Thomas Chant

Zestimate Improvement

In [1]:
```
#packages
import numpy as np
import pandas as pd
import random
import datetime as dt
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn as sk
from sklearn.feature_selection import SelectKBest, mutual_info_regression, RFE
from sklearn.linear_model import LinearRegression, LassoCV
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import RandomizedSearchCV
from sklearn import tree
from dtreeviz.trees import dtreeviz
```

In [2]:
```
#import the data
train_2016 = pd.read_csv(r'C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2022\D
train_2017 = pd.read_csv(r'C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2022\D
properties_2016 = pd.read_csv(r"C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2
properties_2017 = pd.read_csv(r"C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2
samplesubmission = pd.read_csv(r'C:\Users\thoma\Desktop\Colorado School of Mines\Fall 
```

In [3]:
```
#properties_2016
samplesubmission
```

Out[3]:

	ParcelId	201610	201611	201612	201710	201711	201712
0	10754147	0	0	0	0	0	0
1	10759547	0	0	0	0	0	0
2	10843547	0	0	0	0	0	0
3	10859147	0	0	0	0	0	0
4	10879947	0	0	0	0	0	0
...	...	...	...	...	...	...	...
2985212	168176230	0	0	0	0	0	0
2985213	14273630	0	0	0	0	0	0
2985214	168040630	0	0	0	0	0	0
2985215	168040830	0	0	0	0	0	0
2985216	168040430	0	0	0	0	0	0

2985217 rows × 7 columns

import the data

train_2016 = pd.read_csv(r'C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2022\DSCI470 - Introduction to Machine Learning\Final Project\train_2016_v2.csv', parse_dates=["transactiondate"]) train_2017 = pd.read_csv(r'C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2022\DSCI470 - Introduction to Machine Learning\Final Project\train_2017.csv', parse_dates=["transactiondate"]) properties_2016 = pd.read_csv(r"C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2022\DSCI470 - Introduction to Machine Learning\Final Project\properties_2016.csv") properties_2017 = pd.read_csv(r"C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2022\DSCI470 - Introduction to Machine Learning\Final Project\properties_2017.csv") samplesubmission = pd.read_csv(r'C:\Users\thoma\Desktop\Colorado School of Mines\Fall 2022\DSCI470 - Introduction to Machine Learning\Final Project\sample_submission.csv')

Data Cleaning

The first major issue is that our y sets are much smaller than our X sets, there are loads of data points in the X set that we do not have the logerror for, so we need to get rid of those first. This will also help massively with reducing memory issues, since instead of a ~3 million point set with 59 variables, we'll be working with less than 100,000. Also, we need to put our 2016 and 2017 sets together.

In [4]:
```
def add_date_features(df):
    df["transaction_year"] = df["transactiondate"].dt.year
```

```
    df["transaction_month"] = (df["transactiondate"].dt.year - 2016)*12 + df["transact
    df["transaction_day"] = df["transactiondate"].dt.day
    df["transaction_quarter"] = (df["transactiondate"].dt.year - 2016)*4 +df["transact
    df.drop(["transactiondate"], inplace=True, axis=1)
    return df
```

In [5]:

```
properties_2016 = pd.merge(train_2016, properties_2016, how = 'left', on = 'parcelid')
properties_2017 = pd.merge(train_2017, properties_2017, how = 'left', on = 'parcelid')

properties_2016 = add_date_features(properties_2016)
properties_2017 = add_date_features(properties_2017)
test_df = properties_2016.copy()

samplesubmission['parcelid'] = samplesubmission['ParcelId']

X = pd.concat([properties_2016, properties_2017], ignore_index=True)
training = pd.concat([train_2016, train_2017], ignore_index=True)
test_df = pd.merge(properties_2016, samplesubmission[['parcelid']],  how = 'left', on
y = training.logerror


print(y.info())
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 167888 entries, 0 to 167887
Series name: logerror
Non-Null Count   Dtype
--------------   -----
167888 non-null  float64
dtypes: float64(1)
memory usage: 1.3 MB
None
```

In [6]:

```
X.describe()
```

Out[6]:

	parcelid	logerror	airconditioningtypeid	architecturalstyletypeid	basementsqft	ba
count	1.678880e+05	167888.000000	53788.000000	468.000000	93.000000	167
mean	1.299536e+07	0.013906	1.814345	7.299145	695.376344	
std	3.016071e+06	0.165706	2.970239	2.719633	583.952144	
min	1.071174e+07	-4.655420	1.000000	2.000000	38.000000	
25%	1.154899e+07	-0.025300	1.000000	7.000000	280.000000	
50%	1.254060e+07	0.006000	1.000000	7.000000	588.000000	
75%	1.421930e+07	0.039200	1.000000	7.000000	819.000000	
max	1.676893e+08	5.262999	13.000000	21.000000	3560.000000	

8 rows × 58 columns

In [7]:

```
X.head()
```

Out[7]:

	parcelid	logerror	airconditioningtypeid	architecturalstyletypeid	basementsqft	bathroomcnt	be
0	11016594	0.0276	1.0	NaN	NaN	2.0	
1	14366692	-0.1684	NaN	NaN	NaN	3.5	
2	12098116	-0.0040	1.0	NaN	NaN	3.0	
3	12643413	0.0218	1.0	NaN	NaN	2.0	
4	14432541	-0.0050	NaN	NaN	NaN	2.5	

5 rows × 63 columns

In [8]:
```
training.head()
```

Out[8]:

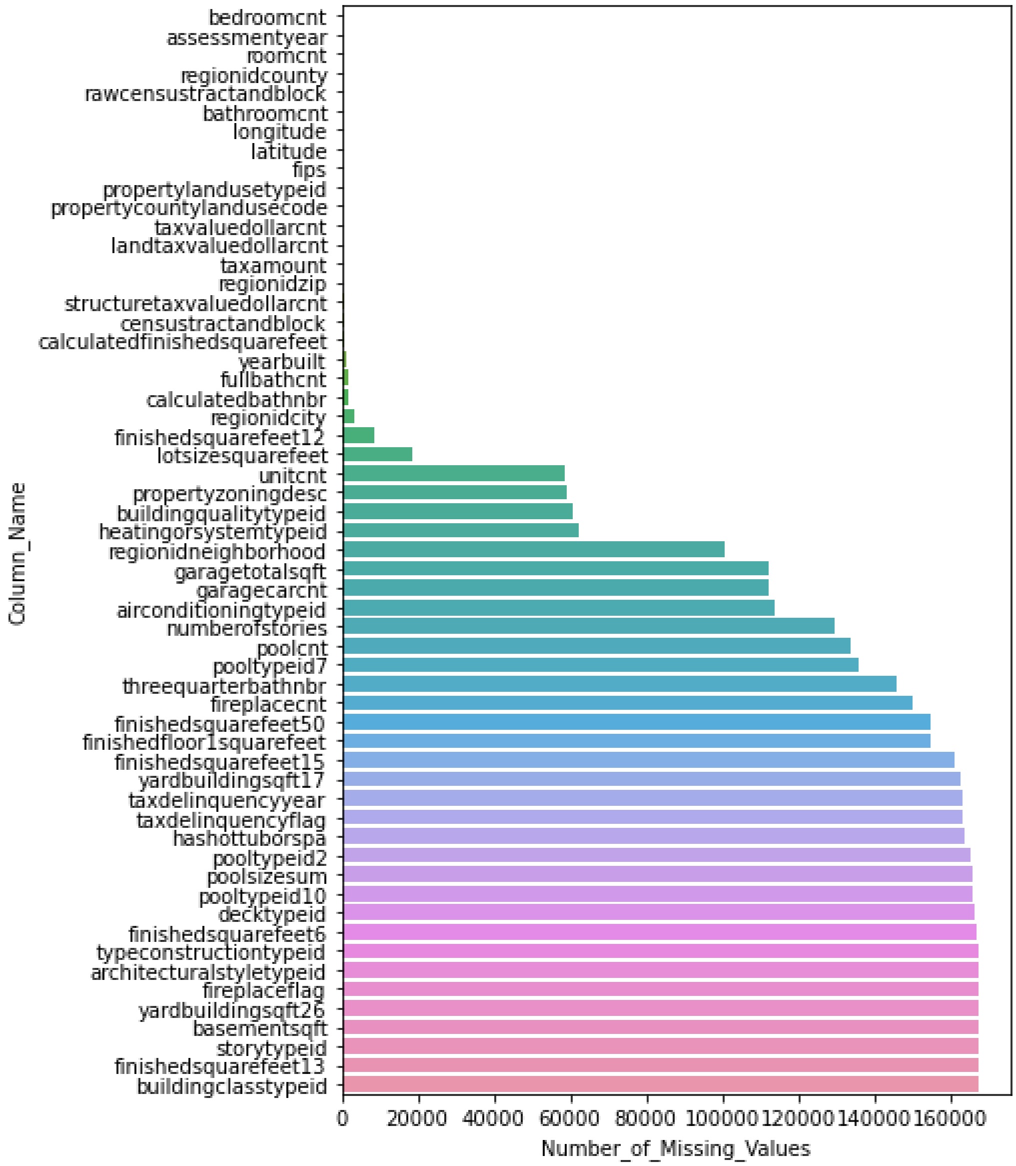
	parcelid	logerror	transactiondate
0	11016594	0.0276	2016-01-01
1	14366692	-0.1684	2016-01-01
2	12098116	-0.0040	2016-01-01
3	12643413	0.0218	2016-01-02
4	14432541	-0.0050	2016-01-02

In [9]:
```
trainingvariables = ['logerror']

X = X.drop(trainingvariables, axis=1)
```

Next, lets examine missing values

In [10]:
```
missingdata = X.isnull().sum(axis=0).reset_index()
missingdata.columns = ['Column_Name', 'Number_of_Missing_Values']
missingdata = missingdata.sort_values(by = 'Number_of_Missing_Values')
missingdata = missingdata[missingdata['Number_of_Missing_Values']>0]

f, ax = plt.subplots(figsize=(6, 10))
sns.set_color_codes("pastel")
sns.barplot(x="Number_of_Missing_Values", y="Column_Name", data=missingdata)
```

Out[10]:
```
<AxesSubplot:xlabel='Number_of_Missing_Values', ylabel='Column_Name'>
```



In [11]:
```
percent_missing = X.isnull().sum() * 100 / len(X)
bad_columns = percent_missing[percent_missing>40].keys()
X = X.drop(bad_columns, axis=1)
X.describe()
test_df = test_df.drop(bad_columns, axis = 1)
```

In [12]:
```
print(X.columns.values)
```

```
['parcelid' 'bathroomcnt' 'bedroomcnt' 'buildingqualitytypeid'
 'calculatedbathnbr' 'calculatedfinishedsquarefeet' 'finishedsquarefeet12'
 'fips' 'fullbathcnt' 'heatingorsystemtypeid' 'latitude' 'longitude'
 'lotsizesquarefeet' 'propertycountylandusecode' 'propertylandusetypeid'
 'propertyzoningdesc' 'rawcensustractandblock' 'regionidcity'
 'regionidcounty' 'regionidzip' 'roomcnt' 'unitcnt' 'yearbuilt'
 'structuretaxvaluedollarcnt' 'taxvaluedollarcnt' 'assessmentyear'
 'landtaxvaluedollarcnt' 'taxamount' 'censustractandblock'
 'transaction_year' 'transaction_month' 'transaction_day'
 'transaction_quarter']
```

Manually dropping redundant information variables

In [13]:
```
redundant_info_variables = [ 'assessmentyear', 'calculatedbathnbr', 'censustractandblc
X = X.drop(redundant_info_variables, axis=1)
test_df = test_df.drop(redundant_info_variables, axis=1)
```

In [14]:
```
print(X.columns.values)
```

```
['parcelid' 'bathroomcnt' 'bedroomcnt' 'buildingqualitytypeid'
 'calculatedfinishedsquarefeet' 'fips' 'heatingorsystemtypeid' 'latitude'
 'longitude' 'lotsizesquarefeet' 'propertylandusetypeid'
 'rawcensustractandblock' 'unitcnt' 'yearbuilt'
 'structuretaxvaluedollarcnt' 'landtaxvaluedollarcnt' 'transaction_year'
 'transaction_month' 'transaction_day' 'transaction_quarter']
```

In [15]:
```
X.describe()
```

Out[15]:

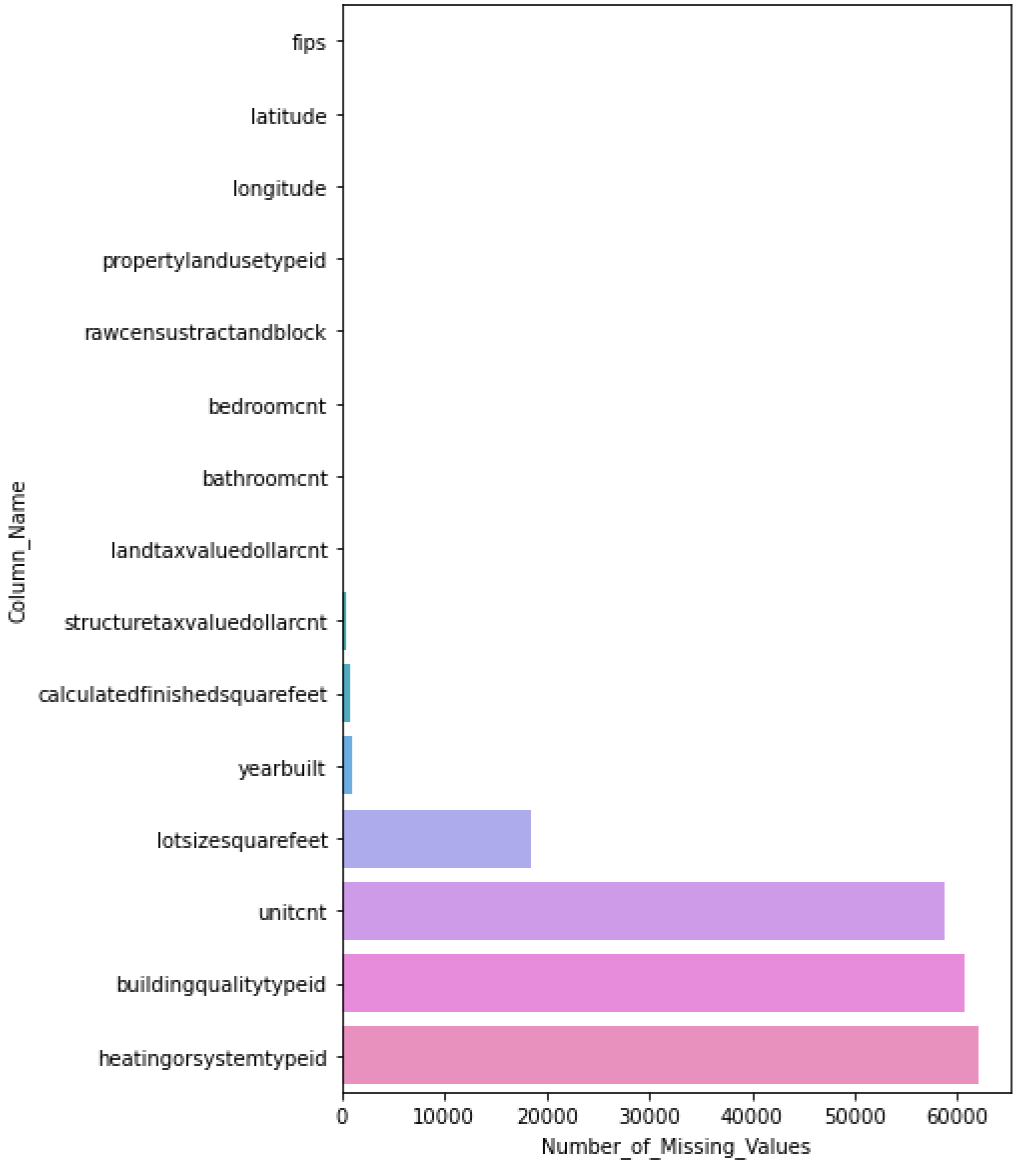
	parcelid	bathroomcnt	bedroomcnt	buildingqualitytypeid	calculatedfinishedsquarefeet
count	1.678880e+05	167854.000000	167854.000000	107173.000000	166992.000000
mean	1.299536e+07	2.288265	3.041739	6.015461	1778.630246
std	3.016071e+06	1.000835	1.149134	1.882799	940.356025
min	1.071174e+07	0.000000	0.000000	1.000000	2.000000
25%	1.154899e+07	2.000000	2.000000	4.000000	1183.000000
50%	1.254060e+07	2.000000	3.000000	7.000000	1541.000000
75%	1.421930e+07	3.000000	4.000000	7.000000	2103.000000
max	1.676893e+08	20.000000	16.000000	12.000000	35640.000000

Imputation Time

In [16]:
```
missingdata = X.isnull().sum(axis=0).reset_index()
missingdata.columns = ['Column_Name', 'Number_of_Missing_Values']
missingdata = missingdata.sort_values(by = 'Number_of_Missing_Values')
missingdata = missingdata[missingdata['Number_of_Missing_Values']>0]

f, ax = plt.subplots(figsize=(6, 10))
sns.set_color_codes("pastel")
sns.barplot(x="Number_of_Missing_Values", y="Column_Name", data=missingdata)
```

Out[16]:

```
<AxesSubplot:xlabel='Number_of_Missing_Values', ylabel='Column_Name'>
```



In [17]:
```
#Mode Imputation Pipeline and execution
listofmodeimputs = ['heatingorsystemtypeid', 'unitcnt', 'yearbuilt', 'propertylanduset
for col in listofmodeimputs:
    X[col] = X[col].fillna(X[col].mode()[0])
    test_df[col] = test_df[col].fillna(test_df[col].mode()[0])
```

In [18]:
```
#Median Imputation Pipeline
listofmedianimputs = ['buildingqualitytypeid', 'lotsizesquarefeet', 'landtaxvaluedolla
for col in listofmedianimputs:
    X[col] = X[col].fillna(X[col].median())
    test_df[col] = test_df[col].fillna(test_df[col].median())
```

Missing values taken care of, now let's see whether anything seems to be the wrong type

In [19]:
```
#just double checking that test_df is correct
#missingdata = test_df.isnull().sum(axis=0).reset_index()
#missingdata.columns = ['Column_Name', 'Number_of_Missing_Values']
#missingdata = missingdata.sort_values(by = 'Number_of_Missing_Values')
#missingdata = missingdata[missingdata['Number_of_Missing_Values']>0]

#f, ax = plt.subplots(figsize=(6, 10))
```

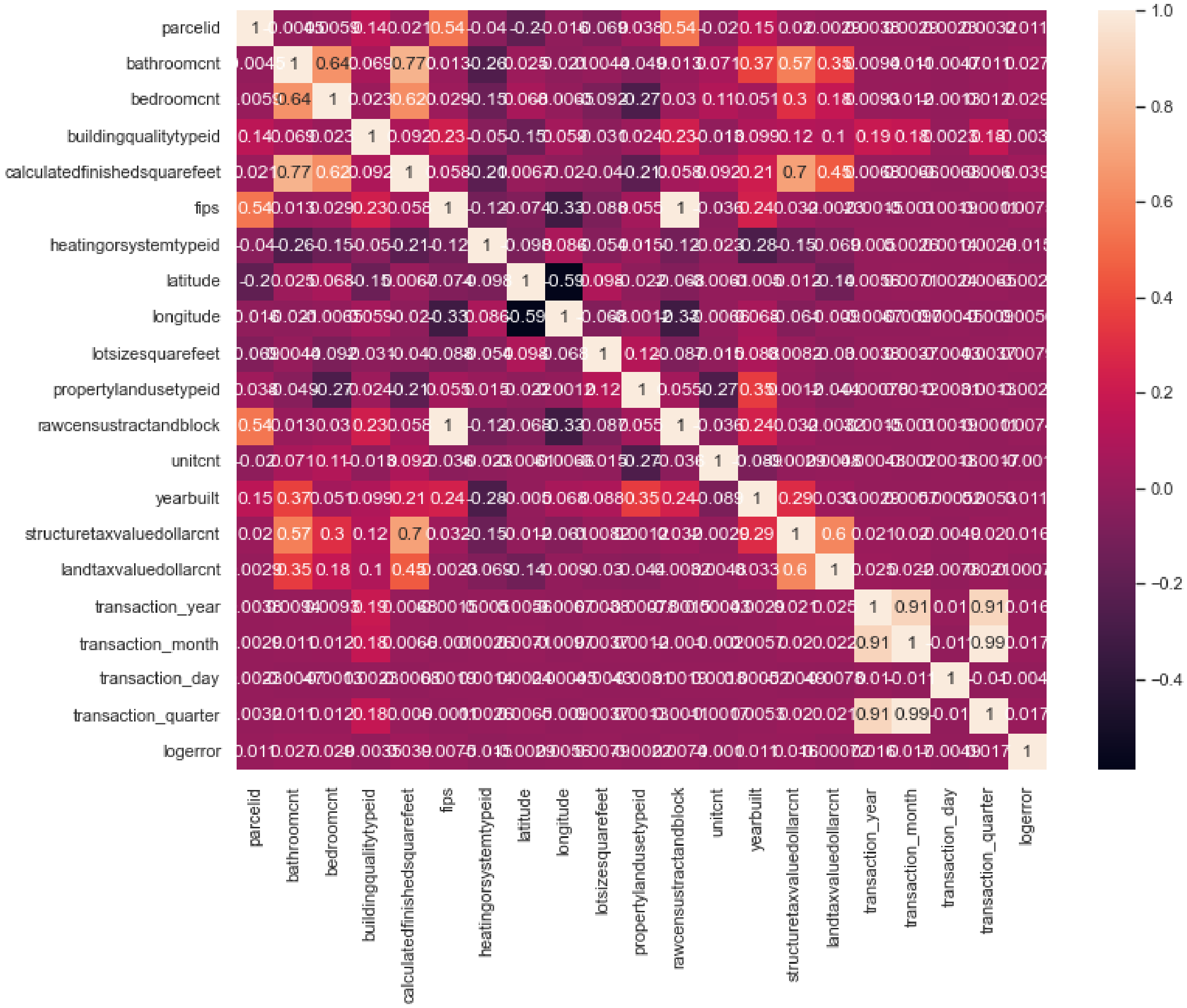
```
#sns.set_color_codes("pastel")
#sns.barplot(x="Number_of_Missing_Values", y="Column_Name", data=missingdata)
```

In [20]:
```
print(X.dtypes)
```

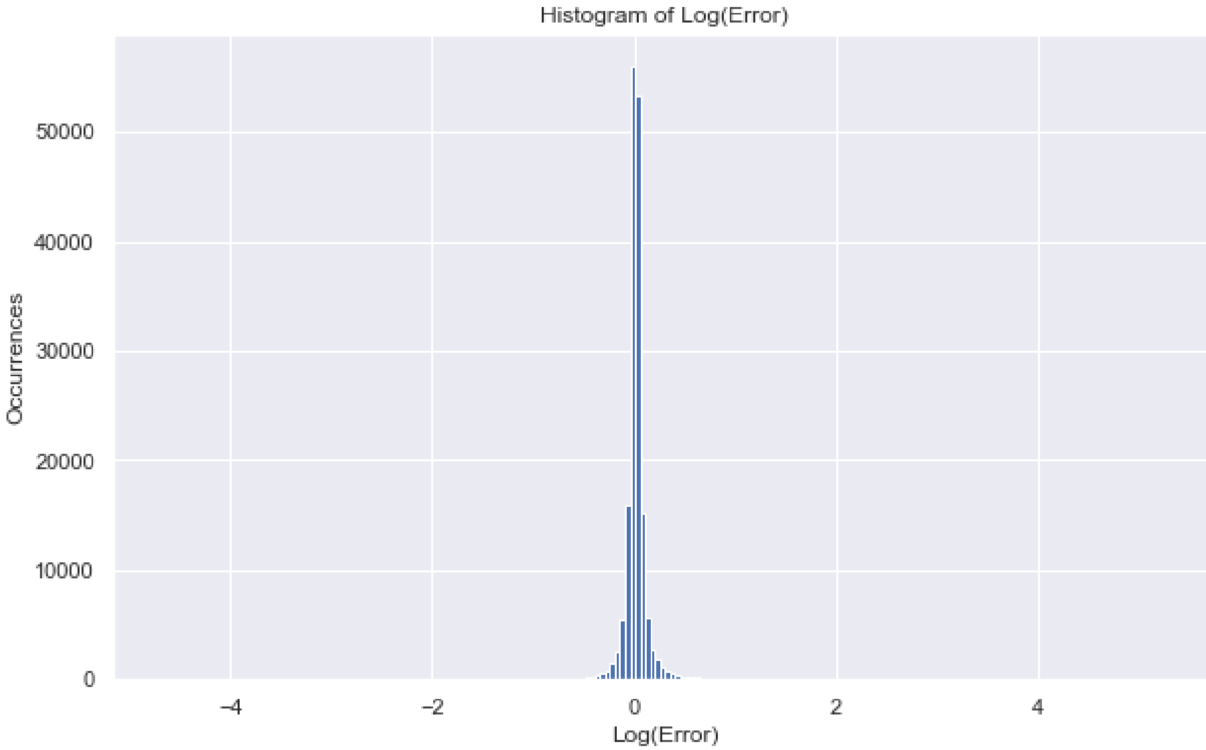
```
parcelid                         int64
bathroomcnt                    float64
bedroomcnt                     float64
buildingqualitytypeid          float64
calculatedfinishedsquarefeet   float64
fips                           float64
heatingorsystemtypeid          float64
latitude                       float64
longitude                      float64
lotsizesquarefeet              float64
propertylandusetypeid          float64
rawcensustractandblock         float64
unitcnt                        float64
yearbuilt                      float64
structuretaxvaluedollarcnt     float64
landtaxvaluedollarcnt          float64
transaction_year                 int64
transaction_month                int64
transaction_day                  int64
transaction_quarter              int64
dtype: object
```

Our data should be useable now, so let's poke around

In [21]:
```
setwithlogerror = X.copy()
setwithlogerror['logerror'] = y

corr_matrix = setwithlogerror.corr()
sns.set(rc={'figure.figsize':(11.7,9)})
sns.heatmap(corr_matrix, annot=True)
plt.show()
#print(properties_2016.columns.values)
```



In [22]:
```
y.hist(bins=200, figsize=(10,6))
plt.xlabel('Log(Error)')
plt.ylabel('Occurrences')
plt.title('Histogram of Log(Error)')
plt.show()
```



Correlations between regressors doesn't seem to be much of an issue, but each and every regressor having a low correlation with logerror is a bit concerning.

Going to do some mutual information score examination before getting into model building

First, let's *finally* split our data into training and testing!

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

In [24]:
```
X_trainwithp = X_train.copy()
X_testwithp = X_test.copy()

X_train = X_train.drop('parcelid', axis = 1)
X_test = X_test.drop('parcelid', axis = 1)
```

In [25]:
```
k=4

mi_transformer=SelectKBest(score_func=mutual_info_regression,k=k)
mi_X_train=mi_transformer.fit_transform(X_train,y_train)
mi_X_test=mi_transformer.fit_transform(X_test,y_test)
```

In [26]:
```
for feature, importance in zip(X.columns, mi_transformer.scores_):
    print(f"The MI score for {feature} is {importance}")
```

```
The MI score for parcelid is 0.013778731807612132
The MI score for bathroomcnt is 0.008295728087625243
The MI score for bedroomcnt is 0.11837855692599808
The MI score for buildingqualitytypeid is 0.012391619604683157
The MI score for calculatedfinishedsquarefeet is 0.008856181556659237
The MI score for fips is 0.006241942296512537
The MI score for heatingorsystemtypeid is 0.02463463439586988
The MI score for latitude is 0.016216521699917053
The MI score for longitude is 0.0013354375912593142
The MI score for lotsizesquarefeet is 0.017001273379602555
The MI score for propertylandusetypeid is 0.023893772082053566
The MI score for rawcensustractandblock is 0.007626116865709243
The MI score for unitcnt is 0.02826282844163419
The MI score for yearbuilt is 0.017541310907482455
The MI score for structuretaxvaluedollarcnt is 0.009575395635973 65
The MI score for landtaxvaluedollarcnt is 0.5643615044854529
The MI score for transaction_year is 0.3781700150062184
The MI score for transaction_month is 0.0016272827025138 88
The MI score for transaction_day is 0.4934936049414995
```

In [29]:

```python
miEst = LinearRegression().fit(mi_X_train, y_train)
print(f"The mean absolute error when training on the MI selected features is {mean_abs
print(f"When testing on the test data, the mean absolute error is {mean_absolute_error
mitrainmae = mean_absolute_error(y_train, miEst.predict(mi_X_train))
mitestmse = mean_absolute_error(y_test, miEst.predict(mi_X_test))
```

```
The mean absolute error when training on the MI selected features is 0.06933187702176
85.
When testing on the test data, the mean absolute error is 0.06981772997544752
```

In [56]:

```python
mitrainmae = []
mitestmae = []
klist =[]
mitrainmaebest = 1000
mitestmaebest = 1000
for k in range(1,7):
    mi_transformer=SelectKBest(score_func=mutual_info_regression,k=k)
    mi_X_train=mi_transformer.fit_transform(X_train,y_train)
    mi_X_test=mi_transformer.fit_transform(X_test,y_test)
    miEst = LinearRegression().fit(mi_X_train, y_train)
    mitrainmaek = mean_absolute_error(y_train, miEst.predict(mi_X_train))
    mitestmaek = mean_absolute_error(y_test, miEst.predict(mi_X_test))
    mitrainmae.append(mitrainmaek)
    mitestmae.append(mitestmaek)
    klist.append(k)
    print(f"With k = {k}, the MAE when training on the MI selected features is {mitrai
    print(f"With k = {k}, the MAE on the test data, the mean absolute error is {mitest
    if mean_absolute_error(y_train, miEst.predict(mi_X_train)) < mitrainmaebest:
        mitrainmaebest = mean_absolute_error(y_train, miEst.predict(mi_X_train))
        mitestmaebest =mean_absolute_error(y_test, miEst.predict(mi_X_test))
```

```
With k = 1, the MAE when training on the MI selected features is 0.0693318770217685.
With k = 1, the MAE on the test data, the mean absolute error is 0.06981772997544752
With k = 2, the MAE when training on the MI selected features is 0.06931598214861559.
With k = 2, the MAE on the test data, the mean absolute error is 0.06980391453972094
With k = 3, the MAE when training on the MI selected features is 0.069315264046791.
With k = 3, the MAE on the test data, the mean absolute error is 0.06980574731375527
With k = 4, the MAE when training on the MI selected features is 0.06932527996705438.
With k = 4, the MAE on the test data, the mean absolute error is 0.06981881076958235
With k = 5, the MAE when training on the MI selected features is 0.06935912518934022.
With k = 5, the MAE on the test data, the mean absolute error is 0.5778381736978622
With k = 6, the MAE when training on the MI selected features is 0.06942589030516527.
With k = 6, the MAE on the test data, the mean absolute error is 0.1981829258801693
```

plt.figure(figsize=(12, 4)) plt.subplot(1, 2, 1) plt.plot(klist, mitrainmae, label = 'Train') plt.title('MI Training set MAE') plt.xlabel('k') plt.ylabel('MAE')

plt.subplot(1, 2, 2) plt.plot(klist, mitestmae) plt.title('Testing Set MAE') plt.xlabel('k') plt.ylabel('MAE')

plt.figure(figsize=(6, 4))

plt.plot(klist, mitestmae) plt.title('Testing Set MAE') plt.xlabel('k') plt.ylabel('MAE') ax = plt.gca()

ax.set_xlim([0, 6.5]) ax.set_ylim([0.0, 2])

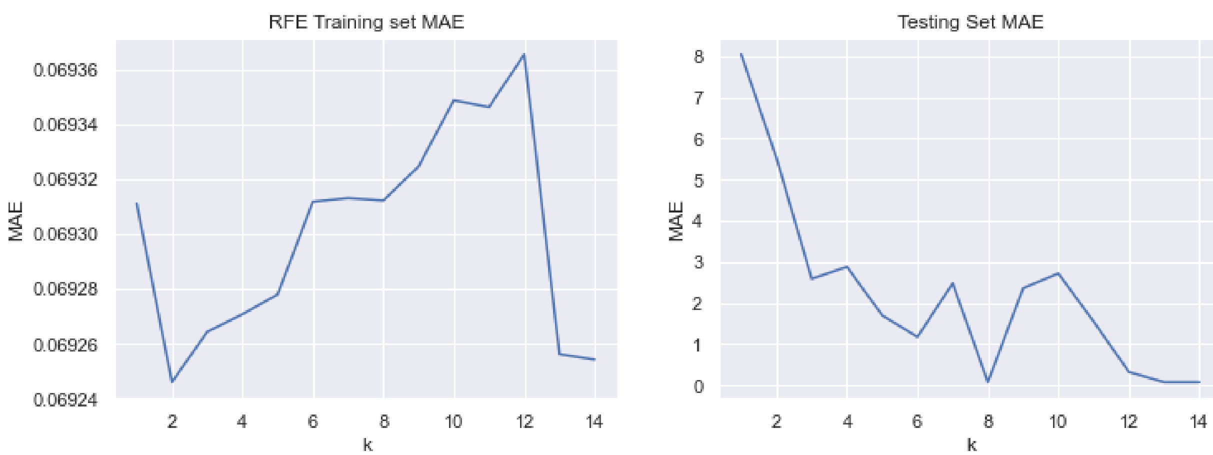
In [31]:

```
rfeEst = LinearRegression()
maeest = 5
klowestmaeest = 0
rfetrainmae = []
rfetestmae = []
klistrfe =[]
for k in range(1,15):
    rfe_transformer=RFE(rfeEst,n_features_to_select=k,step=2)
    rfe_X_train=rfe_transformer.fit_transform(X_train,y_train)
    rfe_X_test=rfe_transformer.fit_transform(X_test,y_test)
    rfeEst = LinearRegression().fit(rfe_X_train, y_train)
    #print(f"With k = {k}, the MSE when training on the RFE selected features is {mean
    #print(f"With k = {k}, the MSE on the test data, the mean squared error is {mean_s

    rfetrainmaek = mean_absolute_error(y_train, rfeEst.predict(rfe_X_train))
    rfetestmaek = mean_absolute_error(y_test, rfeEst.predict(rfe_X_test))
    rfetrainmae.append(rfetrainmaek)
    rfetestmae.append(rfetestmaek)
    klistrfe.append(k)
    if rfetestmaek < maeest:
        maeest = rfetestmaek
        maetrain = rfetrainmaek
        klowestmaeest = k

rfe_transformer=RFE(rfeEst,n_features_to_select=klowestmaeest,step=2)
rfe_X_train=rfe_transformer.fit_transform(X_train,y_train)
rfe_X_test=rfe_transformer.fit_transform(X_test,y_test)
rfeEst = LinearRegression().fit(rfe_X_train, y_train)
print(f"The lowest MAE was found using k={klowestmaeest}, where the train mae was {mae
print(f"The most important features as determined by RFE were {list(X_train.columns[rf
rfemaetrain = maetrain
rfemaetest = maeest
```

```
The lowest MAE was found using k=13, where the train mae was 0.06925614996508915 and
the test mae was 0.06967287690845514.
The most important features as determined by RFE were ['bathroomcnt', 'bedroomcnt',
'buildingqualitytypeid', 'calculatedfinishedsquarefeet', 'fips', 'heatingorsystemtype
id', 'propertylandusetypeid', 'unitcnt', 'yearbuilt', 'transaction_year', 'transactio
n_month', 'transaction_day', 'transaction_quarter']
```

In [32]:
```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(klistrfe, rfetrainmae)
plt.title('RFE Training set MAE')
plt.xlabel('k')
plt.ylabel('MAE')

plt.subplot(1, 2, 2)
plt.plot(klistrfe, rfetestmae)
plt.title('Testing Set MAE')
plt.xlabel('k')
plt.ylabel('MAE')
```

Out[32]:
```
Text(0, 0.5, 'MAE')
```



In [33]:
```
#plt.figure(figsize=(6, 4))
#plt.plot(klistrfe, rfetestmae)
#ax = plt.gca()
#ax.set_xlim([0, 14])
#ax.set_ylim([0.027, 0.03])
#plt.title('Testing Set MAE')
#plt.xlabel('k')
#plt.ylabel('MAE')
```

In [43]:
```
lassoEst=LassoCV(n_alphas=10).fit(X_train,y_train)
lassocoeffeaturemags = []
lassofeaturenames = []
for feature, coef in zip(X_train.columns, lassoEst.coef_):
    print(f"The magniture of the feature coefficient for {feature} is {abs(coef)}.")
    lassocoeffeaturemags.append(abs(coef))
    lassofeaturenames.append(feature)
print(f"The mean absolute error when training using lasso is {mean_absolute_error(y_tr
print(f"When testing on the test data, the mean absolute error is {mean_absolute_error
maelassotrain = mean_absolute_error(y_train, lassoEst.predict(X_train))
maelassotest = mean_absolute_error(y_test, lassoEst.predict(X_test))
```

```
The magnitude of the feature coefficient for bathroomcnt is 0.0.
The magnitude of the feature coefficient for bedroomcnt is 0.0.
The magnitude of the feature coefficient for buildingqualitytypeid is 0.0.
The magnitude of the feature coefficient for calculatedfinishedsquarefeet is 8.007656
92692766e-06.
The magnitude of the feature coefficient for fips is 0.0.
The magnitude of the feature coefficient for heatingorsystemtypeid is 0.0.
The magnitude of the feature coefficient for latitude is 1.2401988252221672e-09.
The magnitude of the feature coefficient for longitude is 5.353729692043439e-09.
The magnitude of the feature coefficient for lotsizesquarefeet is 1.6023571090250776e
-08.
The magnitude of the feature coefficient for propertylandusetypeid is 0.0.
The magnitude of the feature coefficient for rawcensustractandblock is 9.007214708005
27e-09.
The magnitude of the feature coefficient for unitcnt is 0.0.
The magnitude of the feature coefficient for yearbuilt is 0.0.
The magnitude of the feature coefficient for structuretaxvaluedollarcnt is 1.67070744
07824902e-09.
The magnitude of the feature coefficient for landtaxvaluedollarcnt is 8.2409009391219
87e-09.
The magnitude of the feature coefficient for transaction_year is 0.0.
The magnitude of the feature coefficient for transaction_month is 0.0.
The magnitude of the feature coefficient for transaction_day is 0.0.
The magnitude of the feature coefficient for transaction_quarter is 0.0.
The mean absolute error when training using lasso is 0.06923641204875139.
When testing on the test data, the mean absolute error is 0.06961625200907737
```

In [35]:

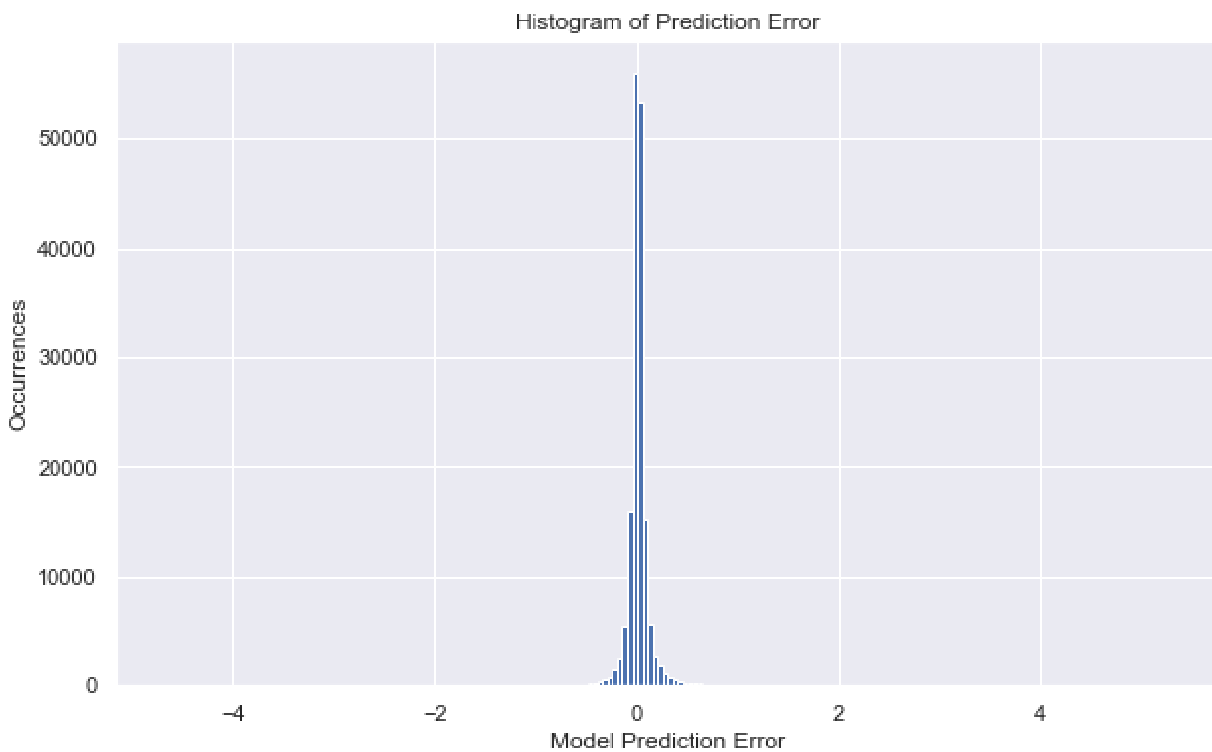
```
X_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33578 entries, 90220 to 33146
Data columns (total 19 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   bathroomcnt                   33578 non-null  float64
 1   bedroomcnt                    33578 non-null  float64
 2   buildingqualitytypeid         33578 non-null  float64
 3   calculatedfinishedsquarefeet  33578 non-null  float64
 4   fips                          33578 non-null  float64
 5   heatingorsystemtypeid         33578 non-null  float64
 6   latitude                      33578 non-null  float64
 7   longitude                     33578 non-null  float64
 8   lotsizesquarefeet             33578 non-null  float64
 9   propertylandusetypeid         33578 non-null  float64
 10  rawcensustractandblock        33578 non-null  float64
 11  unitcnt                       33578 non-null  float64
 12  yearbuilt                     33578 non-null  float64
 13  structuretaxvaluedollarcnt    33578 non-null  float64
 14  landtaxvaluedollarcnt         33578 non-null  float64
 15  transaction_year              33578 non-null  int64  
 16  transaction_month             33578 non-null  int64  
 17  transaction_day               33578 non-null  int64  
 18  transaction_quarter           33578 non-null  int64  
dtypes: float64(15), int64(4)
memory usage: 5.1 MB
```

In [36]:

```
yhatlasso = lassoEst.predict(X_test)
lassopredminusactual = yhatlasso-y_test
parcelid = X_testwithp.parcelid
```

```
#plt.boxplot(lassopredminusactual)

y.hist(bins=200, figsize=(10,6))
plt.xlabel('Model Prediction Error')
plt.ylabel('Occurrences')
plt.title('Histogram of Prediction Error')
plt.show()

#plt.figure(figsize=(6, 4))
#plt.plot(parcelid, yhatlasso,  label = 'Predicted Log(error)')
#plt.plot(X_test, y_test, label = 'Actual Log(error)')
#plt.plot
#ax = plt.gca()
#ax.set_xlim([0, 14])
#ax.set_ylim([0.027, 0.03])
#plt.title('Testing Set MSE')
#plt.xlabel('Log(error)')
#plt.ylabel('Predicted Log(error)')

print('R squared training set', round(lassoEst.score(X_train, y_train)*100, 2))
print('R squared test set', round(lassoEst.score(X_test, y_test)*100, 2))
```




```
R squared training set 0.22
R squared test set 0.18
```

In [37]:
```
RFmodel= RandomForestRegressor(n_estimators=200,max_depth=5, min_samples_leaf=100,n_jo
RFmodel.fit(X_train,y_train)
y_predRF = RFmodel.predict(X_test)
print(f"The mean absolute error when training using Random Forest is {mean_absolute_er
print(f"When testing on the test data, the mean absolute error is {mean_absolute_error
```

```
The mean absolute error when training using Random Forest is 0.06899952938090646.
When testing on the test data, the mean absolute error is 0.06949202544000915
```

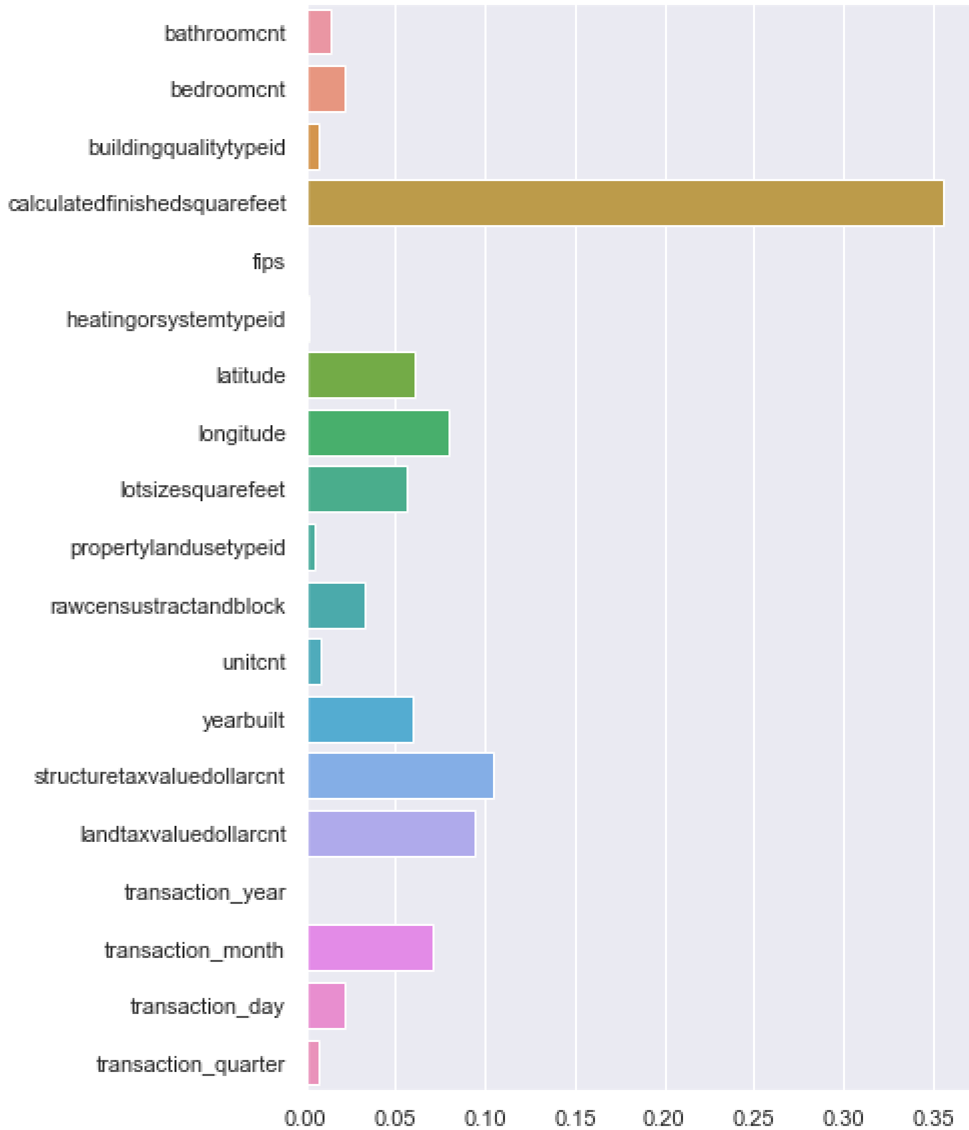
In [38]:
```
rfcoeffeaturemags = []
rffeaturenames = []
for feature, coef in zip(X_train.columns, RFmodel.feature_importances_):
```

```
    print(f"The magnitude of the feature coefficient for {feature} is {abs(coef)}.")
    rfcoeffeaturemags.append(abs(coef))
    rffeaturenames.append(feature)
print(f"The mean absolute error when training using random forest is {mean_absolute_er
print(f"When testing on the test data, the mean absolute error is {mean_absolute_error
rfmaetrain = mean_absolute_error(y_train, RFmodel.predict(X_train))
rfmaetest = mean_absolute_error(y_test, RFmodel.predict(X_test))
```

```
The magnitude of the feature coefficient for bathroomcnt is 0.014411847350793377.
The magnitude of the feature coefficient for bedroomcnt is 0.021566366877137352.
The magnitude of the feature coefficient for buildingqualitytypeid is 0.0066926434117
86007.
The magnitude of the feature coefficient for calculatedfinishedsquarefeet is 0.356246
9866811653.
The magnitude of the feature coefficient for fips is 0.0.
The magnitude of the feature coefficient for heatingorsystemtypeid is 0.0019823744365
46648.
The magnitude of the feature coefficient for latitude is 0.060712102576590904.
The magnitude of the feature coefficient for longitude is 0.07961152003446124.
The magnitude of the feature coefficient for lotsizesquarefeet is 0.0559675369151787
4.
The magnitude of the feature coefficient for propertylandusetypeid is 0.0045708392391
94539.
The magnitude of the feature coefficient for rawcensustractandblock is 0.032644870418
09076.
The magnitude of the feature coefficient for unitcnt is 0.00827618909284073.
The magnitude of the feature coefficient for yearbuilt is 0.05950825034138778.
The magnitude of the feature coefficient for structuretaxvaluedollarcnt is 0.10405331
729798499.
The magnitude of the feature coefficient for landtaxvaluedollarcnt is 0.0946961035071
1948.
The magnitude of the feature coefficient for transaction_year is 0.0.
The magnitude of the feature coefficient for transaction_month is 0.0707089890936050
5.
The magnitude of the feature coefficient for transaction_day is 0.021580574057370936.
The magnitude of the feature coefficient for transaction_quarter is 0.006769488668746
24.
The mean absolute error when training using random forest is 0.06899952938090646.
When testing on the test data, the mean absolute error is 0.06949202544000915
```

In [39]:
```
f, ax = plt.subplots(figsize=(6, 10))
sns.set_color_codes("pastel")
sns.barplot(x= rfcoeffeaturemags, y = rffeaturenames)
```

Out[39]:
```
<AxesSubplot:>
```



In [40]:

```
rsquared_RF = r2_score(y_test, y_predRF)
print('R Squared value using Random Forest = ', rsquared_RF)
```

```
R Squared value using Random Forest =  0.004371688626128134
```

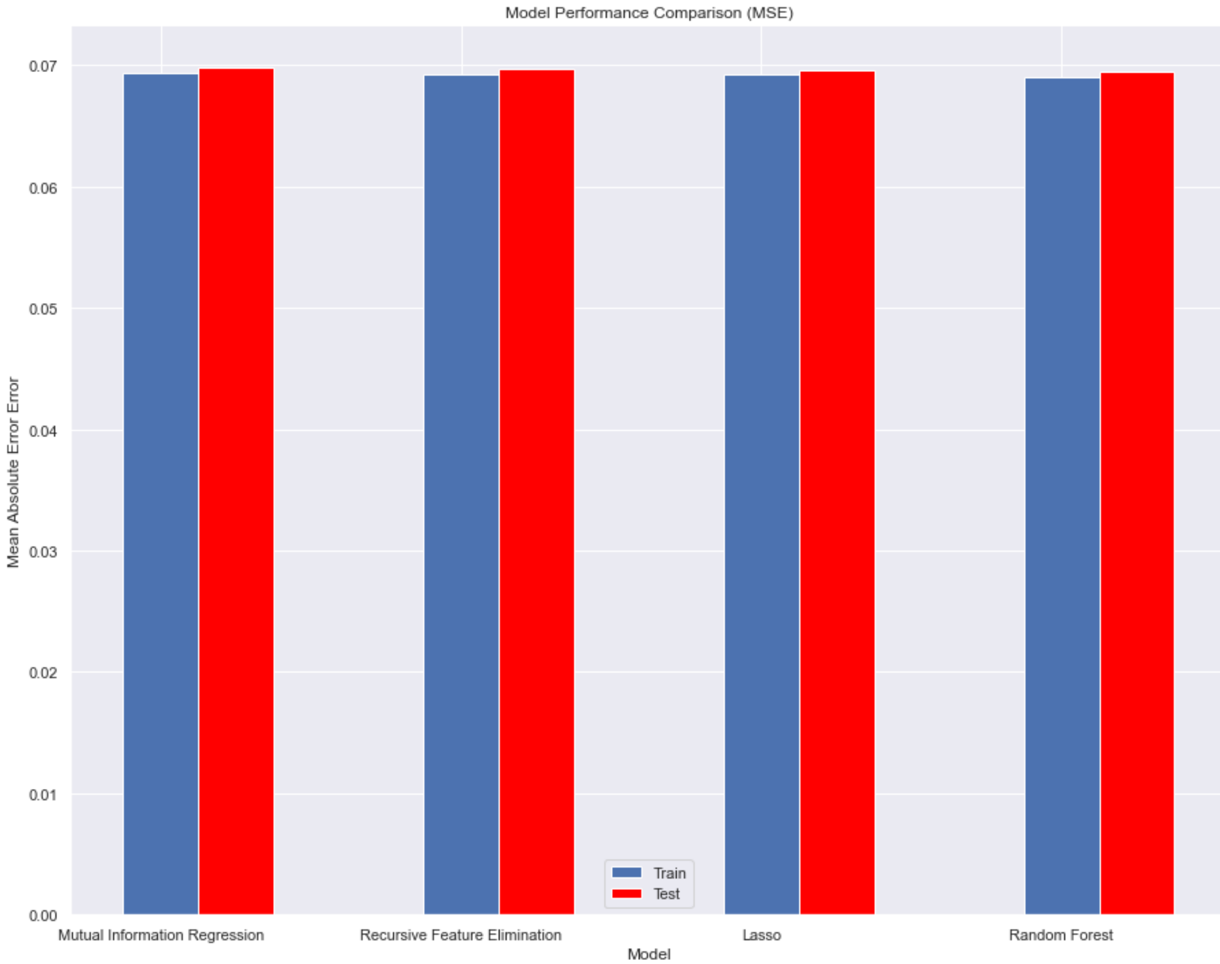
In [44]:

```
MAEtrainlist = [mitrainmaebest, rfemaetrain, maelassotrain, rfmaetrain]
MAEtestlist = [mitestmaebest, rfemaetest, maelassotest, rfmaetest]
```

In [49]:

```
models = ['Mutual Information Regression', 'Recursive Feature Elimination', 'Lasso', '
fig = plt.figure()
ind = np.arange(4)
ax = fig.add_axes([0,0,1,1])
br1 = np.arange(len(MAEtrainlist))
br2 = [x + 0.25 for x in br1]
ax.bar(br1, MAEtrainlist, width = 0.25)
ax.bar(br2, MAEtestlist, color = 'red', width = 0.25)

plt.xlabel('Model')
plt.ylabel('Mean Absolute Error Error')

plt.legend(["Train", "Test"])
plt.title('Model Performance Comparison (MSE)')
```

```
plt.xticks(ind, models)
plt.show()
```



In [55]:
```
for i in range(len(models)):
    print(f"For the model {models[i]},  the mean ansolute error is {MAEtestlist[i]}")
```

```
For the model Mutual Information Regression,  the mean ansolute error is 0.0698057473
1375527
For the model Recursive Feature Elimination,  the mean ansolute error is 0.0696728769
0845514
For the model Lasso,  the mean ansolute error is 0.06961625200907737
For the model Random Forest,  the mean ansolute error is 0.06949202544000915
```

Submission Creation!

In [ ]:
```
test_df['transactiondate'] = pd.Timestamp('2016-12-01')
test_df = add_date_features(test_df)
```

In [ ]:
```
test_df
```

In [ ]:
```
submission = pd.DataFrame({
    'parcelid': test_df['parcelid'],
})
unavailables = ['parcelid', 'logerror']
test_df = test_df.drop(unavailables, axis = 1)
submission
```

In [ ]:
```
y_pred = RFmodel.predict(test_df)
sub = pd.read_csv('sample_submission.csv')
test_dates = {
    '201610': pd.Timestamp('2016-09-30'),
    '201611': pd.Timestamp('2016-10-31'),
    '201612': pd.Timestamp('2016-11-30'),
    '201710': pd.Timestamp('2017-09-30'),
    '201711': pd.Timestamp('2017-10-31'),
    '201712': pd.Timestamp('2017-11-30')
}


for label, test_date in test_dates.items():
    print("Predicting for: %s ... " % (label))
    submission[label] = y_pred
#for c in sub.columns[sub.columns != 'ParcelId']:
    #sub[c] = final_pred

submission.to_csv('submission.csv', index=False, float_format='%.4f')
submission
```

In [ ]:
```
_ = tree.plot_tree(RFmodel.estimators_[0], feature_names=X_train.columns, filled=True)
```

In [ ]:

In [ ]: