project

December 5, 2020

1 CSCI 3022 Final Project - Regression

[1]:
```
NAME = "Vu Dang"
COLLABORATORS = ""
```

[45]:
```
%matplotlib inline
import numpy as np
import scipy as sp
import scipy.stats as stats
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Set color map to have light blue background
sns.set()
import statsmodels.formula.api as smf
import statsmodels.api as sm
import patsy
import sklearn
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
```

1.1 1. Linear Regression 1

In this section, I will perform an initial pass through of loading, cleaning the data and finding an initial model through forward stepwise selection using the linear regression model.

[31]:
```
# load in the data sets
data_test = pd.read_csv('test.csv', comment='#')
data_train = pd.read_csv('train.csv', comment='#')
```

The data has been loaded in. The first thing I will do is drop the "Id" column. I believe that this column is useless and should have no effect on the prediction of the sale price.

[32]:
```
data_train = data_train.drop(["Id"], axis=1)
data_test = data_test.drop(["Id"], axis=1)
print(data_train)
print(data_test)
```

```
     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
…           …       …           …       …     …   …       …
1455         60       RL         62.0     7917   Pave   NaN      Reg
1456         20       RL         85.0    13175   Pave   NaN      Reg
1457         70       RL         66.0     9042   Pave   NaN      Reg
1458         20       RL         68.0     9717   Pave   NaN      Reg
1459         20       RL         75.0     9937   Pave   NaN      Reg

    LandContour Utilities LotConfig  … PoolArea PoolQC  Fence MiscFeature  \
0           Lvl    AllPub    Inside  …        0    NaN    NaN         NaN
1           Lvl    AllPub       FR2  …        0    NaN    NaN         NaN
2           Lvl    AllPub    Inside  …        0    NaN    NaN         NaN
3           Lvl    AllPub    Corner  …        0    NaN    NaN         NaN
4           Lvl    AllPub       FR2  …        0    NaN    NaN         NaN
…           …        …       …  …       …     …     …          …
1455        Lvl    AllPub    Inside  …        0    NaN    NaN         NaN
1456        Lvl    AllPub    Inside  …        0    NaN  MnPrv         NaN
1457        Lvl    AllPub    Inside  …        0    NaN  GdPrv        Shed
1458        Lvl    AllPub    Inside  …        0    NaN    NaN         NaN
1459        Lvl    AllPub    Inside  …        0    NaN    NaN         NaN

    MiscVal MoSold  YrSold  SaleType  SaleCondition  SalePrice
0         0      2    2008        WD         Normal     208500
1         0      5    2007        WD         Normal     181500
2         0      9    2008        WD         Normal     223500
3         0      2    2006        WD        Abnorml     140000
4         0     12    2008        WD         Normal     250000
…       …    …      …         …              …          …
1455      0      8    2007        WD         Normal     175000
1456      0      2    2010        WD         Normal     210000
1457   2500      5    2010        WD         Normal     266500
1458      0      4    2010        WD         Normal     142125
1459      0      6    2008        WD         Normal     147500

[1460 rows x 80 columns]
     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
…           …       …           …       …     …   …       …
1454        160       RM         21.0     1936   Pave   NaN      Reg
```

```
1455         160        RM          21.0     1894   Pave   NaN       Reg
1456          20        RL         160.0    20000   Pave   NaN       Reg
1457          85        RL          62.0    10441   Pave   NaN       Reg
1458          60        RL          74.0     9627   Pave   NaN       Reg

     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
…          …       …       …  …         …      …    …    …
1454         Lvl    AllPub    Inside  …           0        0    NaN    NaN
1455         Lvl    AllPub    Inside  …           0        0    NaN    NaN
1456         Lvl    AllPub    Inside  …           0        0    NaN    NaN
1457         Lvl    AllPub    Inside  …           0        0    NaN  MnPrv
1458         Lvl    AllPub    Inside  …           0        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
…          …     …     …     …      …        …
1454         NaN       0       6    2006        WD         Normal
1455         NaN       0       4    2006        WD        Abnorml
1456         NaN       0       9    2006        WD        Abnorml
1457        Shed     700       7    2006        WD         Normal
1458         NaN       0      11    2006        WD         Normal

[1459 rows x 79 columns]
```

I notice that there are lots of NaNs in both the test and train data. For this section, I will naively fill any numerical NaNs with 0's. In the next section I will perform a more educated cleaning procedure.

[33]:
```python
data_train = data_train.fillna(0.0)
data_test = data_test.fillna(0.0)
print(data_train.info())
print(data_test.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1460 non-null   int64
```

