In [3]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from scipy import stats
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import KFold

from sklearn.metrics import r2_score

import seaborn as sns
import matplotlib.pyplot as plt

import re

pd.set_option('display.max_columns', None)
```

In [4]:
```
df = pd.read_csv('Existing_Buildings_Energy_Performance_Ordinance_Report.csv')
```

In [65]:
```
df.columns
```

Out[65]:
```
Index(['Parcel(s)', 'Building Name', 'Building Address', 'Postal Code',
       'Full.Address', 'Floor Area', 'Property Type',
       'Property Type - Self Selected', 'PIM Link', 'Year Built',
       ...
       '2012 Weather Normalized Source EUI (kBtu/ft2)',
       '2011 ENERGY STAR Score', '2011 Site EUI (kBtu/ft2)',
       '2011 Source EUI (kBtu/ft2)',
       '2011 Percent Better than National Median Site EUI',
       '2011 Percent Better than National Median Source EUI',
       '2011 Total GHG Emissions (Metric Tons CO2e)',
       '2011 Total GHG Emissions Intensity (kgCO2e/ft2)',
       '2011 Weather Normalized Site EUI (kBtu/ft2)',
       '2011 Weather Normalized Source EUI (kBtu/ft2)'],
      dtype='object', length=113)
```

Explore the raw data

In [5]:
```
[x for x in df.columns]
```

Out[5]:
```
['Parcel(s)',
 'Building Name',
 'Building Address',
 'Postal Code',
 'Full.Address',
 'Floor Area',
 'Property Type',
 'Property Type - Self Selected',
 'PIM Link',
 'Year Built',
 'Energy Audit Due Date',
 'Energy Audit Status',
 'Benchmark 2019 Status',
 '2019 Reason for Exemption',
 'Benchmark 2018 Status',
 '2018 Reason for Exemption',
 'Benchmark 2017 Status',
 '2017 Reason for Exemption',
 'Benchmark 2016 Status',
 '2016 Reason for Exemption',
 'Benchmark 2015 Status',
 '2015 Reason for Exemption',
 'Benchmark 2014 Status',
 '2014 Reason for Exemption',
 'Benchmark 2013 Status',
 '2013 Reason for Exemption',
 'Benchmark 2012 Status',
 '2012 Reason for Exemption',
 'Benchmark 2011 Status',
 '2011 Reason for Exemption',
 'Benchmark 2010 Status',
 '2010 Reason for Exemption',
 '2019 ENERGY STAR Score',
 '2019 Site EUI (kBtu/ft2)',
 '2019 Source EUI (kBtu/ft2)',
 '2019 Percent Better than National Median Site EUI',
 '2019 Percentage Better than National Median Source EUI',
 '2019 Total GHG Emissions (Metric Tons CO2e)',
 '2019 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2019 Weather Normalized Site EUI (kBtu/ft2)',
 '2019 Weather Normalized Source EUI (kBtu/ft2)',
 '2018 ENERGY STAR Score',
 '2018 Site EUI (kBtu/ft2)',
 '2018 Source EUI (kBtu/ft2)',
 '2018 Percent Better than National Median Site EUI',
 '2018 Percent Better than National Median Source EUI',
 '2018 Total GHG Emissions (Metric Tons CO2e)',
 '2018 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2018 Weather Normalized Site EUI (kBtu/ft2)',
 '2018 Weather Normalized Source EUI (kBtu/ft2)',
 '2017 ENERGY STAR Score',
 '2017 Site EUI (kBtu/ft2)',
 '2017 Source EUI (kBtu/ft2)',
 '2017 Percent Better than National Median Site EUI',
 '2017 Percent Better than National Median Source EUI',
 '2017 Total GHG Emissions (Metric Tons CO2e)',
 '2017 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2017 Weather Normalized Site EUI (kBtu/ft2)',
 '2017 Weather Normalized Source EUI (kBtu/ft2)',
 '2016 ENERGY STAR Score',
 '2016 Site EUI (kBtu/ft2)',
 '2016 Source EUI (kBtu/ft2)',
 '2016 Percent Better than National Median Site EUI',
 '2016 Percent Better than National Median Source EUI',
 '2016 Total GHG Emissions (Metric Tons CO2e)',
 '2016 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2016 Weather Normalized Site EUI (kBtu/ft2)',
 '2016 Weather Normalized Source EUI (kBtu/ft2)',
 '2015 ENERGY STAR Score',
 '2015 Site EUI (kBtu/ft2)',
 '2015 Source EUI (kBtu/ft2)',
 '2015 Percent Better than National Median Site EUI',
 '2015 Percent Better than National Median Source EUI',
 '2015 Total GHG Emissions (Metric Tons CO2e)',
 '2015 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2015 Weather Normalized Site EUI (kBtu/ft2)',
 '2015 Weather Normalized Source EUI (kBtu/ft2)',
 '2014 ENERGY STAR Score',
 '2014 Site EUI (kBtu/ft2)',
 '2014 Source EUI (kBtu/ft2)',
 '2014 Percent Better than National Median Site EUI',
 '2014 Percent Better than National Median Source EUI',
 '2014 Total GHG Emissions (Metric Tons CO2e)',
 '2014 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2014 Weather Normalized Site EUI (kBtu/ft2)',
 '2014 Weather Normalized Source EUI (kBtu/ft2)',
 '2013 ENERGY STAR Score',
 '2013 Site EUI (kBtu/ft2)',
 '2013 Source EUI (kBtu/ft2)',
 '2013 Percent Better than National Median Site EUI',
 '2013 Percent Better than National Median Source EUI',
 '2013 Total GHG Emissions (Metric Tons CO2e)',
 '2013 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2013 Weather Normalized Site EUI (kBtu/ft2)',
 '2013 Weather Normalized Source EUI (kBtu/ft2)',
 '2012 ENERGY STAR Score',
 '2012 Site EUI (kBtu/ft2)',
 '2012 Source EUI (kBtu/ft2)',
 '2012 Percent Better than National Median Site EUI',
 '2012 Percent Better than National Median Source EUI',
 '2012 Total GHG Emissions (Metric Tons CO2e)',
 '2012 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2012 Weather Normalized Site EUI (kBtu/ft2)',
 '2012 Weather Normalized Source EUI (kBtu/ft2)',
 '2011 ENERGY STAR Score',
 '2011 Site EUI (kBtu/ft2)',
 '2011 Source EUI (kBtu/ft2)',
 '2011 Percent Better than National Median Site EUI',
 '2011 Percent Better than National Median Source EUI',
 '2011 Total GHG Emissions (Metric Tons CO2e)',
 '2011 Total GHG Emissions Intensity (kgCO2e/ft2)',
 '2011 Weather Normalized Site EUI (kBtu/ft2)',
 '2011 Weather Normalized Source EUI (kBtu/ft2)']
```

In [6]:
```
df.sample()
```

Out[6]:

	Parcel(s)	Building Name	Building Address	Postal Code	Full.Address	Floor Area	Property Type	Property Type - Self Selected	PIM Link	Year Built
1013	4700/031	900 EARL ST	900 EARL ST	94124	900 EARL ST\nSAN FRANCISCO, CA 94124\n(37.7290...	89761	Mixed Residential	NaN	http://propertymap.sfplanning.org/?&search=470...	1900.0

In [7]:
```
df.shape
```

Out[7]:
```
(2629, 113)
```

Retabulate data to building-year level

In [3]:
```
# Unstack the data just the year-based data columns
temp = df.set_index('Parcel(s)')
temp2 = pd.DataFrame(pd.DataFrame(temp[[x for x in df.columns if '201' in x]].unstack()).to_records
())
```

In [15]:
```
# Extract the years and make them their own column
year_starts = [x.find('201') for x in temp2.level_0.values]

