House Prices - Advanced Regression Techniques

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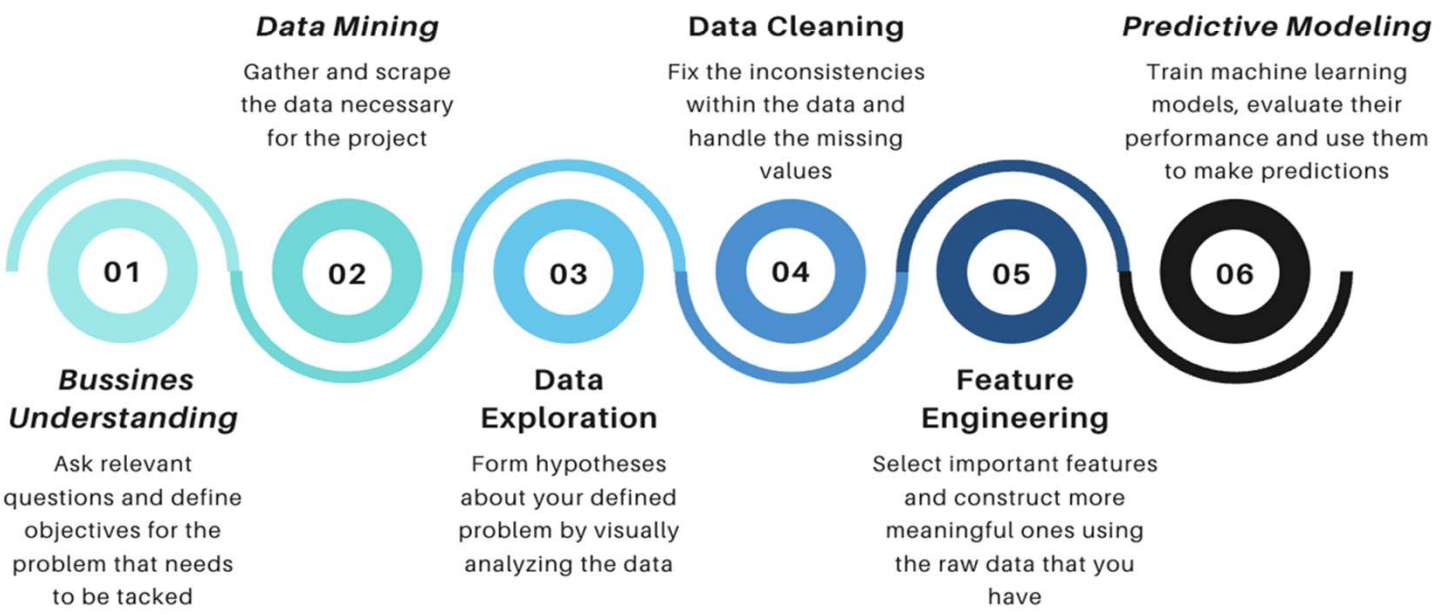
CESTE

kaggle

INDICE

Data Science Lifecycle



01

BUSSINESS UNDERSTANDING

OBJETIVO	Predecir el precio de cada casa
KPI	RMSE entre el logaritmo del valor real y el valor predicho

02

DATA MINING

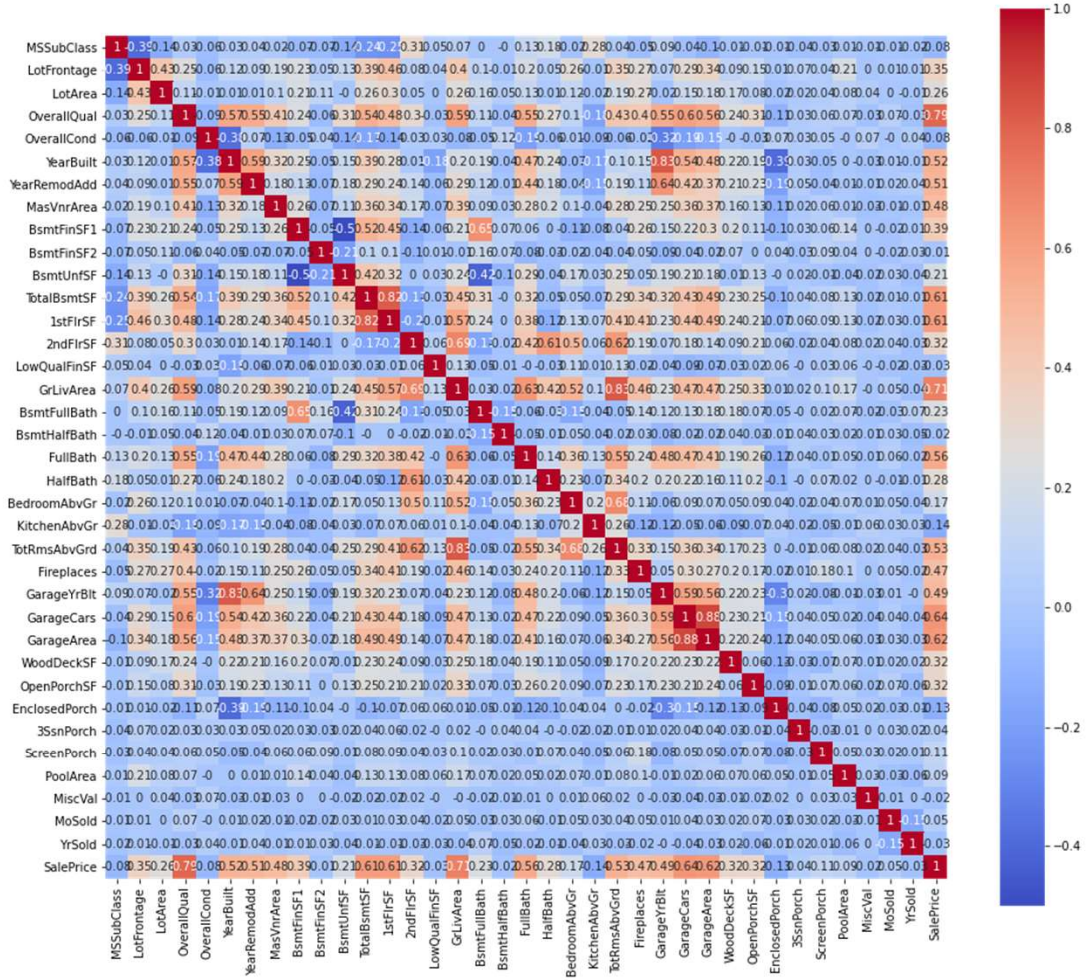
En este caso los datos se descargan directamente de la página de kaggle:

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

03

DATA EXPLORATION

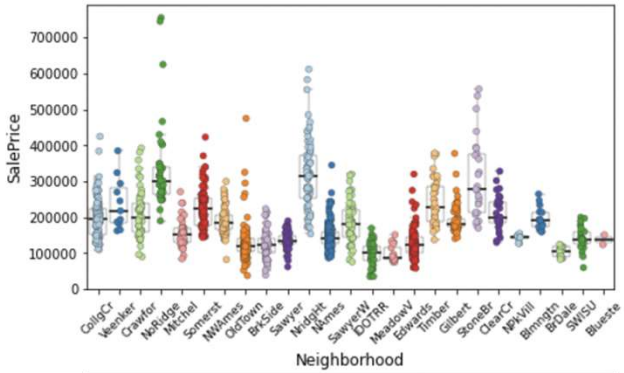
CORRELACIÓN DE VARIABLES

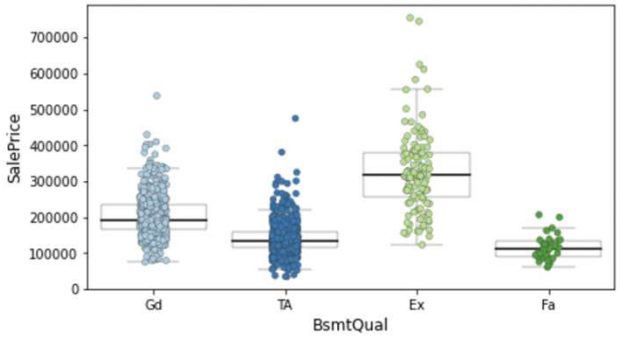


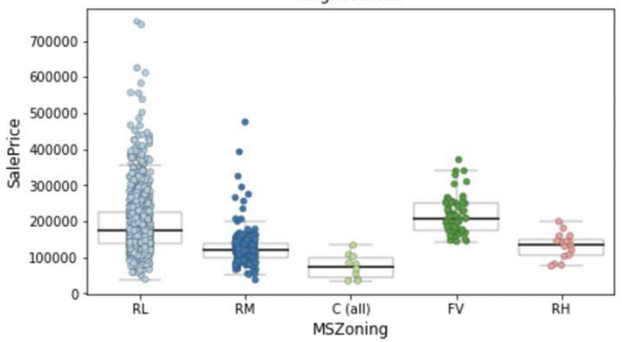
03

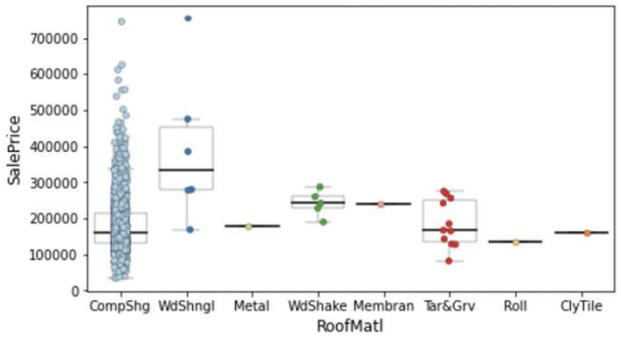
DATA EXPLORATION

VARIABLES CATEGÓRICAS





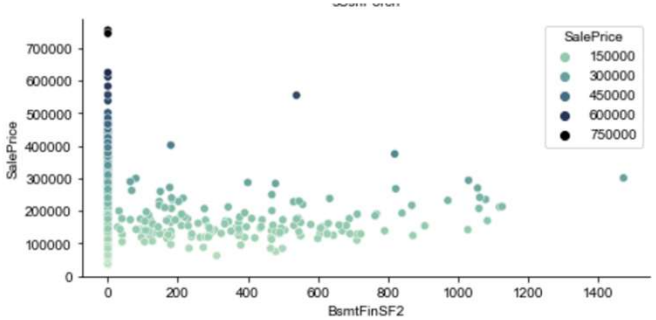


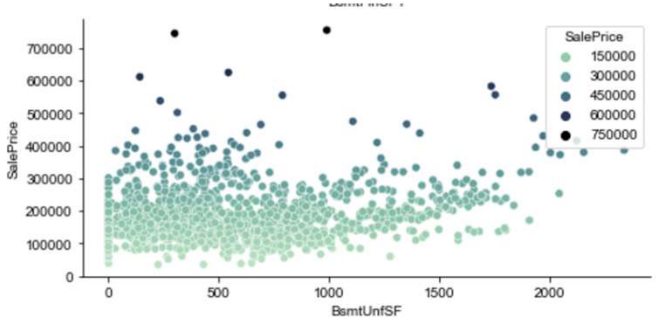


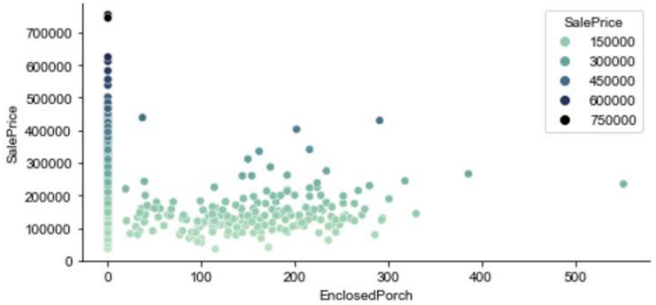
03

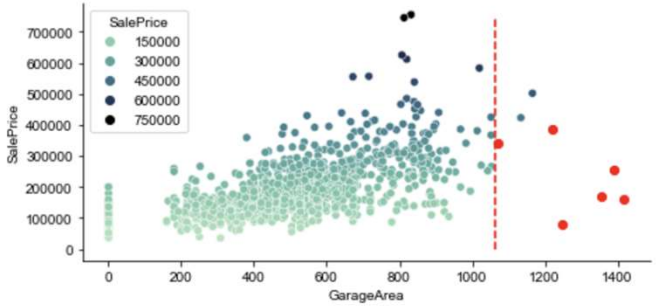
DATA EXPLORATION

VARIABLES NUMÉRICAS





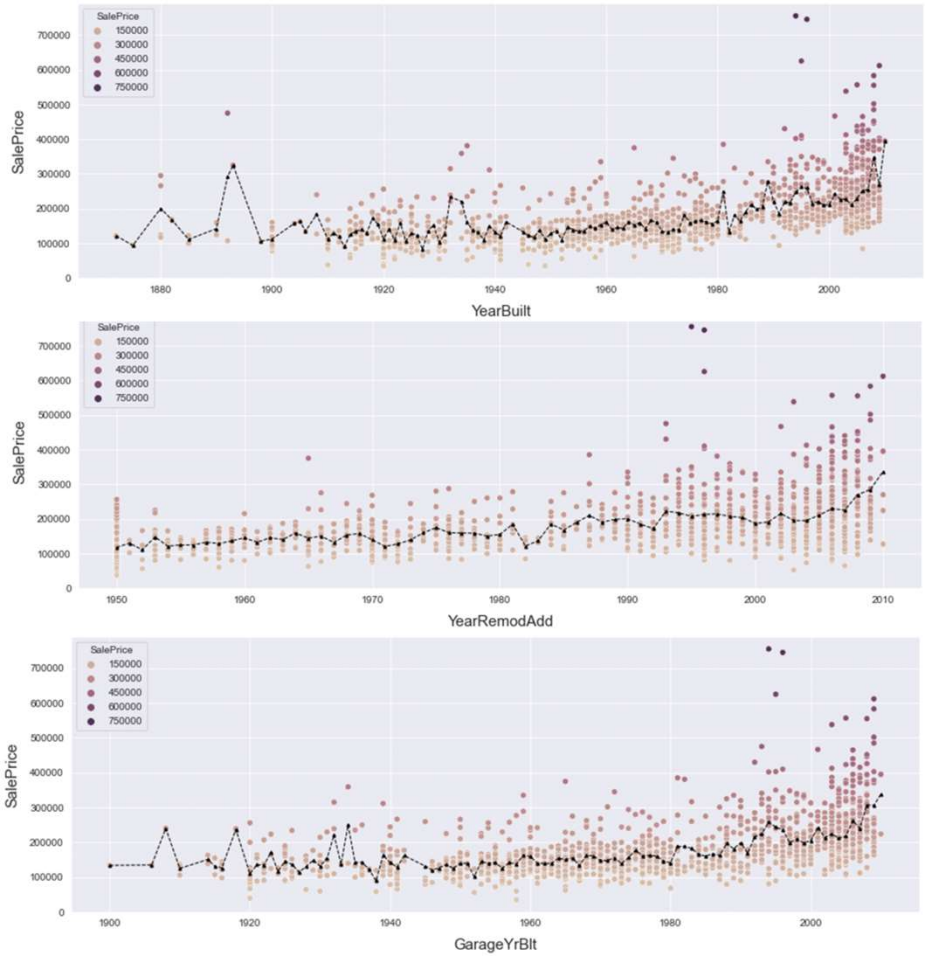




03

DATA EXPLORATION

VARIABLES TEMPORALES



03

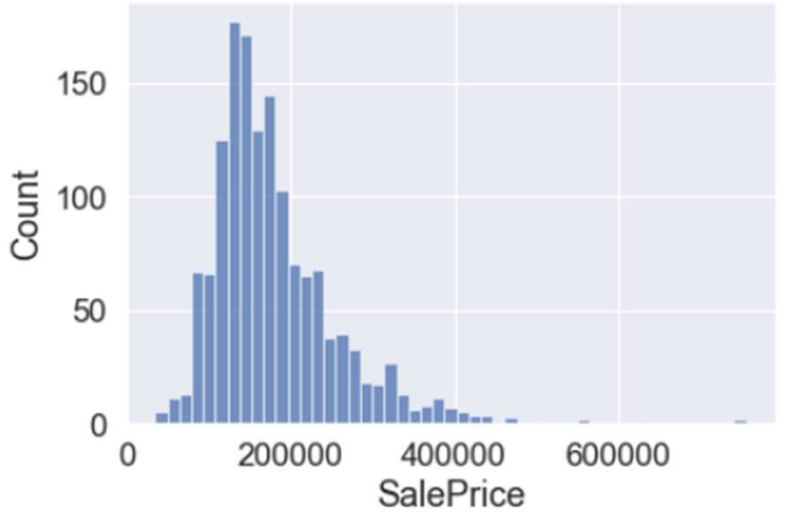
DATA EXPLORATION

VARIABLE TARGET

```
df_train['SalePrice'].describe()
```

```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

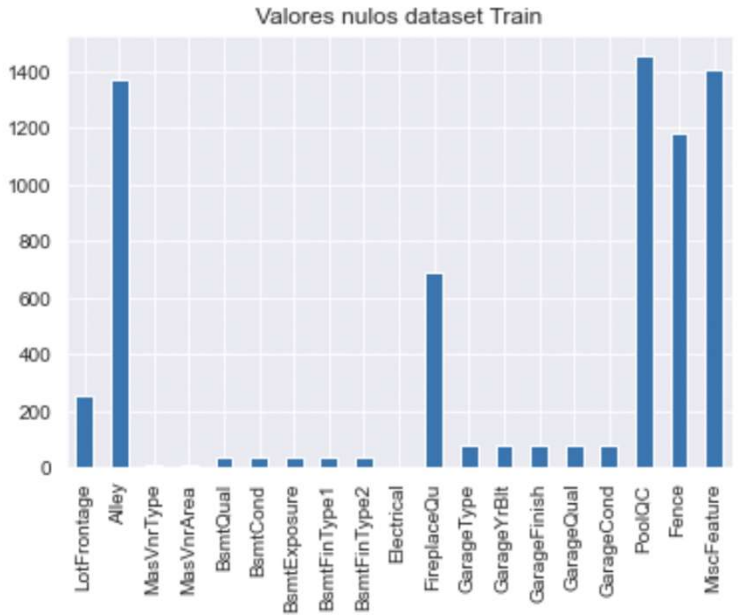
```
sns.histplot(df_train['SalePrice']);
```

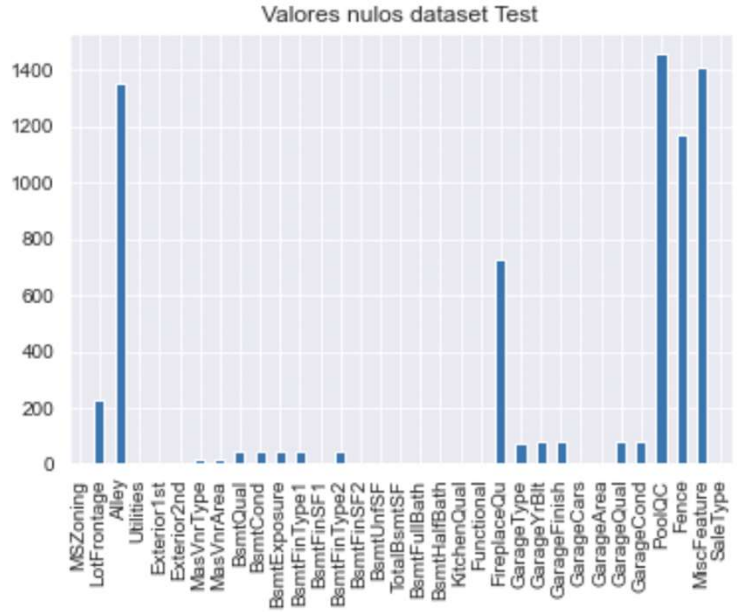


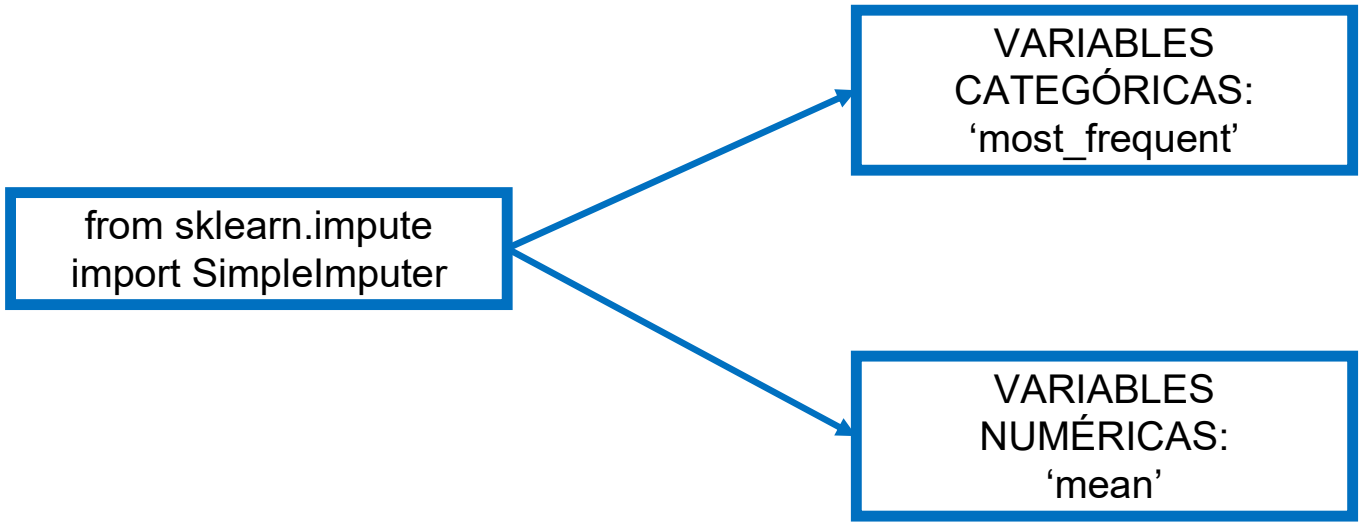
04

DATA CLEANING

VALORES NULOS | **PRUEBAS**






from sklearn.impute
import SimpleImputer
VARIABLES
CATEGÓRICAS:
‘most_frequent’
VARIABLES
NUMÉRICAS:
‘mean’