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

```
 49  HalfBath       1460 non-null   int64
 50  BedroomAbvGr   1460 non-null   int64
 51  KitchenAbvGr   1460 non-null   int64
 52  KitchenQual    1460 non-null   object
 53  TotRmsAbvGrd   1460 non-null   int64
 54  Functional     1460 non-null   object
 55  Fireplaces     1460 non-null   int64
 56  FireplaceQu    1460 non-null   object
 57  GarageType     1460 non-null   object
 58  GarageYrBlt    1460 non-null   float64
 59  GarageFinish   1460 non-null   object
 60  GarageCars     1460 non-null   int64
 61  GarageArea     1460 non-null   int64
 62  GarageQual     1460 non-null   object
 63  GarageCond     1460 non-null   object
 64  PavedDrive     1460 non-null   object
 65  WoodDeckSF     1460 non-null   int64
 66  OpenPorchSF    1460 non-null   int64
 67  EnclosedPorch  1460 non-null   int64
 68  3SsnPorch      1460 non-null   int64
 69  ScreenPorch    1460 non-null   int64
 70  PoolArea       1460 non-null   int64
 71  PoolQC         1460 non-null   object
 72  Fence          1460 non-null   object
 73  MiscFeature    1460 non-null   object
 74  MiscVal        1460 non-null   int64
 75  MoSold         1460 non-null   int64
 76  YrSold         1460 non-null   int64
 77  SaleType       1460 non-null   object
 78  SaleCondition  1460 non-null   object
 79  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(43)
memory usage: 912.6+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 79 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1459 non-null   int64
 1   MSZoning       1459 non-null   object
 2   LotFrontage    1459 non-null   float64
 3   LotArea        1459 non-null   int64
 4   Street         1459 non-null   object
 5   Alley          1459 non-null   object
 6   LotShape       1459 non-null   object
 7   LandContour    1459 non-null   object
 8   Utilities      1459 non-null   object
```

```
9   LotConfig      1459 non-null   object
10  LandSlope      1459 non-null   object
11  Neighborhood   1459 non-null   object
12  Condition1     1459 non-null   object
13  Condition2     1459 non-null   object
14  BldgType       1459 non-null   object
15  HouseStyle     1459 non-null   object
16  OverallQual    1459 non-null   int64
17  OverallCond    1459 non-null   int64
18  YearBuilt      1459 non-null   int64
19  YearRemodAdd   1459 non-null   int64
20  RoofStyle      1459 non-null   object
21  RoofMatl       1459 non-null   object
22  Exterior1st    1459 non-null   object
23  Exterior2nd    1459 non-null   object
24  MasVnrType     1459 non-null   object
25  MasVnrArea     1459 non-null   float64
26  ExterQual      1459 non-null   object
27  ExterCond      1459 non-null   object
28  Foundation     1459 non-null   object
29  BsmtQual       1459 non-null   object
30  BsmtCond       1459 non-null   object
31  BsmtExposure   1459 non-null   object
32  BsmtFinType1   1459 non-null   object
33  BsmtFinSF1     1459 non-null   float64
34  BsmtFinType2   1459 non-null   object
35  BsmtFinSF2     1459 non-null   float64
36  BsmtUnfSF      1459 non-null   float64
37  TotalBsmtSF    1459 non-null   float64
38  Heating        1459 non-null   object
39  HeatingQC      1459 non-null   object
40  CentralAir     1459 non-null   object
41  Electrical     1459 non-null   object
42  1stFlrSF       1459 non-null   int64
43  2ndFlrSF       1459 non-null   int64
44  LowQualFinSF   1459 non-null   int64
45  GrLivArea      1459 non-null   int64
46  BsmtFullBath   1459 non-null   float64
47  BsmtHalfBath   1459 non-null   float64
48  FullBath       1459 non-null   int64
49  HalfBath       1459 non-null   int64
50  BedroomAbvGr   1459 non-null   int64
51  KitchenAbvGr   1459 non-null   int64
52  KitchenQual    1459 non-null   object
53  TotRmsAbvGrd   1459 non-null   int64
54  Functional     1459 non-null   object
55  Fireplaces     1459 non-null   int64
56  FireplaceQu    1459 non-null   object
```

```
 57  GarageType     1459 non-null   object
 58  GarageYrBlt    1459 non-null   float64
 59  GarageFinish   1459 non-null   object
 60  GarageCars     1459 non-null   float64
 61  GarageArea     1459 non-null   float64
 62  GarageQual     1459 non-null   object
 63  GarageCond     1459 non-null   object
 64  PavedDrive     1459 non-null   object
 65  WoodDeckSF     1459 non-null   int64
 66  OpenPorchSF    1459 non-null   int64
 67  EnclosedPorch  1459 non-null   int64
 68  3SsnPorch      1459 non-null   int64
 69  ScreenPorch    1459 non-null   int64
 70  PoolArea       1459 non-null   int64
 71  PoolQC         1459 non-null   object
 72  Fence          1459 non-null   object
 73  MiscFeature    1459 non-null   object
 74  MiscVal        1459 non-null   int64
 75  MoSold         1459 non-null   int64
 76  YrSold         1459 non-null   int64
 77  SaleType       1459 non-null   object
 78  SaleCondition  1459 non-null   object
dtypes: float64(11), int64(25), object(43)
memory usage: 900.6+ KB
None
```

The NaNs have been filled with 0s. Now, I'm going to rename some columns, purely due to the fact that the statsmodel library doesn't like variable names with numerical digits as prefixes. As you can see, I'm simply replacing the bad variable names with the working ones.

[34]:
```
data_train.rename(columns={'1stFlrSF':'FirstFlrSF'}, inplace=True)
data_train.rename(columns={'2ndFlrSF':'SecondFlrSF'}, inplace=True)
data_train.rename(columns={'3SsnPorch':'ThreeSsnPorch'}, inplace=True)

data_test.rename(columns={'1stFlrSF':'FirstFlrSF'}, inplace=True)
data_test.rename(columns={'2ndFlrSF':'SecondFlrSF'}, inplace=True)
data_test.rename(columns={'3SsnPorch':'ThreeSsnPorch'}, inplace=True)
```

In this next part, I'm setting up the prerequisites for performing forward stepwise selection. In a nutshell, what I'm trying to do is create a vector of what I think are useful variables. In this case, useful variables are variables that are non-categorical. As you can see in the code and the resulting print results, I'm only keeping variables that have numbers.

[80]:
```
# get the list of columns
# this is the list of potential variables
cols = list(data_train.columns)
# drop "SalePrice" from this list because it's the variable we're trying to␣
 ↪predict
```

```
cols.remove("SalePrice")

print(cols)
print(len(cols))

to_remove = []
for var in cols:
    if data_train[var].dtypes == "object":
        to_remove.append(var)

for elem in to_remove:
    cols.remove(elem)

print(cols)
print(len(cols))
```

```
['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'Alley',
'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure',
'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF',
'TotalBsmtSF', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'FirstFlrSF',
'SecondFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch',
'ThreeSsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature',
'MiscVal', 'MoSold', 'YrSold', 'SaleType', 'SaleCondition']
79
['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
'BsmtUnfSF', 'TotalBsmtSF', 'FirstFlrSF', 'SecondFlrSF', 'LowQualFinSF',
'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces', 'GarageYrBlt',
'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch',
'ThreeSsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal', 'MoSold', 'YrSold']
36
```

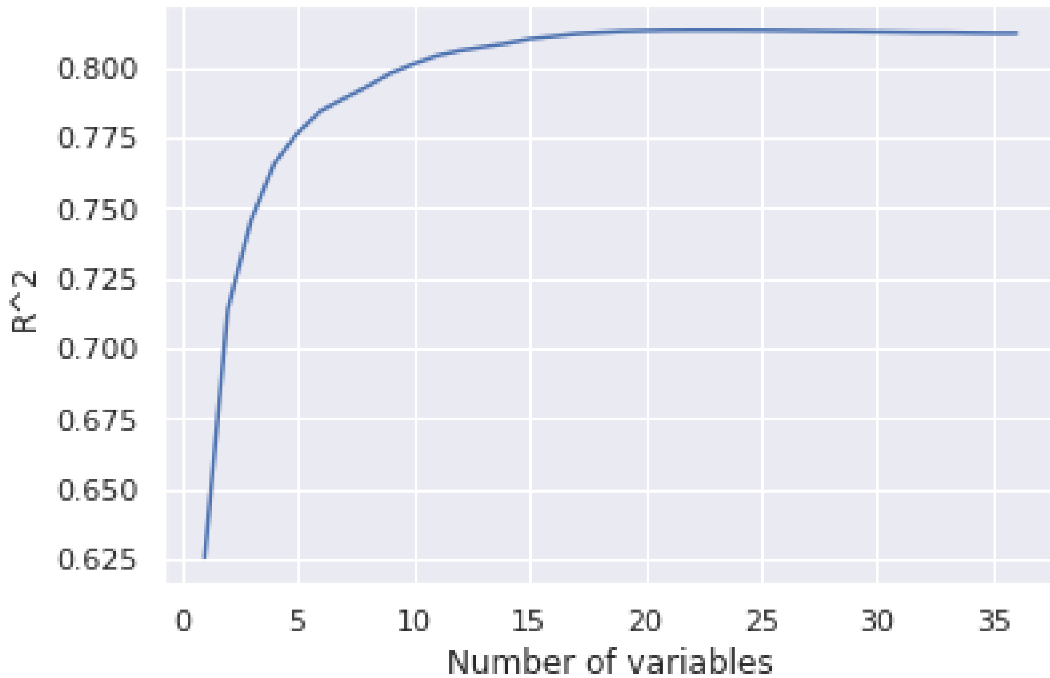
The good thing about forward selection is that it doesn't really matter how the variables correlate with one another. Simply iterating through all of them will eventually land on the "best" model. Since there are 36 variables that I want to keep, there will be 36 "best" models generated, one for each "number of variables". Then, I will plot the R^2 score for each model.

[36]:
```
# forward selection implementation
```

```
# a list of the best smf.ols object created for each model
m_list = []
# k is the number of possible factors
k = len(cols)
# a list of the best r score for each k, using the training set
r_train_list = []
# a list of the best r score for each k, using the test set
r_test_list = []
# a list of the best model for each k
model_list = []
# allowed factors
allowed_factors = cols
# initialize the first model
m_k = smf.ols("SalePrice ~ MSSubClass", data=data_train).fit()
model = "SalePrice ~ "
for i in range(k):
    # loop through the allowed factors
    if (i > 0):
        model_temp = model + allowed_factors[0]
        m_k = smf.ols(model_temp, data=data_train).fit()
    for factor in allowed_factors:
        # create the string representing the model
        model_temp = model + factor
        #print(model_temp)
        # fit the model
        m = smf.ols(model_temp, data=data_train).fit()
        # if the r^2 score of the temporary model is higher than that of the baseline model
        # then update the baseline model to the temporary model
        # also update the best_model variable to reflect the current best model
        # and also record the factor that was chosen
        if (m.rsquared_adj >= m_k.rsquared_adj):
            m_k = m
            best_model_mk = model_temp
            chosen_factor = factor
    model = best_model_mk + " + "
    model_list.append(model)
    m_list.append(m_k)
    allowed_factors.remove(chosen_factor)
    r_train_list.append(m_k.rsquared_adj)

x = range(1, len(r_train_list)+1)
plt.plot(x, r_train_list)
plt.xlabel("Number of variables")
plt.ylabel("R^2")
```

[36]:
```
Text(0, 0.5, 'R^2')
```



The forward selection process is now finished. To find the best model, I simply need to find the index at which the R^2 score was the highest in the r_train_list vector. This can be accomplished using the np.argmax() function. Once this is done, I can use this index and print out the best model selection and also use the model to predict the sale prices from the test dataset.

[63]:
```
max_idx = np.argmax(r_train_list)
best_model = m_list[max_idx]
print(f"The best model is {model_list[max_idx]}")
print(f"This model uses {max_idx+1} variables.")
print(f"This model has an R^2 of {r_train_list[max_idx]}.")
predict_price = best_model.predict(data_test)
print(predict_price)

best_linear_regression_1_model = model_list[max_idx]
```

```
The best model is SalePrice ~ OverallQual + GrLivArea + BsmtFinSF1 + GarageCars
+ MSSubClass + YearBuilt + BedroomAbvGr + OverallCond + GarageYrBlt + LotArea +
MasVnrArea + BsmtFullBath + TotRmsAbvGrd + ScreenPorch + WoodDeckSF +
KitchenAbvGr + TotalBsmtSF + Fireplaces + YearRemodAdd + FullBath + LowQualFinSF
+ PoolArea + YrSold +
This model uses 23 variables.
This model has an R^2 of 0.8131253479855177.
0       116762.584782
1       160461.401492
2       173429.464588
```

```
3        200721.259106
4        195038.498874
             …
1454      75531.691530
1455      61551.235844
1456     178515.338047
1457     116506.028507
1458     258825.504074
Length: 1459, dtype: float64
```

The R^2 for this model is around 0.8, which is not bad! However, this model doesn't account for the interactions between the variables and the NaNs were filled in very naively. In the next section, I will be making improvements for the data clean up process, which I think will help a lot.

1.2 2. Linear Regression 2

The first step to improving the data cleanup process is by filling NaNs with values that actually make sense. To keep things simple, I will fill NaNs with the average* value of each column. If the column is a floating point column, NaNs will be filled with the "true" average, otherwise they will be filled with a rounded version of the avergage.

To start fresh, I will load back in the data sets and drop the "Id" column as before.

[19]:
```
# load in the data sets
data_test = pd.read_csv('test.csv', comment='#')
data_train = pd.read_csv('train.csv', comment='#')
```

[20]:
```
data_train = data_train.drop(["Id"], axis=1)
data_test = data_test.drop(["Id"], axis=1)
print(data_test.info())
print(data_train.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 79 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1459 non-null   int64
 1   MSZoning       1455 non-null   object
 2   LotFrontage    1232 non-null   float64
 3   LotArea        1459 non-null   int64
 4   Street         1459 non-null   object
 5   Alley          107 non-null    object
 6   LotShape       1459 non-null   object
 7   LandContour    1459 non-null   object
 8   Utilities      1457 non-null   object
 9   LotConfig      1459 non-null   object
 10  LandSlope      1459 non-null   object
 11  Neighborhood   1459 non-null   object
```

```
12  Condition1     1459 non-null   object
13  Condition2     1459 non-null   object
14  BldgType       1459 non-null   object
15  HouseStyle     1459 non-null   object
16  OverallQual    1459 non-null   int64
17  OverallCond    1459 non-null   int64
18  YearBuilt      1459 non-null   int64
19  YearRemodAdd   1459 non-null   int64
20  RoofStyle      1459 non-null   object
21  RoofMatl       1459 non-null   object
22  Exterior1st    1458 non-null   object
23  Exterior2nd    1458 non-null   object
24  MasVnrType     1443 non-null   object
25  MasVnrArea     1444 non-null   float64
26  ExterQual      1459 non-null   object
27  ExterCond      1459 non-null   object
28  Foundation     1459 non-null   object
29  BsmtQual       1415 non-null   object
30  BsmtCond       1414 non-null   object
31  BsmtExposure   1415 non-null   object
32  BsmtFinType1   1417 non-null   object
33  BsmtFinSF1     1458 non-null   float64
34  BsmtFinType2   1417 non-null   object
35  BsmtFinSF2     1458 non-null   float64
36  BsmtUnfSF      1458 non-null   float64
37  TotalBsmtSF    1458 non-null   float64
38  Heating        1459 non-null   object
39  HeatingQC      1459 non-null   object
40  CentralAir     1459 non-null   object
41  Electrical     1459 non-null   object
42  1stFlrSF       1459 non-null   int64
43  2ndFlrSF       1459 non-null   int64
44  LowQualFinSF   1459 non-null   int64
45  GrLivArea      1459 non-null   int64
46  BsmtFullBath   1457 non-null   float64
47  BsmtHalfBath   1457 non-null   float64
48  FullBath       1459 non-null   int64
49  HalfBath       1459 non-null   int64
50  BedroomAbvGr   1459 non-null   int64
51  KitchenAbvGr   1459 non-null   int64
52  KitchenQual    1458 non-null   object
53  TotRmsAbvGrd   1459 non-null   int64
54  Functional     1457 non-null   object
55  Fireplaces     1459 non-null   int64
56  FireplaceQu    729 non-null    object
57  GarageType     1383 non-null   object
58  GarageYrBlt    1381 non-null   float64
59  GarageFinish   1381 non-null   object
```

```
 60  GarageCars     1458 non-null   float64
 61  GarageArea     1458 non-null   float64
 62  GarageQual     1381 non-null   object 
 63  GarageCond     1381 non-null   object 
 64  PavedDrive     1459 non-null   object 
 65  WoodDeckSF     1459 non-null   int64  
 66  OpenPorchSF    1459 non-null   int64  
 67  EnclosedPorch  1459 non-null   int64  
 68  3SsnPorch      1459 non-null   int64  
 69  ScreenPorch    1459 non-null   int64  
 70  PoolArea       1459 non-null   int64  
 71  PoolQC         3 non-null      object 
 72  Fence          290 non-null    object 
 73  MiscFeature    51 non-null     object 
 74  MiscVal        1459 non-null   int64  
 75  MoSold         1459 non-null   int64  
 76  YrSold         1459 non-null   int64  
 77  SaleType       1458 non-null   object 
 78  SaleCondition  1459 non-null   object 
dtypes: float64(11), int64(25), object(43)
memory usage: 900.6+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MSSubClass     1460 non-null   int64  
 1   MSZoning       1460 non-null   object 
 2   LotFrontage    1201 non-null   float64
 3   LotArea        1460 non-null   int64  
 4   Street         1460 non-null   object 
 5   Alley          91 non-null     object 
 6   LotShape       1460 non-null   object 
 7   LandContour    1460 non-null   object 
 8   Utilities      1460 non-null   object 
 9   LotConfig      1460 non-null   object 
 10  LandSlope      1460 non-null   object 
 11  Neighborhood   1460 non-null   object 
 12  Condition1     1460 non-null   object 
 13  Condition2     1460 non-null   object 
 14  BldgType       1460 non-null   object 
 15  HouseStyle     1460 non-null   object 
 16  OverallQual    1460 non-null   int64  
 17  OverallCond    1460 non-null   int64  
 18  YearBuilt      1460 non-null   int64  
 19  YearRemodAdd   1460 non-null   int64  
 20  RoofStyle      1460 non-null   object 
```

```
21  RoofMatl       1460 non-null   object
22  Exterior1st    1460 non-null   object
23  Exterior2nd    1460 non-null   object
24  MasVnrType     1452 non-null   object
25  MasVnrArea     1452 non-null   float64
26  ExterQual      1460 non-null   object
27  ExterCond      1460 non-null   object
28  Foundation     1460 non-null   object
29  BsmtQual       1423 non-null   object
30  BsmtCond       1423 non-null   object
31  BsmtExposure   1422 non-null   object
32  BsmtFinType1   1423 non-null   object
33  BsmtFinSF1     1460 non-null   int64
34  BsmtFinType2   1422 non-null   object
35  BsmtFinSF2     1460 non-null   int64
36  BsmtUnfSF      1460 non-null   int64
37  TotalBsmtSF    1460 non-null   int64
38  Heating        1460 non-null   object
39  HeatingQC      1460 non-null   object
40  CentralAir     1460 non-null   object
41  Electrical     1459 non-null   object
42  1stFlrSF       1460 non-null   int64
43  2ndFlrSF       1460 non-null   int64
44  LowQualFinSF   1460 non-null   int64
45  GrLivArea      1460 non-null   int64
46  BsmtFullBath   1460 non-null   int64
47  BsmtHalfBath   1460 non-null   int64
48  FullBath       1460 non-null   int64
49  HalfBath       1460 non-null   int64
50  BedroomAbvGr   1460 non-null   int64
51  KitchenAbvGr   1460 non-null   int64
52  KitchenQual    1460 non-null   object
53  TotRmsAbvGrd   1460 non-null   int64
54  Functional     1460 non-null   object
55  Fireplaces     1460 non-null   int64
56  FireplaceQu    770 non-null    object
57  GarageType     1379 non-null   object
58  GarageYrBlt    1379 non-null   float64
59  GarageFinish   1379 non-null   object
60  GarageCars     1460 non-null   int64
61  GarageArea     1460 non-null   int64
62  GarageQual     1379 non-null   object
63  GarageCond     1379 non-null   object
64  PavedDrive     1460 non-null   object
65  WoodDeckSF     1460 non-null   int64
66  OpenPorchSF    1460 non-null   int64
67  EnclosedPorch  1460 non-null   int64
68  3SsnPorch      1460 non-null   int64
```

```
 69  ScreenPorch    1460 non-null   int64
 70  PoolArea       1460 non-null   int64
 71  PoolQC         7 non-null      object
 72  Fence          281 non-null    object
 73  MiscFeature    54 non-null     object
 74  MiscVal        1460 non-null   int64
 75  MoSold         1460 non-null   int64
 76  YrSold         1460 non-null   int64
 77  SaleType       1460 non-null   object
 78  SaleCondition  1460 non-null   object
 79  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(43)
memory usage: 912.6+ KB
None
```

[21]:

```
# fill NaNs for non-object variables only.

for col in data_train.columns:
    if (data_train[col].dtypes != "object"):
        avg = data_train[col].mean()
        data_train[col] = data_train[col].fillna(avg)

for col in data_test.columns:
    if (data_test[col].dtypes != "object"):
        avg = data_test[col].mean()
        data_test[col] = data_test[col].fillna(avg)
```

[22]:

```
print(data_train.info())
print(data_test.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1460 non-null   int64
 1   MSZoning       1460 non-null   object
 2   LotFrontage    1460 non-null   float64
 3   LotArea        1460 non-null   int64
 4   Street         1460 non-null   object
 5   Alley          91 non-null     object
 6   LotShape       1460 non-null   object
 7   LandContour    1460 non-null   object
 8   Utilities      1460 non-null   object
 9   LotConfig      1460 non-null   object
 10  LandSlope      1460 non-null   object
 11  Neighborhood   1460 non-null   object
 12  Condition1     1460 non-null   object
```

13	Condition2	1460 non-null	object
14	BldgType	1460 non-null	object
15	HouseStyle	1460 non-null	object
16	OverallQual	1460 non-null	int64
17	OverallCond	1460 non-null	int64
18	YearBuilt	1460 non-null	int64
19	YearRemodAdd	1460 non-null	int64
20	RoofStyle	1460 non-null	object
21	RoofMatl	1460 non-null	object
22	Exterior1st	1460 non-null	object
23	Exterior2nd	1460 non-null	object
24	MasVnrType	1452 non-null	object
25	MasVnrArea	1460 non-null	float64
26	ExterQual	1460 non-null	object
27	ExterCond	1460 non-null	object
28	Foundation	1460 non-null	object
29	BsmtQual	1423 non-null	object
30	BsmtCond	1423 non-null	object
31	BsmtExposure	1422 non-null	object
32	BsmtFinType1	1423 non-null	object
33	BsmtFinSF1	1460 non-null	int64
34	BsmtFinType2	1422 non-null	object
35	BsmtFinSF2	1460 non-null	int64
36	BsmtUnfSF	1460 non-null	int64
37	TotalBsmtSF	1460 non-null	int64
38	Heating	1460 non-null	object
39	HeatingQC	1460 non-null	object
40	CentralAir	1460 non-null	object
41	Electrical	1459 non-null	object
42	1stFlrSF	1460 non-null	int64
43	2ndFlrSF	1460 non-null	int64
44	LowQualFinSF	1460 non-null	int64
45	GrLivArea	1460 non-null	int64
46	BsmtFullBath	1460 non-null	int64
47	BsmtHalfBath	1460 non-null	int64
48	FullBath	1460 non-null	int64
49	HalfBath	1460 non-null	int64
50	BedroomAbvGr	1460 non-null	int64
51	KitchenAbvGr	1460 non-null	int64
52	KitchenQual	1460 non-null	object
53	TotRmsAbvGrd	1460 non-null	int64
54	Functional	1460 non-null	object
55	Fireplaces	1460 non-null	int64
56	FireplaceQu	770 non-null	object
57	GarageType	1379 non-null	object
58	GarageYrBlt	1460 non-null	float64
59	GarageFinish	1379 non-null	object
60	GarageCars	1460 non-null	int64

```
 61  GarageArea     1460 non-null   int64
 62  GarageQual     1379 non-null   object
 63  GarageCond     1379 non-null   object
 64  PavedDrive     1460 non-null   object
 65  WoodDeckSF     1460 non-null   int64
 66  OpenPorchSF    1460 non-null   int64
 67  EnclosedPorch  1460 non-null   int64
 68  3SsnPorch      1460 non-null   int64
 69  ScreenPorch    1460 non-null   int64
 70  PoolArea       1460 non-null   int64
 71  PoolQC         7 non-null      object
 72  Fence          281 non-null    object
 73  MiscFeature    54 non-null     object
 74  MiscVal        1460 non-null   int64
 75  MoSold         1460 non-null   int64
 76  YrSold         1460 non-null   int64
 77  SaleType       1460 non-null   object
 78  SaleCondition  1460 non-null   object
 79  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(43)
memory usage: 912.6+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 79 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1459 non-null   int64
 1   MSZoning       1455 non-null   object
 2   LotFrontage    1459 non-null   float64
 3   LotArea        1459 non-null   int64
 4   Street         1459 non-null   object
 5   Alley          107 non-null    object
 6   LotShape       1459 non-null   object
 7   LandContour    1459 non-null   object
 8   Utilities      1457 non-null   object
 9   LotConfig      1459 non-null   object
 10  LandSlope      1459 non-null   object
 11  Neighborhood   1459 non-null   object
 12  Condition1     1459 non-null   object
 13  Condition2     1459 non-null   object
 14  BldgType       1459 non-null   object
 15  HouseStyle     1459 non-null   object
 16  OverallQual    1459 non-null   int64
 17  OverallCond    1459 non-null   int64
 18  YearBuilt      1459 non-null   int64
 19  YearRemodAdd   1459 non-null   int64
 20  RoofStyle      1459 non-null   object
```

```
21  RoofMatl       1459 non-null   object
22  Exterior1st    1458 non-null   object
23  Exterior2nd    1458 non-null   object
24  MasVnrType     1443 non-null   object
25  MasVnrArea     1459 non-null   float64
26  ExterQual      1459 non-null   object
27  ExterCond      1459 non-null   object
28  Foundation     1459 non-null   object
29  BsmtQual       1415 non-null   object
30  BsmtCond       1414 non-null   object
31  BsmtExposure   1415 non-null   object
32  BsmtFinType1   1417 non-null   object
33  BsmtFinSF1     1459 non-null   float64
34  BsmtFinType2   1417 non-null   object
35  BsmtFinSF2     1459 non-null   float64
36  BsmtUnfSF      1459 non-null   float64
37  TotalBsmtSF    1459 non-null   float64
38  Heating        1459 non-null   object
39  HeatingQC      1459 non-null   object
40  CentralAir     1459 non-null   object
41  Electrical     1459 non-null   object
42  1stFlrSF       1459 non-null   int64
43  2ndFlrSF       1459 non-null   int64
44  LowQualFinSF   1459 non-null   int64
45  GrLivArea      1459 non-null   int64
46  BsmtFullBath   1459 non-null   float64
47  BsmtHalfBath   1459 non-null   float64
48  FullBath       1459 non-null   int64
49  HalfBath       1459 non-null   int64
50  BedroomAbvGr   1459 non-null   int64
51  KitchenAbvGr   1459 non-null   int64
52  KitchenQual    1458 non-null   object
53  TotRmsAbvGrd   1459 non-null   int64
54  Functional     1457 non-null   object
55  Fireplaces     1459 non-null   int64
56  FireplaceQu    729 non-null    object
57  GarageType     1383 non-null   object
58  GarageYrBlt    1459 non-null   float64
59  GarageFinish   1381 non-null   object
60  GarageCars     1459 non-null   float64
61  GarageArea     1459 non-null   float64
62  GarageQual     1381 non-null   object
63  GarageCond     1381 non-null   object
64  PavedDrive     1459 non-null   object
65  WoodDeckSF     1459 non-null   int64
66  OpenPorchSF    1459 non-null   int64
67  EnclosedPorch  1459 non-null   int64
68  3SsnPorch      1459 non-null   int64
```

```
 69  ScreenPorch    1459 non-null   int64
 70  PoolArea       1459 non-null   int64
 71  PoolQC         3 non-null      object
 72  Fence          290 non-null    object
 73  MiscFeature    51 non-null     object
 74  MiscVal        1459 non-null   int64
 75  MoSold         1459 non-null   int64
 76  YrSold         1459 non-null   int64
 77  SaleType       1458 non-null   object
 78  SaleCondition  1459 non-null   object
dtypes: float64(11), int64(25), object(43)
memory usage: 900.6+ KB
None
```

Now that the cleanup part is over, I will create a pairplot of the data and look for any relationships between the variables. In order to do this, I will first reduce the data set by dropping the categorical variables again.

[23]:

```
# Renaming some columns too
data_train.rename(columns={'1stFlrSF':'FirstFlrSF'}, inplace=True)
data_train.rename(columns={'2ndFlrSF':'SecondFlrSF'}, inplace=True)
data_train.rename(columns={'3SsnPorch':'ThreeSsnPorch'}, inplace=True)

data_test.rename(columns={'1stFlrSF':'FirstFlrSF'}, inplace=True)
data_test.rename(columns={'2ndFlrSF':'SecondFlrSF'}, inplace=True)
data_test.rename(columns={'3SsnPorch':'ThreeSsnPorch'}, inplace=True)
```

[53]:

```
# get the list of columns
# this is the list of potential variables
cols = list(data_train.columns)
# drop "SalePrice" from this list because it's the variable we're trying to␣
 ↪predict
cols.remove("SalePrice")

print(cols)
print(len(cols))

to_remove = []
for var in cols:
    if data_train[var].dtypes == "object":
        to_remove.append(var)

for elem in to_remove:
    cols.remove(elem)

print(cols)
print(len(cols))
```

```
['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'Alley',
'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure',
'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF',
'TotalBsmtSF', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'FirstFlrSF',
'SecondFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch',
'ThreeSsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature',
'MiscVal', 'MoSold', 'YrSold', 'SaleType', 'SaleCondition']
79
['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
'BsmtUnfSF', 'TotalBsmtSF', 'FirstFlrSF', 'SecondFlrSF', 'LowQualFinSF',
'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces', 'GarageYrBlt',
'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch',
'ThreeSsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal', 'MoSold', 'YrSold']
36
```

Now that I have a list of allowed variables, I will reduce the size of the DataFrame to only include the allowed variables.

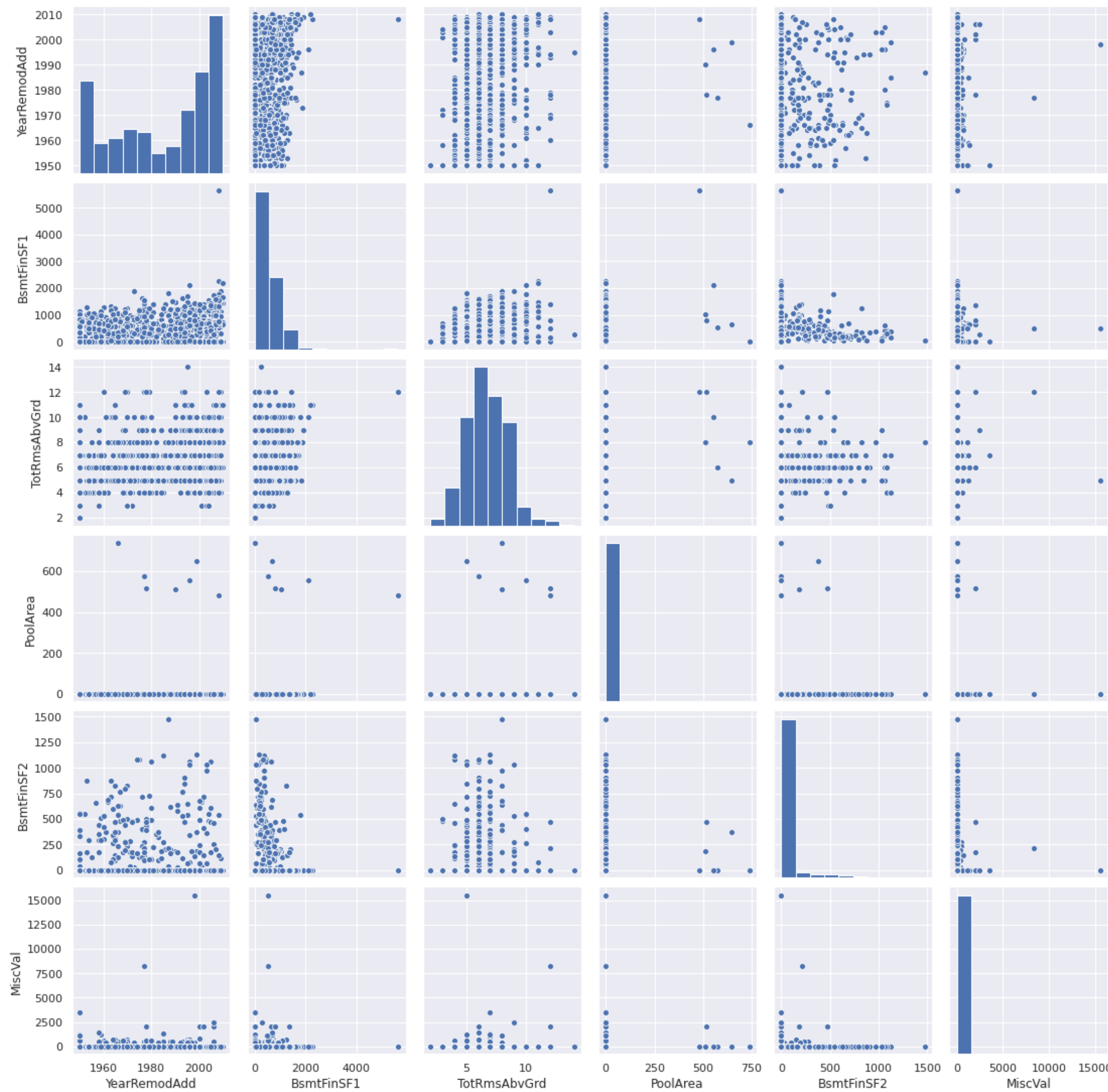
[25]:
```
data_test = data_test[cols]
cols.append("SalePrice")
data_train = data_train[cols]
```

[26]:
```
# drop SalePrice from the list again
cols.remove("SalePrice")
```

There are 36 variables. A pairplot would need to create 36^2 = 1296 plots. It would take a very long time to finish. So instead of doing that, I'll create 36 pairplots, each with 6 randomly chosen variables. That shouldn't take as long. I couldn't figure out how to create multiple different pairplots so I'll just create 1.

[27]:
```
# 1
random_vars = np.random.choice(cols, 6)
small_set = data_train[random_vars]
sns.pairplot(small_set)
```

[27]:
```
<seaborn.axisgrid.PairGrid at 0x7fb4c8046610>
```



There doesn't realy seem to be any correlations between the 6 randomly chosen variables, but the way the plots look make me feel like a logistic regression might give really good results. So, I'll explore that in the next section. For now, I will keep going forward with linear regression. The code is the same as in Section 1. A plot of the R^2 score is included and the model is also included.

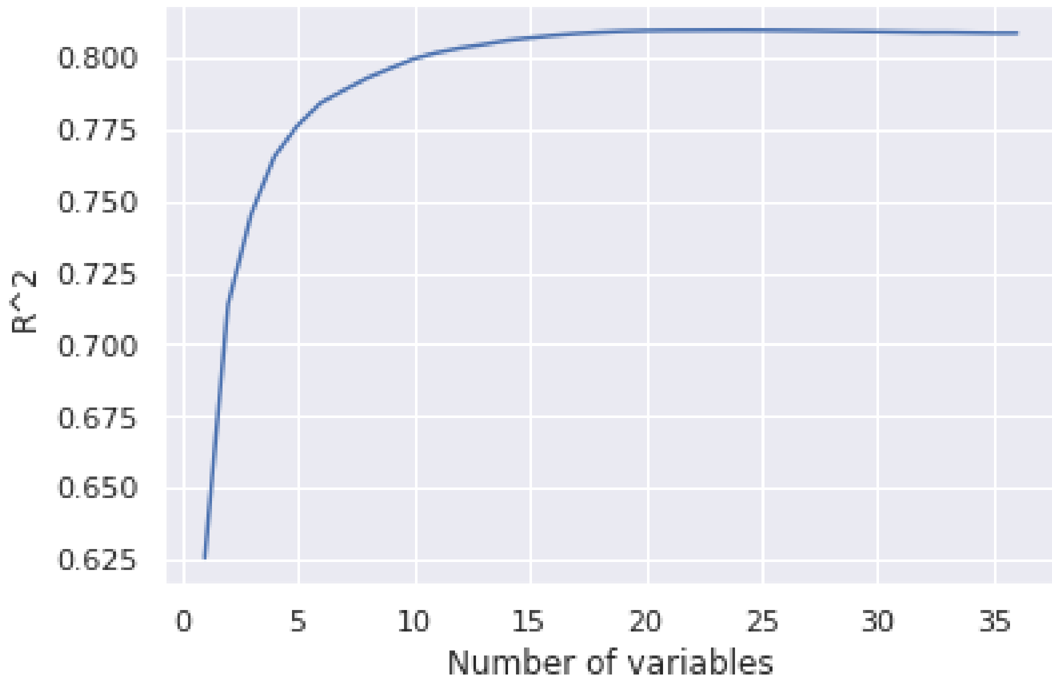
[28]:
```
# forward selection implementation

# a list of the best smf.ols object created for each model
m_list = []
# k is the number of possible factors
k = len(cols)
# a list of the best r score for each k, using the training set
r_train_list = []
# a list of the best r score for each k, using the test set
```

```
r_test_list = []
# a list of the best model for each k
model_list = []
# allowed factors
allowed_factors = cols
# initialize the first model
m_k = smf.ols("SalePrice ~ MSSubClass", data=data_train).fit()
model = "SalePrice ~ "
for i in range(k):
    # loop through the allowed factors
    if (i > 0):
        model_temp = model + allowed_factors[0]
        m_k = smf.ols(model_temp, data=data_train).fit()
    for factor in allowed_factors:
        # create the string representing the model
        model_temp = model + factor
        #print(model_temp)
        # fit the model
        m = smf.ols(model_temp, data=data_train).fit()
        # if the r^2 score of the temporary model is higher than that of the␣
 ↪baseline model
        # then update the baseline model to the temporary model
        # also update the best_model variable to reflect the current best model
        # and also record the factor that was chosen
        if (m.rsquared_adj >= m_k.rsquared_adj):
            m_k = m
            best_model_mk = model_temp
            chosen_factor = factor
    model = best_model_mk + " + "
    model_list.append(model)
    m_list.append(m_k)
    allowed_factors.remove(chosen_factor)
    r_train_list.append(m_k.rsquared_adj)

x = range(1, len(r_train_list)+1)
plt.plot(x, r_train_list)
plt.xlabel("Number of variables")
plt.ylabel("R^2")
```