years = []
for year_start, value in zip(year_starts, temp2.level_0.values):
    years.append(value[year_start:year_start+4])

temp2['year'] = years
```

In [60]:
```
# take out the mention of years to normalize the values of the columns
years_list = ['2010', '2011', '2012', '2013', '2014', '2015', '2016', '2017', '2018', '2019']
col_names = temp2.level_0.values

res = []
for col_name in col_names:
    for sub in years_list:
        if sub in col_name:
            col_name = col_name.replace(sub, '')
            res.append(" ".join(col_name.split()))
        else:
            continue

temp2['metric_year_stripped'] = res
```

In [65]:
```
temp3 = temp2.pivot(index=['Parcel(s)', 'year'], columns='metric_year_stripped', values='0')
```

In [72]:
```
# Rejoin the non-year-level data
cols_no_years = [x for x in df.columns if ('201' not in x)]
temp4 = temp3.reset_index().merge(df[cols_no_years], left_on='Parcel(s)', right_on='Parcel(s)', how=
'left')
```

In [76]:
```
temp4.to_csv('energy_building_data_retabulated.csv', index=False)
```

Spot check a few

In [91]:
```
df.sample()
```

Out[91]:

	Parcel(s)	Building Name	Building Address	Postal Code	Full.Address	Floor Area	Property Type	Property Type - Self Selected	PIM Link	Year Built
1567	0259/026	555 California	555 CALIFORNIA ST	94104	555 CALIFORNIA ST\nSAN FRANCISCO, CA 94104\n(3...	1978104	Commercial	Office	http://propertymap.sfplanning.org/?&search=025...	1969.0

In [92]:
```
temp4[temp4['Parcel(s)']=='0259/026']
```

Out[92]:

	Parcel(s)	year	Benchmark Status	ENERGY STAR Score	Percent Better than National Median Site EUI	Percent Better than National Median Source EUI	Percentage Better than National Median Source EUI	Reason for Exemption	Site EUI (kBtu/ft2)	Source EUI (kBtu/ft2)	Total GHG Emissions (Metric Tons CO2e)	Total GHG Emissions Intensity (kgCO2e/ft2)
3670	0259/026	2010	Complied	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3671	0259/026	2011	Complied	70	-19.1	NaN	NaN	NaN	96.7	NaN	15049.7	NaN
3672	0259/026	2012	Complied	71	-20.6	NaN	NaN	NaN	91.7	234	14336.9	NaN
3673	0259/026	2013	Violation - Insufficient Data	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3674	0259/026	2014	Complied	68	-19.4	-19.4	NaN	NaN	83.4	204.7	11499.5	6.4
3675	0259/026	2015	Complied	69	-19.7	-19.7	NaN	NaN	87.7	205.7	11956.8	6.6
3676	0259/026	2016	Complied	77	-28	-28	NaN	NaN	75.9	179.7	10798.1	6
3677	0259/026	2017	Complied	78	-29.5	-29.5	NaN	NaN	75.2	177.7	9804	5.4
3678	0259/026	2018	Complied	58	-10.6	-10.6	NaN	NaN	75.4	161.7	9385.5	5.2
3679	0259/026	2019	Complied	62	-15.3	NaN	-15.3	NaN	80	166	9921.7	5.5

In [3]:
```
df = pd.read_csv('energy_building_data_final.csv')
```

Modeling (retabulated data)

In [13]:
```
df[df['ENERGY STAR Score'].notnull()].isnull().mean()
```

Out[13]:
```
Unnamed: 0                                         0.000000
Parcel(s)                                          0.000000
year                                               0.000000
Benchmark Status                                   0.000000
ENERGY STAR Score                                  0.000000
Percent Better than National Median Site EUI       0.017278
Percent Better than National Median Source EUI     0.253865
Percentage Better than National Median Source EUI  0.863443
Reason for Exemption                               0.998788
Site EUI (kBtu/ft2)                                0.000455
Source EUI (kBtu/ft2)                              0.046681
Total GHG Emissions (Metric Tons CO2e)             0.001819
Total GHG Emissions Intensity (kgCO2e/ft2)         0.101849
Weather Normalized Site EUI (kBtu/ft2)             0.012580
Weather Normalized Source EUI (kBtu/ft2)           0.058351
Building Name                                      0.000000
Building Address                                   0.000000
Postal Code                                        0.000000
Full.Address                                       0.000606
Floor Area                                         0.000000
Property Type                                      0.000000
Property Type - Self Selected                      0.000000
PIM Link                                           0.000000
Year Built                                         0.009548
Energy Audit Due Date                              0.043346
Energy Audit Status                                0.044711
Previous Year ENERGY STAR Score                    0.210064
Two Years Ago ENERGY STAR Score                    0.366475
Current Year YoY Change                            0.210064
Previous Year YoY Change                           0.366475
Age In Years                                       0.009548
Recalculated GHG Emissions Intensity (kgCO2e/ft2)  0.001819
Is Downtown                                        0.000000
dtype: float64
```

In [14]:
```
df.dtypes
```

Out[14]:
```
Unnamed: 0                                            int64
Parcel(s)                                            object
year                                                  int64
Benchmark Status                                     object
ENERGY STAR Score                                   float64
Percent Better than National Median Site EUI        float64
Percent Better than National Median Source EUI      float64
Percentage Better than National Median Source EUI   float64
Reason for Exemption                                 object
Site EUI (kBtu/ft2)                                 float64
Source EUI (kBtu/ft2)                               float64
Total GHG Emissions (Metric Tons CO2e)              float64
Total GHG Emissions Intensity (kgCO2e/ft2)          float64
Weather Normalized Site EUI (kBtu/ft2)              float64
Weather Normalized Source EUI (kBtu/ft2)            float64
Building Name                                        object
Building Address                                     object
Postal Code                                           int64
Full.Address                                         object
Floor Area                                            int64
Property Type                                        object
Property Type - Self Selected                        object
PIM Link                                             object
Year Built                                          float64
Energy Audit Due Date                                object
Energy Audit Status                                  object
Previous Year ENERGY STAR Score                     float64
Two Years Ago ENERGY STAR Score                     float64
Current Year YoY Change                             float64
Previous Year YoY Change                            float64
Age In Years                                        float64
Recalculated GHG Emissions Intensity (kgCO2e/ft2)   float64
Is Downtown                                            bool
dtype: object
```

Modeling

In [15]:
```
df['Year Built'] = df['Year Built'].replace(0, np.NaN)
```

Linear Regression

Using all the features

In [6]:
```
dummy_features = ['Property Type', 'Postal Code']
```

In [7]:
```
features = [col for col in df_train_numeric.columns if col not in ['Reason for Exemption',
                                                                   'Percentage Better than National Median Source
 EUI',
                                                                   'Percent Better than National Median Source EU
I',
                                                                   'ENERGY STAR Score']]

print(features)

# Drop na's
df_train_dropped_nas = df_train_numeric.dropna(subset=features + ['ENERGY STAR Score'])

X_train_no_constant = df_train_dropped_nas[features]
y_train = df_train_dropped_nas['ENERGY STAR Score']

X_train = sm.add_constant(X_train_no_constant)

print(X_train.shape)

est = sm.OLS(y_train, X_train).fit()
print(est.summary())
```

```
['year', 'Percent Better than National Median Site EUI', 'Site EUI (kBtu/ft2)', 'Source EUI (kBtu/ft
2)', 'Total GHG Emissions (Metric Tons CO2e)', 'Total GHG Emissions Intensity (kgCO2e/ft2)', 'Weather
Normalized Site EUI (kBtu/ft2)', 'Weather Normalized Source EUI (kBtu/ft2)', 'Postal Code', 'Floor Ar
ea', 'Year Built', 'years_since_built']
(3849, 13)
                            OLS Regression Results
==============================================================================
Dep. Variable:      ENERGY STAR Score   R-squared:                       0.347
Model:                            OLS   Adj. R-squared:                  0.345
Method:                 Least Squares   F-statistic:                     185.2
Date:                Sun, 29 Nov 2020   Prob (F-statistic):               0.00
Time:                        16:05:37   Log-Likelihood:                -17246.
No. Observations:                3849   AIC:                         3.452e+04
Df Residuals:                    3837   BIC:                         3.459e+04
Df Model:                          11
Covariance Type:            nonrobust
==============================================================================================
===========
                                              coef    std err          t      P>|t|      [0.025
    0.975]
----------------------------------------------------------------------------------------------
-----------
const                                    2.587e+04   4018.487      6.439      0.000     1.8e+04
   3.38e+04
year                                        0.1585      0.160      0.992      0.321      -0.155
     0.472
Percent Better than National Median Site EUI     0.0024      0.000      6.138      0.000       0.002
     0.003
Site EUI (kBtu/ft2)                        -0.4177      0.258     -1.617      0.106      -0.924
     0.089
Source EUI (kBtu/ft2)                      -0.7315      0.166     -4.414      0.000      -1.056
    -0.407
Total GHG Emissions (Metric Tons CO2e)      0.0002      0.001      0.296      0.767      -0.001
     0.001
Total GHG Emissions Intensity (kgCO2e/ft2)      4.9747      1.104      4.507      0.000       2.811
     7.139
Weather Normalized Site EUI (kBtu/ft2)     -0.1419      0.253     -0.561      0.575      -0.638
     0.354
Weather Normalized Source EUI (kBtu/ft2)      0.7212      0.166      4.351      0.000       0.396
     1.046
Postal Code                                -0.2787      0.042     -6.582      0.000      -0.362
    -0.196
Floor Area                               1.848e-05   3.18e-06      5.813      0.000    1.22e-05
   2.47e-05
Year Built                                  0.0588      0.080      0.732      0.464      -0.099
     0.216
years_since_built                           0.0993      0.080      1.243      0.214      -0.057
     0.256
==============================================================================
Omnibus:                      639.774   Durbin-Watson:                   0.750
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9142.267
Skew:                          -0.331   Prob(JB):                         0.00
Kurtosis:                      10.521   Cond. No.                     8.14e+16
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 4.26e-20. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

In [14]:
```
df.columns
```

Out[14]:
```
Index(['Parcel(s)', 'year', 'Benchmark Status', 'ENERGY STAR Score',
       'Percent Better than National Median Site EUI',
       'Percent Better than National Median Source EUI',
       'Percentage Better than National Median Source EUI',
       'Reason for Exemption', 'Site EUI (kBtu/ft2)', 'Source EUI (kBtu/ft2)',
       'Total GHG Emissions (Metric Tons CO2e)',
       'Total GHG Emissions Intensity (kgCO2e/ft2)',
       'Weather Normalized Site EUI (kBtu/ft2)',
       'Weather Normalized Source EUI (kBtu/ft2)', 'Building Name',
       'Building Address', 'Postal Code', 'Full.Address', 'Floor Area',
       'Property Type', 'Property Type - Self Selected', 'PIM Link',
       'Year Built', 'Energy Audit Due Date', 'Energy Audit Status'],
      dtype='object')
```

In [3]:
```
df.head()
```

Out[3]:

	Unnamed: 0	Parcel(s)	year	Benchmark Status	ENERGY STAR Score	Percent Better than National Median Site EUI	Percent Better than National Median Source EUI	Percentage Better than National Median Source EUI	Reason for Exemption	Site EUI (kBtu/ft2)	Source EUI (kBtu/ft2)	Total GHG Emissions (Metric Tons CO2e)
0	2	0010/001	2012	Complied	81.0	-34.5	NaN	NaN	NaN	71.0	149.9	696.4
1	3	0010/001	2013	Complied	74.0	-26.2	-26.2	NaN	NaN	81.3	166.9	786.5
2	4	0010/001	2014	Complied	56.0	-6.5	-6.5	NaN	NaN	73.4	158.5	668.9
3	5	0010/001	2015	Complied	72.0	-23.0	-23.0	NaN	NaN	72.0	153.9	653.2
4	6	0010/001	2016	Complied	75.0	-26.3	-26.3	NaN	NaN	68.2	149.7	652.4

In [5]:
```
# make full list of all relevant features
features_relevant = ['year',
                     'Benchmark Status',
                     'Percent Better than National Median Site EUI',
                     'Percent Better than National Median Source EUI',
                     'Site EUI (kBtu/ft2)',
                     'Source EUI (kBtu/ft2)',
                     'Total GHG Emissions (Metric Tons CO2e)',
                     #'Total GHG Emissions Intensity (kgCO2e/ft2)', # recalculated below
                     'Weather Normalized Site EUI (kBtu/ft2)',
                     'Weather Normalized Source EUI (kBtu/ft2)',
                     'Postal Code', # dummify or just use downtown
                     'Floor Area',
                     'Property Type', # dummify
                     'Property Type - Self Selected',
                     'Previous Year ENERGY STAR Score',
                     'Two Years Ago ENERGY STAR Score',
                     'Current Year YoY Change',
                     'Previous Year YoY Change',
                     'Age In Years',
                     'Recalculated GHG Emissions Intensity (kgCO2e/ft2)',
                     'Is Downtown'
                     ]
```

In [5]:
```
df[features_relevant].head()
```

Out[5]:

	Benchmark Status	Percent Better than National Median Site EUI	Percent Better than National Median Source EUI	Site EUI (kBtu/ft2)	Source EUI (kBtu/ft2)	Total GHG Emissions (Metric Tons CO2e)	Weather Normalized Site EUI (kBtu/ft2)	Weather Normalized Source EUI (kBtu/ft2)	Postal Code	Floor Area	Property Type	Property Type - Self Selected
0	Complied	-34.5	NaN	71.0	149.9	696.4	70.7	149.7	94109	133675	Commercial	Office
1	Complied	-26.2	-26.2	81.3	166.9	786.5	81.6	167.2	94109	133675	Commercial	Office
2	Complied	-6.5	-6.5	73.4	158.5	668.9	77.1	162.4	94109	133675	Commercial	Office
3	Complied	-23.0	-23.0	72.0	153.9	653.2	73.7	155.6	94109	133675	Commercial	Office
4	Complied	-26.3	-26.3	68.2	149.7	652.4	71.5	153.2	94109	133675	Commercial	Office

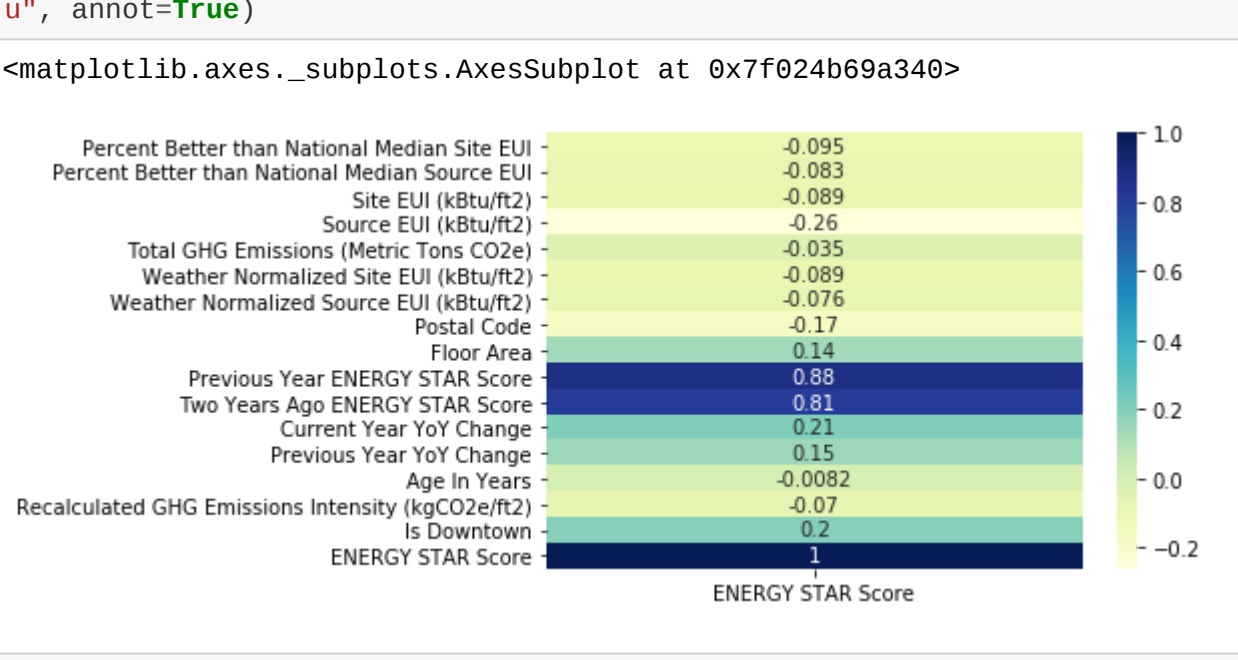
In [6]:
```
df[features_relevant].corr()
```

Out[6]:

	Percent Better than National Median Site EUI	Percent Better than National Median Source EUI	Site EUI (kBtu/ft2)	Source EUI (kBtu/ft2)	Total GHG Emissions (Metric Tons CO2e)	Weather Normalized Site EUI (kBtu/ft2)	Weather Normalized Source EUI (kBtu/ft2)	Postal Code	Floor Area	Previous Year ENERGY STAR Score	Two Years Ago ENERGY STAR Score
Percent Better than National Median Site EUI	1.000000	1.000000	0.541813	0.331405	0.505267	0.541836	0.107165	-0.001484	0.017363	-0.629496	-0.692431
Percent Better than National Median Source EUI	1.000000	1.000000	0.320454	0.369592	0.046188	0.320874	0.370344	0.004211	-0.011450	-0.747729	-0.688712
Site EUI (kBtu/ft2)	0.541813	0.320454	1.000000	0.976556	0.988061	0.999996	0.311532	-0.003660	0.058741	-0.468445	-0.480293
Source EUI (kBtu/ft2)	0.331405	0.369592	0.976556	1.000000	0.363663	0.975969	0.999954	0.034772	0.027929	-0.398987	-0.426978
Total GHG Emissions (Metric Tons CO2e)	0.505267	0.046188	0.988061	0.363663	1.000000	0.988128	0.112370	-0.013593	0.073425	-0.013241	-0.021322
Weather Normalized Site EUI (kBtu/ft2)	0.541836	0.320874	0.999996	0.975969	0.988128	1.000000	0.311295	-0.003715	0.058921	-0.468582	-0.479767
Weather Normalized Source EUI (kBtu/ft2)	0.107165	0.370344	0.311532	0.999954	0.112370	0.311295	1.000000	0.017701	0.004465	-0.399114	-0.427147
Postal Code	-0.001484	0.004211	-0.003660	0.034772	-0.013593	-0.003715	0.017701	1.000000	-0.163200	-0.181261	-0.176079
Floor Area	0.017363	-0.011450	0.058741	0.027929	0.073425	0.058921	0.004465	-0.163200	1.000000	0.144040	0.139260
Previous Year ENERGY STAR Score	-0.629496	-0.747729	-0.468445	-0.398987	-0.013241	-0.468582	-0.399114	-0.181261	0.144040	1.000000	0.889080
Two Years Ago ENERGY STAR Score	-0.692431	-0.688712	-0.480293	-0.426978	-0.021322	-0.479767	-0.427147	-0.176079	0.139260	0.889080	1.000000
Current Year YoY Change	-0.157385	-0.165862	-0.008966	0.000683	-0.007109	-0.005291	0.003872	-0.003458	0.005700	-0.270621	-0.202551
Previous Year YoY Change	-0.121866	-0.140485	-0.017262	-0.016883	0.000529	-0.020566	-0.020786	-0.002176	0.016218	0.214960	-0.255933
Age In Years	-0.002531	-0.002337	0.005557	0.036065	0.000444	0.004619	0.008779	-0.021440	0.059143	-0.003136	-0.005911
Recalculated GHG Emissions Intensity (kgCO2e/ft2)	0.539781	0.400893	0.998786	0.969472	0.991470	0.998786	0.310287	-0.008407	0.059073	-0.433598	-0.470165
Is Downtown	-0.005797	0.004601	-0.025159	-0.045407	-0.010820	-0.025334	-0.027068	-0.578798	0.145728	0.209342	0.207887