```
# se cambian los valores ausentes por el valor "No_Fireplace"
df["FireplaceQu"] = df["FireplaceQu"].fillna("No_Fireplace")
# se cambian los valores ausentes por el valor "No_Garage"
df["GarageCond"] = df["GarageCond"].fillna("No_Garage")
# se cambian los valores ausentes por el valor "No_Garage"
df["GarageType"] = df["GarageType"].fillna("No_Garage")
# se cambian los valores ausentes por el valor "No_Garage"
df["GarageFinish"] = df["GarageFinish"].fillna("No_Garage")
# se cambian los valores ausentes por el valor "No_Garage"
df["GarageQual"] = df["GarageQual"].fillna("No_Garage")
# se cambian los valores ausentes por el valor "No_Basement"
df["BsmtExposure"] = df["BsmtExposure"].fillna("No_Basement")
# se cambian los valores ausentes por el valor "No_Basement"
df["BsmtFinType2"] = df["BsmtFinType2"].fillna("No_Basement")
# se cambian los valores ausentes por el valor "No_Basement"
df["BsmtCond"] = df["BsmtCond"].fillna("No_Basement")
# se cambian los valores ausentes por el valor "No_Basement"
df["BsmtQual"] = df["BsmtQual"].fillna("No_Basement")
# se cambian los valores ausentes por el valor "No_Basement"
df["BsmtFinType1"] = df["BsmtFinType1"].fillna("No_Basement")
```

04

DATA CLEANING

VALORES NULOS

MEJOR RESULTADO

```
# Se cambian los 8 valores nulos por el valor 'None' que es el más veces se repite
df["MasVnrType"] = df["MasVnrType"].fillna("None")
# Se cambia el valor nulo por el valor 'SBrkr' que es el más veces se repite
df["Electrical"] = df["Electrical"].fillna("SBrkr")
# Se sustituyen los valores nulos por la media de toda la columna
df["LotFrontage"] = df["LotFrontage"].transform(lambda x: x.fillna(x.mean()))
# Se sustituyen los valores nulos por el año de construcción de la casa 'YearBuilt'
df["GarageYrBlt"] = df["GarageYrBlt"].transform(lambda x: x.fillna(df_train["YearBuilt"]))
# Se sustituyen los 8 valores nulos por 0 debido a que en estos casos se ha
#sustituido el valor de la columna 'MasVnrType' por el valor 'None'
df["MasVnrArea"] = df["MasVnrArea"].fillna(0)
```

04

DATA CLEANING

VALORES NULOS

MEJOR RESULTADO

TEST

```
# Se sustituyen los 2 valores nulos por 0 debido a que es el más frecuente
df_test["BsmtFullBath"] = df_test["BsmtFullBath"].fillna(0)
# Se sustituyen los 2 valores nulos por la media de toda la columna
df_test["BsmtHalfBath"] = df_test["BsmtHalfBath"].transform(lambda x: x.fillna(x.mean()))
# Se sustituye el valor nulo por la media de toda la columna
df_test["TotalBsmtSF"] = df_test["TotalBsmtSF"].transform(lambda x: x.fillna(x.mean()))
# Se sustituye el valor nulo por la media de toda la columna
df_test["BsmtUnfSF"] = df_test["BsmtUnfSF"].transform(lambda x: x.fillna(x.mean()))
# Se sustituye el valor nulo por la media de toda la columna
df_test["BsmtFinSF2"] = df_test["BsmtFinSF2"].transform(lambda x: x.fillna(x.mean()))
# Se sustituye el valor nulos por 2 debido a que es el más frecuente
df_test["GarageCars"] = df_test["GarageCars"].fillna(2)
# Se sustituye el valor nulo por la media de toda la columna
df_test["BsmtFinSF1"] = df_test["BsmtFinSF1"].transform(lambda x: x.fillna(x.mean()))
# Se sustituye el valor nulo por la media de toda la columna
df_test["GarageArea"] = df_test["GarageArea"].transform(lambda x: x.fillna(x.mean()))
# Se sustituye los valores nulos por 'RL' debido a que es el más frecuente
df_test["MSZoning"] = df_test["MSZoning"].fillna('RL')
# Se sustituye los valores nulos por 'AllPub' debido a que es el más frecuente
df_test["Utilities"] = df_test["Utilities"].fillna('AllPub')
# Se sustituye los valores nulos por 'Typ' debido a que es el más frecuente
df_test["Functional"] = df_test["Functional"].fillna('Typ')
# Se sustituye los valores nulos por 'VinylSd' debido a que es el más frecuente
df_test["Exterior2nd"] = df_test["Exterior2nd"].fillna('VinylSd')
# Se sustituye los valores nulos por 'TA' debido a que es el más frecuente
df_test["KitchenQual"] = df_test["KitchenQual"].fillna('TA')
# Se sustituye los valores nulos por 'WD' debido a que es el más frecuente
df_test["SaleType"] = df_test["SaleType"].fillna('WD')
# Se sustituye los valores nulos por 'VinylSd' debido a que es el más frecuente
df_test["Exterior1st"] = df_test["Exterior1st"].fillna('VinylSd')
```

04

DATA CLEANING

OUTLIERS → PRUEBAS

```
from sklearn.ensemble
import IsolationForest
```

```
from sklearn.neighbors
import LocalOutlierFactor
```

OUTLIERS → MEJOR RESULTADO

No se realiza limpieza de outliers

CON POCAS CATEGORÍAS

from category_encoders import OneHotEncoder

CON MUCHAS CATEGORÍAS

from category_encoders import TargetEncoder

04

DATA CLEANING

VARIABLES CATEGORICAS

MEJOR RESULTADO

VARIABLES CON ORDEN NUMÉRICO

Se eliminan las variables con una correlación menor a 0.2 con la variable objetivo

```
rating = {'None': 0, 'Po': 1, 'Fa': 2, 'TA': 3, 'Gd': 4, 'Ex': 5}
ordinal_encoding = {
        'LotShape': {'None': 0, 'Reg': 1, 'IR1': 2, 'IR2': 3, 'IR3': 4},
        'Utilities': {'None': 0, 'ElO': 1, 'NoSeWa': 2, 'NoSeWr': 3, 'AllPub': 4},
        'LandSlope': {'None': 0, 'Gtl': 1, 'Mod': 2, 'Sev': 3},
        'ExterQual': rating,
        'ExterCond': rating,
        'BsmtQual': {'No_Basement': 0, 'Po': 1, 'Fa': 2, 'TA': 3, 'Gd': 4, 'Ex': 5},
        'BsmtCond': {'No_Basement': 0, 'Po': 1, 'Fa': 2, 'TA': 3, 'Gd': 4, 'Ex': 5},
        'BsmtExposure': {'No_Basement': 0, 'No': 1, 'Mn': 2, 'Av': 3, 'Gd': 4},
        'BsmtFinType1': {'No_Basement': 0, 'Unf': 1, 'LwQ': 2, 'Rec': 3, 'BLQ': 4, 'ALQ': 5, 'GLQ': 6},
        'BsmtFinType2': {'No_Basement': 0, 'Unf': 1, 'LwQ': 2, 'Rec': 3, 'BLQ': 4, 'ALQ': 5, 'GLQ': 6},
        'HeatingQC': rating,
        'CentralAir': {'None': 0, 'N': 1, 'Y': 2},
        'Electrical': {'None': 0, 'Mix': 1, 'FuseP': 2, 'FuseF': 3, 'FuseA': 4, 'SBrkr': 5},
        'KitchenQual': rating,
        'Functional': {'None': 0, 'Sal': 1, 'Sev': 2, 'Maj2': 3, 'Maj1': 4, 'Mod': 5,
                       'Min2': 6, 'Min1': 7, 'Typ': 8},
        'FireplaceQu': {'No_Fireplace': 0, 'Po': 1, 'Fa': 2, 'TA': 3, 'Gd': 4, 'Ex': 5},
        'GarageFinish': {'No_Garage': 0, 'Unf': 1, 'RFn': 2, 'Fin': 3},
        'GarageQual': {'No_Garage': 0, 'Po': 1, 'Fa': 2, 'TA': 3, 'Gd': 4, 'Ex': 5},
        'GarageCond': {'No_Garage': 0, 'Po': 1, 'Fa': 2, 'TA': 3, 'Gd': 4, 'Ex': 5},
        'PavedDrive': {'None': 0, 'N': 1, 'P': 2, 'Y': 3}
    }
```

```
[('ExterQual', 0.6826392416562593),
 ('KitchenQual', 0.6595997207286625),
 ('BsmtQual', 0.5852071991725201),
 ('GarageFinish', 0.5492467563332124),
 ('FireplaceQu', 0.5204376059504018),
 ('HeatingQC', 0.4276487073988035),
 ('BsmtExposure', 0.37469622100088673),
 ('BsmtFinType1', 0.30490787307063333),
 ('GarageQual', 0.2738390740062235),
 ('GarageCond', 0.2631907844703991),
 ('CentralAir', 0.2513281638401551),
 ('PavedDrive', 0.23135695225722716),
 ('BsmtCond', 0.21260715648557876),
 ('PoolQC', 0.11548430473054794),
 ('Functional', 0.10761889324399436),
 ('Street', 0.04103553550004947),
 ('ExterCond', 0.018899118482413036),
 ('BsmtFinType2', -0.005323160673474943),
 ('LandSlope', -0.05115224817946656),
 ('Fence', -0.146941526435884),
 ('LotShape', -0.2677593139178232)]
```

04

DATA CLEANING

VARIABLES CATEGORICAS

MEJOR RESULTADO

VARIABLES SIN ORDEN NUMÉRICO

```
['MSSubClass',
 'MSZoning',
 'Alley',
 'LandContour',
 'Utilities',
 'LotConfig',
 'Neighborhood',
 'Condition1',
 'Condition2',
 'BldgType',
 'HouseStyle',
 'RoofStyle',
 'RoofMatl',
 'Exterior1st',
 'Exterior2nd',
 'MasVnrType',
 'Foundation',
 'Heating',
 'Electrical',
 'GarageType',
 'MiscFeature',
 'MoSold',
 'SaleType',
 'SaleCondition']
```

from category_encoders import OneHotEncoder

Una vez realizado OneHotEncoder, se eliminan las columnas que tienen menos de 42 apariciones

```
# Se cuentan las columnas con pocas apariciones
cont = 0
list_poca_apa = []
y_col = df_train['SalePrice']
df_train = df_train.drop(['SalePrice'], axis=1)
for x in df_train.columns:
    if (df_train[x].sum()<42) & (df_test[x].sum()<42):
        cont = cont + 1
        list_poca_apa.append(x)
```

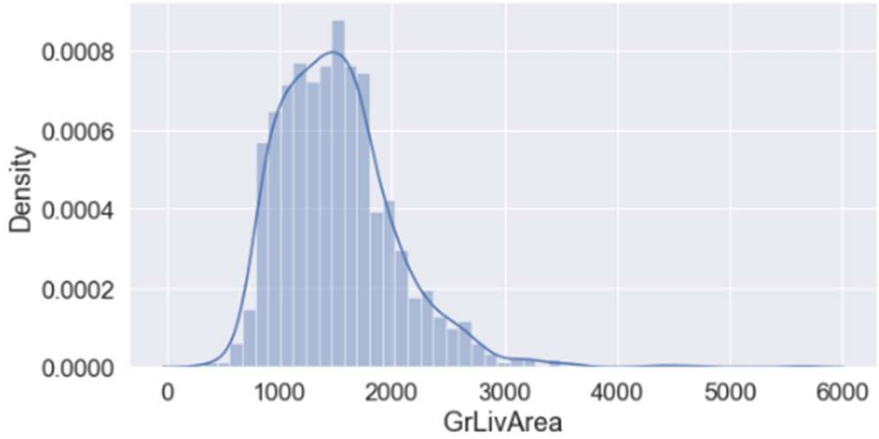
04

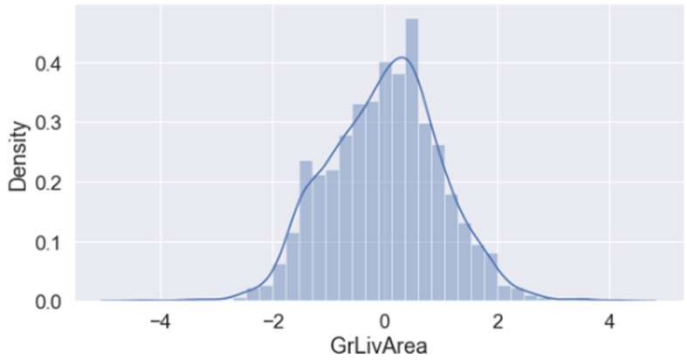
DATA CLEANING

SKEWNESS

PRUEBAS

VARIABLES NUMÉRICAS:
BOX COX





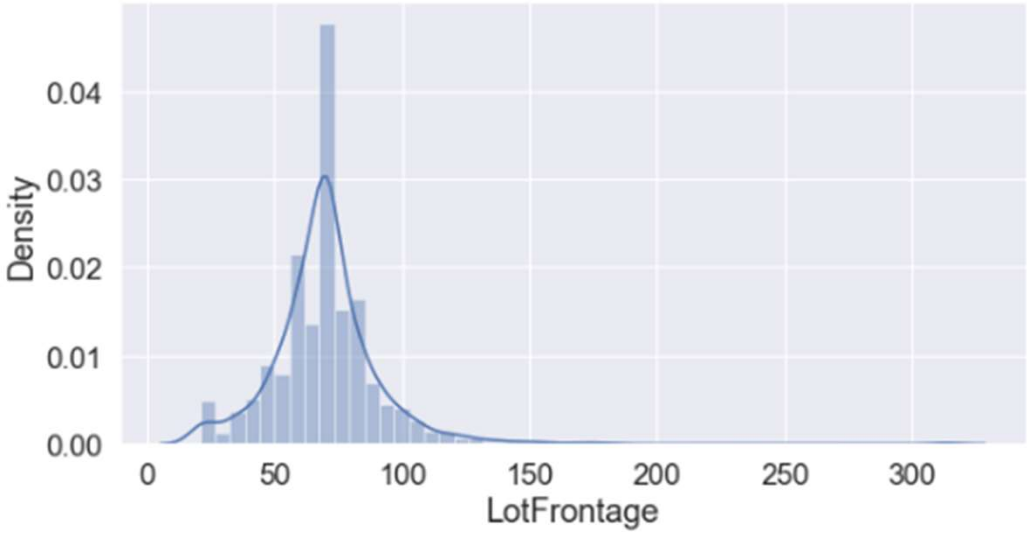
04

DATA CLEANING

SKEWNESS

MEJOR RESULTADO

VARIABLES NUMÉRICAS:
LOG TRANSFORMATION




```
df_train['LotFrontage'] = np.log1p(df_train['LotFrontage'])
df_test['LotFrontage'] = np.log1p(df_test['LotFrontage'])
```

04

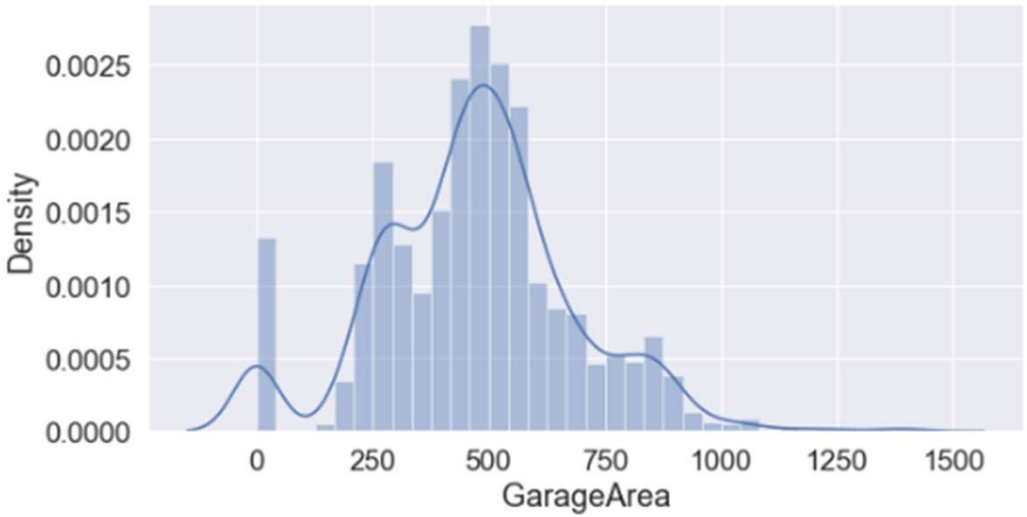
DATA CLEANING

SKEWNESS

MEJOR RESULTADO

VARIABLES NUMÉRICAS:
SEGMENTAR VARIABLES

```
def Gar_category(cat):
    if cat <= 250:
        return 1
    elif cat <= 500 and cat > 250:
        return 2
    elif cat <= 1000 and cat > 500:
        return 3
    return 4
```



04

DATA CLEANING

MEJOR RESULTADO

VARIABLES TEMPORALES:
CREACIÓN DE VARIABLES

```
df_train['YearBuilt_age'] = df_train['YearBuilt'].apply(lambda x: 0 if x==0 else (2022 - x))
df_test['YearBuilt_age'] = df_test['YearBuilt'].apply(lambda x: 0 if x==0 else (2022 - x))
df_train['YearRemodAdd_age'] = df_train['YearRemodAdd'].apply(lambda x: 0 if x==0 else (2022 - x))
df_test['YearRemodAdd_age'] = df_test['YearRemodAdd'].apply(lambda x: 0 if x==0 else (2022 - x))
df_train['YrSold_age'] = df_train['YrSold'].apply(lambda x: 0 if x==0 else (2022 - x))
df_test['YrSold_age'] = df_test['YrSold'].apply(lambda x: 0 if x==0 else (2022 - x))
df_train['GarageYrBlt_age'] = df_train['GarageYrBlt'].apply(lambda x: 0 if x==0 else (2022 - x))
df_test['GarageYrBlt_age'] = df_test['GarageYrBlt'].apply(lambda x: 0 if x==0 else (2022 - x))

df_train['renovated'] = df_train['YearRemodAdd'] + df_train['YearBuilt']
df_test['renovated'] = df_test['YearRemodAdd'] + df_test['YearBuilt']

df_train = df_train.drop(['YearBuilt', 'YearRemodAdd', 'YrSold', 'GarageYrBlt'], axis=1)
df_test = df_test.drop(['YearBuilt', 'YearRemodAdd', 'YrSold', 'GarageYrBlt'], axis=1)
```

05

FEATURE ENGINEERING

PRUEBAS

CREACIÓN DE VARIABLES

```
df['haspool'] = df['PoolArea'].apply(lambda x: 1 if x > 0 else 0)
df['has2ndfloor'] = df['2ndFlrSF'].apply(lambda x: 1 if x > 0 else 0)
df['hasgarage'] = df['GarageArea'].apply(lambda x: 1 if x > 0 else 0)
df['hasbsmt'] = df['TotalBsmtSF'].apply(lambda x: 1 if x > 0 else 0)
df['hasfireplace'] = df['Fireplaces'].apply(lambda x: 1 if x > 0 else 0)
```

```
df['TotalBsmtBath'] = df['BsmtFullBath']+(1/2)*df['BsmtHalfBath']
df['TotalBath'] = df['FullBath']+(1/2)*df['HalfBath']
df['TotalSf'] = df['1stFlrSF']+df['2ndFlrSF']+df['TotalBsmtSF']
df['TotalSqrFootage'] = df['BsmtFinSF1']+df['BsmtFinSF2']+df['1stFlrSF']+df['2ndFlrSF']
```

05

FEATURE ENGINEERING

MEJOR RESULTADO

CREACIÓN DE VARIABLES

```
df_train["SqFtPerRoom"] = df_train["GrLivArea"] / (df_train["TotRmsAbvGrd"] + df_train["FullBath"] +
                                                   df_train["HalfBath"] + df_train["KitchenAbvGr"])

df_train['TotalBath'] = df_train['FullBath'] + df_train['BsmtFullBath'] + 0.5 * df_train['BsmtHalfBath'] +
                        0.5 * df_train['HalfBath']

df_train['HighQualSF'] = df_train['1stFlrSF'] + df_train['2ndFlrSF']
```

05

FEATURE ENGINEERING

PRUEBAS

LASSO PARA VER LA IMPORTANCIA DE VARIABLES