[28]:
```
Text(0, 0.5, 'R^2')
```



[29]:
```
max_idx = np.argmax(r_train_list)
best_model = m_list[max_idx]
print(f"The best model is {model_list[max_idx]}")
print(f"This model uses {max_idx+1} variables.")
print(f"This model has an R^2 of {r_train_list[max_idx]}.")


predict_price = best_model.predict(data_test)
print(predict_price)
```

```
The best model is SalePrice ~ OverallQual + GrLivArea + BsmtFinSF1 + GarageCars
+ MSSubClass + YearBuilt + BedroomAbvGr + OverallCond + LotArea + MasVnrArea +
BsmtFullBath + TotRmsAbvGrd + WoodDeckSF + ScreenPorch + TotalBsmtSF +
YearRemodAdd + KitchenAbvGr + Fireplaces + FullBath + GarageYrBlt + PoolArea +
YrSold + LowQualFinSF + LotFrontage +
This model uses 24 variables.
This model has an R^2 of 0.8097002534319625.
0       118504.813973
1       163042.668599
2       173608.497914
3       200027.557758
4       195343.381853
            …
1454     58924.834755
1455     66808.129661
```

```
1456    171623.264178
1457     98969.768138
1458    253322.571866
Length: 1459, dtype: float64
```

Well the results are surprising! Using the average value results in a worse best R^2 score and more variables had to be used. So, moving on to the next section, perhaps using a logistic regression might yield better results.

1.3 3. Logistic Regression

In this section, instead of using forward selection to pick my model, I will use all 36 variables. I will also clean and format the data the same way as in Section 1.

[81]:
```
# load in the data sets
data_test = pd.read_csv('test.csv', comment='#')
data_train = pd.read_csv('train.csv', comment='#')
data_train = data_train.drop(["Id"], axis=1)
data_test = data_test.drop(["Id"], axis=1)
data_train = data_train.fillna(0.0)
data_test = data_test.fillna(0.0)
data_train.rename(columns={'1stFlrSF':'FirstFlrSF'}, inplace=True)
data_train.rename(columns={'2ndFlrSF':'SecondFlrSF'}, inplace=True)
data_train.rename(columns={'3SsnPorch':'ThreeSsnPorch'}, inplace=True)
data_test.rename(columns={'1stFlrSF':'FirstFlrSF'}, inplace=True)
data_test.rename(columns={'2ndFlrSF':'SecondFlrSF'}, inplace=True)
data_test.rename(columns={'3SsnPorch':'ThreeSsnPorch'}, inplace=True)
```

Let's get rid of all the "object" columns.

[82]:
```
cols.append("SalePrice")
data_train_new = data_train[cols]
cols.remove("SalePrice")
data_test_new = data_test[cols]
```

[85]:
```
model = "SalePrice ~ "
for i in range(len(cols)):
    if (i != (len(cols)-1)):
        model += cols[i] + " + "
    else:
        model += cols[i]
print(model)
lr = sklearn.linear_model.LogisticRegression()
y,X = patsy.dmatrices(model, data=data_train_new)
log_reg_model_full = lr.fit(X, y.ravel())
print('Score is', log_reg_model_full.score(X, y.ravel()))
```

```
SalePrice ~ MSSubClass + LotFrontage + LotArea + OverallQual + OverallCond +
YearBuilt + YearRemodAdd + MasVnrArea + BsmtFinSF1 + BsmtFinSF2 + BsmtUnfSF +
```

```
TotalBsmtSF + FirstFlrSF + SecondFlrSF + LowQualFinSF + GrLivArea + BsmtFullBath
+ BsmtHalfBath + FullBath + HalfBath + BedroomAbvGr + KitchenAbvGr +
TotRmsAbvGrd + Fireplaces + GarageYrBlt + GarageCars + GarageArea + WoodDeckSF +
OpenPorchSF + EnclosedPorch + ThreeSsnPorch + ScreenPorch + PoolArea + MiscVal +
MoSold + YrSold
Score is 0.05342465753424658
```

```
/opt/conda/lib/python3.8/site-packages/sklearn/linear_model/_logistic.py:762:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

Wow…The result is very disappointing here. It seems like logistic regression is the wrong way to go here! Or perhaps my code is wrong somehow.

1.4 4. Results Discussion

2 a. Linear Regression

It definitely seems that linear regression was the way to go for this project. The initial "naive" way of cleaning up the data and using forward selection to algorithmically select variables proved to be the best way to predict the housing prices. The best R^2 score was around 0.831. When trying to improve the data clean up process by filling in NaNs with the average value of each column, the R^2 score went down. This was a very surprising result since I thought that having more realistic values would improve prediction results.

3 b. Logistic Regression

The result here was extremely disappointing, to say the least. Some of the variables looked like they could do very well with a logistic regression model. However, the end result was a score of 0.0534. That indicates extremely poor fit. To recap, here are the best prediction scores for: Linear Regression with 0's for NaNs : 0.831 Linear Regression with average for NaNs: 0.8097 Logistic Regression with all variables: 0.0534

3.1 5. Conclusion

To recap, linear regression using forward regression and filling NaNs with 0's was the best method for obtaining a decent prediction model. The best model used 23 out of 36 numerical variables. However, there are 79 variables in total that could have been used. I think a few of the categorical variables could be used to improve prediction results. For example, whether or not a house has a garage should definitely influence the price of a house. Furthermore, there should be some interactions between whether or not there is a garage and the size of the garage. A larger garage should mean a higher sale price! In order to turn these categorical variables into numerical variables, numerical values must be assigned to them. The variable that describes whether or not there is a garage could be represented by a boolean. I didn't do this because the description of said variable included more than 2 choices. There are other categorical variables that are the same way, i.e. they have more than 2 values. To fully clean up and prepare the data, a full understanding of the data set, which includes understanding the values that each variable represents and assigning numerical values as appropriate. It would be great to be able to see a full pairplot of all 79 variables. The interactions between variables would be fully shown then. I'm not sure how the logistic regression model could be improved. Perhaps logistic regression is out of the question for this data set.

[ ]:

```

```