assignment 1

January 9, 2022

1 MSDS 422 Assignment 1

The dependent variable of interest is house prices in Ames, Iowa ('SalePrice')

1.1 Data preparation

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```
#import data
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

[3]:
```
train.head()
```

[3]:
```
   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]
```

[4]:
```
train.tail()
```

[4]:
```
        Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
1455  1456          60       RL         62.0     7917   Pave   NaN      Reg
1456  1457          20       RL         85.0    13175   Pave   NaN      Reg
1457  1458          70       RL         66.0     9042   Pave   NaN      Reg
1458  1459          20       RL         68.0     9717   Pave   NaN      Reg
1459  1460          20       RL         75.0     9937   Pave   NaN      Reg

     LandContour Utilities  … PoolArea PoolQC  Fence MiscFeature MiscVal  \
1455         Lvl    AllPub  …        0    NaN    NaN         NaN       0
1456         Lvl    AllPub  …        0    NaN  MnPrv         NaN       0
1457         Lvl    AllPub  …        0    NaN  GdPrv        Shed    2500
1458         Lvl    AllPub  …        0    NaN    NaN         NaN       0
1459         Lvl    AllPub  …        0    NaN    NaN         NaN       0

     MoSold YrSold  SaleType  SaleCondition  SalePrice
1455      8   2007        WD         Normal     175000
1456      2   2010        WD         Normal     210000
1457      5   2010        WD         Normal     266500
1458      4   2010        WD         Normal     142125
1459      6   2008        WD         Normal     147500

[5 rows x 81 columns]
```

[5]:
```
train.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     1452 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
```

[6]:
```
train.describe()
```

[6]:
```
                Id   MSSubClass  LotFrontage        LotArea  OverallQual  \
count  1460.000000  1460.000000  1201.000000    1460.000000  1460.000000
mean    730.500000    56.897260    70.049958   10516.828082     6.099315
std     421.610009    42.300571    24.284752    9981.264932     1.382997
min       1.000000    20.000000    21.000000    1300.000000     1.000000
25%     365.750000    20.000000    59.000000    7553.500000     5.000000
50%     730.500000    50.000000    69.000000    9478.500000     6.000000
75%    1095.250000    70.000000    80.000000   11601.500000     7.000000
max    1460.000000   190.000000   313.000000  215245.000000    10.000000

       OverallCond    YearBuilt  YearRemodAdd   MasVnrArea   BsmtFinSF1  …  \
count  1460.000000  1460.000000   1460.000000  1452.000000  1460.000000  …
mean      5.575342  1971.267808   1984.865753   103.685262   443.639726  …
std       1.112799    30.202904     20.645407   181.066207   456.098091  …
min       1.000000  1872.000000   1950.000000     0.000000     0.000000  …
25%       5.000000  1954.000000   1967.000000     0.000000     0.000000  …
50%       5.000000  1973.000000   1994.000000     0.000000   383.500000  …
75%       6.000000  2000.000000   2004.000000   166.000000   712.250000  …
max       9.000000  2010.000000   2010.000000  1600.000000  5644.000000  …

        WoodDeckSF  OpenPorchSF  EnclosedPorch    3SsnPorch  ScreenPorch  \
count  1460.000000  1460.000000    1460.000000  1460.000000  1460.000000
```

