In [1]:

```
import os
mingw_path = 'C:\\Program Files\\mingw-w64\\x86_64-5.3.0-posix-seh-rt_v4-rev0\\mingw64
\\bin'
os.environ['PATH'] = mingw_path + ';' + os.environ['PATH']
os.environ['PATH'] = mingw_path + ';' + os.environ['PATH']
import xgboost as xgb
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import warnings
from sklearn.cross_validation import train_test_split
from sklearn.linear_model import LinearRegression
warnings.filterwarnings("ignore", category=DeprecationWarning)
from mpl_toolkits.basemap import Basemap
import missingno as msno
import matplotlib.pylab as pylab
import gmplot
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import Imputer
import numpy as np
import numpy as np
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
sns.set(style="whitegrid", color_codes=True)
pylab.rcParams['figure.figsize'] = 16, 12
pd.options.mode.chained_assignment = None
%matplotlib inline
```

```
C:\Users\sugan\Anaconda3\lib\site-packages\sklearn\cross_validation.py:44:
DeprecationWarning: This module was deprecated in version 0.18 in favor of
the model_selection module into which all the refactored classes and funct
ions are moved. Also note that the interface of the new CV iterators are d
ifferent from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [2]:

```
train = pd.read_csv('train_2017.csv') #this data includes log error and parcel ID of ye
ar 2017
prop = pd.read_csv('properties_2017.csv') #this data includes log error and parcel ID o
f year 2017
train.head()
```

```
C:\Users\sugan\Anaconda3\lib\site-packages\IPython\core\interactiveshell.p
y:2717: DtypeWarning: Columns (49) have mixed types. Specify dtype option
on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Out[2]:

	parcelid	logerror	transactiondate
0	14297519	0.025595	2017-01-01
1	17052889	0.055619	2017-01-01
2	14186244	0.005383	2017-01-01
3	12177905	-0.103410	2017-01-01
4	10887214	0.006940	2017-01-01

chaging the data types of the given data

In [3]:

```
categorical = ['airconditioningtypeid', 'architecturalstyletypeid', 'buildingclasstypei
d', 'fips', 'hashottuborspa',
               'propertycountylandusecode', 'propertyzoningdesc', 'rawcensustractandblo
ck', 'censustractandblock', 'regionidcounty', 'regionidcity',
               'regionidzip', 'regionidneighborhood','buildingqualitytypeid', 'decktype
id', 'heatingorsystemtypeid', 'pooltypeid10', 'pooltypeid2', 'pooltypeid7',
     'propertylandusetypeid', 'storytypeid', 'typeconstructiontypeid', 'taxdelinquencyf
lag', 'taxdelinquencyyear']
for col in categorical:
    prop[col] =prop[col].astype('category')
train['transactiondate'] = pd.to_datetime(train['transactiondate'])
```

Renaming the columns

In [4]:

```
data_dict = pd.read_excel('zillow_data_dictionary.xlsx', parse_cols="A:B")
features = data_dict['Feature'].apply(lambda x:x.strip("'"))
data_dict['Feature'] = features
d = {} #forming a dictionary to rename columns
for a,b in data_dict.iterrows():
    d[b['Feature']] = b['Rename']

#Rename Columns
prop.rename_axis(d,axis=1,inplace=True)

#Making a copy of data frame for future analysis purpose
prop_copy = prop.copy()
```

Merging the house attributes data and house transaction data

In [6]:

```
merge_df = prop.merge(train, how ='inner')
total_df = prop.merge(train, how = 'left')
total_df['transactiondate'] = pd.to_datetime(total_df['transactiondate'])
```

In [8]:

```
merge_df['transactiondate'] = pd.to_datetime(merge_df['transactiondate'])
merge_df['month']=merge_df['transactiondate'].dt.month
merge_df['day'] = merge_df['transactiondate'].dt.day
merge_df['quarter'] = merge_df['transactiondate'].dt.quarter
merge_df['transaction_year'] = merge_df['transactiondate'].dt.year
merge_df['age'] = 2017 - merge_df['yearbuilt']
merge_df['month'] = merge_df['month'].astype('category')
merge_df['quarter'] = merge_df['quarter'].astype('category')
```

View of the data

In [9]:

```
merge_df.head()
```

Out[9]:

	parcelid	ac_type	arch_Type	basementsqft	total_bathcnt	bedroomcnt	building_
0	17054981	NaN	NaN	NaN	5.0	4.0	NaN
1	17055743	NaN	NaN	NaN	2.0	3.0	NaN
2	17068109	NaN	NaN	NaN	1.5	3.0	NaN
3	17073952	NaN	NaN	NaN	2.0	2.0	NaN
4	17078502	NaN	NaN	NaN	1.0	2.0	NaN

5 rows × 65 columns

- Data consists of 64 columns and we can see that Null values are present we have to process the data to remove them

In [10]:

```
merge_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77613 entries, 0 to 77612
Data columns (total 65 columns):
parcelid                     77613 non-null int64
ac_type                      25007 non-null category
arch_Type                    207 non-null category
basementsqft                 50 non-null float64
total_bathcnt                77579 non-null float64
bedroomcnt                   77579 non-null float64
building_class               15 non-null category
building_quality             49809 non-null category
calculatedbathnbr            76963 non-null float64
decktypeid                   614 non-null category
firstfloor_finisharea        6037 non-null float64
total_finisharea             77378 non-null float64
finished_living              73923 non-null float64
perimeter_living             42 non-null float64
total_area                   3027 non-null float64
firstfloor_finisharea        6037 non-null float64
basetotalarea                386 non-null float64
fips                         77579 non-null category
fireplacecnt                 8289 non-null float64
fullbathcnt                  76963 non-null float64
garagecarcnt                 25520 non-null float64
garagetotalsqft              25520 non-null float64
hashottuborspa               1539 non-null category
heatingid                    49571 non-null category
latitude                     77579 non-null float64
longitude                    77579 non-null float64
lotsizesquarefeet            69321 non-null float64
poolcnt                      16174 non-null float64
poolsizesum                  869 non-null float64
pooltypeid10                 465 non-null category
pooltypeid2                  1074 non-null category
pooltypeid7                  15079 non-null category
landusecode                  77579 non-null category
landusetypeid                77579 non-null category
zoningdesc                   50476 non-null category
rawcensustractandblock       77579 non-null category
city                         76107 non-null category
county                       77579 non-null category
neighborhood                 30974 non-null category
zip                          77529 non-null category
roomcnt                      77579 non-null float64
storytypeid                  50 non-null category
3/4bathnbr                   10106 non-null float64
typeconstructiontypeid       223 non-null category
unitcnt                      50703 non-null float64
yardbuildingsqft17           2393 non-null float64
yardbuildingsqft26           70 non-null float64
yearbuilt                    77309 non-null float64
numberofstories              17599 non-null float64
fireplaceflag                172 non-null object
structuretaxvaluedollarcnt   77464 non-null float64
totaltax                     77578 non-null float64
assessmentyear               77579 non-null float64
landtaxvaluedollarcnt        77577 non-null float64
taxperyear                   77574 non-null float64
taxdelinquencyflag           2900 non-null category
taxdelinquencyyear           2900 non-null category
censustractandblock          77332 non-null category
```

```
logerror                     77613 non-null float64
transactiondate              77613 non-null datetime64[ns]
month                        77613 non-null category
day                          77613 non-null int64
quarter                      77613 non-null category
transaction_year             77613 non-null int64
age                          77309 non-null float64
dtypes: category(26), datetime64[ns](1), float64(34), int64(3), object
(1)
memory usage: 33.2+ MB
```

Descriptive Statistics (count, mean, std, min, Max) of numerical attributes in the the data

In [11]:

```
merge_df.describe()
```

Out[11]:

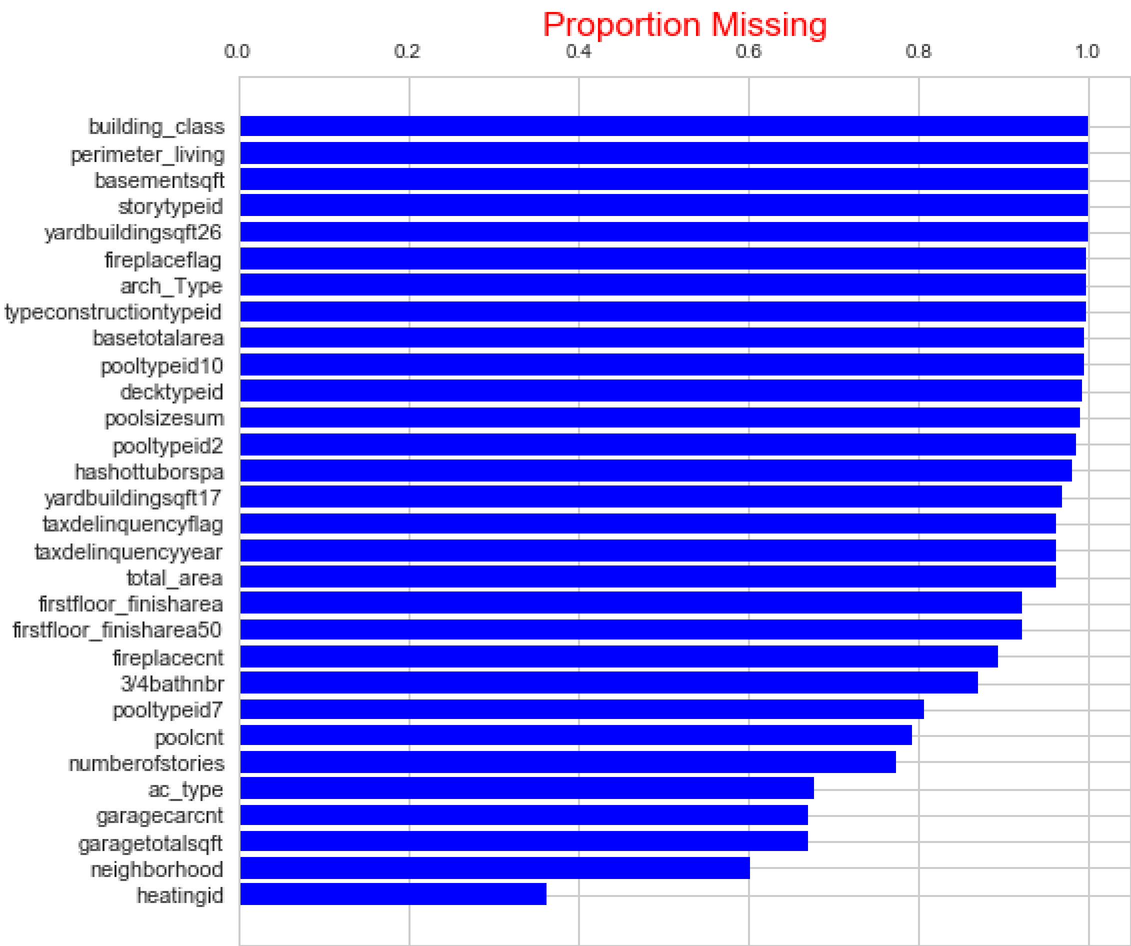
	parcelid	basementsqft	total_bathcnt	bedroomcnt	calculatedbathnbr
count	7.761300e+04	50.000000	77579.000000	77579.000000	76963.000000
mean	1.300781e+07	679.720000	2.298496	3.053223	2.316392
std	3.518717e+06	689.703546	0.996732	1.140480	0.979689
min	1.071186e+07	38.000000	0.000000	0.000000	1.000000
25%	1.153821e+07	273.000000	2.000000	2.000000	2.000000
50%	1.253004e+07	515.000000	2.000000	3.000000	2.000000
75%	1.421101e+07	796.500000	3.000000	4.000000	3.000000
max	1.676893e+08	3560.000000	18.000000	16.000000	18.000000

8 rows × 37 columns

Percentage and Graphical analysis of Null values in the data

In [104]:

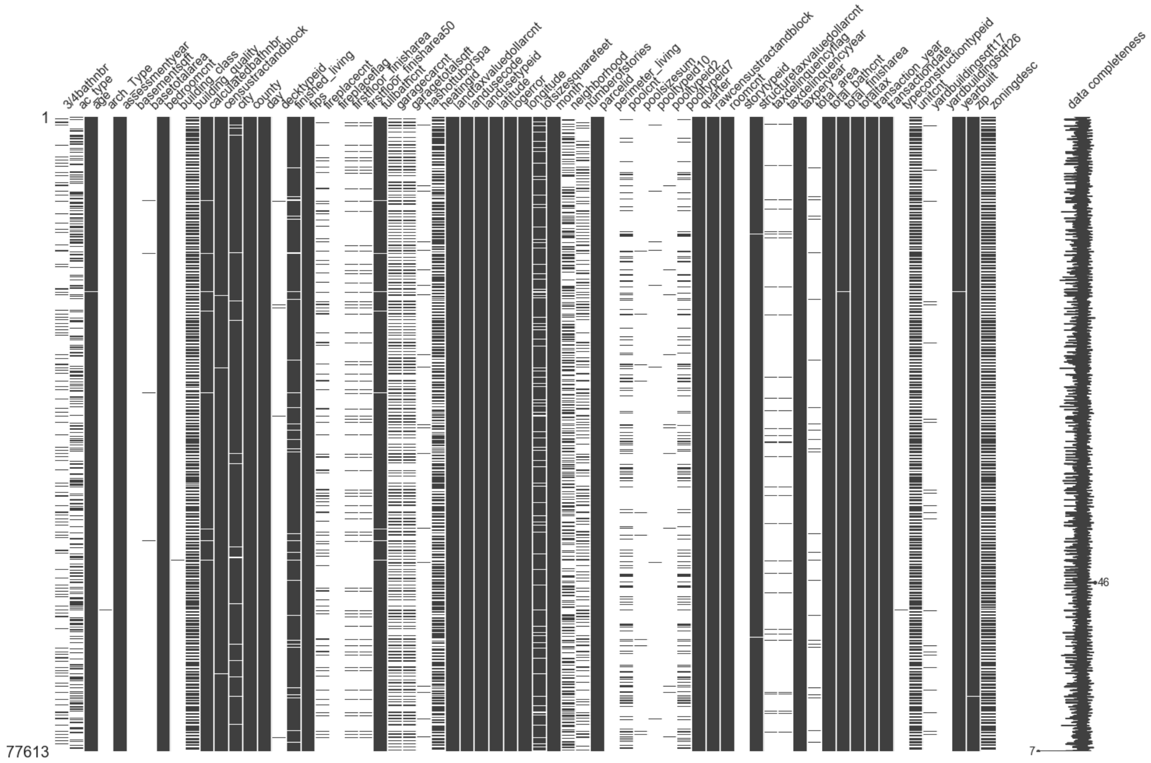
```
total_nulls = merge_df.isnull().sum().sort_values(ascending = False)
percent = ((merge_df.isnull().sum().sort_values())/(len(merge_df))).sort_values(ascendi
ng = False)
missin_val = pd.concat([total_nulls, percent], axis = 1, keys =['Total', 'Percent_missi
ng'])
missin_val.sort_values('Percent_missing', ascending = False)
missin_val.reset_index(inplace=True)
missin_val.rename({'index': 'Column_name'})
missin_val.sort_values(by= ['Percent_missing'], axis = 0, ascending = True, inplace=Tru
e)
missin_val.head()
plt.figure(figsize=(8,8))
plt.barh(bottom= np.arange(30), width= missin_val.Percent_missing.values[35:], tick_lab
el = missin_val['index'].values[35:], color = 'blue')
plt.xlabel('Proportion Missing', fontsize = 'xx-large', color = 'red')
plt.tick_params(axis = 'y', labelsize =11.0)
ax = plt.gca()
ax.xaxis.tick_top()
ax.xaxis.set_label_position('top')
plt.savefig('missing_values')
```



visualizing the Null values in a dataframe Graphically

In [106]:

```
merge_df = merge_df.reindex_axis(sorted(merge_df.columns), axis=1)
msno.matrix(merge_df, figsize= (24, 15), labels = True, width_ratios=(15,1))
```



In [12]:

```
## For Exploratory data analysis i am not including the log error values which are belo
w 1 percent and above 99 percent
nomerge_df = merge_df[(merge_df['logerror']  < np.percentile(merge_df['logerror'], 99))
 & (merge_df['logerror'] > np.percentile(merge_df['logerror'], 1))]
omerge_df = merge_df[~((merge_df['logerror']  < np.percentile(merge_df['logerror'], 99
)) & (merge_df['logerror'] > np.percentile(merge_df['logerror'], 1)))]
```

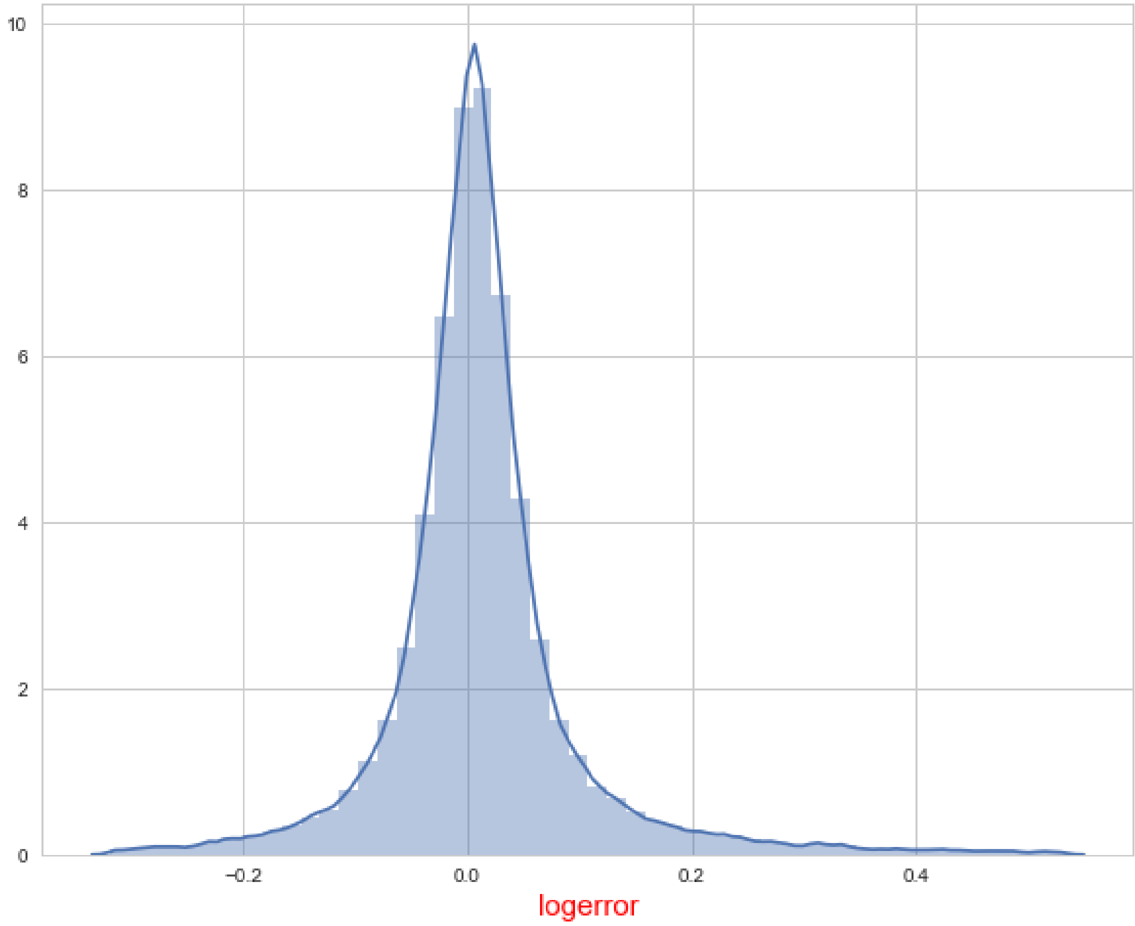
Zestimate (log error) analysis

In [13]:

```
plt.figure(figsize = (10,8))
ax1 = sns.distplot(nomerge_df.logerror.values)
ax1.set_xlabel('logerror', size =15, color = 'red')
```

Out[13]:

```
<matplotlib.text.Text at 0x1a6ff7464e0>
```



In [14]:

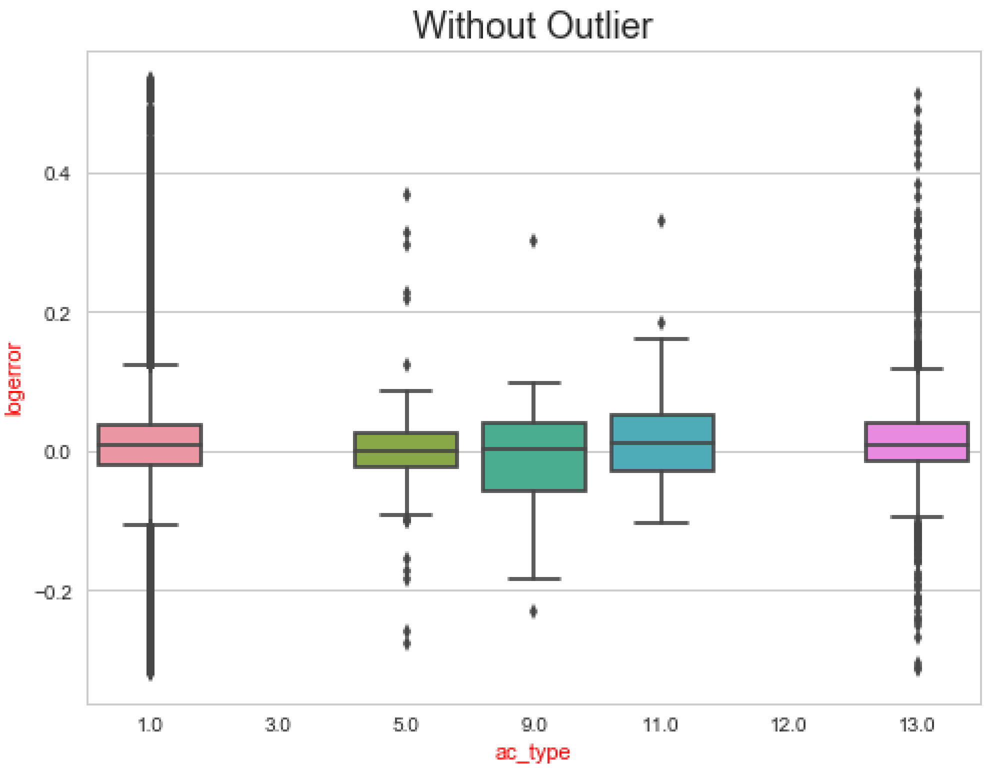
```
merge_df['abs_logerror']= merge_df.logerror.abs()
nomerge_df['abs_logerror']= nomerge_df.logerror.abs()
omerge_df['abs_logerror']= merge_df.logerror.abs()
```

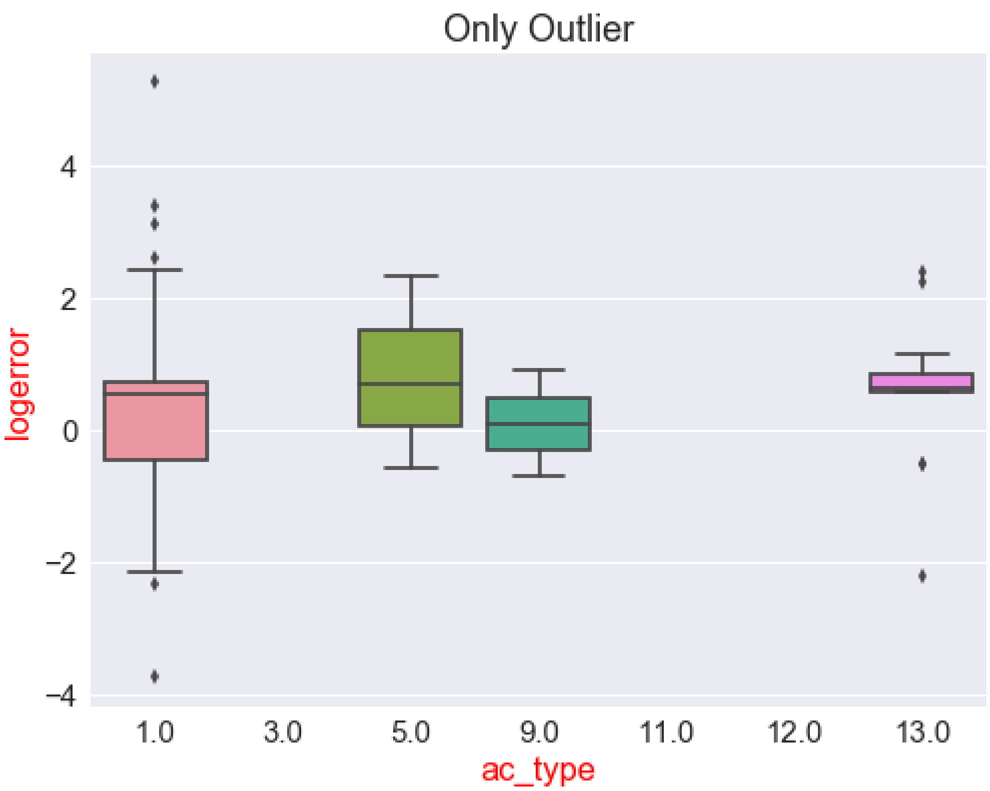
In [15]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['ac_type'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')

# --------------------------------------------------------------------
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = omerge_df['ac_type'], y= omerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Only Outlier')
```

Out[15]:

<matplotlib.text.Text at 0x1a6f272d940>



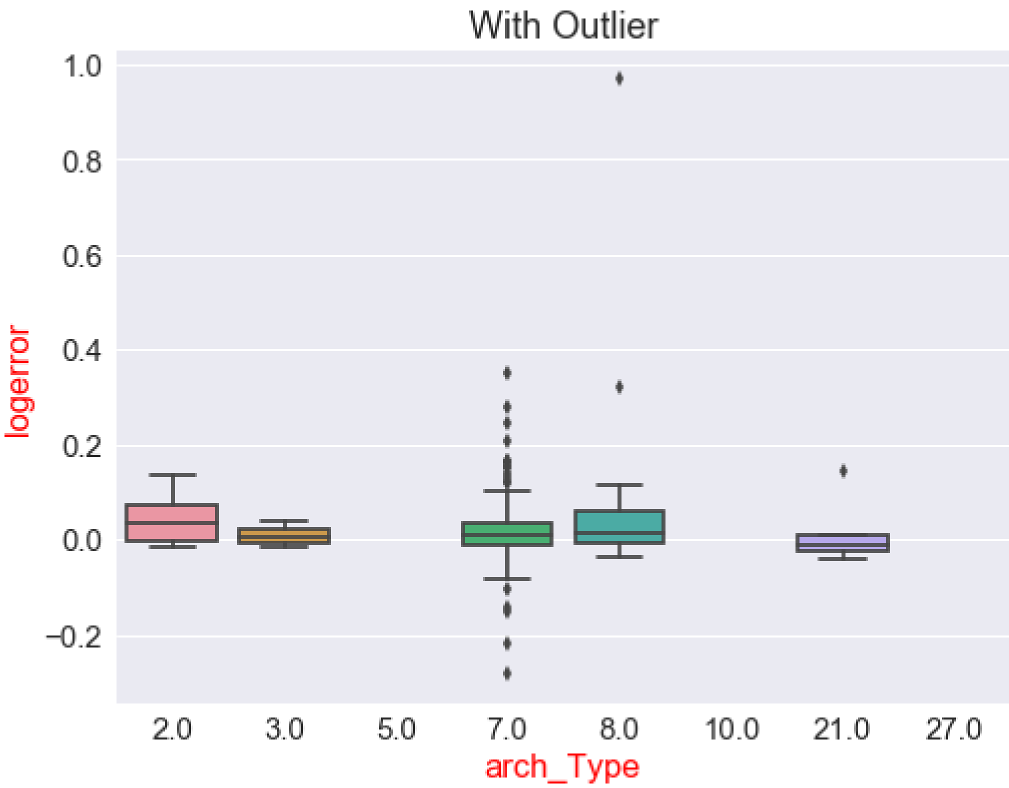


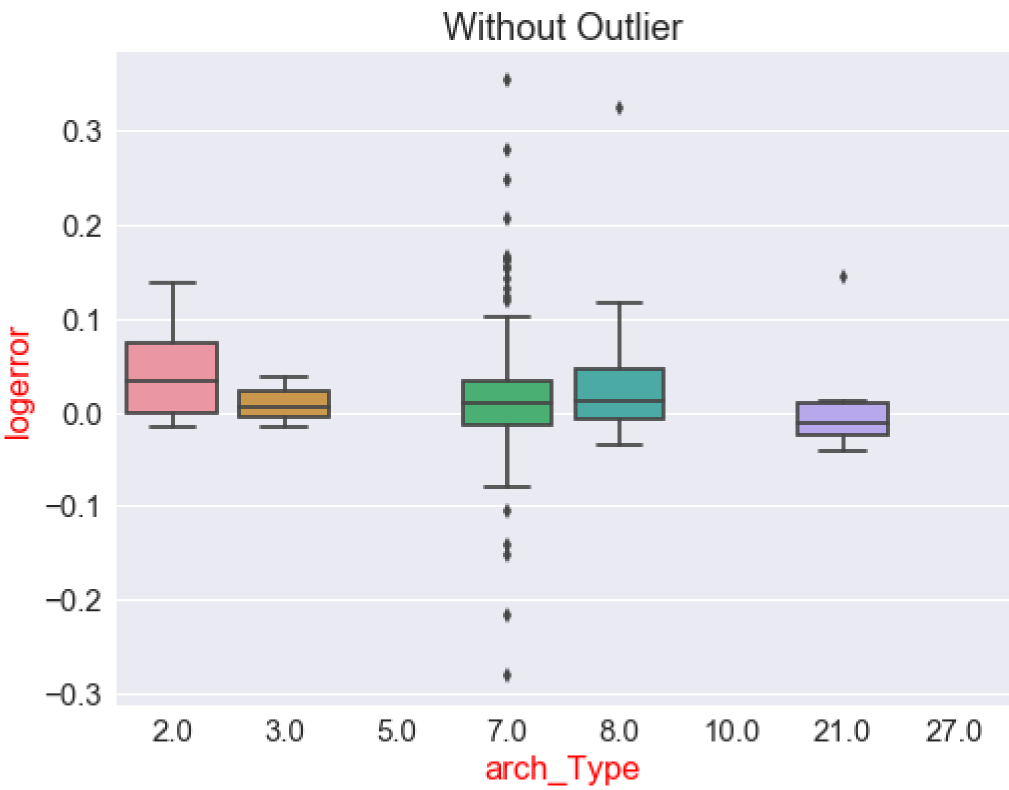
In [111]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = merge_df['arch_Type'], y= merge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('With Outlier')

#---------------------------------------------
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['arch_Type'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
```

Out[111]:

```
<matplotlib.text.Text at 0x1d7fc7e9390>
```





In [112]:

```
categorical_cols = merge_df.dtypes[merge_df.dtypes == 'category'].index.tolist()
categorical_cols
```

Out[112]:

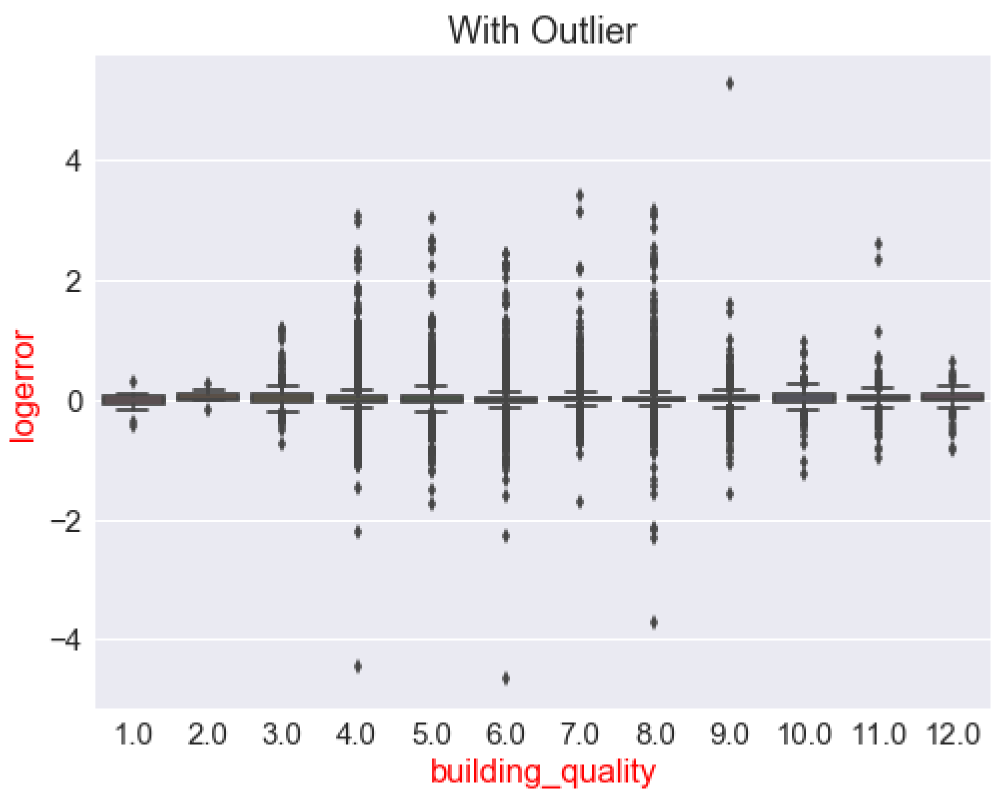
```
['ac_type',
 'arch_Type',
 'building_class',
 'building_quality',
 'censustractandblock',
 'city',
 'county',
 'decktypeid',
 'fips',
 'hashottuborspa',
 'heatingid',
 'landusecode',
 'landusetypeid',
 'month',
 'neighborhood',
 'pooltypeid10',
 'pooltypeid2',
 'pooltypeid7',
 'quarter',
 'rawcensustractandblock',
 'storytypeid',
 'taxdelinquencyflag',
 'taxdelinquencyyear',
 'typeconstructiontypeid',
 'zip',
 'zoningdesc']
```

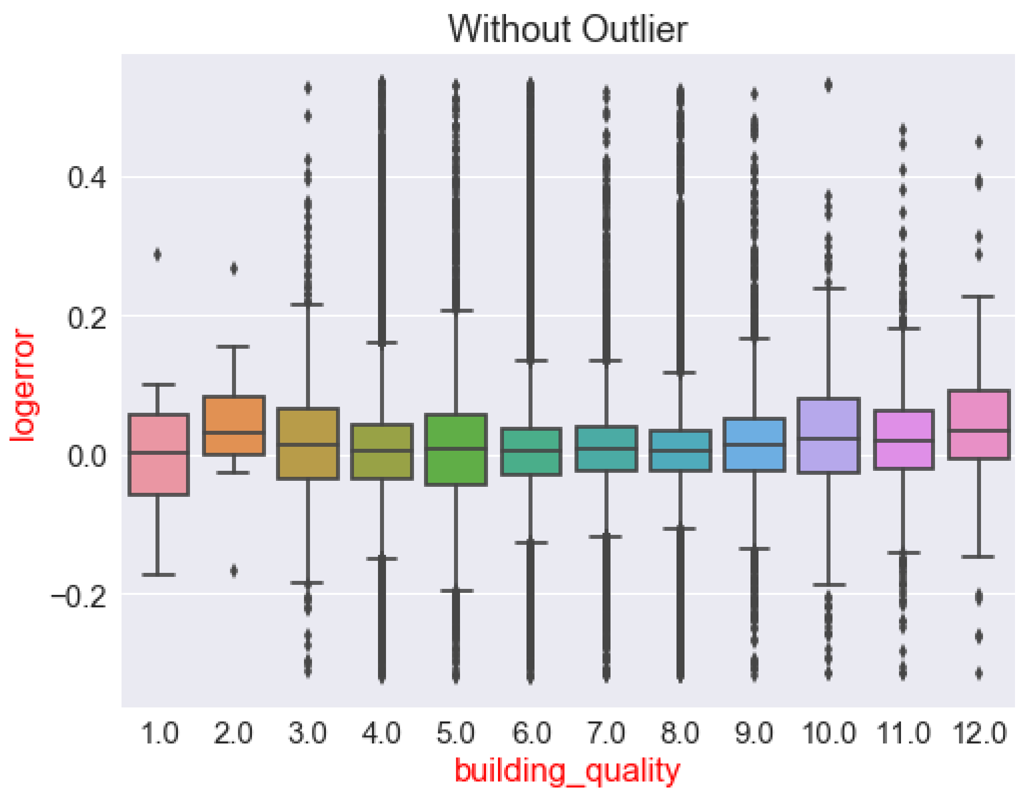
In [113]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = merge_df['building_quality'], y= merge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('With Outlier')

#-------------------------------------------
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['building_quality'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
```

Out[113]:

<matplotlib.text.Text at 0x1d7f9ae4d68>



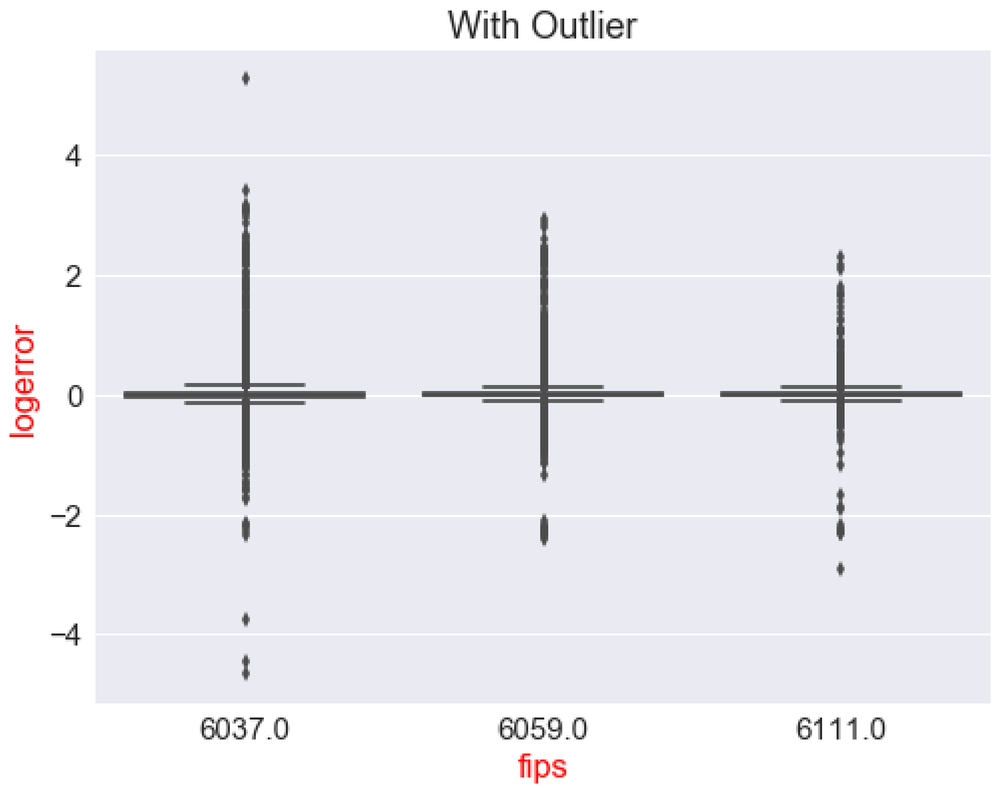


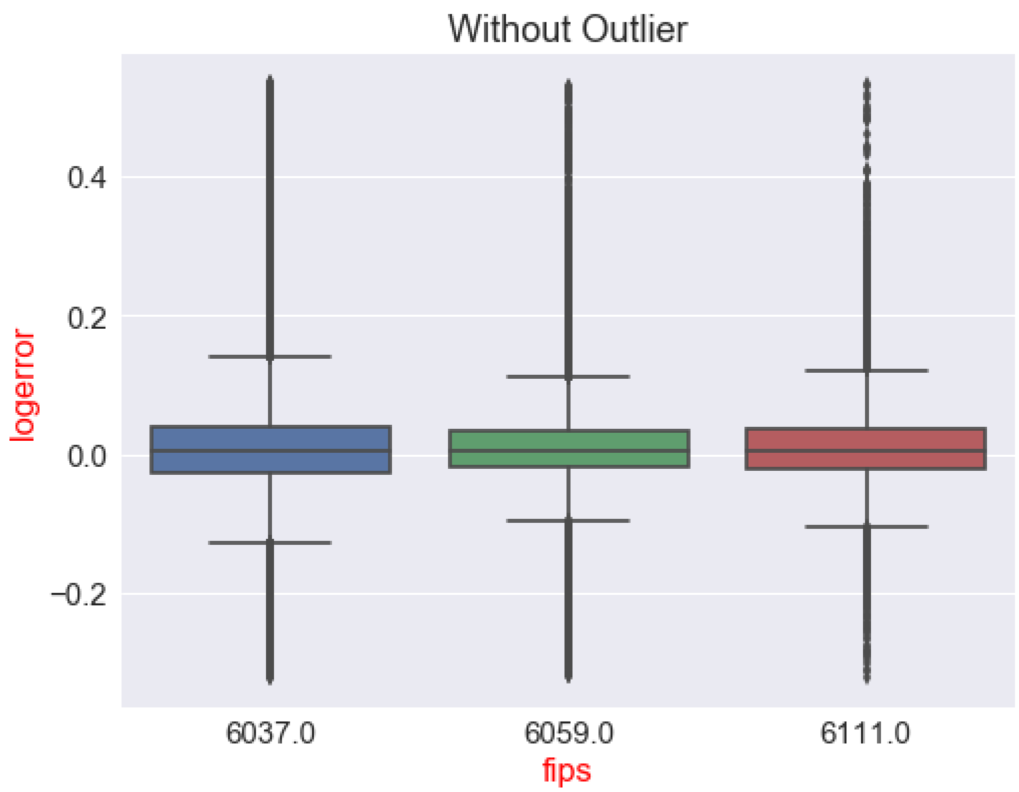
In [114]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = merge_df['fips'], y= merge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('With Outlier')

#-------------------------------------------
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['fips'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
```

