2919 entries, ('train', 0) to ('test', 1458)
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             2919 non-null   int64  
 1   MSSubClass     2919 non-null   object 
 2   MSZoning       2919 non-null   object 
 3   LotFrontage    2919 non-null   float64
 4   LotArea        2919 non-null   int64  
 5   Street         2919 non-null   object 
 6   Alley          2919 non-null   object 
 7   LotShape       2919 non-null   object 
 8   LandContour    2919 non-null   object 
 9   Utilities      2919 non-null   object 
 10  LotConfig      2919 non-null   object 
 11  LandSlope      2919 non-null   object 
 12  Neighborhood   2919 non-null   object 
 13  Condition1     2919 non-null   object 
 14  Condition2     2919 non-null   object 
 15  BldgType       2919 non-null   object 
 16  HouseStyle     2919 non-null   object 
 17  OverallQual    2919 non-null   int64  
 18  OverallCond    2919 non-null   int64  
 19  YearBuilt      2919 non-null   int64  
 20  YearRemodAdd   2919 non-null   int64  
 21  RoofStyle      2919 non-null   object 
 22  RoofMatl       2919 non-null   object 
 23  Exterior1st    2919 non-null   object 
 24  Exterior2nd    2919 non-null   object 
 25  MasVnrType     2919 non-null   object 
 26  MasVnrArea     2919 non-null   float64
 27  ExterQual      2919 non-null   object 
 28  ExterCond      2919 non-null   object 
 29  Foundation     2919 non-null   object 
 30  BsmtQual       2919 non-null   object 
 31  BsmtCond       2919 non-null   object 
 32  BsmtExposure   2919 non-null   object 
 33  BsmtFinType1   2919 non-null   object 
 34  BsmtFinSF1     2919 non-null   float64
 35  BsmtFinType2   2919 non-null   object 
 36  BsmtFinSF2     2919 non-null   float64
 37  BsmtUnfSF      2919 non-null   float64
 38  TotalBsmtSF    2919 non-null   float64
 39  Heating        2919 non-null   object 
 40  HeatingQC      2919 non-null   object 
 41  CentralAir     2919 non-null   object 
 42  Electrical     2919 non-null   object 
 43  1stFlrSF       2919 non-null   int64  
 44  2ndFlrSF       2919 non-null   int64  
 45  LowQualFinSF   2919 non-null   int64  
 46  GrLivArea      2919 non-null   int64  
 47  BsmtFullBath   2919 non-null   float64
 48  BsmtHalfBath   2919 non-null   float64
 49  FullBath       2919 non-null   int64  
 50  HalfBath       2919 non-null   int64  
 51  BedroomAbvGr   2919 non-null   int64  
 52  KitchenAbvGr   2919 non-null   int64  
 53  KitchenQual    2919 non-null   object 
 54  TotRmsAbvGrd   2919 non-null   int64  
 55  Functional     2919 non-null   object 
 56  Fireplaces     2919 non-null   int64  
 57  FireplaceQu    2919 non-null   object 
 58  GarageType     2919 non-null   object 
 59  GarageYrBlt    2919 non-null   float64
 60  GarageFinish   2919 non-null   object 
 61  GarageCars     2919 non-null   float64
 62  GarageArea     2919 non-null   float64
 63  GarageQual     2919 non-null   object 
 64  GarageCond     2919 non-null   object 
 65  PavedDrive     2919 non-null   object 
 66  WoodDeckSF     2919 non-null   int64  
 67  OpenPorchSF    2919 non-null   int64  
 68  EnclosedPorch  2919 non-null   int64  
 69  3SsnPorch      2919 non-null   int64  
 70  ScreenPorch    2919 non-null   int64  
 71  PoolArea       2919 non-null   int64  
 72  PoolQC         2919 non-null   object 
 73  Fence          2919 non-null   object 
 74  MiscFeature    2919 non-null   object 
 75  MiscVal        2919 non-null   int64  
 76  MoSold         2919 non-null   object 
 77  YrSold         2919 non-null   int64  
 78  SaleType       2919 non-null   object 
 79  SaleCondition  2919 non-null   object 
 80  SalePrice      1460 non-null   float64
dtypes: float64(12), int64(24), object(45)
memory usage: 1.9+ MB
```

2. Explorando los datos

En esta parte se hará una exploración de los datos para ganar un poco de intuición a cerca de como se comportan las variables.

In [368…

```python
data.describe()
```

Out[368…

	Id	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFi
count	2919.000000	2919.000000	2919.000000	2919.000000	2919.000000	2919.000000	2919.000000	2919.000000	2919.000000	2919.00
mean	1460.000000	69.305795	10168.114080	6.089072	5.564577	1971.312778	1984.264474	102.201312	441.423235	49.58
std	842.787043	21.312345	7886.996359	1.409947	1.113131	30.291442	20.894344	178.626089	455.532750	169.17
min	1.000000	21.000000	1300.000000	1.000000	1.000000	1872.000000	1950.000000	0.000000	0.000000	0.00
25%	730.500000	60.000000	7478.000000	5.000000	5.000000	1953.500000	1965.000000	0.000000	0.000000	0.00
50%	1460.000000	69.305795	9453.000000	6.000000	5.000000	1973.000000	1993.000000	0.000000	369.000000	0.00
75%	2189.500000	78.000000	11570.000000	7.000000	6.000000	2001.000000	2004.000000	163.500000	733.000000	0.00
max	2919.000000	313.000000	215245.000000	10.000000	9.000000	2010.000000	2010.000000	1600.000000	5644.000000	1526.00

8 rows × 36 columns

In [369…

```python
print(data.shape)

target = data.loc["train"].copy()
target["SalePrice"] = y
#target = target.drop(['SalePrice'], axis=1)
```

```
(2919, 81)
```

Construyendo histogramas para las variables numéricas para ver su comportamiento

In [370…

```python
for x in continuas:
    sb.displot(target, x = x)
sb.displot(target, x = y)
```

```
MSSubClass
MoSold
MSZoning
Street
Alley
LotShape
LandContour
Utilities
LotConfig
LandSlope
Neighborhood
Condition1
Condition2
BldgType
HouseStyle
RoofStyle
RoofMatl
Exterior1st
Exterior2nd
MasVnrType
Foundation
Heating
Electrical
Functional
GarageType
/home/hugog/GitHub/Proyecto2---Inteligencia-Artificial/venv/lib/python3.9/site-packages/pandas/plotting/_matplotlib/core.py:345: RuntimeWarning: More than 20 figures have been opened. Figures created through the pyplot interface (`matplotlib.pyplot.figure`) are retained until explicitly closed and may consume too much memory. (To control this warning, see the rcParam `figure.max_open_warning`).
  fig = self.plt.figure(figsize=self.figsize)
PavedDrive
Fence
MiscFeature
SaleType
SaleCondition
OverallQual
OverallCond
Fireplaces
ExterQual
ExterCond
BsmtQual
BsmtCond
BsmtExposure
BsmtFinType2
HeatingQC
KitchenQual
FireplaceQu
GarageFinish
GarageQual
GarageCond
PoolQC
```

De acá vemos, que además de que la variable MoSold ya tenía poco sentido, parace no tener mayor relación con el modelo ya que no se ve diferencias significativas entre las distintas categorías. Esta variable es candidata a ser removida del modelo.

In [374…

```
print(continuas)
correlaciones = target[continuas].corr()
correlaciones.shape
```

```
['LotFrontage', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalfBath', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'SalePrice', 'LowQualFinSF', '3SsnPorch', 'PoolArea', 'MiscVal', 'YrSold', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'LotArea', 'YearBuilt', 'YearRemodAdd', '1stFlrSF', '2ndFlrSF', 'GrLivArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', 'ScreenPorch']
```

Out[374…

```
(32, 32)
```

Como es era esperado, la matriz de correlaciones es de 23x23. Como resulta díficil visualizar la matriz de correlaciones se construye una visualización utilizando la biblioteca seaborn.

In [375…

```
mask = np.triu(np.ones_like(correlaciones, dtype="bool"))
_, ax = mpl.pyplot.subplots(figsize=(20,20))
sb.heatmap(correlaciones, mask=mask, cmap='BrBG', ax = ax)
```

Out[375…

<AxesSubplot:>

Se observan variables fuertemente correlacionadas. Con correlación positiva:

- YearBuilt y GarageYrBlt y YearRemodAdd
- YearRemodAdd y YearBuilt
- 1stFlrSF1 y TotalBsmtSF: Total square feet of basement area

Con correlación negativa:

- BsmtUnfSF y BsmTFinSF1
- EnclosedPorch y GarageYrBlt
- EnclosedPorch y YearBuilt

3. Preparación de datos finales

En esta parte agregamos las variables dummies y se separan los datos en datos de entrenamiento y datos de validación.

In [376…

```
print(data.shape)
enc = OrdinalEncoder()
enc.fit(data[ordinal])
data[ordinal] = enc.transform(data[ordinal])
```

```
(2919, 81)
```

In [376…

In [377…

```
final_features =continuas + dicotomicas + nominales + ordinal
final_data = data[final_features]
print(final_data.shape)
```

```
(2919, 79)
```

In [378…

```
X_dummies = pd.get_dummies(final_data)
X = X_dummies.loc["train"]
print(X.shape)
X.drop("SalePrice", axis=1, inplace=True)
print(X.shape)
#X_dummies.loc["test"].info()
```

```
(1460, 268)
(1460, 267)
/home/hugog/GitHub/Proyecto2---Inteligencia-Artificial/venv/lib/python3.9/site-packages/pandas/core/frame.py:49
06: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  return super().drop(
```

In [379…

```
X_train, X_holdout, y_train, y_holdout = train_test_split(X,y,test_size=0.2, random_state=5)
```

4. Modelos propuestos

Ahora haremos una regresión lineal normal utilizando las 269 variables (incluidas las dummies). Cabe destacar que, siguiendo los lineamientos de Gerón, usaremos como medida del desempeño el RSME. En la literatura se acostumbra decir que con un RSME <=0.5 se considera que el modelo tiene buena capacidad de predicción y entre más pequeño sea el RSME mejor es el modelo.

In [380…

```
from math import exp
import statsmodels.api as sm
reg = LinearRegression()
reg.fit(X_train, y_train)

print("**********Estadisticas training********")
y_predicted = reg.predict(X_train)
estadisticas(y_predicted,y_train)

print("*******Estadisticas testeo*****")
y_predicted = reg.predict(X_holdout)
estadisticas(y_predicted,y_holdout)
```

```
**********Estadisticas training********
R-Square Value 0.9439162737192711


mean_absolute_error : 0.06549455740507339


mean_squared_error :  0.008817315954081558


root_mean_squared_error :  0.09390056418404288
*******Estadisticas testeo*****
R-Square Value -308504.2356959959


mean_absolute_error : 17.520054942404062


mean_squared_error :  51925.77000896375


root_mean_squared_error :  227.8722668710779
```

In [381…

```
X2 = sm.add_constant(X_train)
est = sm.OLS(y_train,X2)
est2 = est.fit()
```

Con esto vemos que el modelo se sobreentrena, ya que en la parte de entrenamiento logra buen ajuste (R2=0.944) y buen RSME (0.09), pero cuando hacemos la validación con los datos de validación, vemos que el ajuste se pierde (R2=-308404) y RSME demasiado alto (227.9). Esto nos está diciendo que este modelo es malo prediciendo, y sacar el promedio de los datos sería un mejor modelo que esta regresión.

In [381…

Debido a que se está observando un sobreentrenamiento (posiblemente al gran número de variables), se hace necesario recurrir a la regularización. Haremos la prueba primero con la regularización de Ridge. Para ello probaremos con valores de alfa muy pequeños y otros más grandes (hasta 100) y comparamos los resultados del RSME.

In [382…

```
from sklearn.preprocessing import StandardScaler
alpha_ridge = [0,1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20,100]
for i in range(len(alpha_ridge)):
    print("*************Alpha = %.2e******************"%alpha_ridge[i])
    ridgereg = make_pipeline(StandardScaler(with_mean=False), Ridge(alpha=alpha_ridge[i]))
    ridgereg.fit(X_train,y_train)
    print("**********Estadisticas training Alpha = %.2e******************"%alpha_ridge[i])
    y_predicted = ridgereg.predict(X_train)
    estadisticas(y_predicted,y_train)

    print("*******Estadisticas testeo Alpha = %.2e******************"%alpha_ridge[i])
    y_predicted = ridgereg.predict(X_holdout)
    estadisticas(y_predicted,y_holdout)
from IPython.display import Image
```

```
*************Alpha = 0.00e+00******************
**********Estadisticas training Alpha = 0.00e+00******************
R-Square Value 0.8567693477066085


mean_absolute_error : 0.1166799253319561


mean_squared_error :  0.022518295401031178


root_mean_squared_error :  0.15006097227804163
*******Estadisticas testeo Alpha = 0.00e+00******************
R-Square Value -3.9906151164084527e+27


mean_absolute_error : 1560133866566.9604


mean_squared_error :  6.716766484090138e+26


root_mean_squared_error :  25916725263987.613
*************Alpha = 1.00e-15******************
**********Estadisticas training Alpha = 1.00e-15******************
R-Square Value 0.9439182710593352


mean_absolute_error : 0.06549574390970525


mean_squared_error :  0.00881700193824165


root_mean_squared_error :  0.09389889210337708
*******Estadisticas testeo Alpha = 1.00e-15******************
R-Square Value -3.7369938665644096


mean_absolute_error : 0.14751885054209732


mean_squared_error :  0.7973026891883245


root_mean_squared_error :  0.8929180752948864
*************Alpha = 1.00e-10******************
**********Estadisticas training Alpha = 1.00e-10******************
R-Square Value 0.9439182710593353


mean_absolute_error : 0.06549574390970479


mean_squared_error :  0.008817001938241644


root_mean_squared_error :  0.09389889210337704
*******Estadisticas testeo Alpha = 1.00e-10******************
R-Square Value 0.9019789065973366


mean_absolute_error : 0.08628343062000196


mean_squared_error :  0.01649832859585375


root_mean_squared_error :  0.12844581969006913
*************Alpha = 1.00e-08******************
**********Estadisticas training Alpha = 1.00e-08******************
R-Square Value 0.9439182710593352


mean_absolute_error : 0.06549574390975421


mean_squared_error :  0.008817001938241645


root_mean_squared_error :  0.09389889210337705
*******Estadisticas testeo Alpha = 1.00e-08******************
R-Square Value 0.9019785942055298


mean_absolute_error : 0.08628465551928587


mean_squared_error :  0.016498381175788338


root_mean_squared_error :  0.12844602436739075
*************Alpha = 1.00e-04******************
**********Estadisticas training Alpha = 1.00e-04******************
R-Square Value 0.9439182710593199


mean_absolute_error : 0.06549574440886843


mean_squared_error :  0.00881700193824407


root_mean_squared_error :  0.09389889210338996
*******Estadisticas testeo Alpha = 1.00e-04******************
R-Square Value 0.9019788519760673


mean_absolute_error : 0.08628464178149801


mean_squared_error :  0.016498337789381572


root_mean_squared_error :  0.1284458554776353
*************Alpha = 1.00e-03******************
**********Estadisticas training Alpha = 1.00e-03******************
R-Square Value 0.9439182710577907


mean_absolute_error : 0.06549574890116157


mean_squared_error :  0.008817001938484479


root_mean_squared_error :  0.09389889210467012
*******Estadisticas testeo Alpha = 1.00e-03******************
R-Square Value 0.9019790954352953


mean_absolute_error : 0.08628458778938436


mean_squared_error :  0.016498296811769488


root_mean_squared_error :  0.12844569596436264
*************Alpha = 1.00e-02******************
**********Estadisticas training Alpha = 1.00e-02******************
R-Square Value 0.9439182709049682


mean_absolute_error : 0.06549579380592488


mean_squared_error :  0.008817001962510777


root_mean_squared_error :  0.09389889223260718
*******Estadisticas testeo Alpha = 1.00e-02******************
R-Square Value 0.9019815295234496


mean_absolute_error : 0.08628404784972354


mean_squared_error :  0.016497887120499915


root_mean_squared_error :  0.12844410115104513
*************Alpha = 1.00e+00******************
**********Estadisticas training Alpha = 1.00e+00******************
R-Square Value 0.9439168174297813


mean_absolute_error : 0.06550229320809607


mean_squared_error :  0.008817230473538926


root_mean_squared_error :  0.09390010901771587
*******Estadisticas testeo Alpha = 1.00e+00******************
R-Square Value 0.9022409917980129


mean_absolute_error : 0.08622488501711884


mean_squared_error :  0.016454215970593555


root_mean_squared_error :  0.12827398789541689
*************Alpha = 5.00e+00******************
**********Estadisticas training Alpha = 5.00e+00******************
R-Square Value 0.9438886154668459


mean_absolute_error : 0.06554826500616642


mean_squared_error :  0.008821664301927604


root_mean_squared_error :  0.09392371533285725
*******Estadisticas testeo Alpha = 5.00e+00******************
R-Square Value 0.9031452032702727


mean_absolute_error : 0.08599213553748818


mean_squared_error :  0.01630202446291263


root_mean_squared_error :  0.12767938151053454
*************Alpha = 1.00e+01******************
**********Estadisticas training Alpha = 1.00e+01******************
R-Square Value 0.9438208691958502


mean_absolute_error : 0.06563123822570238


mean_squared_error :  0.008832315168332057


root_mean_squared_error :  0.09398039778768792
*******Estadisticas testeo Alpha = 1.00e+01******************
R-Square Value 0.9040281460098804


mean_absolute_error : 0.08573153013129467


mean_squared_error :  0.016153412782062164


root_mean_squared_error :  0.12709607697353276
*************Alpha = 2.00e+01******************
**********Estadisticas training Alpha = 2.00e+01******************
R-Square Value 0.943627932617562


mean_absolute_error : 0.06584572220465652


mean_squared_error :  0.008862648080973265


root_mean_squared_error :  0.09414163840178938
*******Estadisticas testeo Alpha = 2.00e+01******************
R-Square Value 0.9052666708544962


mean_absolute_error : 0.08536424116157658


mean_squared_error :  0.015944951632004788


root_mean_squared_error :  0.1262733211411056
*************Alpha = 1.00e+02******************
**********Estadisticas training Alpha = 1.00e+02******************
R-Square Value 0.9414348555977063


mean_absolute_error : 0.06750905576562441


mean_squared_error :  0.009207437100499353


root_mean_squared_error :  0.0959553912008041
*******Estadisticas testeo Alpha = 1.00e+02******************
R-Square Value 0.9077834704750479


mean_absolute_error : 0.08455365962957911


mean_squared_error :  0.015521338859402786


root_mean_squared_error :  0.12458466542637896
```

Acá, vemos que el mejor RSME (0.1245) se obtiene con alfa = 100. Hacemos la predicción para los datos de testeo con este modelo y lo subimos al Kaggle. Vemos que obtiene un RSME de 0.14481

salida.csv | 0.14481
an hour ago by Hugo Garcia
Prueba 1

In [383…

```
test = X_dummies.loc["test"]
test.drop("SalePrice",axis=1, inplace=True)
y_predicted = ridgereg.predict(test)
y_predicted = np.exp(y_predicted)
Id=pd.read_csv('../Datos/test.csv').Id
salida = pd.DataFrame(y_predicted,Id.tolist())
salida.to_csv('../Datos/salida.csv', index=True)
```

```
/home/hugog/GitHub/Proyecto2---Inteligencia-Artificial/venv/lib/python3.9/site-packages/pandas/core/frame.py:49
06: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  return super().drop(
```

Con Ridge Cross Validation (RidgeCV), podemos automatizar el proceso de encontrar el mejor alfa, en este caso lo buscamos con rangos entre 10^-2 y 10^3. Al utilizar el alfa que optimiza corremos la predicción con los datos de test, pero al subirlo a Kaggle, el puntaje no mejora.

In [384…

```
alpha_range = 10.**np.arange(-2, 3)
ridgereg = make_pipeline(StandardScaler(with_mean=False), RidgeCV(alphas=alpha_range,scoring='neg_mean_squared_
ridgereg.fit(X_train,y_train)
print("**********Estadisticas training RidgeCV******************")
y_predicted = ridgereg.predict(X_train)
estadisticas(y_predicted,y_train)

print("*******Estadisticas testeo RidgeCV******************")
y_predicted = ridgereg.predict(X_holdout)
estadisticas(y_predicted,y_holdout)
```

```
**********Estadisticas training RidgeCV******************
R-Square Value 0.9414348555977072


mean_absolute_error : 0.06750905576562512


mean_squared_error :  0.009207437100499215


root_mean_squared_error :  0.09595539120080339
*******Estadisticas testeo RidgeCV******************
R-Square Value 0.9077834704750518


mean_absolute_error : 0.08455365962958113


mean_squared_error :  0.01552133885940213


root_mean_squared_error :  0.12458466542637633
```

In [385…

```
test = X_dummies.loc["test"]
test.drop("SalePrice",axis=1, inplace=True)
y_predicted = ridgereg.predict(test)
y_predicted = np.exp(y_predicted)
Id=pd.read_csv('../Datos/test.csv').Id
salida = pd.DataFrame(y_predicted,Id.tolist())
print(salida)
salida.to_csv('../Datos/salida_RidgeCV.csv', index=True)
```

```
                  0
1461  124117.840737
1462  118786.923146
1463  181346.566044
1464  201528.276367
1465  191117.112345
...             ...
2915   84687.549599
2916   80734.269344
2917  169613.050229
2918  110683.687406
2919  226770.975831