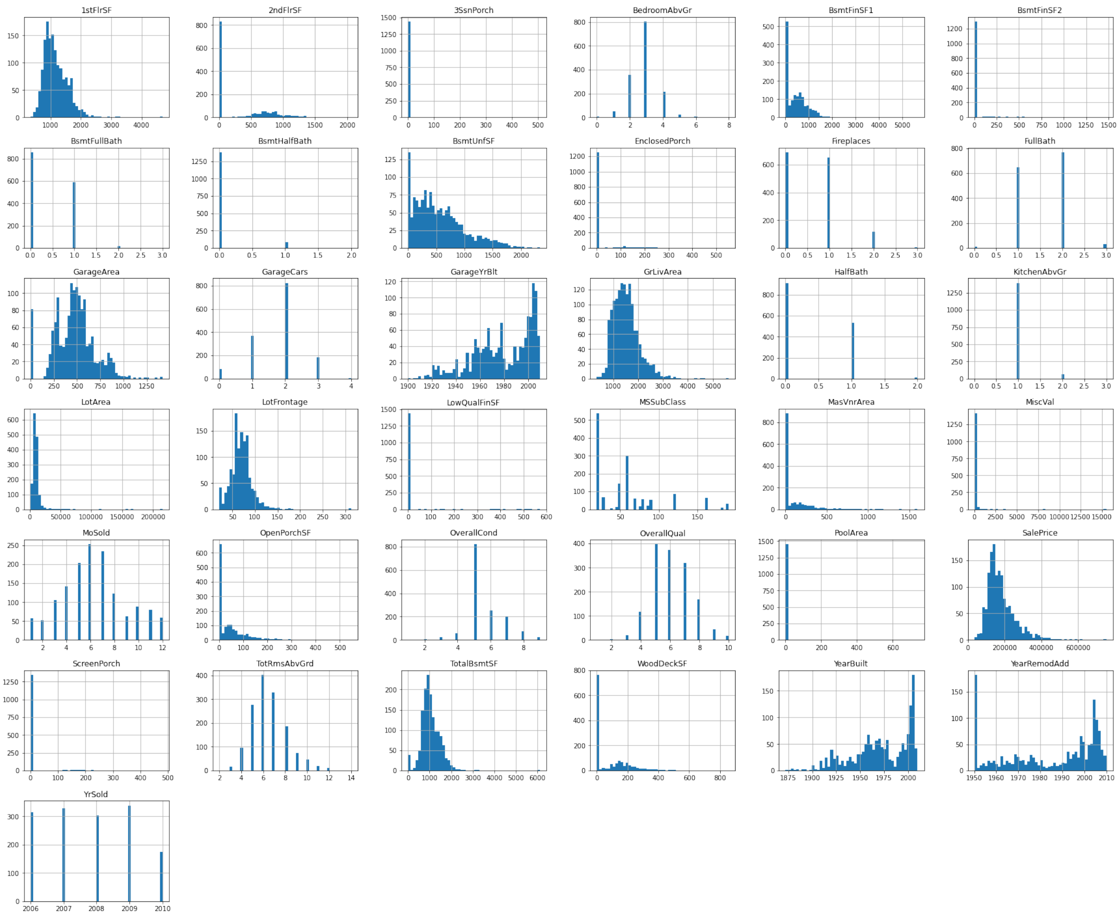
```
mean     94.244521    46.660274      21.954110     3.409589    15.060959
std     125.338794    66.256028      61.119149    29.317331    55.757415
min       0.000000     0.000000       0.000000     0.000000     0.000000
25%       0.000000     0.000000       0.000000     0.000000     0.000000
50%       0.000000    25.000000       0.000000     0.000000     0.000000
75%     168.000000    68.000000       0.000000     0.000000     0.000000
max     857.000000   547.000000     552.000000   508.000000   480.000000

          PoolArea       MiscVal       MoSold       YrSold      SalePrice
count  1460.000000   1460.000000  1460.000000  1460.000000    1460.000000
mean      2.758904     43.489041     6.321918  2007.815753  180921.195890
std      40.177307    496.123024     2.703626     1.328095   79442.502883
min       0.000000      0.000000     1.000000  2006.000000   34900.000000
25%       0.000000      0.000000     5.000000  2007.000000  129975.000000
50%       0.000000      0.000000     6.000000  2008.000000  163000.000000
75%       0.000000      0.000000     8.000000  2009.000000  214000.000000
max     738.000000  15500.000000    12.000000  2010.000000  755000.000000

[8 rows x 38 columns]
```

[7]:
```
train.shape
```

[7]:
```
(1460, 81)
```

[8]:
```
#no need for ID (arbitrary number)
train = train.drop(labels = 'Id',axis=1)
```

[9]:
```
#distributions
train.hist(bins=50, figsize=(30,25))
plt.show()
```



1. Provide appropriate descriptive statistics and visualizations to help understand the marginal distribution of the dependent variable.

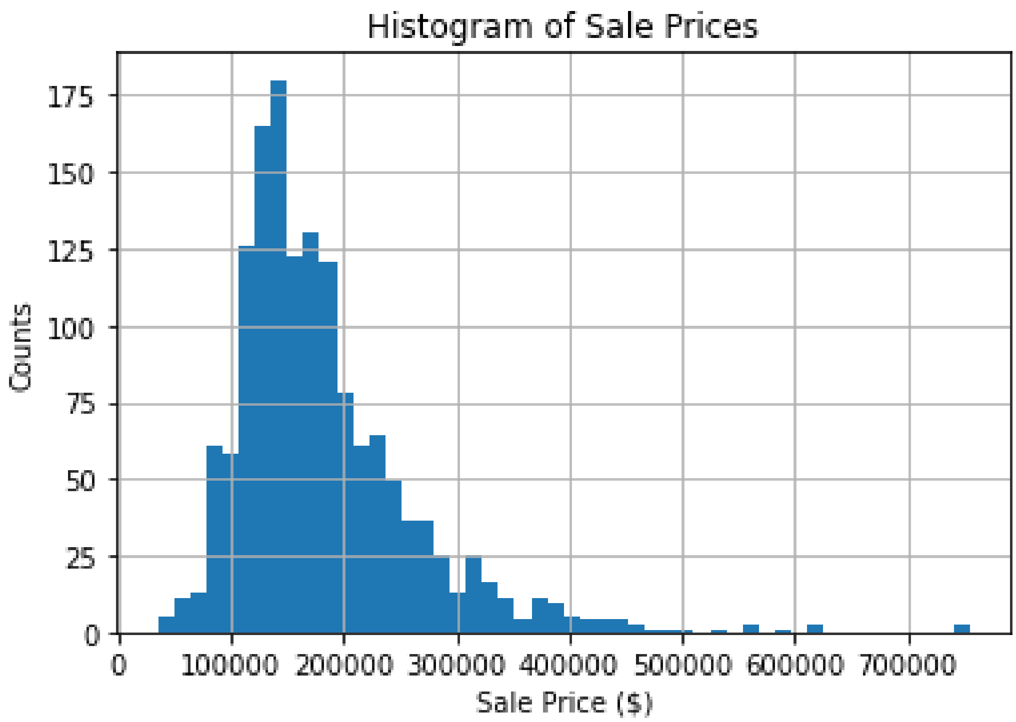
[10]:
```python
#code
train["SalePrice"].describe()
```

[10]:
```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

The average sale price from this data set is 180,921. Sale prices range from 129,975 to 755,000 with a median value of 163,000.

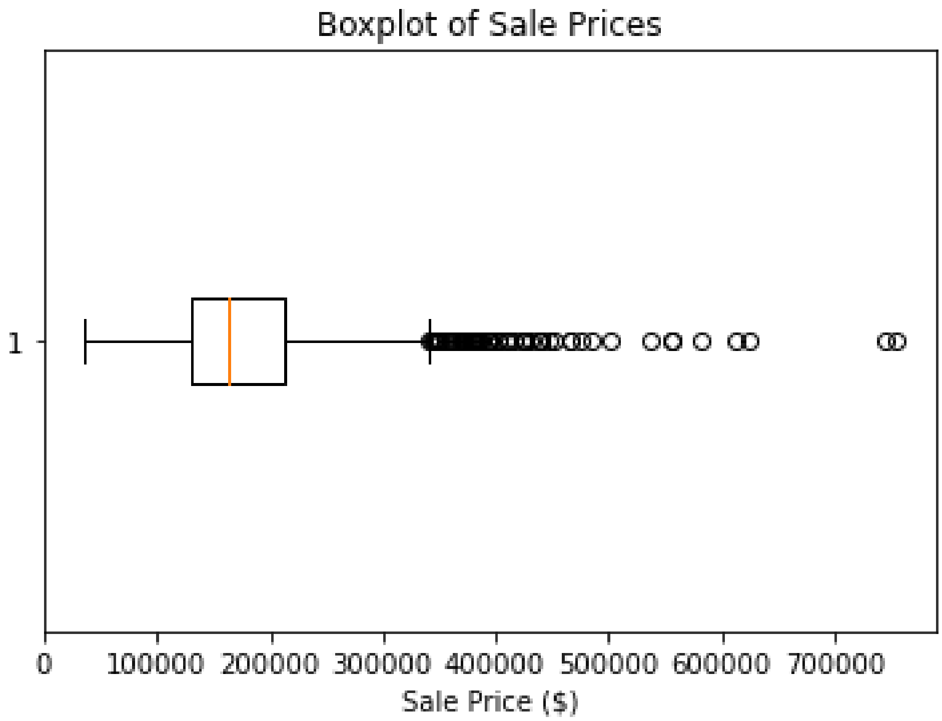
[11]:
```
fig, ax = plt.subplots()
train["SalePrice"].hist(bins=50)
plt.xlabel('Sale Price ($)')
plt.ylabel('Counts')
plt.title('Histogram of Sale Prices')
```

[11]: Text(0.5, 1.0, 'Histogram of Sale Prices')



[12]:
```
fig, ax = plt.subplots()
plt.boxplot(train["SalePrice"], vert=False)
plt.xlabel('Sale Price ($)')
plt.title('Boxplot of Sale Prices')

#high end of boxplot
214000 + 1.5*(214000 - 129975)
```

[12]: 340037.5

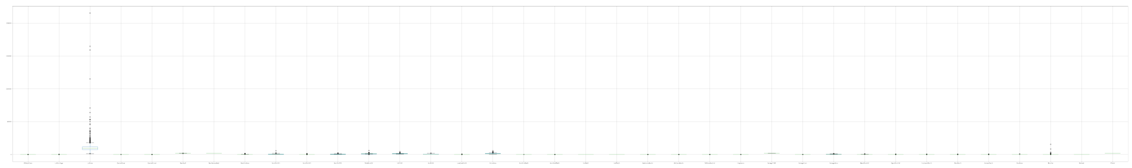


The histogram and boxplot above show that SalePrice is skewed to the right. Outliers may range from any SalePrice greater than ~340,000

2. Investigate missing data and outliers.

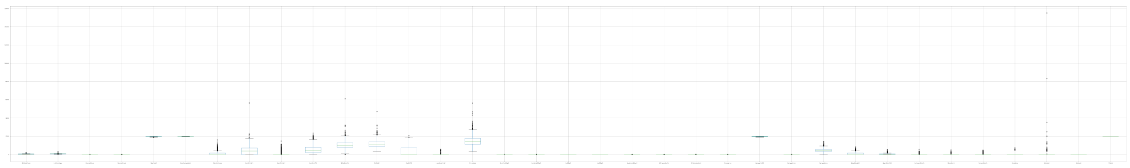
[13]:
```
#outliers
plt.figure(figsize = (140,20))
train.loc[:, train.columns!='SalePrice'].boxplot()
```

[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd8c4d18100>
```



[14]:
```
#outliers
plt.figure(figsize = (140,20))
train.loc[:, ~train.columns.isin(['SalePrice', 'LotArea'])].boxplot()
```

[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd8c7552760>
```



SalePrice and LotArea have values with magnitudes greater than other independent variables. When looking at other variables, many of their boxplots indicate several outliers.

[15]:
```
#missing data
train.isnull().sum()[train.isnull().sum()>0]
```

[15]:
```
LotFrontage      259
Alley           1369
MasVnrType         8
MasVnrArea         8
BsmtQual          37
BsmtCond          37
BsmtExposure      38
BsmtFinType1      37
BsmtFinType2      38
Electrical         1
FireplaceQu      690
GarageType        81
GarageYrBlt       81
GarageFinish      81
GarageQual        81
GarageCond        81
PoolQC          1453
Fence           1179
MiscFeature     1406
dtype: int64
```

The variables above have numerous outliers. Of which, Alley, PoolQC, Fence, and MiscFeature have over 1000 null values relative to the 1460 total records.

[16]:
```
#dupes
train.duplicated().sum()
```

[16]:
```
0
```

There are no duplicate rows in the dataset.

3. Investigate at least three potential predictors of the dependent variable and provide appropriate graphs / statistics to demonstrate the relationships.

[17]:
```
#correlation matrix
train.corr().style.background_gradient(cmap='coolwarm').set_precision(2)
```

[17]: <pandas.io.formats.style.Styler at 0x7fd8cb2ccd30>

[18]:
```
#highest correlations with SalePrice
train.corr()['SalePrice'].sort_values(ascending=False)
```

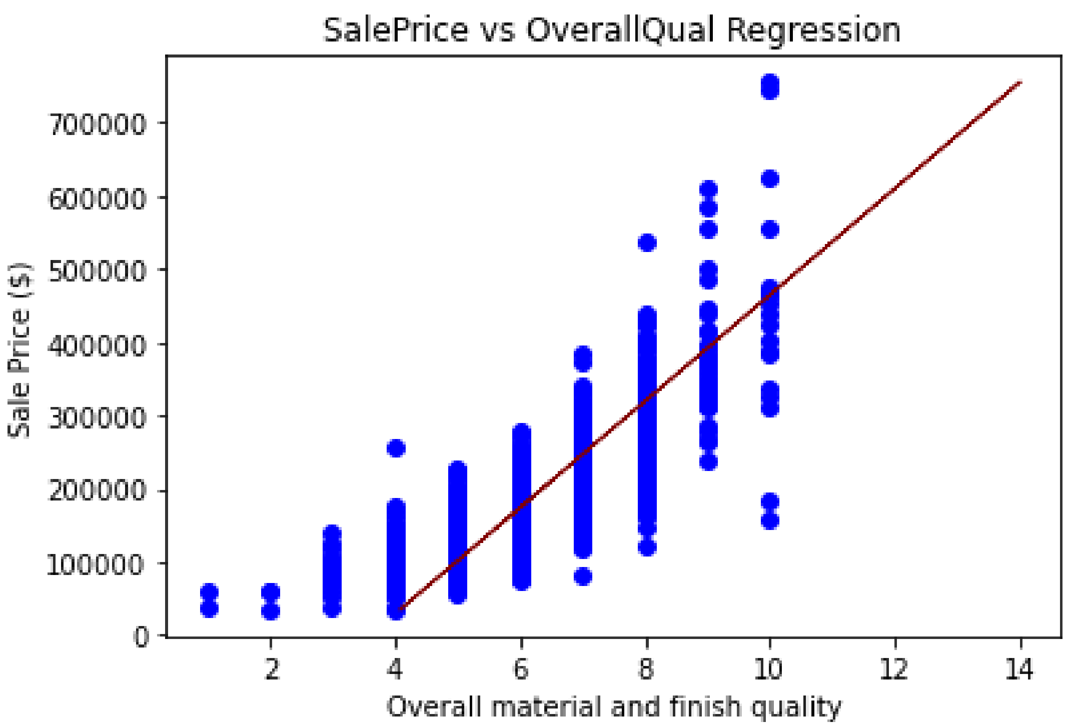
[18]:
```
SalePrice        1.000000
OverallQual      0.790982
GrLivArea        0.708624
GarageCars       0.640409
GarageArea       0.623431
TotalBsmtSF      0.613581
1stFlrSF         0.605852
FullBath         0.560664
TotRmsAbvGrd     0.533723
YearBuilt        0.522897
YearRemodAdd     0.507101
GarageYrBlt      0.486362
MasVnrArea       0.477493
Fireplaces       0.466929
BsmtFinSF1       0.386420
LotFrontage      0.351799
WoodDeckSF       0.324413
2ndFlrSF         0.319334
OpenPorchSF      0.315856
HalfBath         0.284108
LotArea          0.263843
BsmtFullBath     0.227122
BsmtUnfSF        0.214479
BedroomAbvGr     0.168213
ScreenPorch      0.111447
PoolArea         0.092404
MoSold           0.046432
3SsnPorch        0.044584
BsmtFinSF2      -0.011378
BsmtHalfBath    -0.016844
MiscVal         -0.021190
LowQualFinSF    -0.025606
YrSold          -0.028923
OverallCond     -0.077856
MSSubClass      -0.084284
EnclosedPorch   -0.128578
KitchenAbvGr    -0.135907
Name: SalePrice, dtype: float64
```

The top 3 variables with the highest correlation with SalePrice are OverallQual (0.790982), GrLivArea (0.708624) and GarageCars (0.640409). All 3 have a positive correlation.

[19]:
```
from sklearn.metrics import mean_squared_error
from sklearn import datasets, linear_model
from scipy import stats
```

[20]:
```
lm_oq = linear_model.LinearRegression()
lm_oq.fit(train[['SalePrice']], train['OverallQual'])
x_oq = lm_oq.predict(train[['SalePrice']])
rmse_oq = mean_squared_error(train['OverallQual'], x_oq, squared=False)

plt.scatter(train['OverallQual'], train['SalePrice'],  color='blue')
plt.plot(x_oq, train['SalePrice'], color='maroon', linewidth=1)
plt.ylabel('Sale Price ($)')
plt.xlabel('Overall material and finish quality')
plt.title('SalePrice vs OverallQual Regression')

