Creation of Model Statistics DataFrame

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This Jupyter Notebook is exclusively for creating a DataFrame, and an excel file, that includes basic model data of multiple possible combinations of variables put into a model using ordinary least squares through the ModelStatistics Python library. It should be treated as a giant function rather than a presentation of the logic behind this. For that, please see the student Jupyter notebook.

In [1]:
```
import pandas as pd
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import numpy as np
import scipy.stats as stats
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import PolynomialFeatures
#from itertools import combinations
#from itertools import combinations_with_replacement
from itertools import product
from itertools import permutations

plt.style.use('seaborn')
data = pd.read_csv('data/kc_house_data.csv')
pd.set_option("display.max_columns", None)
```

This next cell scrubs the data the same way described in the Student Jupyter Notebook.

In [2]:
```
#Dropping columns advised by client.
columns_to_drop = ['date', 'view', 'sqft_above', 'sqft_basement',
                   'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15',
                   'sqft_lot15']
data = data.drop(columns_to_drop,axis='columns')

#Fixing Waterfront data
data.loc[data['waterfront'].isna(),'waterfront'] = 'NO'
data['waterfront'].replace({'NO':0,'YES':1},inplace=True)

#Fixing Condition data
change_numerical_condition = {'Poor' : 1, 'Fair' : 2, 'Average' : 3,
                              'Good' : 4, 'Very Good' : 5}
data['condition'].replace(change_numerical_condition, inplace=True)

#Fixing Grade data
change_numerical_grade = {'3 Poor' : 3, '4 Low' : 4, '5 Fair' : 5,
                          '6 Low Average' : 6, '7 Average' : 7, '8 Good' : 8,
                          '9 Better' : 9, '10 Very Good' : 10,
                          '11 Excellent' : 11, '12 Luxury' : 12,
                          '13 Mansion' : 13}

data['grade'].replace(change_numerical_grade, inplace=True)
```

```
#Dropping id column
model_data = data.drop(columns='id')

index_nums = model_data.reset_index()

#Dropping a single outlier due to bad bedroom data.
bedrooms_max = 12
bed_drop = index_nums['bedrooms'][index_nums['bedrooms']>=bedrooms_max]
model_data = index_nums.drop(index=bed_drop.index,columns='index')
```

These next cells create the functions to create the transformations needed for this analysis.

In [3]:
```
#This logs all the independent variables in the data.
def log_data(df, var,keep=False):
    order = df.columns
    df_log = pd.DataFrame()
    new_col = []
    for i in range(len(order)):
        if order[i] not in var:
            df_log[order[i]] = df[order[i]]
        else:
            new_col.append(order[i] + '_log')
            df_log[order[i] + '_log'] = df[order[i]].map(lambda x : np.log(x))
    if keep == True:
        df_new = df.copy()
        for col in new_col:
            df_new[new_col] = df_log[new_col]
        return df_new
    return df_log
```

In [4]:
```
#This performs a min-max scaling of all independent variables in the data.
def scale_data(df,var,keep=False):
    order = df.columns
    df_scale = pd.DataFrame()
    new_col = []
    for i in range(len(order)):
        if order[i] not in var:
            df_scale[order[i]] = df[order[i]]
        else:
            mn = df[order[i]].min()
            mx = df[order[i]].max()
            new_col.append(order[i] + '_scale')
            df_scale[order[i] + '_scale'] = df[
                order[i]].map(lambda x : (x-mn)/(mx-mn))
    if keep == True:
        df_new = df.copy()
        for col in new_col:
            df_new[new_col] = df_scale[new_col]
        return df_new
    return df_scale
```

In [5]:
```
#This squares all the independent variables in the data.
def sq_data(df, var,keep=False):
    order = df.columns
    df_pow2 = pd.DataFrame()
    new_col = []
    for i in range(len(order)):
        if order[i] not in var:
            df_pow2[order[i]] = df[order[i]]
        else:
```

```
            new_col.append(order[i] + '_sq')
            df_pow2[order[i] + '_sq'] = df[order[i]].map(lambda x : x**2)
    if keep == True:
        df_new = df.copy()
        for col in new_col:
            df_new[new_col] = df_pow2[new_col]
        return df_new
    return df_pow2
```

In [6]:

```
#This returns five DataFrames, one for untransformed data and one for each
#transformation this model analyzes.
def tran_data(df,var):
    if 'waterfront' in var:
        var.remove('waterfront')
    df_scale = scale_data(df, var)
    df_log = log_data(df, var)
    df_log_scale = scale_data(df_log,
                list(df_log.drop(columns=['price','waterfront']).columns))
    df_sq = sq_data(df,var)
    return [df, df_scale, df_log, df_log_scale, df_sq]
```

Since the testing for the multicollinearity is critical to the function definitons below, I will leave this test here.

In [7]:

```
#This creates the initial DataFrame to be added to later.
multicollinearity_test_data = model_data.copy()

#This returns five DataFrames, one for untransformed data and one for each
#transformation this model analyzes.
dfr,dfs,dfl,dfls,dfsq = tran_data(
    model_data,list(model_data.iloc[0:1,1:].columns))

#Getting rid of values I don't want repeated.
dfs = dfs.drop(columns=['price','waterfront'])
dfl = dfl.drop(columns=['price','waterfront'])
dfls = dfls.drop(columns=['price','waterfront'])
dfsq = dfsq.drop(columns=['price','waterfront'])

#Constructiong a large DataFrame with all raw and transformed values.
multicollinearity_test_data = pd.concat([dfr,dfs,dfl,dfls,dfsq],axis=1)
del dfr,dfs,dfl,dfls,dfsq

#Running the multicollinearity test and displaying the results.
multicollinearity_test = multicollinearity_test_data.corr()
for c in multicollinearity_test.columns:
    multicollinearity_test[c] = multicollinearity_test[c].map('{:.3f}'.format)
multicollinearity_test
```

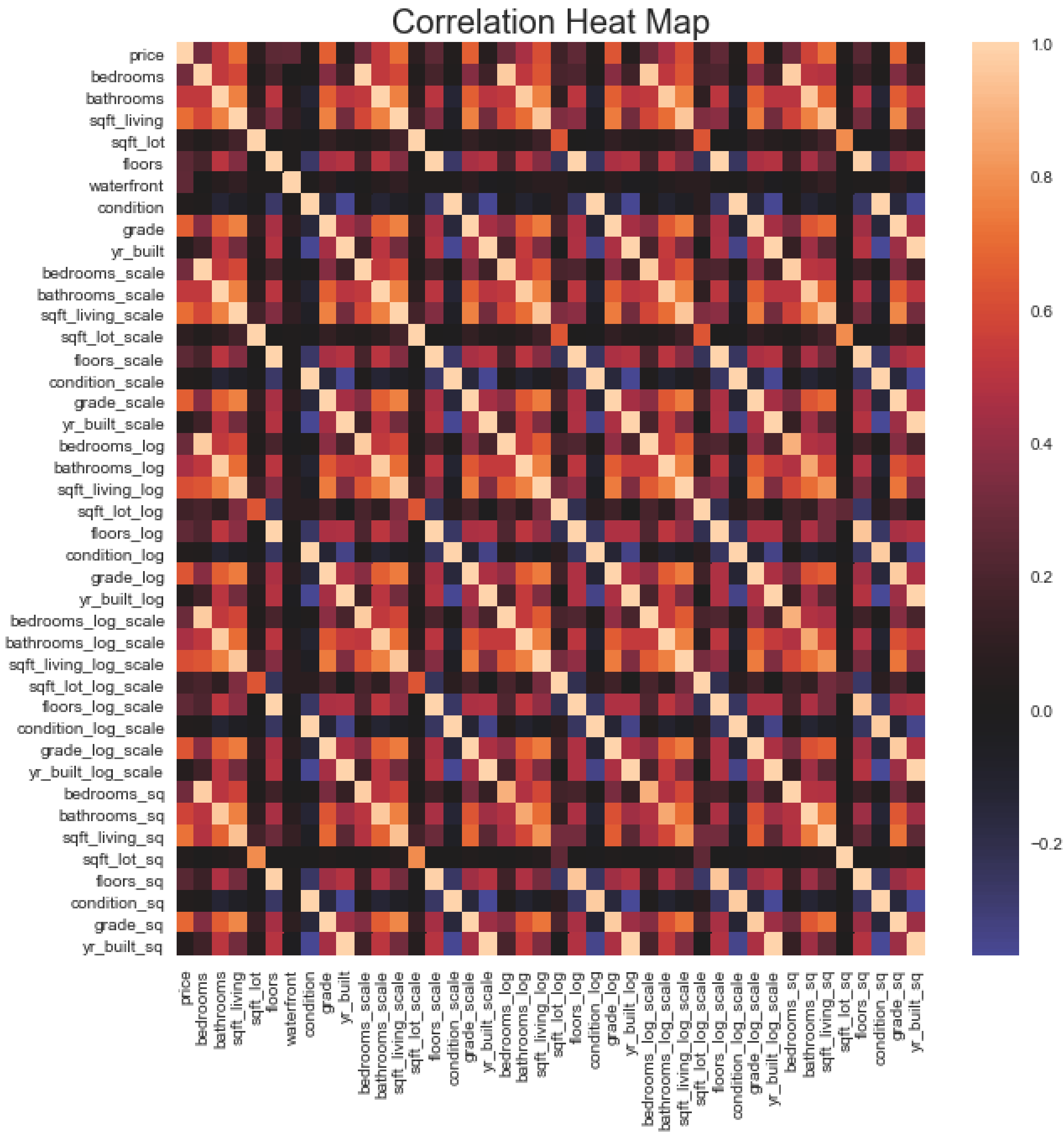
Out[7]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr_bui
price	1.000	0.316	0.526	0.702	0.090	0.257	0.264	0.036	0.668	0.05
bedrooms	0.316	1.000	0.528	0.593	0.034	0.184	-0.002	0.023	0.366	0.16
bathrooms	0.526	0.528	1.000	0.756	0.088	0.503	0.064	-0.126	0.666	0.50
sqft_living	0.702	0.593	0.756	1.000	0.173	0.354	0.105	-0.059	0.763	0.3
sqft_lot	0.090	0.034	0.088	0.173	1.000	-0.005	0.021	-0.009	0.115	0.05
floors	0.257	0.184	0.503	0.354	-0.005	1.000	0.021	-0.264	0.459	0.48
waterfront	0.264	-0.002	0.064	0.105	0.021	0.021	1.000	0.017	0.083	-0.02

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr_bui
condition	0.036	0.023	-0.126	-0.059	-0.009	-0.264	0.017	1.000	-0.147	-0.36
grade	0.668	0.366	0.666	0.763	0.115	0.459	0.083	-0.147	1.000	0.44
yr_built	0.054	0.161	0.507	0.318	0.053	0.489	-0.024	-0.362	0.448	1.00
bedrooms_scale	0.316	1.000	0.528	0.593	0.034	0.184	-0.002	0.023	0.366	0.16
bathrooms_scale	0.526	0.528	1.000	0.756	0.088	0.503	0.064	-0.126	0.666	0.50
sqft_living_scale	0.702	0.593	0.756	1.000	0.173	0.354	0.105	-0.059	0.763	0.31
sqft_lot_scale	0.090	0.034	0.088	0.173	1.000	-0.005	0.021	-0.009	0.115	0.05
floors_scale	0.257	0.184	0.503	0.354	-0.005	1.000	0.021	-0.264	0.459	0.48
condition_scale	0.036	0.023	-0.126	-0.059	-0.009	-0.264	0.017	1.000	-0.147	-0.36
grade_scale	0.668	0.366	0.666	0.763	0.115	0.459	0.083	-0.147	1.000	0.44
yr_built_scale	0.054	0.161	0.507	0.318	0.053	0.489	-0.024	-0.362	0.448	1.00
bedrooms_log	0.299	0.972	0.525	0.581	0.033	0.192	-0.008	0.026	0.381	0.19
bathrooms_log	0.456	0.521	0.971	0.708	0.075	0.501	0.047	-0.113	0.644	0.53
sqft_living_log	0.612	0.638	0.762	0.955	0.150	0.368	0.079	-0.050	0.743	0.35
sqft_lot_log	0.162	0.190	0.101	0.345	0.639	-0.237	0.072	0.074	0.184	-0.00
floors_log	0.267	0.206	0.513	0.377	0.001	0.991	0.021	-0.261	0.468	0.47
condition_log	0.037	0.028	-0.118	-0.052	-0.011	-0.255	0.015	0.989	-0.133	-0.34
grade_log	0.635	0.374	0.665	0.743	0.104	0.463	0.073	-0.145	0.993	0.46
yr_built_log	0.053	0.161	0.506	0.317	0.053	0.485	-0.024	-0.360	0.447	1.00
bedrooms_log_scale	0.299	0.972	0.525	0.581	0.033	0.192	-0.008	0.026	0.381	0.19
bathrooms_log_scale	0.456	0.521	0.971	0.708	0.075	0.501	0.047	-0.113	0.644	0.53
sqft_living_log_scale	0.612	0.638	0.762	0.955	0.150	0.368	0.079	-0.050	0.743	0.35
sqft_lot_log_scale	0.162	0.190	0.101	0.345	0.639	-0.237	0.072	0.074	0.184	-0.00
floors_log_scale	0.267	0.206	0.513	0.377	0.001	0.991	0.021	-0.261	0.468	0.47
condition_log_scale	0.037	0.028	-0.118	-0.052	-0.011	-0.255	0.015	0.989	-0.133	-0.34
grade_log_scale	0.635	0.374	0.665	0.743	0.104	0.463	0.073	-0.145	0.993	0.46
yr_built_log_scale	0.053	0.161	0.506	0.317	0.053	0.485	-0.024	-0.360	0.447	1.00
bedrooms_sq	0.310	0.974	0.499	0.565	0.031	0.165	0.003	0.021	0.327	0.11
bathrooms_sq	0.573	0.500	0.961	0.757	0.099	0.456	0.078	-0.124	0.639	0.43
sqft_living_sq	0.727	0.487	0.674	0.936	0.178	0.299	0.123	-0.058	0.692	0.25
sqft_lot_sq	0.035	0.003	0.031	0.054	0.788	0.009	0.002	-0.004	0.034	0.01
floors_sq	0.237	0.150	0.472	0.311	-0.013	0.985	0.020	-0.258	0.431	0.48
condition_sq	0.037	0.021	-0.126	-0.061	-0.008	-0.262	0.018	0.995	-0.151	-0.36
grade_sq	0.693	0.354	0.657	0.772	0.123	0.445	0.091	-0.145	0.994	0.42
yr_built_sq	0.055	0.161	0.509	0.319	0.052	0.493	-0.025	-0.363	0.449	1.00

In [8]:

```
import seaborn as sns
plt.figure(figsize = (10,10))
heat = sns.heatmap(multicollinearity_test_data.corr(), center=0)
heat.set_title('Correlation Heat Map',size=20);
```



These functions provide the means to create the excel file with the model statistics needed.

In [9]:

```
#This function creates a model from a Pandas DataFrame and a list of variables
#to include. Price will always be the dependent variable.
def make_model(mod, lst):
    outcome = 'price'
    predictors = mod[lst]
    pred_sum = '+'.join(predictors.columns)
    formula = outcome + '~' + pred_sum
    return ols(formula=formula, data=mod).fit()
```

In [10]:

```
#This reformats the variable names into a more aesthetic format.
```

```python
def new_name(var):
    rename_var = {'bedrooms' : 'Bed', 'bathrooms' : 'Bath',
        'sqft_living': 'SF Liv', 'grade' : 'Grade',
        'sqft_lot' : 'SF Lot','floors': 'Floors',
        'waterfront': 'WF' ,'condition': 'Cond',
        'yr_built' : 'Yr',
        'bedrooms_log' : 'Log(Bed)', 'bathrooms_log' : 'Log(Bath)',
        'sqft_living_log': 'Log(SF Liv)', 'grade_log' : 'Log(Grade)',
        'sqft_lot_log' : 'Log(SF Lot)','floors_log': 'Log(Floors)',
        'waterfront_log': 'Log(WF)' ,'condition_log': 'Log(Cond)',
        'yr_built_log' : 'Log(Yr)',
        'bedrooms_scale' : 'Norm Bed','bathrooms_scale':'Norm Bath',
        'sqft_living_scale':'Norm SF Liv','grade_scale':'Norm Grade',
        'sqft_lot_scale':'Norm SF Lot','floors_scale':'Norm Floors',
        'waterfront_scale': 'Norm WF' ,'condition_scale':'Norm Cond',
        'yr_built_scale' : 'Norm Yr',
        'bedrooms_log_scale':'Norm Log(Bed)',
        'bathrooms_log_scale':'Norm Log(Bath)',
        'sqft_living_log_scale':'Norm Log(SF Liv)',
        'grade_log_scale':'Norm Log(Grade)',
        'sqft_lot_log_scale':'Norm Log(SF Lot)',
        'floors_log_scale':'Norm Log(Floors)',
        'waterfront_log_scale': 'Norm Log(WF)' ,
        'condition_log_scale':'Norm Log(Cond)',
        'yr_built_log_scale' : 'Norm Log(Yr)',
        'bedrooms_sq' : 'Bed²', 'bathrooms_sq' : 'Bath²',
        'sqft_living_sq': 'SF Liv²', 'grade_sq' : 'Grade²',
        'sqft_lot_sq' : 'SF Lot²','floors_sq': 'Floors²',
        'waterfront_sq': 'WF²' ,'condition_sq': 'Cond²',
        'yr_built_sq' : 'Yr²'}
    new_var = []
    for v in var:
        new_var.append(rename_var[v])
    return new_var
```

In [11]:

```python
#This returns a list of strings that identify the variables used in that
#row's model.
def model_variables(lst):
    fv = new_name(lst) #fv = fomatted variable
    if len(fv) == 1:
        text = f'{fv[0]}'
        return text
    elif len(fv) == 2:
        text = f'{fv[0]} & {fv[1]}'
        return text
    text = f'{fv[0]}, {fv[1]}, {fv[2]}'
    i = 3
    while i < len(fv):
        text = text + f', {fv[i]}'
        i += 1
    return text
```

In [12]:

```python
#This formats the DataFrame's column names with better aesthetics.
def format_df(df, var):
    rename_coefficients = {'bedrooms' : 'Bed Coef', 'bathrooms' : 'Bath Coef',
        'sqft_living': 'SF Liv Coef', 'grade' : 'Grade Coef',
        'sqft_lot' : 'SF Lot Coef','floors': 'Floors Coef',
        'waterfront': 'WF Coef' ,'condition': 'Cond Coef',
        'yr_built' : 'Yr Coef',
        'bedrooms_log' : 'Log(Bed) Coef', 'bathrooms_log' : 'Log(Bath) Coef',
        'sqft_living_log': 'Log(SF Liv) Coef', 'grade_log' : 'Log(Grade) Coef',
```

```
        'sqft_lot_log' : 'Log(SF Lot) Coef','floors_log': 'Log(Floors) Coef',
        'waterfront_log': 'Log(WF) Coef' ,'condition_log': 'Log(Cond) Coef',
        'yr_built_log' : 'Log(Yr) Coef',
        'bedrooms_scale' : 'Norm Bed Coef','bathrooms_scale':'Norm Bath Coef',
        'sqft_living_scale':'Norm SF Liv Coef','grade_scale':'Norm Grade Coef',
        'sqft_lot_scale':'Norm SF Lot Coef','floors_scale':'Norm Floors Coef',
        'waterfront_scale': 'Norm WF Coef' ,'condition_scale':'Norm Cond Coef',
        'yr_built_scale' : 'Norm Yr Coef',
        'bedrooms_log_scale':'Norm Log(Bed) Coef',
        'bathrooms_log_scale':'Norm Log(Bath) Coef',
        'sqft_living_log_scale':'Norm Log(SF Liv) Coef',
        'grade_log_scale':'Norm Log(Grade) Coef',
        'sqft_lot_log_scale':'Norm Log(SF Lot) Coef',
        'floors_log_scale':'Norm Log(Floors) Coef',
        'waterfront_log_scale': 'Norm Log(WF) Coef' ,
        'condition_log_scale':'Norm Log(Cond) Coef',
        'yr_built_log_scale' : 'Norm Log(Yr) Coef',
        'bedrooms_sq' : 'Bed² Coef', 'bathrooms_sq' : 'Bath² Coef',
        'sqft_living_sq': 'SF Liv² Coef', 'grade_sq' : 'Grade² Coef',
        'sqft_lot_sq' : 'SF Lot² Coef','floors_sq': 'Floors² Coef',
        'waterfront_sq': 'WF² Coef' ,'condition_sq': 'Cond² Coef',
        'yr_built_sq' : 'Yr² Coef'}

    df['R²'] = df['R²'].map('{:.3f}'.format)
    df['P-value'] = df['P-value'].map('{:.1f}'.format)
    df['Intercept'] = df['Intercept'].map('{:.0f}'.format)
    for v in var:
        if v in df.columns:
            df[v] = df[v].map('{:.2f}'.format)
    floats = list(df.iloc[:,1:].columns)
    for obj in floats:
        df[obj] = df[obj].astype(float)

    df = df.rename(columns = rename_coefficients)
    return df
```

In [13]:

```
#Splitting the DataFrame parameter into individual DataFrames, each all the
#same variable with all the applicable applications.
def var_tran_dfs(df):
    drop = ['price','waterfront']
    var = list(df.drop(columns=drop).columns)
    num = len(var) + 1
    dfr,dfs,dfl,dfls,dfsq = tran_data(df,var)
    dfp,dfbd,dfbt,dflv,dflt,dffl,dfwf,dfct,dfgd,dfyb=0,0,0,0,0,0,0,0,0,0
    create_dfs = [dfp,dfbd,dfbt,dflv,dflt,dffl,dfwf,dfct,dfgd,dfyb]
    for i in range(len(df.columns)):
        create_dfs[i] = pd.DataFrame()
        for dfi in [dfr,dfs,dfl,dfls,dfsq]:
            create_dfs[i][dfi.iloc[:,i].name] = dfi.iloc[:,i]
    iter_df = []
    static_df = []
    static_df_num = [0]
    for i in range(len(create_dfs)):
        if i in static_df_num:
            static_df.append(create_dfs[i])
        else:
            iter_df.append(create_dfs[i])
    return static_df, iter_df
```

In [14]:

```
#This creates the DataFrame with the included model's pertinent statistics.
def model_stats(df,var):
```

```python
    #A DataFrame to sort the outcomes and make it look pretty.
    dfr = pd.DataFrame(columns =['Model Variable(s)',
                                 'R²','P-value','Neg Coef?'])

    neg = False

    #Running StatsModels
    m = make_model(df,var)

    #Testing to see if this model meets the requirements. The function returns
    #an empty DataFrame if it does not.
    d = dict(m.params)
    if m.rsquared <= 0.54:
        return dfr
    for v in var:
        if d[v] < 0:
            neg = True
            return dfr

    #Building the DataFrame to return.
    d.update({'Model Variable(s)' : model_variables(var),
              'R²' : m.rsquared,'P-value' : m.f_pvalue,
              'Neg Coef?' : neg})
    dfr = dfr.append(d,ignore_index = True)

    #Formatting the DataFrame to return.
    dfr = format_df(dfr,var)
    dfr['Neg Coef?'] = dfr['Neg Coef?'].astype(bool)

    return dfr
```

In [15]:

```python
#This runs thousands of models, with the specified number of variables per
#model and returns a DataFrame with the pertinent statistics.
def mega_models(df,beg,end):

    #Variable declaration
    #Variable that keeps a list of the column names of each df iteration.
    check = []
    #Variables related to printing text to provide feedback to the user to
    #ensure the function is still running.
    skip = False
    skip_count = 0
    discarded_models = 0
    cnt_var = 0
    cur_var = beg
    #Creating an empty list of DataFrames (dfs) that I will use to build each
    #iteration of the DataFrames in the for loop below.
    dfs = [None,None,None,None,None,None,None,None,None]

    #Splitting the DataFrame parameter into individual DataFrames, each all the
    #same variable with all the applicable applications.
    dep_df, ind_df =var_tran_dfs(df)

    #Creating the DataFrame with the columns in an order that makes sense.
    dfr_col = ['Model Variable(s)','R²','P-value','Neg Coef?','Intercept']
    for i in range(len(ind_df[0].columns)):
        for df_temp in ind_df:
            if i > len(df_temp.columns)-1:
                continue
            else:
                dfr_col.append(df_temp.iloc[:,i].name)
    dfr = pd.DataFrame(columns=dfr_col)
```

```python
    dfr = format_df(dfr, dfr_col)
    dfr['Neg Coef?'] = dfr['Neg Coef?'].astype(bool)

    #Creating dictionary of combinations. The key is the number of variables
    #per iteration, and the value is a list of which variables to include.
    num_var = dict(zip([0,1,2,3,4,5,6,7,8,9],
                  [[],[],[],[],[],[],[],[],[],[]]))
    for lst in product(range(2),repeat=9):
        num_var[sum(lst)].append(lst)

    #This for loop is the major work of this function. It creates a DataFrame
    #with pertinent information on different combinations of variables
    #specified in the parameters.
    for num in range(beg,end+1):

        #Prints feedback text so the user knows the program is running.
        cnt_var += 1
        print(f'Combos of {cur_var} variables ({cnt_var}/{end-beg+1}).')
        cur_var += 1

        #Resetting count variables related to each combination of variables
        model_count = 0
        skipped = 0

        #Calculating the total number of iterations for this combination of
        #variables.
        var_tot_iter = len(num_var[num])*len(list(product(
            range(len(ind_df[0].columns)),repeat=num)))

        #This first for loop iterates through the combinations of which
        #variables to include in the current interation.
        for vars_used in num_var[num]:
            #The second for loop specifies which transformations to use for
            #the current iteration.
            for tran_nums in product(range(len(ind_df[0].columns)),repeat=num):
                i,j,=0,0 #Specifies iteration of transformation.

                #Prints feedback so the user knows the program is running.
                #if ten thousand DataFrames are skipped, it prints this.
                if skip == True:
                    skip_count += 1
                    if skip_count % 10000 == 0:
                        print(f'Model {model_count} of {var_tot_iter}.')
                #If the program completed a thousand DataFrame iterations:
                if skip == False:
                    if model_count % 1000 == 0:
                        print(f'Model {model_count} of {var_tot_iter}.')
                        skip_count = 0

                #Sets a list of which variables are used to check if the
                #the current iteration is a repeat.
                check_iter = []

                #Checks if current iteration includes variables that are
                #I previously learned are multicollinear. This portion of code
                #doesn't check for multicollinearity, but rather filters out
                #variables I previously tested positive for multicollinearity.
                if vars_used[2] == 1:
                    if vars_used[1] == 1 or vars_used[7] == 1:
                        #This function returns True or False whether the
                        #values are multicollinear.
                        if multi_corr(vars_used,tran_nums):
```

```
                        skip=True
                        skipped += 1
                        var_tot_iter -= 1
                        continue

            #This creates the list of DataFrames for this iteration.
            for var in vars_used:
                if var == 1:
                    if i == 5:
                        dfs[i] = ind_df[i].copy()
                        check_iter.append(var)
                    else:
                        dfs[i] = ind_df[i].iloc[:,tran_nums[j]].copy()
                        check_iter.append([var,tran_nums[j]])
                    i+=1
                    j+=1

                #This creates the list to check if this iteration
                #is a repeat.
                else:
                    dfs[i]=None
                    check_iter.append(var)
                    i+=1

            #If the iteration is a repeat, this skips the model creation,
            #which saves time to run the function. Otherwise, the iteration
            #list is added to the check list to be filtered out later.
            if check_iter in check:
                skip=True
                skipped += 1
                var_tot_iter -= 1
                continue
            else:
                check.append(check_iter)

            #This puts the gleaned variables together into one DataFrame.
            iter_df = pd.concat([dep_df[0],dfs[0],dfs[1],dfs[2],
                                 dfs[3],dfs[4],dfs[5],dfs[6],
                                 dfs[7],dfs[8],],axis = 1)

            #And finally, the program runs the iteration through
            #StatsModels, and creates a DataFrame of the critical
            #statistics.
            col = list(iter_df.iloc[:,1:].columns)
            dfr_temp = model_stats(iter_df,col)
            model_count += 1 #We have successfully created a model.
            skip=False #We didn't skip this iteration.

            #The model_stats function will return a an empty DataFrame if
            #the model's data didn't meet certain requirements.
            if dfr_temp.empty:
                discarded_models += 1
                continue

            #DataFrame statistics is now added to the DataFrame to return.
            dfr = dfr.append(dfr_temp, ignore_index=True)

    #Ending text to confirm the function performed correctly.
    print(f'Model {model_count} of {var_tot_iter}.',
          f'Skipped {skipped} iterations.')
    print(f'{discarded_models} models discarded due to',
           'low R² or negative coefficients.')
```

```
    print(len(dfr), 'Models met minimum requirements.')

    #Organizing the DataFrame to return.
    dfr = dfr.sort_values('R²',ascending=False)
    dfr = dfr.reset_index(drop=True)
    return dfr
```

In [16]:

```
#This tests if the current iteration is multicollinear. It returns a boolean.
def multi_corr(var_tup,tran_tup):
    #Variable declaration
    detected = False
    var_lst = []

    #This creates a list of which variables are included and which
    #transformation form it is in.
    i=0
    for n in range(9):
        var_lst.append(var_tup[n] - 1)
        if var_lst[n] == 0:
            var_lst[n] = tran_tup[i]
            i+=1

    #These two if loops test if the combination of variables match the
    #previously calculated multicollinear pairs.
    if var_lst[2] in [0,1]:
        if var_lst[1] in [0,1,4] or var_lst[7] in [0,1,4]:
            detected = True
            return detected
    if var_lst[2] in [2,3]:
        if var_lst[1] in [0,1,2,3]:
            detected = True

    return detected
```

In [17]:

```
mega1 = mega_models(model_data,1,1)
mega1
```

```
Combos of 1 variables (1/1).
Model 0 of 45.
Model 41 of 41. Skipped 4 iterations.
41 models discarded due to low R² or negative coefficients.
0 Models met minimum requirements.
```

Out[17]:

Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Grade Coef	Yr Coef	Norm Bed Coef	Norm Bath Coef

There were no single variable models that met the requirements.

In [18]:

```
mega2 = mega_models(model_data,2,2)
mega2
```

```
Combos of 2 variables (1/1).
Model 0 of 900.
Model 720 of 720. Skipped 180 iterations.
714 models discarded due to low R² or negative coefficients.
6 Models met minimum requirements.
```

Out[18]:

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Grade Coef	Yr Coef	N
0	SF Liv^2 & Grade^2	0.588	0.0	False	-29632.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	SF Liv^2 & Grade	0.581	0.0	False	-396479.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	98988.34	NaN	
2	SF Liv^2 & Norm Grade	0.581	0.0	False	-99514.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	SF Liv^2 & Log(Grade)	0.573	0.0	False	-1035517.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	SF Liv^2 & Norm Log(Grade)	0.573	0.0	False	-284330.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
5	SF Liv^2 & WF	0.560	0.0	False	287040.0	NaN	NaN	NaN	NaN	NaN	795513.11	NaN	NaN	NaN	

In [19]:

```
mega3 = mega_models(model_data,3,3)
mega3
```

```
Combos of 3 variables (1/1).
Model 0 of 10500.
Model 1000 of 9900.
Model 2000 of 9134.
Model 3000 of 8874.
Model 4000 of 8374.
Model 5000 of 7598.
Model 6000 of 7368.
Model 7000 of 7168.
Model 7098 of 7098. Skipped 3402 iterations.
7046 models discarded due to low R² or negative coefficients.
52 Models met minimum requirements.
```

Out[19]:

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Gr C
0	SF Liv^2, WF, Grade^2	0.619	0.0	False	-26515.0	NaN	NaN	NaN	NaN	NaN	791493.93	NaN	N
1	SF Liv^2, WF, Grade	0.612	0.0	False	-395900.0	NaN	NaN	NaN	NaN	NaN	798901.88	NaN	9923
2	SF Liv^2, WF, Norm Grade	0.612	0.0	False	-98181.0	NaN	NaN	NaN	NaN	NaN	798901.88	NaN	N
3	SF Liv^2, WF, Log(Grade)	0.605	0.0	False	-1043976.0	NaN	NaN	NaN	NaN	NaN	804722.88	NaN	N
4	SF Liv^2, WF, Norm Log(Grade)	0.605	0.0	False	-286654.0	NaN	NaN	NaN	NaN	NaN	804722.88	NaN	N

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Gr C
5	SF Liv², Cond², Grade²	0.602	0.0	False	-164589.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
6	SF Liv², Norm Cond, Grade²	0.602	0.0	False	-214731.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
7	SF Liv², Cond, Grade²	0.602	0.0	False	-281149.0	NaN	NaN	NaN	NaN	NaN	NaN	66417.20	N
8	SF Liv², Log(Cond), Grade²	0.600	0.0	False	-323805.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
9	SF Liv², Norm Log(Cond), Grade²	0.600	0.0	False	-323805.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
10	SF Liv², Cond², Norm Grade	0.595	0.0	False	-238729.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
11	SF Liv², Cond², Grade	0.595	0.0	False	-559145.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	10680
12	SF Liv², Norm Cond, Grade	0.594	0.0	False	-605894.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	10634
13	SF Liv², Norm Cond, Norm Grade	0.594	0.0	False	-286858.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
14	SF Liv², Cond, Grade	0.594	0.0	False	-670812.0	NaN	NaN	NaN	NaN	NaN	NaN	64917.49	10634
15	SF Liv², Cond, Norm Grade	0.594	0.0	False	-351775.0	NaN	NaN	NaN	NaN	NaN	NaN	64917.49	N
16	SF Liv², Norm Log(Cond), Norm Grade	0.593	0.0	False	-391080.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
17	SF Liv², Log(Cond), Norm Grade	0.593	0.0	False	-391080.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Gr C
18	SF Liv², Log(Cond), Grade	0.593	0.0	False	-706788.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	10523
19	SF Liv², Norm Log(Cond), Grade	0.593	0.0	False	-706788.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	10523
20	SF Liv², Cond², Log(Grade)	0.586	0.0	False	-1246753.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
21	SF Liv², Cond², Norm Log(Grade)	0.586	0.0	False	-435195.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
22	SF Liv², Cond, Norm Log(Grade)	0.585	0.0	False	-542413.0	NaN	NaN	NaN	NaN	NaN	NaN	62542.59	N
23	SF Liv², Cond, Log(Grade)	0.585	0.0	False	-1349787.0	NaN	NaN	NaN	NaN	NaN	NaN	62542.59	N
24	SF Liv², Norm Cond, Norm Log(Grade)	0.585	0.0	False	-479871.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
25	SF Liv², Norm Cond, Log(Grade)	0.585	0.0	False	-1287244.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
26	SF Liv², Norm Log(Cond), Norm Log(Grade)	0.584	0.0	False	-576344.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
27	SF Liv², Norm Log(Cond), Log(Grade)	0.584	0.0	False	-1374211.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
28	SF Liv², Log(Cond), Norm Log(Grade)	0.584	0.0	False	-576344.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
29	SF Liv², Log(Cond), Log(Grade)	0.584	0.0	False	-1374211.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
30	SF Liv², WF, Cond²	0.566	0.0	False	217108.0	NaN	NaN	NaN	NaN	NaN	786995.54	NaN	N

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Gr C
31	SF Liv², WF, Norm Cond	0.566	0.0	False	184220.0	NaN	NaN	NaN	NaN	NaN	787443.36	NaN	N
32	SF Liv², WF, Cond	0.566	0.0	False	142192.0	NaN	NaN	NaN	NaN	NaN	787443.36	42027.65	N
33	SF Liv², WF, Norm Log(Cond)	0.565	0.0	False	109045.0	NaN	NaN	NaN	NaN	NaN	788560.10	NaN	N
34	SF Liv², WF, Log(Cond)	0.565	0.0	False	109045.0	NaN	NaN	NaN	NaN	NaN	788560.10	NaN	N
35	Bath, SF Liv², WF	0.563	0.0	False	231335.0	NaN	34390.81	NaN	NaN	NaN	801848.71	NaN	N
36	Norm Bath, SF Liv², WF	0.563	0.0	False	248531.0	NaN	NaN	NaN	NaN	NaN	801848.71	NaN	N
37	Bath², SF Liv², WF	0.563	0.0	False	267377.0	NaN	NaN	NaN	NaN	NaN	800290.82	NaN	N
38	SF Liv², Floors, WF	0.562	0.0	False	244630.0	NaN	NaN	NaN	NaN	31659.19	798899.39	NaN	N
39	SF Liv², Norm Floors, WF	0.562	0.0	False	276289.0	NaN	NaN	NaN	NaN	NaN	798899.39	NaN	N
40	SF Liv², Log(Floors), WF	0.562	0.0	False	276163.0	NaN	NaN	NaN	NaN	NaN	799081.53	NaN	N
41	SF Liv², Norm Log(Floors), WF	0.562	0.0	False	276163.0	NaN	NaN	NaN	NaN	NaN	799081.53	NaN	N
42	SF Liv², Floors², WF	0.562	0.0	False	266888.0	NaN	NaN	NaN	NaN	NaN	798438.93	NaN	N
43	Log(Bath), SF Liv², WF	0.562	0.0	False	263839.0	NaN	NaN	NaN	NaN	NaN	801614.78	NaN	N
44	Norm Log(Bath), SF Liv², WF	0.562	0.0	False	228725.0	NaN	NaN	NaN	NaN	NaN	801614.78	NaN	N
45	Norm SF Liv, WF, Norm Log(Grade)	0.559	0.0	False	-384242.0	NaN	NaN	NaN	NaN	NaN	870100.03	NaN	N
46	Norm SF Liv, WF, Log(Grade)	0.559	0.0	False	-1074987.0	NaN	NaN	NaN	NaN	NaN	870100.03	NaN	N
47	SF Liv, WF, Log(Grade)	0.559	0.0	False	-1147789.0	NaN	NaN	196.76	NaN	NaN	870100.03	NaN	N

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Gr C
48	SF Liv, WF, Norm Log(Grade)	0.559	0.0	False	-457044.0	NaN	NaN	196.76	NaN	NaN	870100.03	NaN	N
49	$Bath^2$, WF, $Grade^2$	0.546	0.0	False	-190870.0	NaN	NaN	NaN	NaN	NaN	890771.52	NaN	N
50	Norm Log(SF Liv), WF, $Grade^2$	0.543	0.0	False	-368537.0	NaN	NaN	NaN	NaN	NaN	897180.44	NaN	N
51	Log(SF Liv), WF, $Grade^2$	0.543	0.0	False	-1500584.0	NaN	NaN	NaN	NaN	NaN	897180.44	NaN	N

In [20]:

```
mega4 = mega_models(model_data,4,4)
mega4
```

```
Combos of 4 variables (1/1).
Model 0 of 78750.
Model 1000 of 77350.
Model 2000 of 75850.
Model 3000 of 75250.
Model 4000 of 75250.
Model 5000 of 72870.
Model 6000 of 71890.
Model 7000 of 70570.
Model 8000 of 70060.
Model 9000 of 68420.
Model 10000 of 68230.
Model 11000 of 67730.
Model 12000 of 66230.
Model 13000 of 66230.
Model 14000 of 65170.
Model 15000 of 64730.
Model 16000 of 64670.
Model 17000 of 63230.
Model 18000 of 63230.
Model 19000 of 61560.
Model 20000 of 58394.
Model 21000 of 56228.
Model 22000 of 55228.
Model 23000 of 54628.
Model 24000 of 54628.
Model 25000 of 53128.
Model 26000 of 53128.
Model 27000 of 51628.
Model 28000 of 51628.
Model 29000 of 51008.
Model 30000 of 50888.
Model 31000 of 49298.
Model 32000 of 49148.
Model 33000 of 48648.
Model 34000 of 48498.
Model 35000 of 47998.
Model 36000 of 47998.
Model 37000 of 46998.
Model 38000 of 46498.
Model 39000 of 46494.
Model 40000 of 45998.
```

```
Model 41000 of 45994.
Model 42000 of 45168.
Model 43000 of 43258.
Model 43118 of 43118. Skipped 35632 iterations.
42832 models discarded due to low R² or negative coefficients.
286 Models met minimum requirements.
```

Out[20]:

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Grade Coef	(
0	SF Liv², WF, Cond², Grade²	0.632	0.0	False	-156463.0	NaN	NaN	NaN	NaN	NaN	778168.02	NaN	NaN	I
1	SF Liv², WF, Cond, Grade²	0.631	0.0	False	-268789.0	NaN	NaN	NaN	NaN	NaN	778932.53	63963.5	NaN	I
2	SF Liv², WF, Norm Cond, Grade²	0.631	0.0	False	-204826.0	NaN	NaN	NaN	NaN	NaN	778932.53	NaN	NaN	I
3	SF Liv², WF, Norm Log(Cond), Grade²	0.630	0.0	False	-310505.0	NaN	NaN	NaN	NaN	NaN	780897.24	NaN	NaN	I
4	SF Liv², WF, Log(Cond), Grade²	0.630	0.0	False	-310505.0	NaN	NaN	NaN	NaN	NaN	780897.24	NaN	NaN	I
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
281	Bath², SF Liv², Log(Floors), Log(Cond)	0.540	0.0	False	28227.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
282	Bath², SF Liv², Norm Floors, Norm Log(Cond)	0.540	0.0	False	26842.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
283	Bath², SF Liv², Norm Floors, Log(Cond)	0.540	0.0	False	26842.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	I
284	Bath², SF Liv², Floors, Norm Log(Cond)	0.540	0.0	False	-7823.0	NaN	NaN	NaN	NaN	34664.69	NaN	NaN	NaN	I
285	Bath, SF Liv², Norm Log(Floors), Cond²	0.540	0.0	False	141943.0	NaN	25720.98	NaN	NaN	NaN	NaN	NaN	NaN	I

286 rows × 46 columns

In [21]:
```python
mega5 = mega_models(model_data,5,5)
mega5
```

```
Combos of 5 variables (1/1).
Model 0 of 393750.
Model 1000 of 390250.
Model 2000 of 388750.
Model 3000 of 388750.
Model 4000 of 388750.
Model 5000 of 386350.
Model 6000 of 382350.
Model 7000 of 378185.
Model 8000 of 377850.
Model 9000 of 377850.
Model 10000 of 373600.
Model 11000 of 369560.
Model 12000 of 369300.
Model 13000 of 369300.
Model 14000 of 364850.
Model 15000 of 360935.
Model 16000 of 360750.
Model 17000 of 360750.
Model 18000 of 360750.
Model 19000 of 360750.
Model 20000 of 360750.
Model 21000 of 360000.
Model 22000 of 360000.
Model 23000 of 358020.
Model 24000 of 353270.
Model 25000 of 349850.
Model 26000 of 349850.
Model 27000 of 349850.
Model 28000 of 349850.
Model 29000 of 345850.
Model 30000 of 342350.
Model 31000 of 342350.
Model 32000 of 342350.
Model 33000 of 342350.
Model 34000 of 338350.
Model 35000 of 334850.
Model 36000 of 334850.
Model 37000 of 334850.
Model 38000 of 334850.
Model 39000 of 334850.
Model 40000 of 334850.
Model 41000 of 334850.
Model 42000 of 334850.
Model 43000 of 334850.
Model 44000 of 334850.
Model 45000 of 331770.
Model 46000 of 327770.
Model 47000 of 325300.
Model 48000 of 316130.
Model 49000 of 314080.
Model 50000 of 312830.
Model 51000 of 311030.
Model 52000 of 303370.
Model 53000 of 300120.
Model 54000 of 298870.
Model 55000 of 296970.
Model 56000 of 292370.
Model 57000 of 286460.
Model 58000 of 284960.
Model 59000 of 283410.
Model 60000 of 282160.
Model 61000 of 277810.
Model 62000 of 276810.
```

```
Model 63000 of 276810.
Model 64000 of 276810.
Model 65000 of 274110.
Model 66000 of 270110.
Model 67000 of 269310.
Model 68000 of 269310.
Model 69000 of 269310.
Model 70000 of 266610.
Model 71000 of 262610.
Model 72000 of 261810.
Model 73000 of 261810.
Model 74000 of 261810.
Model 75000 of 261810.
Model 76000 of 261810.
Model 77000 of 261810.
Model 78000 of 261810.
Model 79000 of 261810.
Model 80000 of 261810.
Model 81000 of 260070.
Model 82000 of 256070.
Model 83000 of 254030.
Model 84000 of 253710.
Model 85000 of 252600.
Model 86000 of 247980.
Model 87000 of 245460.
Model 88000 of 245160.
Model 89000 of 245010.
Model 90000 of 245010.
Model 91000 of 245010.
Model 92000 of 244860.
Model 93000 of 244560.
Model 94000 of 244260.
Model 95000 of 241021.
Model 96000 of 236585.
Model 97000 of 236210.
Model 98000 of 235860.
Model 99000 of 235860.
Model 100000 of 235860.
Model 101000 of 235860.
Model 102000 of 235651.
Model 103000 of 235276.
Model 104000 of 234570.
Model 105000 of 229820.
Model 106000 of 227460.
Model 107000 of 227460.
Model 108000 of 227460.
Model 109000 of 227310.
Model 110000 of 227010.
Model 111000 of 226710.
Model 112000 of 226710.
Model 113000 of 226710.
Model 114000 of 226710.
Model 115000 of 224210.
Model 116000 of 224210.
Model 117000 of 224210.
Model 118000 of 224110.
Model 119000 of 220110.
Model 120000 of 216710.
Model 121000 of 216710.
Model 122000 of 216710.
Model 123000 of 216710.
Model 124000 of 216710.
Model 125000 of 216710.
Model 126000 of 216710.
Model 127000 of 216710.
Model 128000 of 216710.
Model 129000 of 216710.
```

```
Model 130000 of 213570.
Model 131000 of 209570.
Model 132000 of 209210.
Model 133000 of 209210.
Model 134000 of 209210.
Model 135000 of 209210.
Model 136000 of 209210.
Model 137000 of 209210.
Model 138000 of 209210.
Model 139000 of 209210.
Model 140000 of 209210.
Model 141000 of 207070.
Model 142000 of 203070.
Model 143000 of 201710.
Model 144000 of 201710.
Model 145000 of 201710.
Model 146000 of 201710.
Model 147000 of 201710.
Model 148000 of 201710.
Model 149000 of 201710.
Model 150000 of 201710.
Model 151000 of 201710.
Model 152000 of 200554.
Model 153000 of 197880.
Model 154000 of 196260.
Model 155000 of 195000.
Model 156000 of 191870.
Model 157000 of 184200.
Model 158000 of 183000.
Model 159000 of 181000.
Model 160000 of 179700.
Model 161000 of 176000.
Model 162000 of 174700.
Model 163000 of 172760.
Model 164000 of 171500.
Model 165000 of 167700.
Model 166000 of 166350.
Model 166200 of 166200. Skipped 227550 iterations.
165640 models discarded due to low R² or negative coefficients.
560 Models met minimum requirements.
```

Out[21]:

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Grade Coef	Yr Coef
0	Bath², SF Liv², WF, Cond², Grade²	0.632	0.0	False	-157416.0	NaN	NaN	NaN	NaN	NaN	778702.83	NaN	NaN	NaN
1	Bath², SF Liv², WF, Cond, Grade²	0.631	0.0	False	-270388.0	NaN	NaN	NaN	NaN	NaN	779482.03	64293.87	NaN	NaN
2	Bath², SF Liv², WF, Norm Cond, Grade²	0.631	0.0	False	-206094.0	NaN	NaN	NaN	NaN	NaN	779482.03	NaN	NaN	NaN
3	Bath², SF Liv², WF, Log(Cond), Grade²	0.630	0.0	False	-312169.0	NaN	NaN	NaN	NaN	NaN	781395.80	NaN	NaN	NaN

	Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Grade Coef	Yr Coef
4	Bath^2, SF Liv^2, WF, Norm Log(Cond), Grade^2	0.630	0.0	False	-312169.0	NaN	NaN	NaN	NaN	NaN	781395.80	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
555	Norm Log(Bed), SF Lot^2, WF, Cond, Grade^2	0.540	0.0	False	-569304.0	NaN	NaN	NaN	NaN	NaN	901755.82	72979.66	NaN	NaN
556	Log(Bath), SF Lot^2, WF, Cond^2, Grade^2	0.540	0.0	False	-385095.0	NaN	NaN	NaN	NaN	NaN	892155.14	NaN	NaN	NaN
557	Log(Bed), SF Lot, WF, Cond, Grade^2	0.540	0.0	False	-569363.0	NaN	NaN	NaN	0.02	NaN	901583.35	72981.20	NaN	NaN
558	Norm Log(Bed), SF Lot^2, WF, Norm Cond, Grade^2	0.540	0.0	False	-496325.0	NaN	NaN	NaN	NaN	NaN	901755.82	NaN	NaN	NaN
559	Log(Bed), Norm SF Lot, WF, Norm Cond, Grade^2	0.540	0.0	False	-496373.0	NaN	NaN	NaN	NaN	NaN	901583.35	NaN	NaN	NaN

560 rows × 46 columns

In [22]:
```
mega6 = mega_models(model_data,6,6)
mega6
```

In [23]:
```
mega7 = mega_models(model_data,7,7)
mega7
```

```
Combos of 7 variables (1/1).
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Model 900 of 2802500.
Model 1000 of 2801505.
Model 1850 of 2791505.
Model 2000 of 2790005.
Model 3000 of 2782250.
Model 4000 of 2778250.
Model 5000 of 2774250.
Model 6000 of 2770250.
Model 7000 of 2766250.
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Model 35000 of 2568000.
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Model 61000 of 2487000.
Model 62000 of 2487000.
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Model 67000 of 2444600.
Model 68000 of 2436855.
Model 68625 of 2426855.
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Model 72000 of 2383350.
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Model 481000 of 919750.
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Model 574000 of 626520.
Model 574750 of 616520.
Model 575000 of 615020.
Model 576000 of 607270.
Model 576875 of 597270.
Model 577000 of 595770.
Model 577875 of 585770.
Model 578000 of 584270.
Model 578750 of 578750. Skipped 2233750 iterations.
578750 models discarded due to low R² or negative coefficients.
0 Models met minimum requirements.
```

Out[23]:

Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Grade Coef	Yr Coef	Norm Bed Coef	Norm Bath Coef

There were no seven variable models that met the requirements.

In [26]:

```
mega8 = mega_models(model_data,8,8)
mega8 = mega8.insert(1,'Var Count',8)

mega8.to_excel("mega8.xlsx")
```

```
Combos of 8 variables (1/1).
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Model 0 of 3505625.
Model 0 of 3495625.
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Model 0 of 3475625.
Model 0 of 3465625.
Model 0 of 3455625.
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Model 3125 of 3431625.
Model 3125 of 3421625.
Model 3125 of 3411625.
Model 3125 of 3401625.
Model 3125 of 3391625.
Model 3125 of 3381625.
Model 4000 of 3375125.
Model 5000 of 3371125.
Model 6000 of 3367125.
Model 7000 of 3357505.
Model 7850 of 3347505.
Model 8000 of 3346005.
Model 8750 of 3336005.
Model 8750 of 3326005.
Model 8750 of 3316005.
Model 8750 of 3306005.
Model 9000 of 3305125.
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Model 11000 of 3297125.
Model 12000 of 3291935.
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Model 14000 of 3268935.
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Model 93000 of 2794125.
Model 94000 of 2790125.
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Model 97000 of 2778125.
Model 98000 of 2774125.
Model 99000 of 2770125.
Model 100000 of 2766125.
Model 101000 of 2762125.
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Model 138000 of 2614125.
Model 139000 of 2610125.
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Model 142000 of 2598125.
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Model 144000 of 2590125.
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Model 162000 of 2518125.
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Model 282000 of 1643125.
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Model 366700 of 1320110.
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Model 374000 of 1223475.
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Model 409925 of 832225.
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Model 417925 of 736475.
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Model 419125 of 722225.
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Model 426450 of 616101.
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Model 431625 of 546725.
Model 432000 of 542725.
Model 432750 of 532725.
Model 433000 of 528725.
Model 433925 of 518725.
Model 434000 of 518475.
Model 435000 of 514475.
Model 435250 of 504475.
Model 435875 of 494475.
Model 436000 of 485475.
Model 437000 of 477726.
Model 437725 of 467726.
Model 438000 of 464612.
Model 438700 of 454612.
Model 439000 of 447225.
Model 440000 of 443225.
Model 440625 of 440625. Skipped 3075000 iterations.
440625 models discarded due to low R² or negative coefficients.
0 Models met minimum requirements.
```

There were no eight variable models that met the requirements.

In [28]:
```
mega9 = mega_models(model_data,9,9)
mega9
```

```
Combos of 9 variables (1/1).
Model 0 of 1953125.
Model 0 of 1943125.
Model 0 of 1933125.
Model 0 of 1923125.
Model 0 of 1913125.
Model 0 of 1903125.
Model 0 of 1893125.
Model 1000 of 1887125.
Model 2000 of 1883125.
Model 3000 of 1879125.
Model 3125 of 1869125.
Model 3125 of 1859125.
Model 3125 of 1849125.
Model 3125 of 1839125.
Model 3125 of 1829125.
Model 3125 of 1819125.
Model 4000 of 1812625.
Model 5000 of 1808625.
Model 6000 of 1804625.
Model 7000 of 1795005.
Model 7850 of 1785005.
Model 8000 of 1783505.
Model 8750 of 1773505.
Model 8750 of 1763505.
Model 8750 of 1753505.
Model 8750 of 1743505.
Model 9000 of 1742625.
Model 10000 of 1738625.
Model 11000 of 1734625.
Model 12000 of 1729435.
Model 12875 of 1719435.
Model 13000 of 1717935.
Model 13875 of 1707935.
Model 14000 of 1706435.
Model 14375 of 1696435.
Model 14375 of 1686435.
Model 14375 of 1676435.
Model 15000 of 1668625.
Model 16000 of 1664625.
Model 17000 of 1660625.
Model 17500 of 1650625.
Model 17500 of 1640625.
Model 17500 of 1630625.
Model 18000 of 1625375.
Model 19000 of 1621375.
Model 20000 of 1617375.
Model 21000 of 1613375.
Model 22000 of 1609375.
Model 23000 of 1605375.
Model 24000 of 1601375.
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Model 26875 of 1573375.
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Model 26875 of 1553375.
Model 26875 of 1543375.
Model 26875 of 1533375.
Model 27000 of 1526875.
Model 28000 of 1522875.
Model 29000 of 1518875.
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Model 32000 of 1444375.
Model 33000 of 1440375.
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Model 34875 of 1419560.
Model 35000 of 1418060.
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Model 35625 of 1388060.
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Model 37000 of 1374375.
Model 38000 of 1370375.
Model 39000 of 1364505.
Model 39850 of 1354505.
Model 40000 of 1353005.
Model 40850 of 1343005.
Model 41000 of 1341505.
Model 41250 of 1331505.
Model 41250 of 1321505.
Model 41250 of 1311505.
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Model 43000 of 1300375.
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Model 44375 of 1286375.
Model 44375 of 1276375.
Model 44375 of 1266375.
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Model 47000 of 1253125.
Model 48000 of 1249125.
Model 49000 of 1245125.
Model 50000 of 1241125.
Model 51000 of 1237125.
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Model 53000 of 1229125.
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Model 56875 of 1124625.
Model 56875 of 1114625.
Model 56875 of 1104625.
Model 56875 of 1094625.
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Model 58000 of 1084125.
Model 59000 of 1080125.
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Model 60850 of 1066125.
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Model 61850 of 1054630.
Model 62000 of 1053130.
Model 62500 of 1043130.
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Model 67875 of 977560.
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Model 68125 of 956060.
Model 68125 of 946060.
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Model 83750 of 730375.
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Model 87000 of 710685.
Model 87875 of 700685.
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Model 89375 of 657685.
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Model 95000 of 581130.
Model 96000 of 575875.
Model 97000 of 571875.
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Model 107500 of 480625.
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Model 110625 of 366125.
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Model 129000 of 156375.
Model 130000 of 152375.
Model 131000 of 148375.
Model 132000 of 144375.
Model 133000 of 140375.
Model 134000 of 136375.
Model 134375 of 134375. Skipped 1818750 iterations.
```

```
134375 models discarded due to low R² or negative coefficients.
0 Models met minimum requirements.
```

Out[28]:

Model Variable(s)	R^2	P-value	Neg Coef?	Intercept	Bed Coef	Bath Coef	SF Liv Coef	SF Lot Coef	Floors Coef	WF Coef	Cond Coef	Grade Coef	Yr Coef	Norm Bed Coef	Norm Bath Coef

There were no nine variable models that met the requirements.

In [ ]:

```
This puts all the data together and then creates the excel file.
mega = mega1.append([mega2,mega3,mega4,mega5,mega6])
mega = mega.sort_values('R²',ascending=False)
mega = mega.reset_index(drop=True)
```

In [ ]:

```
mega.to_excel("Mega Pertinent Stats.xlsx")
```