CSCI567_Project_StochasticResults

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CSCI 567 - Machine Learning - Spring 2021

Project: Chekcpoint 1 - Data Preprocessing (03/10/21)

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The "Housing Price" dataset consists of 79 predictors for the house prices in Ames, Iowa. The training and testing set are already pre-split for us from the Kaggle version (https://www.kaggle.com/c/house-prices-advanced-regression-techniques/overview), and we will focus on different regression techniques to predict the housing SalePrice based on the given features.

This notebook focuses on the data pre-processing, wrangling, visualization, and statistical analysis. It is a crucial step in any machine-learning/data-analytics application to ensure proper data formatting in order to optimize the techniques implemented.

1 Table of Contents:

---

2 1. Load required libraries

[1]:
```
# Basic data management packages
import os
import numpy as np
import pandas as pd

# Visualization packages
import matplotlib.pyplot as plt
import seaborn as sns
```

```
import pandas.plotting as pd_plot
%matplotlib inline
```

[2]:
```
# Exploratory Data Analysis packages
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.mixture import GaussianMixture
from sklearn.neighbors import LocalOutlierFactor
```

[3]:
```
# Regression and Modeling packages
import tensorflow as tf
import keras
from scipy import stats
from sklearn.metrics import mean_squared_error, r2_score

# Verify GPU compatibility
print("Tensorflow Version:", tf.__version__)
print("Tensorflow built with CUDA?", tf.test.is_built_with_cuda())
print(tf.config.list_physical_devices('CPU'))
print(tf.config.list_physical_devices('GPU'))
print("Num GPU Available:", len(tf.config.list_physical_devices('GPU')))
```

```
Using TensorFlow backend.

Tensorflow Version: 2.4.0
Tensorflow built with CUDA? True
[PhysicalDevice(name='/physical_device:CPU:0', device_type='CPU')]
[PhysicalDevice(name='/physical_device:GPU:0', device_type='GPU')]
Num GPU Available: 1
```

---

3 2. Data Wrangling

[4]:
```
# Read CSV files for Train/Test datasets
train_df = pd.read_csv('train.csv')
test_df  = pd.read_csv('test.csv')
```

After loading the data, we display the dataframe shapes for the training and testing sets. We notice that they are not the same shape, and therefore we will have to investigate the reason for this, and try to solve as best as possible. The original training set contains 1460 samples of 81 features, while the original testing set contains 1459 samples of 80 features. We can throw away the "Id" column, and obtain the true 79-feature datasets.

We also see that there are a lot of features that contain NaN's, as well as a mixture of numeric and string types for the predictors. This will become problematic for some regression techniques, and therefore we must devise a technique to transform as best as possible all data into numeric.

```
[5]: print('Train Shape: {} | types: {} \nTest Shape:  {} | types: {}'.
     ↪format(train_df.shape, pd.unique(train_df.dtypes),
                                                                    test_df.
     ↪shape, pd.unique(test_df.dtypes)))
     print('Set difference train-vs-test: {}'.format(set(train_df.columns).
     ↪difference(set(test_df.columns))))
```

```
Train Shape: (1460, 81) | types: [dtype('int64') dtype('O') dtype('float64')]
Test Shape:  (1459, 80) | types: [dtype('int64') dtype('O') dtype('float64')]
Set difference train-vs-test: {'SalePrice'}
```

```
[6]: x_train = train_df.iloc[:,1:-1]  #79 train features
     y_train = train_df.iloc[:,-1]    #SalePrice training target
     x_test  = test_df.iloc[:,1:]     #79 test features
     print('x_train {} | y_train {} \nx_test  {}'.format(x_train.shape, y_train.
     ↪shape, x_test.shape))
```

```
x_train (1460, 79) | y_train (1460,)
x_test  (1459, 79)
```

We preview the first 5 rows of the training set. This allows to explore the data type for some of the features provided in this set. From here, we realize that 79 features is a very large number of features to visually display each time, and so we will restrict future visualizations to the most important features, or the features of interests for the specific operations we are performing at the moment.

```
[7]: #preview the training data set
     x_train.head()
```

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

       LandContour Utilities LotConfig  … ScreenPorch PoolArea PoolQC Fence  \
     0         Lvl    AllPub    Inside  …           0        0    NaN   NaN
     1         Lvl    AllPub       FR2  …           0        0    NaN   NaN
     2         Lvl    AllPub    Inside  …           0        0    NaN   NaN
     3         Lvl    AllPub    Corner  …           0        0    NaN   NaN
     4         Lvl    AllPub       FR2  …           0        0    NaN   NaN

       MiscFeature MiscVal  MoSold  YrSold  SaleType  SaleCondition
     0         NaN       0       2    2008        WD         Normal
     1         NaN       0       5    2007        WD         Normal
     2         NaN       0       9    2008        WD         Normal
     3         NaN       0       2    2006        WD        Abnorml
     4         NaN       0      12    2008        WD         Normal
```

```
[5 rows x 79 columns]
```

[8]:
```python
#preview the testing data set
x_test.head()
```

[8]:
```
   MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0          20       RH         80.0    11622   Pave   NaN      Reg
1          20       RL         81.0    14267   Pave   NaN      IR1
2          60       RL         74.0    13830   Pave   NaN      IR1
3          60       RL         78.0     9978   Pave   NaN      IR1
4         120       RL         43.0     5005   Pave   NaN      IR1

  LandContour Utilities LotConfig  … ScreenPorch PoolArea PoolQC  Fence  \
0         Lvl    AllPub    Inside  …         120        0    NaN  MnPrv
1         Lvl    AllPub    Corner  …           0        0    NaN    NaN
2         Lvl    AllPub    Inside  …           0        0    NaN  MnPrv
3         Lvl    AllPub    Inside  …           0        0    NaN    NaN
4         HLS    AllPub    Inside  …         144        0    NaN    NaN

  MiscFeature MiscVal  MoSold  YrSold  SaleType  SaleCondition
0         NaN       0       6    2010        WD         Normal
1        Gar2   12500       6    2010        WD         Normal
2         NaN       0       3    2010        WD         Normal
3         NaN       0       6    2010        WD         Normal
4         NaN       0       1    2010        WD         Normal

[5 rows x 79 columns]
```

We check to see how many of the features in the training set are categorical and how many are numerical. We see an almost even split, and therefore we are going to have to change the categorical predictors from strings into some sort of integer mapping.

[9]:
```python
numerical_feats = x_train.dtypes[x_train.dtypes != "object"].index
print("Number of Numerical features: ", len(numerical_feats))

categorical_feats = x_train.dtypes[x_train.dtypes == "object"].index
print("Number of Categorical features: ", len(categorical_feats))
```

```
Number of Numerical features:  36
Number of Categorical features:  43
```

We also count to see what percentage of the features are NaNs. For some variables, we observe a lot of missing data. This might indicate that it could be worth eliminating these features where the majority of the data is null.

[10]:
```python
total = x_train.isnull().sum().sort_values(ascending=False)
percent = (x_train.isnull().sum()/x_train.isnull().count()).
 ↪sort_values(ascending=False)
```

```
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data.head(10)
```

[10]:

	Total	Percent
PoolQC	1453	0.995205
MiscFeature	1406	0.963014
Alley	1369	0.937671
Fence	1179	0.807534
FireplaceQu	690	0.472603
LotFrontage	259	0.177397
GarageCond	81	0.055479
GarageType	81	0.055479
GarageYrBlt	81	0.055479
GarageFinish	81	0.055479

Let's now focus on fixing the training and testing features in order to remove NaN's, change strings and objects into numerics, and other important data preprocessing and wrangling operations. We will go one-by-one on the features that require some fixing or reinterpretation for future regression modeling.

[11]:

```
# Non-numeric variables that require attention
non_num_vars = x_train.dtypes[x_train.dtypes=='object'].index
print(non_num_vars)
```

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

It is also important to know that some features have a slightly different definition than others in terms of their categorical values. For PoolQC, for example, NaN is not missing data but means no pool, likewise for Fence, FireplaceQu etc.

[12]:

```
# Replace object/string values with categorial values from the␣
 ↪"data_description" file from Kaggle
mappings = dict(
MSZoning_mapping      = {'nan':0, 'A':1, 'C (all)':2, 'FV':3, 'I':4, 'RH':5,␣
 ↪'RL':6, 'RP':7, 'RM':8},
Street_mapping        = {'nan':0, 'Grvl':1, 'Pave':2},
Alley_mapping         = {'nan':0, 'Grvl':1, 'Pave':2, 'NaN':0},
LotShape_mapping      = {'nan':0, 'Reg':1, 'IR1':2, 'IR2':3, 'IR3':4 },
LandContour_mapping   = {'nan':0, 'Lvl':1, 'Bnk':2, 'HLS':3, 'Low':4},
```

