eda

June 18, 2023

1 Exploratory Data Analysis

The data originates from the kaggle copetition

1.1 Dataset Description

File descriptions * train.csv - the training set. * test.csv - the test set. * data_description.txt - full description of each column, originally prepared by Dean De Cock but lightly edited to match the column names used here.

Target Variable

The variable we aim to predict is `SalePrice`.

1.2 EDA:

[ ]:
```
import warnings
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt  # Matlab-style plotting
import seaborn as sns
from scipy import stats
from scipy.stats import skew
from scipy.stats.stats import pearsonr
from scipy.stats import shapiro
from statsmodels.stats.outliers_influence import variance_inflation_factor
from plot_tools import plot_distribution, plot_corration_map, PlotRelations
from bayesian_opt import Optimizer
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import Lasso
from sklearn.model_selection import train_test_split
from skopt.space import Integer, Real, Categorical
```

```
/var/folders/0m/mtf6psc91_l02bjt_n2nd7bh0000gn/T/ipykernel_7563/4000899093.py:8:
DeprecationWarning: Please use `pearsonr` from the `scipy.stats` namespace, the
`scipy.stats.stats` namespace is deprecated.
  from scipy.stats.stats import pearsonr
```

[ ]:
```
df = pd.read_csv('data/train.csv')
display(df.head())
```

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

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

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

[5 rows x 81 columns]
```

[ ]:
```
df_target = df[['SalePrice']]
df_features = df.drop(['Id', 'SalePrice'], axis=1)
```

1.2.1 Feature engineering

First, let's examine the missing data and input it accordingly.

[ ]:
```
def get_missing(X: pd.DataFrame) -> pd.DataFrame:
    missing_rate = (X.isnull().sum() / len(X)) * 100
    missing_rate = missing_rate.drop(
        missing_rate[missing_rate == 0].index).sort_values(ascending=False)[:30]
    missing_data = pd.DataFrame({'Missing Ratio': missing_rate})
    return missing_data
```

[ ]:
```
get_missing(df_target)
```

[ ]:
```
Empty DataFrame
Columns: [Missing Ratio]
Index: []
```

[ ]:
```
missing_data = get_missing(df_features)
display(missing_data.head(10))
```

```
             Missing Ratio
PoolQC           99.520548
MiscFeature      96.301370
```

```
Alley           93.767123
Fence           80.753425
MasVnrType      59.726027
FireplaceQu     47.260274
LotFrontage     17.739726
GarageType       5.547945
GarageYrBlt      5.547945
GarageFinish     5.547945
```

Alley: Type of alley access to property

- NA: No alley access

BsmtQual: Evaluates the height of the basement

- NA: No Basement

BsmtCond: Evaluates the general condition of the basement

- NA: No Basement

BsmtExposure: Refers to walkout or garden level walls

- NA: No Basement

BsmtFinType1: Rating of basement finished area

- NA: No Basement

BsmtFinType2: Rating of basement finished area (if multiple types)

- NA: No Basement

FireplaceQu: Fireplace quality * NA: No Fireplace

GarageType: Garage location * NA: No Garage

GarageFinish: Interior finish of the garage * NA: No Garage

GarageQual: Garage quality * NA: No Garage

GarageCond: Garage condition * NA: No Garage

PoolQC: Pool quality * NA: No Pool

Fence: Fence quality * NA: No Fence

MiscFeature: Miscellaneous feature not covered in other categories * NA: None

[ ]:
```
variables_where_null_is_0 = [
                'BsmtQual', 'BsmtCond', 'BsmtExposure',
                'BsmtFinType1', 'BsmtFinType2', 'FireplaceQu',
                'GarageType', 'GarageFinish', 'GarageQual',
                'GarageCond', 'PoolQC', 'Fence'
            ]
values = {"Functional": "Typ",
          "Alley": "None",
```

```
        "MasVnrType": "None",
        "MiscFeature": "no_misc_feature",
        **{v:0 for v in variables_where_null_is_0}}
df_features.fillna(value=values, inplace=True)
```

[ ]:
```
missing_data = get_missing(df_features)
display(missing_data.head(10))
```

```
             Missing Ratio
LotFrontage      17.739726
GarageYrBlt       5.547945
MasVnrArea        0.547945
Electrical        0.068493
```

[ ]:
```
numeric_feats = df_features.dtypes[df_features.dtypes != "object"].index
```

[ ]:
```
df_features = pd.get_dummies(df_features)
df_features = df_features.fillna(df_features.mean())
missing_data = get_missing(df_features)
display(missing_data.head(10))
```

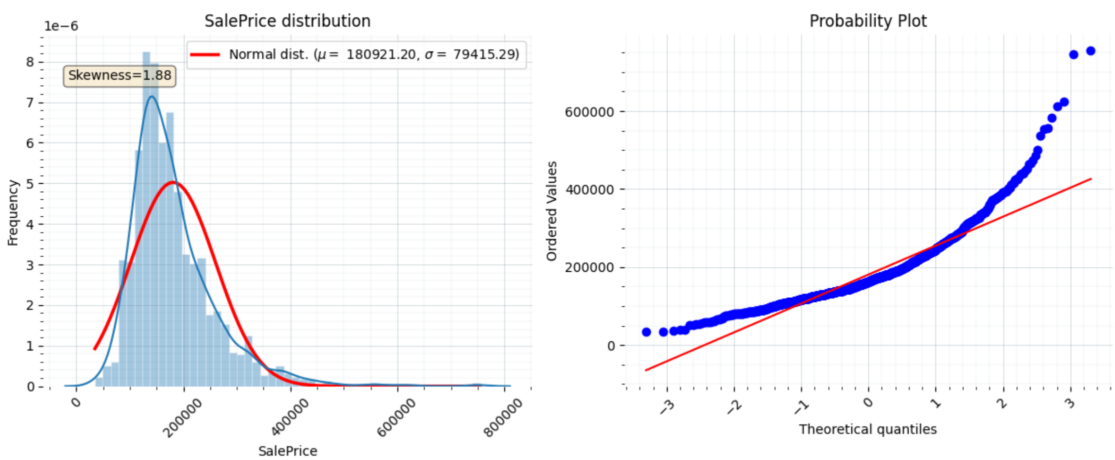
```
Empty DataFrame
Columns: [Missing Ratio]
Index: []
```

1.2.2 Target

We're going to check the distribution of the target variable and observe its asymmetry. However, for now, we won't perform any transformations. Then we will fit two models: Lasso and Random Forest.

[ ]:
```
print("Skewness: %f" % df_target['SalePrice'].skew())
plot_distribution(df_target, 'SalePrice')
```

```
Skewness: 1.882876
```

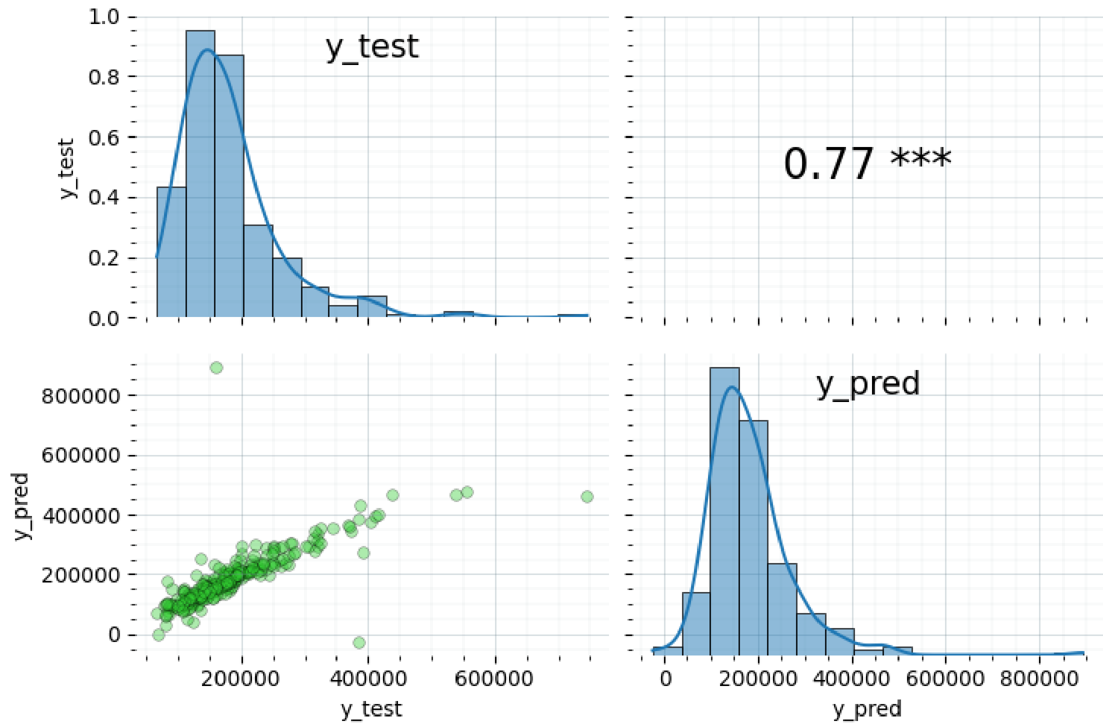


1.2.3 Regression

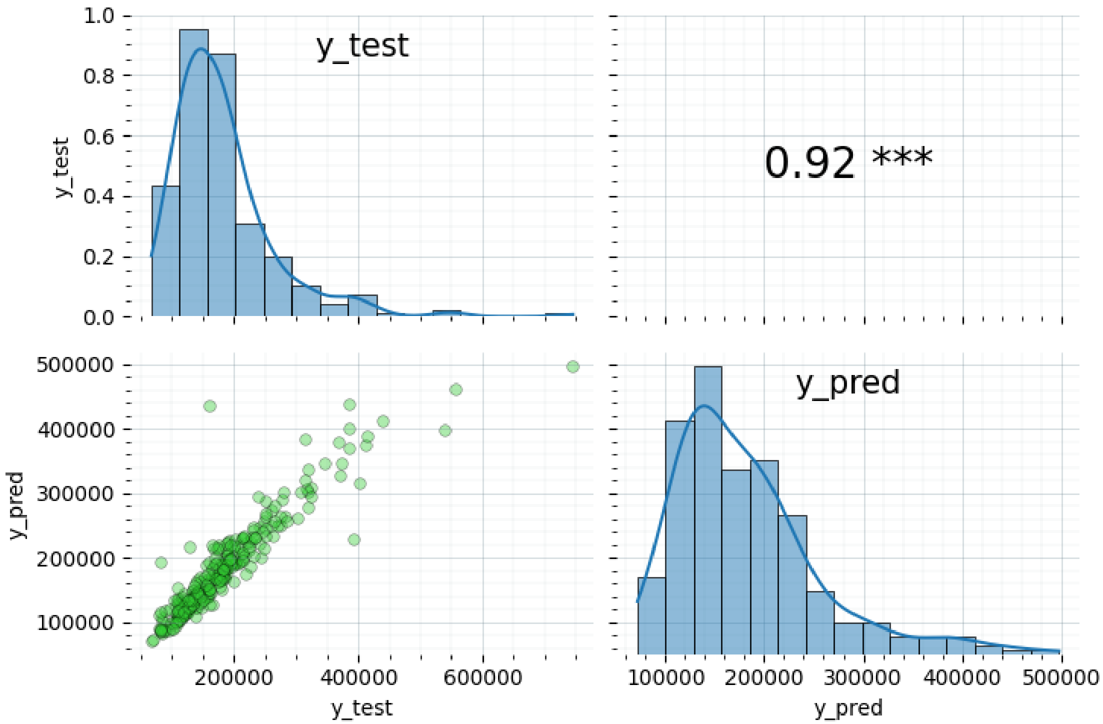
[ ]:
```
warnings.simplefilter("ignore", UserWarning)

y = df_target['SalePrice'].astype(float)
X = df_features.reset_index(drop=True)

X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.2, random_state=0)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
dict_models = {
'lasso': {
    'model': Lasso(),
    'space': [
        Real(0, 0.02, name='alpha'),
    ]
},

'rf': {
    'space': [
                Integer(100, 1000, name='n_estimators'),
                Integer(2, 100, name='min_samples_split'),
                Integer(1, 10, name='min_samples_leaf')
                ],
    'model': RandomForestRegressor()}
}

for model in dict_models:
    model_name = model
    space = dict_models[model]['space']
    model = dict_models[model]['model']
    optimizer = Optimizer(space=space, model=model,
                          model_name=model_name, n_calls=20)

    optimizer.find_optimal_params(X=X_train, y=y_train)
    best_model = optimizer.best_model.fit(X_train, y_train.ravel())
    y_pred = best_model.predict(X_test)
    plot_rel = PlotRelations(pd.DataFrame({'y_test': y_test, 'y_pred':␣
↪y_pred}), f'./pairplot_{model_name}.png')
    plot_rel.plot_graph()
    print(f"Test accuracy -> cor: {pearsonr(y_pred, y_test)[0]:.4f}, mse: {np.
↪mean((y_pred - y_test)**2):.4f}")
```

```
(1168, 302) (292, 302) (1168,) (292,)
```

```
Wait: Finding the best parameters …
Otimization done …
Trainin acuracy: 620902055.0649436
Best params: {'alpha': 0.0}
```



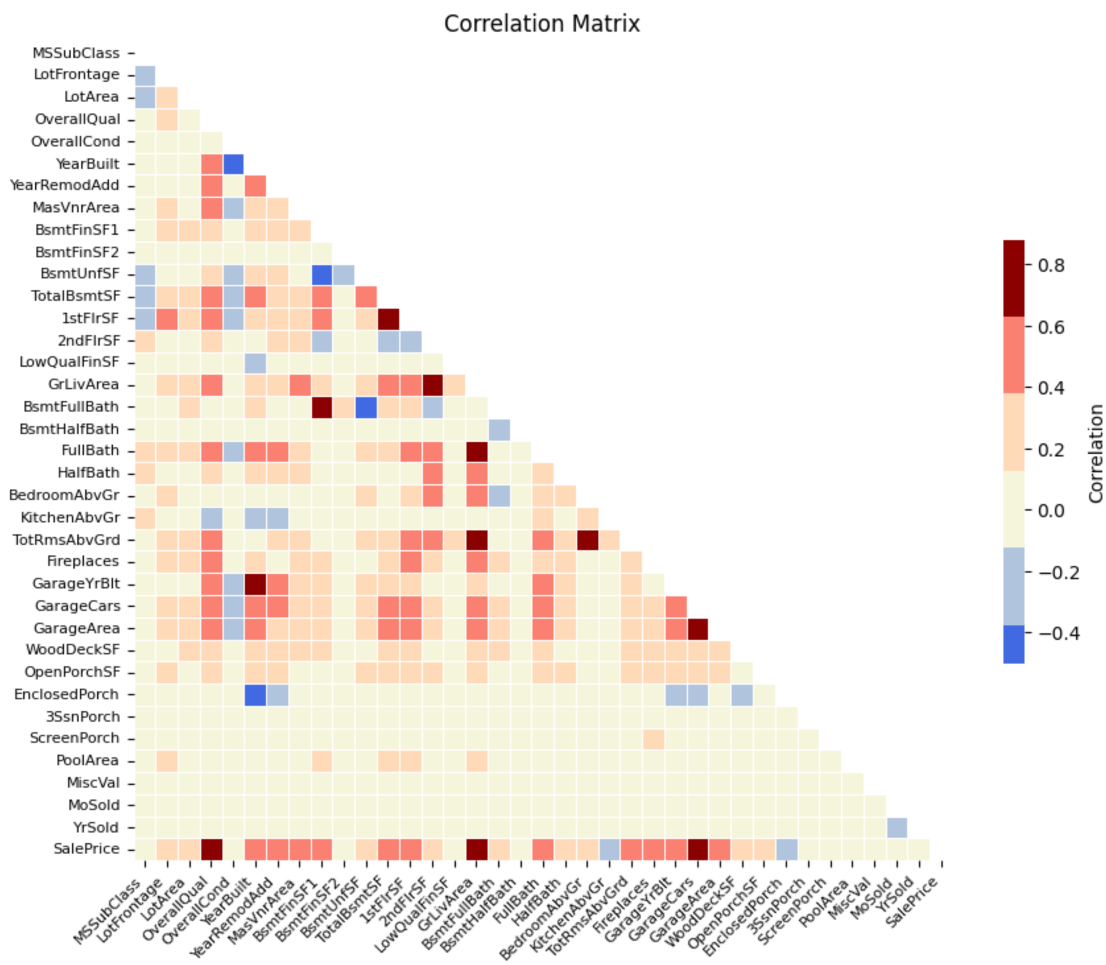

```
Test accuracy -> cor: 0.7747, mse: 3382109599.0223
Wait: Finding the best parameters …
Otimization done …
Trainin acuracy: 668485302.2799114
Best params: {'n_estimators': 100, 'min_samples_split': 3, 'min_samples_leaf':
1}
```




```
Test accuracy -> cor: 0.9202, mse: 1066485485.9711
```

1.2.4 Multicollinearity and Normality

[ ]:
```python
vars = list(numeric_feats)
vars.append('SalePrice')
plot_corration_map(pd.concat([df_features, df_target], axis=1)[vars])
```



Variance inflation factor, VIF, for one exogenous variable

The variance inflation factor is a measure for the increase of the variance of the parameter estimates if an additional variable, is added to the linear regression. It is a measure for multicollinearity of the design matrix.

One recommendation is that if VIF is greater than 5, then the explanatory variable is highly collinear with the other explanatory variables, and the parameter estimates will have large standard errors because of this.

[ ]:
```
vif_data = pd.DataFrame()
vif_data["feature"] = numeric_feats

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(df_features[numeric_feats].values, i)
                          for i in range(len(df_features[numeric_feats].columns))]
```

```
display(vif_data)
```

```
/Users/cristianooliveira/Documents/eda/.venv/lib/python3.10/site-
packages/statsmodels/stats/outliers_influence.py:198: RuntimeWarning: divide by
zero encountered in double_scalars
  vif = 1. / (1. - r_squared_i)
```

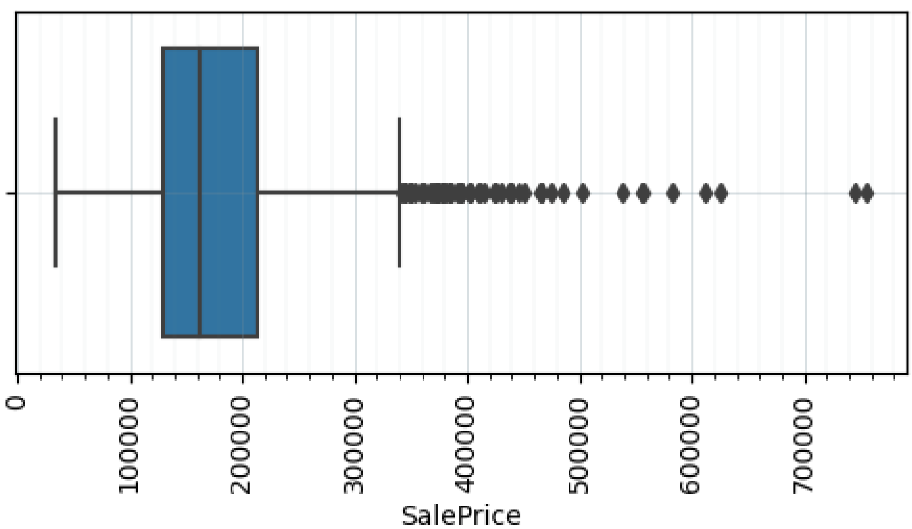
	feature	VIF
0	MSSubClass	4.648278e+00
1	LotFrontage	1.746100e+01
2	LotArea	2.647732e+00
3	OverallQual	6.661049e+01
4	OverallCond	4.165451e+01
5	YearBuilt	2.137223e+04
6	YearRemodAdd	2.240954e+04
7	MasVnrArea	1.854573e+00
8	BsmtFinSF1	inf
9	BsmtFinSF2	inf
10	BsmtUnfSF	inf
11	TotalBsmtSF	inf
12	1stFlrSF	inf
13	2ndFlrSF	inf
14	LowQualFinSF	inf
15	GrLivArea	inf
16	BsmtFullBath	3.694431e+00
17	BsmtHalfBath	1.219182e+00
18	FullBath	2.667373e+01
19	HalfBath	3.419675e+00
20	BedroomAbvGr	3.108831e+01
21	KitchenAbvGr	3.751478e+01
22	TotRmsAbvGrd	8.344349e+01
23	Fireplaces	3.019152e+00
24	GarageYrBlt	2.290578e+04
25	GarageCars	3.675316e+01
26	GarageArea	3.223857e+01
27	WoodDeckSF	1.904942e+00
28	OpenPorchSF	1.825531e+00
29	EnclosedPorch	1.447123e+00
30	3SsnPorch	1.036873e+00
31	ScreenPorch	1.190952e+00
32	PoolArea	1.106470e+00
33	MiscVal	1.031182e+00
34	MoSold	6.644392e+00
35	YrSold	2.411126e+04

[ ]:
```
shapiro_test = stats.shapiro(df_target['SalePrice'])
```

```
print(f'H0: The data was drawn from a normal distribution. If pvalue > 0.05, we␣
↪cannot reject the null hypothesis.')
print(f'Shapiro Test: shapiro.statistic = {shapiro_test.statistic:.4f}, shapiro.
↪pvalue = {shapiro_test.pvalue:.4f}')
```

```
H0: The data was drawn from a normal distribution. If pvalue > 0.05, we cannot
reject the null hypothesis.
Shapiro Test: shapiro.statistic = 0.8697, shapiro.pvalue = 0.0000
```

[ ]:
```
fig, ax = plt.subplots(1, 1, figsize=(5, 3))
sns.boxplot(x=df_target['SalePrice'], ax=ax)
ax.grid(which = "major", axis='both', color='#758D99', zorder=1, linewidth = 0.
↪5, alpha = 0.4,linestyle='-')
ax.grid(which = "minor", axis='both', color='#758D99', zorder=1, linewidth = 0.
↪3, alpha = 0.2,linestyle='-')
ax.minorticks_on()
ax.tick_params(axis='x', rotation=90)
plt.tight_layout()
plt.show()
```



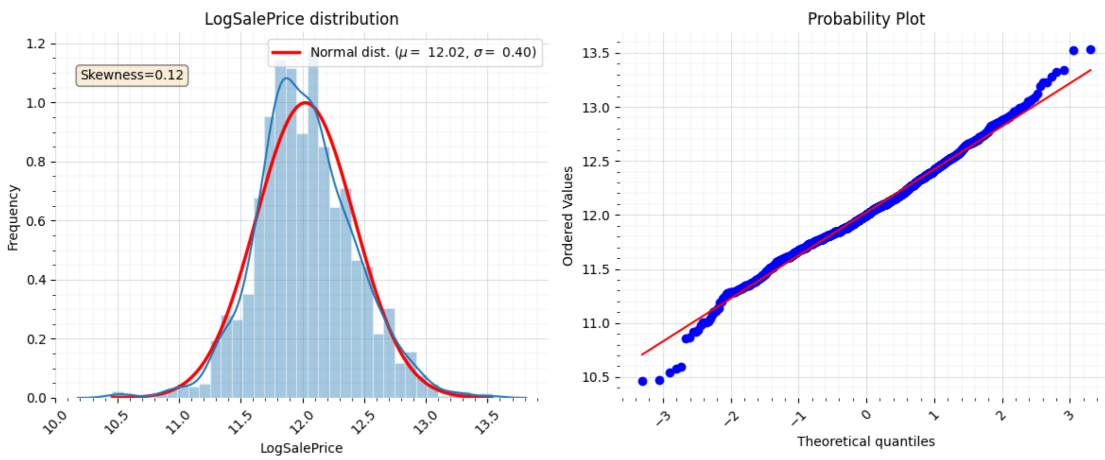
As we can observe, Random Forest demonstrates superior performance compared to Lasso. Despite our target data initially following a normal distribution, there is multicollinearity among our features. Consequently, employing Ordinary Least Squares (OLS) would not be a suitable option, even though the best Lasso model found has an alpha value of zero. Lasso effectively addresses multicollinearity through regularization.

To enhance the accuracy of Lasso, we will explore a data transformation approach, once the skewness of target variable is equal 1.882876.

[ ]:
```
df_target.loc[:,'LogSalePrice'] = np.log1p(df_target['SalePrice'].values)
```

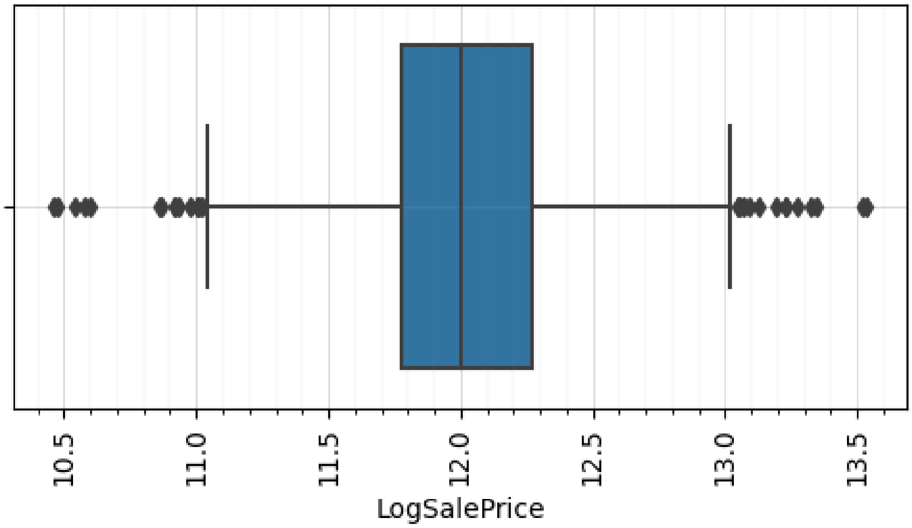
```
/var/folders/0m/mtf6psc91_l02bjt_n2nd7bh0000gn/T/ipykernel_7563/2508633438.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_target.loc[:,'LogSalePrice'] = np.log1p(df_target['SalePrice'].values)
```

[ ]:
```
plot_distribution(df_target, 'LogSalePrice')
shapiro_test = stats.shapiro(df_target['LogSalePrice'])
print(f'H0: The data was drawn from a normal distribution. If pvalue > 0.05, we␣
↪cannot reject the null hypothesis.')
print(f'Shapiro Test: shapiro.statistic = {shapiro_test.statistic:.4f}, shapiro.
↪pvalue = {shapiro_test.pvalue:.6f}')
```




```
H0: The data was drawn from a normal distribution. If pvalue > 0.05, we cannot
reject the null hypothesis.
Shapiro Test: shapiro.statistic = 0.9912, shapiro.pvalue = 0.000000
```

[ ]:
```
fig, ax = plt.subplots(1, 1, figsize=(5, 3))
sns.boxplot(x=df_target['LogSalePrice'], ax=ax)
ax.grid(which = "major", axis='both', color='#758D99', zorder=1, linewidth = 0.
↪5, alpha = 0.4,linestyle='-')
ax.grid(which = "minor", axis='both', color='#758D99', zorder=1, linewidth = 0.
↪3, alpha = 0.2,linestyle='-')
ax.minorticks_on()
ax.tick_params(axis='x', rotation=90)
plt.tight_layout()
plt.show()
```



[ ]:
```
print("Skewness: %f" % df_target['LogSalePrice'].skew())
```

```
Skewness: 0.121347
```

1.2.5 Regression

[ ]:
```
warnings.simplefilter("ignore", UserWarning)
y = df_target['LogSalePrice'].astype(float)
X = df_features.reset_index(drop=True)

X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.2, random_state=0)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
dict_models = {
'lasso': {
    'model': Lasso(),
    'space': [
        Real(0, 0.02, name='alpha'),
    ]
},

'rf': {
    'space': [
                Integer(100, 1000, name='n_estimators'),
                Integer(2, 100, name='min_samples_split'),
                Integer(1, 10, name='min_samples_leaf')
                ],
    'model': RandomForestRegressor()}
```

```
}

for model in dict_models:
    model_name = model
    space = dict_models[model]['space']
    model = dict_models[model]['model']
    optimizer = Optimizer(space=space, model=model,
                          model_name=model_name, n_calls=20)

    optimizer.find_optimal_params(X=X_train, y=y_train)
    best_model = optimizer.best_model.fit(X_train, y_train.ravel())
    y_pred = best_model.predict(X_test)
    print(f"Test accuracy -> cor: {pearsonr(np.expm1(y_pred), np.
 ↪expm1(y_test))[0]:.4f}, mse: {np.mean((y_pred - y_test)**2):.4f}")
```

```
(1168, 302) (292, 302) (1168,) (292,)
Wait: Finding the best parameters …
Otimization done …
Trainin acuracy: 0.014125085987874627
Best params: {'alpha': 0.0011342595463488638}
Test accuracy -> cor: 0.4515, mse: 0.0401
Wait: Finding the best parameters …
Otimization done …
Trainin acuracy: 0.01984058606185011
Best params: {'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf':
1}
Test accuracy -> cor: 0.9221, mse: 0.0192
```

1.2.6 Feature engineering

Now let's examine the skewness of our features and apply a transformation to specific variables.

[ ]:
```
skewed_feats = df_features[numeric_feats].apply(lambda x: skew(x.dropna())).
 ↪sort_values(ascending=False)
skewness = pd.DataFrame({'Skew' :skewed_feats})
display(skewness.sort_values(by=['Skew'], ascending=False).head(10))
```

	Skew
MiscVal	24.451640
PoolArea	14.813135
LotArea	12.195142
3SsnPorch	10.293752
LowQualFinSF	9.002080
KitchenAbvGr	4.483784
BsmtFinSF2	4.250888
ScreenPorch	4.117977
BsmtHalfBath	4.099186
EnclosedPorch	3.086696

[ ]:
```
skewed_feats = df_features[numeric_feats].apply(
    lambda x: skew(x.dropna()))  # compute skewness
skewed_feats = skewed_feats[skewed_feats > 0.75]
skewed_feats = skewed_feats.index
df_features[skewed_feats] = np.log1p(df_features[skewed_feats])
```

[ ]:
```
skewed_feats = df_features[numeric_feats].apply(lambda x: skew(x.dropna())).
 ↪sort_values(ascending=False)
skewness = pd.DataFrame({'Skew' :skewed_feats})
display(skewness.sort_values(by=['Skew'], ascending=False).head(10))
```

	Skew
PoolArea	14.348342
3SsnPorch	7.727026
LowQualFinSF	7.452650
MiscVal	5.165390
BsmtHalfBath	3.929022
KitchenAbvGr	3.865437
ScreenPorch	3.147171
BsmtFinSF2	2.521100
EnclosedPorch	2.110104
OverallCond	0.692355

1.2.7 Regression

[ ]:
```
warnings.simplefilter("ignore", UserWarning)
y = df_target['LogSalePrice'].astype(float)
X = df_features.reset_index(drop=True)

X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.2, random_state=0)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
dict_models = {
'lasso': {
    'model': Lasso(),
    'space': [
        Real(0, 0.02, name='alpha'),
    ]
},

'rf': {
    'space': [
                Integer(100, 1000, name='n_estimators'),
                Integer(2, 100, name='min_samples_split'),
                Integer(1, 10, name='min_samples_leaf')
                ],
```

```python
    'model': RandomForestRegressor()}
}

for model in dict_models:
    model_name = model
    space = dict_models[model]['space']
    model = dict_models[model]['model']
    optimizer = Optimizer(space=space, model=model,
                          model_name=model_name, n_calls=20)

    optimizer.find_optimal_params(X=X_train, y=y_train)
    best_model = optimizer.best_model.fit(X_train, y_train.ravel())
    y_pred = best_model.predict(X_test)
    print(f"Test accuracy -> cor: {pearsonr(np.expm1(y_pred), np.
 ↪expm1(y_test))[0]:.4f}, mse: {np.mean((y_pred - y_test)**2):.4f}")
```

```
(1168, 302) (292, 302) (1168,) (292,)
Wait: Finding the best parameters …
Otimization done …
Trainin acuracy: 0.013536651943483215
Best params: {'alpha': 0.0013912031696438143}
Test accuracy -> cor: 0.8379, mse: 0.0227
Wait: Finding the best parameters …
Otimization done …
Trainin acuracy: 0.019250869629480444
Best params: {'n_estimators': 1000, 'min_samples_split': 2, 'min_samples_leaf':
1}
Test accuracy -> cor: 0.9195, mse: 0.0192
```

Random Forest outperformed Lasso and was minimally affected by data transformations, maintaining its accuracy. On the other hand, Lasso exhibited significantly lower performance when using the data in its original scale, with a correlation coefficient of 0.77, while Random Forest achieved a correlation coefficient of 0.92.

However, after applying transformations to reduce the asymmetry of the target and features, Lasso showed improvement with a correlation coefficient of 0.84, while Random Forest maintained its high accuracy.