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January 24, 2022

# 1 Feature Scaling and Normalization - Lab

## 1.1 Introduction

In this lab, you'll practice your feature scaling and normalization skills!

## 1.2 Objectives

You will be able to: * Identify if it is necessary to perform log transformations on a set of features * Perform log transformations on different features of a dataset * Determine if it is necessary to perform normalization/standardization for a specific model or set of data * Compare the different standardization and normalization techniques * Use standardization/normalization on features of a dataset

## 1.3 Back to the Ames Housing data

Let's import our Ames Housing data.

[11]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
plt.style.use('seaborn')

ames = pd.read_csv('ames.csv')
```

## 1.4 Look at the histograms for the continuous variables

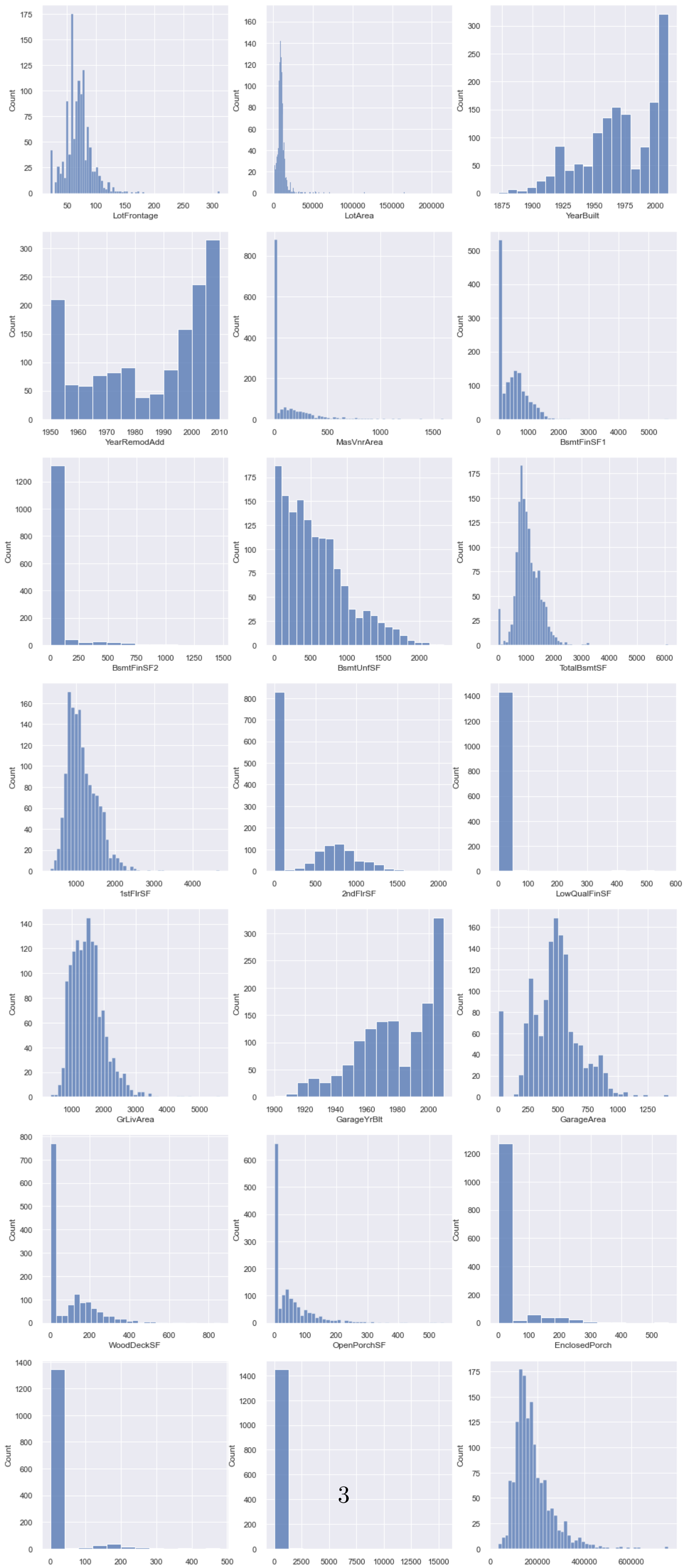
Since there are so many features it is helpful to filter the columns by datatype and number of unique values. A heuristic you might use to select continous variables might be a combination of features that are not object datatypes and have at least a certain amount of unique values.

[32]:
```
# Your code here
## From GitHub
to_pick = ames.loc[:, (ames.dtypes != "object") & (ames.nunique() > 20)]
to_plot = to_pick[to_pick.columns[1:]]
lis = to_plot.columns
to_plot.info()
```

```
# to_pick.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   LotFrontage    1201 non-null   float64
 1   LotArea        1460 non-null   int64
 2   YearBuilt      1460 non-null   int64
 3   YearRemodAdd   1460 non-null   int64
 4   MasVnrArea     1452 non-null   float64
 5   BsmtFinSF1     1460 non-null   int64
 6   BsmtFinSF2     1460 non-null   int64
 7   BsmtUnfSF      1460 non-null   int64
 8   TotalBsmtSF    1460 non-null   int64
 9   1stFlrSF       1460 non-null   int64
 10  2ndFlrSF       1460 non-null   int64
 11  LowQualFinSF   1460 non-null   int64
 12  GrLivArea      1460 non-null   int64
 13  GarageYrBlt    1379 non-null   float64
 14  GarageArea     1460 non-null   int64
 15  WoodDeckSF     1460 non-null   int64
 16  OpenPorchSF    1460 non-null   int64
 17  EnclosedPorch  1460 non-null   int64
 18  ScreenPorch    1460 non-null   int64
 19  MiscVal        1460 non-null   int64
 20  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(18)
memory usage: 239.7 KB
```

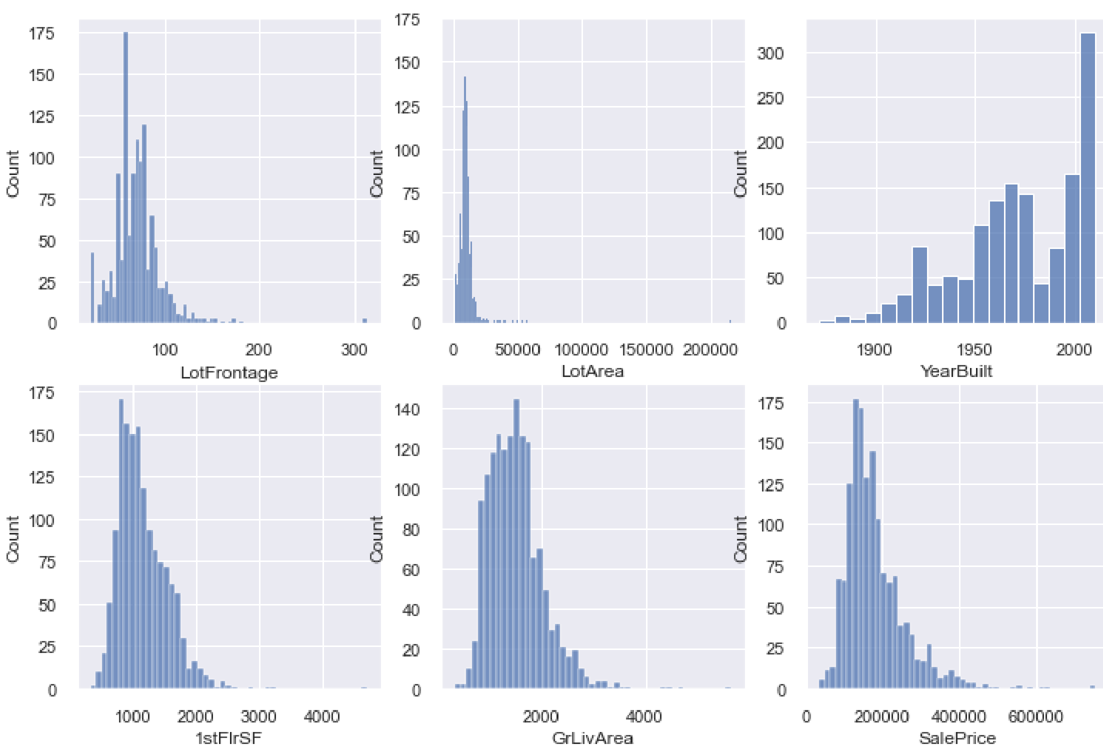
[35]:
```
# sns.set(rc={"figure.figsize":(16, 40)})
fig, axes = plt.subplots(nrows = 7, ncols = 3, figsize = (16,40))

for i,item in enumerate(lis):
    ax = axes[i//3][i%3]
    sns.histplot(to_plot[item], ax = ax);
```


LotFrontage
LotArea
YearBuilt
YearRemodAdd
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
LowQualFinSF
GrLivArea
GarageYrBlt
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
ScreenPorch
MiscVal
SalePrice
Count

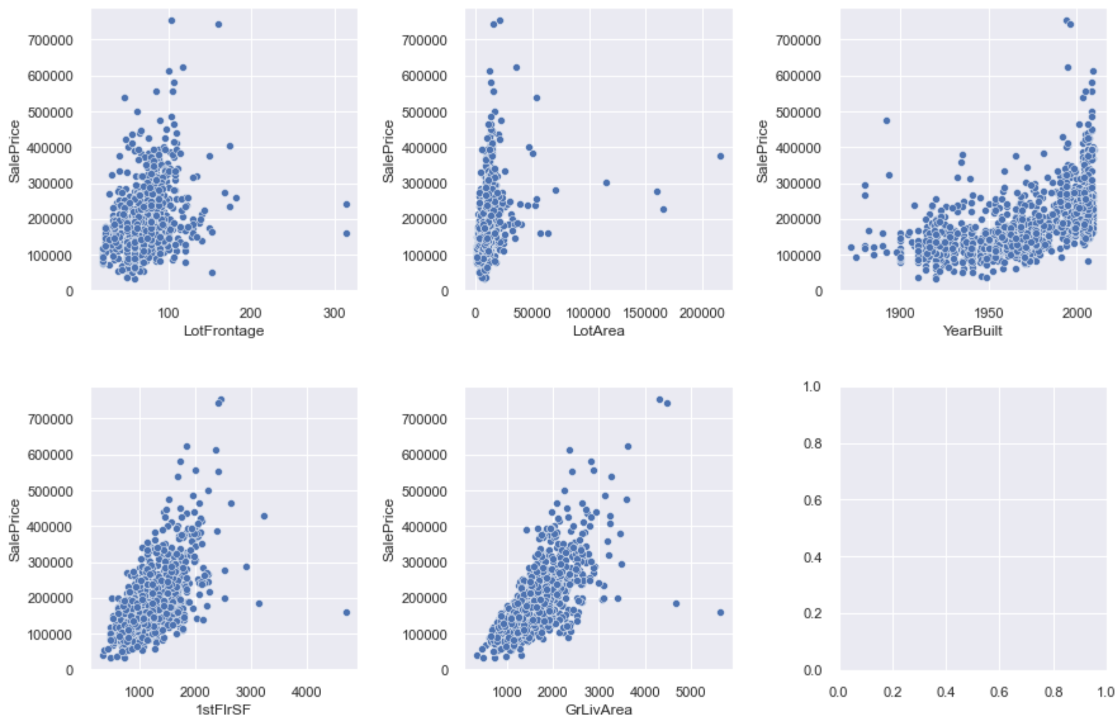
We can see from our histogram of the contiuous features that there are many examples where there are a ton of zeros. For example, WoodDeckSF (square footage of a wood deck) gives us a positive number indicating the size of the deck and zero if no deck exists. It might have made sense to categorize this variable to ”deck exists or not (binary variable 1/0). Now you have a zero-inflated variable which is cumbersome to work with.

Lets drop these zero-inflated variables for now and select the features which don't have this characteristic.

[42]:
```python
# Select non zero-inflated continuous features as ames_cont
to_select = ['LotFrontage', 'LotArea', 'YearBuilt', '1stFlrSF', 'GrLivArea', 'SalePrice']
ames_cont = to_plot[to_select]

fig, axes = plt.subplots(nrows = int(len(to_select)/2-1), ncols = 3,
                         figsize = (12,8))

for i,item in enumerate(to_select):
    ax = axes[i//3][i%3]
    sns.histplot(ames_cont[item], ax = ax);
```



[63]:
```
to_select = ['LotFrontage', 'LotArea', 'YearBuilt', '1stFlrSF', 'GrLivArea',␣
↪'SalePrice']
ames_cont = to_plot[to_select]

fig, axes = plt.subplots(nrows = int(len(to_select)/2-1), ncols = 3,
                         figsize = (12,8))
fig.tight_layout(h_pad = 4, w_pad = 4)
for i,item in enumerate(to_select[:-1]):
    ax = axes[i//3][i%3]
    sns.scatterplot(x = ames_cont[item], y = ames_cont['SalePrice'], ax = ax);
```




### 1.5 Perform log transformations for the variables where it makes sense

[57]:
```
# Your code here
import numpy as np

col = ames_cont.columns
ames_cont_log = pd.DataFrame([])

def col_log(data):

    return np.log(data)
```

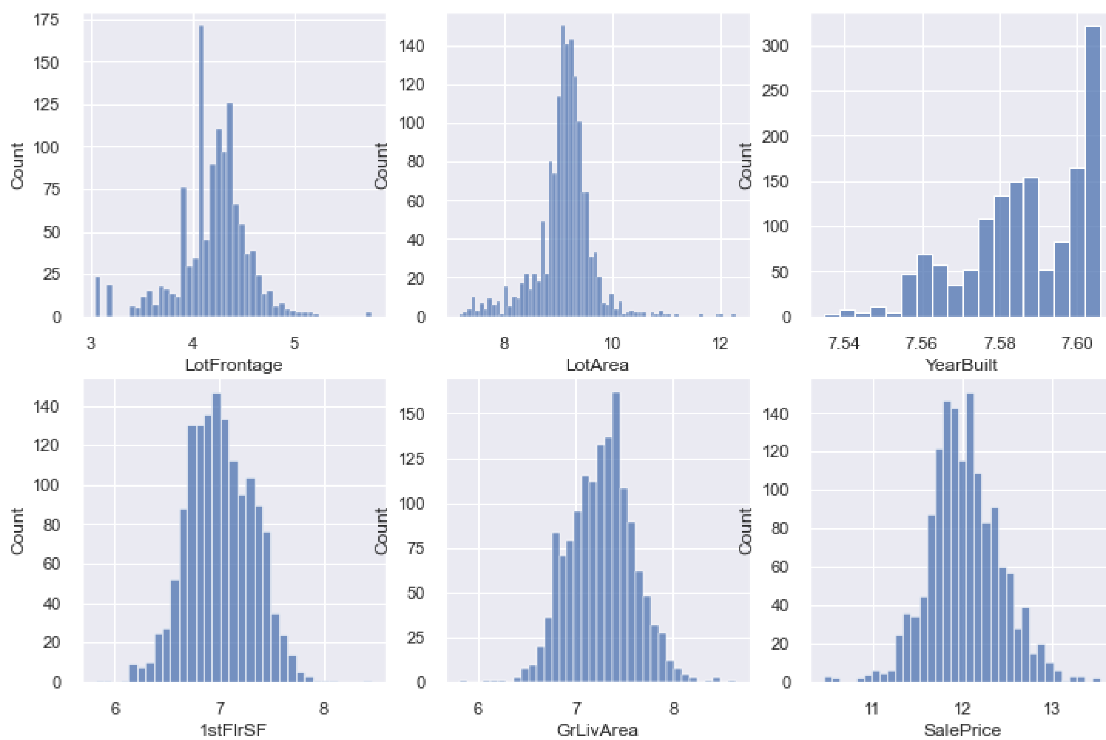
```
# for item in col:
#     ames_cont_log[item + "_log"] = ames_cont[item].apply(col_log)
ames_cont_log = ames_cont.apply(col_log)
```

[58]:
```
ames_cont_log.head()
```

[58]:

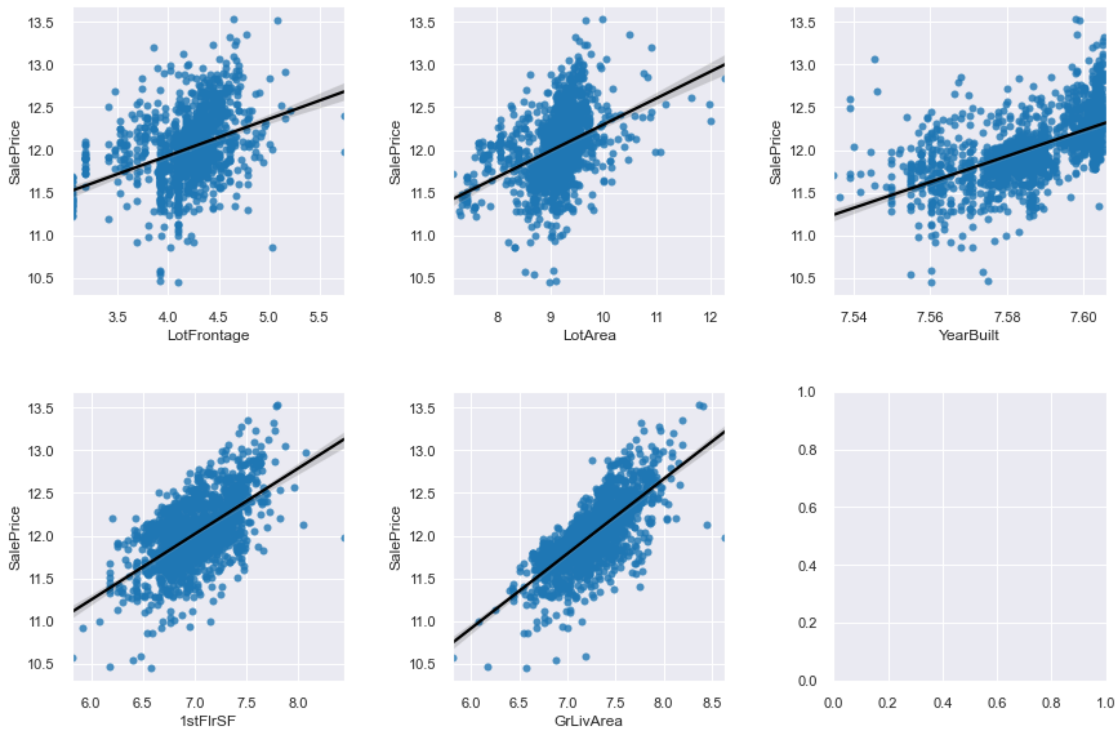
| | LotFrontage | LotArea | YearBuilt | 1stFlrSF | GrLivArea | SalePrice |
|---|---|---|---|---|---|---|
| 0 | 4.174387 | 9.041922 | 7.602401 | 6.752270 | 7.444249 | 12.247694 |
| 1 | 4.382027 | 9.169518 | 7.588830 | 7.140453 | 7.140453 | 12.109011 |
| 2 | 4.219508 | 9.328123 | 7.601402 | 6.824374 | 7.487734 | 12.317167 |
| 3 | 4.094345 | 9.164296 | 7.557473 | 6.867974 | 7.448334 | 11.849398 |
| 4 | 4.430817 | 9.565214 | 7.600902 | 7.043160 | 7.695303 | 12.429216 |

[59]:
```
fig, axes = plt.subplots(nrows = int(len(to_select)/2-1), ncols = 3,
                         figsize = (12,8))
to_select_log = ames_cont_log.columns
for i,item in enumerate(to_select_log):
    ax = axes[i//3][i%3]
    sns.histplot(ames_cont_log[item], ax = ax);
```



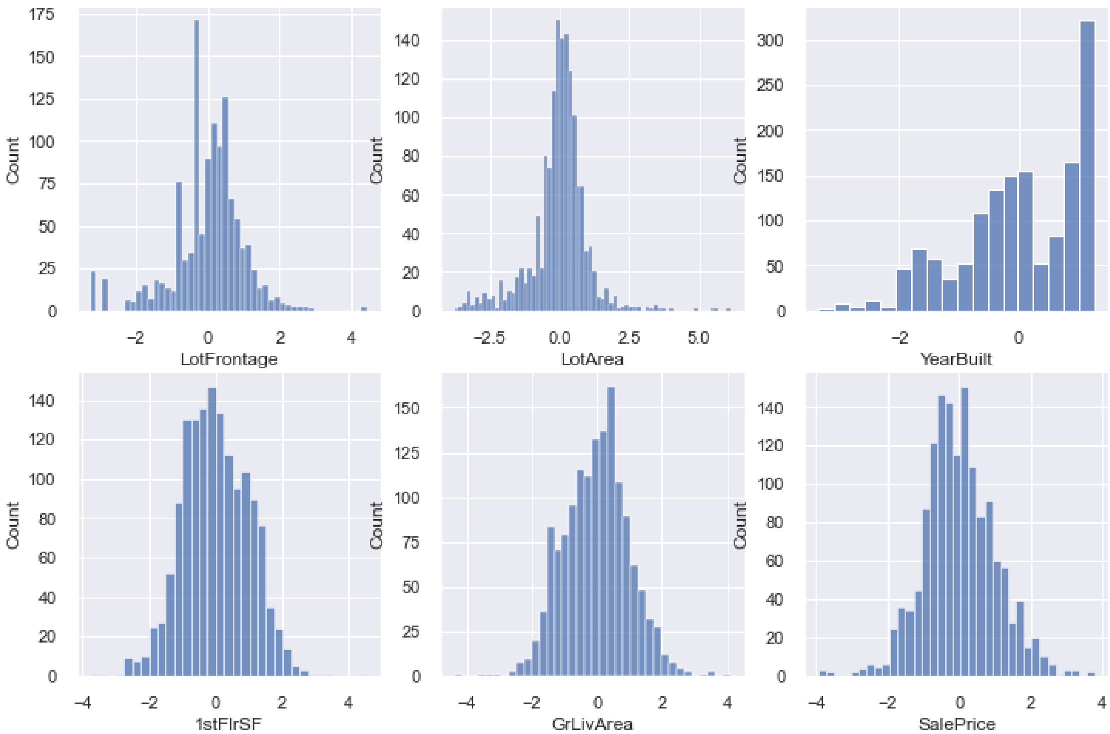

[62]:
```
fig, axes = plt.subplots(nrows = int(len(to_select)/2-1), ncols = 3,
                         figsize = (12,8))
fig.tight_layout(h_pad = 4, w_pad = 4)
```

```
for i,item in enumerate(to_select_log[:-1]):
    ax = axes[i//3][i%3]
    sns.regplot(x = ames_cont_log[item], y = ames_cont_log['SalePrice'],
                scatter_kws={"color": "tab:blue"}, line_kws={"color": "black"},
                ax = ax);
```

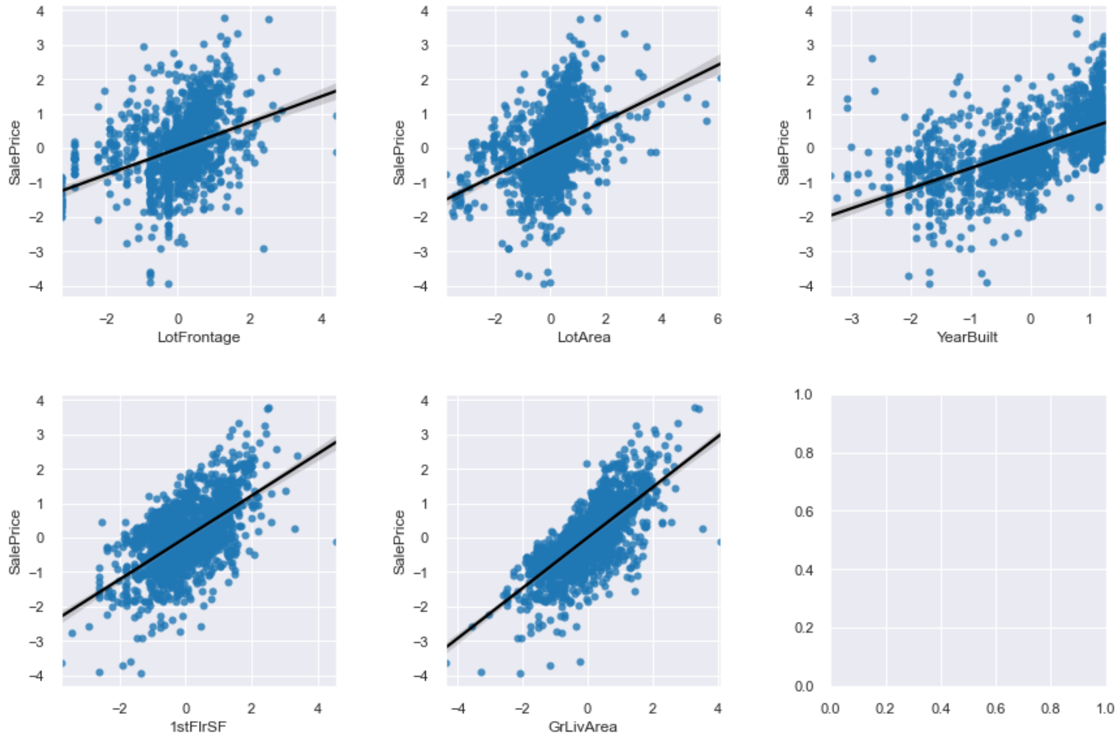



```
[64]: def normalize(data):
          return (data - data.mean()) / data.std()

      features_final = ames_cont_log.apply(normalize)

      # features_final.hist(figsize  = [8, 8]);
```

```
[65]: fig, axes = plt.subplots(nrows = int(len(to_select)/2-1), ncols = 3,
                               figsize = (12,8))
      to_select_log = features_final.columns
      for i,item in enumerate(to_select_log):
          ax = axes[i//3][i%3]
          sns.histplot(features_final[item], ax = ax);
```




[66]:
```
fig, axes = plt.subplots(nrows = int(len(to_select)/2-1), ncols = 3,
                         figsize = (12,8))
fig.tight_layout(h_pad = 4, w_pad = 4)

for i,item in enumerate(to_select_log[:-1]):
    ax = axes[i//3][i%3]
    sns.regplot(x = features_final[item], y = features_final['SalePrice'],
                scatter_kws={"color": "tab:blue"}, line_kws={"color": "black"},
                ax = ax);
```



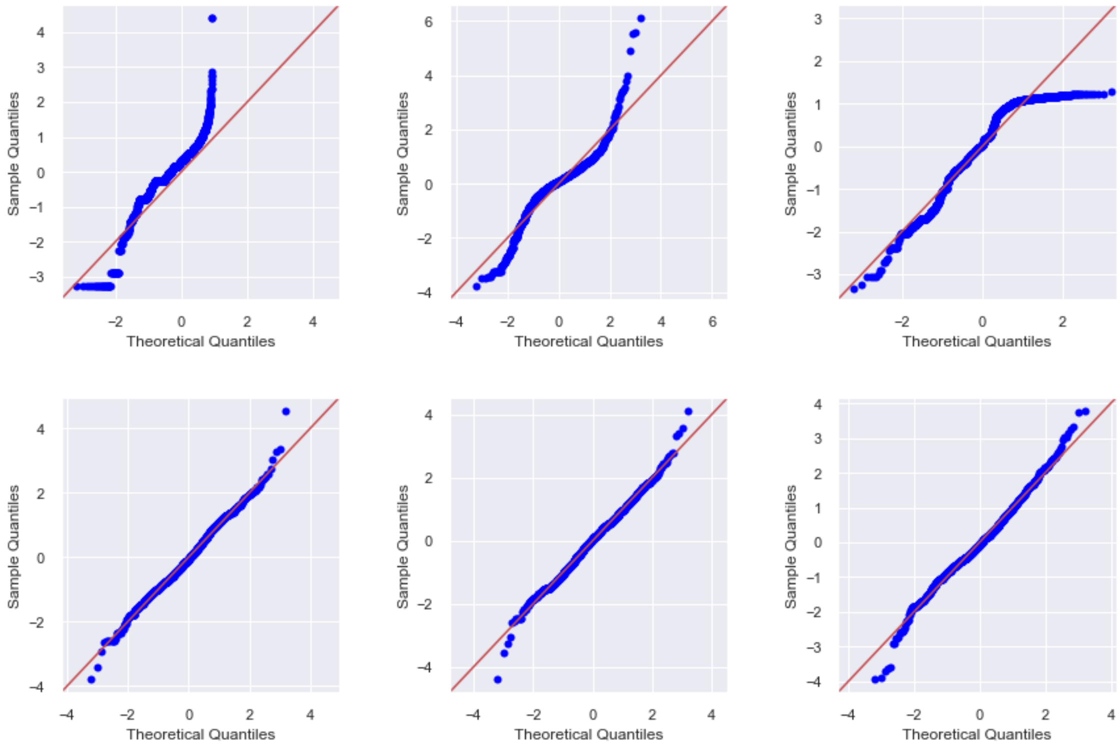

## 1.6 Standardize the continuous variables

Store your final features in a DataFrame `features_final`:

[ ]:
```
# Your code here
```

[89]:
```
import statsmodels.api as sm
import matplotlib.pyplot as plt

fig, axes = plt.subplots(nrows = int(len(to_select)/2-1), ncols = 3,
                         figsize = (12,8))
fig.tight_layout(h_pad = 4, w_pad = 4)

for i,item in enumerate(to_select_log):
    ax = axes[i//3][i%3]
    fig = sm.qqplot(features_final[item], line='45', ax = ax);
print(to_select_log)
```

```
Index(['LotFrontage', 'LotArea', 'YearBuilt', '1stFlrSF', 'GrLivArea',
       'SalePrice'],
      dtype='object')
```




[93]:
```python
import scipy.stats as stats
alpha = 0.05
for i,item in enumerate(features_final.columns):
    results = stats.kstest(features_final[item], 'norm')
    if results.pvalue < alpha:
        print(f"{item}: ", results.pvalue, "---- Not Normal")
    else:
        print(f"{item}: ", results.pvalue, "---- Cannot say")
```

```
LotFrontage:  nan ---- Cannot say
LotArea:  3.6842560351374844e-19 ---- Not Normal
YearBuilt:  4.336818809563862e-19 ---- Not Normal
1stFlrSF:  0.24583391534551713 ---- Cannot say
GrLivArea:  0.18824723813817024 ---- Cannot say
SalePrice:  0.014665968087434231 ---- Not Normal
```

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-
packages/scipy/stats/_distn_infrastructure.py:1847: RuntimeWarning: invalid
value encountered in greater_equal
  cond2 = (x >= np.asarray(_b)) & cond0
```

[96]:
```python
features_final["LotFrontage"]
```

[96]:
```
0      -0.047224
1       0.541293
2       0.080662
3      -0.274090
4       0.679580
          …
1455   -0.181153
1456    0.713122
1457   -0.003951
1458    0.080662
1459    0.358370
Name: LotFrontage, Length: 1460, dtype: float64
```

[ ]:
```
### From GitHub

# Commentary:

# We decided not to include the zero inflated features anymore
# We decided to perform log transformations on the data,
# except for "YearBuilt" where the logtransforms did not improve the skewness.
```

## 1.7 Summary

Great! You've now got some hands-on practice transforming data using log transforms, feature scaling, and normalization!