[1459 rows x 1 columns]
/home/hugog/GitHub/Proyecto2---Inteligencia-Artificial/venv/lib/python3.9/site-packages/pandas/core/frame.py:49
06: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  return super().drop(
```

Finalmente, probamos suerte con regularización de Lasso, utilizando LassoCV para encontrar el mejor parámetro para alpha. En este caso es alpha = 0.0001776256891830261. Corremos el modelo con este parámetro y subimos los datos al Kaggle. El puntaje RSME mejora, aunque no significativamente, el mismo se ubica en 0.14165.

salida_LassoCV.csv | 0.14165
21 minutes ago by Hugo Garcia
Lasso

In [386…

```
lassoregcv = LassoCV(n_alphas=100, normalize=True, random_state=1)
lassoregcv.fit(X_train, y_train)
print('alpha : ',lassoregcv.alpha_)

print("**********Estadisticas training LassoCV******************")
y_predicted = lassoregcv.predict(X_train)
estadisticas(y_predicted,y_train)

print("*******Estadisticas testeo LassoCV******************")
y_predicted = lassoregcv.predict(X_holdout)
estadisticas(y_predicted,y_holdout)
```

```
alpha :  0.0001776256891830261
**********Estadisticas training LassoCV******************
R-Square Value 0.9262244369738492


mean_absolute_error : 0.07535574219992669


mean_squared_error :  0.011598773691243675


root_mean_squared_error :  0.10769760299674118
*******Estadisticas testeo LassoCV******************
R-Square Value 0.9164912230235194


mean_absolute_error : 0.07989199364955359


mean_squared_error :  0.014055701638994462


root_mean_squared_error :  0.11855674438425873
/home/hugog/GitHub/Proyecto2---Inteligencia-Artificial/venv/lib/python3.9/site-packages/sklearn/linear_model/_b
ase.py:141: FutureWarning: 'normalize' was deprecated in version 1.0 and will be removed in 1.2.
If you wish to scale the data, use Pipeline with a StandardScaler in a preprocessing stage. To reproduce the pr
evious behavior:

from sklearn.pipeline import make_pipeline

model = make_pipeline(StandardScaler(with_mean=False), Lasso())

If you wish to pass a sample_weight parameter, you need to pass it as a fit parameter to each step of the pipel
ine as follows:

kwargs = {s[0] + '__sample_weight': sample_weight for s in model.steps}
model.fit(X, y, **kwargs)

Set parameter alpha to: original_alpha * np.sqrt(n_samples).
  warnings.warn(
```

In [387…

```
test = X_dummies.loc["test"]
test.drop("SalePrice",axis=1, inplace=True)
y_predicted = lassoregcv.predict(test)
y_predicted = np.exp(y_predicted)
Id=pd.read_csv('../Datos/test.csv').Id
salida = pd.DataFrame(y_predicted,Id.tolist())
print(salida)
salida.to_csv('../Datos/salida_LassoCV.csv', index=True)
```

```
                  0
1461  123072.210011
1462  154171.888269
1463  176272.231306
1464  193615.612475
1465  196731.871988
...             ...
2915   87445.728624
2916   88112.488746
2917  169032.770636
2918  118378.722318
2919  234475.091769

[1459 rows x 1 columns]
/home/hugog/GitHub/Proyecto2---Inteligencia-Artificial/venv/lib/python3.9/site-packages/pandas/core/frame.py:49
06: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  return super().drop(
```

5. Conclusiones

1. Es importante hacer una buena exploración de los datos antes de comenzar con los modelos. Conocer los datos permitirá comprender de mejor manera el problema y abordarlo con las herramientas adecuadas.
2. La regresión lineal múltiple utilizando todos los parámetros produce un sobreentrenamiento, arrojando un modelo que es peor que si solo utilizaramos el promedio como predictor.
3. Al utilizar regularización de Ridge, se logra relajar la función de error, lo que permite tener un modelo más flexible. También es importante conocer la herramienta RidgeCV para encontrar de forma automatizada mejores parámetros de penalización.
4. La regularización de Lasso tiene la bondad de "eliminar" algunas variables que no son significativas en el modelo (pone coeficientes cero). En esta parte sería importante analizar que variables está quitando para ver si concuerdan con la intuición construida en la parte exploratoria.
5. Es importante continuar mejorando el modelo y en su momento utilizar las técnicas que originalmente proponía el ejercicio, esto es **random forest** y **gradient boosting**.

6. Referencias

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