```
lasso=Lasso(alpha=0.001)
lasso.fit(X_train[variables_numericas],y_train)
FI_lasso = pd.DataFrame({"Feature Importance":lasso.coef_}, index=X_train[variables_numericas].columns)
FI_lasso['feature imp abs']=abs(FI_lasso["Feature Importance"])
FI_lasso.sort_values("feature imp abs",ascending=False)
```

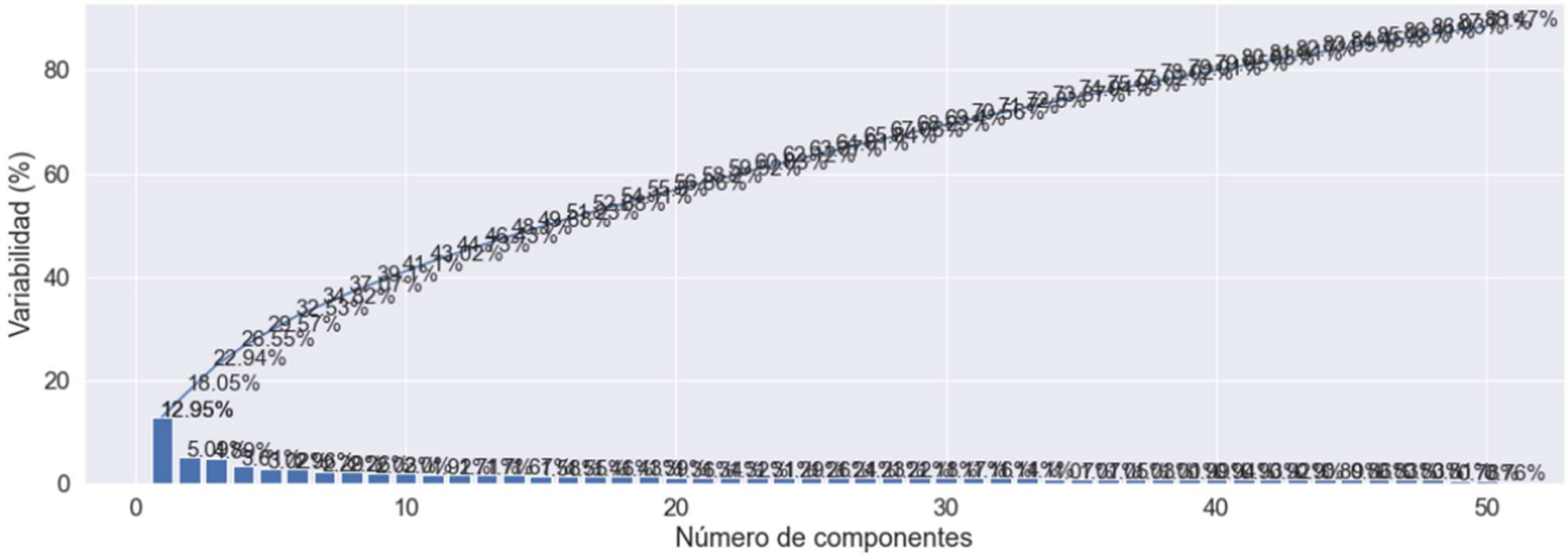
```
variables_to_drop_lasso=['MSSubClass', 'LotArea', 'MasVnrArea', 'BsmtHalfBath', 'BedroomAbvGr',
       'KitchenAbvGr', 'GarageYrBlt', 'OpenPorchSF', 'MiscVal', 'MoSold',
       'YrSold']
```

05

FEATURE ENGINEERING

PRUEBAS

PCA todas las variables numéricas

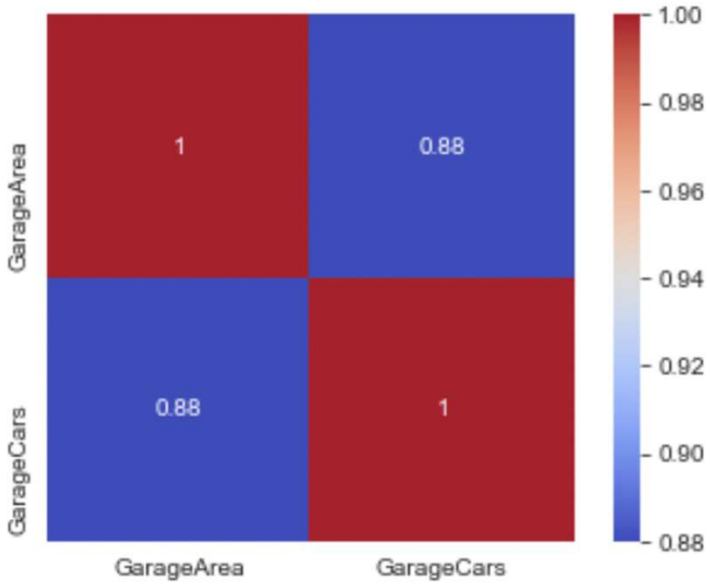


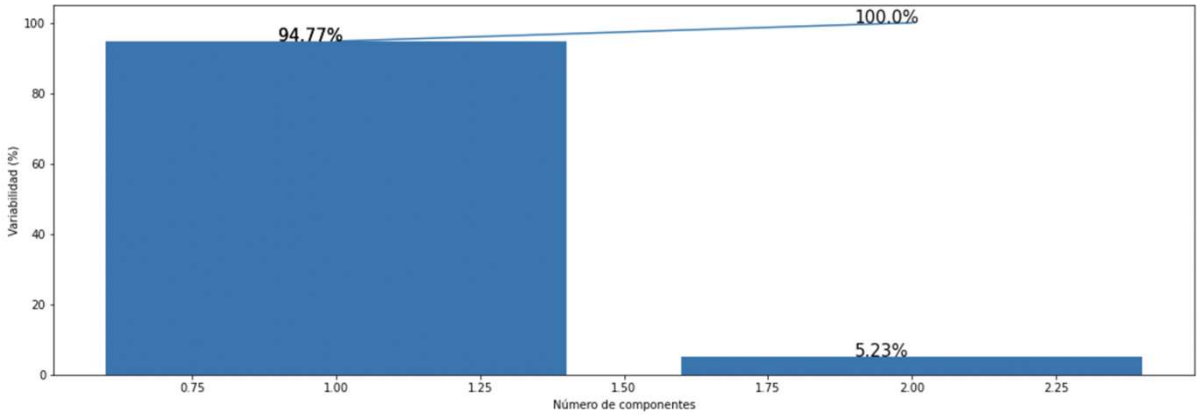
05

FEATURE ENGINEERING

PRUEBAS

PCA Garage Cars & Garage Area



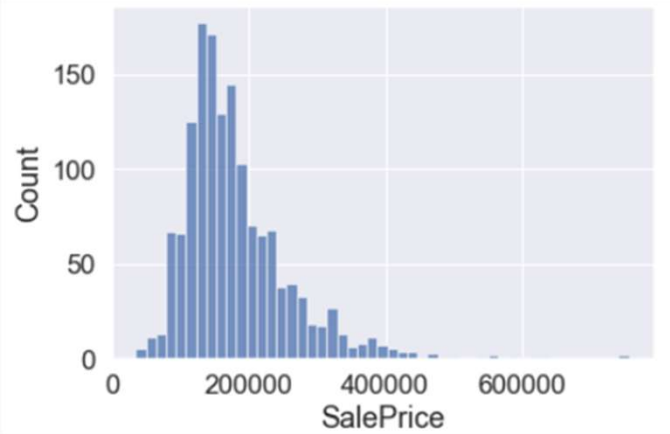


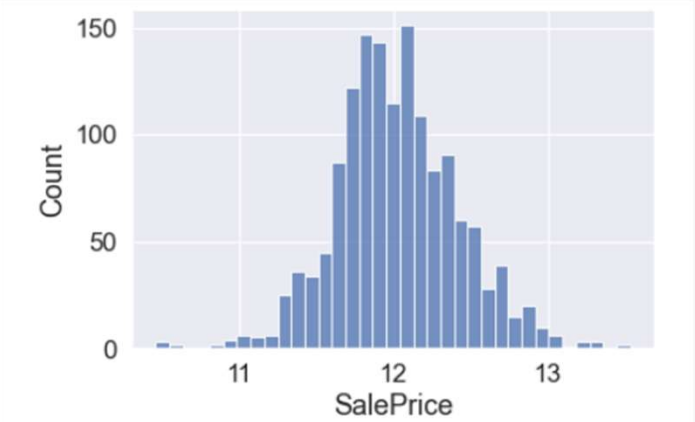
05

FEATURE ENGINEERING

MEJOR RESULTADO

LOG TRANSFORMATION A LA VARIABLE TARGET





06

PREDICTIVE MODELING

PRUEBAS

LASSO

RIDGE

SVR

LGBM REGRESSOR

ELASTIC NET

XGB REGRESSOR

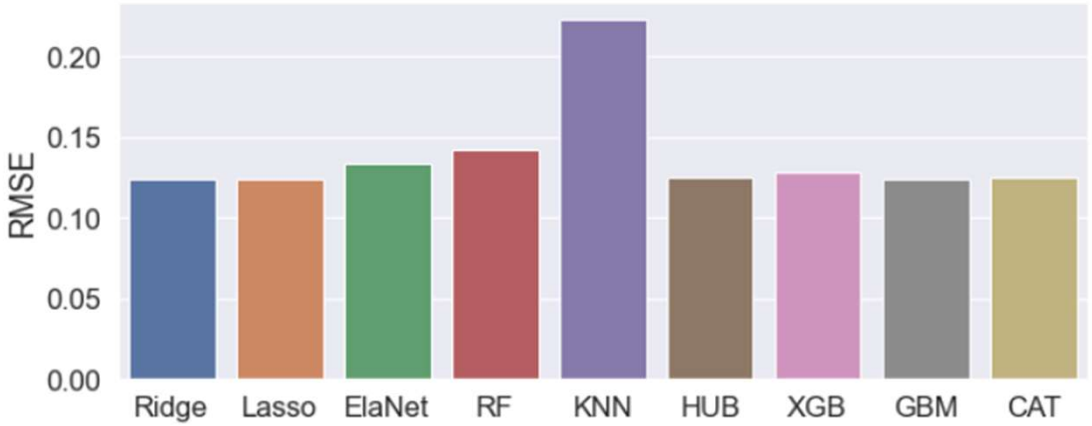
AVERAGING MODELS:

- LGMR
- Lasso
- Ridge
- XGBR

RANDOM FOREST

HISTGRADIENT BOOST REGRESSOR

GRADIENT BOOST REGRESSOR



MEJOR RESULTADO

```
estimators = [ ('ridge', Ridge()), ('lasso', Lasso())]
reg = StackingRegressor(estimators=estimators,
            final_estimator=Ridge())
grid_stack1 = reg.fit(X_train, y_train)
r2_score_stack1 = grid_stack1.score(X_test, y_test)
```

from sklearn.ensemble import StackingRegressor

```
estimators = [('cat', CatBoostRegressor()), ('xgb', XGBRegressor())]
reg = StackingRegressor(estimators=estimators,
            final_estimator=CatBoostRegressor())
grid_stack4 = reg.fit(X_train, y_train)
r2_score_stack4 = grid_stack4.score(X_test, y_test)
```

MEJOR RESULTADO

BLENDING MODELS:

```
y_xgb = grid_xgb.predict(X_test)
y_gbm = grid_gbm.predict(X_test)
y_cat = grid_cat.predict(X_test)
y_stack1 = grid_stack1.predict(X_test)
y_stack4 = grid_stack4.predict(X_test)
y_mean_models = (0.35 * y_stack1 + 0.15 * y_xgb + 0.15 * y_gbm + 0.1 * y_cat + 0.25 * y_stack4) / 1.0
```

CLASIFICACIÓN

PUESTO	SCORE	JUGADORES TOTALES	PORCENTAJE
105	0.11574	4186	2%