Course Project: Supervised Machine Learning Regression

Objective:

The objective of this report is to deepen in the interpretation of the data collected corresponding to housing sales in Ames Iowa USA. From the results obtained, we will be able to analyze the influence of the different features to determine the sailing price. It is relevant to determine the influences of the study variables. With this information, we will be able to maximize the benefit of future investments in real estate projects in the area.

Description of the Data Set and its attributes

The study data set is the one provided in the course. Among the main attributes of the data can be found those described below.

Predictor

- SalePrice: The property's sale price in dollars.

Features

- MoSold: Month Sold
- YrSold: Year Sold
- SaleType: Type of sale
- SaleCondition: Condition of sale
- MSSubClass: The building class
- MSZoning: The general zoning classification

Exploratory Data Analisis

Initial plan for data exploration and actions for data cleaning and feature engineering.

Since we start from the base of the EDA Project data set, it is already correct concerning Data Cleaning, the data set does not have null values. However, we will do the corresponding variables transformations to carry out the different linear regressions of the adequate tide. Then we will preliminarily analyze the existing correlations between the features, to generate a better understanding of linear regression.

Data Cleaning and Feature Engineering

In [171…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```python
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from scipy import stats
from IPython.display import display
```

Analyzing the data set

In [172…

```python
filepath = 'Ames_Housing_Sales.csv'
data = pd.read_csv(filepath)
display(data.head())
print(data.info())
```

	1stFlrSF	2ndFlrSF	3SsnPorch	Alley	BedroomAbvGr	BldgType	BsmtCond	BsmtExposure	BsmtFin
0	856.0	854.0	0.0	None	3	1Fam	TA	No	70
1	1262.0	0.0	0.0	None	3	1Fam	TA	Gd	97
2	920.0	866.0	0.0	None	3	1Fam	TA	Mn	48
3	961.0	756.0	0.0	None	3	1Fam	Gd	No	21
4	1145.0	1053.0	0.0	None	4	1Fam	TA	Av	65

5 rows × 80 columns

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1379 entries, 0 to 1378
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   1stFlrSF       1379 non-null   float64
 1   2ndFlrSF       1379 non-null   float64
 2   3SsnPorch      1379 non-null   float64
 3   Alley          1379 non-null   object 
 4   BedroomAbvGr   1379 non-null   int64  
 5   BldgType       1379 non-null   object 
 6   BsmtCond       1379 non-null   object 
 7   BsmtExposure   1379 non-null   object 
 8   BsmtFinSF1     1379 non-null   float64
 9   BsmtFinSF2     1379 non-null   float64
 10  BsmtFinType1   1379 non-null   object 
 11  BsmtFinType2   1379 non-null   object 
 12  BsmtFullBath   1379 non-null   int64  
 13  BsmtHalfBath   1379 non-null   int64  
 14  BsmtQual       1379 non-null   object 
 15  BsmtUnfSF      1379 non-null   float64
 16  CentralAir     1379 non-null   object 
 17  Condition1     1379 non-null   object 
 18  Condition2     1379 non-null   object 
 19  Electrical     1379 non-null   object 
 20  EnclosedPorch  1379 non-null   float64
 21  ExterCond      1379 non-null   object 
 22  ExterQual      1379 non-null   object 
 23  Exterior1st    1379 non-null   object 
 24  Exterior2nd    1379 non-null   object 
 25  Fence          1379 non-null   object 
```

```
 26  FireplaceQu    1379 non-null   object
 27  Fireplaces     1379 non-null   int64
 28  Foundation     1379 non-null   object
 29  FullBath       1379 non-null   int64
 30  Functional     1379 non-null   object
 31  GarageArea     1379 non-null   float64
 32  GarageCars     1379 non-null   int64
 33  GarageCond     1379 non-null   object
 34  GarageFinish   1379 non-null   object
 35  GarageQual     1379 non-null   object
 36  GarageType     1379 non-null   object
 37  GarageYrBlt    1379 non-null   float64
 38  GrLivArea      1379 non-null   float64
 39  HalfBath       1379 non-null   int64
 40  Heating        1379 non-null   object
 41  HeatingQC      1379 non-null   object
 42  HouseStyle     1379 non-null   object
 43  KitchenAbvGr   1379 non-null   int64
 44  KitchenQual    1379 non-null   object
 45  LandContour    1379 non-null   object
 46  LandSlope      1379 non-null   object
 47  LotArea        1379 non-null   float64
 48  LotConfig      1379 non-null   object
 49  LotFrontage    1379 non-null   float64
 50  LotShape       1379 non-null   object
 51  LowQualFinSF   1379 non-null   float64
 52  MSSubClass     1379 non-null   int64
 53  MSZoning       1379 non-null   object
 54  MasVnrArea     1379 non-null   float64
 55  MasVnrType     1379 non-null   object
 56  MiscFeature    1379 non-null   object
 57  MiscVal        1379 non-null   float64
 58  MoSold         1379 non-null   int64
 59  Neighborhood   1379 non-null   object
 60  OpenPorchSF    1379 non-null   float64
 61  OverallCond    1379 non-null   int64
 62  OverallQual    1379 non-null   int64
 63  PavedDrive     1379 non-null   object
 64  PoolArea       1379 non-null   float64
 65  PoolQC         1379 non-null   object
 66  RoofMatl       1379 non-null   object
 67  RoofStyle      1379 non-null   object
 68  SaleCondition  1379 non-null   object
 69  SaleType       1379 non-null   object
 70  ScreenPorch    1379 non-null   float64
 71  Street         1379 non-null   object
 72  TotRmsAbvGrd   1379 non-null   int64
 73  TotalBsmtSF    1379 non-null   float64
 74  Utilities      1379 non-null   object
 75  WoodDeckSF     1379 non-null   float64
 76  YearBuilt      1379 non-null   int64
 77  YearRemodAdd   1379 non-null   int64
 78  YrSold         1379 non-null   int64
 79  SalePrice      1379 non-null   float64
dtypes: float64(21), int64(16), object(43)
memory usage: 862.0+ KB
None
```

There is no missing data, since this data set have been previously modified

In [173…
```
data.dtypes.value_counts()
```

Out[173…
```
object     43
float64    21
int64      16
dtype: int64
```

We get the columns with the data type corresponding to objects, useful later for One-Hot Encoding.

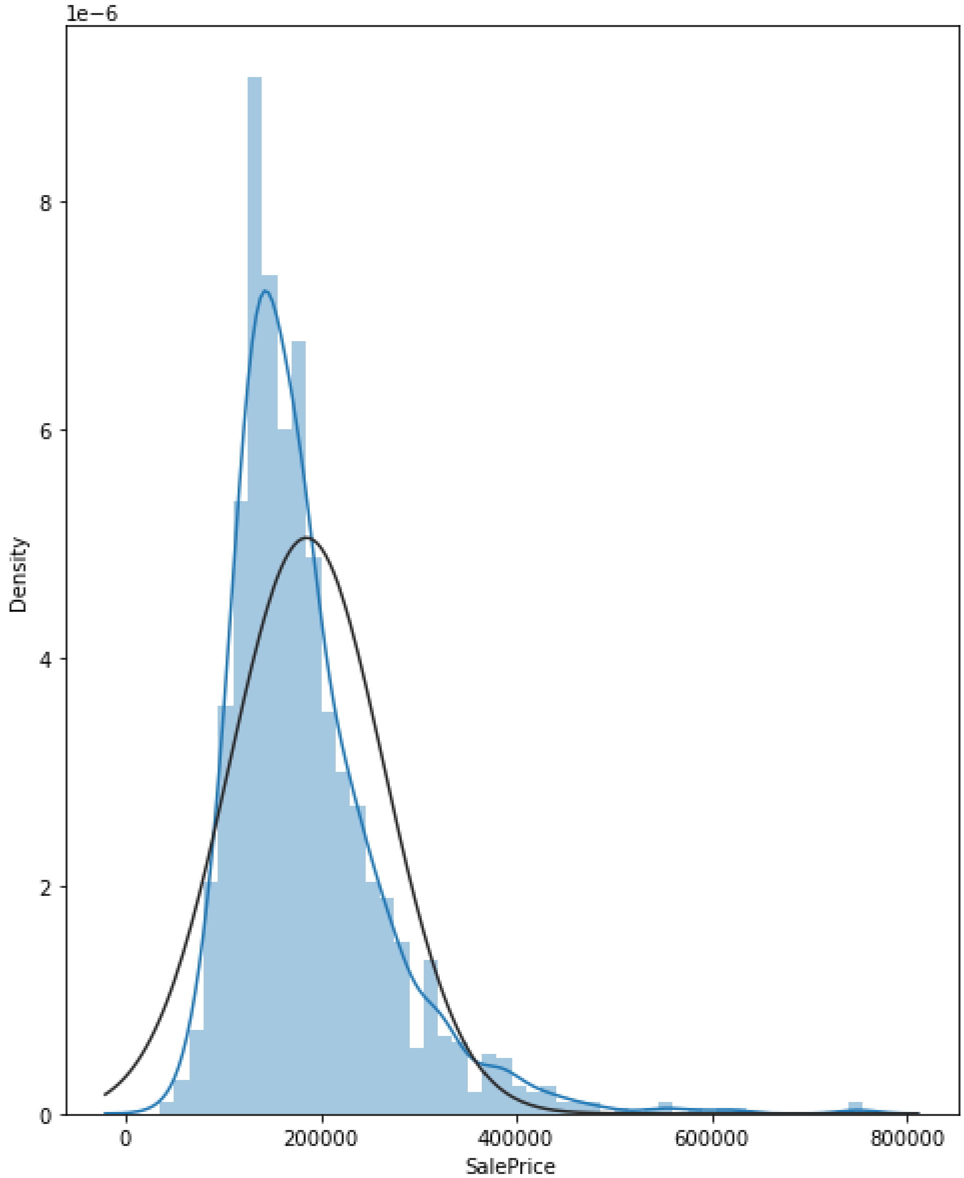
In [174…
```
object_columns = data.columns[data.dtypes == object]
object_columns.values
```

Out[174…
```
array(['Alley', 'BldgType', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',
       'BsmtFinType2', 'BsmtQual', 'CentralAir', 'Condition1',
       'Condition2', 'Electrical', 'ExterCond', 'ExterQual',
       'Exterior1st', 'Exterior2nd', 'Fence', 'FireplaceQu', 'Foundation',
       'Functional', 'GarageCond', 'GarageFinish', 'GarageQual',
       'GarageType', 'Heating', 'HeatingQC', 'HouseStyle', 'KitchenQual',
       'LandContour', 'LandSlope', 'LotConfig', 'LotShape', 'MSZoning',
       'MasVnrType', 'MiscFeature', 'Neighborhood', 'PavedDrive',
       'PoolQC', 'RoofMatl', 'RoofStyle', 'SaleCondition', 'SaleType',
       'Street', 'Utilities'], dtype=object)
```

Analyzing the target value: Sale Price

In [175…
```
sns.distplot(data['SalePrice'], fit=stats.norm);
print(stats.normaltest(data.SalePrice),'\n', 'Skew: ', data.SalePrice.skew(), '\n', 'Ku
```

```
C:\Users\enzof\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please adap
t your code to use either `displot` (a figure-level function with similar flexibility) o
r `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
NormaltestResult(statistic=594.3267259061613, pvalue=8.781955774010152e-130)
 Skew:  1.935362098363132
 Kurt:  6.735649337267559
```



Normalizing the Sale Price.

In [176…

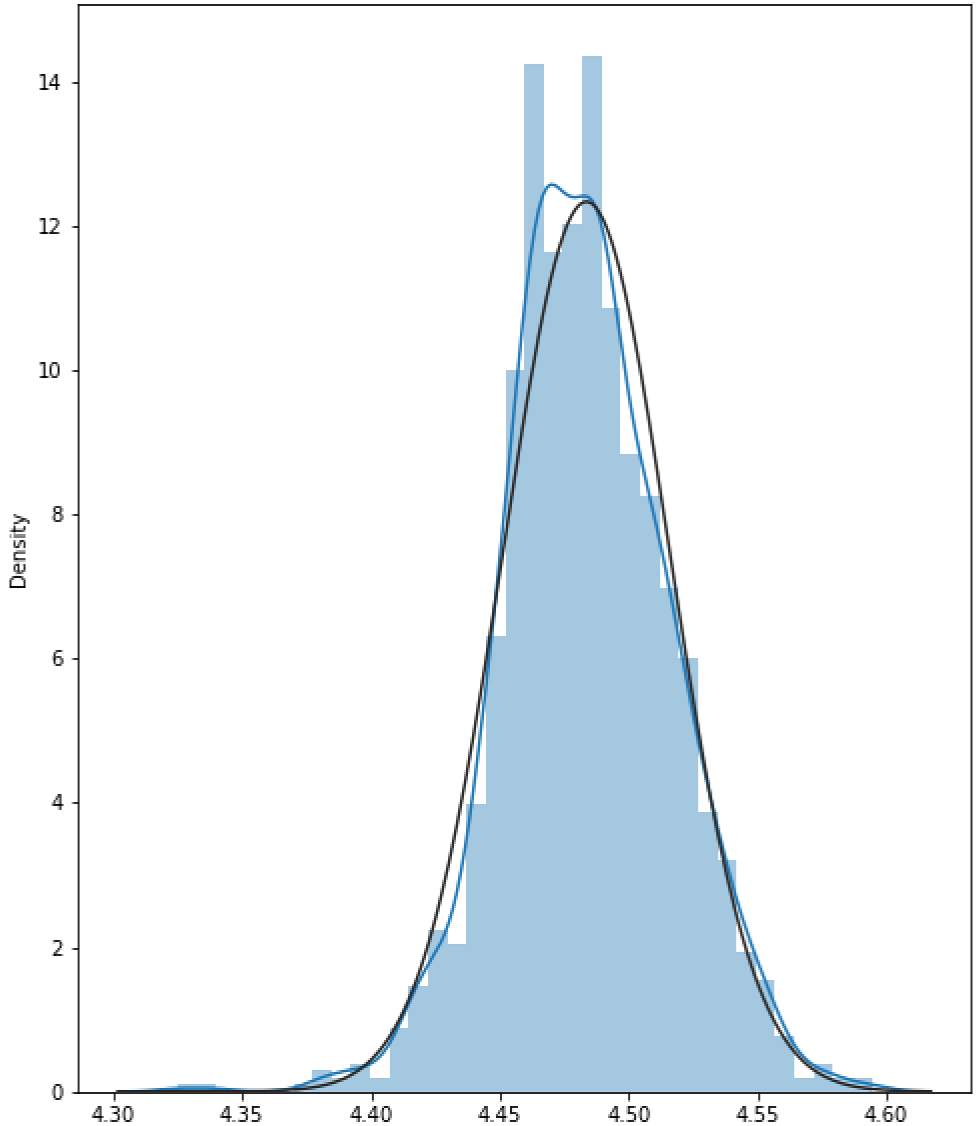
```
#Box-Cox
bc_SalePrice = stats.boxcox(data.SalePrice)
boxcox_SalePrice = bc_SalePrice[0]
lam = bc_SalePrice[1]
print('Lambda: ', lam)

sns.distplot(boxcox_SalePrice, fit=stats.norm);

df_bc_SalePrice = pd.DataFrame(bc_SalePrice[0])[0]
print(stats.normaltest(bc_SalePrice[0]), '\n', 'Skew: ', df_bc_SalePrice.skew(), '\n',
# skew_limit = 0.75
```

```
Lambda:  -0.2038831773965207
NormaltestResult(statistic=20.60421626101897, pvalue=3.356226691547964e-05)
 Skew:  -0.018305129116178546
 Kurt:  0.8031335636865577
C:\Users\enzof\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please adap
t your code to use either `displot` (a figure-level function with similar flexibility) o
```

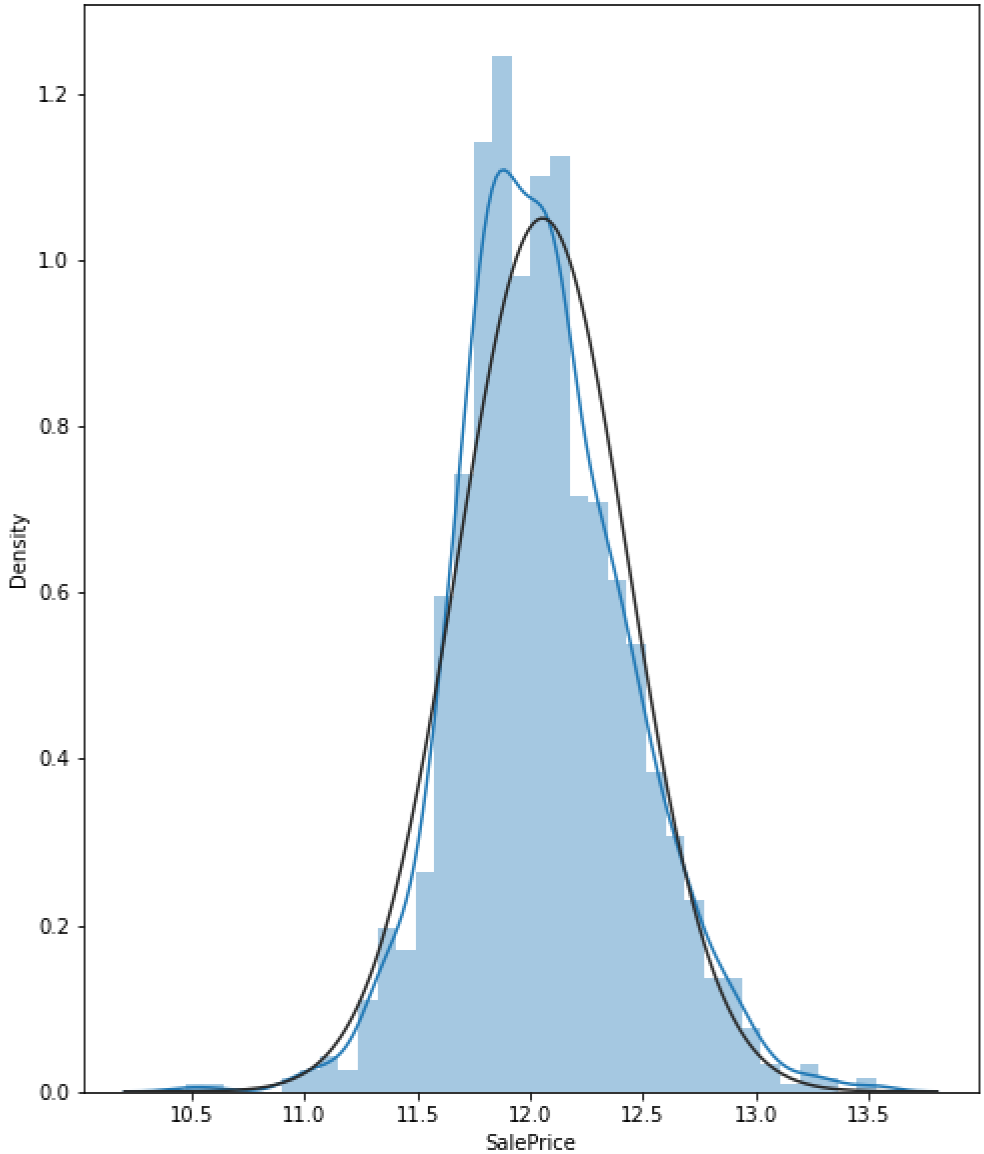
```
r `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [177…

```
#log1p
log_SalePrice = data.SalePrice.apply(np.log1p)
sns.distplot(log_SalePrice, fit=stats.norm);
print(stats.normaltest(log_SalePrice), '\n', 'Skew: ', log_SalePrice.skew(), '\n', 'Kur
# skew_limit = 0.75
```

```
C:\Users\enzof\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please adap
t your code to use either `displot` (a figure-level function with similar flexibility) o
r `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
NormaltestResult(statistic=34.99556530598817, pvalue=2.5165730895928392e-08)
 Skew:  0.2901665026629582
 Kurt:  0.6856843282078717
```



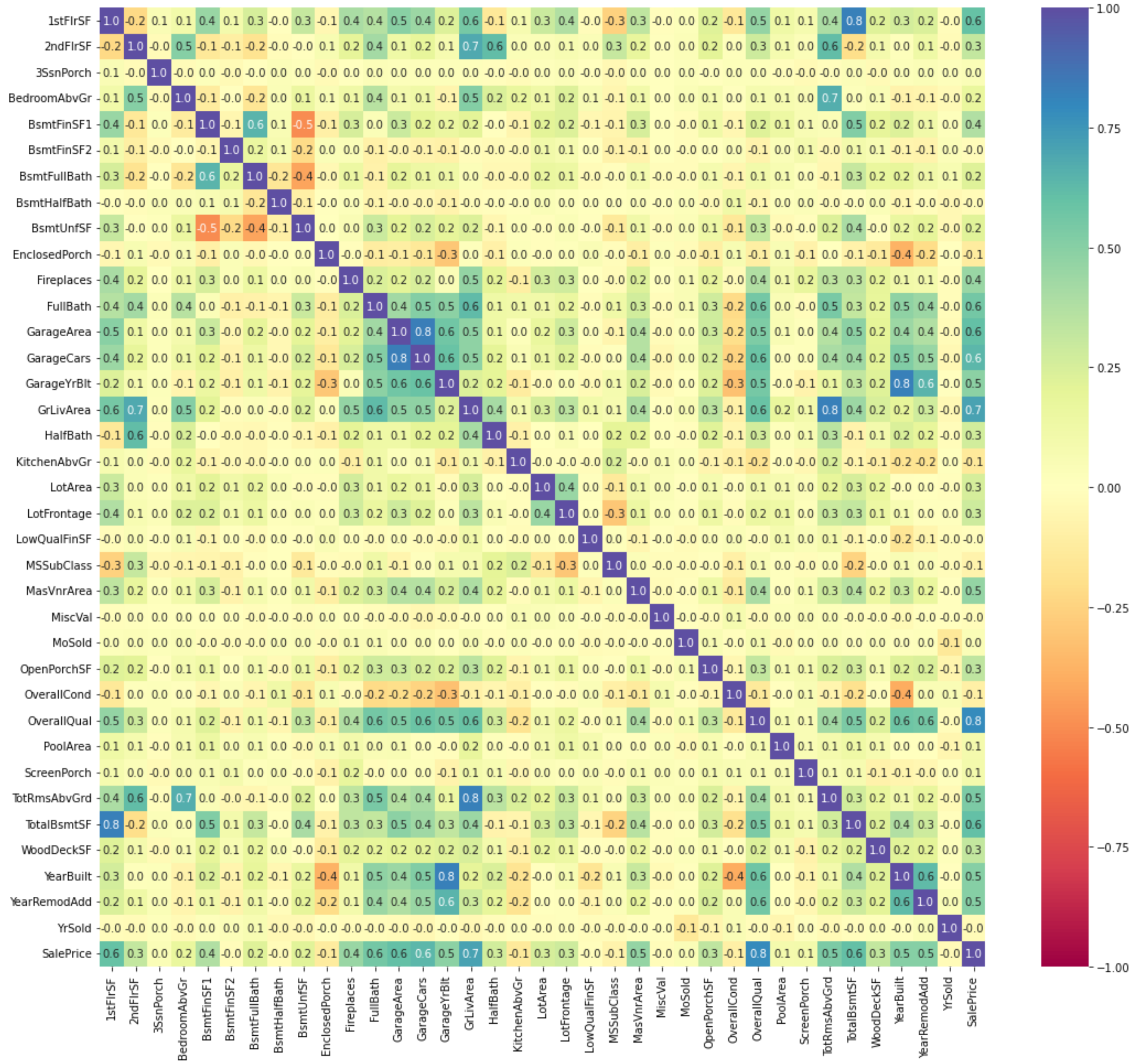
We are going to analyze the correlations between variables in order to determine multicollinearity.

In [178…

```
correlation = data.corr()
f, ax = plt.subplots(figsize=(18, 16))
sns.heatmap(correlation, annot=True, vmin=-1, vmax=1, fmt=".1f", cmap="Spectral")
```

Out[178…

```
<AxesSubplot:>
```



In [179…

```
correlation.sort_values(["SalePrice"], ascending = False, inplace = True)
print(correlation.SalePrice.apply(abs))
```

```
SalePrice       1.000000
OverallQual     0.787228
GrLivArea       0.708172
GarageCars      0.637095
GarageArea      0.608405
TotalBsmtSF     0.603583
1stFlrSF        0.594935
FullBath        0.556550
TotRmsAbvGrd    0.538309
YearBuilt       0.507584
YearRemodAdd    0.505434
GarageYrBlt     0.486362
MasVnrArea      0.463139
Fireplaces      0.448877
BsmtFinSF1      0.375563
OpenPorchSF     0.333036
2ndFlrSF        0.313336
WoodDeckSF      0.312631
```

```
LotFrontage      0.281976
HalfBath         0.270721
LotArea          0.252921
BsmtFullBath     0.225988
BsmtUnfSF        0.213135
BedroomAbvGr     0.164655
ScreenPorch      0.099453
PoolArea         0.091518
MoSold           0.043749
3SsnPorch        0.039226
LowQualFinSF     0.008364
MiscVal          0.017933
BsmtFinSF2       0.023243
BsmtHalfBath     0.025651
YrSold           0.026726
MSSubClass       0.077707
OverallCond      0.095278
EnclosedPorch    0.120164
KitchenAbvGr     0.135574
Name: SalePrice, dtype: float64
```

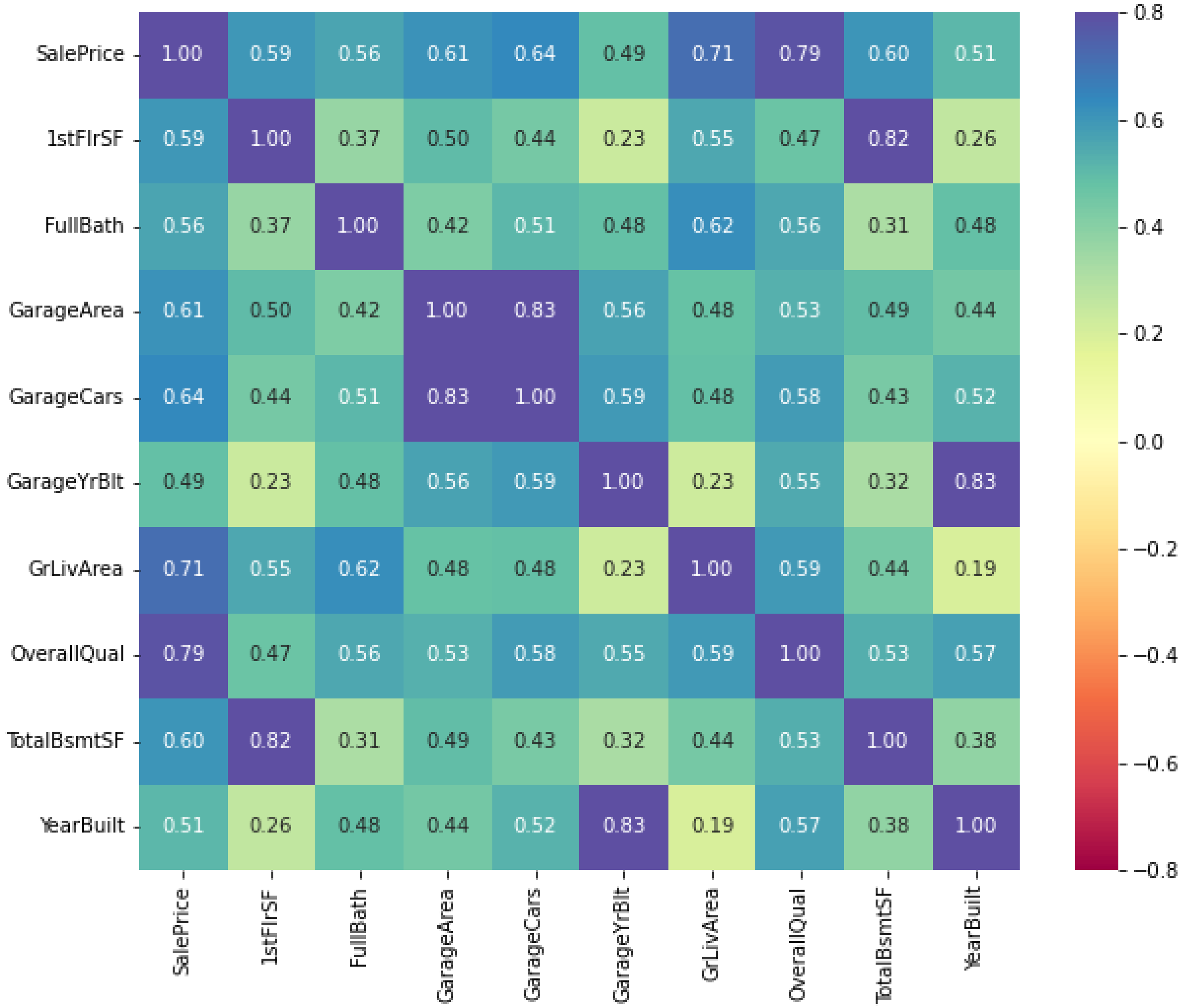
We are going to analyze in more depth the features with high correlation with the terget value.

In [180…

```
columns = ['SalePrice','1stFlrSF','FullBath','GarageArea','GarageCars','GarageYrBlt','G
correlation = data[columns].corr()
f, ax = plt.subplots(figsize=(10, 8))
sns.heatmap(correlation, annot=True, vmin=-0.8, vmax=0.8, fmt=".2f", cmap="Spectral")
```

Out[180…

```
<AxesSubplot:>
```



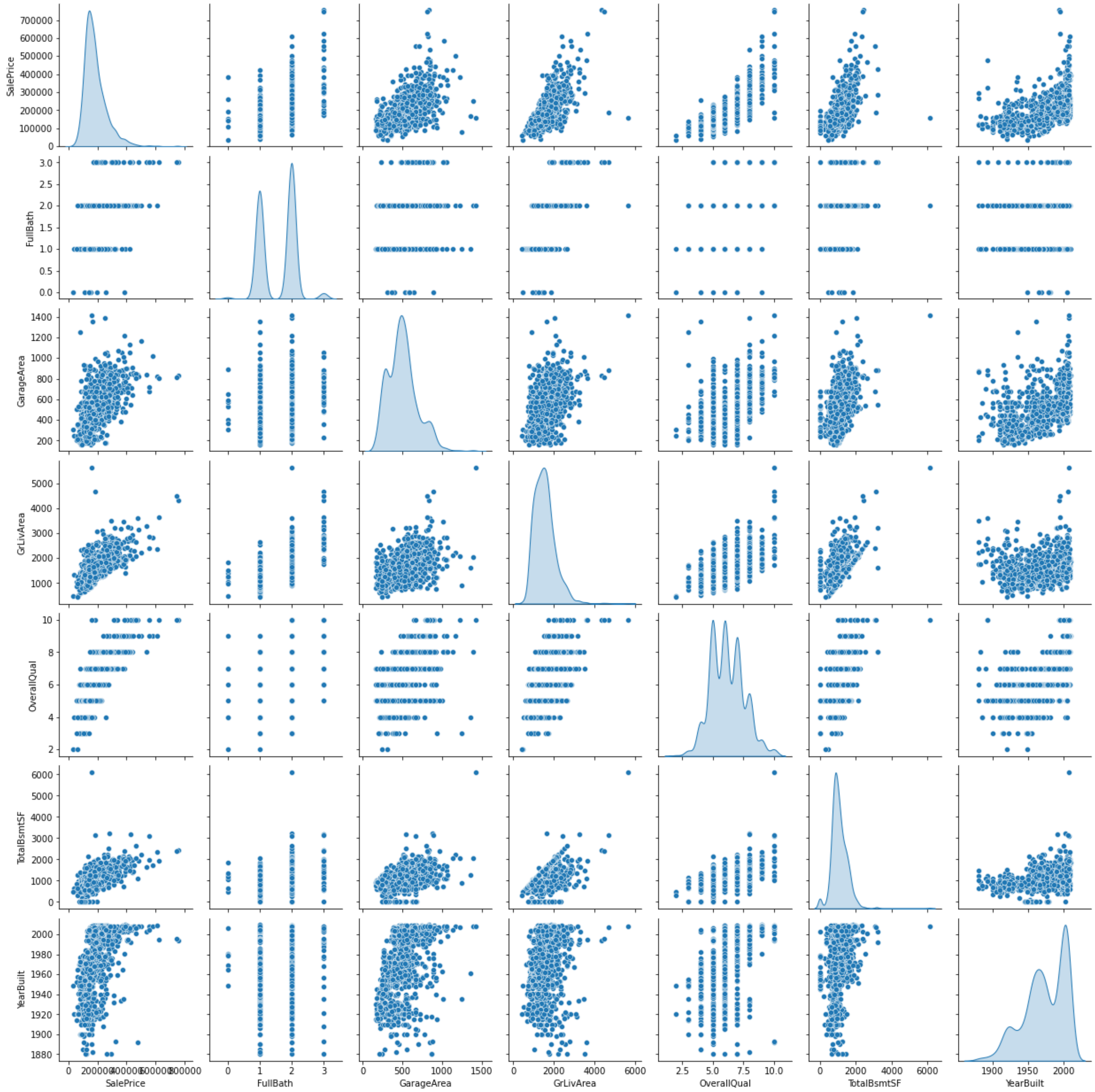
As we can see the variables '1stFlrSF'/'TotalBsmtSF' and 'GarageArea'/'GarageCars'/'GarageYrBlt' are highly correlated. Since the correlation is so strong this can be an indication of multicollinearity. We are then going to eliminate the variables from the data set and study the rest of the variables with high correlation with the target value.

In [181…

```
original_data= data.copy()
data = data.drop(['1stFlrSF','GarageCars','GarageYrBlt'], axis=1)
columns = ['SalePrice','FullBath','GarageArea','GrLivArea','OverallQual','TotalBsmtSF',
sns.pairplot(data[columns], diag_kind="kde")
```

Out[181…

```
<seaborn.axisgrid.PairGrid at 0x1a515e60d00>
```



Encoding features

In [182…

```
from sklearn.preprocessing import OneHotEncoder

data_ohc = data.copy()
ohc = OneHotEncoder()

for column in object_columns:
    Sparse_Matrix = ohc.fit_transform(data_ohc[[column]]) # When working with sklearn t
    data_ohc = data_ohc.drop(column, axis=1) # Drop original column from the dataframe
    unique_values = ohc.categories_ # Get names of all unique values in columns
    new_columns = ['_'.join([column, categorie]) for categorie in unique_values[0]] # C
    new_df = pd.DataFrame(Sparse_Matrix.toarray(), columns=new_columns) # Create the ne
    data_ohc = pd.concat([data_ohc, new_df], axis=1) # Append the new data to the dataf
data_ohc.head()
```

Out[182…

2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUr

	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUr
0	854.0	0.0	3	706.0	0.0	1	0	15
1	0.0	0.0	3	978.0	0.0	0	1	28
2	866.0	0.0	3	486.0	0.0	1	0	43
3	756.0	0.0	3	216.0	0.0	1	0	54
4	1053.0	0.0	4	655.0	0.0	1	0	49

5 rows × 292 columns

In [183…

```
data_ohc = pd.get_dummies(data, columns = object_columns, drop_first=True)
data_ohc.head()
```

Out[183…

	2ndFlrSF	3SsnPorch	BedroomAbvGr	BsmtFinSF1	BsmtFinSF2	BsmtFullBath	BsmtHalfBath	BsmtUr
0	854.0	0.0	3	706.0	0.0	1	0	15
1	0.0	0.0	3	978.0	0.0	0	1	28
2	866.0	0.0	3	486.0	0.0	1	0	43
3	756.0	0.0	3	216.0	0.0	1	0	54
4	1053.0	0.0	4	655.0	0.0	1	0	49

5 rows × 249 columns

Linear Regression Models

Now we are going to develop the following linear regression models.

- sklearn.linear_model.LinearRegression
- sklearn.linear_model.LinearRegression & sklearn.preprocessing.PolynomialFeatures
- sklearn.linear_model.Lasso & sklearn.linear_model.ElasticNet

Linear Regression

Here we develop a simple linear regression

In [184…

```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import KFold, cross_val_predict
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.pipeline import Pipeline
```

Since for all three cases we will use the same cross-validation method:

In [185…

```
kf = KFold(shuffle=True, random_state=72018, n_splits=3) # Same cross-validation method
```

Let's first perform the linear regression for the data set with the modified categorical features (one-hot-encoded).

In [186…

```
estimator = Pipeline([("scaler", StandardScaler()),
                      ("regression", LinearRegression())])
# column = [col for col in data_ohc.columns if col != 'SalePrice']
features = data_ohc.drop('SalePrice', axis=1)
target = data_ohc.SalePrice

estimator.fit(features, target)
predictions = cross_val_predict(estimator, features, target, cv=kf)
r2_score(predictions, target)

lr = estimator.named_steps["regression"].coef_
```

R^2 is very small, this may be due to the presence of outliers in the predictions.By removing the outliers and plotting the correlation, result in a clear linear correlation between the predictions and the target value.

In [187…

```
f = plt.figure(figsize=(6,6))
ax = plt.axes()

ax.plot(predictions, target,
         marker='o', ls='', ms=3.0)

lim = (0, target.mean() + 3*target.std())

ax.set(xlabel='Actual Price',
       ylabel='Predicted Price',
       xlim=lim,
       ylim=lim,
       title='Linear Regression Results');
```

Now let's see the correlation for a model with no categorical values and a log transformation of the target value.

In [188…

```
estimator = Pipeline([("scaler", StandardScaler()),
                      ("linear_regression", LinearRegression())])

object_columns = data.columns[data.dtypes == object]
new_data = data.drop(object_columns, axis=1)

features = new_data.drop('SalePrice', axis=1)
target = log_SalePrice
predictions = cross_val_predict(estimator, features, target, cv=kf)

r2_score(predictions, target)
#r2_score(np.exp(predictions) - 1, np.exp(target) - 1)
```

Out[188…

```
0.8115758219323024
```

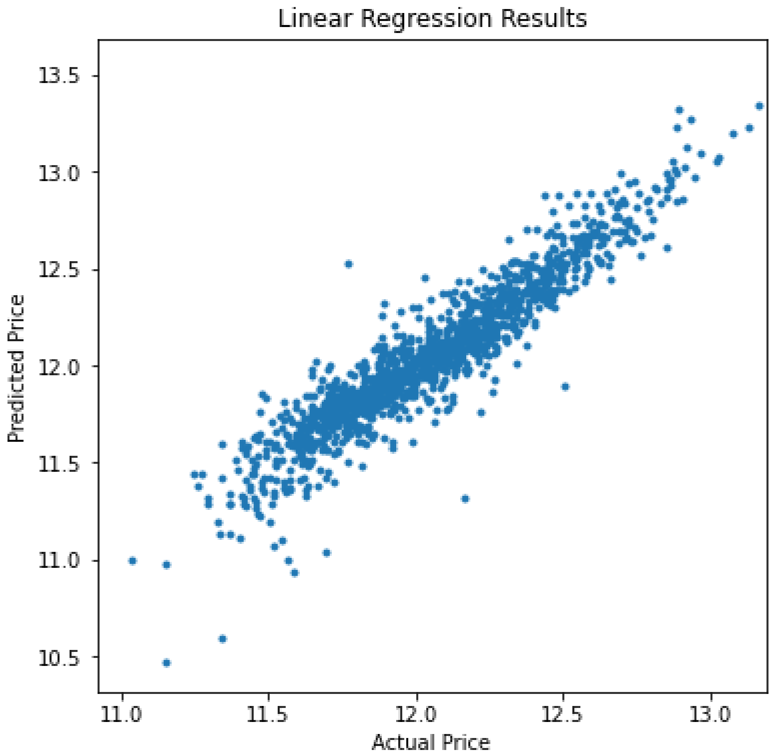
In [189…

```
f = plt.figure(figsize=(6,6))
ax = plt.axes()

ax.plot(predictions, target,
         marker='o', ls='', ms=3.0)

lim = (target.mean() - 3*target.std(), target.mean() + 3*target.std())

ax.set(xlabel='Actual Price',
       ylabel='Predicted Price',
       xlim=lim,
       title='Linear Regression Results');
```



Result of a stronger correlation between the predictions and de target value.

Linear Regression & Polynomial Features

Let's do the same but adding polynomial features to the mix.

In [190…

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
```

Linear regression with polynomial features for the data set with the modified categorical features (one-hot-encoded).

In [191…

```
estimator = Pipeline([
        ("polynomial_features", PolynomialFeatures()),
        ("scaler", StandardScaler()),
        ("linear_regression", LinearRegression())])

params = {
    'polynomial_features__degree': [1, 2]
}

grid = GridSearchCV(estimator, params, cv=kf)

features = data_ohc.drop('SalePrice', axis=1)
target = data_ohc.SalePrice

estimator.fit(features, target)
grid.fit(features, target)
print(grid.best_score_, grid.best_params_)

y_predict = grid.predict(features)
```

```
print(r2_score(y_predict, target))
lr_poly = estimator.named_steps["linear_regression"].coef_
```

```
0.7498354260598211 {'polynomial_features__degree': 2}
1.0
```

Since the R^2 = 1, it is an indication of overfitting. Therefore, extrapolating our model to another data set will have high dispersion. We will try to correct this by applying a regularization regression.

In [192…

```
df_importances = pd.DataFrame(zip(estimator.named_steps["polynomial_features"].get_feat
                    estimator.named_steps["linear_regression"].coef_,
))
df_importances.round(0).sort_values(by=1)
```

Out[192…

	0	1
5247	x21^2	-12283.0
5263	x21 x37	-3228.0
1126	x3 x139	-3096.0
5413	x21 x187	-2899.0
7193	x29 x187	-2848.0
...	...	...
32	x31	5466.0
7473	x31 x32	5551.0
7472	x31^2	5582.0
5253	x21 x27	7712.0
4102	x16 x21	16082.0

31125 rows × 2 columns

When we work with a model with no categorical values and a log transformation of the target value, we get a higher average of R^2 scores and more reliable results.

In [193…

```
estimator = Pipeline([
        ("polynomial_features", PolynomialFeatures()),
        ("scaler", StandardScaler()),
        ("linear_regression", LinearRegression())])

params = {
    'polynomial_features__degree': [1, 2]
}

grid = GridSearchCV(estimator, params, cv=kf)

features = new_data.drop('SalePrice', axis=1)
target = log_SalePrice

estimator.fit(features, target)
grid.fit(features, target)
```

```
print(grid.best_score_, grid.best_params_)

y_predict = grid.predict(features)
print(r2_score(y_predict, target))
# r2_score(np.exp(predictions) - 1, np.exp(target) - 1)
```

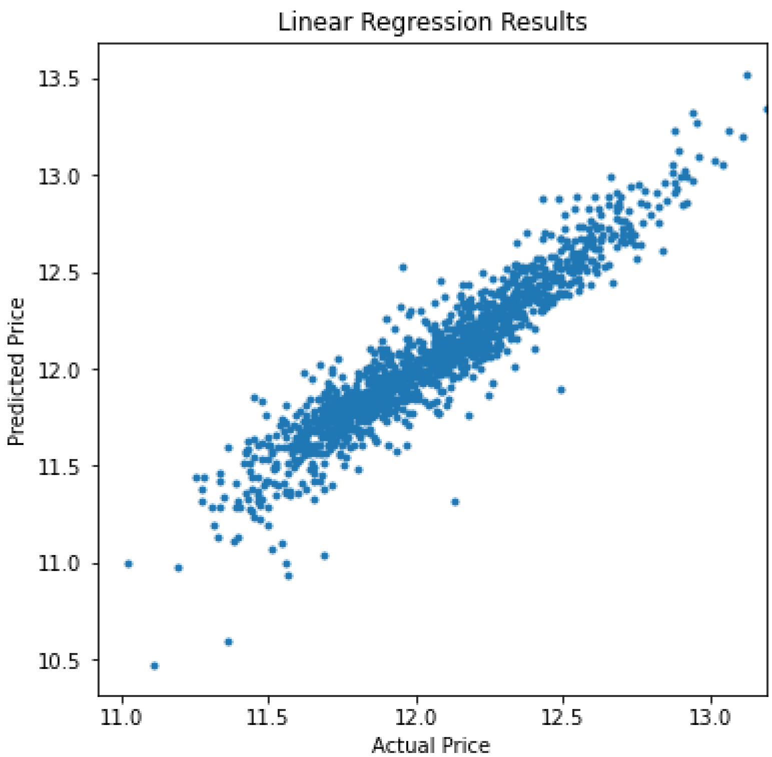
```
0.8342688944832054 {'polynomial_features__degree': 1}
0.8361798502015325
```

In [194…

```
f = plt.figure(figsize=(6,6))
ax = plt.axes()

ax.plot(y_predict, target,
         marker='o', ls='', ms=3.0)
lim = (target.mean() - 3*target.std(), target.mean() + 3*target.std())

ax.set(xlabel='Actual Price',
       ylabel='Predicted Price',
       xlim=lim,
       title='Linear Regression Results');
```



Regularization Regression

Finally, since we will focus on the interpretability of the data set, we will use the Lasso regularization regression model. It will decrease the coefficients of the variables of minor importance to 0.

In [195…

```
from sklearn.linear_model import Lasso

estimator = Pipeline([
        ("polynomial_features", PolynomialFeatures()),
        ("scaler", StandardScaler()),
        ("lasso_regression", Lasso(max_iter=5e4))])
```

```
params = {
    'polynomial_features__degree': [2],
    'lasso_regression__alpha': np.array([934,935,936]) # Iteration 1: np.array([0.005,
}                                                      # Iteration 2: np.array([140,200
                                                       # Iteration 3: np.array([500,100
                                                       # Iteration 4: np.array([900,950
                                                       # Iteration 5: np.array([920,930
                                                       # Iteration 6: np.array([934,935
grid = GridSearchCV(estimator, params, cv=kf)

features = new_data.drop('SalePrice', axis=1)
target = new_data.SalePrice

estimator.fit(features, target)
grid.fit(features, target)
print(grid.best_score_, grid.best_params_)

y_predict = grid.predict(features)
print(r2_score(y_predict, target))
lasso_ = estimator.named_steps["lasso_regression"].coef_
```

```
C:\Users\enzof\anaconda3\lib\site-packages\sklearn\linear_model\_coordinate_descent.py:5
30: ConvergenceWarning: Objective did not converge. You might want to increase the numbe
r of iterations. Duality gap: 79139121106.77234, tolerance: 860530034.3448577
  model = cd_fast.enet_coordinate_descent(
0.7789888340713257 {'lasso_regression__alpha': 935, 'polynomial_features__degree': 2}
0.8649551854986306
```

In [196…

```
df_importances = pd.DataFrame(zip(estimator.named_steps["polynomial_features"].get_feat
                  estimator.named_steps["lasso_regression"].coef_,
))
df_importances.round(0).sort_values(by=1)
```

Out[196…

	0	1
539	x22 x32	-144320.0
341	x10 x32	-142325.0
363	x11 x32	-138459.0
577	x27 x30	-129925.0
364	x12^2	-127653.0
...	...	...
572	x26 x31	116655.0
456	x16 x30	128747.0
362	x11 x31	137363.0
339	x10 x30	157674.0
538	x22 x31	181247.0

595 rows × 2 columns

In [197…

```
f = plt.figure(figsize=(6,6))
ax = plt.axes()

ax.plot(y_predict, target,
         marker='o', ls='', ms=3.0)
lim = (0, target.mean() + 3*target.std())

ax.set(xlabel='Actual Price',
       ylabel='Predicted Price',
       xlim=lim,
       ylim=lim,
       title='Linear Regression Results');
```

Summary

In summary, the following can be highlighted.

All the regressions were favored when log transforming the target value. Standardizing the variables is advantageous in all terms. Broadly speaking, an increase in r^2 is appreciable as new models are proposed.

Results:

- Linear Regression: $r^2 = 0.81$
- Linear Regression with Polynomial effects: $r^2 = 0.84$
- Lasso (with alpha optimization): $r^2 = 0.87$

In conclusion, good linear relationships were obtained in all cases. The best model for this particular case is the Regression Regularization Lasso model with the corresponding alpha optimization. It offers a greater reduction of features, which favors the interpretability of the data set, and has the larger r^2.

In [201…

```
len(lasso_)
```

Out[201…

```
595
```

In [213…

```
lrdf = pd.DataFrame()
lrdf['Linear Regression'] = lr
display(lrdf.round(0).describe())

lrpfdf = pd.DataFrame()
lrpfdf['Linear Regression & Polynomial Features'] = lr_poly
display(lrpfdf.round(0).describe())

lassodf = pd.DataFrame()
lassodf['Lasso Regression'] = lasso_
display(lassodf.round(0).describe())
```

	Linear Regression
count	2.480000e+02
mean	1.612326e+14
std	4.234589e+15
min	-2.763824e+16
25%	-1.376000e+03
50%	3.565000e+02
75%	2.839750e+03
max	2.911521e+16

	Linear Regression & Polynomial Features
count	31125.00000
mean	2.86053
std	231.75228
min	-12283.00000
25%	-15.00000
50%	0.00000
75%	15.00000
max	16082.00000

	Lasso Regression
count	595.000000
mean	175.968067

	Lasso Regression
std	28759.417910
min	-144320.000000
25%	-3905.000000
50%	0.000000
75%	3512.500000
max	181247.000000

In [215…

```
print((lrdf > 0).sum())
print((lrpfdf > 0).sum())
print((lassodf > 0).sum())
```

```
Linear Regression    146
dtype: int64
Linear Regression & Polynomial Features    10020
dtype: int64
Lasso Regression    247
dtype: int64
```