Out[114]:

<matplotlib.text.Text at 0x1d7f9494080>



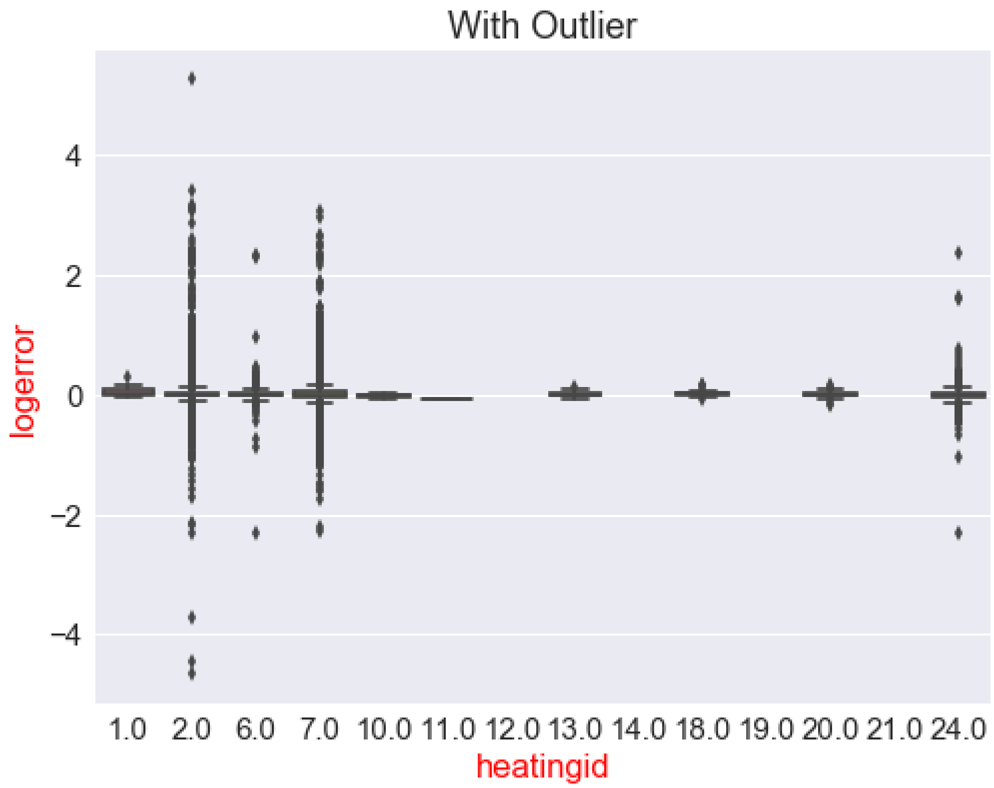


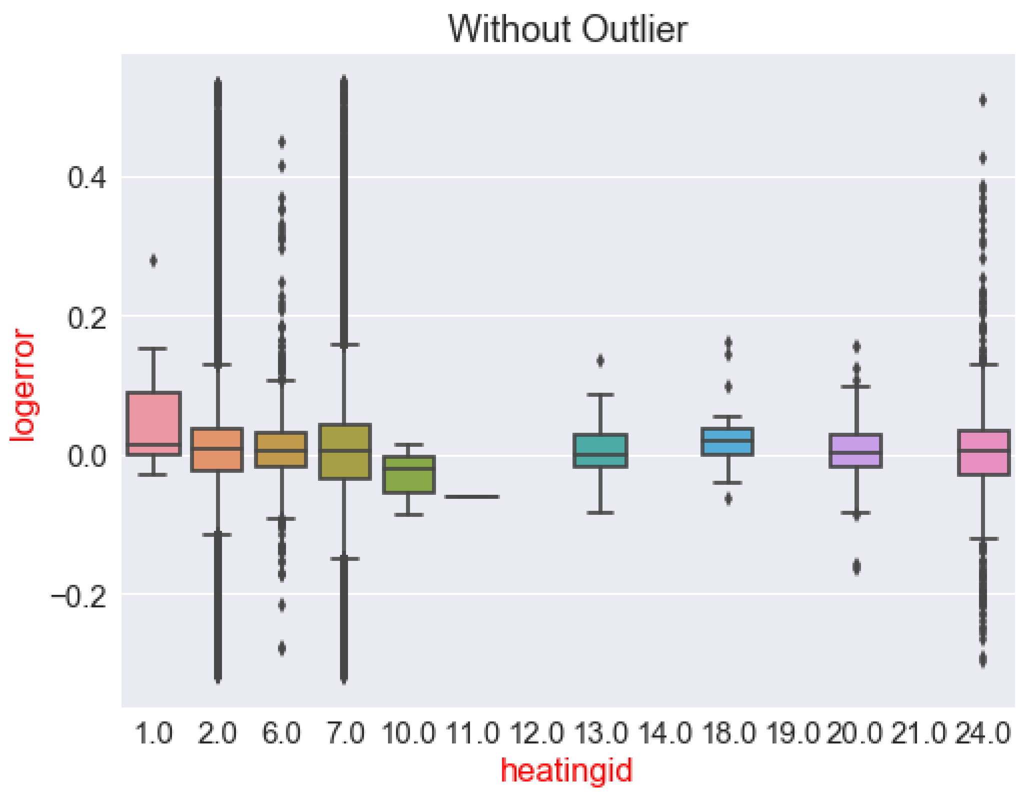
In [115]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = merge_df['heatingid'], y= merge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('With Outlier')

#---------------------------------------------
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['heatingid'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
```

Out[115]:

<matplotlib.text.Text at 0x1d7fc947320>



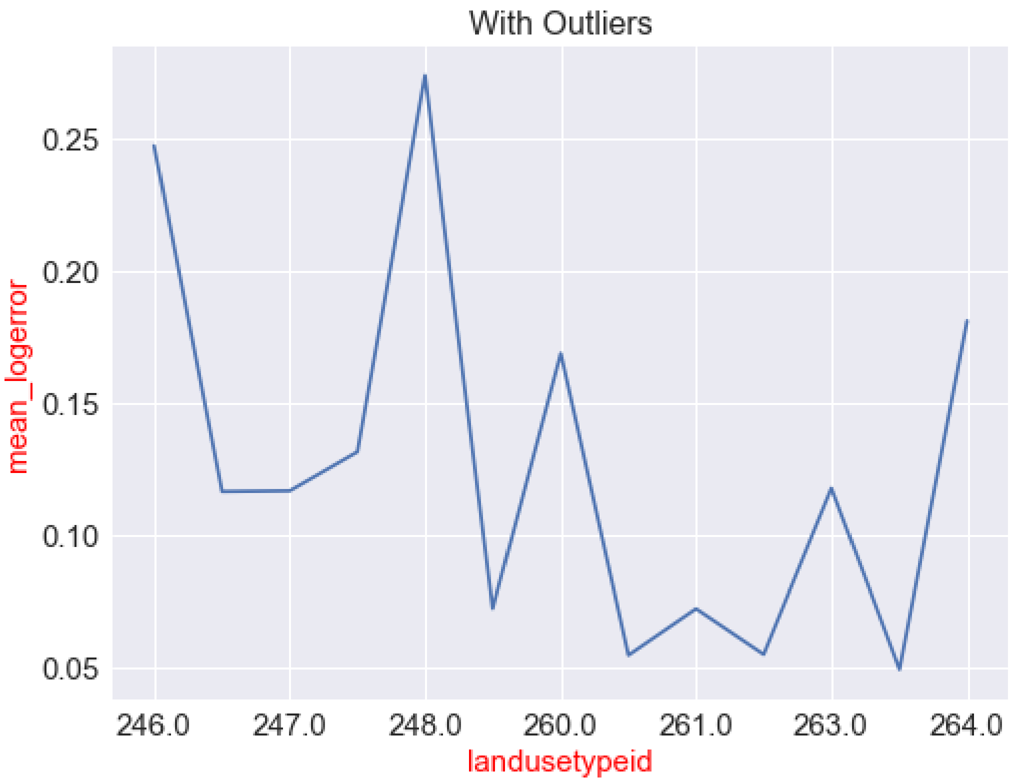


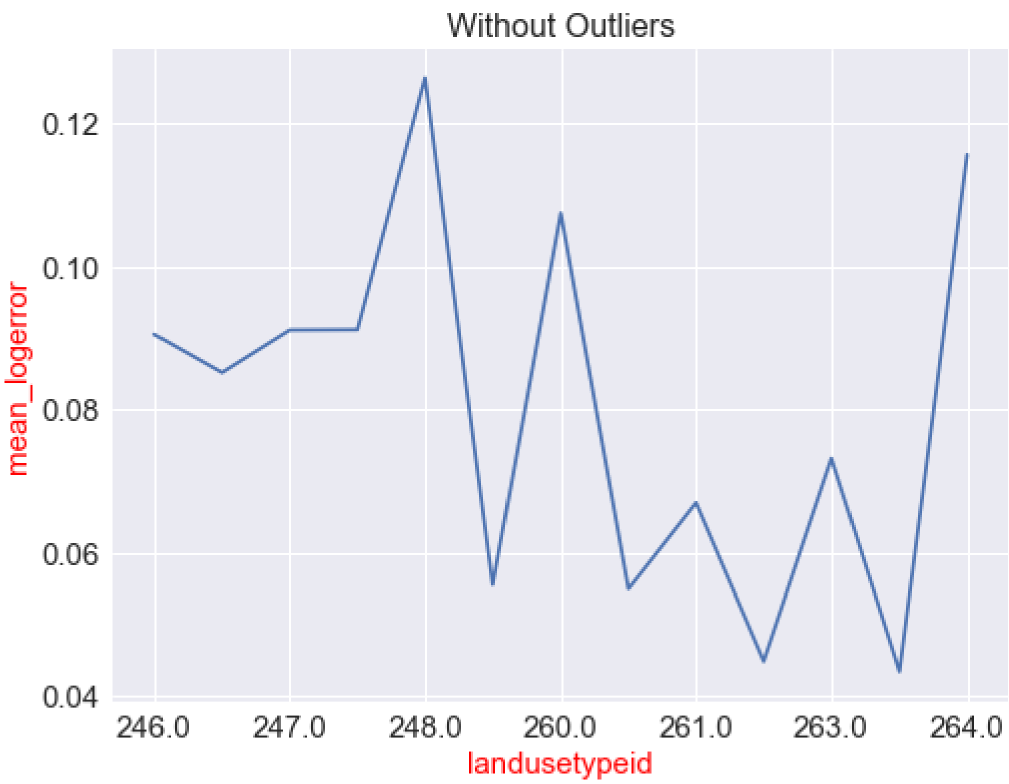
In [116]:

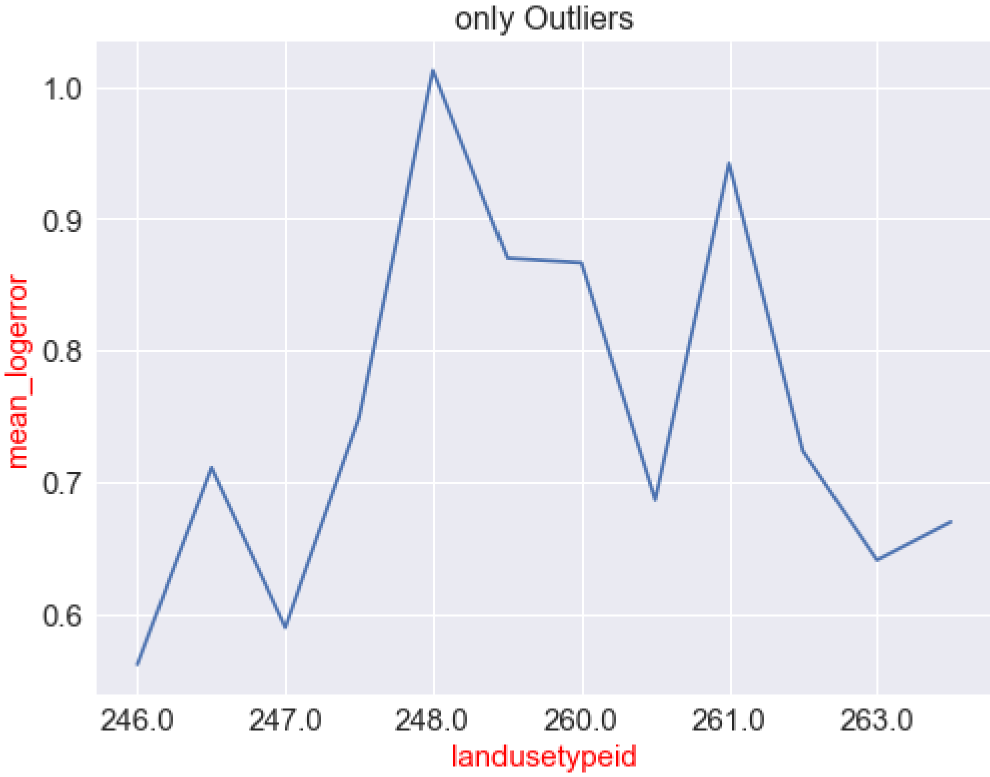
```
bools = merge_df.groupby(by='landusetypeid').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(merge_df.groupby(by='landusetypeid').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(merge_df.groupby(by='landusetypeid').mean()['abs_logerror'][bools].
index.tolist(), size = 'small')
ax1.set_xlabel('landusetypeid', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('With Outliers', fontsize = 16)

#---------------------------------------------------------------------------------------
-----
bools = nomerge_df.groupby(by='landusetypeid').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(nomerge_df.groupby(by='landusetypeid').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(nomerge_df.groupby(by='landusetypeid').mean()['abs_logerror'][bools
].index.tolist(), size = 'small')
ax1.set_xlabel('landusetypeid', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('Without Outliers', fontsize = 16)

#---------------------------------------------------------------------------------------
-----------
bools = omerge_df.groupby(by='landusetypeid').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(omerge_df.groupby(by='landusetypeid').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(omerge_df.groupby(by='landusetypeid').mean()['abs_logerror'][bools]
.index.tolist(), size = 'small')
ax1.set_xlabel('landusetypeid', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('only Outliers', fontsize = 16)
```

Out[116]:

<matplotlib.text.Text at 0x1d7e099b668>



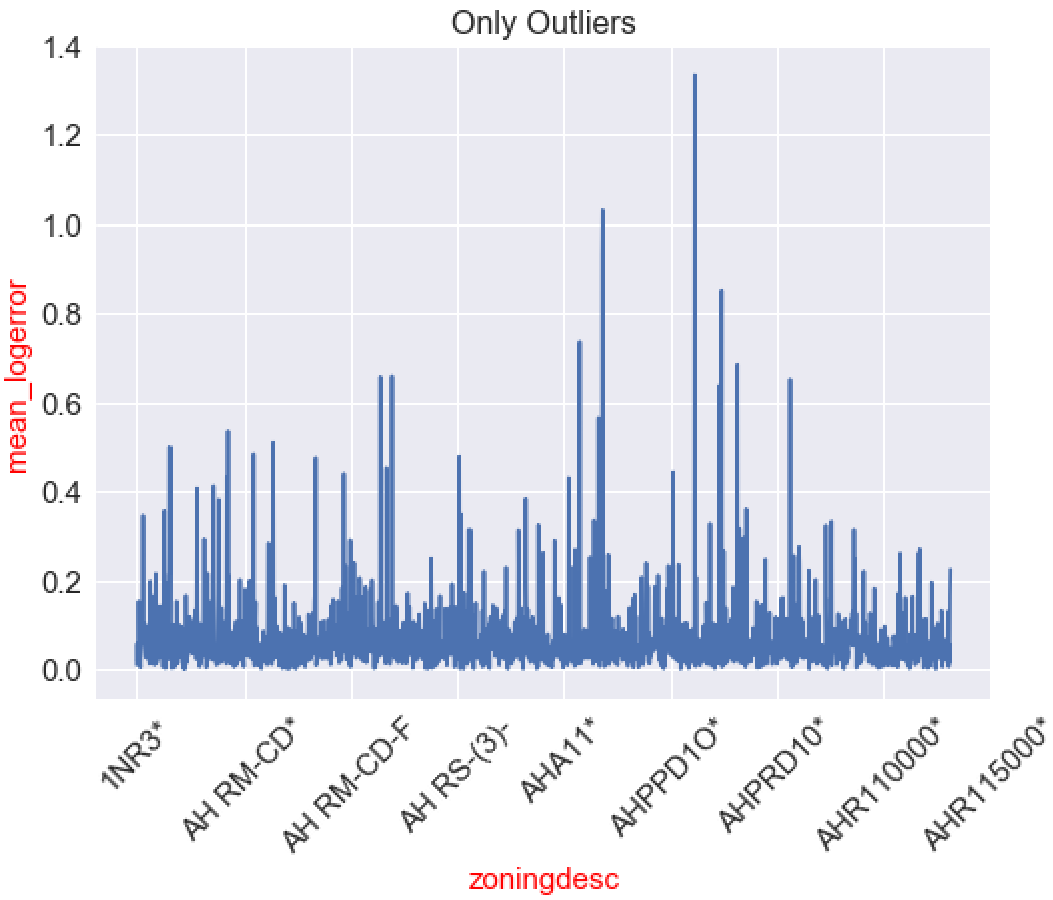


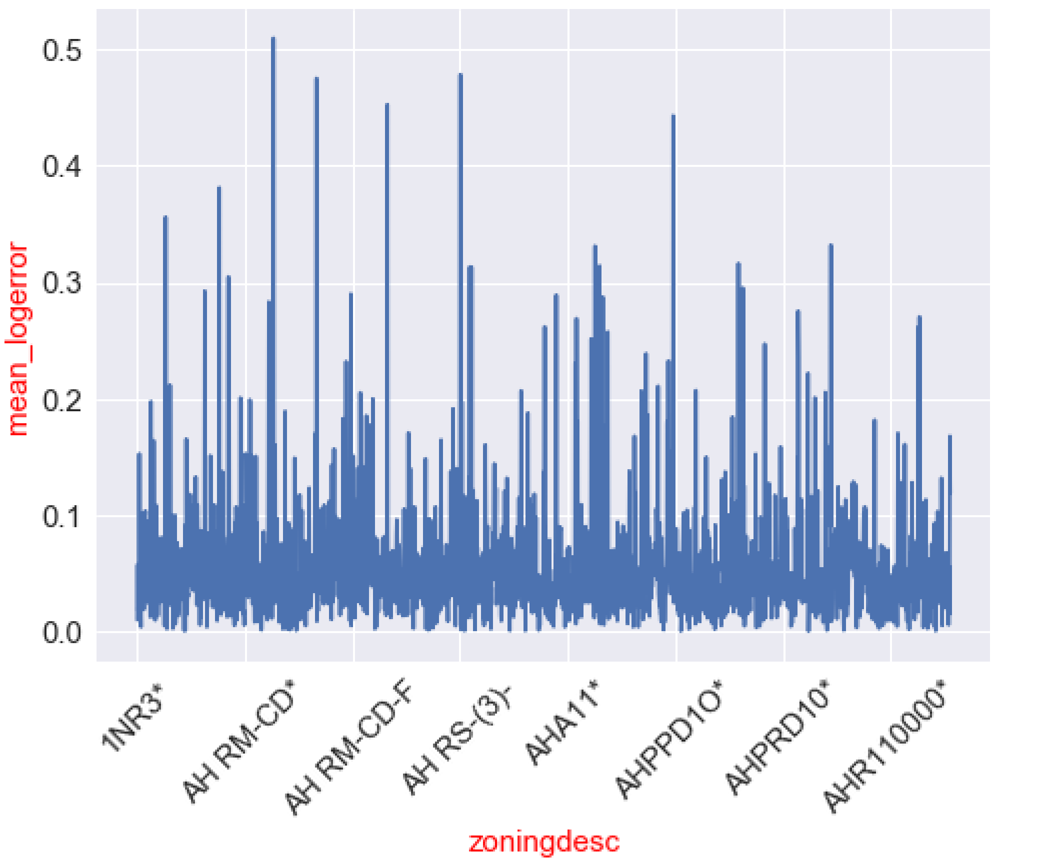

only Outliers
1.0
0.9
0.8
0.7
0.6
mean_logerror
246.0
247.0
248.0
260.0
261.0
263.0
landusetypeid

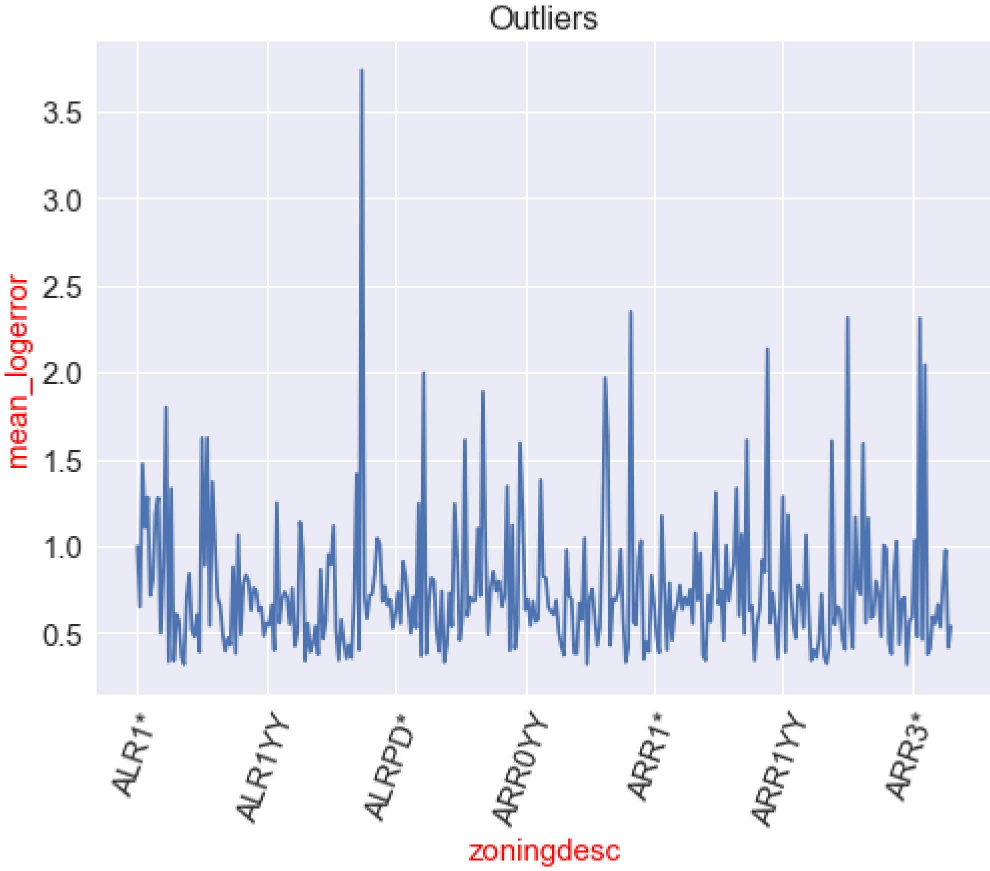
In [117]:

```
bools = merge_df.groupby(by='zoningdesc').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(merge_df.groupby(by='zoningdesc').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(merge_df.groupby(by='zoningdesc').mean()['abs_logerror'][bools].ind
ex.tolist(), size = 'small')
ax1.set_xlabel('zoningdesc', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('With Outliers', fontsize = 16)
plt.title('Only Outliers', fontsize = 16)
plt.xticks(rotation=45)


#-------------------------------------------------------------------------------------
-----
bools = nomerge_df.groupby(by='zoningdesc').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(nomerge_df.groupby(by='zoningdesc').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(nomerge_df.groupby(by='zoningdesc').mean()['abs_logerror'][bools].i
ndex.tolist(), size = 'small')
ax1.set_xlabel('zoningdesc', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.xticks(rotation=45)

#-------------------------------------------------------------------------------------
-----------
bools = omerge_df.groupby(by='zoningdesc').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(omerge_df.groupby(by='zoningdesc').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(omerge_df.groupby(by='zoningdesc').mean()['abs_logerror'][bools].in
dex.tolist(), size = 'small')
ax1.set_xlabel('zoningdesc', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('Outliers', fontsize = 16)
plt.xticks(rotation=70)
```

```
Out[117]:

(array([ -50.,    0.,   50.,  100.,  150.,  200.,  250.,  300.,  350.]),
 <a list of 9 Text xticklabel objects>)
```





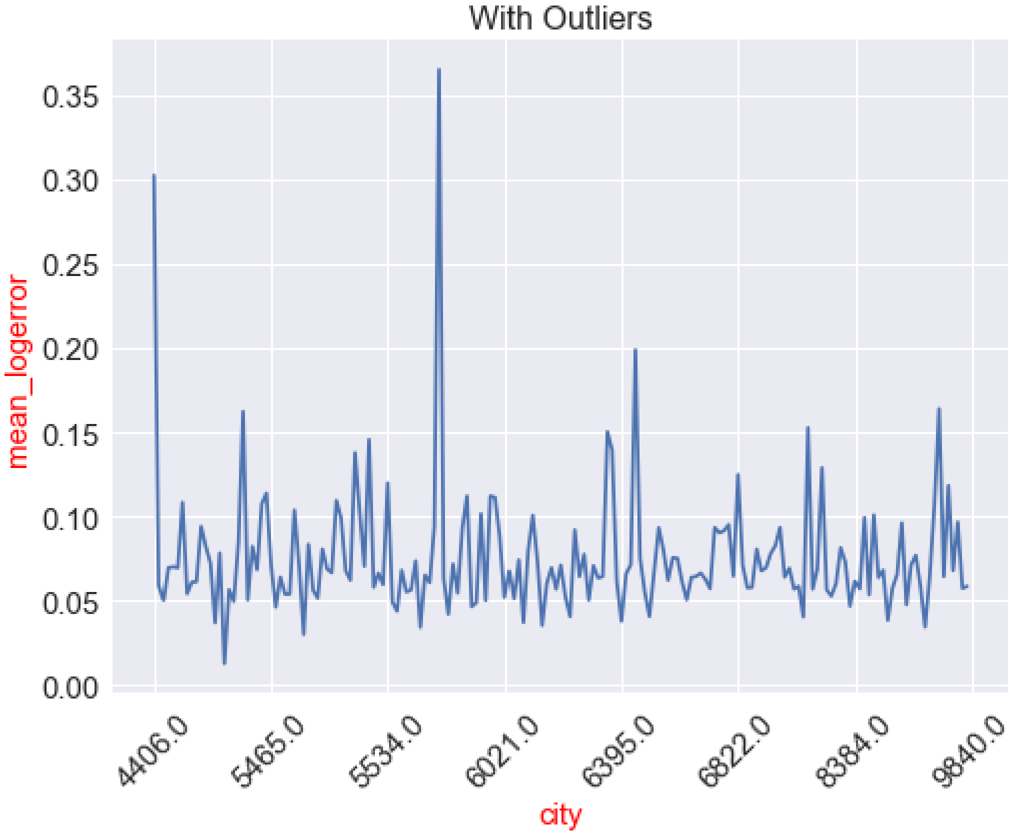

Outliers
mean_logerror
3.5
3.0
2.5
2.0
1.5
1.0
0.5
ALR1*
ALR1YY
ALRPD*
ARR0YY
ARR1*
ARR1YY
ARR3*
zoningdesc

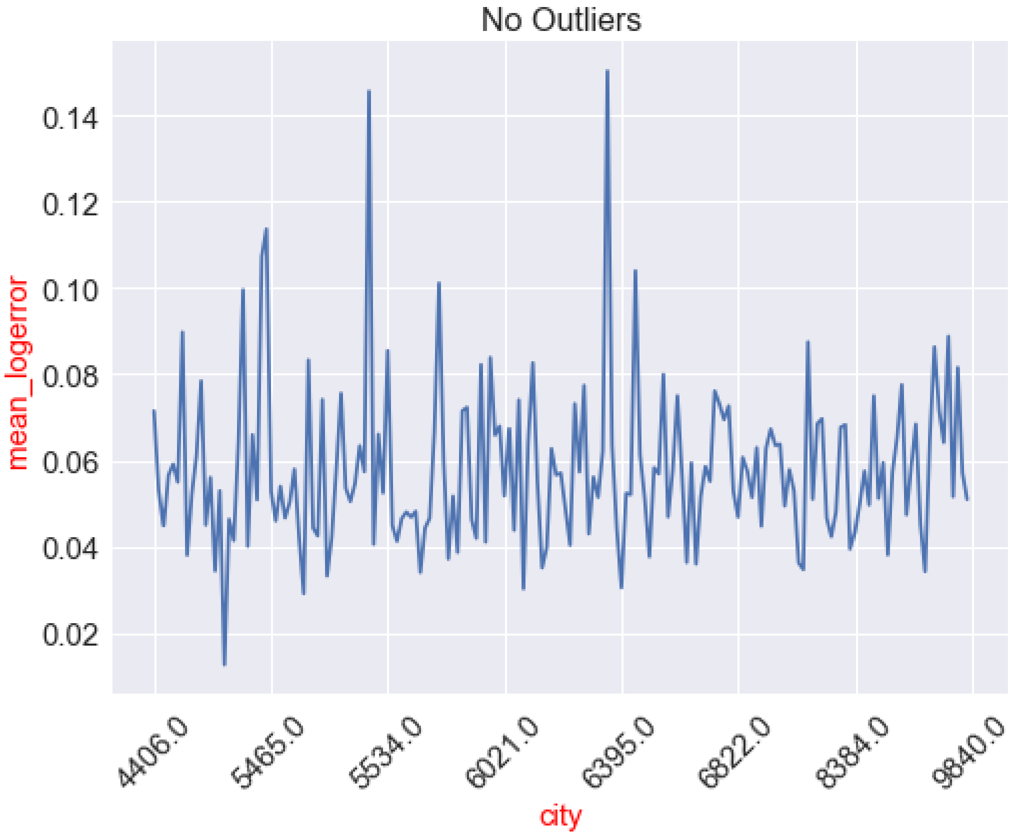
In [118]:

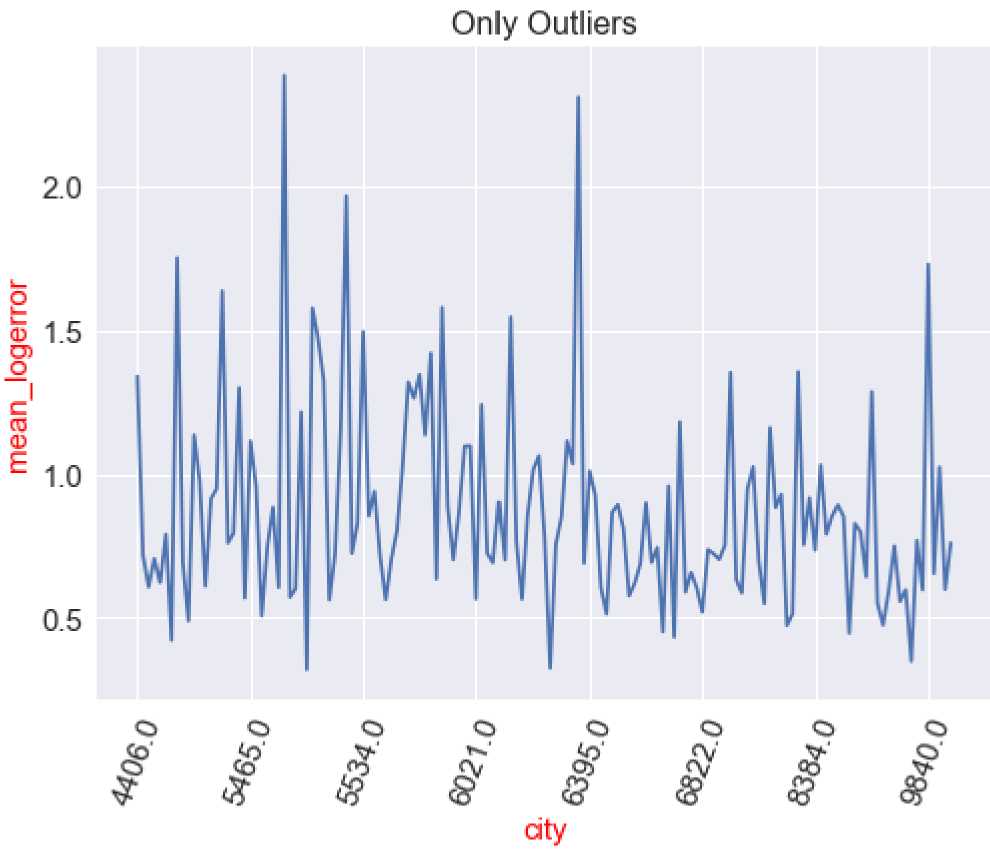
```
bools = merge_df.groupby(by='city').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(merge_df.groupby(by='city').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(merge_df.groupby(by='city').mean()['abs_logerror'][bools].index.tol
ist(), size = 'small')
ax1.set_xlabel('city', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('With Outliers', fontsize = 16)
plt.xticks(rotation=45)


#---------------------------------------------------------------------------------------
-----
bools = nomerge_df.groupby(by='city').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(nomerge_df.groupby(by='city').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(nomerge_df.groupby(by='city').mean()['abs_logerror'][bools].index.t
olist(), size = 'small')
ax1.set_xlabel('city', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('No Outliers', fontsize = 16)
plt.xticks(rotation=45)

#---------------------------------------------------------------------------------------
-----------
bools = omerge_df.groupby(by='city').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(omerge_df.groupby(by='city').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(omerge_df.groupby(by='city').mean()['abs_logerror'][bools].index.to
list(), size = 'small')
ax1.set_xlabel('city', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('Only Outliers', fontsize = 16)
plt.xticks(rotation=70)
```

Out[118]:

```
(array([ -20.,    0.,   20.,   40.,   60.,   80.,  100.,  120.,  140.,  16
0.]),
 <a list of 10 Text xticklabel objects>)
```



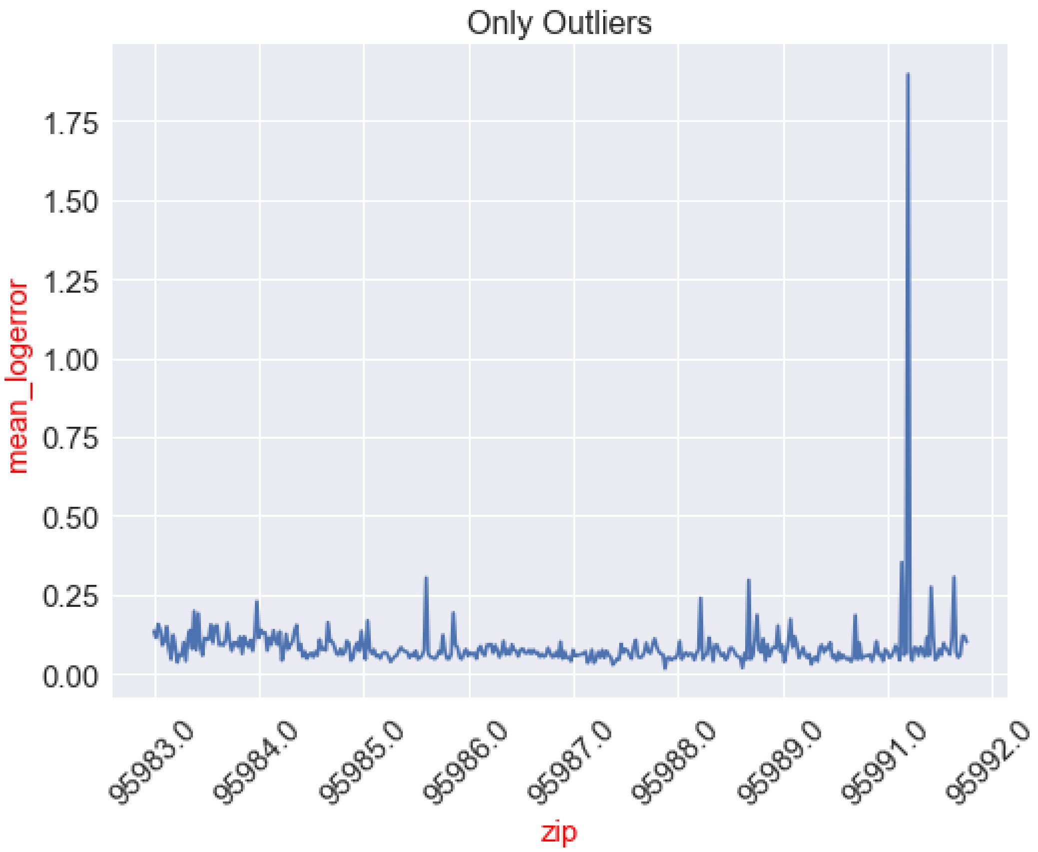


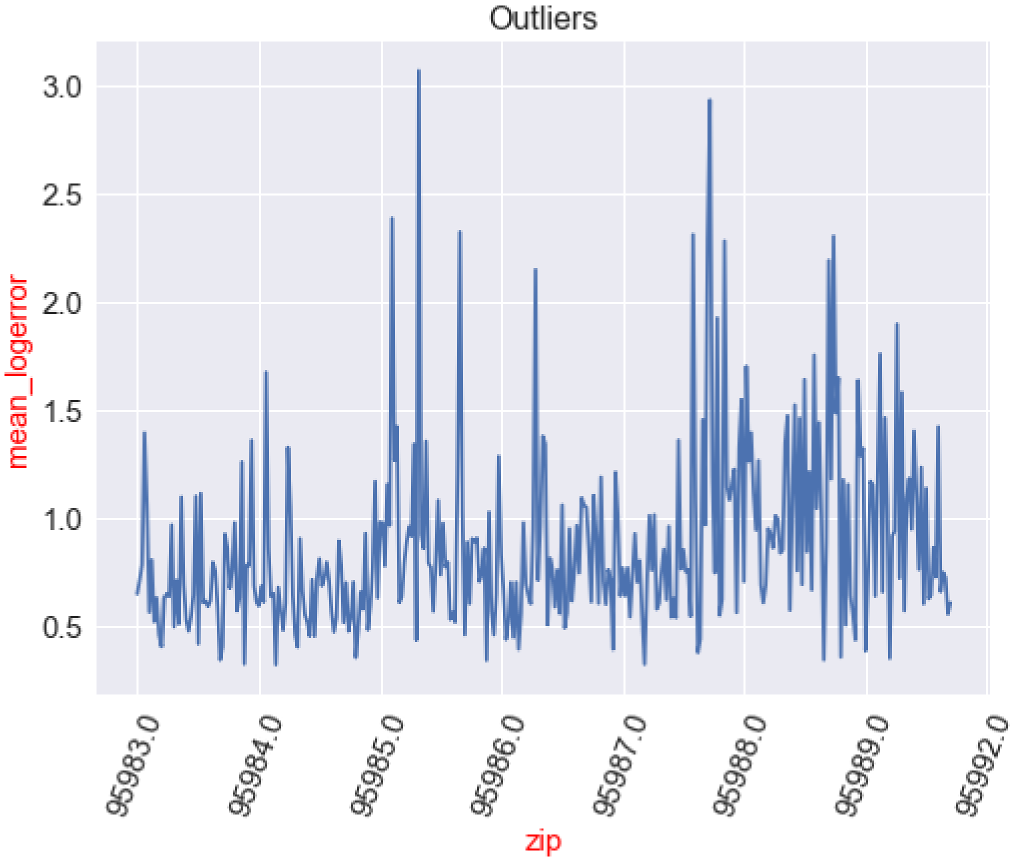

Only Outliers
mean_logerror
2.0
1.5
1.0
0.5
4406.0
5465.0
5534.0
6021.0
6395.0
6822.0
8384.0
9840.0
city

In [119]:

```
bools = merge_df.groupby(by='zip').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(merge_df.groupby(by='zip').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(merge_df.groupby(by='zip').mean()['abs_logerror'][bools].index.toli
st(), size = 'small')
ax1.set_xlabel('zip', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('With Outliers', fontsize = 16)
plt.title('Only Outliers', fontsize = 16)
plt.xticks(rotation=45)


#------------------------------------------------------------------------------------
-----
bools = nomerge_df.groupby(by='zip').mean()['logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(nomerge_df.groupby(by='zip').mean()['logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(nomerge_df.groupby(by='zip').mean()['logerror'][bools].index.tolist
(), size = 'small')
ax1.set_xlabel('zip', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.xticks(rotation=45)

#------------------------------------------------------------------------------------
-----------
bools = omerge_df.groupby(by='zip').mean()['abs_logerror'].notnull()
plt.figure(figsize = (8,6))
plt.plot(omerge_df.groupby(by='zip').mean()['abs_logerror'][bools].values)
ax1 = plt.gca()
ax1.set_xticklabels(omerge_df.groupby(by='zip').mean()['abs_logerror'][bools].index.tol
ist(), size = 'small')
ax1.set_xlabel('zip', size ='small', color = 'red')
ax1.set_ylabel('mean_logerror', size ='small', color = 'red')
plt.title('Outliers', fontsize = 16)
plt.xticks(rotation=70)
```

```
Out[119]:

(array([ -50.,    0.,   50.,  100.,  150.,  200.,  250.,  300.,  350.,  40
0.]),
 <a list of 10 Text xticklabel objects>)
```



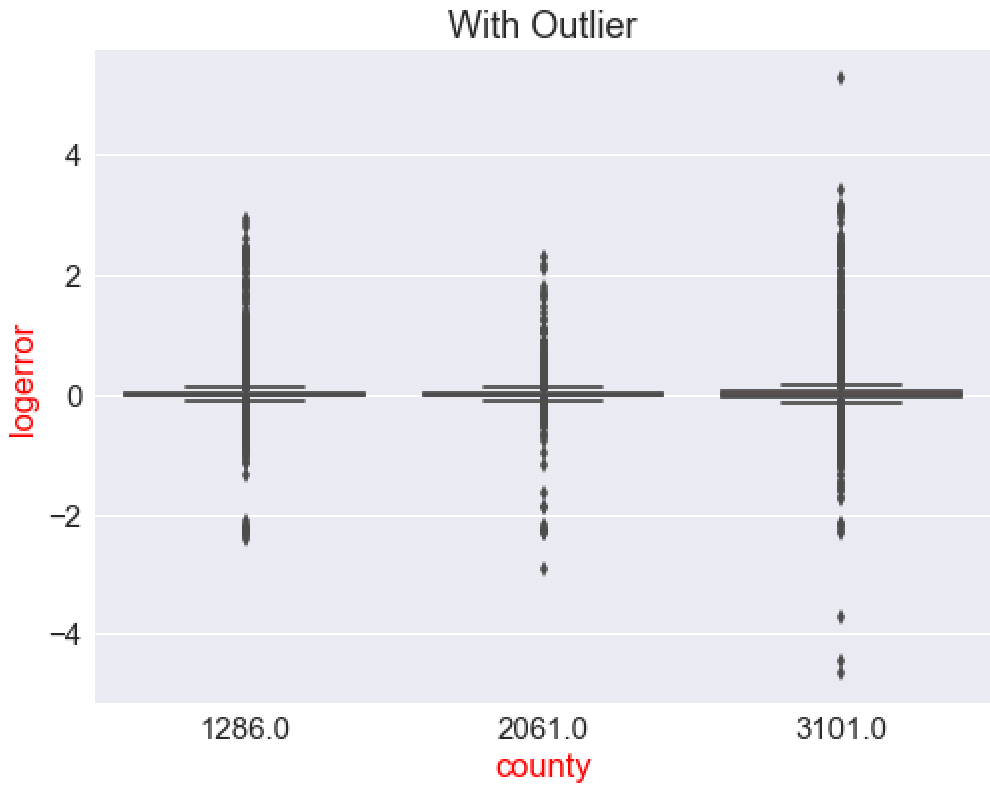

Outliers
mean_logerror
3.0
2.5
2.0
1.5
1.0
0.5
95983.0
95984.0
95985.0
95986.0
95987.0
95988.0
95989.0
95992.0
zip

In [120]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = merge_df['county'], y= merge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('With Outlier')

#---------------------------------------------
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['county'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
```

Out[120]:

```
<matplotlib.text.Text at 0x1d7f7a56b70>
```



from the above analysis unnecessary category attributes are removed

- if they have large number of null values (90% of values being null)
- no deivation in the mean log error with the category and standar deviation being same
- attributes which give same amount of information (for examples, city and zip code provide insights to same information)

In [16]:

```
copy_merge_df = merge_df.copy() #making a copy of dataframe before altering it
copy_nomerge_df = nomerge_df.copy()
copy_omerge_df = omerge_df.copy()
```

In [17]:

```
copy_merge_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77613 entries, 0 to 77612
Data columns (total 66 columns):
parcelid                      77613 non-null int64
ac_type                       25007 non-null category
arch_Type                     207 non-null category
basementsqft                  50 non-null float64
total_bathcnt                 77579 non-null float64
bedroomcnt                    77579 non-null float64
building_class                15 non-null category
building_quality              49809 non-null category
calculatedbathnbr             76963 non-null float64
decktypeid                    614 non-null category
firstfloor_finisharea         6037 non-null float64
total_finisharea              77378 non-null float64
finished_living               73923 non-null float64
perimeter_living              42 non-null float64
total_area                    3027 non-null float64
firstfloor_finisharea         6037 non-null float64
basetotalarea                 386 non-null float64
fips                          77579 non-null category
fireplacecnt                  8289 non-null float64
fullbathcnt                   76963 non-null float64
garagecarcnt                  25520 non-null float64
garagetotalsqft               25520 non-null float64
hashottuborspa                1539 non-null category
heatingid                     49571 non-null category
latitude                      77579 non-null float64
longitude                     77579 non-null float64
lotsizesquarefeet             69321 non-null float64
poolcnt                       16174 non-null float64
poolsizesum                   869 non-null float64
pooltypeid10                  465 non-null category
pooltypeid2                   1074 non-null category
pooltypeid7                   15079 non-null category
landusecode                   77579 non-null category
landusetypeid                 77579 non-null category
zoningdesc                    50476 non-null category
rawcensustractandblock        77579 non-null category
city                          76107 non-null category
county                        77579 non-null category
neighborhood                  30974 non-null category
zip                           77529 non-null category
roomcnt                       77579 non-null float64
storytypeid                   50 non-null category
3/4bathnbr                    10106 non-null float64
typeconstructiontypeid        223 non-null category
unitcnt                       50703 non-null float64
yardbuildingsqft17            2393 non-null float64
yardbuildingsqft26            70 non-null float64
yearbuilt                     77309 non-null float64
numberofstories               17599 non-null float64
fireplaceflag                 172 non-null object
structuretaxvaluedollarcnt    77464 non-null float64
totaltax                      77578 non-null float64
assessmentyear                77579 non-null float64
landtaxvaluedollarcnt         77577 non-null float64
taxperyear                    77574 non-null float64
taxdelinquencyflag            2900 non-null category
taxdelinquencyyear            2900 non-null category
censustractandblock           77332 non-null category
```

```
logerror                        77613 non-null float64
transactiondate                 77613 non-null datetime64[ns]
month                           77613 non-null category
day                             77613 non-null int64
quarter                         77613 non-null category
transaction_year                77613 non-null int64
age                             77309 non-null float64
abs_logerror                    77613 non-null float64
dtypes: category(26), datetime64[ns](1), float64(35), int64(3), object
(1)
memory usage: 33.8+ MB
```

In [18]:

```
merge_df.drop(['landusecode', 'building_class', 'decktypeid', 'fips', 'pooltypeid10',
'pooltypeid2', 'pooltypeid7', 'county',
              'typeconstructiontypeid', 'storytypeid', 'taxdelinquencyflag', 'taxdelinq
uencyyear', 'zip', 'neighborhood'], axis = 1, inplace =True)
nomerge_df.drop(['landusecode', 'building_class', 'decktypeid', 'fips', 'pooltypeid10',
 'pooltypeid2', 'pooltypeid7', 'county',
              'typeconstructiontypeid', 'storytypeid', 'taxdelinquencyflag', 'taxdelinq
uencyyear', 'zip', 'neighborhood'], axis = 1, inplace =True)
omerge_df.drop(['landusecode', 'building_class', 'decktypeid', 'fips', 'pooltypeid10',
'pooltypeid2', 'pooltypeid7', 'county',
              'typeconstructiontypeid', 'storytypeid', 'taxdelinquencyflag', 'taxdelinq
uencyyear', 'zip', 'neighborhood'], axis = 1, inplace =True)
```

Numerical attribute analysis

In [19]:

```
numerical_col = merge_df.dtypes[(merge_df.dtypes =='int64')|(merge_df.dtypes =='float6
4')].index.tolist()
```

In [20]:

```
merge_df[numerical_col].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77613 entries, 0 to 77612
Data columns (total 40 columns):
parcelid                       77613 non-null int64
basementsqft                   50 non-null float64
total_bathcnt                  77579 non-null float64
bedroomcnt                     77579 non-null float64
calculatedbathnbr              76963 non-null float64
firstfloor_finisharea          6037 non-null float64
firstfloor_finisharea          6037 non-null float64
total_finisharea               77378 non-null float64
finished_living                73923 non-null float64
perimeter_living               42 non-null float64
total_area                     3027 non-null float64
firstfloor_finisharea          6037 non-null float64
firstfloor_finisharea          6037 non-null float64
basetotalarea                  386 non-null float64
fireplacecnt                   8289 non-null float64
fullbathcnt                    76963 non-null float64
garagecarcnt                   25520 non-null float64
garagetotalsqft                25520 non-null float64
latitude                       77579 non-null float64
longitude                      77579 non-null float64
lotsizesquarefeet              69321 non-null float64
poolcnt                        16174 non-null float64
poolsizesum                    869 non-null float64
roomcnt                        77579 non-null float64
3/4bathnbr                     10106 non-null float64
unitcnt                        50703 non-null float64
yardbuildingsqft17             2393 non-null float64
yardbuildingsqft26             70 non-null float64
yearbuilt                      77309 non-null float64
numberofstories                17599 non-null float64
structuretaxvaluedollarcnt     77464 non-null float64
totaltax                       77578 non-null float64
assessmentyear                 77579 non-null float64
landtaxvaluedollarcnt          77577 non-null float64
taxperyear                     77574 non-null float64
logerror                       77613 non-null float64
day                            77613 non-null int64
transaction_year               77613 non-null int64
age                            77309 non-null float64
abs_logerror                   77613 non-null float64
dtypes: float64(37), int64(3)
memory usage: 26.8 MB
```

In [21]:

```
numerical_col
```

Out[21]:

```
['parcelid',
 'basementsqft',
 'total_bathcnt',
 'bedroomcnt',
 'calculatedbathnbr',
 'firstfloor_finisharea',
 'total_finisharea',
 'finished_living',
 'perimeter_living',
 'total_area',
 'firstfloor_finisharea',
 'basetotalarea',
 'fireplacecnt',
 'fullbathcnt',
 'garagecarcnt',
 'garagetotalsqft',
 'latitude',
 'longitude',
 'lotsizesquarefeet',
 'poolcnt',
 'poolsizesum',
 'roomcnt',
 '3/4bathnbr',
 'unitcnt',
 'yardbuildingsqft17',
 'yardbuildingsqft26',
 'yearbuilt',
 'numberofstories',
 'structuretaxvaluedollarcnt',
 'totaltax',
 'assessmentyear',
 'landtaxvaluedollarcnt',
 'taxperyear',
 'logerror',
 'day',
 'transaction_year',
 'age',
 'abs_logerror']
```

In [127]:

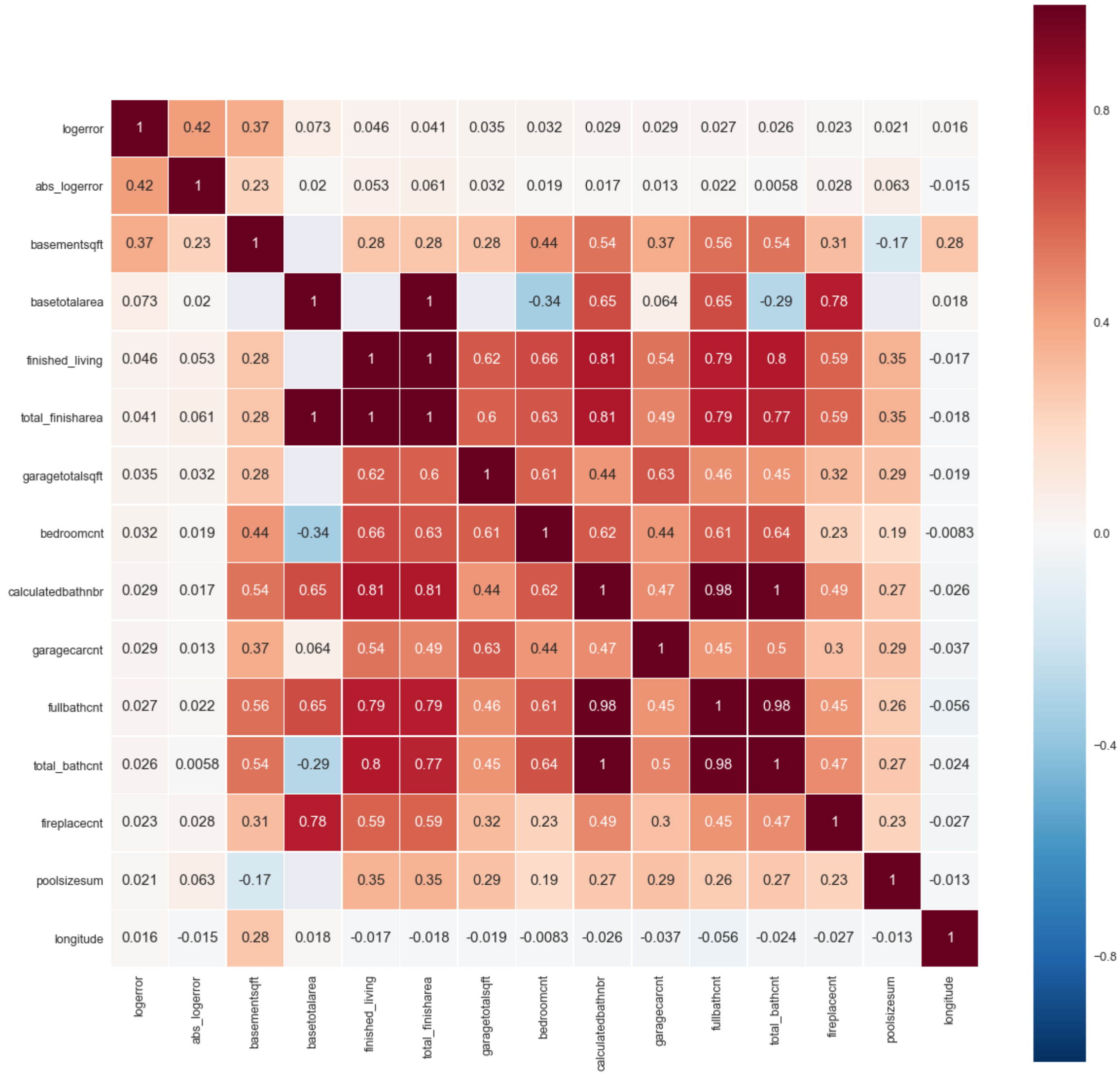
```
corr_mat = merge_df.corr()
plt.figure(figsize = (30, 20))
sns.set(font_scale = 1.25)
sns.heatmap(corr_mat, annot = True)
```

Out[127]:

<matplotlib.axes._subplots.AxesSubplot at 0x1d7f7a1b240>

In [128]:

```
#coorelation matrix arranged in descending order of correlation with log error
cols = corr_mat.nlargest(15, 'logerror')['logerror'].index
plt.figure(figsize= (20,20))
coor_mat_10 = merge_df[cols].corr()
sns.heatmap(coor_mat_10, square = True, annot=True, linewidths =0.5)
sns.set_style(style = 'darkgrid')
sns.set(font_scale = 1)
```



In [129]:

```
plt.figure(figsize=(8, 6))
g = sns.factorplot(x = 'month', y= 'abs_logerror', data= merge_df, estimator= np.mean,
size = 6, aspect=2)
sns.set(font_scale=1.5)
g.set_axis_labels("month", "mean_abs_logerror")
g.set_xticklabels(labels =['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Se
p'])
g.set_xlabels(color ='red')
g.set_ylabels(color ='red')
```

Out[129]:

```
<seaborn.axisgrid.FacetGrid at 0x1d7f7b04128>
```

```
<matplotlib.figure.Figure at 0x1d7f1de7208>
```

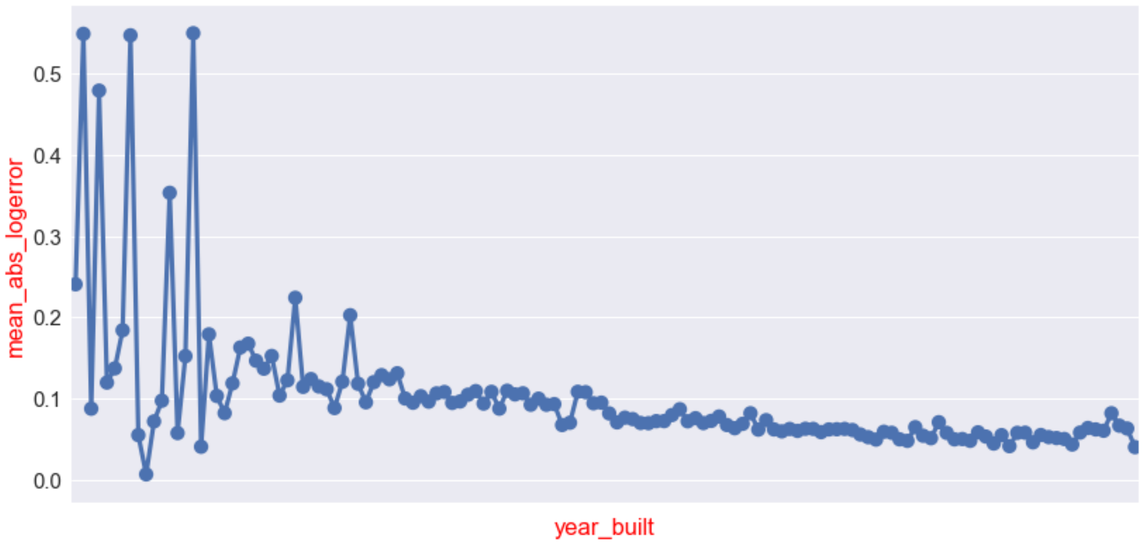
In [130]:

```
plt.figure(figsize=(8, 6))
g = sns.factorplot(x = 'yearbuilt', y= 'abs_logerror', data= merge_df, estimator= np.me
an, size = 6, aspect=2, ci = None)
sns.set(font_scale=1.5)
g.set_axis_labels("year_built", "mean_abs_logerror")
g.set_xticklabels(labels =[])
g.set_xlabels(color ='red')
g.set_ylabels(color ='red')
```

Out[130]:

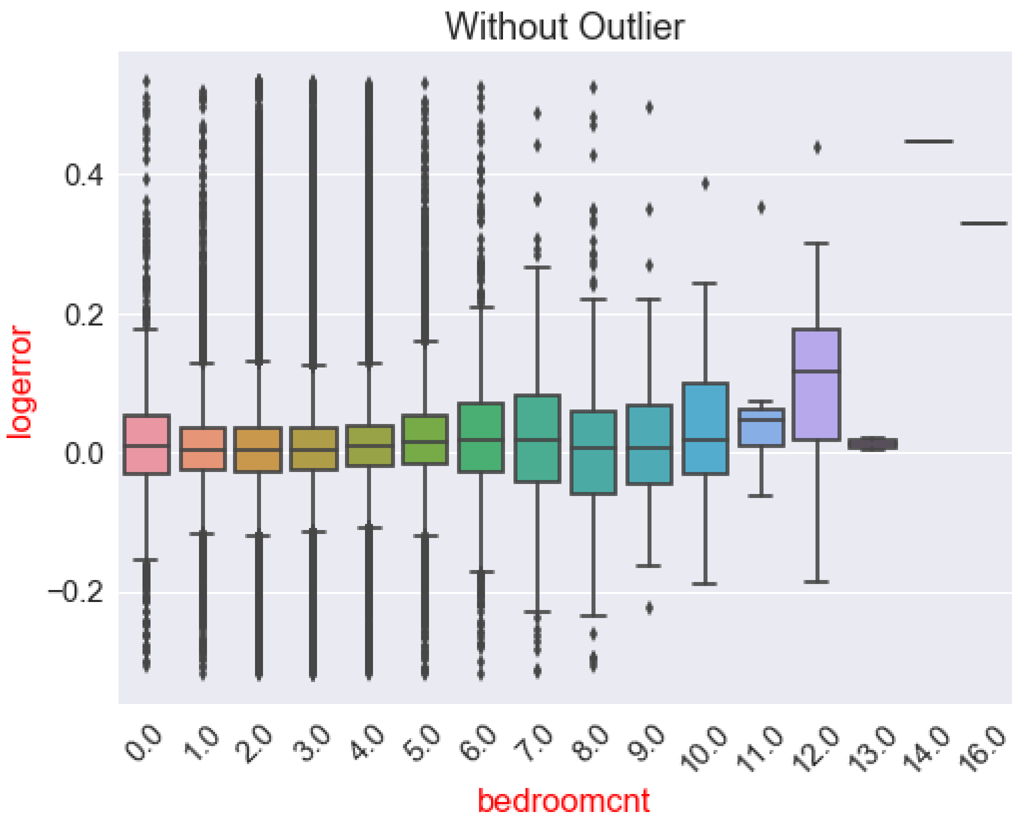
```
<seaborn.axisgrid.FacetGrid at 0x1d77fa57ef0>
```

```
<matplotlib.figure.Figure at 0x1d7efa9cb70>
```



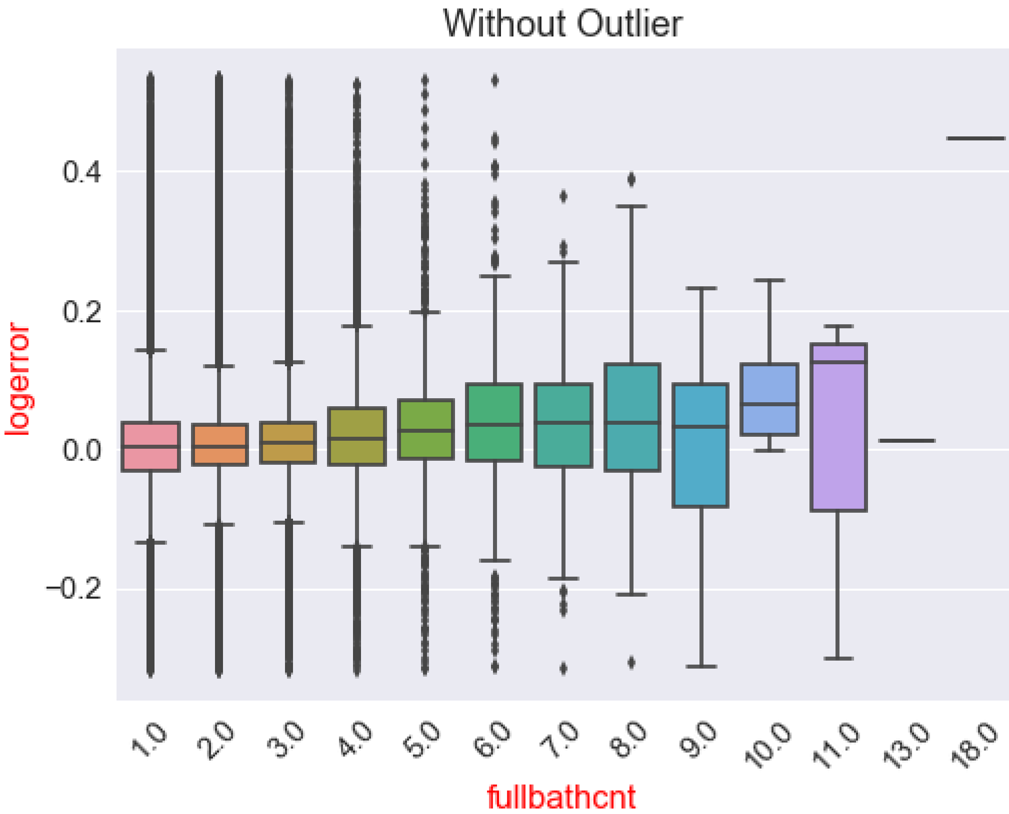
In [131]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['bedroomcnt'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
for item in g.get_xticklabels():
    item.set_rotation(45)
```



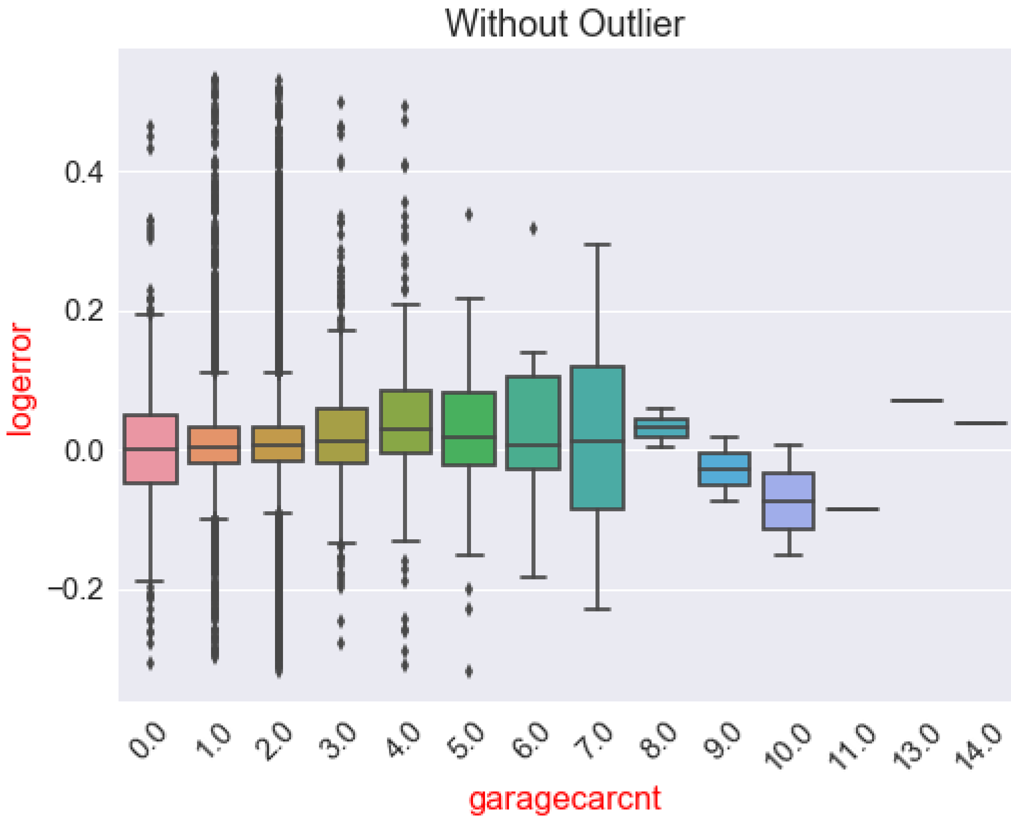
In [132]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['fullbathcnt'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
for item in g.get_xticklabels():
    item.set_rotation(45)
```



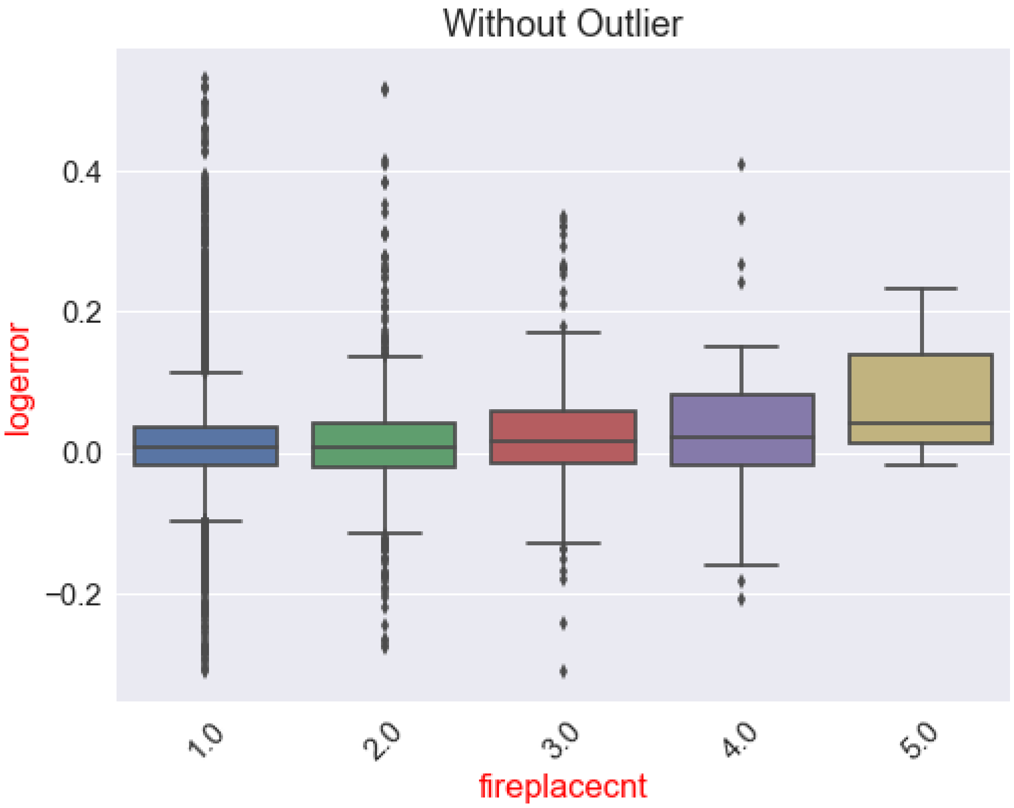
In [133]:

```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['garagecarcnt'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
for item in g.get_xticklabels():
    item.set_rotation(45)
```



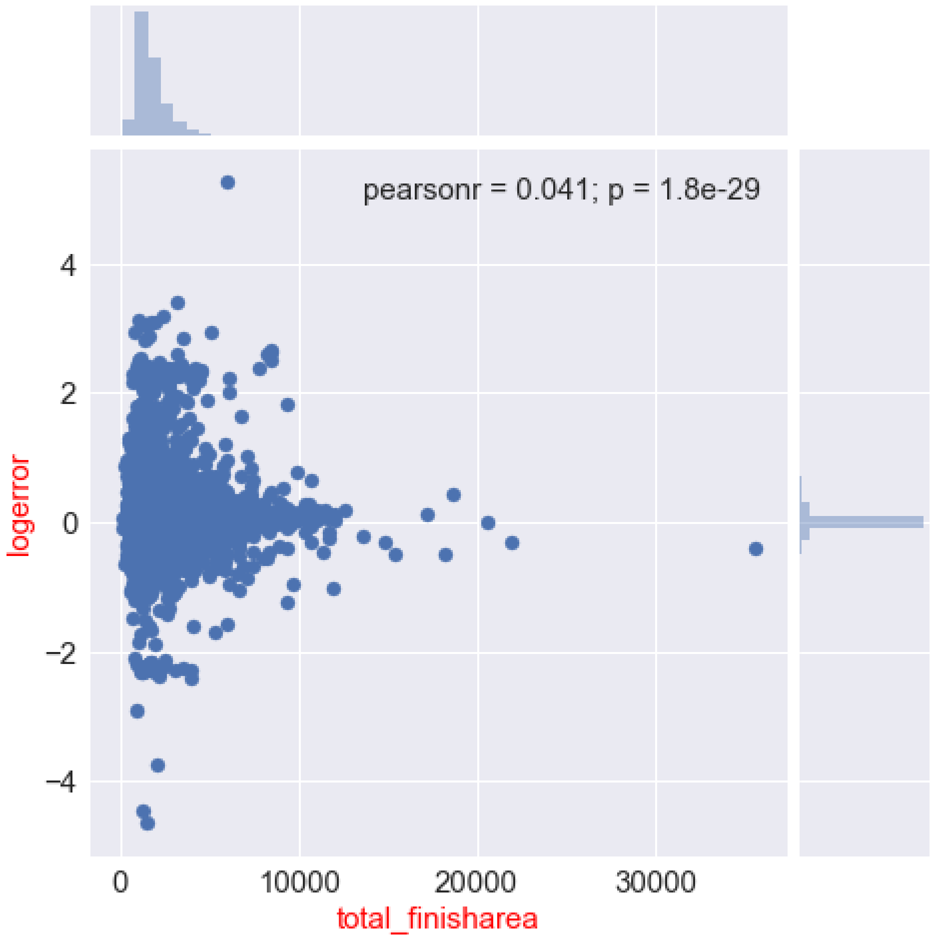
In [134]:

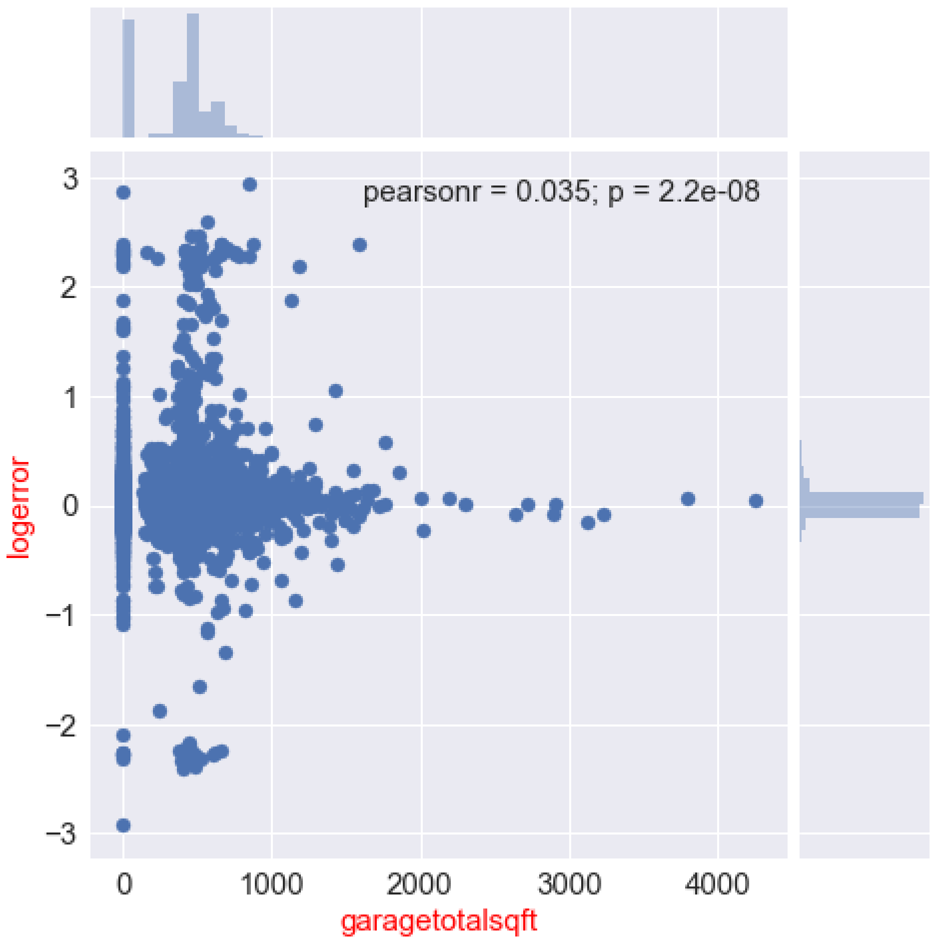
```
plt.figure(figsize=(8, 6))
g = sns.boxplot(x = nomerge_df['fireplacecnt'], y= nomerge_df['logerror'])
sns.set(font_scale=1.5)
g.set_xlabel(g.get_xlabel(), color = 'red')
g.set_ylabel(g.get_ylabel(), color ='red')
g.set_title('Without Outlier')
for item in g.get_xticklabels():
    item.set_rotation(45)
```

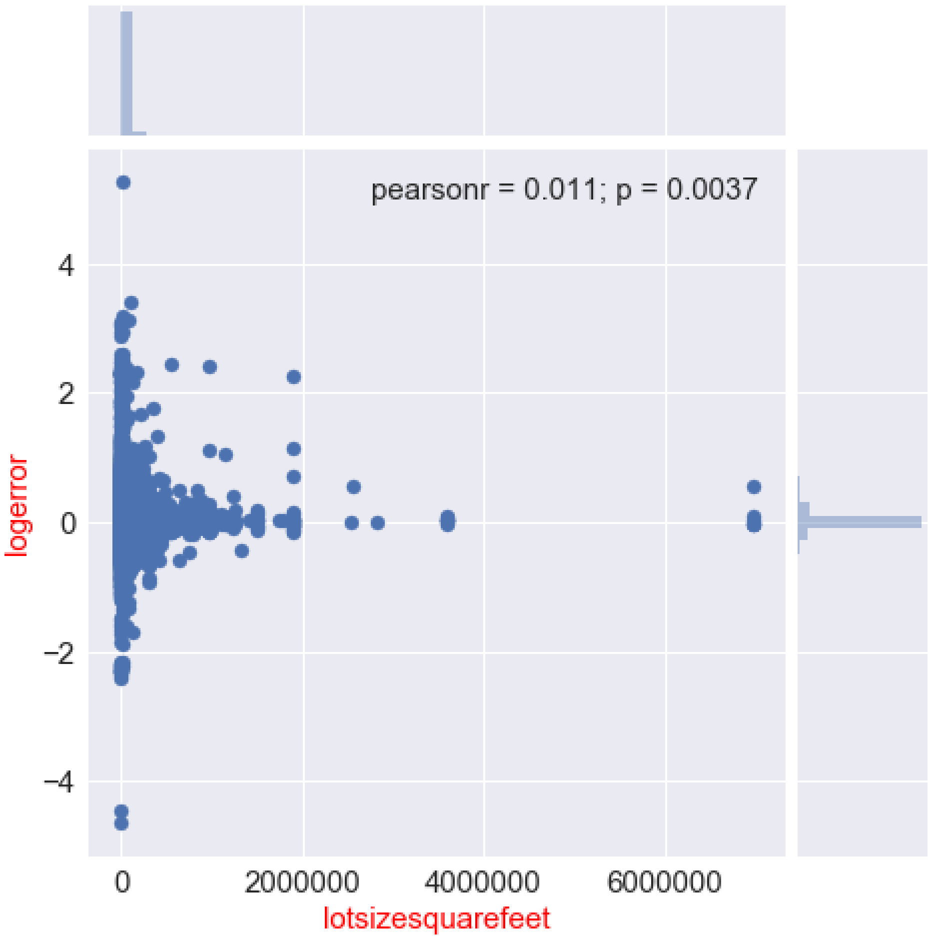


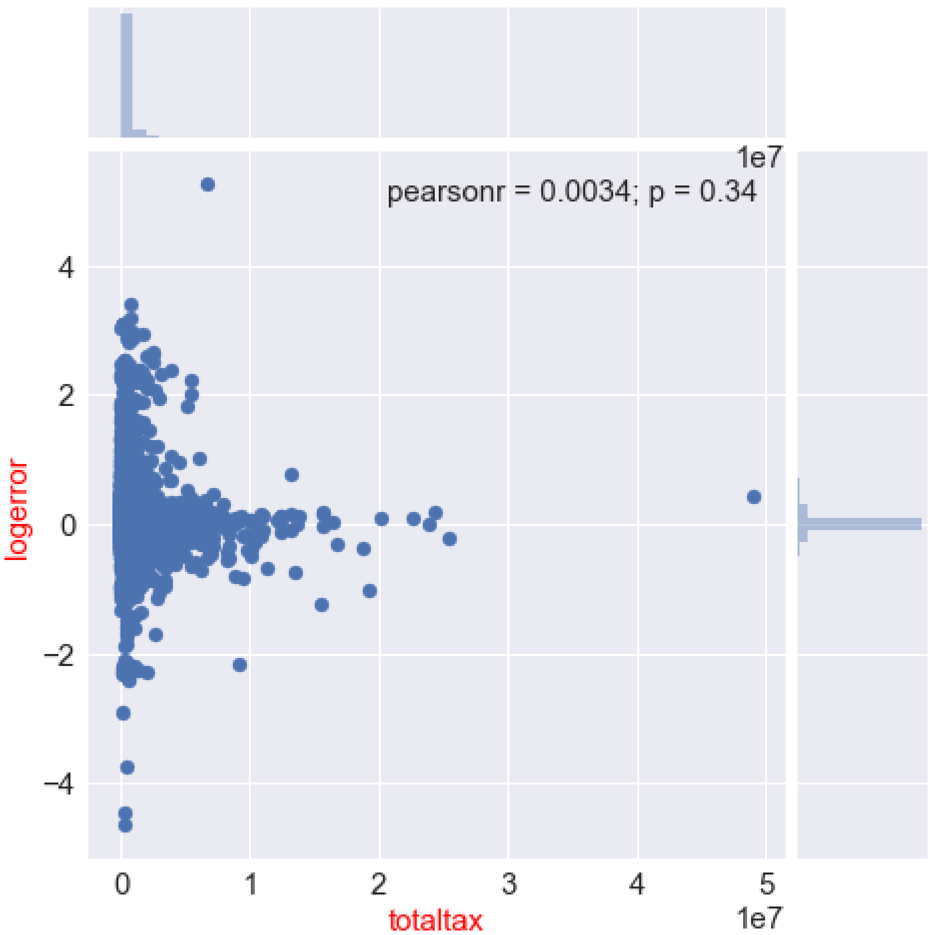
In [135]:

```
for feature in ['total_finisharea', 'garagetotalsqft', 'lotsizesquarefeet', 'totaltax'
]:
    a =sns.jointplot(merge_df[feature], merge_df['logerror'], size = 7, space =0.1)
    a.set_axis_labels(xlabel= feature, ylabel='logerror', color ='red', size = 15)
```


pearsonr = 0.041; p = 1.8e-29
logerror
total_finisharea
4
2
0
−2
−4
0
10000
20000
30000


pearsonr = 0.035; p = 2.2e-08
logerror
garagetotalsqft
3
2
1
0
−1
−2
−3
0
1000
2000
3000
4000


pearsonr = 0.011; p = 0.0037
logerror
lotsizesquarefeet
0
2000000
4000000
6000000
4
2
0
−2
−4

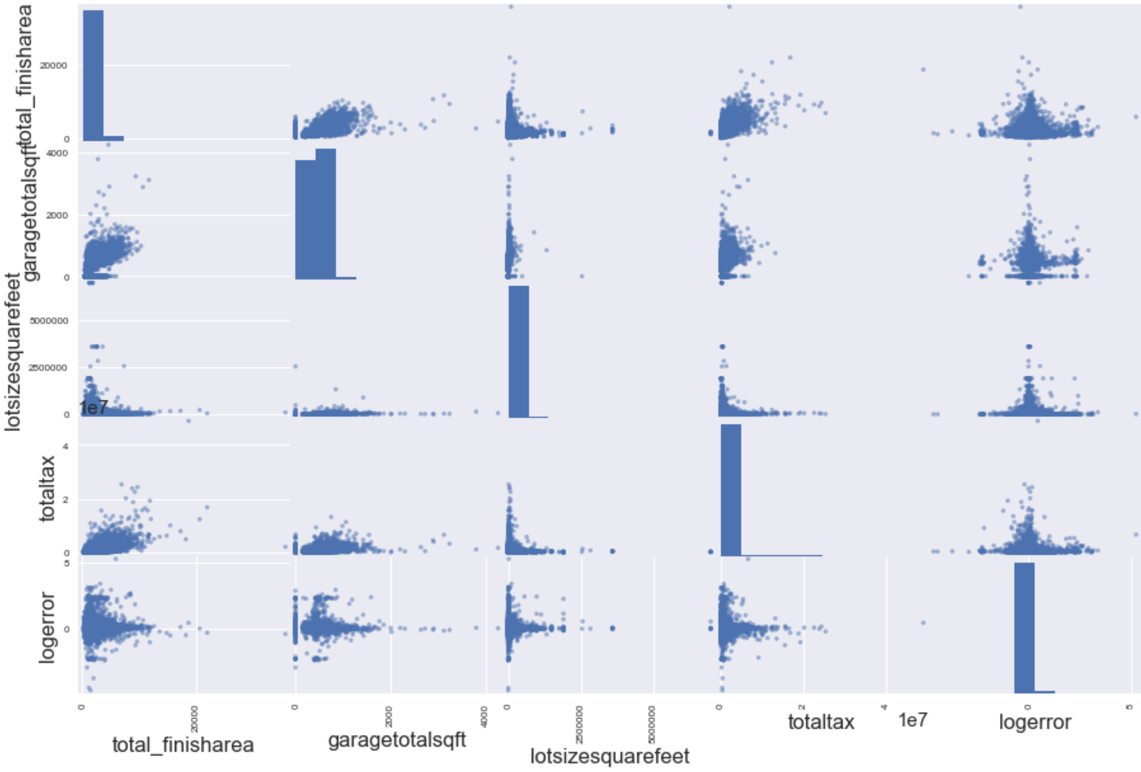

pearsonr = 0.0034; p = 0.34
1e7
logerror
totaltax
0
1
2
3
4
5
1e7
4
2
0
−2
−4

In [136]:

```
scatter_matrix(merge_df[['total_finisharea', 'garagetotalsqft', 'lotsizesquarefeet', 't
otaltax', 'logerror']], figsize = (15,10))
```

Out[136]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000001D7E0147C8
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D7F1D2686
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D722A2C2E
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D723334F2
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72339990
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001D72339994
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D7238E7B7
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72C3864E
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72C41616
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72C4266D
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001D72EC8EBE
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72ECED90
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F1DD6A
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F239F6
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F2BB27
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F31D20
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F359B3
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F3E87B
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F3F6DA
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F4B819
8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F505F6
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F57DC1
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F5E35F
8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F65D8D
0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001D72F6BE86
0>]], dtype=object)
```



dropping the columns with more than 68 percent of missing values and imputing the missing values with mean in the case of numerical variable and most frequent in the case of categorical variable

In [22]:

```
cp_merge_df = merge_df.copy()
cp_nomerge_df = nomerge_df.copy()
cp_omerge_df = omerge_df.copy()
```

In [23]:

```
merge_df.dropna(thresh=0.327*len(merge_df), axis=1, inplace=True)
nomerge_df.dropna(thresh=0.327*len(nomerge_df), axis=1, inplace=True)
omerge_df.dropna(thresh=0.327*len(omerge_df), axis=1, inplace=True)

#removing the rows which have null values (the row is removed even if it has one null v
alue)
```

impute the missing values with mean for numerical variables and mostfrequent values for categorical variables

In [24]:

```
imp_df =merge_df.copy()
```

In [25]:

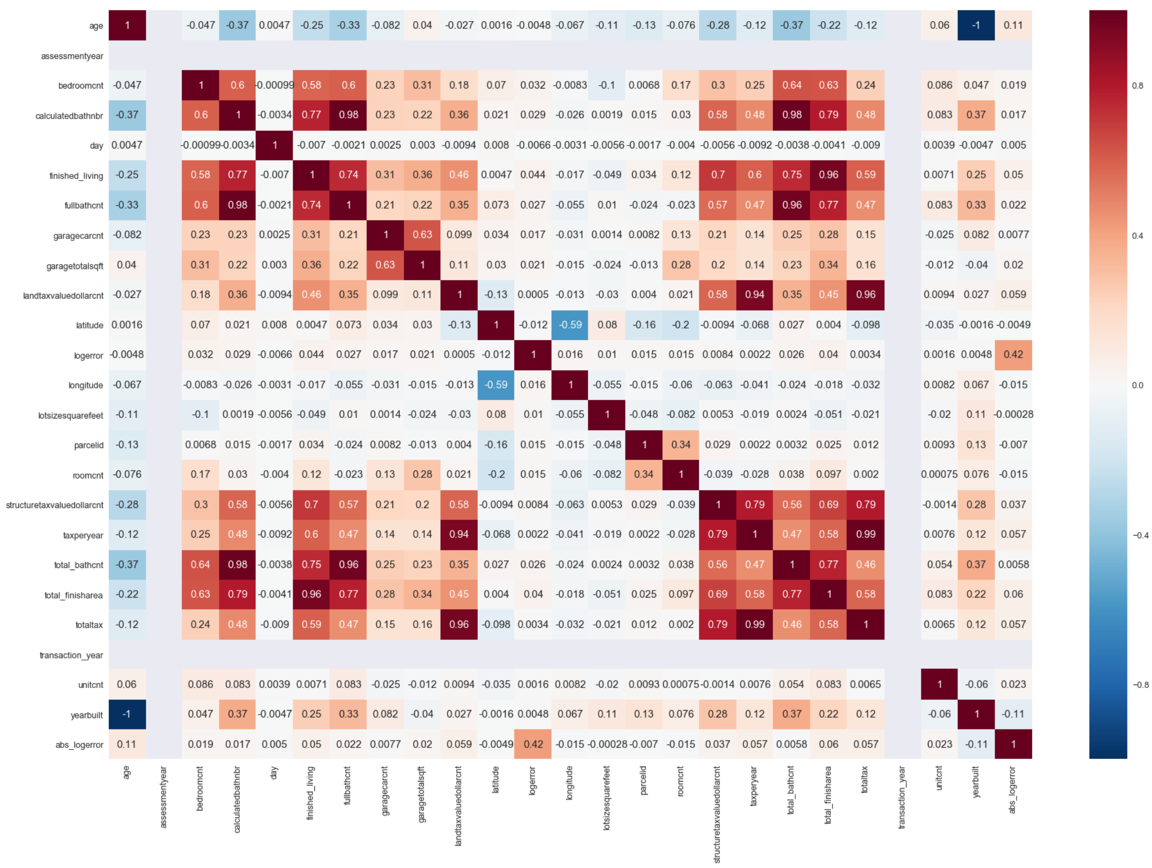
```
for col in imp_df.columns:
    if imp_df[col].dtype  == 'float64' and col not in ('month', 'day', 'quarter'):
        imp_df[col].fillna(float(imp_df[col].mean()), inplace =True)
    if imp_df[col].dtype  == 'int64' and col not in ('month', 'day', 'quarter'):
        imp_df[col].fillna(int(imp_df[col].mean()), inplace =True)
for col in imp_df.columns:
    if imp_df[col].dtype not in ('float64', 'int64'):
        imp_df[col]= imp_df[col].astype(dtype= object)
        imp_df[col].fillna(imp_df[col].mode().values[0], inplace = True)
        imp_df[col]= imp_df[col].astype('category')
```

In [141]:

```
imp_mat = imp_df.corr()
plt.figure(figsize = (30, 20))
sns.set(font_scale = 1.25)
sns.heatmap(imp_mat, annot = True)
```

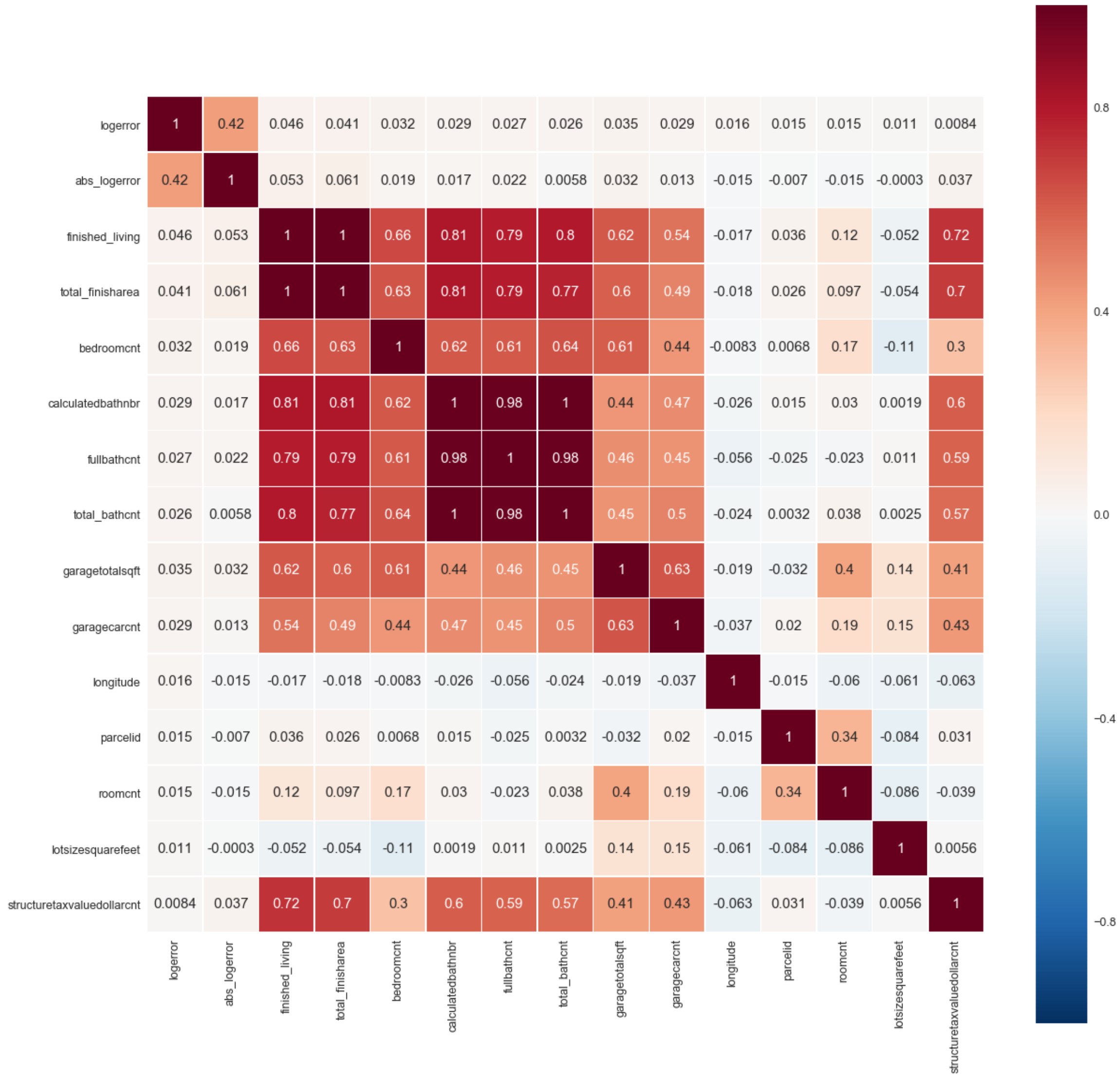
Out[141]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d72ee9a710>
```



In [142]:

```
cols = imp_mat.nlargest(15, 'logerror')['logerror'].index
plt.figure(figsize= (20,20))
imp_mat_15 = merge_df[cols].corr()
sns.heatmap(imp_mat_15, square = True, annot=True, linewidths =0.5)
sns.set_style(style = 'darkgrid')
sns.set(font_scale = 1)
```



In [26]:

```
from sklearn.preprocessing import LabelEncoder
```

Gradient Boosting Variable Importance

In [144]:

```
y = imp_df['logerror']
x = imp_df.drop(['logerror','abs_logerror', 'yearbuilt', 'day', 'month', 'quarter', 'tr
ansactiondate', 'parcelid'], axis=1)

for c in x.columns:
    if (x[c].dtype.name == 'category'):
        le = LabelEncoder()
        le.fit(x[c].values)
        x[c]=le.transform(x[c].values)
```

In [145]:

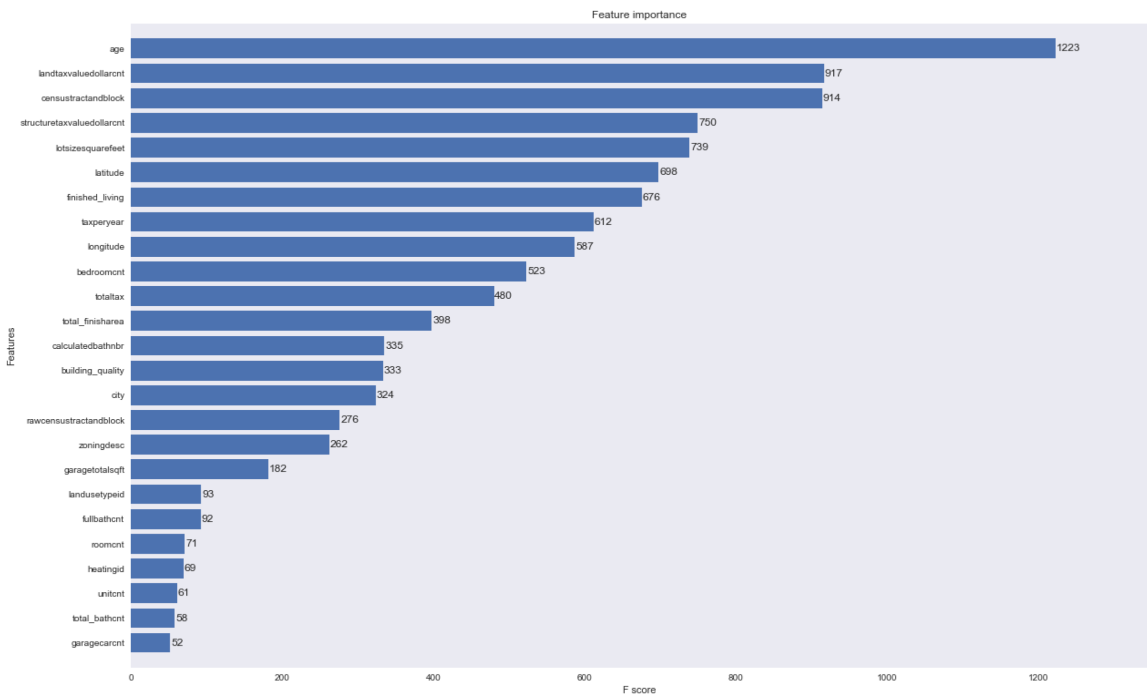
```
xgb_params = {
    'eta': 0.05,
    'max_depth': 8,
    'subsample': 0.7,
    'colsample_bytree': 0.7,
    'objective': 'reg:linear',
    'silent': 1,
    'seed' : 0,
    'lambda':5
}

train = xgb.DMatrix(x,y)
boost_model = xgb.train(xgb_params,train,num_boost_round=150)
```

In [146]:

```
fig, ax = plt.subplots(1,1,figsize= (20, 13))
xgb.plot_importance(boost_model, grid = False, height= 0.8, ax=ax)
```

Out[146]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d7f1e3ee80>
```



feature engineering with the help of gradient boosting and correlation matrix

- finsihed_living and total_finisharea have same correlation so total_finisharea is picked
- bedroomcnt, calculatebathnbr, full_bathcnt, total_bathcnt have same correlation so bedroomcnt and total bath cnt are merged to total no of living rooms
- taxperyear, structuretax value dollar cnt, land tax value dollar count have same correlation so total tax is picked

In [27]:

```
imp_df['totalroomcnt'] = imp_df['total_bathcnt'] + imp_df['bedroomcnt']
```

In [148]:

```
def funct(c):
    if (c['logerror'] > np.percentile(imp_df.logerror.values, 95)):
        val = 'positive_outlier'
    elif (c['logerror'] < np.percentile(imp_df.logerror.values, 5)):
        val ='negative_outlier'
    else:
        val = 'not_outlier'
    return val
imp_df['log_group'] = imp_df.apply(funct, axis=1)
```

Variable used for regression

- 'age', 'totalroomcnt','total_finisharea','latitude', 'longitude', 'totaltax', 'lotsizesquarefeet'

In [28]:

```
imp_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77613 entries, 0 to 77612
Data columns (total 36 columns):
parcelid                     77613 non-null int64
total_bathcnt                77613 non-null float64
bedroomcnt                   77613 non-null float64
building_quality             77613 non-null category
calculatedbathnbr            77613 non-null float64
total_finisharea             77613 non-null float64
finished_living              77613 non-null float64
fullbathcnt                  77613 non-null float64
garagecarcnt                 77613 non-null float64
garagetotalsqft              77613 non-null float64
heatingid                    77613 non-null category
latitude                     77613 non-null float64
longitude                    77613 non-null float64
lotsizesquarefeet            77613 non-null float64
landusetypeid                77613 non-null category
zoningdesc                   77613 non-null category
rawcensustractandblock       77613 non-null category
city                         77613 non-null category
roomcnt                      77613 non-null float64
unitcnt                      77613 non-null float64
yearbuilt                    77613 non-null float64
structuretaxvaluedollarcnt   77613 non-null float64
totaltax                     77613 non-null float64
assessmentyear               77613 non-null float64
landtaxvaluedollarcnt        77613 non-null float64
taxperyear                   77613 non-null float64
censustractandblock          77613 non-null category
logerror                     77613 non-null float64
transactiondate              77613 non-null category
month                        77613 non-null category
day                          77613 non-null int64
quarter                      77613 non-null category
transaction_year             77613 non-null int64
age                          77613 non-null float64
abs_logerror                 77613 non-null float64
totalroomcnt                 77613 non-null float64
dtypes: category(10), float64(23), int64(3)
memory usage: 20.6 MB
```

Linear Regression

In [30]:

```
imp_df[['age', 'totalroomcnt','total_finisharea','latitude', 'longitude', 'totaltax',
'lotsizesquarefeet' ]].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 77613 entries, 0 to 77612
Data columns (total 7 columns):
age                  77613 non-null float64
totalroomcnt         77613 non-null float64
total_finisharea     77613 non-null float64
latitude             77613 non-null float64
longitude            77613 non-null float64
totaltax             77613 non-null float64
lotsizesquarefeet    77613 non-null float64
dtypes: float64(7)
memory usage: 4.7 MB
```

In [31]:

```
X = imp_df[['age', 'totalroomcnt','total_finisharea','latitude', 'longitude', 'totalta
x', 'lotsizesquarefeet']]
Y = imp_df['logerror']

#n = pd.get_dummies(imp_df.log_group)
#X = pd.concat([X, n], axis=1)
#m = pd.get_dummies(imp_df.censustractandblock)
#X = pd.concat([X, m], axis=1)
#drops = ['censustractandblock']
#X.drop(drops, inplace=True, axis=1)
X.head()
```

Out[31]:

	age	totalroomcnt	total_finisharea	latitude	longitude	totaltax	lotsizesqu
0	35.0	9.0	3760.0	34449407.0	-119254052.0	872850.0	42688.000(
1	66.0	5.0	1444.0	34454169.0	-119237898.0	436157.0	7108.0000(
2	38.0	4.5	1698.0	34365693.0	-119448392.0	286606.0	2588.0000(
3	28.0	4.0	986.0	34305600.0	-119284000.0	258888.0	29973.437(
4	69.0	3.0	1170.0	34278012.0	-119257047.0	592930.0	5643.0000(

In [37]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.4, random_state=0
)
regressor = LinearRegression(normalize=False)
regressor.fit(X_train, y_train,)
```

Out[37]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=Fals
e)
```

In [154]:

```
y_pred = regressor.predict(X_test)
#print('Linear Regression R squared: ', regressor.score(X_test, y_test))
lin_mse = mean_squared_error(y_pred, y_test)
lin_rmse = np.sqrt(lin_mse)
print('Linear Regression RMSE: ', lin_rmse)
print('Linear Regression AME: ', mean_absolute_error(y_pred, y_test))
```

```
Linear Regression RMSE:  0.173057429591
Linear Regression AME:  0.0708969525796
```

In [155]:

```
print('Coefficients: \n', regressor.coef_)
```

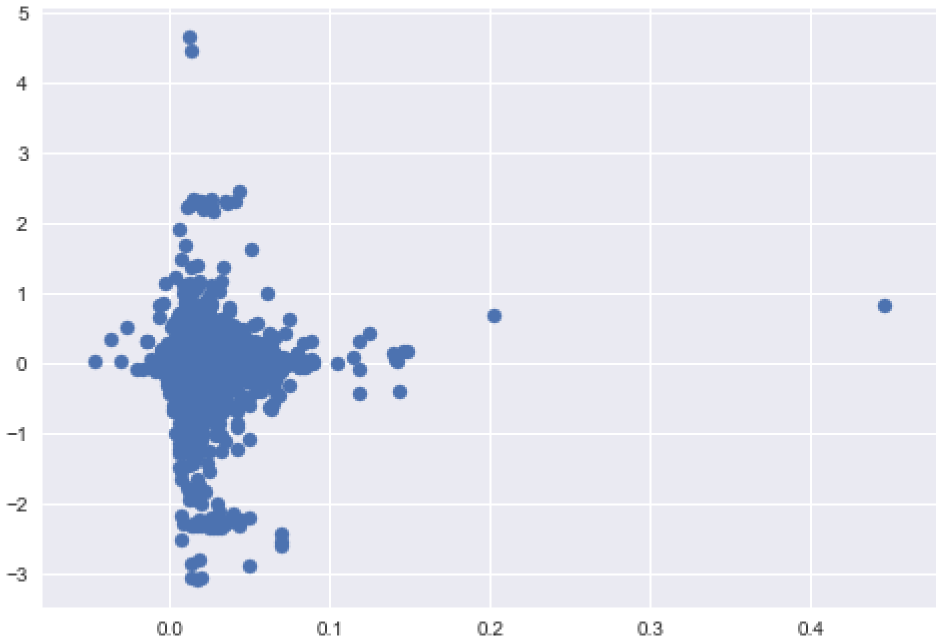
```
Coefficients: 
 [  1.44328811e-05  -1.60302881e-03   1.26306182e-05  -4.42832689e-09
   8.21271980e-09  -6.20066147e-09   1.84672058e-08]
```

In [156]:

```
plt.scatter(y_pred, (y_pred- y_test))
```

Out[156]:

```
<matplotlib.collections.PathCollection at 0x1d7bfc1e668>
```

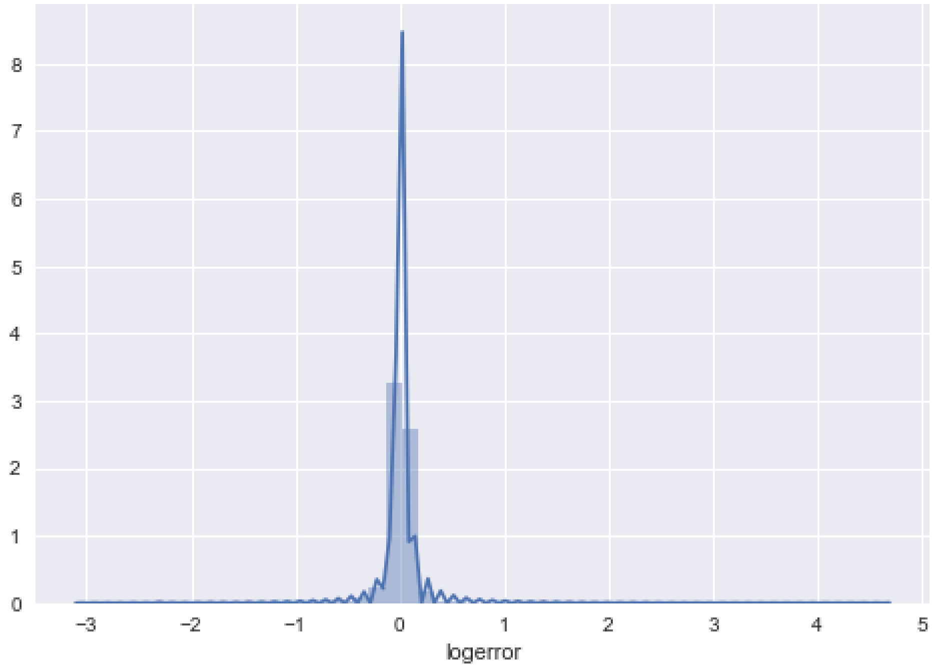


In [157]:

```
sns.distplot((y_pred- y_test),norm_hist=False)
```

Out[157]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d734823e80>
```



Ridge Regression

In [158]:

```
from sklearn.linear_model import Ridge, RidgeCV, ElasticNet, LassoCV, LassoLarsCV
from sklearn.model_selection import cross_val_score
```

In [159]:

```
RMSE = []
alphas = [0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 50, 75, 100, 125, 150, 175, 200, 225, 25
0, 1000]
for tuning_param in alphas:
    ridge_model = Ridge(alpha=tuning_param)
    ridge_model.fit(X_train, y_train)
    ridge_model.score(X_test, y_test)
    print('Coefficients: ', tuning_param, '\n', ridge_model.coef_)
    #print(cross_val_score(ridge_model, X_train, y_train, scoring=None, cv = 5))
    RMSE.append((sum((ridge_model.predict(X_test) - y_test)**2)/len(y_test))**0.5)
```

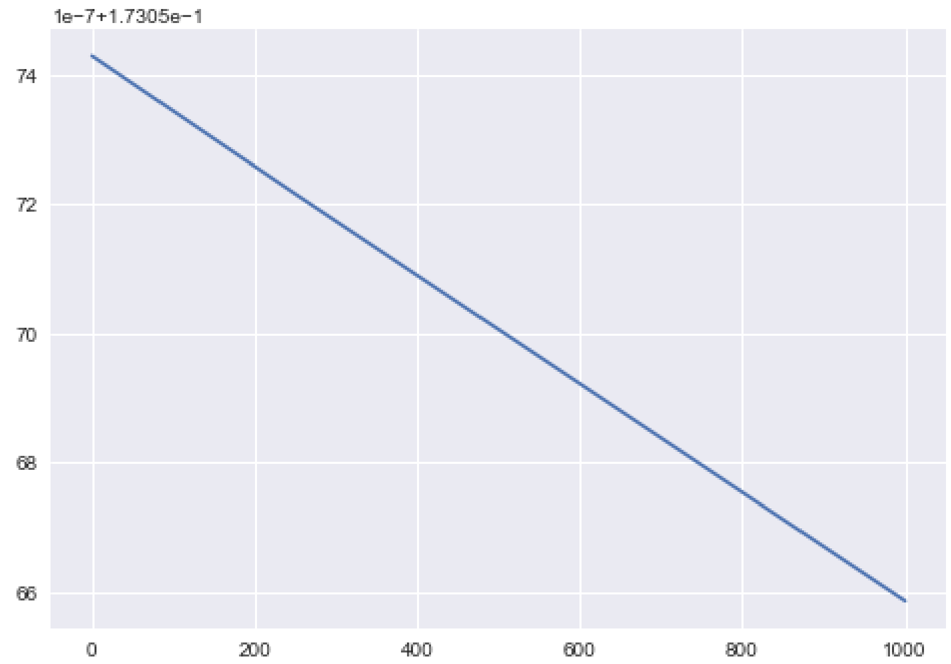
```
Coefficients:  0.05
 [  1.44328861e-05  -1.60302764e-03   1.26306163e-05  -4.42832743e-09
   8.21271963e-09  -6.20066116e-09   1.84672065e-08]
Coefficients:  0.1
 [  1.44328912e-05  -1.60302646e-03   1.26306143e-05  -4.42832797e-09
   8.21271946e-09  -6.20066084e-09   1.84672072e-08]
Coefficients:  0.3
 [  1.44329113e-05  -1.60302176e-03   1.26306065e-05  -4.42833013e-09
   8.21271877e-09  -6.20065959e-09   1.84672098e-08]
Coefficients:  1
 [  1.44329819e-05  -1.60300531e-03   1.26305792e-05  -4.42833770e-09
   8.21271638e-09  -6.20065521e-09   1.84672189e-08]
Coefficients:  3
 [  1.44331835e-05  -1.60295830e-03   1.26305012e-05  -4.42835934e-09
   8.21270955e-09  -6.20064268e-09   1.84672451e-08]
Coefficients:  5
 [  1.44333852e-05  -1.60291129e-03   1.26304231e-05  -4.42838097e-09
   8.21270271e-09  -6.20063016e-09   1.84672712e-08]
Coefficients:  10
 [  1.44338892e-05  -1.60279378e-03   1.26302281e-05  -4.42843503e-09
   8.21268563e-09  -6.20059885e-09   1.84673366e-08]
Coefficients:  15
 [  1.44343931e-05  -1.60267630e-03   1.26300331e-05  -4.42848909e-09
   8.21266855e-09  -6.20056754e-09   1.84674020e-08]
Coefficients:  30
 [  1.44359044e-05  -1.60232394e-03   1.26294483e-05  -4.42865123e-09
   8.21261732e-09  -6.20047366e-09   1.84675980e-08]
Coefficients:  50
 [  1.44379185e-05  -1.60185437e-03   1.26286689e-05  -4.42886730e-09
   8.21254905e-09  -6.20034855e-09   1.84678593e-08]
Coefficients:  75
 [  1.44404344e-05  -1.60126779e-03   1.26276954e-05  -4.42913720e-09
   8.21246377e-09  -6.20019226e-09   1.84681856e-08]
Coefficients:  100
 [  1.44429485e-05  -1.60068164e-03   1.26267225e-05  -4.42940691e-09
   8.21237855e-09  -6.20003609e-09   1.84685118e-08]
Coefficients:  125
 [  1.44454607e-05  -1.60009593e-03   1.26257504e-05  -4.42967642e-09
   8.21229339e-09  -6.19988003e-09   1.84688377e-08]
Coefficients:  150
 [  1.44479711e-05  -1.59951064e-03   1.26247790e-05  -4.42994574e-09
   8.21220829e-09  -6.19972409e-09   1.84691633e-08]
Coefficients:  175
 [  1.44504796e-05  -1.59892577e-03   1.26238083e-05  -4.43021485e-09
   8.21212326e-09  -6.19956826e-09   1.84694887e-08]
Coefficients:  200
 [  1.44529862e-05  -1.59834134e-03   1.26228383e-05  -4.43048377e-09
   8.21203829e-09  -6.19941254e-09   1.84698139e-08]
Coefficients:  225
 [  1.44554910e-05  -1.59775733e-03   1.26218690e-05  -4.43075250e-09
   8.21195338e-09  -6.19925694e-09   1.84701388e-08]
Coefficients:  250
 [  1.44579940e-05  -1.59717375e-03   1.26209004e-05  -4.43102103e-09
   8.21186853e-09  -6.19910145e-09   1.84704635e-08]
Coefficients:  1000
 [  1.45322344e-05  -1.57986244e-03   1.25921683e-05  -4.43898667e-09
   8.20935157e-09  -6.19448903e-09   1.84800949e-08]
```

In [160]:

```
plt.plot(alphas, RMSE)
```

Out[160]:

```
[<matplotlib.lines.Line2D at 0x1d72ca887b8>]
```



Random Forest

In [161]:

```
from sklearn.ensemble import RandomForestRegressor
forest_reg = RandomForestRegressor(random_state=42)
forest_reg.fit(X_train, y_train)
```

Out[161]:

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_split=1e-07, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=10, n_jobs=1, oob_score=False, random_state=42,
           verbose=0, warm_start=False)
```

In [162]:

```
y_pred = forest_reg.predict(X_test)
forest_mse = mean_squared_error(y_pred, y_test)
forest_rmse = np.sqrt(forest_mse)
print('Random Forest RMSE: ', forest_rmse)
print('Random Forest AME:  ', mean_absolute_error(y_pred, y_test))
```

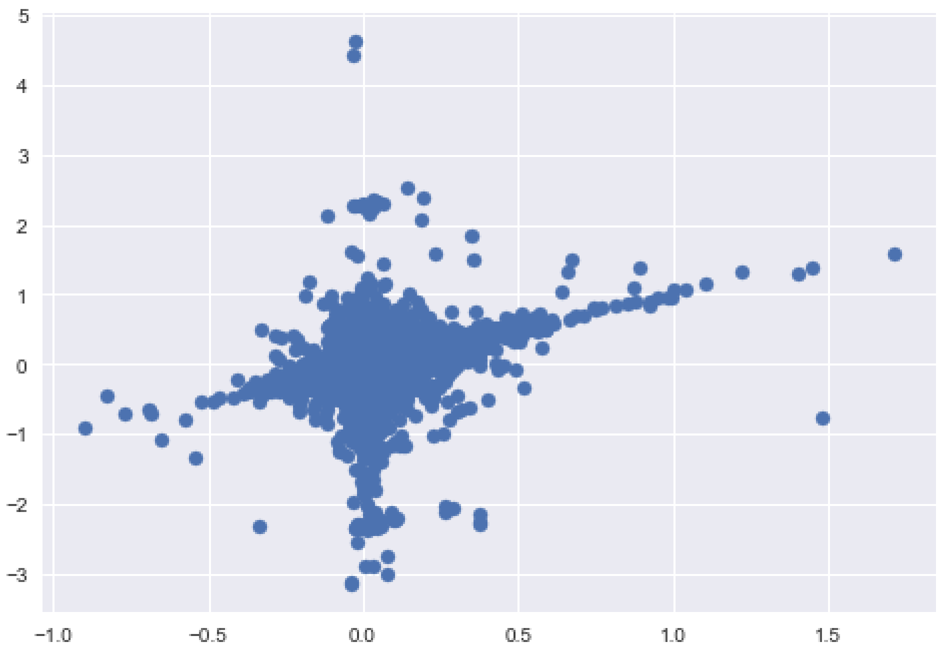
```
Random Forest RMSE:  0.184491342476
Random Forest AME:   0.0862187977687
```

In [163]:

```
plt.scatter(y_pred, (y_pred- y_test))
```

Out[163]:

```
<matplotlib.collections.PathCollection at 0x1d72fa799e8>
```



Gradient Boosting

In [38]:

```
from sklearn import ensemble
from sklearn.ensemble import GradientBoostingRegressor
model = ensemble.GradientBoostingRegressor(n_estimators=100, max_depth=4, min_samples_s
plit=40, learning_rate=0.01)
model.fit(X_train, y_train)
```

Out[38]:

```
GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', init=None,
             learning_rate=0.01, loss='ls', max_depth=4, max_features=Non
e,
             max_leaf_nodes=None, min_impurity_split=1e-07,
             min_samples_leaf=1, min_samples_split=40,
             min_weight_fraction_leaf=0.0, n_estimators=100,
             presort='auto', random_state=None, subsample=1.0, verbose=0,
             warm_start=False)
```

In [165]:

```
y_pred = model.predict(X_test)
model_mse = mean_squared_error(y_pred, y_test)
model_rmse = np.sqrt(model_mse)
#print('Gradient Boosting R squared": %.4f' % model.score(X_test, y_test))
print('Gradient Boosting RMSE: ', model_rmse)
print('Gradient Boosting RMSE: ', mean_absolute_error(y_pred, y_test))
```

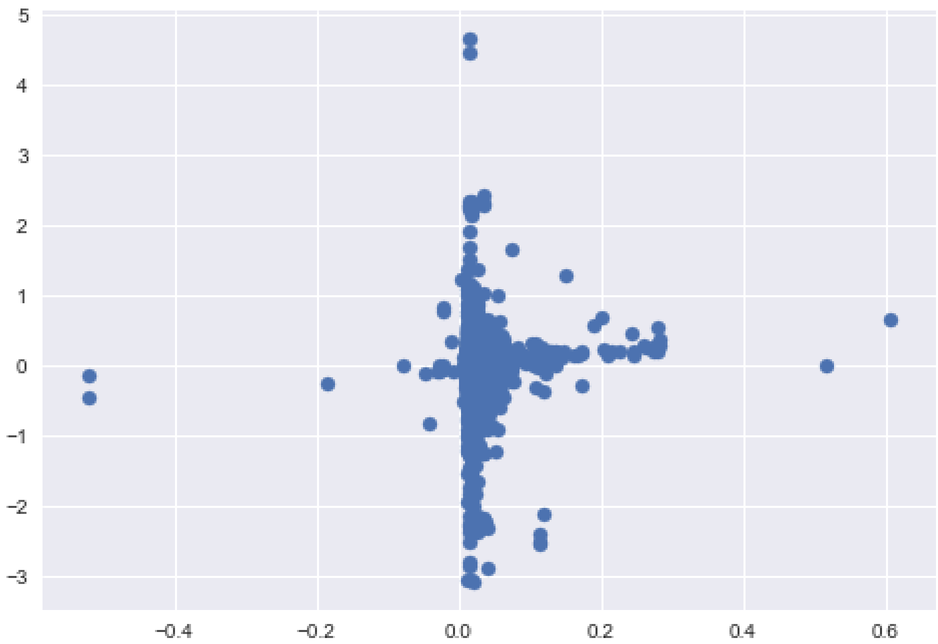
```
Gradient Boosting RMSE:  0.173087825491
Gradient Boosting RMSE:  0.0709582747472
```

In [166]:

```
plt.scatter(y_pred, (y_pred- y_test))
```

Out[166]:

```
<matplotlib.collections.PathCollection at 0x1d7311f2cc0>
```



Cross_validation

In [51]:

```
from sklearn.cross_validation import cross_val_score
#Features after Cross Validation
features=['age', 'totalroomcnt','total_finisharea','latitude']
x = X[features]
gb_score=cross_val_score(model,x,Y,cv=10,scoring='mean_absolute_error')
-gb_score.mean()
```

Out[51]:

```
0.070531605180707557
```

In [52]:

```
X1_train, X1_test, Y1_train, Y1_test = train_test_split(x, Y, test_size=0.4, random_sta
te=0)
```

In [53]:

```
#XGB after Cross validation
model = ensemble.GradientBoostingRegressor(n_estimators=100, max_depth=4, min_samples_s
plit=40, learning_rate=0.01)
model.fit(X1_train, Y1_train)
y_pred = model.predict(X1_test)
model_mse = mean_squared_error(y_pred, y_test)
#print('Gradient Boosting R squared": %.4f' % model.score(X_test, y_test))
print('Gradient Boosting MAE: ', mean_absolute_error(y_pred, y_test))
```

```
Gradient Boosting MAE:  0.070872994978
```

Principal Component Analysis