```
Utilities_mapping     = {'nan':0, 'AllPub':1, 'NoSewr':2, 'NoSeWa':3, 'ELO':4},
LotConfig_mapping     = {'nan':0, 'Inside':1, 'Corner':2, 'CulDSac':3, 'FR2':4,␣
 ↪'FR3':5},
LandSlope_mapping     = {'nan':0, 'Gtl':1, 'Mod':2, 'Sev':3},
Neighborhood_mapping  = {'nan':0, 'Blmngtn':1, 'Blueste':2, 'BrDale':3,␣
 ↪'BrkSide':4, 'ClearCr':5, 'CollgCr':6, 'Crawfor':7,
                         'Edwards':8, 'Gilbert':9, 'IDOTRR':10, 'MeadowV':11,␣
 ↪'Mitchel':12, 'NAmes':13, 'NoRidge':14,
                         'NPkVill':15, 'NridgHt':16, 'NWAmes':17, 'OldTown':18,␣
 ↪'SWISU':19, 'Sawyer':20, 'SawyerW':21,
                         'Somerst':22, 'StoneBr':23, 'Timber':24, 'Veenker':25},
Condition1_mapping    = {'nan':0, 'Artery':1, 'Feedr':2, 'Norm':3, 'RRNn':4,␣
 ↪'RRAn':5, 'PosN':6, 'PosA':7, 'RRNe':8, 'RRAe':9},
Condition2_mapping    = {'nan':0, 'Artery':1, 'Feedr':2, 'Norm':3, 'RRNn':4,␣
 ↪'RRAn':5, 'PosN':6, 'PosA':7, 'RRNe':8, 'RRAe':9},
BldgType_mapping      = {'nan':0, '1Fam':1, '2fmCon':2, 'Duplex':3, 'Twnhs':4,␣
 ↪'TwnhsE':4, 'TwnhsI':5},
HouseStyle_mapping    = {'nan':0, '1Story':1, '1.5Fin':2, '1.5Unf':3, '2Story':
 ↪4, '2.5Fin':5, '2.5Unf':6, 'SFoyer':7, 'SLvl':8},
RoofStyle_mapping     = {'nan':0, 'Flat':1, 'Gable':2, 'Gambrel':3, 'Hip':4,␣
 ↪'Mansard':5, 'Shed':6},
RoofMatl_mapping      = {'nan':0, 'ClyTile':1, 'CompShg':2, 'Membran':3,␣
 ↪'Metal':4,
                         'Roll':5, 'Tar&Grv':6, 'WdShake':7, 'WdShngl':8},
Exterior1st_mapping   = {'nan':0, 'AsbShng':1, 'AsphShn':2, 'BrkComm':3,␣
 ↪'BrkFace':4, 'CBlock':5, 'CemntBd':6,
                         'HdBoard':7, 'ImStucc':8, 'MetalSd':9, 'Other':10,␣
 ↪'Plywood':11, 'PreCast':12, 'Stone':13,
                         'Stucco':14, 'VinylSd':15,'Wd Sdng':16, 'WdShing':17},
Exterior2nd_mapping   = {'nan':0, 'AsbShng':1, 'AsphShn':2, 'Brk Cmn':3,␣
 ↪'BrkFace':4, 'CBlock':5, 'CmentBd':6,
                         'HdBoard':7, 'ImStucc':8, 'MetalSd':9, 'Other':10,␣
 ↪'Plywood':11, 'PreCast':12, 'Stone':13,
                         'Stucco':14, 'VinylSd':15, 'Wd Shng':16, 'Wd Sdng':16,␣
 ↪'WdShing':17},
MasVnrType_mapping    = {'nan':0, 'BrkCmn':1, 'BrkFace':2, 'CBlock':3, 'None':
 ↪4, 'Stone':5},
ExterQual_mapping     = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5},
ExterCond_mapping     = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5},
Foundation_mapping    = {'nan':0, 'BrkTil':1, 'CBlock':2, 'PConc':3, 'Slab':4,␣
 ↪'Stone':5, 'Wood':6},
BsmtQual_mapping      = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5, 'NA':
 ↪0},
BsmtCond_mapping      = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5, 'NA':
 ↪0},
BsmtExposure_mapping  = {'nan':0, 'Gd':1, 'Av':2, 'Mn':3, 'No':4, 'NA':5},
```

```
BsmtFinType1_mapping  = {'nan':0, 'GLQ':1, 'ALQ':2, 'BLQ':3, 'Rec':4, 'LwQ':5,␣
↪'Unf':6, 'NA':0},
BsmtFinType2_mapping  = {'nan':0, 'GLQ':1, 'ALQ':2, 'BLQ':3, 'Rec':4, 'LwQ':5,␣
↪'Unf':6, 'NA':0},
Heating_mapping       = {'nan':0, 'Floor':1, 'GasA':2, 'GasW':3, 'Grav':4,␣
↪'OthW':5, 'Wall':6},
HeatingQC_mapping     = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5},
CentralAir_mapping    = {'nan':0, 'N':1, 'Y':2},
Electrical_mapping    = {'nan':0, 'SBrkr':1, 'FuseA':2, 'FuseF':3, 'FuseP':4,␣
↪'Mix':5},
KitchenQual_mapping   = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5},
Functional_mapping    = {'nan':0, 'Typ':1, 'Min1':2, 'Min2':3, 'Mod':4, 'Maj1':
↪5, 'Maj2':6, 'Sev':7, 'Sal':8},
FireplaceQu_mapping   = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5, 'NA':
↪0},
GarageType_mapping    = {'nan':0, '2Types':1, 'Attchd':2, 'Basment':3,␣
↪'BuiltIn':4, 'CarPort':5, 'Detchd':6, 'NA':0},
GarageFinish_mapping  = {'nan':0, 'Fin':1, 'RFn':2, 'Unf':3, 'NA':0},
GarageQual_mapping    = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5, 'NA':
↪0},
GarageCond_mapping    = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'Po':5, 'NA':
↪0},
PavedDrive_mapping    = {'nan':0, 'Y':1, 'P':2, 'N':3},
PoolQC_mapping        = {'nan':0, 'Ex':1, 'Gd':2, 'TA':3, 'Fa':4, 'NA':0},
Fence_mapping         = {'nan':0, 'GdPrv':1, 'MnPrv':2, 'GdWo':3, 'MnWw':4,␣
↪'NA':0},
MiscFeature_mapping   = {'nan':0, 'Elev':1, 'Gar2':2, 'Othr':3, 'Shed':4,␣
↪'TenC':5, 'NA':0},
SaleType_mapping      = {'nan':0, 'WD':1, 'CWD':2, 'VWD':3, 'New':4, 'COD':5,␣
↪'Con':6, 'ConLw':7, 'ConLI':8,
                          'ConLD':9, 'Oth':10},
SaleCondition_mapping = {'nan':0, 'Normal':1, 'Abnorml':2, 'AdjLand':3,␣
↪'Alloca':4, 'Family':5, 'Partial':6})
```

With the dictionaries for relabeling the object/string-types as integer classes, we can now recursively replace all of the unuseful features with more meaningful values. We also replace all NaN's with 0's, so that they don't have an impact on the future regression models.

[13]:
```
x_train = x_train.replace({list(non_num_vars)[k] : list(mappings.values())[k]
                           for k in np.arange(len(list(non_num_vars)))}).
↪fillna(0)
x_test  = x_test.replace({list(non_num_vars)[k] : list(mappings.values())[k]
                           for k in np.arange(len(list(non_num_vars)))}).
↪fillna(0)
```

[14]:
```
x_train.head(3)
```

```
[14]:    MSSubClass  MSZoning  LotFrontage  LotArea  Street  Alley  LotShape  \
      0          60         6         65.0     8450       2    0.0         1
      1          20         6         80.0     9600       2    0.0         1
      2          60         6         68.0    11250       2    0.0         2

         LandContour  Utilities  LotConfig  …  ScreenPorch  PoolArea  PoolQC  \
      0            1          1          1  …            0         0     0.0
      1            1          1          4  …            0         0     0.0
      2            1          1          1  …            0         0     0.0

         Fence  MiscFeature  MiscVal  MoSold  YrSold  SaleType  SaleCondition
      0    0.0          0.0        0       2    2008         1              1
      1    0.0          0.0        0       5    2007         1              1
      2    0.0          0.0        0       9    2008         1              1

      [3 rows x 79 columns]
```

```
[15]: x_test.head(3)
```

```
[15]:    MSSubClass  MSZoning  LotFrontage  LotArea  Street  Alley  LotShape  \
      0          20       5.0         80.0    11622       2    0.0         1
      1          20       6.0         81.0    14267       2    0.0         2
      2          60       6.0         74.0    13830       2    0.0         2

         LandContour  Utilities  LotConfig  …  ScreenPorch  PoolArea  PoolQC  \
      0            1        1.0          1  …          120         0     0.0
      1            1        1.0          2  …            0         0     0.0
      2            1        1.0          1  …            0         0     0.0

         Fence  MiscFeature  MiscVal  MoSold  YrSold  SaleType  SaleCondition
      0    2.0          0.0        0       6    2010       1.0              1
      1    0.0          2.0    12500       6    2010       1.0              1
      2    2.0          0.0        0       3    2010       1.0              1

      [3 rows x 79 columns]
```

We confirm that we are now rid of any NaN's and null values in the training and testing datasets.

```
[16]: print('Training set null values: %i' %x_train.isnull().sum().sum())
      print('Testing set null values:  %i' %x_test.isnull().sum().sum())
```

```
Training set null values: 0
Testing set null values:  0
```

```
[17]: numerical_feats = x_train.dtypes[x_train.dtypes != "object"].index
      print("Number of Numerical features: ", len(numerical_feats))

      categorical_feats = x_train.dtypes[x_train.dtypes == "object"].index
```

```
print("Number of Categorical features: ", len(categorical_feats))
```

```
Number of Numerical features:  79
Number of Categorical features:  0
```

---

4 3. Data Visualization

[18]:
```
# Declare a function to plot a graphical correlation matrix
def plot_corr(dataframe,size=8):
    corr = dataframe.corr()
    fig, ax = plt.subplots(figsize=(size, size))
    im = ax.matshow(corr,vmin = -1.0, vmax = 1.0, cmap='seismic')
    #plt.xticks(range(len(corr.columns)), corr.columns);
    #plt.yticks(range(len(corr.columns)), corr.columns);
    plt.xticks([]); plt.yticks([])
    plt.colorbar(im, orientation = 'vertical', shrink=0.8)
    plt.title('Correlation Matrix')
```

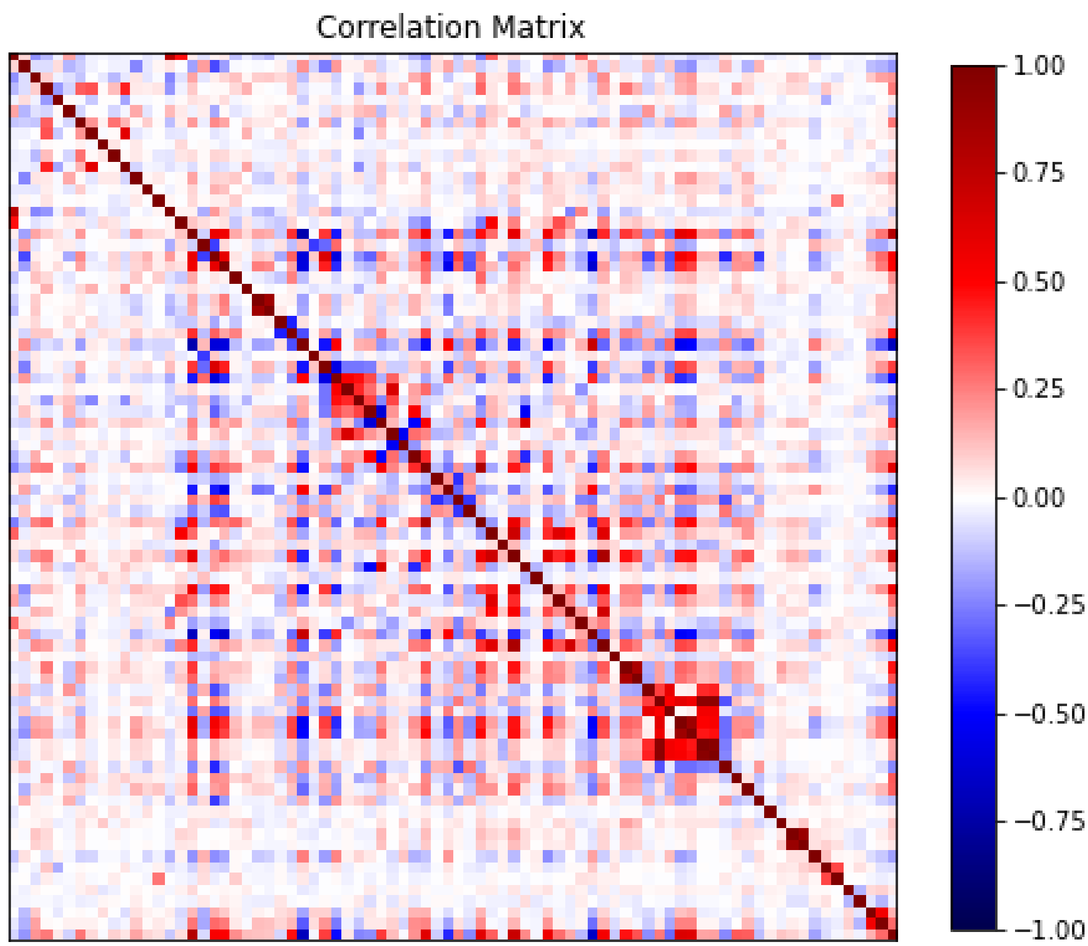
We start by visualizing the correlation between the 79 predictors and the target variable. This will tell us which predictors are highly correlated with each other, as well as which predictors have the highest correlation with the target SalePrice. We then select the last row (or column) of the matrix and select which predictors have the highest correlation to the target.

[19]:
```
corr_mat = np.corrcoef(x_train.join(y_train),rowvar = False)
corr_vec = corr_mat[:-1,-1]   #correlation of features to target only
print(corr_mat.round(2))
```

```
[[ 1.    0.08 -0.22 … -0.   -0.04 -0.08]
 [ 0.08  1.   -0.07 … -0.13 -0.16 -0.21]
 [-0.22 -0.07  1.   …  0.11  0.18  0.21]
 …
 [-0.   -0.13  0.11 …  1.    0.54  0.15]
 [-0.04 -0.16  0.18 …  0.54  1.    0.29]
 [-0.08 -0.21  0.21 …  0.15  0.29  1.  ]]
```

The following correlation matrix/heatmap shows the effect of multicollinearity for some highly correlated variables that might be describing the same thing. For some cases, it might be important to note that we don't always need those pairs 2 or more variables that essentially describe the same thing - such as totalbsmtSF and 1stflrSF, or garageCars and garageArea.

[20]:
```
plot_corr(x_train.join(y_train))
```



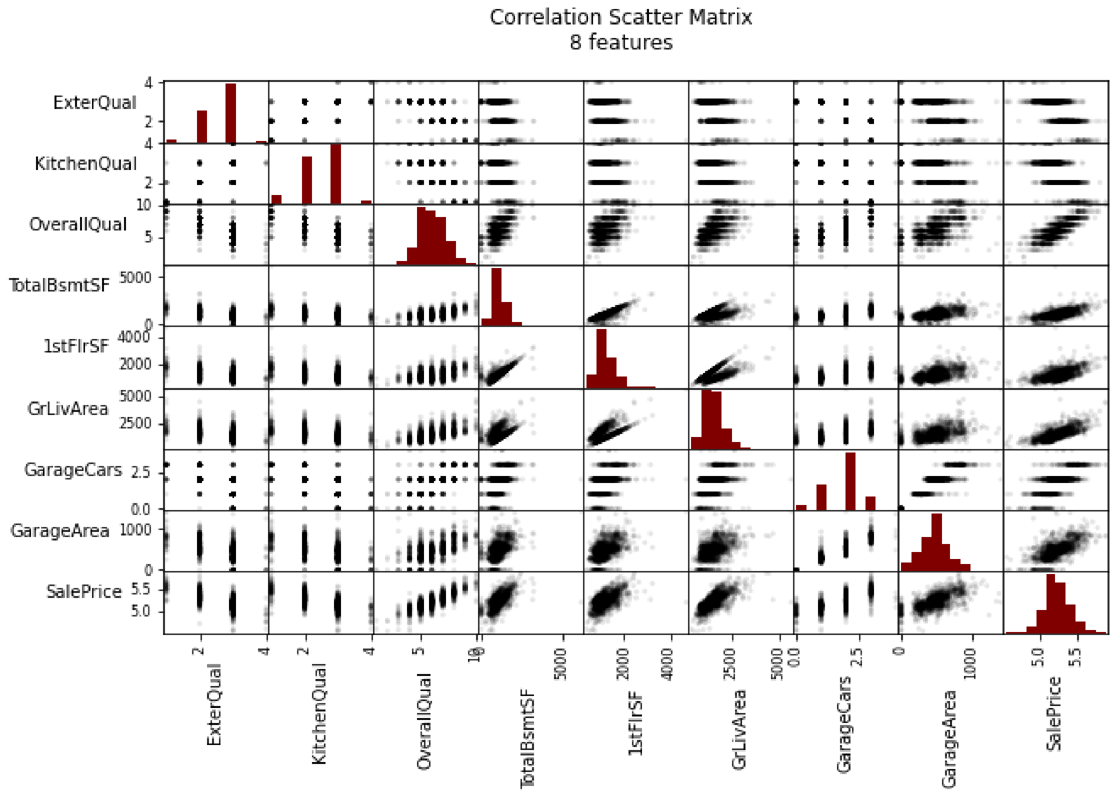
The user selects a level of correlation to cut-off; meaning that anything between this percentage will be considered as uncorrelated. For instance, a corr_bound=0.7 means that anything between -0.7-to-0.7 is considered uncorrelated to SalePrice, while anything greater than 0.7 or less tha -0.7 is considered correlated. We further explore these correlated features to the target variables in different ways.

[21]:
```
#View features that have a +/- correlation greater than the user-specified␣
↪corrrelation bound (corr_bound)
corr_bound = 0.6
corr_dat = (x_train.iloc[:, corr_vec<-corr_bound]).join(x_train.iloc[:,␣
↪corr_vec>corr_bound])
corr_dat
```

[21]:
```
   ExterQual  KitchenQual  OverallQual  TotalBsmtSF  1stFlrSF  GrLivArea  \
0          2            2            7          856       856       1710
1          3            3            6         1262      1262       1262
2          2            2            7          920       920       1786
```

```
3           3          2          7        756      961     1717
4           2          2          8       1145     1145     2198
…         …          …          …          …        …        …
1455        3          3          6        953      953     1647
1456        3          3          6       1542     2073     2073
1457        1          2          7       1152     1188     2340
1458        3          2          5       1078     1078     1078
1459        2          3          5       1256     1256     1256

      GarageCars  GarageArea
0              2         548
1              2         460
2              2         608
3              3         642
4              3         836
…            …          …
1455           2         460
1456           2         500
1457           1         252
1458           1         240
1459           1         276

[1460 rows x 8 columns]
```

[22]:
```python
axes = pd_plot.scatter_matrix(corr_dat.join(np.log10(y_train)), alpha=0.1,␣
↪figsize=(10, 6),
                              color='black', hist_kwds={'color':['maroon']})
for ax in axes.flatten():
    ax.xaxis.label.set_rotation(90)
    ax.yaxis.label.set_rotation(0)
    ax.yaxis.label.set_ha('right')
plt.suptitle('Correlation Scatter Matrix\n{} features'.format(corr_dat.
↪shape[-1]))
plt.show();
```



[23]:
```python
#full training set basic statistics
x_train.describe()
```

[23]:
```
         MSSubClass     MSZoning  LotFrontage        LotArea       Street  \
count   1460.000000  1460.000000  1460.000000    1460.000000  1460.000000
mean      56.897260     6.126712    57.623288   10516.828082     1.995890
std       42.300571     1.050330    34.664304    9981.264932     0.063996
min       20.000000     2.000000     0.000000    1300.000000     1.000000
25%       20.000000     6.000000    42.000000    7553.500000     2.000000
50%       50.000000     6.000000    63.000000    9478.500000     2.000000
75%       70.000000     6.000000    79.000000   11601.500000     2.000000
max      190.000000     8.000000   313.000000  215245.000000     2.000000

              Alley     LotShape  LandContour   Utilities    LotConfig  …  \
count   1460.000000  1460.000000  1460.000000  1460.000000  1460.000000  …
mean       0.090411     1.408219     1.185616     1.001370     1.416438  …
std        0.372151     0.582296     0.606509     0.052342     0.773448  …
min        0.000000     1.000000     1.000000     1.000000     1.000000  …
25%        0.000000     1.000000     1.000000     1.000000     1.000000  …
50%        0.000000     1.000000     1.000000     1.000000     1.000000  …
75%        0.000000     2.000000     1.000000     1.000000     2.000000  …
```

```
max       2.000000     4.000000     4.000000     3.000000     5.000000  ...

        ScreenPorch     PoolArea        PoolQC        Fence  MiscFeature  \
count   1460.000000  1460.000000  1460.000000  1460.000000  1460.000000
mean      15.060959     2.758904     0.010959     0.396575     0.144521
std       55.757415    40.177307     0.177224     0.875914     0.742569
min        0.000000     0.000000     0.000000     0.000000     0.000000
25%        0.000000     0.000000     0.000000     0.000000     0.000000
50%        0.000000     0.000000     0.000000     0.000000     0.000000
75%        0.000000     0.000000     0.000000     0.000000     0.000000
max      480.000000   738.000000     4.000000     4.000000     5.000000

             MiscVal       MoSold       YrSold     SaleType  SaleCondition
count    1460.000000  1460.000000  1460.000000  1460.000000    1460.000000
mean       43.489041     6.321918  2007.815753     1.490411       1.582192
std       496.123024     2.703626     1.328095     1.368616       1.475209
min         0.000000     1.000000  2006.000000     1.000000       1.000000
25%         0.000000     5.000000  2007.000000     1.000000       1.000000
50%         0.000000     6.000000  2008.000000     1.000000       1.000000
75%         0.000000     8.000000  2009.000000     1.000000       1.000000
max     15500.000000    12.000000  2010.000000    10.000000       6.000000

[8 rows x 79 columns]
```

[24]:

```
#main features (based on correlation coefficient) basic statistics
corr_dat.describe()
```

[24]:

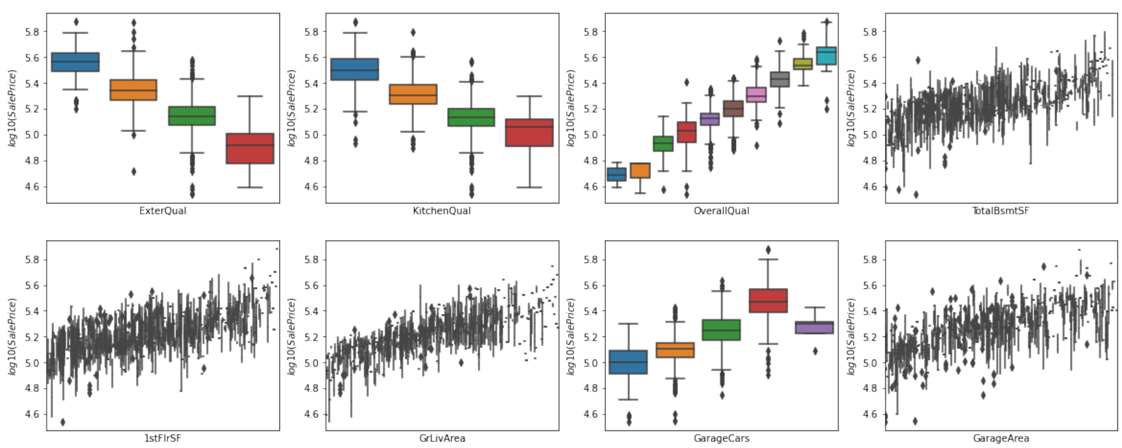
```
         ExterQual  KitchenQual  OverallQual  TotalBsmtSF     1stFlrSF  \
count  1460.00000  1460.000000  1460.000000  1460.000000  1460.000000
mean      2.60411     2.488356     6.099315  1057.429452  1162.626712
std       0.57428     0.663760     1.382997   438.705324   386.587738
min       1.00000     1.000000     1.000000     0.000000   334.000000
25%       2.00000     2.000000     5.000000   795.750000   882.000000
50%       3.00000     3.000000     6.000000   991.500000  1087.000000
75%       3.00000     3.000000     7.000000  1298.250000  1391.250000
max       4.00000     4.000000    10.000000  6110.000000  4692.000000

          GrLivArea   GarageCars   GarageArea
count   1460.000000  1460.000000  1460.000000
mean    1515.463699     1.767123   472.980137
std      525.480383     0.747315   213.804841
min      334.000000     0.000000     0.000000
25%     1129.500000     1.000000   334.500000
50%     1464.000000     2.000000   480.000000
75%     1776.750000     2.000000   576.000000
max     5642.000000     4.000000  1418.000000
```

With these N correlated features, we now explore how the strong is the correlation with the SalePrice target variable. We observe the numerical value, as well as the boxplot behavior of these highly-correlated features.

[25]:
```
corr_dat.join(y_train).corr()['SalePrice']
```

[25]:
```
ExterQual     -0.682639
KitchenQual   -0.659600
OverallQual    0.790982
TotalBsmtSF    0.613581
1stFlrSF       0.605852
GrLivArea      0.708624
GarageCars     0.640409
GarageArea     0.623431
SalePrice      1.000000
Name: SalePrice, dtype: float64
```

[26]:
```
plt.figure(figsize=(20,corr_dat.shape[-1]))
for k in np.arange(corr_dat.shape[-1]):
    plt.subplot(corr_dat.shape[-1]//4,4,k+1)
    sns.boxplot(x=corr_dat.iloc[:,k], y=np.log10(y_train))
    plt.xticks([]); plt.ylabel('$log10(SalePrice)$')
plt.show();
```



We also visualize the target variable, SalePrice. We notice that these values are log-normally distributed. There are a very small amount of extremely expensive houses, while the vast majority are closer to the average. Therefore, taking the logarithm of this will make them Normally distributed. This will help a lot for the regression techniques, and therefore we will be working with the natural log of SalePrice from now on.

[27]:
```
target = np.log10(y_train)
print('       SalePrice: Mean {:.3e} | Std. Dev {:.3e}'.format(y_train.mean(),␣
↪y_train.std()))
```

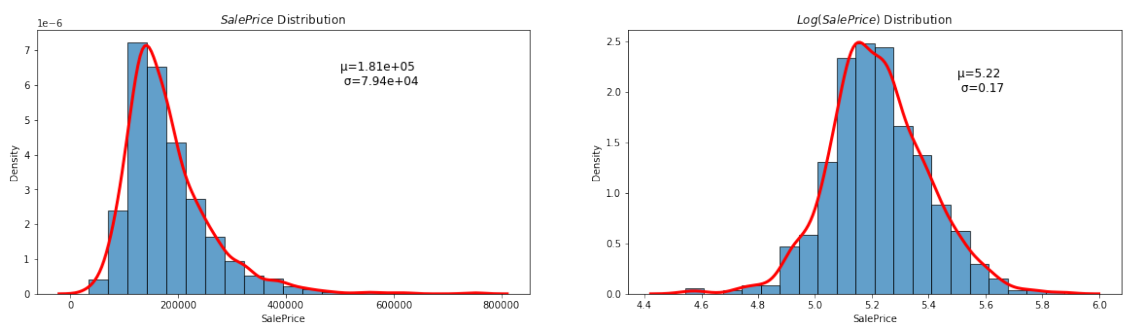
```
print('Log10(SalePrice): Mean {:.3f}      | Std. Dev {:.3f}'.format(target.
↪mean(), target.std()))
```

```
       SalePrice: Mean 1.809e+05 | Std. Dev 7.944e+04
Log10(SalePrice): Mean 5.222     | Std. Dev 0.173
```

[28]:
```
print('       SalePrice: Skewness={:.3f} | Kurtosis={:.3f}'.format(y_train.
↪skew(), y_train.kurt()))
print('Log10(SalePrice): Skewness={:.3f} | Kurtosis={:.3f}'.format(target.
↪skew(), target.kurt()))
```

```
       SalePrice: Skewness=1.883 | Kurtosis=6.536
Log10(SalePrice): Skewness=0.121 | Kurtosis=0.810
```

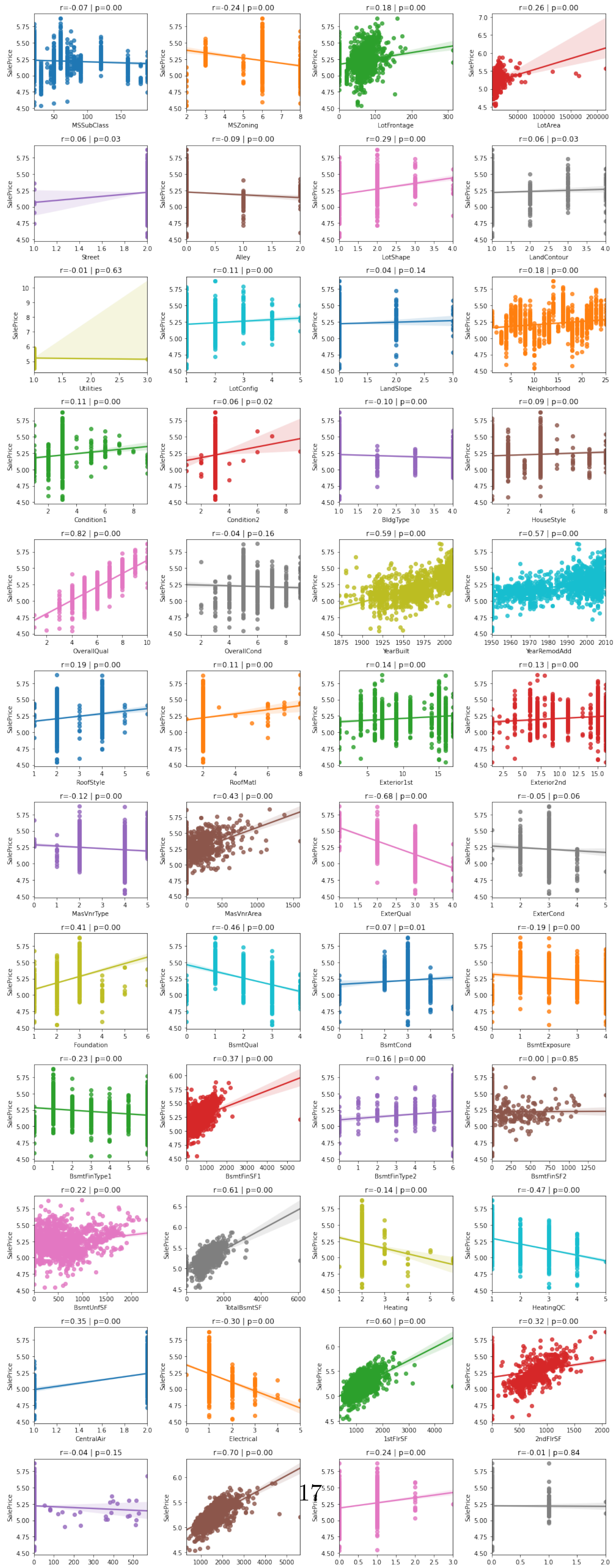
[29]:
```
plt.figure(figsize=(20,5))

ax1 = plt.subplot(121)
plt.title('$SalePrice$ Distribution')
ax1.text(5E5,6E-6, ' ={:.2e}\n ={:.2e}'.format(y_train.mean(), y_train.std()),␣
↪fontsize=12)
plt.hist(y_train, density=True, bins=20, alpha=0.7, histtype='bar', ec='black')
sns.kdeplot(y_train, linewidth=3, c='r')

ax2 = plt.subplot(122)
plt.title('$Log(SalePrice)$ Distribution')
ax2.text(5.5, 2, ' ={:.2f}\n ={:.2f}'.format(target.mean(), target.std()),␣
↪fontsize=12)
plt.hist(target, density=True, bins=20, alpha=0.7, histtype='bar', ec='black')
sns.kdeplot(target, linewidth=3, c='r')

plt.show();
```



On a slightly different note, we will plot the relationship between two variables at a time and the target log10(SalePrice), using Seaborn, and try to fit a linear regressor onto the data. This will test for linearity and for possible colinearity, and will also compute the r^2 coefficient and p value for the regression estimate.

[30]:

```
nr_rows, nr_cols = 12, 4
colors = sns.color_palette()

fig, axs = plt.subplots(nr_rows, nr_cols, figsize=(nr_cols*3.5,nr_rows*3))

li_num_feats = list(numerical_feats)
li_not_plot = ['Id', 'SalePrice', 'SalePrice_Log']
li_plot_num_feats = [c for c in list(numerical_feats) if c not in li_not_plot]


for r in range(0,nr_rows):
    for c in range(0,nr_cols):
        i = r*nr_cols+c
        if i < len(li_plot_num_feats):
            sns.regplot(x=x_train[li_plot_num_feats[i]], y=target,
                        ax = axs[r][c], color=colors[i % 10])
            stp = stats.pearsonr(x_train[li_plot_num_feats[i]], target)
            str_title = "r="+"{0:.2f}".format(stp[0])+" | "+"p="+"{0:.2f}".
↪format(stp[1])
            axs[r][c].set_title(str_title,fontsize=12)

plt.tight_layout()
plt.show()
```


r=-0.07 | p=0.00
MSSubClass
r=-0.24 | p=0.00
MSZoning
r=0.18 | p=0.00
LotFrontage
r=0.26 | p=0.00
LotArea
r=0.06 | p=0.03
Street
r=-0.09 | p=0.00
Alley
r=0.29 | p=0.00
LotShape
r=0.06 | p=0.03
LandContour
r=-0.01 | p=0.63
Utilities
r=0.11 | p=0.00
LotConfig
r=0.04 | p=0.14
LandSlope
r=0.18 | p=0.00
Neighborhood
r=0.11 | p=0.00
Condition1
r=0.06 | p=0.02
Condition2
r=-0.10 | p=0.00
BldgType
r=0.09 | p=0.00
HouseStyle
r=0.82 | p=0.00
OverallQual
r=-0.04 | p=0.16
OverallCond
r=0.59 | p=0.00
YearBuilt
r=0.57 | p=0.00
YearRemodAdd
r=0.19 | p=0.00
RoofStyle
r=0.11 | p=0.00
RoofMatl
r=0.14 | p=0.00
Exterior1st
r=0.13 | p=0.00
Exterior2nd
r=-0.12 | p=0.00
MasVnrType
r=0.43 | p=0.00
MasVnrArea
r=-0.68 | p=0.00
ExterQual
r=-0.05 | p=0.06
ExterCond
r=0.41 | p=0.00
Foundation
r=-0.46 | p=0.00
BsmtQual
r=0.07 | p=0.01
BsmtCond
r=-0.19 | p=0.00
BsmtExposure
r=-0.23 | p=0.00
BsmtFinType1
r=0.37 | p=0.00
BsmtFinSF1
r=0.16 | p=0.00
BsmtFinType2
r=0.00 | p=0.85
BsmtFinSF2
r=0.22 | p=0.00
BsmtUnfSF
r=0.61 | p=0.00
TotalBsmtSF
r=-0.14 | p=0.00
Heating
r=-0.47 | p=0.00
HeatingQC
r=0.35 | p=0.00
CentralAir
r=-0.30 | p=0.00
Electrical
r=0.60 | p=0.00
1stFlrSF
r=0.32 | p=0.00
2ndFlrSF
r=-0.04 | p=0.15
LowQualFinSF
r=0.70 | p=0.00
GrLivArea
r=0.24 | p=0.00
BsmtFullBath
r=-0.01 | p=0.84
BsmtHalfBath
SalePrice

---

5 4. Exploratory Data Analysis

After understanding the data statistics and relationships, we will now try to do some basic data analytics on the preprocessed data.

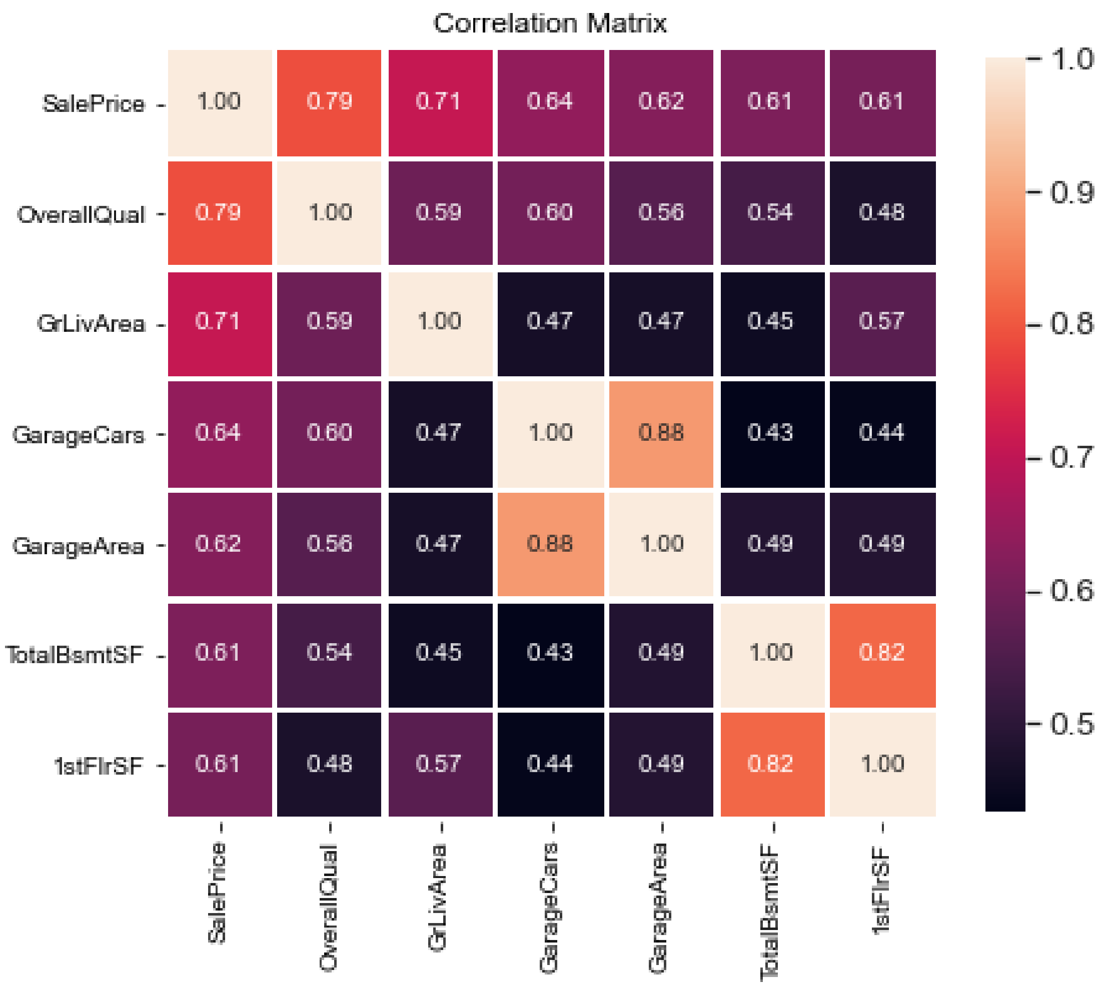
[31]:
```
def plot_corr_matrix(df, nr_c, targ) :
    corr_abs = df.corr().abs()
    cols = corr_abs.nlargest(nr_c, targ)[targ].index
    cm = np.corrcoef(df[cols].values.T)
    plt.figure(figsize=(nr_c, nr_c))
    plt.title('Correlation Matrix')
    sns.set(font_scale=1.25)
    sns.heatmap(cm, linewidths=1.5, annot=True, square=True,
                fmt='.2f', annot_kws={'size': 10}, cbar_kws={'shrink':0.8},
                yticklabels=cols.values, xticklabels=cols.values)
    plt.show();
```

[32]:
```
print('Significant Correlation Bound: ', corr_bound)
print('Shape of training data above correlation bound: ', corr_dat.shape)
```

```
Significant Correlation Bound:  0.6
Shape of training data above correlation bound:  (1460, 8)
```

[33]:
```
target_name = 'SalePrice'

corr_abs = train_df.corr().abs()
ser_corr = corr_abs.nlargest(len(numerical_feats), target_name)[target_name]

cols_abv_corr_limit = list(ser_corr[ser_corr.values >= corr_bound].index)
cols_bel_corr_limit = list(ser_corr[ser_corr.values < corr_bound].index)

nr_feats = len(cols_abv_corr_limit)
```

[34]:
```
plot_corr_matrix(train_df, nr_feats, target_name)
```



From the covariance matrix, we see that for some features like 'OverallQual' there is a strong linear correlation (0.8 approximately) to the target. For other features like 'MSSubClass' or 'MiscFeature' the correlation is very weak.

Scale the correlation-based data so that all features values are between 0 and 1. This will help greatly for the regression modeling and the visualization and interpretation of the models and the data.

[35]:
```
scaler = StandardScaler()
x_train_s = scaler.fit_transform(corr_dat)
```

Perform PCA to encode the correlation-based data into orthogonal singular vectors that will best describe the variability of the data. This will help visualize and try and classify clusters of data based on these new principal directions.

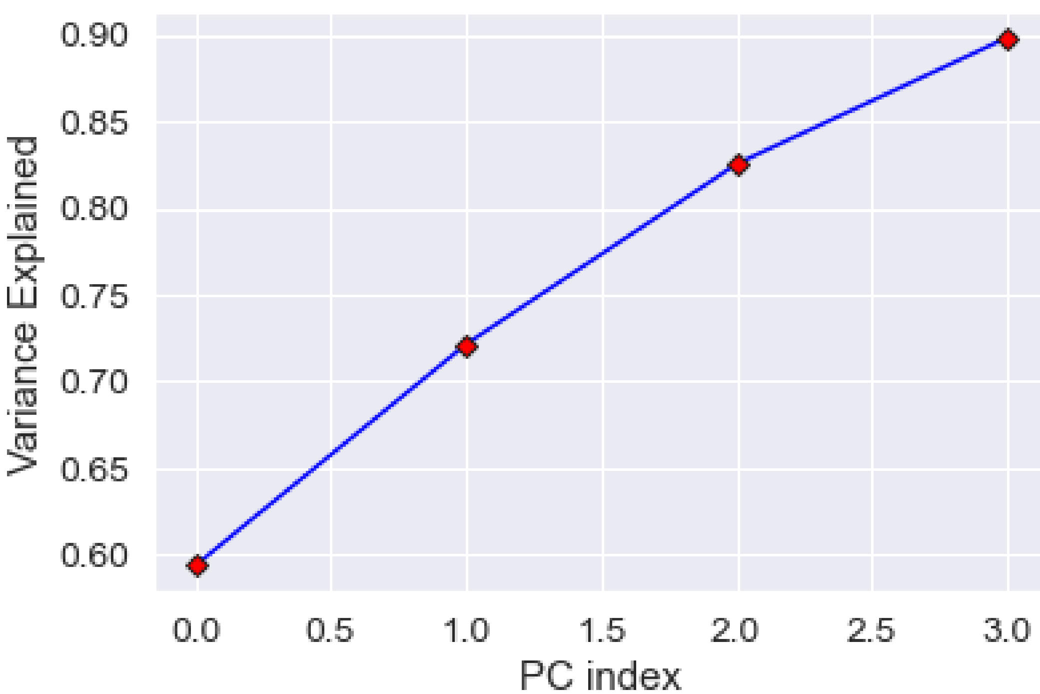
[36]:
```
n_components = 4
pca = PCA(n_components=n_components)
```

```
pca.fit(x_train_s)

#variance explained by each PC
print('PC Variance Explained: {}'.format(pca.explained_variance_ratio_))
print('Cumulative Variance Explained: {}'.format(np.sum(pca.
↪explained_variance_ratio_).round(4)))
```

```
PC Variance Explained: [0.59394484 0.12746352 0.10382664 0.07290565]
Cumulative Variance Explained: 0.8981
```

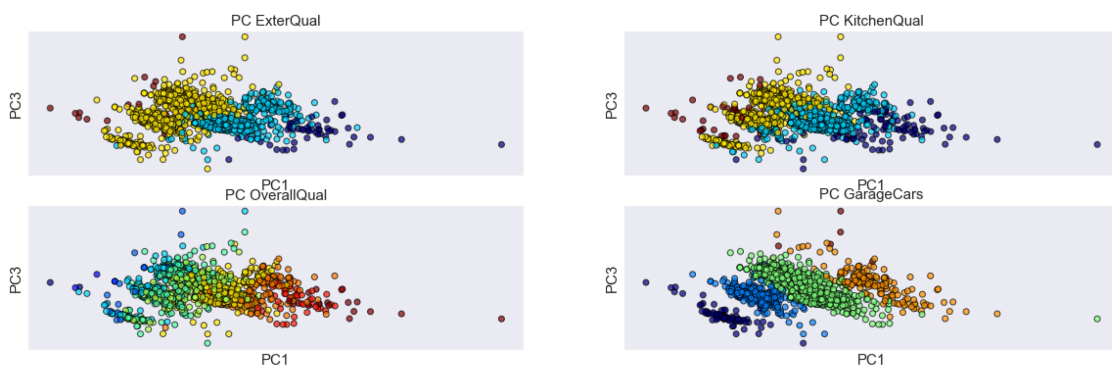
We see that with 4 PC's, for instance, we can explain approximately 90% of the variance in the scaled, clean data set.

[37]:
```
#plot n_PC-vs-varExplained
plt.figure()
plt.plot(range(len(np.cumsum(pca.explained_variance_ratio_))), np.cumsum(pca.
↪explained_variance_ratio_),
         '-bD',  c='blue', mfc='red', mec='k')
plt.xlabel('PC index')
plt.ylabel('Variance Explained')
plt.grid('on')
plt.show();
```



We can see that PC1 and PC3 help us find a slight classification in PC-space for the categorical variables 'ExterQual', 'KitchenQual', 'OverallQual', and 'GarageCars'; especially the last one.

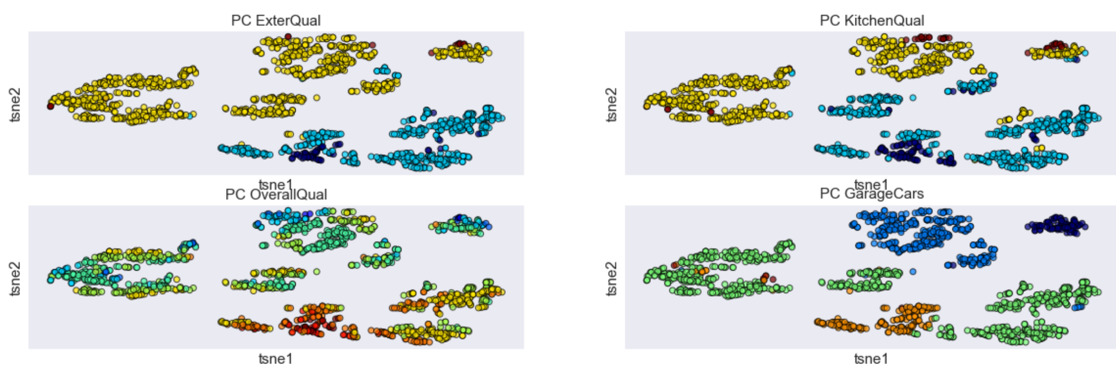
[38]:
```
x_trans = pca.transform(x_train_s)

plt.figure(figsize=(20,6))
plt.subplot(221)
plt.scatter(x_trans[:,0], x_trans[:,2], c=corr_dat['ExterQual'], cmap='jet',␣
 ↪edgecolors="black", alpha=0.7)
plt.title('PC ExterQual'); plt.xlabel('PC1'); plt.ylabel('PC3'); plt.xticks([]);
 ↪ plt.yticks([])
plt.subplot(222)
plt.scatter(x_trans[:,0], x_trans[:,2], c=corr_dat['KitchenQual'], cmap='jet',␣
 ↪edgecolors="black", alpha=0.7)
plt.title('PC KitchenQual'); plt.xlabel('PC1'); plt.ylabel('PC3'); plt.
 ↪xticks([]); plt.yticks([])
plt.subplot(223)
plt.scatter(x_trans[:,0], x_trans[:,2], c=corr_dat['OverallQual'], cmap='jet',␣
 ↪edgecolors="black", alpha=0.7)
plt.title('PC OverallQual'); plt.xlabel('PC1'); plt.ylabel('PC3'); plt.
 ↪xticks([]); plt.yticks([])
plt.subplot(224)
plt.scatter(x_trans[:,0], x_trans[:,2], c=corr_dat['GarageCars'], cmap='jet',␣
 ↪edgecolors="black", alpha=0.7)
plt.title('PC GarageCars'); plt.xlabel('PC1'); plt.ylabel('PC3'); plt.
 ↪xticks([]); plt.yticks([])
plt.show();
```



On the other hand, we can perform t-distributed Stochastic Neighbor Embedding (TSNE), which converts similarities between data points to joint probabilities and tries to minimize the Kullback-Leibler divergence between the joint probabilities of the low-dimensional embedding and the high-dimensional data. Here, we can see a good separation for 'ExterQual' and 'GarageCars' features, proving useful for predicting sale price using these variables.

[39]:
```
tsne = TSNE(n_components = 2).fit_transform(x_train_s)
```

```python
plt.figure(figsize=(20,6))
plt.subplot(221)
plt.scatter(tsne[:,0], tsne[:,1], c=corr_dat['ExterQual'], cmap='jet', edgecolors="black", alpha=0.7)
plt.title('PC ExterQual'); plt.xlabel('tsne1'); plt.ylabel('tsne2'); plt.xticks([]); plt.yticks([])
plt.subplot(222)
plt.scatter(tsne[:,0], tsne[:,1], c=corr_dat['KitchenQual'], cmap='jet', edgecolors="black", alpha=0.7)
plt.title('PC KitchenQual'); plt.xlabel('tsne1'); plt.ylabel('tsne2'); plt.xticks([]); plt.yticks([])
plt.subplot(223)
plt.scatter(tsne[:,0], tsne[:,1], c=corr_dat['OverallQual'], cmap='jet', edgecolors="black", alpha=0.7)
plt.title('PC OverallQual'); plt.xlabel('tsne1'); plt.ylabel('tsne2'); plt.xticks([]); plt.yticks([])
plt.subplot(224)
plt.scatter(tsne[:,0], tsne[:,1], c=corr_dat['GarageCars'], cmap='jet', edgecolors="black", alpha=0.7)
plt.title('PC GarageCars'); plt.xlabel('tsne1'); plt.ylabel('tsne2'); plt.xticks([]); plt.yticks([])
plt.show();
```

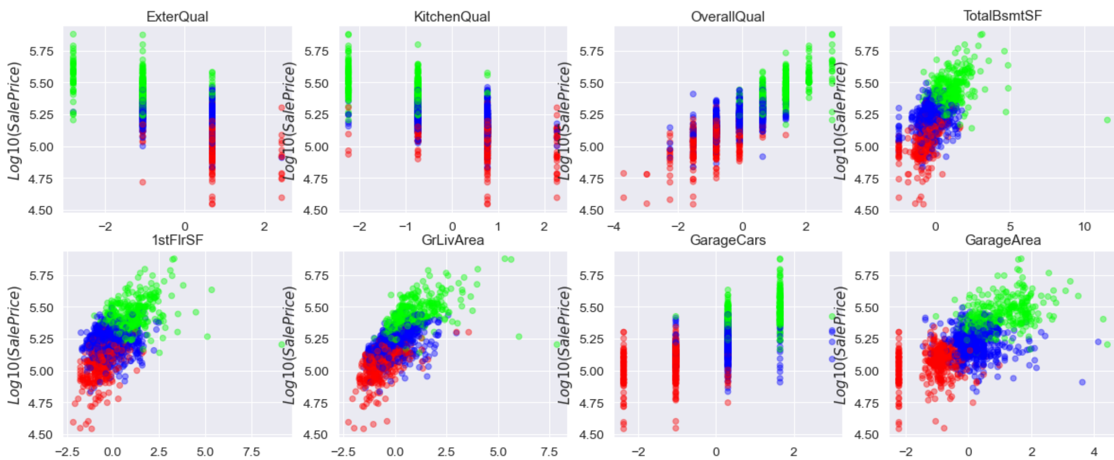


Next, we use K-Means Clustering and Hierarchical Clustering to try and find some relationships in the data. This algorihtm is unsupervised, and therefore tries to cluster the data based on similar predictor values toward the target. This will allow us to observe how we can start classifying and relating the data to the SalePrice. Using 3 clusters we might be able to visualize high/medium/low price houses based on these different highly-correlated predcitor features.

[40]:
```python
n_clusters = 3
kmeans = KMeans(n_clusters = n_clusters).fit(X=x_train_s, y=target).labels_
hclust = AgglomerativeClustering(n_clusters = n_clusters).fit(X=x_train_s, y=target).labels_
```

```
gmm    = GaussianMixture(n_components=n_clusters).fit_predict(X=x_train_s,␣
 ↪y=target)
```

[41]:
```
#select the clustering method to visualize
clust_method = kmeans

plt.figure(figsize=(20,8))
for k in range(len(corr_dat.columns)):
    plt.subplot(x_train_s.shape[-1]//4,4,k+1)
    plt.title('{}'.format(corr_dat.columns[k]))
    plt.scatter(x_train_s[:,k], target, c=clust_method, cmap='brg', alpha=0.4)
    plt.ylabel('$Log10(SalePrice)$')
plt.show();
```



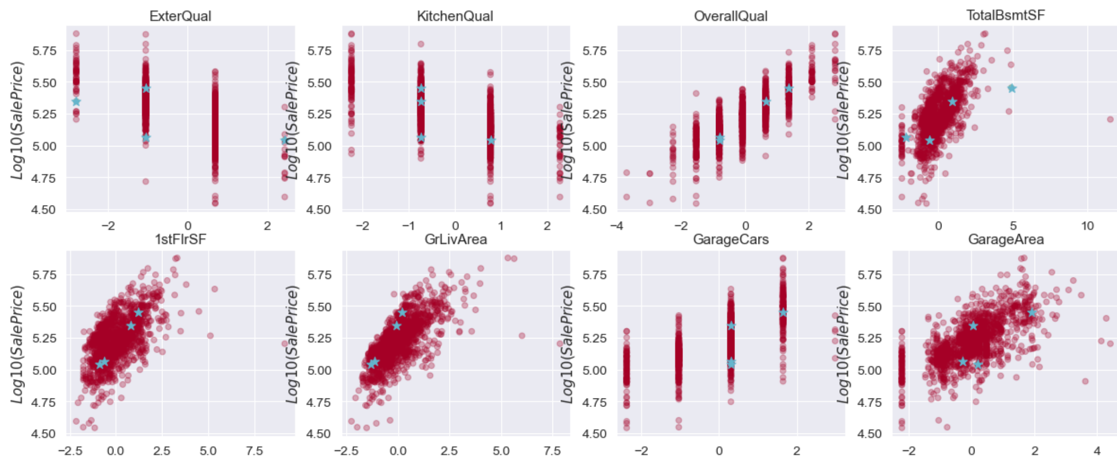
We now perform Local Outlier Factor analysis to try and see if we can find any major outliers in the highly-correlated subset of the data.

[42]:
```
lof = LocalOutlierFactor(n_neighbors=5)
lof.fit_predict(X=x_train_s, y=target)
lof_factors = -lof.negative_outlier_factor_
print('Local Outlier Factors: {}'.format(lof_factors)) #outliers are further␣
 ↪away from 1

# let outliers be those that are more than this upper bound value
lof_outliers_bound = 5
```

```
Local Outlier Factors: [0.9848064  0.97417749 1.10287748 … 2.64963468
0.95880616 1.08014456]
```

[43]:
```
plt.figure(figsize=(20,8))
for k in range(len(corr_dat.columns)):
    plt.subplot(x_train_s.shape[-1]//4,4,k+1)
```

```
    plt.title('{}'.format(corr_dat.columns[k]))
    plt.scatter(x_train_s[:,k], target, c=lof_factors>lof_outliers_bound,␣
 ↪cmap='RdYlGn', alpha=0.3)
    plt.scatter(x_train_s[:,k][lof_factors>lof_outliers_bound],␣
 ↪target[lof_factors>lof_outliers_bound],
                c='c', alpha=1, marker="*", s=100)
    plt.ylabel('$Log10(SalePrice)$')
plt.show();
```



Concluding Remarks:

- Remarks
  - The data has a different types of predictor features, including categorical and numerical. We mapped all categorical features into classes, which can then be used for supervised learning techniques.
  - The target variables, SalePrice, is log-normally distributed and thus any regression algorithms should be predicting the log10(SalePrice) pseudofeature instead.
  - Data preprocessing and analysis included statistical and visual analysis; as well as unsupervised learning, also known as clustering analysis.
  - Some outliers are still present in the data, though they are only but a small percentage of the instances in the highly-correlated features selected.
- Conclusion
  - The Ames Housing data set is a complex yet versatile data set from machine learning projects.
  - Preprocessing and data wrangling is crucial for explointing the full potential of all features.
  - The data is now ready to be used in different regression models to predict SalePrice from the features.
- Part 2: Regression We will attempt to use 6 different regression algorithms on the preprocessed data set. These potentially include linear regression, regularized regression, boosting,

SVM, random forest, and neural networks. We will then compare the performance of the differnet algorithms in predicting the (logarithm) SalePrice using the (subset) 79 (preprocessed) predictors provided. The mean-squared error metric will be used for optimization, and we hope to produce very accurate and itneresting predictive models for the Ames Housing dataset.

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6 End of Notebook