print("RMSE:", rmse_oq)
```

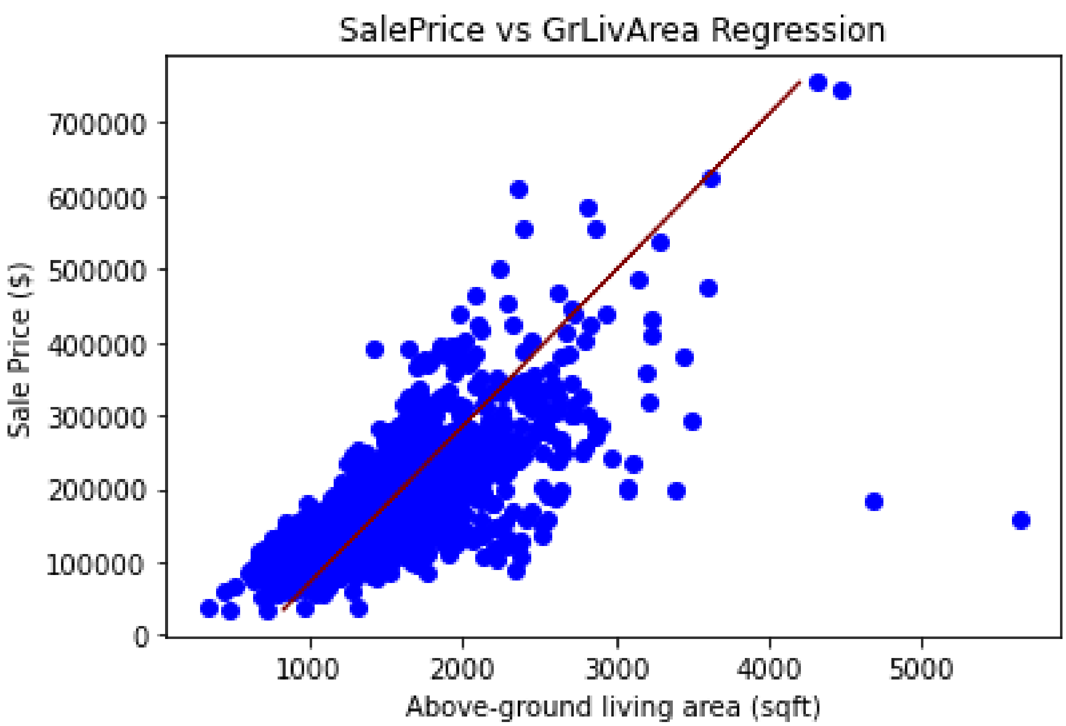
```
RMSE: 0.8458826841860243
```



[21]:
```
lm_gla = linear_model.LinearRegression()
lm_gla.fit(train[['SalePrice']], train['GrLivArea'])
```

```
x_gla = lm_gla.predict(train[['SalePrice']])
rmse_gla = mean_squared_error(train['GrLivArea'], x_gla, squared=False)

plt.scatter(train['GrLivArea'], train['SalePrice'],  color='blue')
plt.plot(x_gla, train['SalePrice'], color='maroon', linewidth=1)
plt.ylabel('Sale Price ($)')
plt.xlabel('Above-ground living area (sqft)')
plt.title('SalePrice vs GrLivArea Regression')

print("RMSE:", rmse_gla)
```

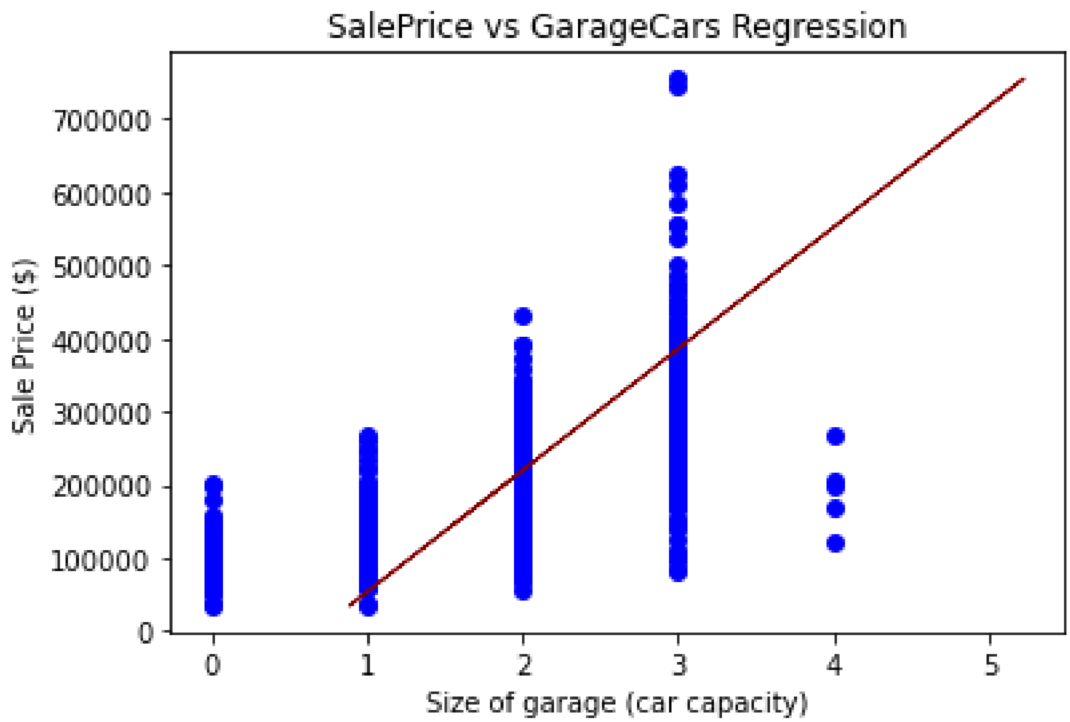
```
RMSE: 370.6445090657199
```



[22]:
```
lm_gc = linear_model.LinearRegression()
lm_gc.fit(train[['SalePrice']], train['GarageCars'])
x_gc = lm_gc.predict(train[['SalePrice']])
rmse_gc = mean_squared_error(train['GarageCars'], x_gc, squared=False)

plt.scatter(train['GarageCars'], train['SalePrice'],  color='blue')
plt.plot(x_gc, train['SalePrice'], color='maroon', linewidth=1)
plt.ylabel('Sale Price ($)')
plt.xlabel('Size of garage (car capacity)')
plt.title('SalePrice vs GarageCars Regression')
```

```python
print("RMSE:", rmse_gc)
```

```
RMSE: 0.573766659729406
```



The best predictors based on RMSE from lowest to highest are GarageCars (0.57), OverallQual (0.84), GrLivArea (370.64). GarageCars has the lowest RMSE which makes it the best predictor of the 3 tested above.

4. Engage in feature creation by splitting, merging, or otherwise generating a new predictor.

[23]:
```python
#Average Overall Condition and Quality
train['OverallCondQual'] = (train['OverallCond'] + train['OverallQual'])/2
```

This predictor may remove the need to include both Condition and Quality into a model if they are highly correlated.

[24]:
```python
# Combine total finished basement sq ft with above ground
train['total_FinSqft'] = train['TotalBsmtSF'] + train['GrLivArea']
```

This predictor may remove the need to include both above and below square footage if they are highly correlated.

[25]:
```python
# Years to sell since last remodel
train['YearsToSell'] = train['YrSold'] - train['YearRemodAdd']
```

This predictor may provide insight on how long it took to sell a property since its last remodel.

[26]:
```python
train.head()
```

[26]:
```
   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  … MiscFeature MiscVal MoSold YrSold  \
0         Lvl    AllPub    Inside  …         NaN       0      2   2008
1         Lvl    AllPub       FR2  …         NaN       0      5   2007
2         Lvl    AllPub    Inside  …         NaN       0      9   2008
3         Lvl    AllPub    Corner  …         NaN       0      2   2006
4         Lvl    AllPub       FR2  …         NaN       0     12   2008

  SaleType SaleCondition  SalePrice  OverallCondQual  total_FinSqft  \
0       WD        Normal     208500              6.0           2566
1       WD        Normal     181500              7.0           2524
2       WD        Normal     223500              6.0           2706
3       WD       Abnorml     140000              6.0           2473
4       WD        Normal     250000              6.5           3343

   YearsToSell
0            5
1           31
2            6
3           36
4            8

[5 rows x 83 columns]
```

5. Using the dependent variable, perform both min-max and standard scaling in Python.

[27]:
```python
#min-max scaling
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
train_minmax = train.copy()

numeric_cols = train_minmax._get_numeric_data().columns
train_minmax[numeric_cols] = scaler.fit_transform(train_minmax[numeric_cols])
```

```
train_minmax[numeric_cols].head()
```

[27]:

```
   MSSubClass  LotFrontage   LotArea  OverallQual  OverallCond  YearBuilt  \
0    0.235294     0.150685  0.033420     0.666667        0.500   0.949275
1    0.000000     0.202055  0.038795     0.555556        0.875   0.753623
2    0.235294     0.160959  0.046507     0.666667        0.500   0.934783
3    0.294118     0.133562  0.038561     0.666667        0.500   0.311594
4    0.235294     0.215753  0.060576     0.777778        0.500   0.927536

   YearRemodAdd  MasVnrArea  BsmtFinSF1  BsmtFinSF2  …  3SsnPorch  \
0      0.883333     0.12250    0.125089         0.0  …        0.0
1      0.433333     0.00000    0.173281         0.0  …        0.0
2      0.866667     0.10125    0.086109         0.0  …        0.0
3      0.333333     0.00000    0.038271         0.0  …        0.0
4      0.833333     0.21875    0.116052         0.0  …        0.0

   ScreenPorch  PoolArea  MiscVal    MoSold  YrSold  SalePrice  \
0          0.0       0.0      0.0  0.090909    0.50   0.241078
1          0.0       0.0      0.0  0.363636    0.25   0.203583
2          0.0       0.0      0.0  0.727273    0.50   0.261908
3          0.0       0.0      0.0  0.090909    0.00   0.145952
4          0.0       0.0      0.0  1.000000    0.50   0.298709

   OverallCondQual  total_FinSqft  YearsToSell
0         0.588235       0.195481     0.098361
1         0.705882       0.191802     0.524590
2         0.588235       0.207742     0.114754
3         0.588235       0.187336     0.606557
4         0.647059       0.263531     0.147541

[5 rows x 40 columns]
```

[28]:

```
#standard scaling
from sklearn.preprocessing import StandardScaler
from scipy.stats import zscore
std_scaler = StandardScaler()
train_std = train.copy()

numeric_cols = train_std._get_numeric_data().columns
train_std[numeric_cols] = std_scaler.fit_transform(train_minmax[numeric_cols])
train_std[numeric_cols].head()
```

[28]:

```
   MSSubClass  LotFrontage   LotArea  OverallQual  OverallCond  YearBuilt  \
0    0.073375    -0.208034 -0.207142     0.651479    -0.517200   1.050994
1   -0.872563     0.409895 -0.091886    -0.071836     2.179628   0.156734
2    0.073375    -0.084449  0.073480     0.651479    -0.517200   0.984752
3    0.309859    -0.414011 -0.096897     0.651479    -0.517200  -1.863632
```

```
4    0.073375     0.574676  0.375148     1.374795    -0.517200   0.951632

   YearRemodAdd  MasVnrArea  BsmtFinSF1  BsmtFinSF2  …  3SsnPorch  \
0      0.878668    0.510015    0.575425   -0.288653  …  -0.116339
1     -0.429577   -0.572835    1.171992   -0.288653  …  -0.116339
2      0.830215    0.322174    0.092907   -0.288653  …  -0.116339
3     -0.720298   -0.572835   -0.499274   -0.288653  …  -0.116339
4      0.733308    1.360826    0.463568   -0.288653  …  -0.116339

   ScreenPorch  PoolArea   MiscVal    MoSold    YrSold  SalePrice  \
0    -0.270208 -0.068692 -0.087688 -1.599111  0.138777   0.347273
1    -0.270208 -0.068692 -0.087688 -0.489110 -0.614439   0.007288
2    -0.270208 -0.068692 -0.087688  0.990891  0.138777   0.536154
3    -0.270208 -0.068692 -0.087688 -1.599111 -1.367655  -0.515281
4    -0.270208 -0.068692 -0.087688  2.100892  0.138777   0.869843

   OverallCondQual  total_FinSqft  YearsToSell
0         0.192175      -0.008372    -0.869941
1         1.373547      -0.059386     0.390141
2         0.192175       0.161672    -0.821476
3         0.192175      -0.121330     0.632464
4         0.782861       0.935372    -0.724547

[5 rows x 40 columns]
```

When using machine learning, models are typically used to tell the distance between data. By scaling using either min-max or standard, we can normalize and/or standardize the data before going into certain analyses or algorithms that require it.

```
[ ]:
```