Zillow Zestimate ADS Nutritional Label

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1 Zillow ADS Preliminary Analysis

[1]:
```python
# Importing Dependencies
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import sklearn as sk
```

1.1 Load the Datasets

[ ]:
```python
# Packages for reading csv file into Colaboratory:
!pip install -U -q PyDrive==1.3.1

from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

# Authenticate and create the PyDrive client.
# Please follow the steps as instructed when you run the following commands.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

```
WARNING: Ignoring invalid distribution -ensorflow
(/usr/local/lib/python3.7/dist-packages)
WARNING: Ignoring invalid distribution -ensorflow
(/usr/local/lib/python3.7/dist-packages)
WARNING: Ignoring invalid distribution -ensorflow
(/usr/local/lib/python3.7/dist-packages)
```

We must load the datasets that are needed to train our machine learning algorithms, handle our data, and to make predictions.

It should be noted that these datasets were the ones provided when entering the competition amd accepting the Terms and Conditions.

[ ]:
```
# train = pd.read_csv('../input/train_2016_v2.csv' ,␣
↪parse_dates=["transactiondate"])
# properties = pd.read_csv('../input/properties_2016.csv')
# test = pd.read_csv('../input/sample_submission.csv')
# test= test.rename(columns={'ParcelId': 'parcelid'})   #To make it easier for␣
↪merging datasets on same column_id later
```

[ ]:
```
# https://drive.google.com/file/d/1U-1rtYTUk4-_n3GWge_uBjgnsJc80cn4/view?
↪usp=sharing
fileid = '1U-1rtYTUk4-_n3GWge_uBjgnsJc80cn4'
filename = 'train_2016_v2.csv'
downloaded = drive.CreateFile({'id':fileid})
downloaded.GetContentFile(filename)
train = pd.read_csv(filename, parse_dates=["transactiondate"])
```

[ ]:
```
train.head(3)
```

[ ]:

	parcelid	logerror	transactiondate
0	11016594	0.0276	2016-01-01
1	14366692	-0.1684	2016-01-01
2	12098116	-0.0040	2016-01-01

[ ]:
```
train.tail(3)
```

[ ]:

	parcelid	logerror	transactiondate
90272	12995401	-0.2679	2016-12-30
90273	11402105	0.0602	2016-12-30
90274	12566293	0.4207	2016-12-30

Since this is for a Colab notebook, we have commented out the above variables in order to implement the csv files from Google Drive directly

[ ]:
```
# https://drive.google.com/file/d/1L2EvrHoBREGb0Yh60rScd8PU2Bvm6RVo/view?
↪usp=sharing
fileid = '1L2EvrHoBREGb0Yh60rScd8PU2Bvm6RVo'
filename = 'properties_2016.csv'
downloaded = drive.CreateFile({'id':fileid})
downloaded.GetContentFile(filename)
properties = pd.read_csv(filename)
```

```
/usr/local/lib/python3.7/dist-packages/IPython/core/interactiveshell.py:2882:
DtypeWarning: Columns (22,32,34,49,55) have mixed types.Specify dtype option on
import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

[ ]:
```
properties.head(3)
```

[ ]:
```
   parcelid  airconditioningtypeid  architecturalstyletypeid  basementsqft  \
0  10754147                    NaN                       NaN           NaN
1  10759547                    NaN                       NaN           NaN
2  10843547                    NaN                       NaN           NaN

   bathroomcnt  bedroomcnt  buildingclasstypeid  buildingqualitytypeid  \
0          0.0         0.0                  NaN                    NaN
1          0.0         0.0                  NaN                    NaN
2          0.0         0.0                  NaN                    NaN

   calculatedbathnbr  decktypeid  …  numberofstories  fireplaceflag  \
0                NaN         NaN  …              NaN            NaN
1                NaN         NaN  …              NaN            NaN
2                NaN         NaN  …              NaN            NaN

   structuretaxvaluedollarcnt  taxvaluedollarcnt  assessmentyear  \
0                         NaN                9.0          2015.0
1                         NaN            27516.0          2015.0
2                    650756.0          1413387.0          2015.0

   landtaxvaluedollarcnt  taxamount  taxdelinquencyflag  taxdelinquencyyear  \
0                    9.0        NaN                 NaN                 NaN
1                27516.0        NaN                 NaN                 NaN
2               762631.0   20800.37                 NaN                 NaN

   censustractandblock
0                  NaN
1                  NaN
2                  NaN

[3 rows x 58 columns]
```

[ ]:
```
# https://drive.google.com/file/d/15D754PtBPHg7e27bKei6E4d1md2Gwao0/view?
↪usp=sharing
fileid = '15D754PtBPHg7e27bKei6E4d1md2Gwao0'
filename = 'sample_submission.csv'
downloaded = drive.CreateFile({'id':fileid})
downloaded.GetContentFile(filename)
test = pd.read_csv(filename)
```

[ ]:
```
test.head(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
```

```
[ ]: test = test.rename(columns={'ParcelId': 'parcelid'})  #To make it easier for␣
      ↪merging datasets on same column_id later
```

##Preliminary research on given data

df_train is a merged dataframe consist of original training data(parcelid and logerror only) and property data(home features)

```
[ ]: df_train_res = train.merge(properties, how='left', on='parcelid')
     df_train_res.head(3)
```

```
[ ]:    parcelid  logerror transactiondate  airconditioningtypeid  \
     0  11016594    0.0276      2016-01-01                    1.0
     1  14366692   -0.1684      2016-01-01                    NaN
     2  12098116   -0.0040      2016-01-01                    1.0

        architecturalstyletypeid  basementsqft  bathroomcnt  bedroomcnt  \
     0                       NaN           NaN          2.0         3.0
     1                       NaN           NaN          3.5         4.0
     2                       NaN           NaN          3.0         2.0

        buildingclasstypeid  buildingqualitytypeid  …  numberofstories  \
     0                  NaN                    4.0  …              NaN
     1                  NaN                    NaN  …              NaN
     2                  NaN                    4.0  …              NaN

        fireplaceflag  structuretaxvaluedollarcnt  taxvaluedollarcnt  \
     0            NaN                    122754.0           360170.0
     1            NaN                    346458.0           585529.0
     2            NaN                     61994.0           119906.0

        assessmentyear  landtaxvaluedollarcnt  taxamount  taxdelinquencyflag  \
     0          2015.0               237416.0    6735.88                 NaN
     1          2015.0               239071.0   10153.02                 NaN
     2          2015.0                57912.0   11484.48                 NaN

        taxdelinquencyyear  censustractandblock
     0                 NaN         6.037107e+13
     1                 NaN                  NaN
     2                 NaN         6.037464e+13

     [3 rows x 60 columns]
```

```
[ ]: df_train_res.shape
```

```
[ ]: (90275, 60)
```

data types

[ ]:
```
df_train_res.dtypes.head(34)
```

[ ]:
```
parcelid                                int64
logerror                              float64
transactiondate                datetime64[ns]
airconditioningtypeid                 float64
architecturalstyletypeid              float64
basementsqft                          float64
bathroomcnt                           float64
bedroomcnt                            float64
buildingclasstypeid                   float64
buildingqualitytypeid                 float64
calculatedbathnbr                     float64
decktypeid                            float64
finishedfloor1squarefeet              float64
calculatedfinishedsquarefeet          float64
finishedsquarefeet12                  float64
finishedsquarefeet13                  float64
finishedsquarefeet15                  float64
finishedsquarefeet50                  float64
finishedsquarefeet6                   float64
fips                                  float64
fireplacecnt                          float64
fullbathcnt                           float64
garagecarcnt                          float64
garagetotalsqft                       float64
hashottuborspa                         object
heatingorsystemtypeid                 float64
latitude                              float64
longitude                             float64
lotsizesquarefeet                     float64
poolcnt                               float64
poolsizesum                           float64
pooltypeid10                          float64
pooltypeid2                           float64
pooltypeid7                           float64
dtype: object
```

[ ]:
```
df_train_res["regionidzip"]
```

[ ]:
```
0         96370.0
1         96962.0
2         96293.0
3         96222.0
4         96961.0
           …
```

```
90270    96364.0
90271    96327.0
90272    96478.0
90273    96133.0
90274    96244.0
Name: regionidzip, Length: 90275, dtype: float64
```

[ ]:
```
df_train_res.dtypes.tail(30)
```

[ ]:
```
poolsizesum                     float64
pooltypeid10                    float64
pooltypeid2                     float64
pooltypeid7                     float64
propertycountylandusecode        object
propertylandusetypeid           float64
propertyzoningdesc               object
rawcensustractandblock          float64
regionidcity                    float64
regionidcounty                  float64
regionidneighborhood            float64
regionidzip                     float64
roomcnt                         float64
storytypeid                     float64
threequarterbathnbr             float64
typeconstructiontypeid          float64
unitcnt                         float64
yardbuildingsqft17              float64
yardbuildingsqft26              float64
yearbuilt                       float64
numberofstories                 float64
fireplaceflag                    object
structuretaxvaluedollarcnt      float64
taxvaluedollarcnt               float64
assessmentyear                  float64
landtaxvaluedollarcnt           float64
taxamount                       float64
taxdelinquencyflag               object
taxdelinquencyyear              float64
censustractandblock             float64
dtype: object
```

null data

[ ]:
```
graphData = df_train_res.isna().sum(axis=0).reset_index(name="count")
graphData = graphData.sort_values(by='count')
graphData.columns=['features','count']
graphData['ratio']=graphData['count']/df_train_res.shape[0]
```

```
graphData.tail(5)
```

```
[ ]:                 features  count     ratio
    48    yardbuildingsqft26  90180  0.998948
    43           storytypeid  90232  0.999524
    5            basementsqft  90232  0.999524
    15  finishedsquarefeet13  90242  0.999634
    8     buildingclasstypeid  90259  0.999823
```

```
[ ]: graphData.head(5)
```

```
[ ]:                   features  count  ratio
    0                  parcelid      0    0.0
    27                longitude      0    0.0
    35    propertylandusetypeid      0    0.0
    37  rawcensustractandblock      0    0.0
    39           regionidcounty      0    0.0
```

```
[ ]: empty_features = graphData[graphData['ratio']>0.95]["features"].tolist()
```

```
[ ]: empty_features
```

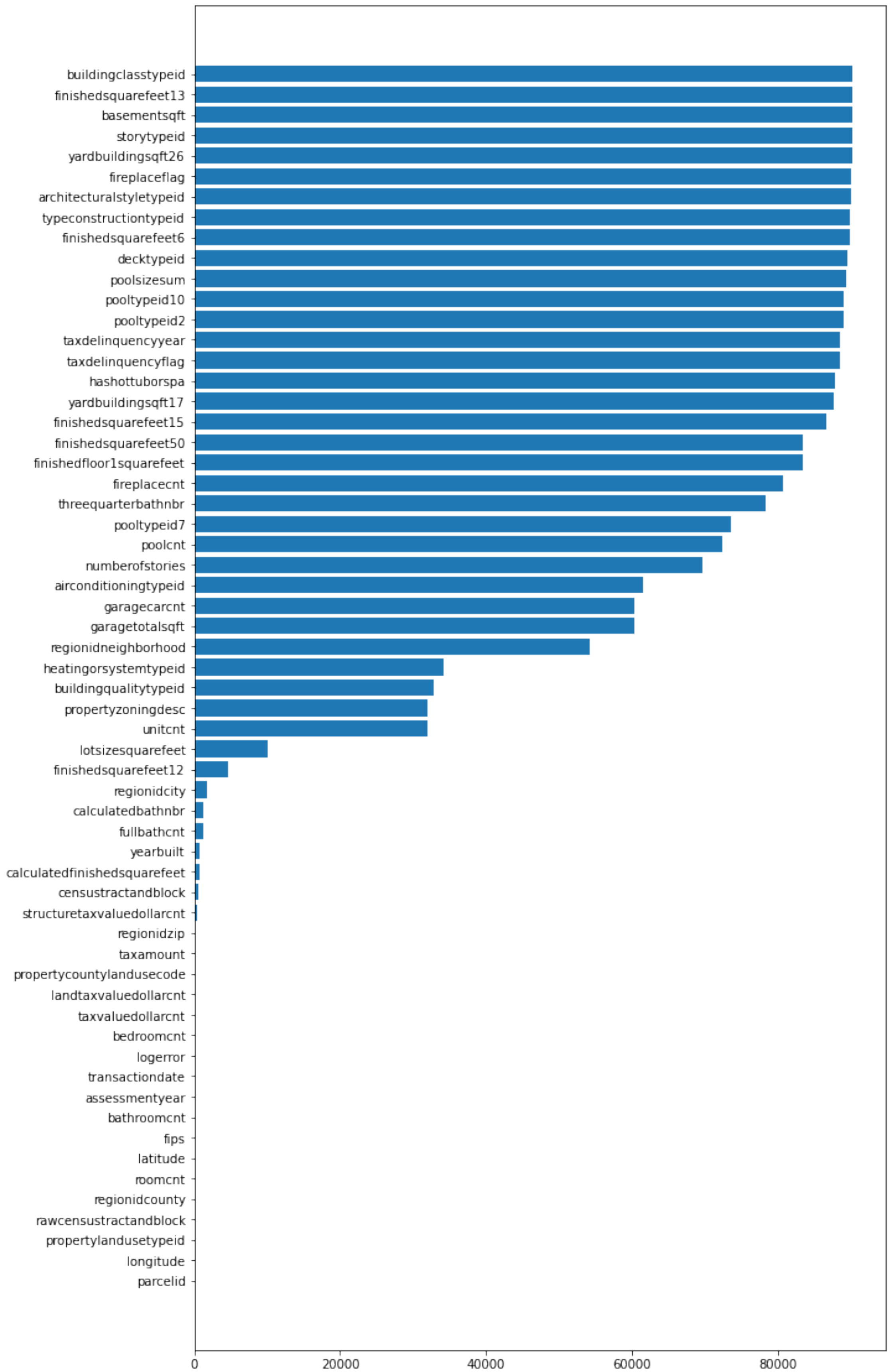
```
[ ]: ['finishedsquarefeet15',
      'yardbuildingsqft17',
      'hashottuborspa',
      'taxdelinquencyflag',
      'taxdelinquencyyear',
      'pooltypeid2',
      'pooltypeid10',
      'poolsizesum',
      'decktypeid',
      'finishedsquarefeet6',
      'typeconstructiontypeid',
      'architecturalstyletypeid',
      'fireplaceflag',
      'yardbuildingsqft26',
      'storytypeid',
      'basementsqft',
      'finishedsquarefeet13',
      'buildingclasstypeid']
```

```
[ ]: len(empty_features)
```

```
[ ]: 18
```

```
[ ]: # graphData.plot.barh(y='count',x='features').tick_params(axis='y', width=0.3)
     # # failed graph, too crowded
```

[ ]:
```
figs, axes = plt.subplots(figsize=(10,20))
new_index = np.arange(graphData.shape[0])
axes.barh(new_index, graphData['count'].values)
plt.yticks(new_index, graphData["features"].values)
plt.show()
```



buildingclasstypeid
finishedsquarefeet13
basementsqft
storytypeid
yardbuildingsqft26
fireplaceflag
architecturalstyletypeid
typeconstructiontypeid
finishedsquarefeet6
decktypeid
poolsizesum
pooltypeid10
pooltypeid2
taxdelinquencyyear
taxdelinquencyflag
hashottuborspa
yardbuildingsqft17
finishedsquarefeet15
finishedsquarefeet50
finishedfloor1squarefeet
fireplacecnt
threequarterbathnbr
pooltypeid7
poolcnt
numberofstories
airconditioningtypeid
garagecarcnt
garagetotalsqft
regionidneighborhood
heatingorsystemtypeid
buildingqualitytypeid
propertyzoningdesc
unitcnt
lotsizesquarefeet
finishedsquarefeet12
regionidcity
calculatedbathnbr
fullbathcnt
yearbuilt
calculatedfinishedsquarefeet
censustractandblock
structuretaxvaluedollarcnt
regionidzip
taxamount
propertycountylandusecode
landtaxvaluedollarcnt
taxvaluedollarcnt
bedroomcnt
logerror
transactiondate
assessmentyear
bathroomcnt
fips
latitude
roomcnt
regionidcounty
rawcensustractandblock
propertylandusetypeid
longitude
parcelid
0
20000
40000
60000
80000

From the index, we extract some interesting features to evaluate:

`logerror;`
`transactiondate`
`bathroomcnt;`
`bedroomcnt;`
`PropertyLandUseTypeID;`
`yearbuilt;`
`taxvaluedollarcnt;`

full dictionary of indexes can be found at https://www.kaggle.com/c/zillow-prize-1/data under zillow_data_dictionary.xlsx

note:

`regionidcounty;`
`regionidcity;`
`regionidcity;`
`regionidneighborhood;`

above features don't have proper dictionaries, we only know numbers but not meanings

ex:

[ ]:
```
df_train_res["regionidcounty"].head(2)
```

[ ]:
```
0    3101.0
1    1286.0
Name: regionidcounty, dtype: float64
```

####logerror:

[ ]:
```
print("mean:\t",df_train_res["logerror"].mean())
print("median:\t",df_train_res["logerror"].median())
print("std:\t",df_train_res["logerror"].std())
```

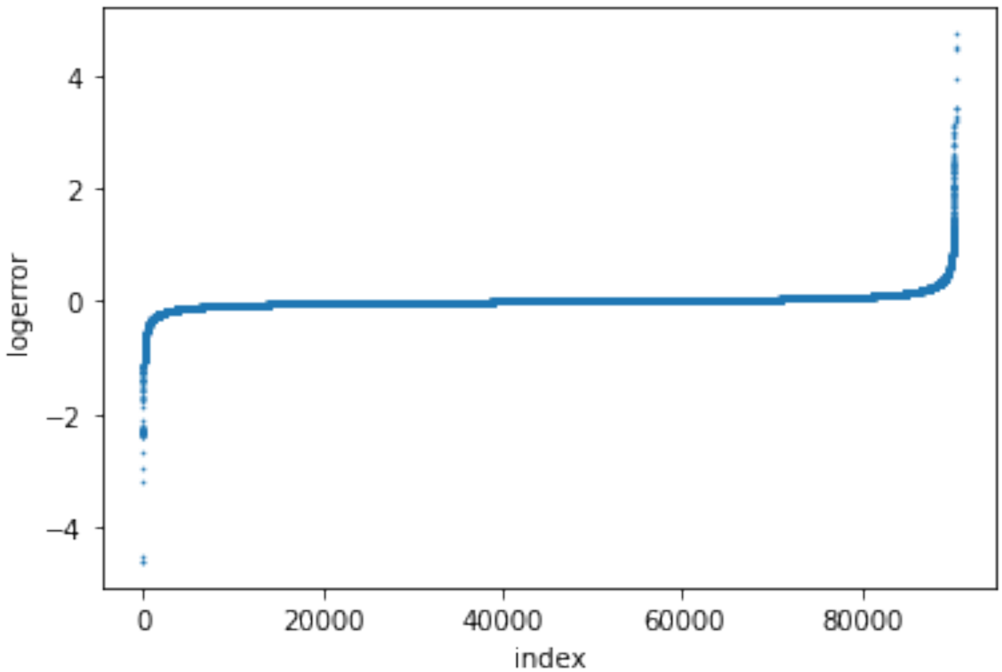
```
mean:    0.011457219606756682
median:  0.006
std:     0.16107883536718484
```

[ ]:
```
df_train_res["logerror"].describe()
```

[ ]:
```
count    90275.000000
mean         0.011457
std          0.161079
min         -4.605000
25%         -0.025300
50%          0.006000
```

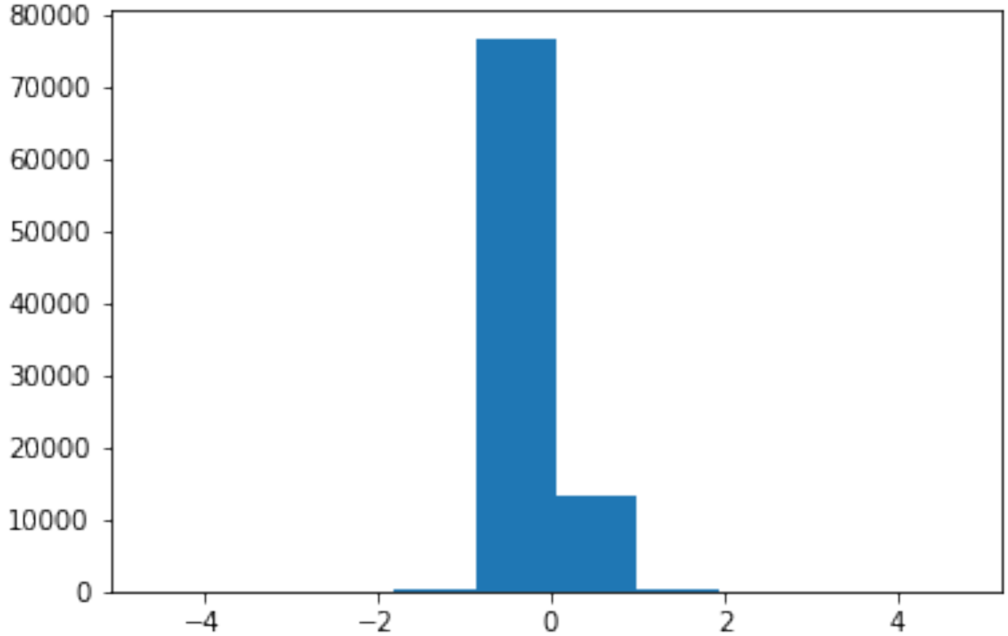
```
75%          0.039200
max          4.737000
Name: logerror, dtype: float64
```

[ ]:
```
plt.scatter(range(df_train_res.index.size), np.sort(df_train_res.logerror.
 ↪values),s=0.4)
plt.xlabel('index')
plt.ylabel('logerror')
plt.show()
```



[ ]:
```
plt.hist(df_train_res["logerror"])
```

[ ]:
```
(array([3.0000e+00, 2.0000e+00, 4.3000e+01, 1.1500e+02, 7.6615e+04,
        1.3271e+04, 1.5800e+02, 5.1000e+01, 1.3000e+01, 4.0000e+00]),
 array([-4.605 , -3.6708, -2.7366, -1.8024, -0.8682,  0.066 ,  1.0002,
         1.9344,  2.8686,  3.8028,  4.737 ]),
 <a list of 10 Patch objects>)
```



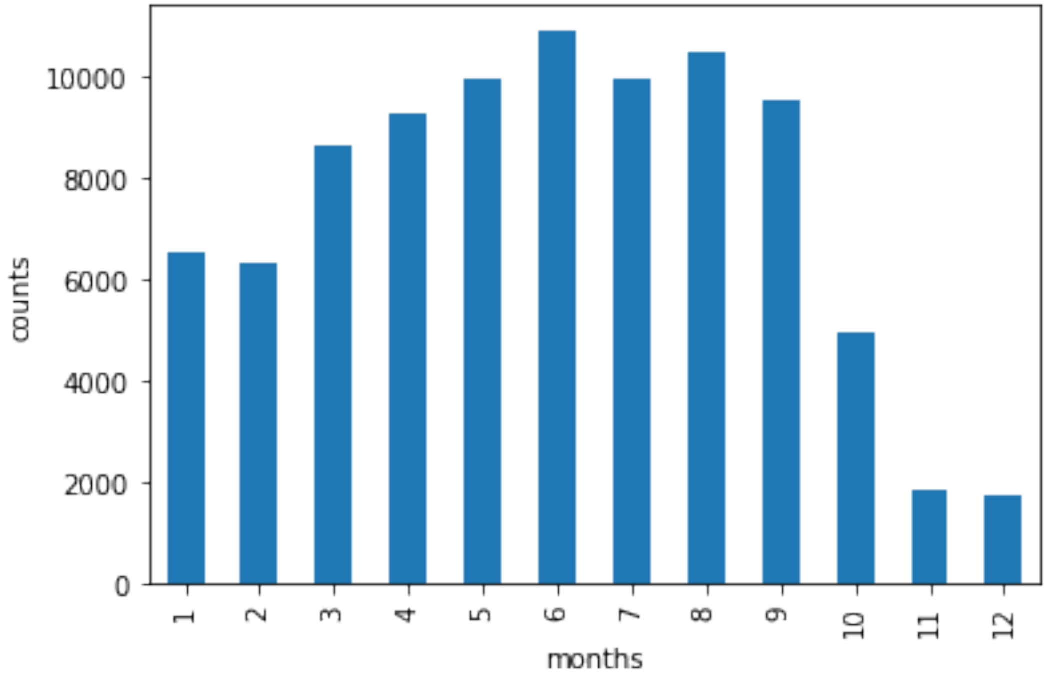
####transactiondate

[ ]:
```
type(df_train_res['transactiondate'][0])
```

[ ]:
```
pandas._libs.tslibs.timestamps.Timestamp
```

[ ]:
```
df_train_res["transactiondate"].groupby(df_train_res["transactiondate"].dt.
 ↪month).count().plot(kind="bar", xlabel="months", ylabel='counts')
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f402225b410>
```



group by property land use id

[ ]:
```
df_train_res.groupby('propertylandusetypeid', as_index=False).size()
```

[ ]:

	propertylandusetypeid	size
0	31.0	17
1	47.0	1
2	246.0	2376
3	247.0	629
4	248.0	879
5	260.0	62
6	261.0	60637
7	263.0	84
8	264.0	11
9	265.0	356
10	266.0	22815
11	267.0	28
12	269.0	2334
13	275.0	46

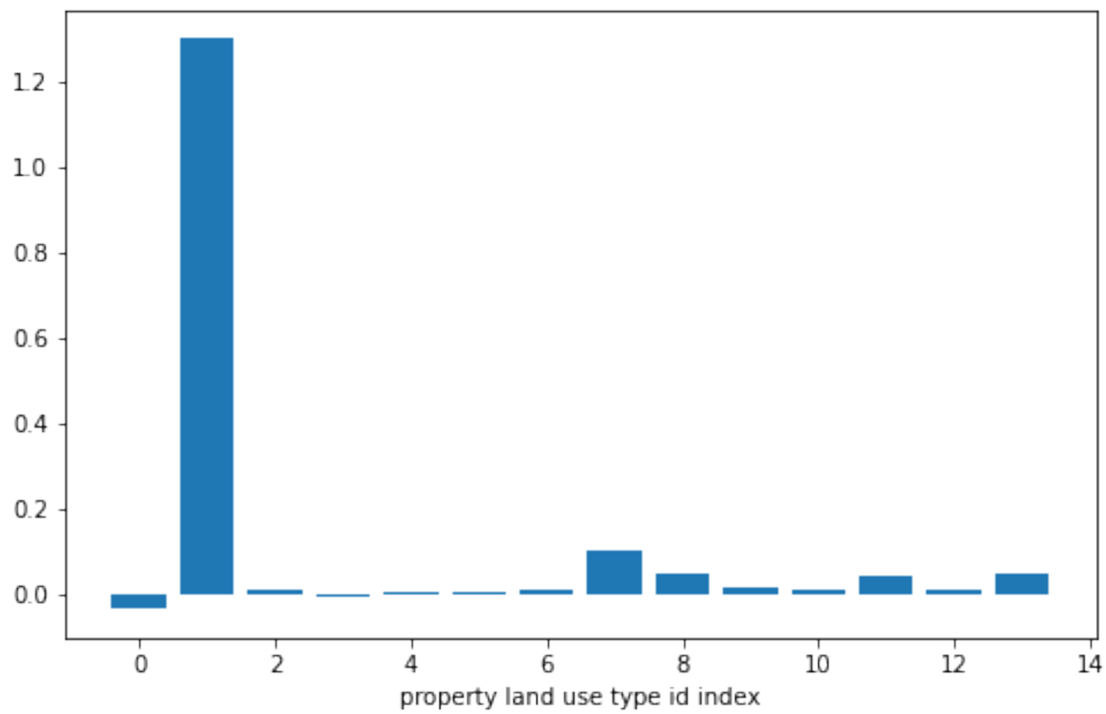
[ ]:
```
df_train_res.groupby('propertylandusetypeid', as_index=False)['logerror'].mean()
```

[ ]:

	propertylandusetypeid	logerror
0	31.0	-0.034371
1	47.0	1.301000

```
2                     246.0  0.009442
3                     247.0 -0.004608
4                     248.0  0.005385
5                     260.0  0.004606
6                     261.0  0.012080
7                     263.0  0.104256
8                     264.0  0.047591
9                     265.0  0.013998
10                    266.0  0.010381
11                    267.0  0.041118
12                    269.0  0.009400
13                    275.0  0.050300
```

[ ]:
```
landuse_mean = df_train_res.groupby('propertylandusetypeid',␣
 ↪as_index=False)['logerror'].mean()
fig, ax = plt.subplots(figsize=(8,5))
plt.bar(range(len(landuse_mean)), landuse_mean["logerror"])
ax.set_xlabel("property land use type id index")
plt.show()
```



####other features

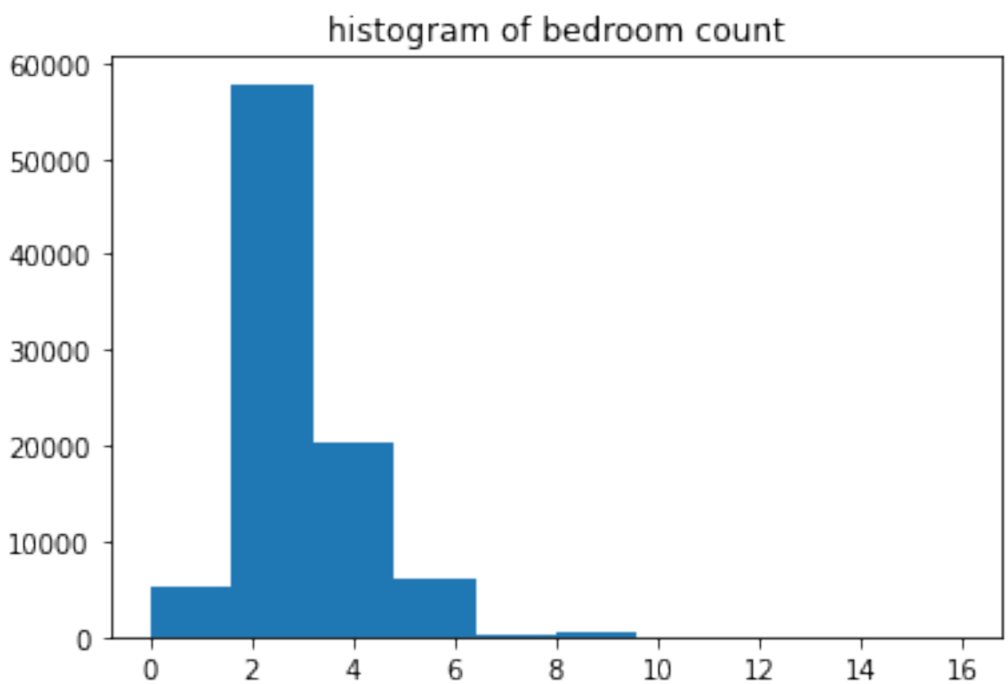
[ ]:
```
df_train_res["bedroomcnt"].describe()
```

[ ]:
```
count    90275.000000
mean         3.031869
std          1.156436
min          0.000000
25%          2.000000
50%          3.000000
75%          4.000000
max         16.000000
Name: bedroomcnt, dtype: float64
```

[ ]:
```
df_train_res["bedroomcnt"].median()
```

[ ]:
```
3.0
```

[ ]:
```
plt.hist(df_train_res["bedroomcnt"])
plt.title("histogram of bedroom count")
plt.show()
```



[ ]:
```
df_train_res["bathroomcnt"].describe()
```

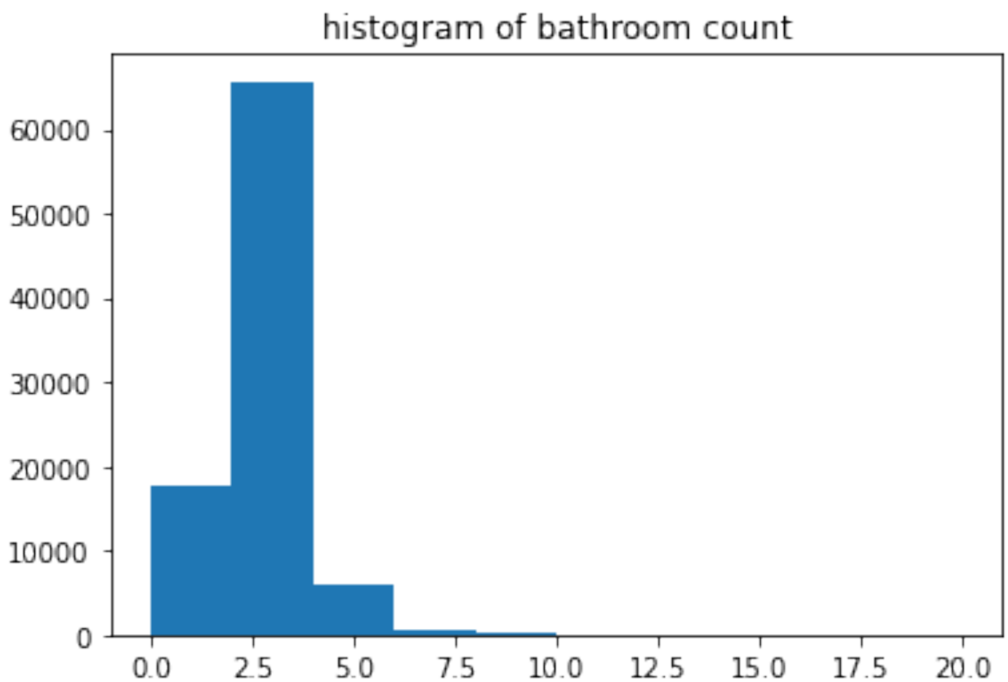
[ ]:
```
count    90275.000000
mean         2.279474
std          1.004271
min          0.000000
```

```
25%          2.000000
50%          2.000000
75%          3.000000
max         20.000000
Name: bathroomcnt, dtype: float64
```

[ ]:
```
df_train_res["bathroomcnt"].median()
```

[ ]:
```
2.0
```

[ ]:
```
plt.hist(df_train_res["bathroomcnt"])
plt.title("histogram of bathroom count")
plt.show()
```

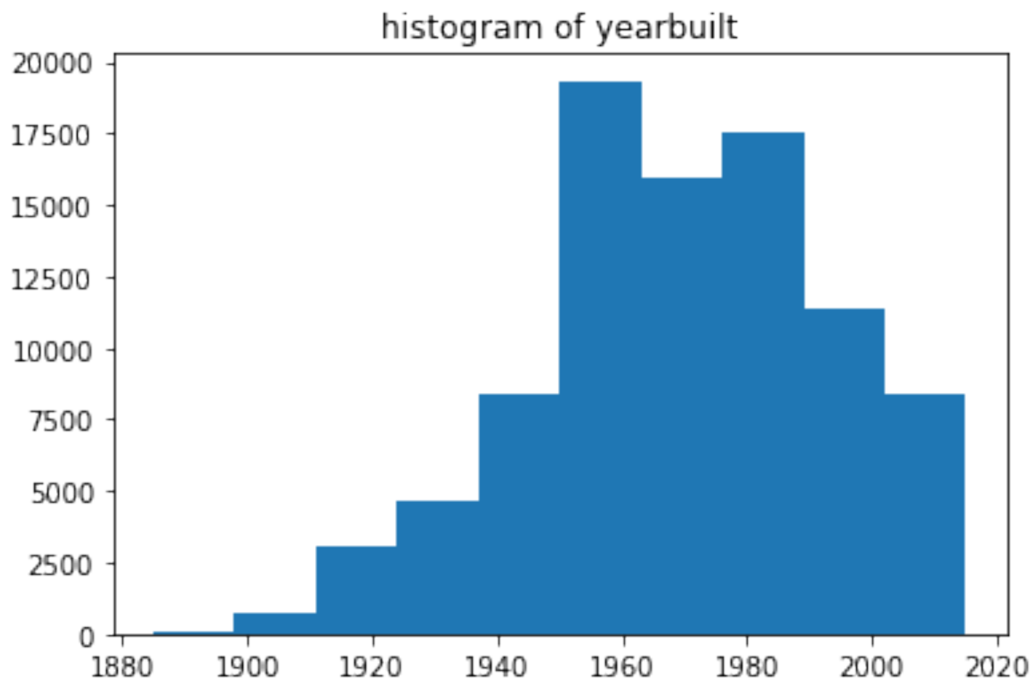


[ ]:
```
df_train_res["yearbuilt"].describe()
```

[ ]:
```
count    89519.000000
mean      1968.532870
std         23.763475
min       1885.000000
25%       1953.000000
50%       1970.000000
75%       1987.000000
max       2015.000000
```

```
Name: yearbuilt, dtype: float64
```

[ ]:
```
plt.hist(df_train_res["yearbuilt"])
plt.title("histogram of yearbuilt")
plt.show()
```



[ ]:
```
df_train_res["taxvaluedollarcnt"].describe()
```

[ ]:
```
count    9.027400e+04
mean     4.576726e+05
std      5.548844e+05
min      2.200000e+01
25%      1.990232e+05
50%      3.428720e+05
75%      5.405890e+05
max      2.775000e+07
Name: taxvaluedollarcnt, dtype: float64
```

[ ]:
```
df_train_res["taxvaluedollarcnt"].mean()
```

[ ]:
```
457672.627356714
```

1.1.1 feature correlations

remove columns that have type other than float and int highly correlated variables are removed from the correlation matrix as they provide repeated and less meaningful information

[ ]:
```
train_res_new = df_train_res.drop(empty_features, axis = 1)
```

[ ]:
```
train_res_new=train_res_new.select_dtypes('float', 'int')
```

[ ]:
```
train_corr=train_res_new.corr().abs()
```

[ ]:
```
upper_tri = train_corr.where(np.triu(np.ones(train_corr.shape),k=1).astype(np.
↪bool))
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
DeprecationWarning: `np.bool` is a deprecated alias for the builtin `bool`. To
silence this warning, use `bool` by itself. Doing this will not modify any
behavior and is safe. If you specifically wanted the numpy scalar type, use
`np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  """Entry point for launching an IPython kernel.
```

[ ]:
```
to_drop = [column for column in upper_tri.columns if any(upper_tri[column] > 0.
↪95)]
```

[ ]:
```
len(to_drop)
```

[ ]: 7

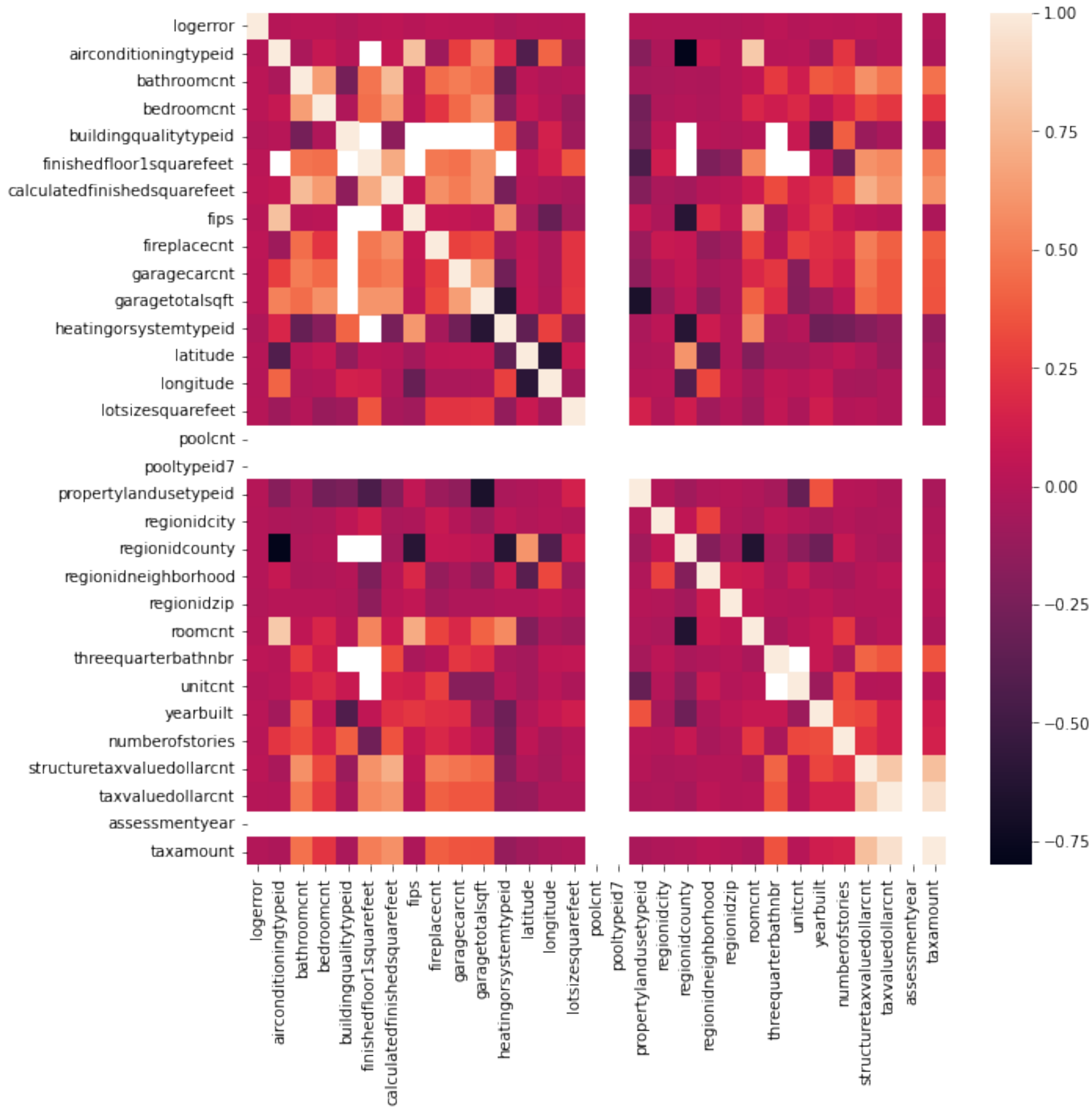
[ ]:
```
train_res_new = train_res_new.drop(to_drop, axis=1)
```

[ ]:
```
reduced_corr = train_res_new.corr()
```

[ ]:
```
reduced_corr.shape
```

[ ]: (31, 31)

[ ]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(reduced_corr)
plt.show()
```



2 Original Zillow ADS

Zillow Zestimate ADS: https://www.kaggle.com/c/zillow-prize-1/overview

ADS Intended Goal and Specifications: https://www.kaggle.com/c/zillow-prize-1/data

Kaggle Original Solution Code: https://www.kaggle.com/code/zusmani/scrpt/script

[ ]:
```
import numpy as np
import pandas as pd
import xgboost as xgb
```

```
import random
import datetime as dt
import gc

import seaborn as sns #python visualization library
color = sns.color_palette()

#%matplotlib inline
np.random.seed(1)
```

2.0.1 Analyze the Dimensions of our Datasets

[ ]:
```
print("Training Data Size:" + str(train.shape))
print("Property Data Size:" + str(properties.shape))
print("Sample Data Size:" + str(test.shape))
```

```
Training Data Size:(90275, 3)
Property Data Size:(2985217, 58)
Sample Data Size:(2985217, 7)
```

2.0.2 Type-Converting the DataSet

Processing some of the algorithms can be made quicker if data representation is made in format **int/float32** instead of the format **int/float64.** Therefore we implement the following lines of code in order to made sure all of our columns are in the float32 type

[ ]:
```
for c, dtype in zip(properties.columns, properties.dtypes):
    if dtype == np.float64:
        properties[c] = properties[c].astype(np.float32)
    if dtype == np.int64:
        properties[c] = properties[c].astype(np.int32)


for column in test.columns:
    if test[column].dtype == int:
        test[column] = test[column].astype(np.int32)
    if test[column].dtype == float:
        test[column] = test[column].astype(np.float32)
```

2.0.3 Let's do some feature engineering

[ ]:
```
### Let's do some feature engineering

#living area proportions
properties['living_area_prop'] = properties['calculatedfinishedsquarefeet'] /␣
↪properties['lotsizesquarefeet']
#tax value ratio
```

```
properties['value_ratio'] = properties['taxvaluedollarcnt'] /␣
↪properties['taxamount']
#tax value proportions
properties['value_prop'] = properties['structuretaxvaluedollarcnt'] /␣
↪properties['landtaxvaluedollarcnt']
```

2.0.4 Merging the Datasets

[ ]:
```
df_train = train.merge(properties, how='left', on='parcelid')
df_test = test.merge(properties, how='left', on='parcelid')
```

[ ]:
```
df_train.head(3)
```

[ ]:
```
   parcelid  logerror transactiondate  airconditioningtypeid  \
0  11016594    0.0276      2016-01-01                    1.0
1  14366692   -0.1684      2016-01-01                    NaN
2  12098116   -0.0040      2016-01-01                    1.0

   architecturalstyletypeid  basementsqft  bathroomcnt  bedroomcnt  \
0                       NaN           NaN          2.0         3.0
1                       NaN           NaN          3.5         4.0
2                       NaN           NaN          3.0         2.0

   buildingclasstypeid  buildingqualitytypeid  …  taxvaluedollarcnt  \
0                  NaN                    4.0  …           360170.0
1                  NaN                    NaN  …           585529.0
2                  NaN                    4.0  …           119906.0

   assessmentyear  landtaxvaluedollarcnt     taxamount  taxdelinquencyflag  \
0          2015.0               237416.0   6735.879883                 NaN
1          2015.0               239071.0  10153.019531                 NaN
2          2015.0                57912.0  11484.480469                 NaN

   taxdelinquencyyear  censustractandblock  living_area_prop  value_ratio  \
0                 NaN         6.037107e+13          0.223698    53.470371
1                 NaN                  NaN          0.621191    57.670429
2                 NaN         6.037464e+13          0.194082    10.440699

   value_prop
0    0.517042
1    1.449185
2    1.070486

[3 rows x 63 columns]
```

[ ]:
```
df_test.head(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

   airconditioningtypeid  architecturalstyletypeid  basementsqft  …  \
0                    NaN                       NaN           NaN  …
1                    NaN                       NaN           NaN  …
2                    NaN                       NaN           NaN  …

   taxvaluedollarcnt  assessmentyear  landtaxvaluedollarcnt     taxamount  \
0                9.0          2015.0                    9.0           NaN
1            27516.0          2015.0                27516.0           NaN
2          1413387.0          2015.0               762631.0  20800.369141

   taxdelinquencyflag  taxdelinquencyyear  censustractandblock  \
0                 NaN                 NaN                  NaN
1                 NaN                 NaN                  NaN
2                 NaN                 NaN                  NaN

   living_area_prop  value_ratio  value_prop
0               NaN          NaN         NaN
1               NaN          NaN         NaN
2          1.157581    67.950089    0.853304

[3 rows x 67 columns]
```

2.0.5 Remove some unused variables in order to retain some memory

[ ]:
```
# del properties, train
# We preserve unused variables for later analysis
gc.collect();

print('Memory usage reduction...')
df_train[['latitude', 'longitude']] /= 1e6
df_test[['latitude', 'longitude']] /= 1e6

df_train['censustractandblock'] /= 1e12
df_test['censustractandblock'] /= 1e12
```

```
Memory usage reduction…
```

2.0.6 We will conduct some pre-exploratory analysis to identify the missing values within our datasets.

We incorporated procedures from user Nikunj in order to deal with missing values within our datasets

Reference: https://www.kaggle.com/nikunjm88/carefully-dealing-with-missing-values

[ ]:
```
# Let's do some engineering with the fireplaceflag variable
print(df_train.fireplaceflag.isnull().sum())
print(df_train.fireplacecnt.isnull().sum())

# By using fireplacecnt variable we can recover some of the fields of␣
 ↪fireplaceflag
df_train['fireplaceflag']= "No"
df_train.loc[df_train['fireplacecnt']>0,'fireplaceflag']= "Yes"

# Remaining Missing fireplacecnt will be replaced with 0
index = df_train.fireplacecnt.isnull()
df_train.loc[index,'fireplacecnt'] = 0

#Tax deliquency flag - assume if it is null then doesn't exist
index = df_train.taxdelinquencyflag.isnull()
df_train.loc[index,'taxdelinquencyflag'] = "None"
```

```
90053
80668
```

[ ]:
```
# Similar step performed for Pool/Spa/hot tub
print(df_train.hashottuborspa.value_counts())
print(df_train.pooltypeid10.value_counts())

#lets remove 'pooltypeid10' as has more missing values
print(df_train.hashottuborspa.value_counts())
print(df_train.pooltypeid10.value_counts())

#Assume if the pooltype id is null then pool/hottub doesnt exist
index = df_train.pooltypeid2.isnull()
df_train.loc[index,'pooltypeid2'] = 0

index = df_train.pooltypeid7.isnull()
df_train.loc[index,'pooltypeid7'] = 0

index = df_train.poolcnt.isnull()
df_train.loc[index,'poolcnt'] = 0
```

```
True    2365
Name: hashottuborspa, dtype: int64
1.0    1161
Name: pooltypeid10, dtype: int64
True    2365
Name: hashottuborspa, dtype: int64
1.0    1161
Name: pooltypeid10, dtype: int64
```

2.0.7 Label Encoding For Machine Learning & Filling Missing Values

We are now label encoding our datasets. All of the machine learning algorithms employed in scikit learn assume that the data being fed to them is in numerical form. LabelEncoding ensures that all of our categorical variables are in numerical representation. Also note that we are filling the missing values in our dataset with a zero before label encoding them. This is to ensure that label encoder function does not experience any problems while carrying out its operation.

[ ]:
```
from sklearn.preprocessing import LabelEncoder

lbl = LabelEncoder()
for c in df_train.columns:
    df_train[c]=df_train[c].fillna(0)
    if df_train[c].dtype == 'object':
        lbl.fit(list(df_train[c].values))
        df_train[c] = lbl.transform(list(df_train[c].values))

for c in df_test.columns:
    df_test[c]=df_test[c].fillna(0)
    if df_test[c].dtype == 'object':
        lbl.fit(list(df_test[c].values))
        df_test[c] = lbl.transform(list(df_test[c].values))
```

2.0.8 Removing the Outliers

[ ]:
```
log_errors = df_train['logerror']
df_train = df_train[df_train.logerror < np.percentile(log_errors, 99.5)]
df_train = df_train[df_train.logerror > np.percentile(log_errors, 0.5)]
```

2.0.9 Rearranging the DataSets

We now drop the features which do not serve an useful purpose. We will then split our data and divide it into representation to make it clear which features are to be treated as the determinants in predicting the outcome for our target feature. We make sure to include the same features in the test set as the ones which were included in the training set.

[ ]:
```
x_train = df_train.drop(['parcelid', 'logerror', 'transactiondate',␣
↪'propertyzoningdesc',
                         'propertycountylandusecode' ], axis=1)

x_test = df_test.drop(['parcelid', 'propertyzoningdesc',
                       'propertycountylandusecode', '201610', '201611',
                       '201612', '201710', '201711', '201712'], axis = 1)

x_train = x_train.values
y_train = df_train['logerror'].values
```

2.0.10 Cross Validation

We divide our datasets into training and validation sets so that we can monitor and test the progress of our machine learning algorithm. This would let us know when our model may be over or under-fitting on a dataset which we have employed.

```
[ ]: from sklearn.model_selection import train_test_split

X = x_train
y = y_train

Xtrain, Xvalid, ytrain, yvalid = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

2.0.11 Implement the Xgboost

We now can select the parameters for Xgboost and monitor the progress of results on our validation set. The explanation of the Xgboost parameters and what they do can be found through the following link: http://xgboost.readthedocs.io/en/latest/parameter.html

```
[ ]: dtrain = xgb.DMatrix(Xtrain, label=ytrain)
dvalid = xgb.DMatrix(Xvalid, label=yvalid)
dtest = xgb.DMatrix(x_test.values)

# Try different parameters!
xgb_params = {'min_child_weight': 5, 'eta': 0.035, 'colsample_bytree': 0.5,␣
↪'max_depth': 4,
            'subsample': 0.85, 'lambda': 0.8, 'nthread': -1, 'booster' :␣
↪'gbtree', 'silent': 1, 'gamma' : 0,
            'eval_metric': 'mae', 'objective': 'reg:linear' }

watchlist = [(dtrain, 'train'), (dvalid, 'valid')]

model_xgb = xgb.train(xgb_params, dtrain, 1000, watchlist,␣
↪early_stopping_rounds=100,
                  maximize=False, verbose_eval=10)
```

```
[0]     train-mae:0.474036      valid-mae:0.471898
Multiple eval metrics have been passed: 'valid-mae' will be used for early
stopping.

Will train until valid-mae hasn't improved in 100 rounds.
[10]    train-mae:0.334328      valid-mae:0.332244
[20]    train-mae:0.238427      valid-mae:0.236558
[30]    train-mae:0.173321      valid-mae:0.171623
[40]    train-mae:0.129685      valid-mae:0.128215
[50]    train-mae:0.1011        valid-mae:0.099863
[60]    train-mae:0.082927      valid-mae:0.081904
```

```
[70]	train-mae:0.071828	valid-mae:0.071027
[80]	train-mae:0.065345	valid-mae:0.064763
[90]	train-mae:0.06166	valid-mae:0.061288
[100]	train-mae:0.059599	valid-mae:0.059366
[110]	train-mae:0.058428	valid-mae:0.058296
[120]	train-mae:0.057761	valid-mae:0.057707
[130]	train-mae:0.057369	valid-mae:0.05738
[140]	train-mae:0.057107	valid-mae:0.057194
[150]	train-mae:0.056955	valid-mae:0.057097
[160]	train-mae:0.056837	valid-mae:0.057025
[170]	train-mae:0.056759	valid-mae:0.056985
[180]	train-mae:0.056702	valid-mae:0.056968
[190]	train-mae:0.056649	valid-mae:0.056954
[200]	train-mae:0.056614	valid-mae:0.056949
[210]	train-mae:0.056579	valid-mae:0.056942
[220]	train-mae:0.056542	valid-mae:0.056936
[230]	train-mae:0.056508	valid-mae:0.056931
[240]	train-mae:0.056479	valid-mae:0.056921
[250]	train-mae:0.05645	valid-mae:0.05692
[260]	train-mae:0.056433	valid-mae:0.05693
[270]	train-mae:0.056409	valid-mae:0.056933
[280]	train-mae:0.056384	valid-mae:0.056927
[290]	train-mae:0.05636	valid-mae:0.056927
[300]	train-mae:0.056343	valid-mae:0.056936
[310]	train-mae:0.056315	valid-mae:0.056938
[320]	train-mae:0.056294	valid-mae:0.056938
[330]	train-mae:0.056267	valid-mae:0.056932
[340]	train-mae:0.056246	valid-mae:0.056934
[350]	train-mae:0.056223	valid-mae:0.056931
Stopping. Best iteration:
[251]	train-mae:0.056446	valid-mae:0.056919
```

###Predicting the results###

We can now predict the target variable for our test dataset. All we need to do now is fit the already trained model on the test dataset which we made from merging the sample file with the properties dataset.

[ ]:
```
Predicted_test_xgb = model_xgb.predict(dtest)
```

[ ]:
```
Predicted_test_xgb
```

[ ]:
```
array([-0.05235672, -0.01327515,  0.00347465, …,  0.10479754,
        0.10479754,  0.10479754], dtype=float32)
```

2.0.12 Submitting the Results

Since we do not need to export the predicitons to csv file, we commented out the cells below to save memory

[ ]:
```
# # Once again load the file and start submitting the results in each column #
# # sample_file = pd.read_csv('../input/sample_submission.csv')

# # https://drive.google.com/file/d/15D754PtBPHg7e27bKei6E4d1md2Gwao0/view?
↪usp=sharing
# fileid = '15D754PtBPHg7e27bKei6E4d1md2Gwao0'
# filename = 'sample_submission.csv'
# downloaded = drive.CreateFile({'id':fileid})
# downloaded.GetContentFile(filename)
# sample_file = pd.read_csv(filename)
# sample_file
```

[ ]:

	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 x 7 columns]

[ ]:
```
# for c in sample_file.columns[sample_file.columns != 'ParcelId']:
#     sample_file[c] = Predicted_test_xgb

# print('Preparing the csv file ...')
# sample_file.to_csv('xgb_predicted_results.csv', index=False, float_format='%.
↪4f')
# print("Finished writing the file")
# # failed to write to the csv file in drive, but predictions are stored in the␣
↪variable sample_file
```

```
Preparing the csv file …
Finished writing the file
```

[ ]:
```
# len(sample_file)
```

[ ]: 2985217

[ ]:
```
# sample_file
```

[ ]:

	ParcelId	201610	201611	201612	201710	201711	201712
0	10754147	-0.052357	-0.052357	-0.052357	-0.052357	-0.052357	-0.052357
1	10759547	-0.013275	-0.013275	-0.013275	-0.013275	-0.013275	-0.013275
2	10843547	0.003475	0.003475	0.003475	0.003475	0.003475	0.003475
3	10859147	0.116168	0.116168	0.116168	0.116168	0.116168	0.116168
4	10879947	0.061894	0.061894	0.061894	0.061894	0.061894	0.061894
…	…	…	…	…	…	…	…
2985212	168176230	0.104798	0.104798	0.104798	0.104798	0.104798	0.104798
2985213	14273630	0.104798	0.104798	0.104798	0.104798	0.104798	0.104798
2985214	168040630	0.104798	0.104798	0.104798	0.104798	0.104798	0.104798
2985215	168040830	0.104798	0.104798	0.104798	0.104798	0.104798	0.104798
2985216	168040430	0.104798	0.104798	0.104798	0.104798	0.104798	0.104798

[2985217 rows x 7 columns]

3 ADS Evaluation

####Sample submission logerror predictions:

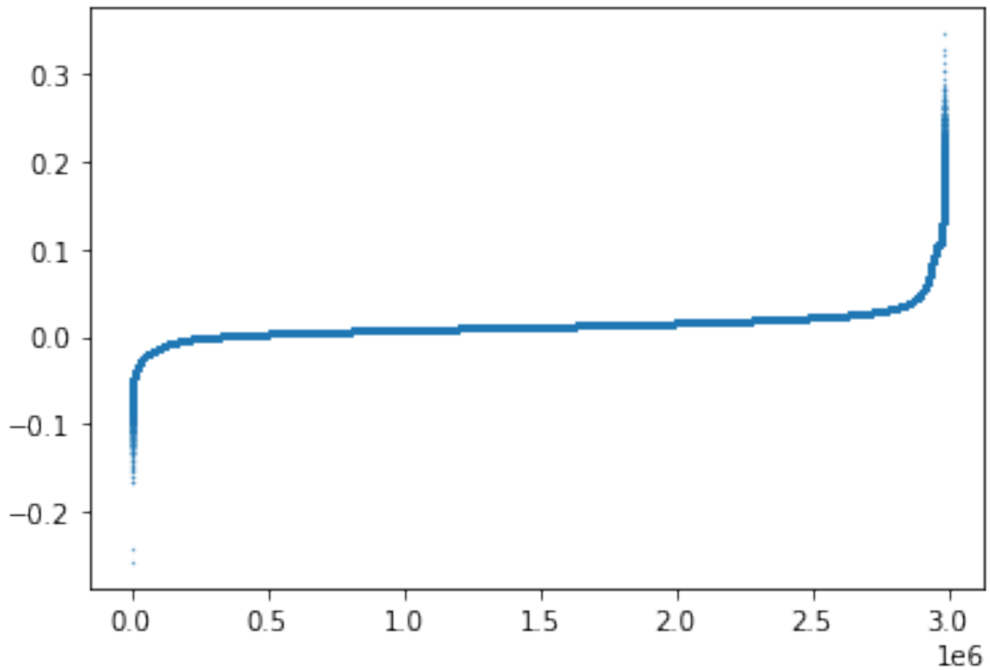
[ ]:
```
def describe_arr(array):
  print("mean:",array.mean())
  print("median:",np.median(array))
  print("min:",array.min())
  print("max:",array.max())
```

[ ]:
```
describe_arr(Predicted_test_xgb)
```

```
mean: 0.013021984
median: 0.011305124
min: -0.25805414
max: 0.34636483
```

[ ]:
```
plt.scatter(range(len(Predicted_test_xgb)), np.sort(Predicted_test_xgb),s=0.1)
```

[ ]:
```
<matplotlib.collections.PathCollection at 0x7f401646de90>
```



####model prediction on test set:

Because we do not have test set for the submission version of logerror prediction, which was the scoring metric for Kaggle competition. Instead, below, we analyze the prediction on test set.

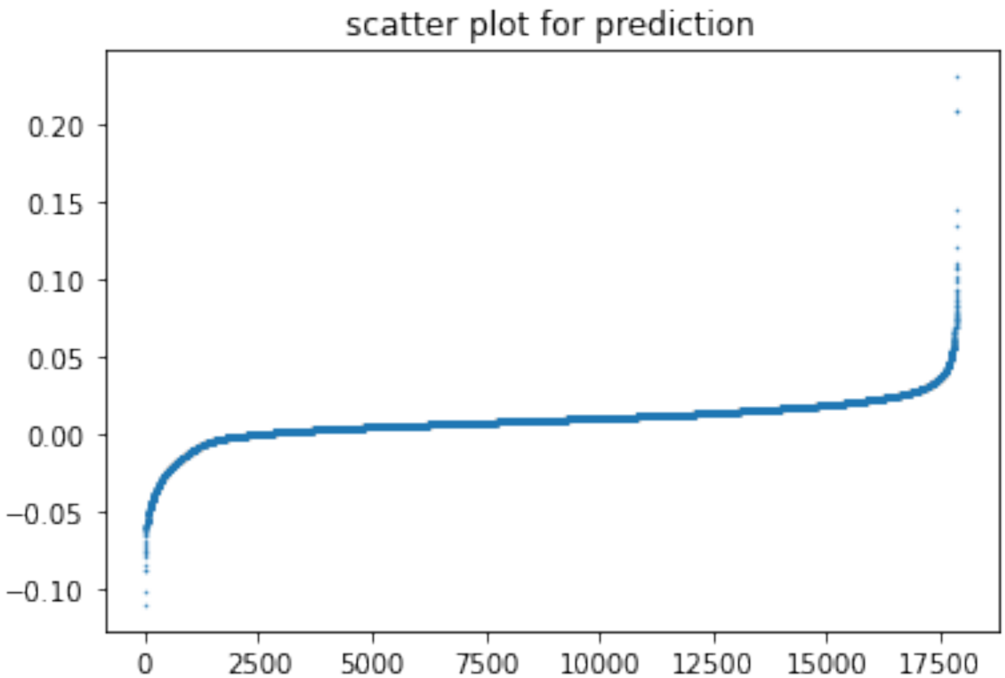
[ ]:
```
y_pred = model_xgb.predict(dvalid)
```

[ ]:
```
describe_arr(y_pred)
```

```
mean: 0.0095409425
median: 0.009667605
min: -0.109619394
max: 0.23125656
```

[ ]:
```
plt.scatter(range(len(y_pred)), np.sort(y_pred),s=0.2)
plt.title("scatter plot for prediction")
```

[ ]:
```
Text(0.5, 1.0, 'scatter plot for prediction')
```



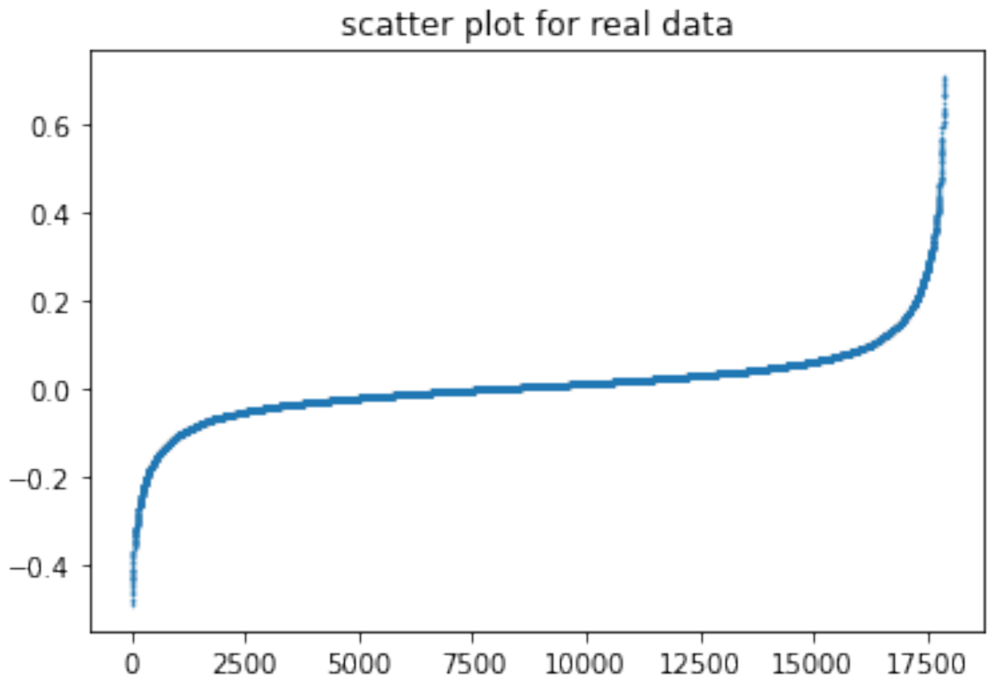
####real test data:

[ ]:
```
describe_arr(yvalid)
```

```
mean: 0.011792033120734027
median: 0.007
min: -0.4878
max: 0.7066
```

[ ]:
```
plt.scatter(range(len(yvalid)), np.sort(yvalid),s=0.2)
plt.title("scatter plot for real data")
```

[ ]:
```
Text(0.5, 1.0, 'scatter plot for real data')
```



####classification of logerror

a set a threshold of 0.1.

For logerror within 0.1 to -0.1 interval, we say we have a good estimate for this estate and represent it as 1. If the logerror is larger, it is replaced with 0, showing that it's an inaccurate estimate

[ ]:
```
import copy
def classify_log(array):
  res = copy.deepcopy(array)
  for i in range(len(res)):
    if abs(res[i])<=0.1: res[i]=1
    else: res[i]=0
  return res
```

real test data:

[ ]:
```
ytest_class = classify_log(yvalid)
```

[ ]:
```
unique, counts = np.unique(ytest_class, return_counts=True)
dict(zip(unique, counts))
```

[ ]:
```
{0.0: 2715, 1.0: 15159}
```

predicted data:

[ ]:
```
ypred_class = classify_log(y_pred)
```

```
[ ]: unique, counts = np.unique(ypred_class, return_counts=True)
     dict(zip(unique, counts))
```

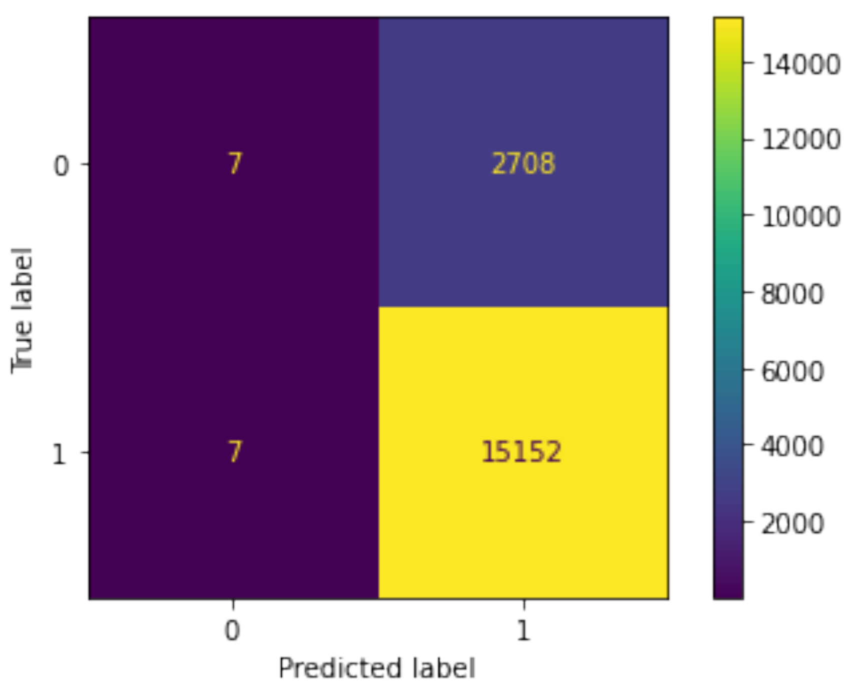
```
[ ]: {0.0: 14, 1.0: 17860}
```

3.0.1 performance and fairness

```
[ ]: import sklearn.metrics as skm
     print("accuracy:", skm.accuracy_score(ytest_class, ypred_class))
     print("AUC:", skm.roc_auc_score(ytest_class, ypred_class))
     print('precision:', skm.precision_score(ytest_class, ypred_class))
     print('recall:', skm.recall_score(ytest_class, ypred_class))
     print('average_precision:', skm.average_precision_score(ytest_class,␣
      ↪ypred_class))
```

```
accuracy: 0.8481033903994629
AUC: 0.5010582484959611
precision: 0.8483762597984322
recall: 0.999538228115311
average_precision: 0.8483761337950155
```

```
[ ]: cm = skm.confusion_matrix(ytest_class, ypred_class)
     skm.ConfusionMatrixDisplay(confusion_matrix=cm).plot()
     plt.show()
```