In [33]:
```
sns.heatmap(df[features_relevant + ['ENERGY STAR Score']].corr()[['ENERGY STAR Score']], cmap="YlGnB
u", annot=True)
```

Out[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f024b69a340>
```



In [34]:
```
df[features_relevant].dtypes
```

Out[34]:
```
Benchmark Status                                     object
Percent Better than National Median Site EUI        float64
Percent Better than National Median Source EUI      float64
Site EUI (kBtu/ft2)                                 float64
Source EUI (kBtu/ft2)                               float64
Total GHG Emissions (Metric Tons CO2e)              float64
Weather Normalized Site EUI (kBtu/ft2)              float64
Weather Normalized Source EUI (kBtu/ft2)            float64
Postal Code                                           int64
Floor Area                                            int64
Property Type                                        object
Property Type - Self Selected                        object
Previous Year ENERGY STAR Score                     float64
Two Years Ago ENERGY STAR Score                     float64
Current Year YoY Change                             float64
Previous Year YoY Change                            float64
Age In Years                                        float64
Recalculated GHG Emissions Intensity (kgCO2e/ft2)   float64
Is Downtown                                            bool
dtype: object
```

In [3]:
```
# dummify features
property_dummies = pd.get_dummies(df['Property Type'])
benchmark_dummies = pd.get_dummies(df['Benchmark Status'])
df['Is Downtown'] = df['Is Downtown'].astype(int)

dummies_all = pd.concat([property_dummies, benchmark_dummies], axis=1)

df_dummies = pd.concat([df, dummies_all], axis=1)
```

In [35]:
```
lm_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

lm_data1 = lm_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                ], axis=1)

lm_data1 = lm_data1.dropna()

X_train = lm_data1[~lm_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axi
s=1)
y_train = lm_data1[~lm_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = lm_data1[lm_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=
1)
y_test = lm_data1[lm_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_train = sm.add_constant(X_train)

est = sm.OLS(y_train, X_train).fit()
print(est.summary())

y_pred = est.predict(X_test)
print(r2_score(y_test, y_pred))
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      ENERGY STAR Score   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 1.237e+26
Date:                Mon, 14 Dec 2020   Prob (F-statistic):               0.00
Time:                        16:35:04   Log-Likelihood:                 63091.
No. Observations:                2765   AIC:                        -1.261e+05
Df Residuals:                    2748   BIC:                        -1.260e+05
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================================
================
                                                        coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------------------------------
----------------
Percent Better than National Median Site EUI       1.38e-13   3.66e-11      0.004      0.997   -7.16
e-11    7.18e-11
Percent Better than National Median Source EUI    1.432e-14   3.66e-11      0.000      1.000   -7.17
e-11    7.17e-11
Site EUI (kBtu/ft2)                               2.498e-15   7.61e-13      0.003      0.997   -1.49
e-12    1.49e-12
Source EUI (kBtu/ft2)                             2.736e-15   5.56e-13      0.005      0.996   -1.09
e-12    1.09e-12
Total GHG Emissions (Metric Tons CO2e)            7.967e-17   9.23e-16      0.086      0.931   -1.73
e-15    1.89e-15
Weather Normalized Site EUI (kBtu/ft2)             1.86e-15   7.57e-13      0.002      0.998   -1.48
e-12    1.49e-12
Weather Normalized Source EUI (kBtu/ft2)         -2.904e-15   5.56e-13     -0.005      0.996   -1.09
e-12    1.09e-12
Floor Area                                       -8.535e-17   4.62e-18    -18.457      0.000   -9.44
e-17   -7.63e-17
Previous Year ENERGY STAR Score                      0.6667   3.18e-14   2.09e+13      0.000
0.667       0.667
Two Years Ago ENERGY STAR Score                      0.3333    2.4e-14   1.39e+13      0.000
0.333       0.333
Current Year YoY Change                              1.0000   6.51e-14   1.54e+13      0.000
1.000       1.000
Previous Year YoY Change                             0.3333   3.61e-14   9.24e+12      0.000
0.333       0.333
Age In Years                                      3.743e-17   1.44e-15      0.026      0.979   -2.78
e-15    2.85e-15
Recalculated GHG Emissions Intensity (kgCO2e/ft2)  7.906e-16   4.79e-13      0.002      0.999   -9.39
e-13    9.41e-13
Is Downtown                                      -7.896e-15   1.19e-12     -0.007      0.995   -2.34
e-12    2.32e-12
Commercial                                        5.237e-15   8.69e-12      0.001      1.000    -1.7
e-11     1.7e-11
Mixed Residential                                -1.991e-20   3.37e-28  -5.91e+07      0.000   -1.99
e-20   -1.99e-20
Multifamily                                               0          0        nan        nan
   0           0
Residential                                               0          0        nan        nan
   0           0
Complied                                          8.653e-15    8.4e-12      0.001      0.999   -1.65
e-11    1.65e-11
Data Not Verified                                -6.811e-15   2.27e-11     -0.000      1.000   -4.46
e-11    4.46e-11
Exempt                                                    0          0        nan        nan
   0           0
Violation - Insufficient Data                    -1.801e-14   1.35e-11     -0.001      0.999   -2.66
e-11    2.65e-11
==============================================================================
Omnibus:                     1481.789   Durbin-Watson:                   0.255
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            15217.793
Skew:                           2.337   Prob(JB):                         0.00
Kurtosis:                      13.499   Cond. No.                          inf
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is      0. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
1.0
```

```
/opt/conda/lib/python3.8/site-packages/statsmodels/regression/linear_model.py:1830: RuntimeWarning: d
ivide by zero encountered in double_scalars
  return np.sqrt(eigvals[0]/eigvals[-1])
/opt/conda/lib/python3.8/site-packages/statsmodels/base/model.py:1362: RuntimeWarning: invalid value
encountered in true_divide
  return self.params / self.bse
/opt/conda/lib/python3.8/site-packages/scipy/stats/_distn_infrastructure.py:1932: RuntimeWarning: inv
alid value encountered in less_equal
  cond2 = cond0 & (x <= _a)
```

In [32]:

```python
# take out multicollinear variables
lm_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

lm_data1 = lm_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                'Two Years Ago ENERGY STAR Score',
                'Weather Normalized Source EUI (kBtu/ft2)',
                'Percent Better than National Median Source EUI',
                'Current Year YoY Change',
                'Total GHG Emissions (Metric Tons CO2e)',
                'Source EUI (kBtu/ft2)',
                ], axis=1)

lm_data1 = lm_data1.dropna()

