linear_regression_interpretability

February 6, 2024

1 Interpretability of a linear regression model

Interpret means to "explain" or to present in understandable terms. The ability to express in understandable terms, what the model has learned and the reasons that affect their output.

Interpretability is about the extent to which a cause and effect can be observed within a system. Or to put it another way, it is the extent to which you are able to predict what is going to happen, given a change in input or algorithmic parameters. It's being able to understand which inputs are the most predictive (i.e., impact the prediction/output the most), and anticipate how predictions will change with differing inputs.

- If a customer is rejected a loan, we can say why
- If an insurance provides a certain premium, we know the reasons.
- If we diagnose a patient with a certain disease, we can tell them why

1.1 Fit an interpretable linear regression model and make global and local interpretations

The idea is to fit an interpretable linear regression model, evaluate the model fit and the coefficients, and then interpret the predictions globally and locally.

In this example, we will use the shrinkage method and variable selection for linear regression models (called lasso regression) is another regularized version of linear regression.

An important peculiarity of lasso regression is that it tends to suppress the weights of less important features (i.e., set them to zero). Roughly speaking, lasso regression automatically performs feature selection and outputs a sparse model (i.e., with few non-zero feature weights).

The workflow is the following:

- Make some data engineer to prepare the data
- Exploratory data analysis and identify multi-colinearity
- Fit a linear model with the highest performance and least number of features
- Evaluate the model fit
- Evaluate the coefficients (global interpretation)
- Evaluate a few observations individually (local interpretation)

[1]:
```
# imports
import warnings
warnings.filterwarnings("ignore")
```

```python
import math
import numpy as np
import pandas as pd
pd.set_option('display.max_columns', 10000)
# pd.set_option('display.max_rows', 10000)
import matplotlib.pyplot as plt
import seaborn as sns
import sweetviz as sv
from itertools import product
from scipy import stats
import statsmodels.api as sm

import scipy.stats as ss
from scipy.stats.contingency import association
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import Lasso
from sklearn.model_selection import cross_validate
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.model_selection import GridSearchCV, train_test_split
```

[2]:
```python
# load dataset
train_set = pd.read_csv('datasets/house_price_train.csv')
train_set.head()
```

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

  LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
0         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
1         Lvl    AllPub       FR2       Gtl      Veenker      Feedr
2         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
3         Lvl    AllPub    Corner       Gtl      Crawfor       Norm
4         Lvl    AllPub       FR2       Gtl      NoRidge       Norm

  Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
0       Norm     1Fam     2Story            7            5       2003
1       Norm     1Fam     1Story            6            8       1976
2       Norm     1Fam     2Story            7            5       2001
```

```
3       Norm     1Fam     2Story            7             5       1915
4       Norm     1Fam     2Story            8             5       2000

   YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
0          2003     Gable  CompShg     VinylSd     VinylSd    BrkFace
1          1976     Gable  CompShg     MetalSd     MetalSd        NaN
2          2002     Gable  CompShg     VinylSd     VinylSd    BrkFace
3          1970     Gable  CompShg     Wd Sdng     Wd Shng        NaN
4          2000     Gable  CompShg     VinylSd     VinylSd    BrkFace

   MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure  \
0       196.0        Gd        TA      PConc       Gd       TA           No
1         0.0        TA        TA     CBlock       Gd       TA           Gd
2       162.0        Gd        TA      PConc       Gd       TA           Mn
3         0.0        TA        TA     BrkTil       TA       Gd           No
4       350.0        Gd        TA      PConc       Gd       TA           Av

  BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF  \
0          GLQ         706          Unf           0        150          856
1          ALQ         978          Unf           0        284         1262
2          GLQ         486          Unf           0        434          920
3          ALQ         216          Unf           0        540          756
4          GLQ         655          Unf           0        490         1145

  Heating HeatingQC CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  \
0    GasA        Ex          Y      SBrkr       856       854             0
1    GasA        Ex          Y      SBrkr      1262         0             0
2    GasA        Ex          Y      SBrkr       920       866             0
3    GasA        Gd          Y      SBrkr       961       756             0
4    GasA        Ex          Y      SBrkr      1145      1053             0

   GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  \
0       1710             1             0         2         1             3
1       1262             0             1         2         0             3
2       1786             1             0         2         1             3
3       1717             1             0         1         0             3
4       2198             1             0         2         1             4

   KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  Fireplaces FireplaceQu  \
0             1          Gd             8        Typ           0         NaN
1             1          TA             6        Typ           1          TA
2             1          Gd             6        Typ           1          TA
3             1          Gd             7        Typ           1          Gd
4             1          Gd             9        Typ           1          TA

  GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea GarageQual  \
0     Attchd       2003.0          RFn           2         548         TA
```

```
1      Attchd       1976.0           RFn            2          460           TA
2      Attchd       2001.0           RFn            2          608           TA
3      Detchd       1998.0           Unf            3          642           TA
4      Attchd       2000.0           RFn            3          836           TA

  GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  \
0         TA          Y           0           61              0          0
1         TA          Y         298            0              0          0
2         TA          Y           0           42              0          0
3         TA          Y           0           35            272          0
4         TA          Y         192           84              0          0

   ScreenPorch  PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold  \
0            0         0    NaN   NaN         NaN        0       2    2008
1            0         0    NaN   NaN         NaN        0       5    2007
2            0         0    NaN   NaN         NaN        0       9    2008
3            0         0    NaN   NaN         NaN        0       2    2006
4            0         0    NaN   NaN         NaN        0      12    2008

  SaleType SaleCondition  SalePrice
0       WD        Normal     208500
1       WD        Normal     181500
2       WD        Normal     223500
3       WD       Abnorml     140000
4       WD        Normal     250000
```

1.2 Exploratory data analysis

This topic we gonna work in an exploration to see what we should do with this data to be able to go to the next steps, readers can skip this step if you are interested just in the model interpretation step.

Link to the dataset

Obs: we don't gonna make an extensive and deep exploratory, because the goal of this notebook is to show how to interpret the models, but in a real project, you should go deeper in the exploration and extract many information as possible.

1.2.1 Univariate data analysis

For this step, we gonna use a very nice tool to make the things faster that is sweetviz tool. If you don't know the tool, have a look in the documentation!

[3]:
```python
# general informations about the dataset
train_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
```

```
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
 18  OverallCond    1460 non-null   int64
 19  YearBuilt      1460 non-null   int64
 20  YearRemodAdd   1460 non-null   int64
 21  RoofStyle      1460 non-null   object
 22  RoofMatl       1460 non-null   object
 23  Exterior1st    1460 non-null   object
 24  Exterior2nd    1460 non-null   object
 25  MasVnrType     588 non-null    object
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object
 28  ExterCond      1460 non-null   object
 29  Foundation     1460 non-null   object
 30  BsmtQual       1423 non-null   object
 31  BsmtCond       1423 non-null   object
 32  BsmtExposure   1422 non-null   object
 33  BsmtFinType1   1423 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
```

```
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

[4]:

```
my_report = sv.analyze(train_set, 'SalePrice')
my_report.show_html() # Default arguments will generate to "SWEETVIZ_REPORT.
 ↪html"
```

```
Feature: SalePrice (TARGET)             |          | [  1%]   00:00 ->
(00:02 left)

Feature: MSZoning                       |          | [  5%]   00:02 ->
(00:45 left)
```

1.2.2 Bivariate Data Analysis

Here we will deal with the descriptive analysis of the **association** between two variables. **In general, we say that there is an association between two variables if knowledge of the value of one of them gives us some information about some characteristic of the distribution (of frequencies) of the other.**

We can highlight three cases:

1. both variables are qualitative.
2. both variables are quantitative.
3. one variable is qualitative and the other is quantitative.

Two qualitative variables and evaluate multicollinearity Here the idea is to check the correlation between two qualitative variables.

What are the consequences of multicollinearity?

If two variables are perfectly collinear, in other words, if they have correlation coefficient equal to 1, then what happens is that there is an infinite combination of coefficients (betas) that would work equally well. So basically we have an infinite number of linear regression models that will predict equally well the target from these two perfectly collinear variables. Which means that we are not able to understand what is the real relationship between those variables and the target.

- Perfect collinearity is rare
- Partial collinearity is unavoidable

So what happens is that when we have correlated variables, one of the therms (feature x coefficient) will account for a degree of the variability, and then the other therm basically accounts for the remaining variability that is not explained, but in both cases the coefficient doesn't really represent the real if you want association between the variable and the target.

[3]:
```python
# filter the qualitative variables
qualitative_features_enconding = [
    'MSZoning', 'Street', 'LotShape', 'LandContour',
    'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood',
    'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
    'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd',
    'Foundation', 'Heating', 'CentralAir', 'Functional',
    'PavedDrive', 'SaleType', 'SaleCondition']

qualitative_features_missing_mode = [
    'Electrical', 'GarageType']

ordinal_features_quality = [
    'ExterQual', 'ExterCond',
    'BsmtQual', 'BsmtCond',
    'HeatingQC', 'KitchenQual',
    'GarageQual', 'GarageCond']

ordinal_features_exposure = ['BsmtExposure']
```

```python
ordinal_features_finish = ['BsmtFinType1', 'BsmtFinType2']

ordinal_features_garage = ['GarageFinish']

qualitative_vars = qualitative_features_enconding +␣
↪qualitative_features_missing_mode + ordinal_features_quality +␣
↪ordinal_features_exposure + ordinal_features_finish + ordinal_features_garage
```

[4]:
```python
# create a dataframe with only categorical variables
categorical_df = train_set[qualitative_vars]

# removing records with at least one null value in a row
df_cat_v1 = categorical_df.dropna()

## let us split this list into two parts
cat_var1 = qualitative_vars
cat_var2 = qualitative_vars

# let us jump to Chi-Square test
# creating all possible combinations between the above two variables list
cat_var_prod = list(product(cat_var1, cat_var2, repeat = 1))

# creating an empty variable and picking only the p value from the output of␣
↪Chi-Square test
result = []
for i in cat_var_prod:
    if i[0] != i[1]:
        contingency_table = pd.crosstab(df_cat_v1[i[0]], df_cat_v1[i[1]])
        chi2_pval = ss.chi2_contingency(contingency_table)[1]
        tschuprow_pval = association(contingency_table, method='tschuprow')
        result.append((i[0], i[1], chi2_pval, tschuprow_pval))

# Creating dataframe
result_df = pd.DataFrame(result, columns=['Variable_1', 'Variable_2',␣
↪'Chi2_P_Value', 'Tschuprow'])

# let's filter the values with tschuprow coefficient higher than 0.7 to catch␣
↪multicollinearity
result_df.loc[(result_df['Tschuprow'] >= 0.7)]
```

[4]:

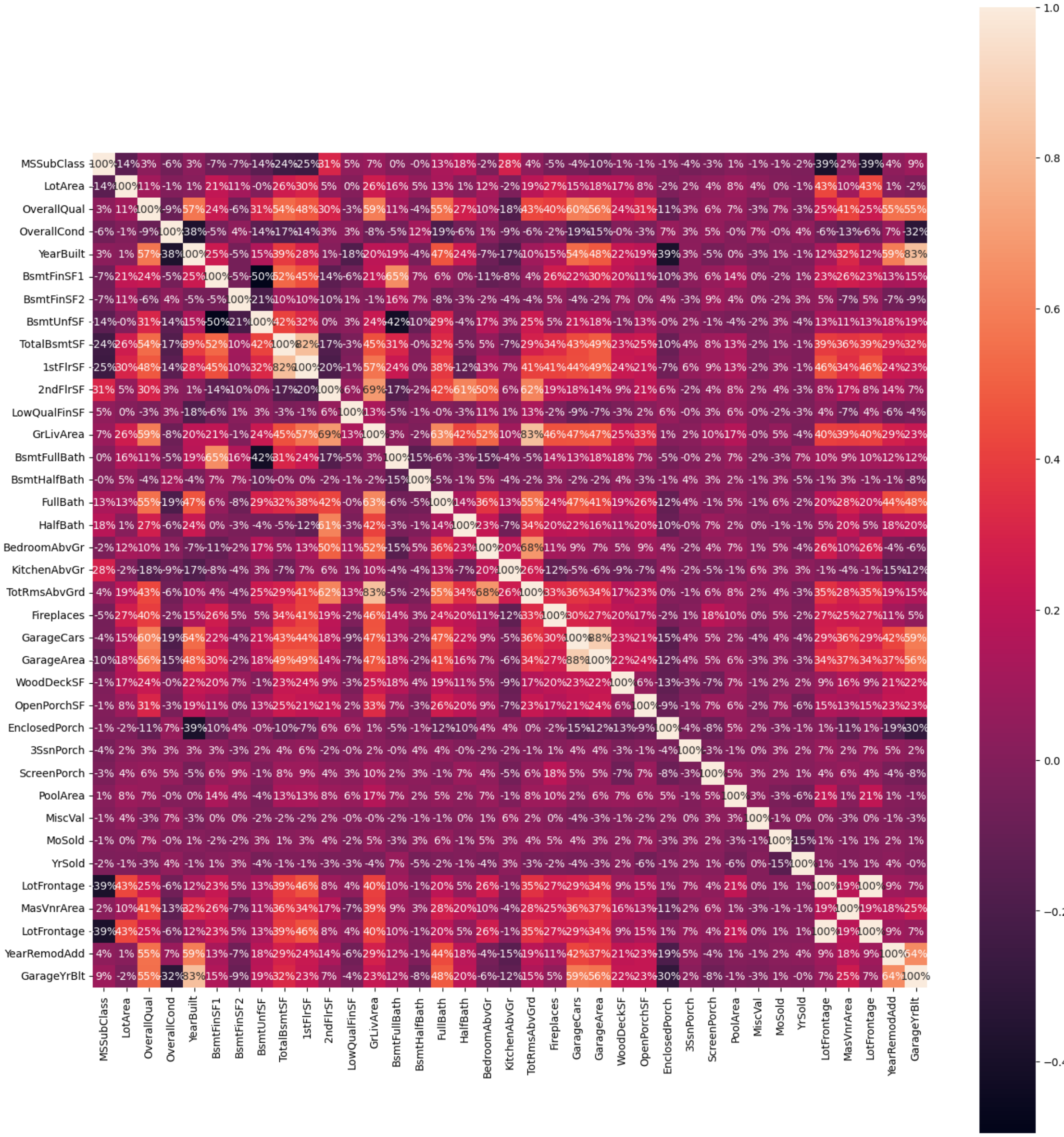
	Variable_1	Variable_2	Chi2_P_Value	Tschuprow
518	Exterior1st	Exterior2nd	0.0	0.744531
554	Exterior2nd	Exterior1st	0.0	0.744531

Maybe we can remove one of these two features, the one that has less correlation with the target is a good choice.

Two quantitative variables and evaluate multicollinearity Here the idea is to check the correlation between two quantitative variables and check multicollinearity.

[5]:
```
# select features according to their types and missing values
quantitative_features = ['MSSubClass', 'LotArea', 'OverallQual', 'OverallCond',
                         'YearBuilt', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF',
                         'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
                         'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',␣
 ↪'FullBath',
                         'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr',␣
 ↪'TotRmsAbvGrd',
                         'Fireplaces', 'GarageCars', 'GarageArea', 'WoodDeckSF',
                         'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',␣
 ↪'ScreenPorch',
                         'PoolArea', 'MiscVal', 'MoSold', 'YrSold']

quantitative_features_missing_median = ['LotFrontage', 'MasVnrArea']

quantitative_features_missing_mode = ['LotFrontage', 'YearRemodAdd',␣
 ↪'GarageYrBlt']

quantitative_vars = quantitative_features +␣
 ↪quantitative_features_missing_median + quantitative_features_missing_mode
```

[6]:
```
# quantitative associations
quantitative_df = train_set[quantitative_vars]
corr = quantitative_df.corr()
plt.figure(figsize=(15,15))
sns.heatmap(corr, fmt='.0%', annot=True, square=True)
plt.tight_layout()
```



From the Pearson correlation, few variables appeared to be highly correlated. Let's check this collinearity with the VIF metric and that could possibly be an indication for feature selection.

The second metric for gauging multicollinearity is the variance inflation factor (VIF). The VIF directly measures the ratio of the variance of the entire model to the variance of a model with only the feature in question.

In layman's terms, it gauges how much a feature's inclusion contributes to the overall variance of the coefficients of the features in the model.

A VIF of 1 indicates that the feature has no correlation with any of the other features.

Typically, a VIF value exceeding 5 or 10 is deemed to be too high. Any feature with such VIF values is likely to be contributing to multicollinearity.

[7]:
```
# Compute VIF data for each independent variable
clean_quantitative_df = quantitative_df.dropna()
vif = pd.DataFrame()
vif["features"] = clean_quantitative_df.columns
vif["vif_Factor"] = [variance_inflation_factor(clean_quantitative_df.values, i)␣
↪for i in range(clean_quantitative_df.shape[1])]
vif.sort_values(by=['vif_Factor'], ascending=False, inplace=True)
vif
```

[7]:

	features	vif_Factor
8	TotalBsmtSF	inf
10	2ndFlrSF	inf
32	LotFrontage	inf
34	LotFrontage	inf
12	GrLivArea	inf
5	BsmtFinSF1	inf
6	BsmtFinSF2	inf
7	BsmtUnfSF	inf
11	LowQualFinSF	inf
9	1stFlrSF	inf
36	GarageYrBlt	2.680925e+04
31	YrSold	2.528962e+04
4	YearBuilt	2.466581e+04
35	YearRemodAdd	2.450464e+04
19	TotRmsAbvGrd	8.364791e+01
2	OverallQual	7.308071e+01
3	OverallCond	4.964269e+01
18	KitchenAbvGr	4.203815e+01
21	GarageCars	3.980117e+01
22	GarageArea	3.517381e+01
17	BedroomAbvGr	3.381041e+01
15	FullBath	2.874419e+01
30	MoSold	6.840270e+00
0	MSSubClass	4.821513e+00
13	BsmtFullBath	3.650975e+00
16	HalfBath	3.594106e+00
1	LotArea	3.451820e+00
20	Fireplaces	3.028183e+00
24	OpenPorchSF	1.965871e+00
23	WoodDeckSF	1.944755e+00
33	MasVnrArea	1.937282e+00
25	EnclosedPorch	1.486659e+00
27	ScreenPorch	1.239925e+00
14	BsmtHalfBath	1.214943e+00
28	PoolArea	1.192611e+00

```
29         MiscVal  1.119622e+00
26       3SsnPorch  1.043918e+00
```

We see that a lot of variables have a high VIF and therefore, it may be variables to eliminate in the modeling that we will do later.

One qualitative and one quantitative variable Here the idea is to check the correlation between the qualitative and quantitative variable (the target) to see if the qualitative variables have a high influence in the target, but for this project we gonna skip this part, but in your project you should go deeper.

1.3 Preprocessing

Based on what we have seen in exploratory data analysis, we gonna make some transformations in the data to be able to fit them in the linear regression model.

[8]:
```
# select only the features that we are going to use
X = train_set.drop(['SalePrice'], axis=1)
y = train_set['SalePrice']
```

[9]:
```
class QualMapper(BaseEstimator, TransformerMixin):
    def __init__(self, qual_vars):
        self.qual_vars = qual_vars

    def fit(self, X, y=None):
        return self  # no need to do anything here

    def transform(self, X):
        def map_quality(entry):
            if entry == 'Po':
                return 1
            elif entry == 'Fa':
                return 2
            elif entry == 'TA':
                return 3
            elif entry == 'Gd':
                return 4
            elif entry == 'Ex':
                return 5
            else:
                return 0  # or 'Missing' if you prefer to keep it as a string

        for var in self.qual_vars:
            X[var] = X[var].fillna('Missing')
            X[var] = X[var].apply(map_quality)

        return X
```

```python
    def get_feature_names_out(self, input_features=None):
        return input_features


class ExposureMapper(BaseEstimator, TransformerMixin):
    def __init__(self, expo_vars):
        self.expo_vars = expo_vars

    def fit(self, X, y=None):
        return self  # no need to do anything here

    def transform(self, X):
        def map_expo(entry):
            if entry == 'No':
                return 1
            elif entry == 'Mn':
                return 2
            elif entry == 'Av':
                return 3
            elif entry == 'Gd':
                return 4
            else:
                return 0  # or 'Missing' if you prefer to keep it as a string

        for var in self.expo_vars:
            X[var] = X[var].fillna('Missing')
            X[var] = X[var].apply(map_expo)

        return X

    def get_feature_names_out(self, input_features=None):
        return input_features


class FinishMapper(BaseEstimator, TransformerMixin):
    def __init__(self, finish_vars):
        self.finish_vars = finish_vars

    def fit(self, X, y=None):
        return self  # no need to do anything here

    def transform(self, X):
        def map_finish(entry):
            if entry == 'Unf':
                return 1
            elif entry == 'LwQ':
                return 2
```

```python
            elif entry == 'Rec':
                return 3
            elif entry == 'BLQ':
                return 4
            elif entry == 'ALQ':
                return 5
            elif entry == 'GLQ':
                return 6
            else:
                return 0  # or 'Missing' if you prefer to keep it as a string

        for var in self.finish_vars:
            X[var] = X[var].fillna('Missing')
            X[var] = X[var].apply(map_finish)

        return X

    def get_feature_names_out(self, input_features=None):
        return input_features


class GarageMapper(BaseEstimator, TransformerMixin):
    def __init__(self, garage_vars):
        self.garage_vars = garage_vars

    def fit(self, X, y=None):
        return self  # no need to do anything here

    def transform(self, X):
        def map_garage(entry):
            if entry == 'Unf':
                return 1
            elif entry == 'RFn':
                return 2
            elif entry == 'Fin':
                return 3
            else:
                return 0  # or 'Missing' if you prefer to keep it as a string

        for var in self.garage_vars:
            X[var] = X[var].fillna('Missing')
            X[var] = X[var].apply(map_garage)

        return X

    def get_feature_names_out(self, input_features=None):
        return input_features
```

```
# class RemoveRareCategories(BaseEstimator, TransformerMixin):
#     def __init__(self, quali_vars):
#         self.quali_vars = quali_vars

#     def fit(self, X, y=None):
#         return self  # no need to do anything here

#     def transform(self, X):
#         def map_rare_entries(series):
#             frequency_entries = series.groupby(series).transform('count') /␣
 ↪len(series)
#             rare_entries = frequency_entries < 0.01
#             print(rare_entries)
#             return np.where(rare_entries, 'Rare', series)

#         for var in self.quali_vars:
#             X[var] = map_rare_entries(X[var])

#         return X
```

[10]:
```
processed_features = quantitative_vars + qualitative_vars

quantitative_preproc = make_pipeline(
    StandardScaler())

quantitative_median_preproc = make_pipeline(
    SimpleImputer(strategy='median'),
    StandardScaler())

quantitative_mode_preproc = make_pipeline(
    SimpleImputer(strategy='most_frequent'),
    StandardScaler())

qualitative_preproc = make_pipeline(
    OneHotEncoder(handle_unknown='ignore'))

qualitative_mode_preproc = make_pipeline(
    OneHotEncoder(handle_unknown='ignore'))

ordinal_quality_preproc = make_pipeline(
    QualMapper(ordinal_features_quality),
    StandardScaler())

ordinal_exposure_preproc = make_pipeline(
    ExposureMapper(ordinal_features_exposure),
```

```
    StandardScaler())

ordinal_finish_preproc = make_pipeline(
    FinishMapper(ordinal_features_finish),
    StandardScaler())

ordinal_garage_preproc = make_pipeline(
    GarageMapper(ordinal_features_garage),
    StandardScaler())

# apply the respective transformations with columntransformer method
preprocessor = ColumnTransformer([
    ('quantitative_preproc', quantitative_preproc, quantitative_features),
    ('quantitative_median_preproc', quantitative_median_preproc,␣
 ↪quantitative_features_missing_median),
    ('quantitative_mode_preproc', quantitative_mode_preproc,␣
 ↪quantitative_features_missing_mode),
    ('qualitative_preproc', qualitative_preproc,␣
 ↪qualitative_features_enconding),
    ('qualitative_mode_preproc', qualitative_mode_preproc,␣
 ↪qualitative_features_missing_mode),
    ('ordinal_quality_preproc', ordinal_quality_preproc,␣
 ↪ordinal_features_quality),
    ('ordinal_exposure_preproc', ordinal_exposure_preproc,␣
 ↪ordinal_features_exposure),
    ('ordinal_finish_preproc', ordinal_finish_preproc, ordinal_features_finish),
    ('ordinal_garage_preproc', ordinal_garage_preproc,␣
 ↪ordinal_features_garage)],
    remainder='drop')
```

1.4 Fit an interpretable linear model

We'll start by understading how linear regression model works, then we'll move on to learning statistical tests that we can use to evaluate the performance of these models, and this is important because if the model doesn't fit the data well then we cannot extract meaningful interpretations, and then we'll move on to interpret the output of the linear regression model (Lasso) at a global and local level.

Using Lasso, train the model that performs the best and has the least number of features.

If you get errors, reduce the penalization.

[11]:
```
def run_regressor_models(X, y, cv, scoring):
    '''Function that trains the following machine learning models:
    DecisionTreeRegressor, RandomForestRegressor, svm, SGDRegressor,
    GradientBoostingRegressor, ElasticNet, MLPRegressor.
    The function applies cross-validation on the dataset and returns the mean
```

```
    and standard deviation of the selected metric on the training and␣
↪validation set.
    The only active metrics are RMSE and R2.

    :param X: (dataframe or numpy array)
    DataFrame or array with the set of independent variables.

    :param y: (series or numpy array)
    Column or array with the dependent variable.

    :param cv: (int)
    Determines the cross-validation splitting strategy.

    :param scoring: (str)
    Strategy to evaluate the performance of the cross-validated model on the␣
↪validation set.
    Should be passed within quotes when calling the function.

    :return: (dataframe)
    DataFrame with models, mean, and standard deviation on training and␣
↪validation set.
    '''
    # Instantiate the models
    reg = Pipeline(
        steps=[('preprocessor', preprocessor),
               ('regressor', Lasso(random_state=42))]
    )
    scores = cross_validate(reg, X, y, return_train_score=True,
                            scoring=scoring, cv=cv, return_estimator=True)

    # Train and test RMSE
    if scoring == 'neg_mean_squared_error':
        train_rmse_scores = np.sqrt(-scores['train_score'])
        test_rmse_scores = np.sqrt(-scores['test_score'])
        mean_train = train_rmse_scores.mean()
        mean_test = test_rmse_scores.mean()
        std_train = train_rmse_scores.std()
        std_test = test_rmse_scores.std()

    # Train and test R2
    if scoring == 'r2':
        train_r2_scores = scores['train_score']
        test_r2_scores = scores['test_score']
        mean_train = train_r2_scores.mean()
        mean_test = test_r2_scores.mean()
        std_train = train_r2_scores.std()
        std_test = test_r2_scores.std()
```

```
    # Create final dataset
    df_result = pd.DataFrame(
        {'MODEL': reg[1], 'MEAN_TRAIN_SCORES': mean_train,
         'MEAN_TEST_SCORES': mean_test, 'STD_TRAIN_SCORES': std_train,
         'STD_TEST_SCORES': std_test}, index=[0])

    return df_result
```

[12]:
```
df_result = run_regressor_models(X, y, 5, 'r2')
df_result
```

[12]:
```
                    MODEL  MEAN_TRAIN_SCORES  MEAN_TEST_SCORES  \
0  Lasso(random_state=42)           0.923311          0.812339

   STD_TRAIN_SCORES  STD_TEST_SCORES
0          0.003282          0.07568
```

As we can see, we have some overfit, probabily because we have a lot of features and a small number of instances. Let's try to decrease this overfitting increasing the regularization parameter.

In this cases when the number of features are big and we don't have a big number of rows, it's better to use the regularized models like Lasso. The term regularization refers to a set of techniques used to specify models that fit a set of data while avoiding overfitting. In general terms, these techniques serve to fit regression models based on a cost function that contains a penalty term. This term is intended to reduce the influence of coefficients responsible for excessive fluctuations.

When there are predictor variables that are not associated with the response variable, the regression models adjusted by least squares (like LinearRegression from sklearn) may be more complex than desired, as the coefficients associated with these variables will not be canceled.

1.5 Fit, evaluate and tune model in test set

To evaluate the model, we often use a metric that is called R^2. To summary, the R^2 is the fraction of variability explained by the model. Independent of the result of R^2, how do we know that this value is statistically significant?

So, to evaluate the R^2 and that fit with confidence, we need statistical tests. The statistical tests that we gonna use are f-statistic that basically capture the relantionship between the variance that is explained by the model versus the variance that is not explained by the model. In this case in we want a big f-statistic (the model explain more variability) and a small p-value. If this is the case, then the model offers a good fit of the data and the interpretations that we derive from it are meaningful.

F-statistic follows a known probability distribuition for situations where a model is not a good fit and we gonna make a hypothesis test.

- Null hypothesis -> the model is not a good fit.
- Alternative hypothesis -> the model is a good fit.

[13]:
```python
# Hyperparameter tunning
# 1. Instantiate the pipeline
final_model = Pipeline(
    steps=[
        ('preprocessor', preprocessor),
        ('regressor', Lasso(random_state=42))
    ]
)

# 2. Hyperparameter interval to be tested
param_grid = {
    'regressor__alpha': [
#         0.01, 0.04, 0.1, 0.5, 1.0, 10.0,
#         100.0, 200.0, 300.0, 500.0, 1000.0,
          2500.0],
} # you should try as many values as possible, but to illustrate we gonna put a␣
 ↪heavy weight

# 3. Training and apply grid search with cross validation
grid_search = GridSearchCV(final_model, param_grid, cv = 5, scoring = 'r2',
                           return_train_score = True)
grid_search.fit(X, y)

# Seeing the best hyperparameters for the model
print('The best hyperparameters were:', grid_search.best_params_)
```

```
The best hyperparameters were: {'regressor__alpha': 2500.0}
```

[14]:
```python
cvres = grid_search.cv_results_
cvres = [(mean_test_score,
            mean_train_score) for mean_test_score,
            mean_train_score in sorted(zip(cvres['mean_test_score'],
                                            cvres['mean_train_score']),
                                        reverse=True) if (math.
 ↪isnan(mean_test_score) != True)]
print(
    'The mean test score and mean train score is, respectively:',
    cvres[0])
```

```
The mean test score and mean train score is, respectively: (0.7999223632635879,
0.8202277519210949)
```

Overfitting continues, but we have a good model with R^2 of 0.8 in test set. In other words, the model explains approximately 80% of the relationship between the dependent and independent variables.

The coefficient of determination must be accompanied by other tools for assessing fit, as it is not aimed at identifying whether all model assumptions are compatible with the data under investigation. Some of these tools are: residual graphs, cook graphs and local influence graphs. Here, we will only talk about the residual graph.

1.6 Assumptions that must be met in a linear regression model

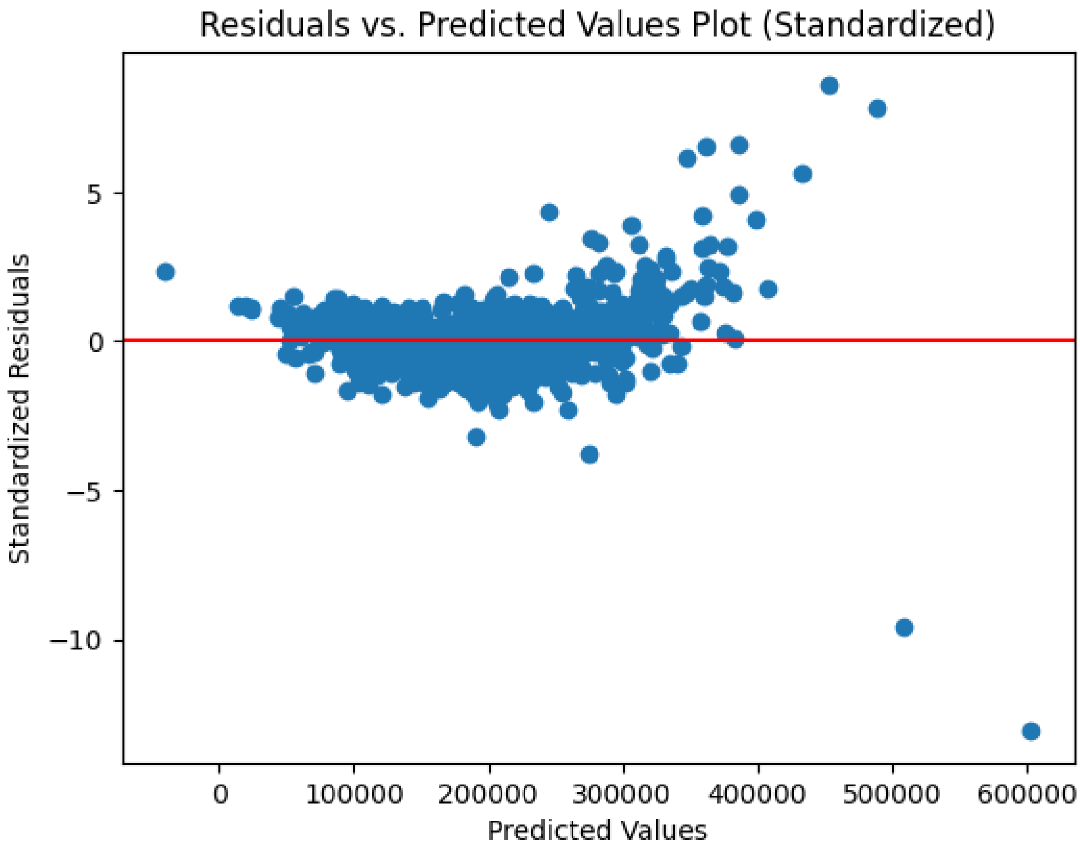
In summary, there are 5 basic assumptions of the regression algorithm that would be interesting to meet:

- Linear relationship between the independent variables and the target (in the case of linear regression)
- Little or no multicollinearity between variables
- Homoscedasticity assumption
- Normal distribution of error terms (if you want to test hypotheses about the model coefficients or construct confidence intervals for them)
- Little or no autocorrelation in residuals

When these assumptions are not met, regression analysis results can be misleading and the model may not perform well.

Here, we will calculate Homoscedasticity and the normal distribution of errors, since the other items have already been checked.

[15]:
```
y_pred = grid_search.predict(X)
residuals = y - y_pred

# Standardize residuals
residuals_standardized = residuals / residuals.std()

# Residuals vs. Predicted Values Plot
plt.scatter(y_pred, residuals_standardized)
plt.xlabel("Predicted Values")
plt.ylabel("Standardized Residuals")
plt.title("Residuals vs. Predicted Values Plot (Standardized)")
plt.axhline(y=0, color='r', linestyle='-')  # Adding a line at y=0
plt.show()
```



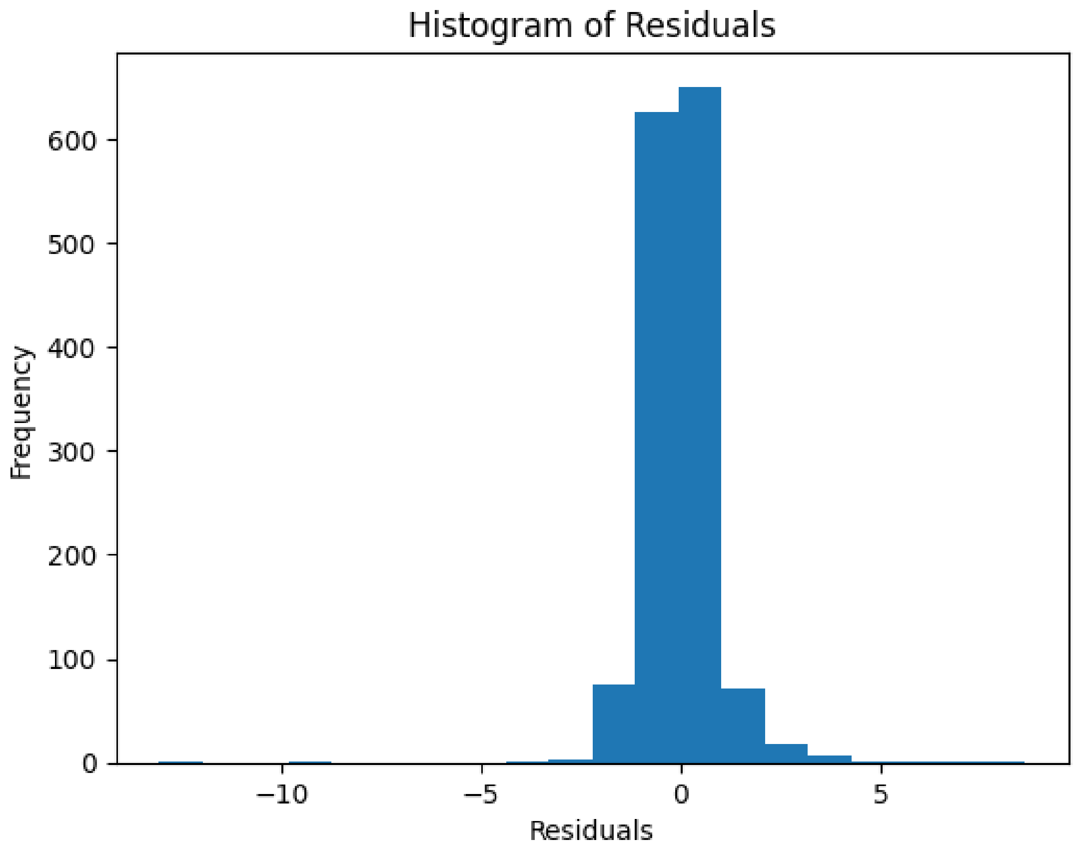
From the graph it appears that the residues are following some systematic pattern, which is not good. This suggests the presence of heteroscedasticity, that is, variances that are not constant over time. Outliers can also contribute to heteroscedasticity.

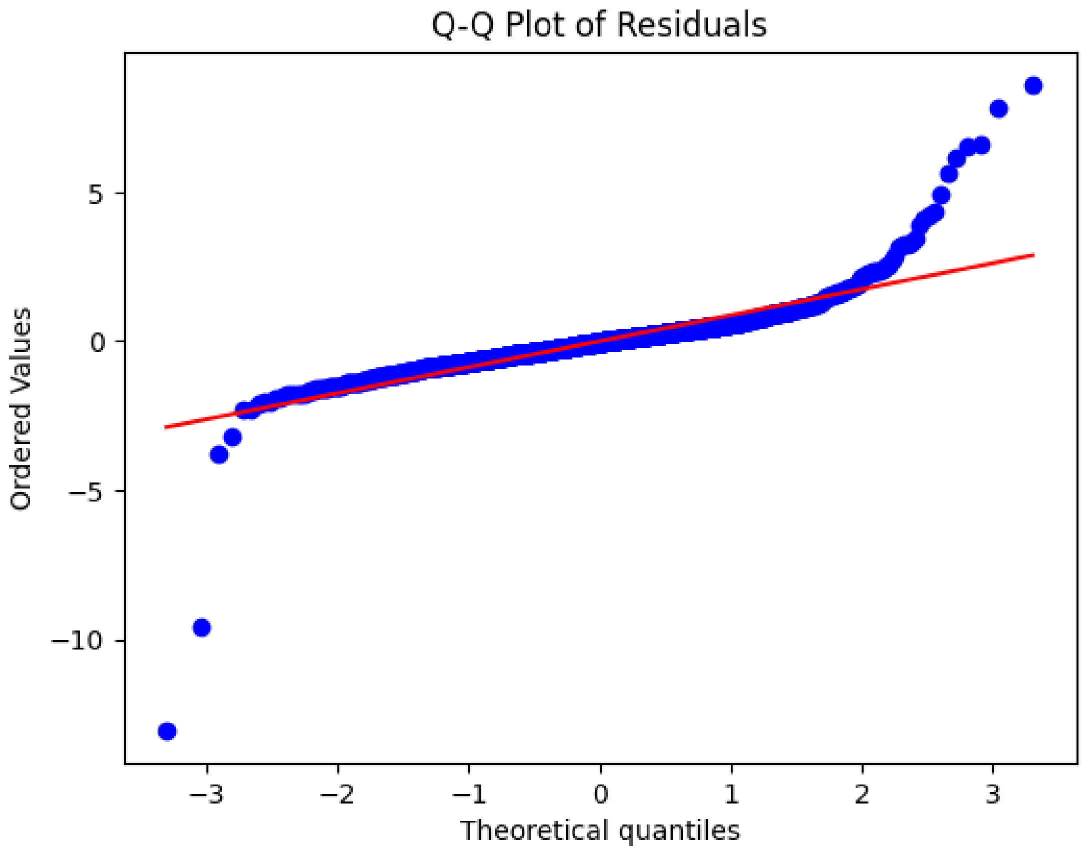
Now, let's check to the normality of errors.

[16]:
```python
# Checking for Normality of Errors
# Example using the Shapiro-Wilk test
_, p_value_sw = stats.shapiro(residuals_standardized)
if p_value_sw > 0.05:
    print("The residuals follow a normal distribution.")
else:
    print("The residuals do not follow a normal distribution.")

# Histogram of Residuals
plt.hist(residuals_standardized, bins=20)
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.title("Histogram of Residuals")
plt.show()
```

```
# Q-Q Plot of Residuals
stats.probplot(residuals_standardized, dist="norm", plot=plt)
plt.title("Q-Q Plot of Residuals")
plt.show()
```

The residuals do not follow a normal distribution.





Whenever we run a model or perform data analysis, it is common to check the distribution of the variables in question. If some are skewed and not normally distributed, we tend to worry. The truth is that the need to assume normality for independent and dependent variables is not always true.

The variable that should be normally distributed is just the prediction error!

The prediction error must follow a normal distribution with mean 0. The calculation of the confidence interval and the significance of the variable is based on this assumption.

You can also use the Shapiro-Wilk test to test the normality assumption. Basically, if the p-value is greater than the threshold (usually 0.05) then we accept the distribution as normal.

How do we fix the normality problem? Typically, there are 2 reasons why this problem occurs:

- Dependent or independent variables are very abnormal (you can see by the asymmetry and/or kurtosis of the variable)
- Existence of some outliers that hinder the model's prediction

We must then check for outliers in the variables and if this does not solve the problem, we must transform some variables that are not normally distributed so that they are normally distributed.

In conclusion, if you try to find a significant predictive factor or define the confidence interval, remember to check the distribution of the error term after building the model. If the dependent variables or independent variables are very non-normal, one can use the box-cox transformation (for example) to transform it and make the error term more normally distributed.

In our case, neither homoscedaticity or the normal distribution of errors were met, which compromises our analysis. In your projects you must fix this, as this work is only at a didactic level, we will not delve into this issue further. One idea to fix this would perhaps be to normalize the target variable.

1.7 Evaluate the model globally

Linear regression models are intrinsically explainable, which means that if we understand how the model works, then we can make sense of their predictions.

Let's now try to interpret the model globally. For this we need to determine:

- Coefficient magnitude and sign
- Coefficient significance (t statistic and p-value)
- Effects plot

Determine the coefficient's error using cross-validation.

[17]:
```
# Function to fit the model with GridSearchCV and return the coefficients
def fit_model_and_get_coeffs(X_train, y_train, param_grid):
    grid_search_globally = GridSearchCV(final_model, param_grid, cv=5,␣
 ↪scoring='r2', return_train_score=True)
    grid_search_globally.fit(X_train, y_train)
    return grid_search_globally.best_estimator_.named_steps.regressor.coef_,␣
 ↪grid_search_globally.best_estimator_.named_steps.preprocessor.
 ↪get_feature_names_out()

# Number of Bootstrap iterations
num_bootstrap_iterations = 100

# List to store coefficients for each Bootstrap iteration
coeffs_bootstrap = []

# Initialize list of coefficient names
coeffs_names = []

# Loop over each Bootstrap iteration
for i in range(num_bootstrap_iterations):
    # Random sampling with replacement of indices
    indices = np.random.choice(range(len(X)), size=len(X), replace=True)
    X_bootstrap, y_bootstrap = X.iloc[indices], y.iloc[indices]

    # Split the sampled dataset into train and test
    X_train, X_test, y_train, y_test = train_test_split(X_bootstrap,␣
 ↪y_bootstrap, test_size=0.2, random_state=42)

    # Fit the model and obtain coefficients for this sample
```

```
    coeffs_boot, new_coeffs_names = fit_model_and_get_coeffs(X_train, y_train,␣
↪param_grid)

    # Add unique coefficient names
    coeffs_names.extend([name for name in new_coeffs_names if name not in␣
↪coeffs_names])

    # Add coefficients of this Bootstrap iteration to the list
    coeffs_bootstrap.append(coeffs_boot)

# Determine the maximum length of coefficients array
max_coeffs_length = max(len(coeffs) for coeffs in coeffs_bootstrap)

# Fill coefficients arrays with zeros so that they all have the same length
coeffs_bootstrap_padded = [np.pad(coeffs, (0, max_coeffs_length - len(coeffs)),␣
↪mode='constant') for coeffs in coeffs_bootstrap]

# Convert the list of coefficients arrays into a numpy matrix
coeffs_bootstrap = np.vstack(coeffs_bootstrap_padded)

# Ensure coeffs_names has the same length as the number of columns in␣
↪coeffs_mean
coeffs_names = coeffs_names[:coeffs_bootstrap.shape[1]]

# Calculate the mean of coefficients
coeffs_mean = np.mean(coeffs_bootstrap, axis=0)

# Calculate the standard deviation of coefficients
coeffs_std = np.std(coeffs_bootstrap, axis=0)

# Create a DataFrame to store the mean and standard deviation of coefficients
coeffs_df = pd.DataFrame({'mean_coeffs_sign': coeffs_mean, 'coeffs_std':␣
↪coeffs_std}, index=coeffs_names).reset_index()
coeffs_df.sort_values(by=['mean_coeffs_sign'], ascending=False, inplace=True)
coeffs_df.rename(columns={'index': 'features'}, inplace=True)

# Visualize the DataFrame
coeffs_df
```

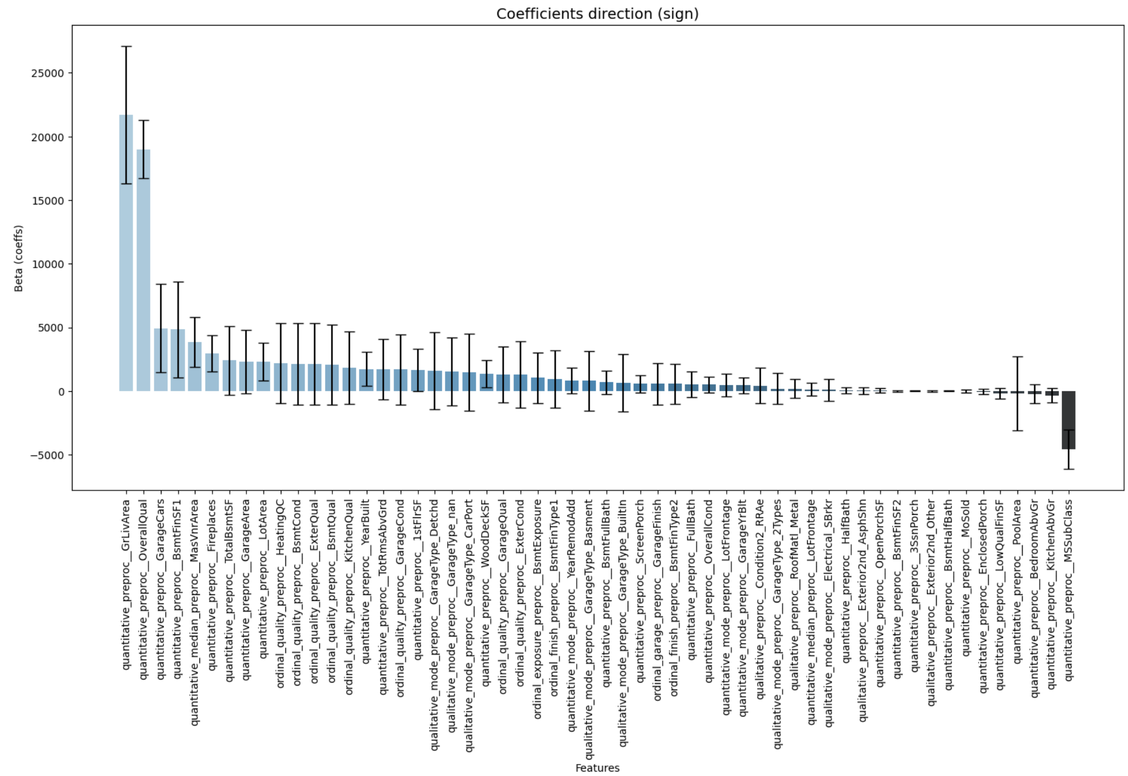
[17]:

	features	mean_coeffs_sign	coeffs_std
12	quantitative_preproc__GrLivArea	21714.189242	5388.545828
2	quantitative_preproc__OverallQual	18998.323970	2305.063393
21	quantitative_preproc__GarageCars	4931.342986	3460.563500
5	quantitative_preproc__BsmtFinSF1	4832.247887	3768.298030
33	quantitative_median_preproc__MasVnrArea	3852.195967	1944.982645
..	…	…	…
11	quantitative_preproc__LowQualFinSF	-164.544205	406.404862

```
28           quantitative_preproc__PoolArea       -207.523591  2912.103439
17       quantitative_preproc__BedroomAbvGr       -221.778399   723.354349
18       quantitative_preproc__KitchenAbvGr       -338.259106   568.481478
0          quantitative_preproc__MSSubClass      -4577.270253  1537.700679

[222 rows x 3 columns]
```

[18]:

```python
# filter df to not show the coeffs that went to 0
filtered_coeffs = coeffs_df.loc[(coeffs_df['mean_coeffs_sign'] != 0.0) &
                                (coeffs_df['mean_coeffs_sign'] != -0.0)]

# Create a function of the graph to reuse later
def barplot(figsize, title, data, x, y, xlabel, ylabel, error_data=None):
    # Plot the graph
    plt.figure(figsize=figsize)

    # Title
    plt.title(title, fontsize=14)

    # Graph
    sns.barplot(data=data, x=x, y=y, ci=None, palette="Blues_d")

    # Adding error bars if error_data is provided
    if error_data is not None:
        std_err = error_data
        plt.errorbar(data[x], data[y], yerr=std_err, fmt='none', color='k',␣
 ↪capsize=5)

    # Label
    plt.xticks(rotation=90)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.show()

# Example usage:
barplot((18, 8), 'Coefficients direction (sign)', filtered_coeffs,
        'features', 'mean_coeffs_sign', 'Features', 'Beta (coeffs)',
        error_data=filtered_coeffs['coeffs_std'])
```

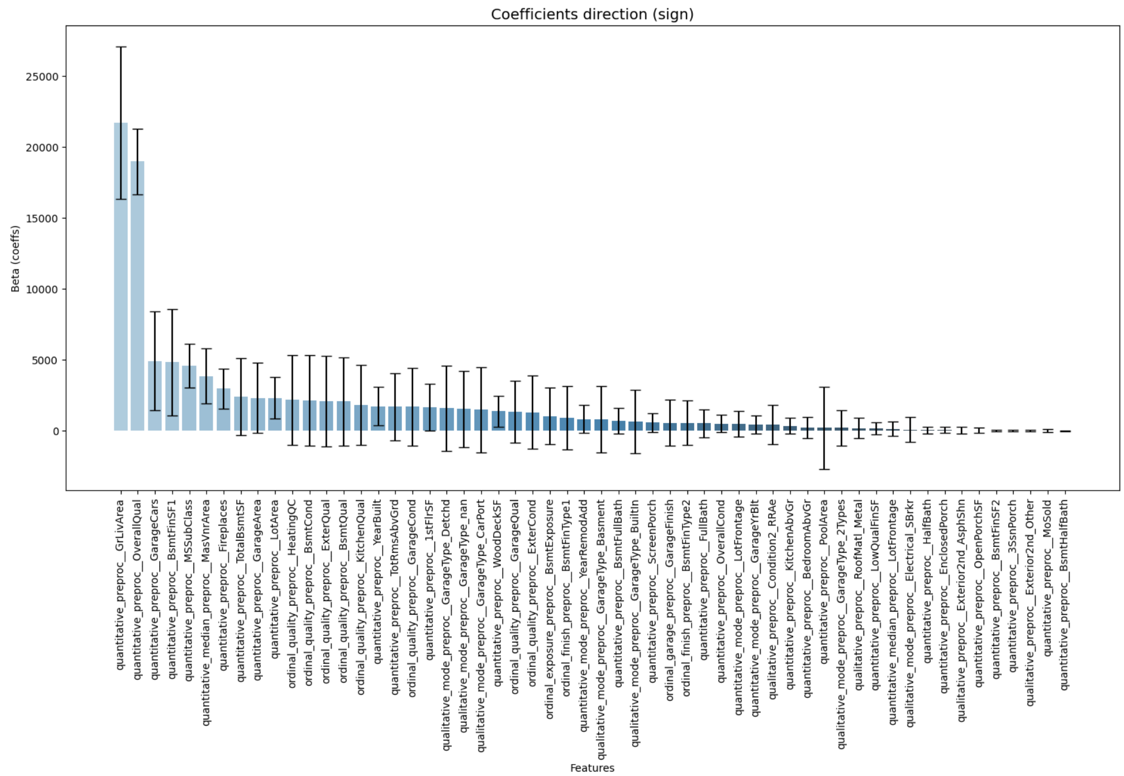


- Beta (coefficients) represents the gradient (slope) of the regression
- Beta is the change in y, per unit change in x (if all the other values stay the same)
- The positive values, if x increases, so does y
- The negative values, if x increases, y decreases

The Beta related to the feature "GrLivArea" > Beta related to the feature "OverallQuall", in other words "GrLivArea" has a greater contribuition than "OverallQuall" to the target value.

Let's compare the absolute value of each coefficient.

[19]:
```
# extract the absolute value of each coeff
filtered_coeffs['mean_coeffs_sign'] = filtered_coeffs['mean_coeffs_sign'].abs()
filtered_coeffs.sort_values(by=['mean_coeffs_sign'], ascending=False,␣
 ↪inplace=True)

barplot((18, 8), 'Coefficients direction (sign)', filtered_coeffs,
        'features', 'mean_coeffs_sign',
        'Features', 'Beta (coeffs)',
        error_data=filtered_coeffs['coeffs_std'])
```



This is what we normally use as a value of feature importance (feature selection methods, Lasso model automatically does this for us). Initially with more than 200 features, we ended with these, which are the most important for the model.

1.7.1 Calculate the t-statistic and p-value for each coefficient

The t-value, also known as the t-test, is an important focus of attention, since it is the link that tells us whether the association between an explanatory variable and the response is statistically significant. The t-value is simply the estimate/standard error, and thus can be interpreted as the distance of the estimate from 0, measured in standard errors. Given a t-value and sample size, the software can provide an accurate p-value; for large samples, t-values greater than 2 or less than –2 correspond to $p < 0.05$, although these thresholds are higher for smaller sample sizes.

- t-test tests the null hypothesis: b=0
- Tests how big b is, compared to its variability

If t is too big or too small -> the probability that b=0 is small, then, the regression coefficient is statistically significant.

[20]:
```
filtered_coeffs['t_test'] = filtered_coeffs['mean_coeffs_sign'] /␣
    ↪filtered_coeffs['coeffs_std']
filtered_coeffs
```

[20]:

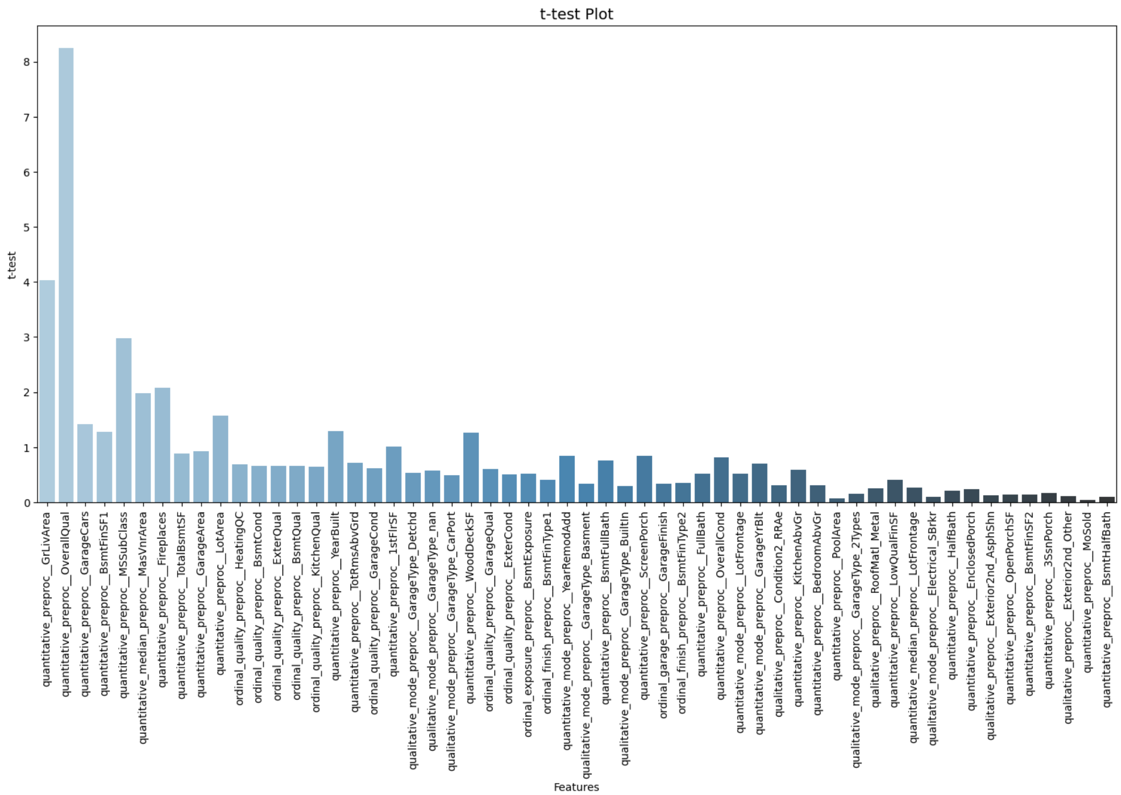
```
                                        features  mean_coeffs_sign  \
12               quantitative_preproc__GrLivArea      21714.189242
2              quantitative_preproc__OverallQual      18998.323970
21              quantitative_preproc__GarageCars       4931.342986
5               quantitative_preproc__BsmtFinSF1       4832.247887
0               quantitative_preproc__MSSubClass       4577.270253
33       quantitative_median_preproc__MasVnrArea       3852.195967
20              quantitative_preproc__Fireplaces       2968.611112
8              quantitative_preproc__TotalBsmtSF       2396.445050
22              quantitative_preproc__GarageArea       2317.755954
1                  quantitative_preproc__LotArea       2305.309418
209           ordinal_quality_preproc__HeatingQC       2166.741426
208            ordinal_quality_preproc__BsmtCond       2132.256908
205           ordinal_quality_preproc__ExterQual       2105.917008
207            ordinal_quality_preproc__BsmtQual       2061.159714
210         ordinal_quality_preproc__KitchenQual       1832.783503
4                quantitative_preproc__YearBuilt       1736.087225
19             quantitative_preproc__TotRmsAbvGrd      1702.281167
212          ordinal_quality_preproc__GarageCond       1694.193995
9                 quantitative_preproc__1stFlrSF       1653.541318
203   qualitative_mode_preproc__GarageType_Detchd      1596.794275
204      qualitative_mode_preproc__GarageType_nan      1531.679661
202  qualitative_mode_preproc__GarageType_CarPort      1472.624617
23              quantitative_preproc__WoodDeckSF       1367.713771
211          ordinal_quality_preproc__GarageQual       1324.697914
206           ordinal_quality_preproc__ExterCond       1301.277717
213      ordinal_exposure_preproc__BsmtExposure       1034.914082
214         ordinal_finish_preproc__BsmtFinType1        921.930767
35       quantitative_mode_preproc__YearRemodAdd        832.259605
200  qualitative_mode_preproc__GarageType_Basment        802.636039
13            quantitative_preproc__BsmtFullBath        691.008010
201  qualitative_mode_preproc__GarageType_BuiltIn        648.813157
27             quantitative_preproc__ScreenPorch        572.670701
216         ordinal_garage_preproc__GarageFinish        563.776395
215         ordinal_finish_preproc__BsmtFinType2        560.662227
15                quantitative_preproc__FullBath        522.115608
3              quantitative_preproc__OverallCond        510.736195
34       quantitative_mode_preproc__LotFrontage        469.228607
36       quantitative_mode_preproc__GarageYrBlt        447.640997
217         qualitative_preproc__Condition2_RRAe        424.845662
18            quantitative_preproc__KitchenAbvGr        338.259106
17            quantitative_preproc__BedroomAbvGr        221.778399
28                quantitative_preproc__PoolArea        207.523591
198   qualitative_mode_preproc__GarageType_2Types        196.123903
218          qualitative_preproc__RoofMatl_Metal        189.083249
11            quantitative_preproc__LowQualFinSF        164.544205
32     quantitative_median_preproc__LotFrontage        132.491923
```

196	qualitative_mode_preproc__Electrical_SBrkr	88.227701
16	quantitative_preproc__HalfBath	50.949524
25	quantitative_preproc__EnclosedPorch	49.487195
219	qualitative_preproc__Exterior2nd_AsphShn	33.511129
24	quantitative_preproc__OpenPorchSF	25.551062
6	quantitative_preproc__BsmtFinSF2	9.872694
26	quantitative_preproc__3SsnPorch	7.166088
220	qualitative_preproc__Exterior2nd_Other	4.998262
30	quantitative_preproc__MoSold	3.972144
14	quantitative_preproc__BsmtHalfBath	2.744620

	coeffs_std	t_test
12	5388.545828	4.029694
2	2305.063393	8.241996
21	3460.563500	1.425012
5	3768.298030	1.282342
0	1537.700679	2.976698
33	1944.982645	1.980581
20	1423.609182	2.085271
8	2727.333788	0.878677
22	2483.236836	0.933361
1	1463.212331	1.575513
209	3144.635952	0.689028
208	3213.690150	0.663492
205	3196.704900	0.658777
207	3127.151470	0.659117
210	2825.582280	0.648639
4	1338.119735	1.297408
19	2364.765482	0.719852
212	2746.198706	0.616923
9	1642.856198	1.006504
203	3009.293957	0.530621
204	2687.776318	0.569869
202	3011.198185	0.489049
23	1080.613787	1.265682
211	2194.282506	0.603704
206	2586.492725	0.503105
213	2001.205826	0.517145
214	2247.865856	0.410136
35	990.156692	0.840533
200	2347.665914	0.341887
13	914.937378	0.755252
201	2241.082752	0.289509
27	684.686922	0.836398
216	1645.095017	0.342701
215	1571.393400	0.356793
15	997.536761	0.523405

```
3      624.005094  0.818481
34     902.797409  0.519750
36     640.038983  0.699396
217   1396.798415  0.304157
18     568.481478  0.595022
17     723.354349  0.306597
28    2912.103439  0.071262
198   1235.710207  0.158714
218    736.645253  0.256682
11     406.404862  0.404878
32     504.524588  0.262607
196    877.854544  0.100504
16     245.818373  0.207265
25     203.050524  0.243719
219    252.710121  0.132607
24     177.900767  0.143625
6       69.226082  0.142615
26      42.233511  0.169678
220     44.351484  0.112697
30     103.620553  0.038334
14      27.308623  0.100504
```

[21]:
```
barplot((18, 8), 't-test Plot', filtered_coeffs,
         'features', 't_test',
         'Features', 't-test')
```



Based on the t values, we can, for example, trust the value of the coefficient of variable “OverallQual” more than that of variable “GrLivArea”.

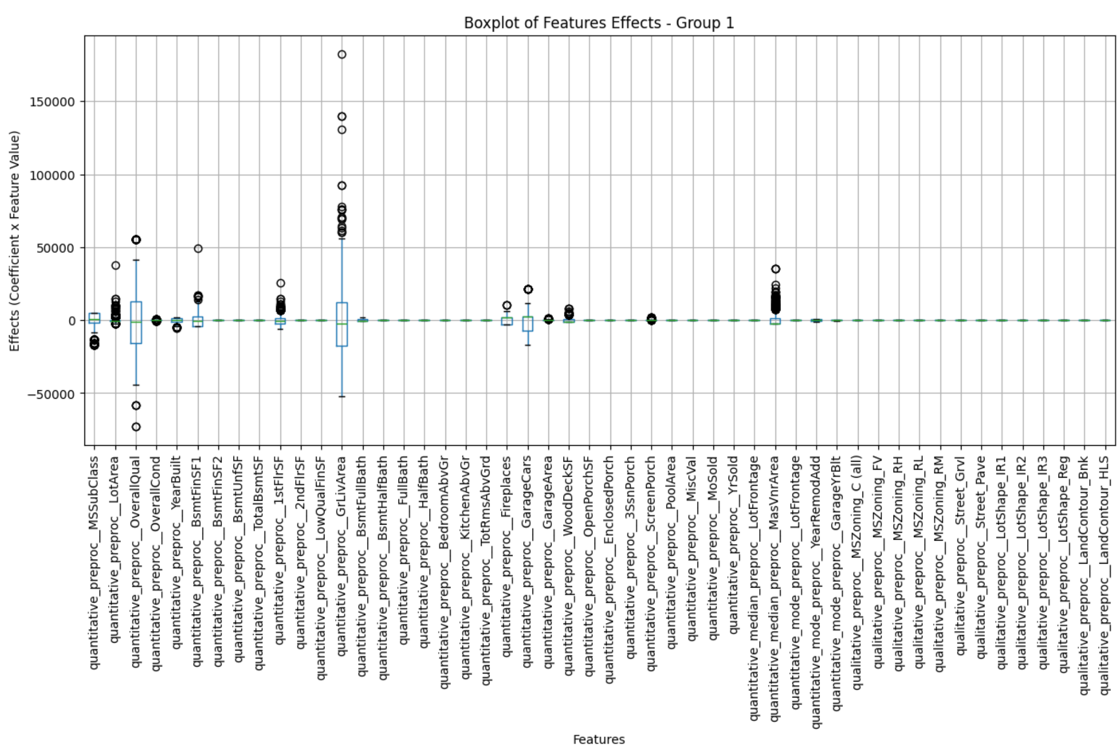
1.7.2 Effect plots

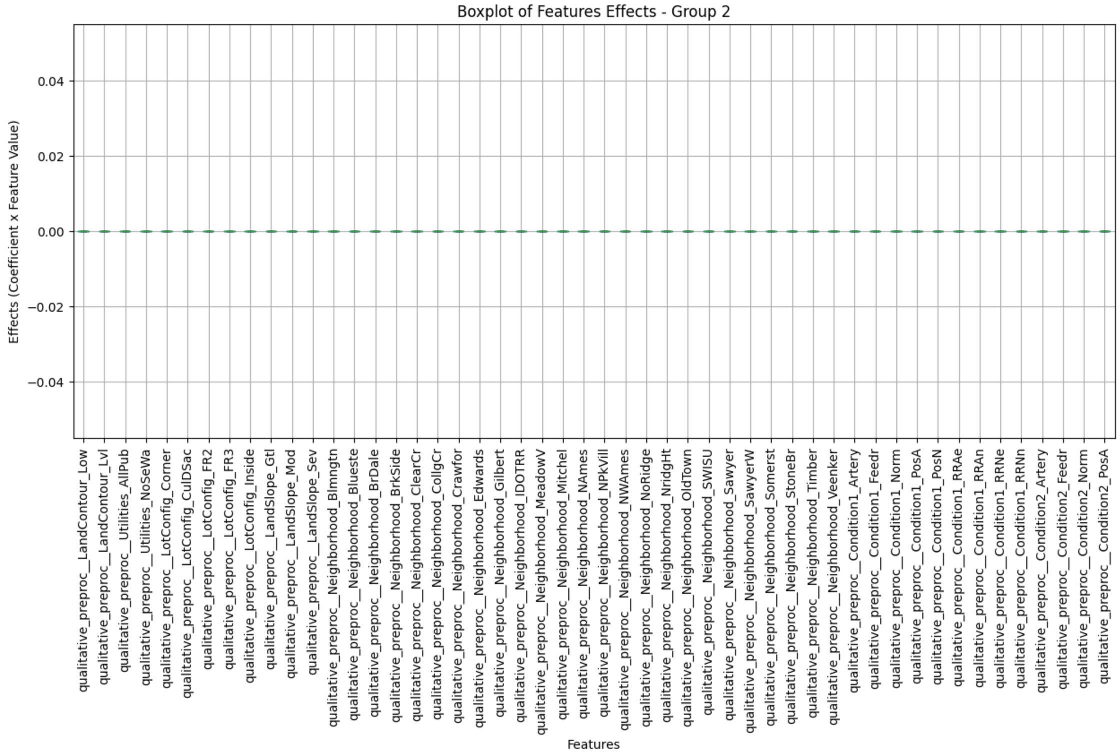
Features whose coefficient is bigger are said to be more important. This coefficients alone don’t determine the value of the target, to have this, we need the combination of these coefficients with the value of the variable, the one that contributes to the final target outcome.

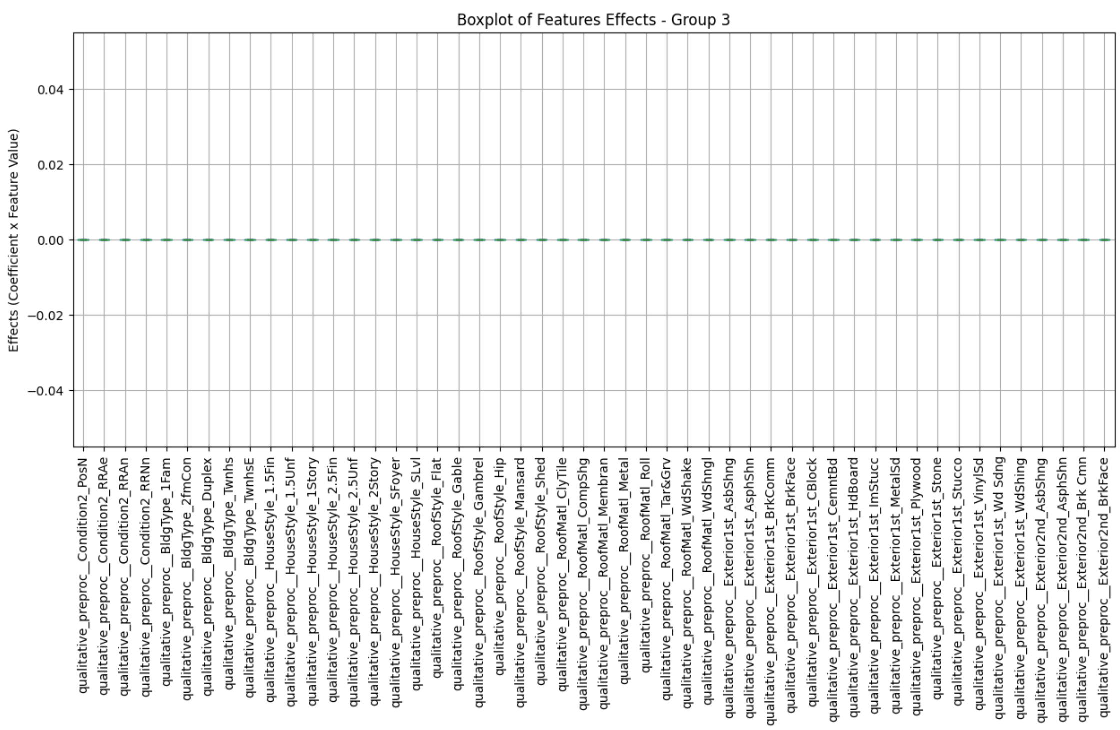
So, instead of plot just the coefficients we can plot the effects.

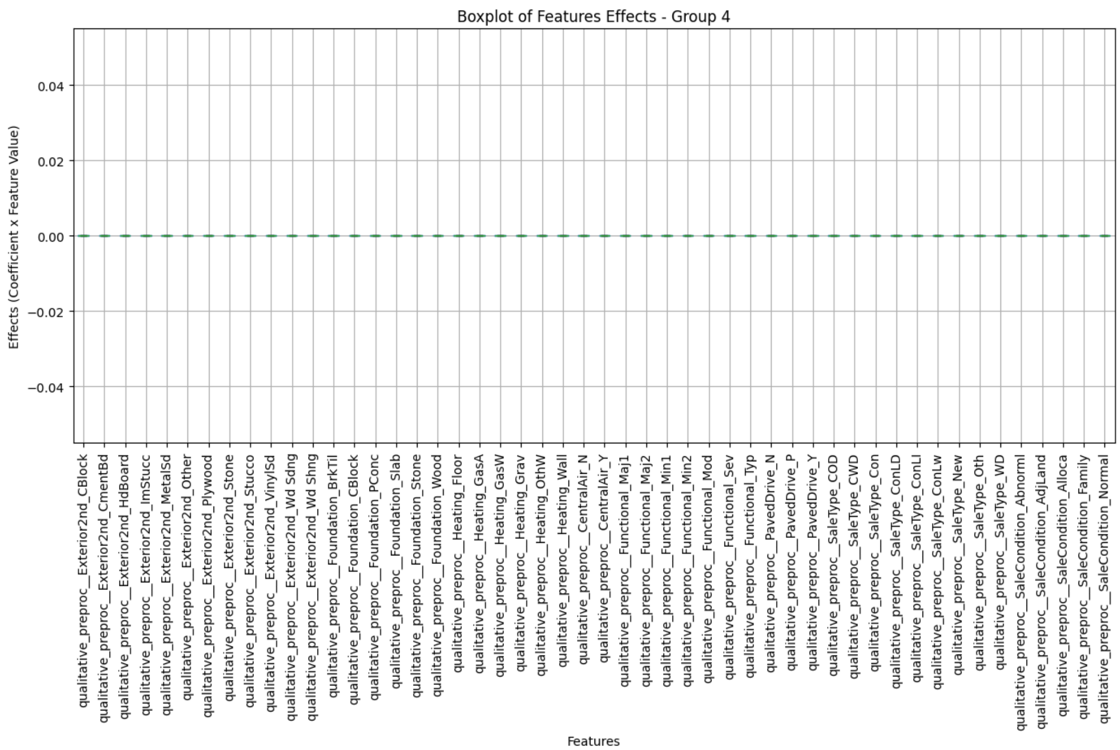
[22]:
```
# get the coefficients and the values of the variables
scaler_names = grid_search.best_estimator_.named_steps.preprocessor.
 ↪get_feature_names_out()
final_coeffs = grid_search.best_estimator_.named_steps.regressor.coef_
X_train_transformed = grid_search.best_estimator_.named_steps['preprocessor'].
 ↪transform(X_train)

# calculate the effects
effects = final_coeffs * X_train_transformed

# dividing the variables in groups of 50
num_variables = len(scaler_names)
```

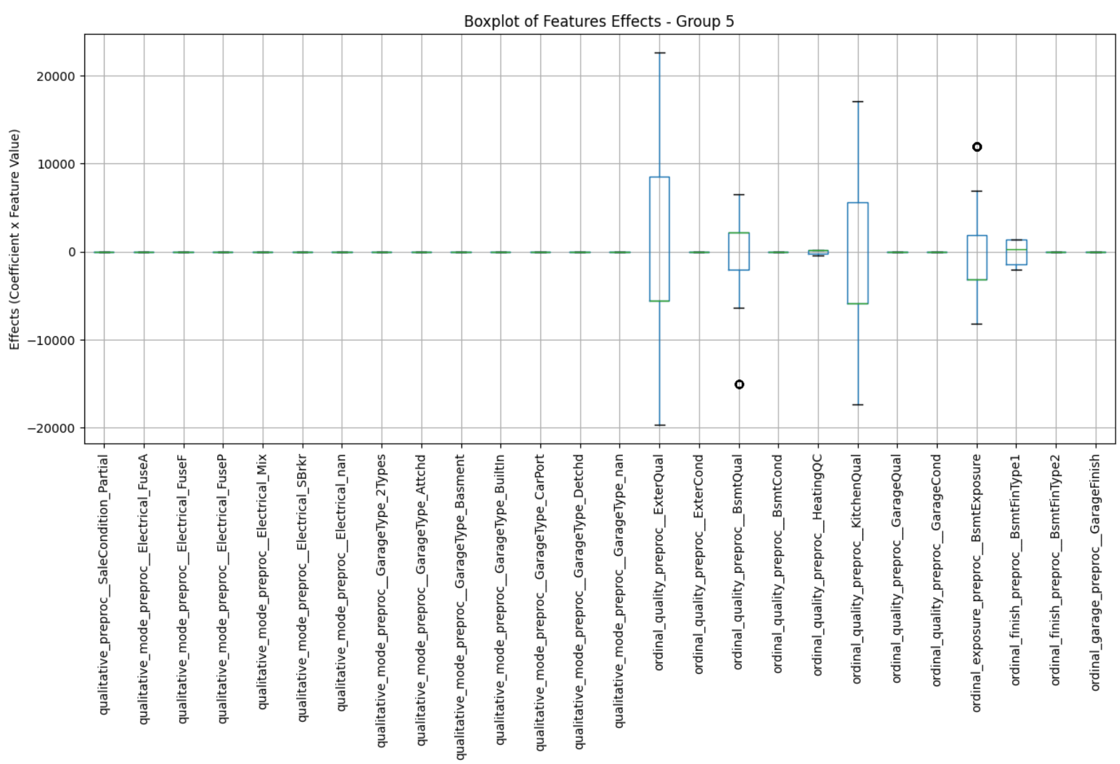
```python
group_size = 50
num_groups = int(np.ceil(num_variables / group_size))

# iterate for the variables groups
for i in range(num_groups):
    start_index = i * group_size
    end_index = min((i + 1) * group_size, num_variables)

    # select the variables for the actual group
    scaler_names_group = scaler_names[start_index:end_index]
    effects_group = effects[:, start_index:end_index]

    # create the dataframe for the actual group
    effects_df_group = pd.DataFrame(effects_group, columns=scaler_names_group)

    # plot the boxplot for the actual group
    plt.figure(figsize=(15, 6))
    effects_df_group.boxplot()
    plt.title(f'Boxplot of Features Effects - Group {i+1}')
    plt.ylabel('Effects (Coefficient x Feature Value)')
    plt.xlabel('Features')
    plt.xticks(rotation=90)
    plt.show()
```




Boxplot of Features Effects - Group 2
Effects (Coefficient x Feature Value)
Features


Boxplot of Features Effects - Group 3
Effects (Coefficient x Feature Value)
Features


Boxplot of Features Effects - Group 4
Effects (Coefficient x Feature Value)
Features

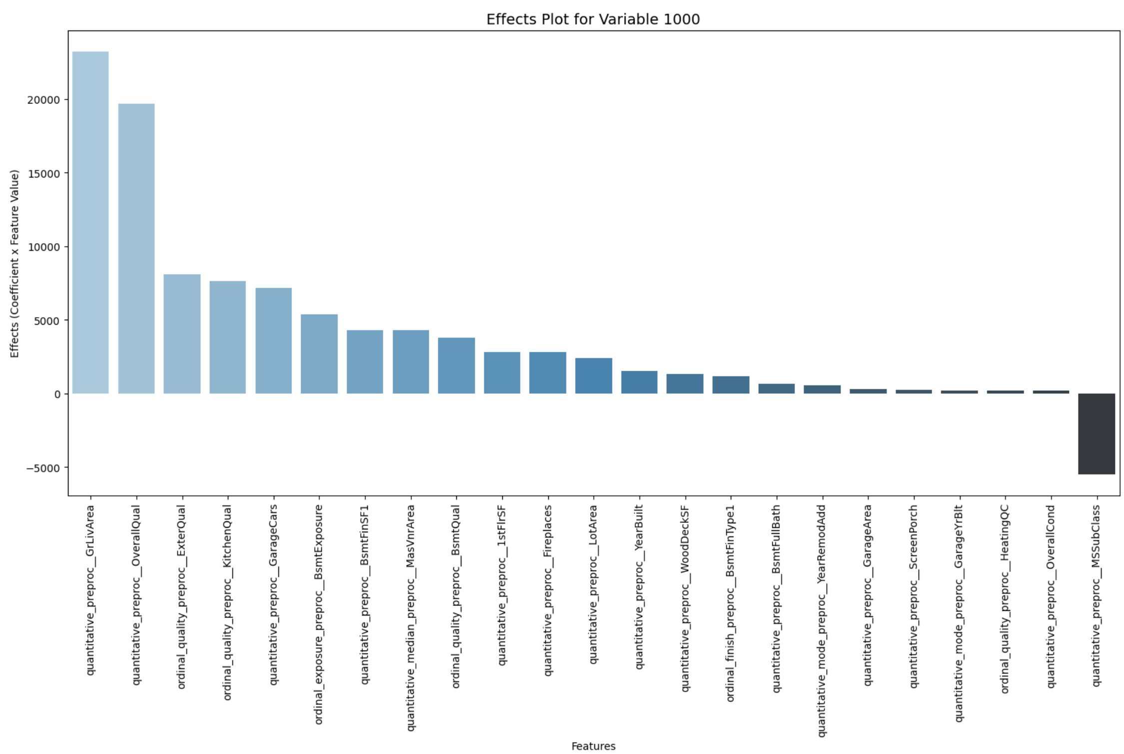

Boxplot of Features Effects - Group 5
Effects (Coefficient x Feature Value)
Features

As we can see, the main drivers of the house price are the variables "OverallQual", "GrLivArea", "ExterQual", "KitchenQual", "BsmtExposure".

1.8 Local interpretability

The same interpretation that we did globally (for all instances) we can also do locally for just one instance if you are interested in a specific case.

[24]:
```
# calculate the effects of instance 1000
effects1000 = final_coeffs * X_train_transformed[1000]

# create the dataframe for the instance 1000
effects_df1000 = pd.DataFrame({'mean_coeffs_sign': final_coeffs},␣
↪index=scaler_names).reset_index()
effects_df1000.sort_values(by=['mean_coeffs_sign'], ascending=False,␣
↪inplace=True)
effects_df1000.rename(columns={'index': 'features'}, inplace=True)
effects_df1000 = effects_df1000.loc[
    (effects_df1000['mean_coeffs_sign'] != 0.0) &
    (effects_df1000['mean_coeffs_sign'] != -0.0)]

# plot the bar graph
barplot((18, 8), 'Effects Plot for Variable 1000', effects_df1000,
        'features', 'mean_coeffs_sign',
        'Features', 'Effects (Coefficient x Feature Value)')
```



As we can see, these are the effects of the most important variables on the final price of the index house equal to 1000.

1.9 Conclusion

Here I want to summarize the main advandages of the linear regression models and also some of the limitations.

Advantages:

- Predict the target as a linear combination of the predictors (weighted sum of the predictors) and as humans we are very good interpreting linear models.
- We can use statistical tests to decide if / how much we can trust the model and its parameters (i)
- Intrinsically explainable by design
- We can use regularization to reduce the feature space
  - Optimize for interpretability

Limitations:

- The interpretation of the weight / coefficient is contrastive (depends on all other features)
  - Features with positive correlation coefficient show a negative weight
- Make assumptions on the data -> when they are not met, we can't trust the model
- Multicolinearity affects interpretability
- Interactions between the variables won't be captured

Credits:

https://www.trainindata.com/