[ ]:
```
cm
```

[ ]:
```
array([[    7,  2708],
       [    7, 15152]])
```

[ ]:
```
true_positive=cm[1,1]
false_positive=cm[0,1]
true_negative=cm[0,0]
false_negative=cm[1,0]
```

[ ]:
```
print("false positive rate is: {:.4f}".format(false_positive/
 ↪(false_positive+true_negative)))
print("false negative rate is: {:.4f}".format(false_negative/
 ↪(false_negative+true_positive)))
```

```
false positive rate is: 0.9974
false negative rate is: 0.0005
```

3.0.2 attempt to analyze subpopulation accuracy

Because the ADS converted dataframes into numerical values when spliting training and test dataset. it is hard to reconstruct test set dataframe and reassociate predictions with features.

In addition, many features like buildingclasstypeid, storytypeid, architecturalstyletypeid obtains about 99% of null data. And features like regionidcounty, regionidcity, and regionidneighborhood do not have have human-interpretable dicitonary on Kaggle.

Therefore, although we originally planned to evaluate ADS's accuracy across subpopulations, we failed to analyze it due to ADS's encoding and preprocessing methods as well as missing documentations.

In the cells below, we attempted to analyze performance of subgroups based on "propertylandusetypeid" by creating a fairlearn.metrics.MetricFrame taught in lab 4. However, in the process of coding, we realized we could not reconstruct predictions' associated features. Thus we failed to anaylze fairness and subpopulation accuracy for this ADS due to above reasons.

[ ]:
```
# !pip install --upgrade fairlearn==v0.6.0
```

[ ]:
```
# from fairlearn.metrics import MetricFrame
# from fairlearn.metrics import selection_rate, false_negative_rate,␣
 ↪false_positive_rate

# import functools
# import numpy as np
```

[ ]:
```
# df_ytrain, df_yvalid = train_test_split(train, test_size=0.2, random_state=42)
```

[ ]:
```
# def insensitive_roc_auc(y_true, y_score):
#     #to handle subgroups with only one class.
```

```
#     if sum(y_true)!=len(y_true) and sum(y_true)!=0:
#         return skm.roc_auc_score(y_true, y_score)
#     else:
#         return np.nan

# def samplesize(y_true, y_score):
#     return len(y_true)

# #Metrics
# metric_fns = {'samplesize': samplesize,
#                 'selection_rate': selection_rate,  # i.e., the percentage of␣
↪the population which have ‘1’ as their label
#                 'FNR': false_negative_rate,
#                 'FPR': false_positive_rate,
#                 'accuracy': skm.accuracy_score,
#                 'average_precision': skm.average_precision_score,
#                 'roc_auc_score': insensitive_roc_auc
#                 }

# grouped_on_race = MetricFrame(metric_fns,
#                               ytest_class, ypred_class,
#                              ␣
↪sensitive_features=df_yvalid['propertylandusetypeid'])
```

3.0.3 XGB factor importance

[ ]:
```
weight = model_xgb.get_score(importance_type='weight')
```

[ ]:
```
# removed columns from training set in pre-processing
removed_col = ['parcelid', 'logerror', 'transactiondate', 'propertyzoningdesc',␣
↪'propertycountylandusecode' ]
```

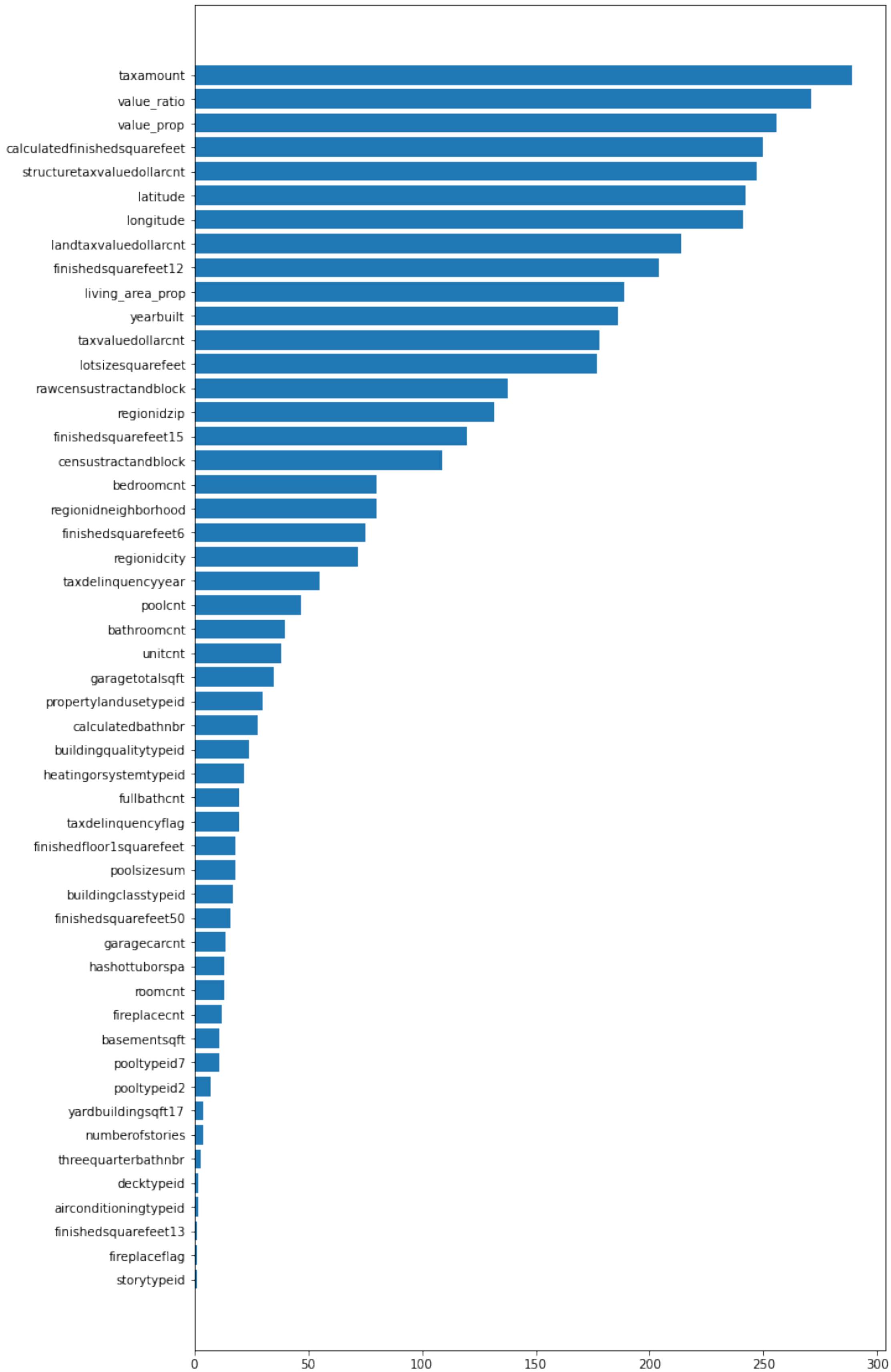
[ ]:
```
# match unreadable coded names to actual feature neams
feat_code = model_xgb.feature_names
feats_names = df_train.drop(removed_col, axis=1).columns
```

[ ]:
```
code_to_names = {}
for key, value in zip(feat_code, feats_names):
      code_to_names[key] = value
```

[ ]:
```
weight_dic = { code_to_names[k]: v for k, v in weight.items() }
```

[ ]:
```
# sort dictionary from largest weight to lowest
import operator
sorted_weight = sorted(weight_dic.items(), key=operator.itemgetter(1),␣
↪reverse=False)
```

[ ]:
```
x, y = zip(*sorted_weight)
figs, axes = plt.subplots(figsize=(10,20))
plt.barh(x,y)
plt.show()
```


taxamount
value_ratio
value_prop
calculatedfinishedsquarefeet
structuretaxvaluedollarcnt
latitude
longitude
landtaxvaluedollarcnt
finishedsquarefeet12
living_area_prop
yearbuilt
taxvaluedollarcnt
lotsizesquarefeet
rawcensustractandblock
regionidzip
finishedsquarefeet15
censustractandblock
bedroomcnt
regionidneighborhood
finishedsquarefeet6
regionidcity
taxdelinquencyyear
poolcnt
bathroomcnt
unitcnt
garagetotalsqft
propertylandusetypeid
calculatedbathnbr
buildingqualitytypeid
heatingorsystemtypeid
fullbathcnt
taxdelinquencyflag
finishedfloor1squarefeet
poolsizesum
buildingclasstypeid
finishedsquarefeet50
garagecarcnt
hashottuborspa
roomcnt
fireplacecnt
basementsqft
pooltypeid7
pooltypeid2
yardbuildingsqft17
numberofstories
threequarterbathnbr
decktypeid
airconditioningtypeid
finishedsquarefeet13
fireplaceflag
storytypeid
0
50
100
150
200
250
300

4 Bibliography

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