X_train = lm_data1[~lm_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_train = lm_data1[~lm_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = lm_data1[lm_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_test = lm_data1[lm_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_train = sm.add_constant(X_train)

est = sm.OLS(y_train, X_train).fit()
print(est.summary())

y_pred = est.predict(X_test)
print(r2_score(y_test, y_pred))
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      ENERGY STAR Score   R-squared:                       0.876
Model:                            OLS   Adj. R-squared:                  0.875
Method:                 Least Squares   F-statistic:                     1762.
Date:                Mon, 14 Dec 2020   Prob (F-statistic):               0.00
Time:                        16:34:02   Log-Likelihood:                -9973.2
No. Observations:                2765   AIC:                         1.997e+04
Df Residuals:                    2753   BIC:                         2.004e+04
Df Model:                          11
Covariance Type:            nonrobust
==================================================================================================
================
                                                     coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------------------------
----------------
Percent Better than National Median Site EUI        -0.1597      0.006    -26.205      0.000      -
0.172      -0.148
Site EUI (kBtu/ft2)                                 -0.1482      0.104     -1.422      0.155      -
0.352       0.056
Weather Normalized Site EUI (kBtu/ft2)               0.1115      0.104      1.075      0.282      -
0.092       0.315
Floor Area                                        2.516e-06   6.88e-07      3.657      0.000    1.17
e-06    3.87e-06
Previous Year ENERGY STAR Score                      0.6548      0.011     61.913      0.000
0.634       0.676
Previous Year YoY Change                            -0.0378      0.016     -2.420      0.016      -
0.068      -0.007
Age In Years                                         0.0002      0.000      0.469      0.639      -
0.001       0.001
Recalculated GHG Emissions Intensity (kgCO2e/ft2)    0.2946      0.139      2.115      0.035
0.021       0.568
Is Downtown                                          1.0287      0.353      2.914      0.004
0.337       1.721
Commercial                                          18.5215      2.566      7.219      0.000      1
3.491      23.552
Mixed Residential                                -3.074e-16   1.76e-15     -0.175      0.861   -3.76
e-15    3.15e-15
Multifamily                                       1.925e-16   4.38e-16      0.440      0.660   -6.65
e-16    1.05e-15
Residential                                               0          0        nan        nan
   0           0
Complied                                             3.2800      2.509      1.307      0.191      -
1.640       8.200
Data Not Verified                                   -1.4084      6.801     -0.207      0.836     -1
4.744      11.927
Exempt                                                    0          0        nan        nan
   0           0
Violation - Insufficient Data                       16.6500      4.036      4.126      0.000
8.737      24.563
==============================================================================
Omnibus:                     1520.982   Durbin-Watson:                   1.654
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           124010.017
Skew:                           1.735   Prob(JB):                         0.00
Kurtosis:                      35.624   Cond. No.                          inf
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is      0. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
0.8104461640486299
```

```
/opt/conda/lib/python3.8/site-packages/statsmodels/regression/linear_model.py:1830: RuntimeWarning: divide by zero encountered in double_scalars
  return np.sqrt(eigvals[0]/eigvals[-1])
/opt/conda/lib/python3.8/site-packages/statsmodels/base/model.py:1362: RuntimeWarning: invalid value encountered in true_divide
  return self.params / self.bse
/opt/conda/lib/python3.8/site-packages/scipy/stats/_distn_infrastructure.py:1932: RuntimeWarning: invalid value encountered in less_equal
  cond2 = cond0 & (x <= _a)
```

In [61]:

```python
# take out multicollinear variables
# and take out insignificant features
# take out dummies where there are no values in that col

lm_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

lm_data1 = lm_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                'Two Years Ago ENERGY STAR Score',
                'Weather Normalized Source EUI (kBtu/ft2)',
                'Percent Better than National Median Source EUI',
                'Current Year YoY Change',
                'Total GHG Emissions (Metric Tons CO2e)',
                'Source EUI (kBtu/ft2)',
                'Age In Years'
                ], axis=1)

lm_data1 = lm_data1.dropna()
nunique_df = lm_data1.apply(pd.Series.nunique)
cols_to_drop = nunique_df[nunique_df == 1].index
lm_data1 = lm_data1.drop(cols_to_drop, axis=1)

X_train = lm_data1[~lm_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_train = lm_data1[~lm_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = lm_data1[lm_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_test = lm_data1[lm_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

# X_train = sm.add_constant(X_train)
# X_test = sm.add_constant(X_test)

est = sm.OLS(y_train, X_train).fit()
print(est.summary())

y_pred = est.predict(X_test)
print(r2_score(y_test, y_pred))
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      ENERGY STAR Score   R-squared:                       0.876
Model:                            OLS   Adj. R-squared:                  0.875
Method:                 Least Squares   F-statistic:                     1939.
Date:                Tue, 15 Dec 2020   Prob (F-statistic):               0.00
Time:                        06:55:08   Log-Likelihood:                -9973.3
No. Observations:                2765   AIC:                         1.997e+04
Df Residuals:                    2754   BIC:                         2.003e+04
Df Model:                          10
Covariance Type:            nonrobust
==================================================================================================
================
                                                     coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------------------------
----------------
Percent Better than National Median Site EUI        -0.1598      0.006    -26.276      0.000      -
0.172      -0.148
Site EUI (kBtu/ft2)                                 -0.1500      0.104     -1.440      0.150      -
0.354       0.054
Weather Normalized Site EUI (kBtu/ft2)               0.1131      0.104      1.092      0.275      -
0.090       0.316
Floor Area                                        2.518e-06   6.88e-07      3.661      0.000    1.17
e-06    3.87e-06
Previous Year ENERGY STAR Score                      0.6547      0.011     61.923      0.000
0.634       0.675
Previous Year YoY Change                            -0.0376      0.016     -2.407      0.016      -
0.068      -0.007
Recalculated GHG Emissions Intensity (kgCO2e/ft2)    0.2999      0.139      2.160      0.031
0.028       0.572
Is Downtown                                          1.0326      0.353      2.927      0.003
0.341       1.724
Complied                                            21.8190      0.782     27.903      0.000      2
0.286      23.352
Data Not Verified                                   17.1038      8.975      1.906      0.057      -
0.494      34.702
Violation - Insufficient Data                       35.2652      4.530      7.785      0.000      2
6.383      44.147
==============================================================================
Omnibus:                     1520.500   Durbin-Watson:                   1.654
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           123926.442
Skew:                           1.734   Prob(JB):                         0.00
Kurtosis:                      35.614   Cond. No.                     1.63e+07
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.63e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
0.8109496927839122
```

In [59]:

```python
X_test.columns
```

Out[59]:

```
Index(['Percent Better than National Median Site EUI', 'Site EUI (kBtu/ft2)',
       'Weather Normalized Site EUI (kBtu/ft2)', 'Floor Area',
       'Previous Year ENERGY STAR Score', 'Previous Year YoY Change',
       'Recalculated GHG Emissions Intensity (kgCO2e/ft2)', 'Is Downtown',
       'Complied', 'Data Not Verified', 'Violation - Insufficient Data'],
      dtype='object')
```

In [60]:

```python
X_train.columns
```

Out[60]:

```
Index(['const', 'Percent Better than National Median Site EUI',
       'Site EUI (kBtu/ft2)', 'Weather Normalized Site EUI (kBtu/ft2)',
       'Floor Area', 'Previous Year ENERGY STAR Score',
       'Previous Year YoY Change',
       'Recalculated GHG Emissions Intensity (kgCO2e/ft2)', 'Is Downtown',
       'Complied', 'Data Not Verified', 'Violation - Insufficient Data'],
      dtype='object')
```

Random Forest

With all relevant features, default hyperparameters

In [16]:

```python
rf_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

rf_data1 = rf_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                ], axis=1)

rf_data1 = rf_data1.dropna()

X_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

regr = RandomForestRegressor()

regr.fit(X_train, y_train.values.ravel())
print(regr.score(X_train, y_train))
print(regr.score(X_test, y_test))

for (x, y) in zip(X_train.columns, regr.feature_importances_):
    print(x, round(y, 3))
```

```
0.9992659778605959
0.9795223362758568
Percent Better than National Median Site EUI 0.464
Percent Better than National Median Source EUI 0.526
Site EUI (kBtu/ft2) 0.001
Source EUI (kBtu/ft2) 0.001
Total GHG Emissions (Metric Tons CO2e) 0.0
Weather Normalized Site EUI (kBtu/ft2) 0.001
Weather Normalized Source EUI (kBtu/ft2) 0.001
Floor Area 0.0
Previous Year ENERGY STAR Score 0.002
Two Years Ago ENERGY STAR Score 0.0
Current Year YoY Change 0.001
Previous Year YoY Change 0.0
Age In Years 0.0
Recalculated GHG Emissions Intensity (kgCO2e/ft2) 0.001
Is Downtown 0.0
Commercial 0.0
Mixed Residential 0.0
Multifamily 0.0
Residential 0.0
Complied 0.0
Data Not Verified 0.0
Exempt 0.0
Violation - Insufficient Data 0.0
```

With cross validation of the complexity parameter

Note that we are using only X_train, so data from prior to 2018

Looks like they are all pretty good, with accuracy 0.99

In [50]:

```python
# With everything
rf_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

rf_data1 = rf_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                ], axis=1)

rf_data1 = rf_data1.dropna()

X_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

CPs = [0.0, 0.005, 0.01, 0.015, 0.02, 0.025]

kf = KFold(n_splits=5)

for cp in CPs:

    regr = RandomForestRegressor(ccp_alpha=cp)
    scores = []

    for k, (train_index, test_index) in enumerate(kf.split(X_train.values)):

        X_train_kfold, X_test_kfold = X_train.values[train_index], X_train.values[test_index]
        y_train_kfold, y_test_kfold = y_train.values[train_index], y_train.values[test_index]

        regr.fit(X_train_kfold, y_train_kfold.ravel())

        scores.append(regr.score(X_test_kfold, y_test_kfold))

    print('Mean score for cp {}: {}'.format(cp, np.round(np.mean(scores), 2)))
    print()
```

```
Mean score for cp 0.0: 0.99

Mean score for cp 0.005: 0.99

Mean score for cp 0.01: 0.99

Mean score for cp 0.015: 0.99

Mean score for cp 0.02: 0.99

Mean score for cp 0.025: 0.99
```

With cross validation of the max number of features to sample

In [52]:

```python
# Starting at all the features, moving towards just 1

# With everything
rf_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

rf_data1 = rf_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                ], axis=1)

rf_data1 = rf_data1.dropna()

X_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

features_to_sample = np.arange(X_train.shape[1], 0, -1)

for f in features_to_sample:

    clf = RandomForestRegressor(max_features=f)
    scores = []

    for k, (train_index, test_index) in enumerate(kf.split(X_train.values)):

        X_train_kfold, X_test_kfold = X_train.values[train_index], X_train.values[test_index]
        y_train_kfold, y_test_kfold = y_train.values[train_index], y_train.values[test_index]

        regr.fit(X_train_kfold, y_train_kfold.ravel())

        scores.append(regr.score(X_test_kfold, y_test_kfold))

    print('Mean score for max_features {}: {}'.format(f, np.round(np.mean(scores), 2)))
    print()
```

```
Mean score for max_features 23: 0.99

Mean score for max_features 22: 0.99

Mean score for max_features 21: 0.99

Mean score for max_features 20: 0.99

Mean score for max_features 19: 0.99

Mean score for max_features 18: 0.99

Mean score for max_features 17: 0.99

Mean score for max_features 16: 0.99

Mean score for max_features 15: 0.99

Mean score for max_features 14: 0.99

Mean score for max_features 13: 0.99

Mean score for max_features 12: 0.99

Mean score for max_features 11: 0.99

Mean score for max_features 10: 0.99

Mean score for max_features 9: 0.99

Mean score for max_features 8: 0.99

Mean score for max_features 7: 0.99

Mean score for max_features 6: 0.99

Mean score for max_features 5: 0.99

Mean score for max_features 4: 0.99

Mean score for max_features 3: 0.99

Mean score for max_features 2: 0.99

Mean score for max_features 1: 0.99
```

In [53]:

```python
# Do the same thing on max depth (max depth of the trees)
# Starting at all the features, moving towards just 1

rf_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

rf_data1 = rf_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                ], axis=1)

rf_data1 = rf_data1.dropna()

X_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

max_depths = np.arange(1, 10)

print([x for x in X_train.columns])

for d in max_depths:

    clf = RandomForestRegressor(max_depth=d)
    scores = []

    for k, (train_index, test_index) in enumerate(kf.split(X_train.values)):

        X_train_kfold, X_test_kfold = X_train.values[train_index], X_train.values[test_index]
        y_train_kfold, y_test_kfold = y_train.values[train_index], y_train.values[test_index]

        regr.fit(X_train_kfold, y_train_kfold.ravel())

        scores.append(regr.score(X_test_kfold, y_test_kfold))

    print('Mean score for max_depth {}: {}'.format(d, np.round(np.mean(scores), 2)))
    print()
```

```
['Percent Better than National Median Site EUI', 'Percent Better than National Median Source EUI', 'Site EUI (kBtu/ft2)', 'Source EUI (kBtu/ft2)', 'Total GHG Emissions (Metric Tons CO2e)', 'Weather Normalized Site EUI (kBtu/ft2)', 'Weather Normalized Source EUI (kBtu/ft2)', 'Floor Area', 'Previous Year ENERGY STAR Score', 'Two Years Ago ENERGY STAR Score', 'Current Year YoY Change', 'Previous Year YoY Change', 'Age In Years', 'Recalculated GHG Emissions Intensity (kgCO2e/ft2)', 'Is Downtown', 'Commercial', 'Mixed Residential', 'Multifamily', 'Residential', 'Complied', 'Data Not Verified', 'Exempt', 'Violation - Insufficient Data']
Mean score for max_depth 1: 0.99

Mean score for max_depth 2: 0.99

Mean score for max_depth 3: 0.99

Mean score for max_depth 4: 0.99

Mean score for max_depth 5: 0.99

Mean score for max_depth 6: 0.99

Mean score for max_depth 7: 0.99

Mean score for max_depth 8: 0.99

Mean score for max_depth 9: 0.99
```

Suppose the building is new, and we must take out the previous 1 and 2 years' scores and YoY change, how do they models perform in this case?

Linear Regression

In [38]:

```python
# take out multicollinear variables
lm_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

lm_data1 = lm_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                'Two Years Ago ENERGY STAR Score',
                'Weather Normalized Source EUI (kBtu/ft2)',
                'Percent Better than National Median Source EUI',
                'Current Year YoY Change',
                'Total GHG Emissions (Metric Tons CO2e)',
                'Source EUI (kBtu/ft2)',
                'Previous Year ENERGY STAR Score',
                'Previous Year YoY Change'
                ], axis=1)

lm_data1 = lm_data1.dropna()

X_train = lm_data1[~lm_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_train = lm_data1[~lm_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = lm_data1[lm_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_test = lm_data1[lm_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_train = sm.add_constant(X_train)

est = sm.OLS(y_train, X_train).fit()
print(est.summary())

y_pred = est.predict(X_test)
print(r2_score(y_test, y_pred))
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:      ENERGY STAR Score   R-squared:                       0.208
Model:                            OLS   Adj. R-squared:                  0.206
Method:                 Least Squares   F-statistic:                     122.5
Date:                Tue, 15 Dec 2020   Prob (F-statistic):          1.20e-227
Time:                        06:06:57   Log-Likelihood:                -21348.
No. Observations:                4684   AIC:                         4.272e+04
Df Residuals:                    4673   BIC:                         4.279e+04
Df Model:                          10
Covariance Type:            nonrobust
==================================================================================================
================
                                                     coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------------------------
----------------
Percent Better than National Median Site EUI        -0.0012      0.000     -3.113      0.002      -
0.002      -0.000
Site EUI (kBtu/ft2)                                 -0.5443      0.170     -3.202      0.001      -
0.878      -0.211
Weather Normalized Site EUI (kBtu/ft2)               0.2369      0.169      1.400      0.161      -
0.095       0.569
Floor Area                                        1.595e-05   1.41e-06     11.323      0.000    1.32
e-05    1.87e-05
Age In Years                                         0.0004      0.001      0.514      0.607      -
0.001       0.002
Recalculated GHG Emissions Intensity (kgCO2e/ft2)    3.4486      0.122     28.319      0.000
3.210       3.687
Is Downtown                                          6.9706      0.692     10.075      0.000
5.614       8.327
Commercial                                          56.1895      5.291     10.621      0.000      4
5.817      66.562
Mixed Residential                                 -6.73e-15   1.86e-15     -3.628      0.000   -1.04
e-14   -3.09e-15
Multifamily                                      -3.673e-15   3.11e-15     -1.181      0.238   -9.77
e-15    2.42e-15
Residential                                       1.431e-15   2.32e-15      0.617      0.537   -3.11
e-15    5.98e-15
Complied                                            15.4958      5.275      2.938      0.003
5.155      25.837
Data Not Verified                                   13.3845     18.654      0.718      0.473     -2
3.187      49.955
Exempt                                              14.4052      7.736      1.862      0.063      -
0.761      29.571
Violation - Insufficient Data                       12.9041      9.585      1.346      0.178      -
5.887      31.695
==============================================================================
Omnibus:                      697.912   Durbin-Watson:                   0.705
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1185.587
Skew:                          -0.984   Prob(JB):                    3.57e-258
Kurtosis:                       4.483   Cond. No.                     7.17e+26
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 7.65e-40. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
-0.6797592718143906
```

In [ ]:

```python
# Previous Year ENERGY STAR Score
# Two Years Ago ENERGY STAR Score
# Current Year YoY Change
# Previous Year YoY Change
```

In [7]:

```python
# No previous years' data
# Default hyperparameters

rf_data1 = df_dummies[features_relevant+ dummies_all.columns.to_list() + ['ENERGY STAR Score']]

rf_data1 = rf_data1.drop(['Benchmark Status',
                'Postal Code',
                'Property Type',
                'Property Type - Self Selected',
                'Previous Year ENERGY STAR Score',
                'Two Years Ago ENERGY STAR Score',
                'Current Year YoY Change',
                'Previous Year YoY Change'
                ], axis=1)

rf_data1 = rf_data1.dropna()

X_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_train = rf_data1[~rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

X_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])].drop(['year', 'ENERGY STAR Score'], axis=1)
y_test = rf_data1[rf_data1['year'].isin(['2018', '2019'])][['ENERGY STAR Score']]

regr = RandomForestRegressor()

regr.fit(X_train, y_train.values.ravel())
print(regr.score(X_train, y_train))
print(regr.score(X_test, y_test))

for (x, y) in zip(X_train.columns, regr.feature_importances_):
    print(x, round(y, 3))
```

```
0.9989187620805361
0.9745513961848253
```

In [15]:

```python
for (x, y) in zip(X_train.columns, regr.feature_importances_):
    print(x, round(y, 3))
```

```
Percent Better than National Median Site EUI 0.444
Percent Better than National Median Source EUI 0.545
Site EUI (kBtu/ft2) 0.002
Source EUI (kBtu/ft2) 0.002
Total GHG Emissions (Metric Tons CO2e) 0.001
Weather Normalized Site EUI (kBtu/ft2) 0.002
Weather Normalized Source EUI (kBtu/ft2) 0.002
Floor Area 0.001
Age In Years 0.001
Recalculated GHG Emissions Intensity (kgCO2e/ft2) 0.001
Is Downtown 0.0
Commercial 0.0
Mixed Residential 0.0
Multifamily 0.0
Residential 0.0
Complied 0.0
Data Not Verified 0.0
Exempt 0.0
Violation - Insufficient Data 0.0
```

In [17]:

```python
frame = { 'Feature': X_train.columns, 'Feature importance': regr.feature_importances_ }
```

In [22]:

```python
pd.DataFrame(frame)
```

Out[22]:

	Feature	Feature importance
0	Percent Better than National Median Site EUI	0.463618
1	Percent Better than National Median Source EUI	0.525884
2	Site EUI (kBtu/ft2)	0.001293
3	Source EUI (kBtu/ft2)	0.000923
4	Total GHG Emissions (Metric Tons CO2e)	0.000491
5	Weather Normalized Site EUI (kBtu/ft2)	0.001181
6	Weather Normalized Source EUI (kBtu/ft2)	0.001027
7	Floor Area	0.000403
8	Previous Year ENERGY STAR Score	0.001688
9	Two Years Ago ENERGY STAR Score	0.000443
10	Current Year YoY Change	0.001369
11	Previous Year YoY Change	0.000225
12	Age In Years	0.000402
13	Recalculated GHG Emissions Intensity (kgCO2e/ft2)	0.000981
14	Is Downtown	0.000065
15	Commercial	0.000000
16	Mixed Residential	0.000000
17	Multifamily	0.000000
18	Residential	0.000000
19	Complied	0.000003
20	Data Not Verified	0.000002
21	Exempt	0.000000
22	Violation - Insufficient Data	0.000002

In [ ]: