```
# Using google colab - this first step is for loading in the data from my personal Dri

# Login with google credentials

from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

# Handle errors from too many requests

import logging
logging.getLogger('googleapiclient.discovery_cache').setLevel(logging.ERROR)

# The ID for my personal Drive folder is 1BVUuroPvozFxMjMIYrGOFtI4r6erSBCx
# I am now listing the ID numbers for the files in this folder to find the data files

#file_list = drive.ListFile({'q': "'1BVUuroPvozFxMjMIYrGOFtI4r6erSBCx' in parents and
#for file1 in file_list:
#  print('title: %s, id: %s' % (file1['title'], file1['id']))

# Data ID: 1F2KojI0d-ZnN8ssQFUWSyZA8I0mAgMEf

# Now that I have the ID files, load the files

data_downloaded = drive.CreateFile({'id': '1F2KojI0d-ZnN8ssQFUWSyZA8I0mAgMEf'})
data_downloaded.GetContentFile('Full.csv')


# Load the data into pandas

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```



```
print(data.isnull().values.any())

# No nulls after import
```

```
False
```

```
data.head(3)
```

	Year_sold	PARCEL	SequenceNum	SaleDate	SalePrice	PrPerSqFt	p_Cat	Record
0	2019	401554180	20191960498	201906	49000	61.790668	6	
1	2019	401554100	20190300552	201901	50500	63.682219	6	
2	2019	401553650	20191970632	201907	58000	63.112078	6	

```
import seaborn as sn
corrMat = data.corr()

#plt.figure(figsize=(30,15))
#sn.heatmap(corrMat, annot=True)

# SalesPrice correlates heavily with CLASS, PrPerSqFt, BATHFIXTUR, MAIN, CONTROL, ACTU

# Years_sold, SequenceNum, SalesDate are all the same

# MAIN, CONTROL, ACTUAL are all about the same


# Feature Engineering

## Years_sold, SequenceNum, SalesDate and RecordingDate all contain basically the same

data = data.drop(columns=['Year_sold', 'SequenceNum'], axis=1)

## Main, Control, Actual are all tax assessments. Let's average them and use thart ins

data['TaxEval'] = (data['MAIN'] + data['CONTROL'] + data['ACTUAL'] ) / 3

data['diff'] = data['SalePrice'] - data['TaxEval']

data = data.drop(columns=['MAIN', 'CONTROL', 'ACTUAL'], axis=1)

## PrPerSqFt is just SalesPrice / Sqft. There's no reason to include that along with s
```



```
data = data.drop(columns=['PARCEL', 'INSPECTION'], axis=1)


features = list(data.columns.values.tolist())

corrMat = data[features].corr()

plt.figure(figsize=(30,15))
sn.heatmap(corrMat, annot=True)
```

```
# Now remove features we can't use in the model

features.remove('diff')
features.remove('PrPerSqFt')
features.remove('TaxEval')
```

Automatic document saving has been pending for 18 minutes. Reloading may fix the problem. Save and reload the page.

```
# Normalize all data. That way my weights will be my importances

normalized_df=(data-data.min())/(data.max()-data.min())

print((normalized_df['SalePrice'] - normalized_df['TaxEval']).mean())

# train test split

data_copy = normalized_df.copy()
trainData = data_copy.sample(frac=0.8, random_state=0)
testData = data_copy.drop(trainData.index)

X_train = trainData[features].to_numpy().astype(float)
y_train = (trainData['diff']).to_numpy().reshape(len(trainData),1).astype(float)

X_test = testData[features].to_numpy().astype(float)
y_test = (testData['diff']).to_numpy().reshape(len(testData),1).astype(float)
```

```
-0.04555994695631326
```

```
class OrdinaryLeastSquares():
  def _init_(self):
    self.coefficients = []

  def _reshape_x(self,X):
    return X.reshape(-1, 1)

  def _concatenate_ones(self, X):
    ones = np.ones(shape = X.shape[0]).reshape(-1,1)
    return np.concatenate((ones, X), 1)

  def fit(self, X, y):

    if len(X.shape) == 1: X = self._reshape_x(X)

    X = self._concatenate_ones(X)

    self.coefficients = np.linalg.inv(X.transpose().dot(X)).dot(X.transpose()).dot(y)
```



```
    w0 = self.coefficients[0]
    other_gammas = self.coefficients[1:]
    prediction = w0

    for xi, wi in zip(y, other_gammas):
      prediction = prediction + (wi * xi)

    return prediction
```

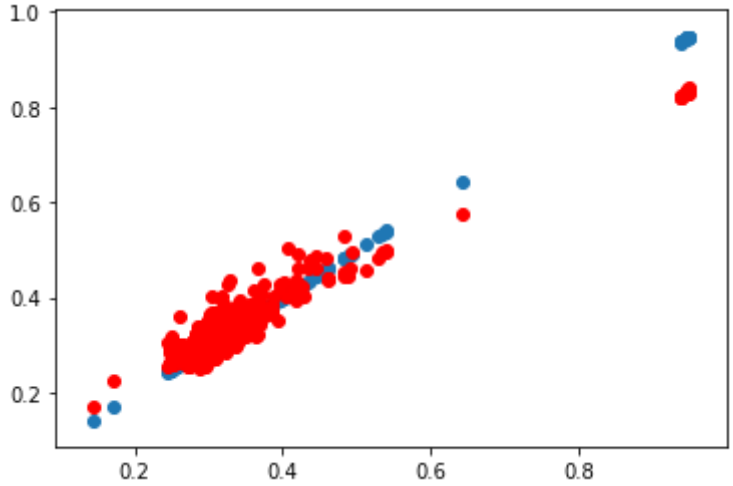
```
    def predict(self, y):

      y_preds = []

      for row in y:
        y_preds.append(self.predict_one(row))

      return y_preds

    def get_importance(self):

      return self.coefficients

  def rmse(y, y_hat):

    #combined rmse value
    rss=((y-y_hat)**2).sum()
    mse=np.mean((y-y_hat)**2)
    rmse = np.sqrt(mse)

    return rmse

  def getImportanceTable(ols, features):

    weights_array = ols.get_importance().astype(float).tolist()
    weights_array = [item for sublist in weights_array for item in sublist]
    weights_array = weights_array[1:]
    weights_sum = sum(list(map(abs, weights_array)))

    weights_array[:] = [x / weights_sum for x in weights_array]

    importances = list(zip(features, weights_array))
    importances = sorted(importances, key=lambda x : abs(x[1]), reverse=True)

    num = np.array(importances)
    reshaped = num.reshape(len(features),2)
    print(pd.DataFrame(reshaped, columns=['Feature','Importance']))


  ols = OrdinaryLeastSquares()
```



```
  y_hat = [item for sublist in y_hat for item in sublist]

  X_plot = y_test

  plt.figure()
  plt.scatter(X_plot,y_test)
  plt.scatter(X_plot,y_hat, color='#FF0000')
```

```
from sklearn.metrics import r2_score

print(r2_score(y_test, y_hat))
print(rmse(y_test, y_hat))
print(np.mean(y_test))
```

```
0.8821828236467271
0.036954835707755804
0.3094048175858326
```



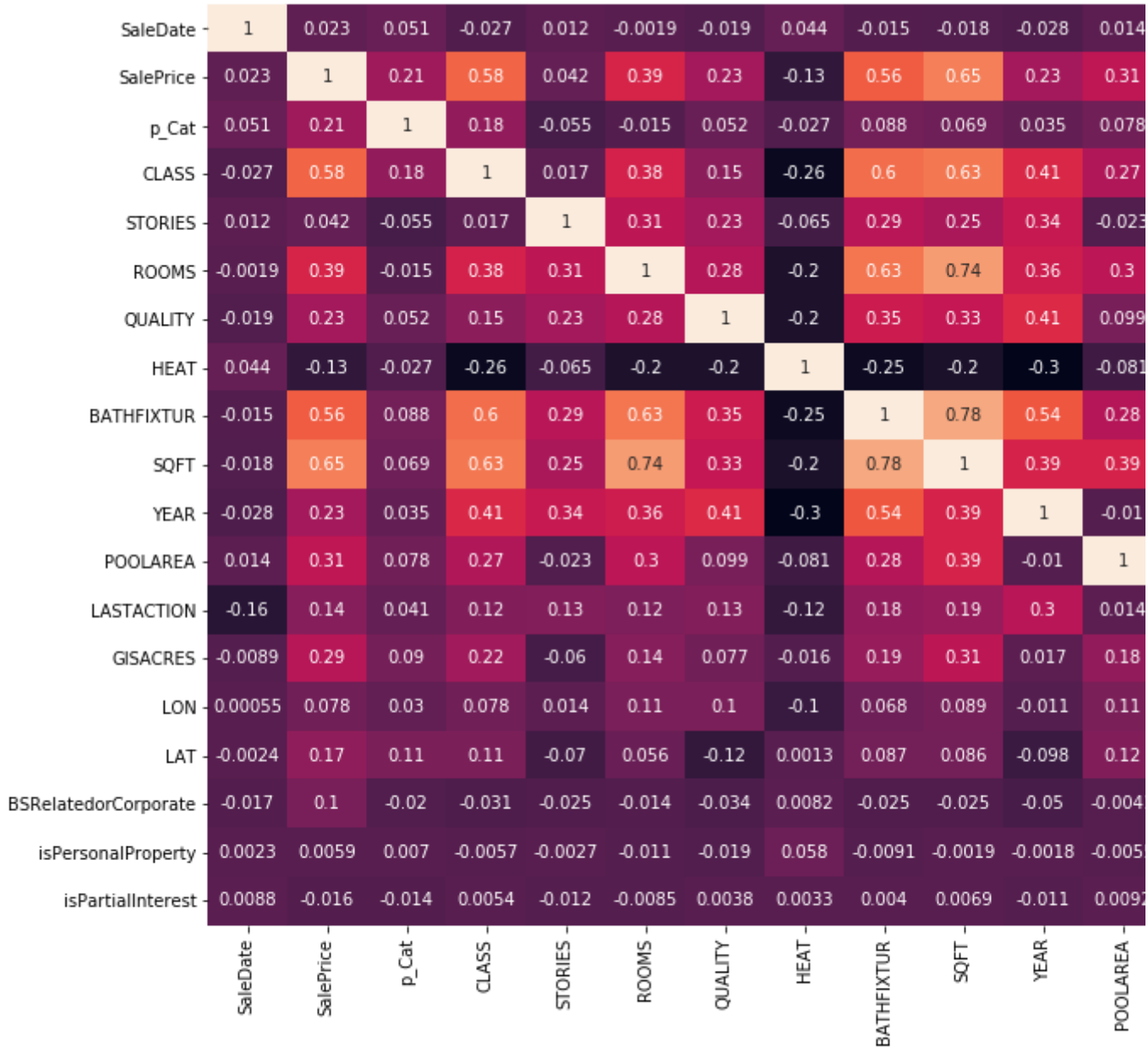

```
getImportanceTable(ols, features)
```

	Feature	Importance
0	SalePrice	0.5238586940004392
1	SQFT	-0.1610867276052656
2	GISACRES	-0.05052674619527425
3	CLASS	-0.04235772289352165
4	ROOMS	0.034389415493254964
5	BATHFIXTUR	-0.017500576640732925
6	PATIONUMBE	-0.015694745631574816
7	LON	-0.015447626332676292
8	LAT	-0.013820349792109683
9	isPartialInterest	-0.013443622589129726
10	YEAR	0.010601727068947926
11	STORIES	0.010408606279021399
12	QUALITY	-0.010342667567723136
13	isBuyerSellerRelated	0.010105126307962632
14	isPersonalProperty	0.007007546973883275
15	p_Cat	-0.006075370807905544
16	POOLAREA	-0.005340433535388927
17	HEAT	-0.005206694505206239
18	GARAGECAPA	-0.0050401740872237895
19	NonPrimary	-0.004100824721960035
20	SaleGovt	0.0033379619939088953
21	LASTACTION	-0.00316410183909218
22	RecordingDate	0.003102959546016357
23	GoodSale	0.003080464486048154
24	Rental	-0.0030583789018807195
25	PrimaryRes	-0.002894368182856445
26	PATIO	-0.0028219387429721738
27	BSOutOfState	0.002706137857961582
28	WALLS	0.002631767818019001
29	BSRelatedorCorporate	-0.0024896089742632104
30	COOL	0.0018649715674562005
31	SaleDate	-0.0014912044390243684
32	CONDITION	0.0013012673921590143
33	SaleUnderDuress	0.0010363281544455455
34	GARAGE	-0.0006315033091777621
35	JointTenancyDeed	0.0005986506137744087
36	ROOF	0.0004005220253590113
37	FinancingCash	-0.00034115991135851166
38	NoAssessmentRole	-0.0003024382514219819
39	ZIP	0.00021900536611992087
40	isSolar	-0.0001311657845844674
41	WarrantyDeed	3.86958128977186e-05


```
features = list(data.columns.values.tolist())

# Weight coefficients say these features are very unimportant

features.remove('NoAssessmentRole')
features.remove('WarrantyDeed')
features.remove('isSolar')
features.remove('ZIP')
features.remove('FinancingCash')
```

```
    features.remove('FinancingCash')
    features.remove('JointTenancyDeed')
    features.remove('GARAGE')
    features.remove('CONDITION')
    features.remove('ROOF')
    features.remove('SaleUnderDuress')
    features.remove('BSOutOfState')
    features.remove('COOL')
    features.remove('PATIO')
    features.remove('SaleGovt')
    features.remove('PrimaryRes')
    features.remove('RecordingDate')
    features.remove('GARAGECAPA')

    # Remove very correlated features based on correlation matrix
    features.remove('GoodSale')
    features.remove('Rental')
    features.remove('NonPrimary')
    features.remove('PATIONUMBE')
    features.remove('isBuyerSellerRelated')
    features.remove('WALLS')

    # Stays in because it hurts my model to remove
    #features.remove('CLASS')

    # Now remove features we can't use in the model

    features.remove('diff')
    features.remove('PrPerSqFt')
    features.remove('TaxEval')

    # Print correlation matrix

    corrMat = data[features].corr()

    plt.figure(figsize=(20,10))
    sn.heatmap(corrMat, annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f840ec55080>
```




```
X_train = trainData[features].to_numpy().astype(float)
```

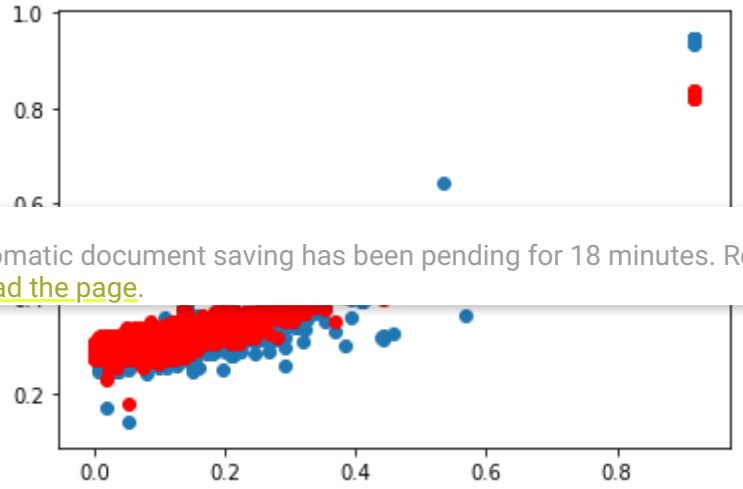


```
X_test = testData[features].to_numpy().astype(float)
y_test = (testData['diff']).to_numpy().reshape(len(testData),1).astype(float)

ols = OrdinaryLeastSquares()

ols.fit(X_train,y_train)
y_hat = ols.predict(X_test)

y_hat = [item for sublist in y_hat for item in sublist]
```

```
X_plot = (testData['SalePrice']).to_numpy().reshape(len(testData),1).astype(float)

plt.figure()
plt.scatter(X_plot,y_test)
plt.scatter(X_plot,y_hat, color='#FF0000')

from sklearn.metrics import r2_score

print(r2_score(y_test, y_hat))
print(rmse(y_test, y_hat))

getImportanceTable(ols, features)
```

```
0.8777362989085593
0.03690838036730064
```

	Feature	Importance
0	SalePrice	0.5542740419336928
1	SQFT	-0.1765944457055261
2	GISACRES	-0.05854365244969522
3	CLASS	-0.04604063133012461
4	ROOMS	0.038649221036096894
5	BATHFIXTUR	-0.01979175525196903
6	LON	-0.014576916416537742
7	LAT	-0.013937638105724303
8	isPartialInterest	-0.012480076120169279
9	STORIES	0.010666380891096677
10	QUALITY	-0.010618087609952451
11	YEAR	0.00915728019565712
12	HEAT	-0.007591248008502165
13	p_Cat	-0.006445846759644615
14	BSRelatedorCorporate	0.0053432230558870305
15	isPersonalProperty	0.005334874975627119
16	POOLAREA	-0.005137657654759445
17	LASTACTION	-0.0038553440272885756
18	SaleDate	0.0009616784720488255

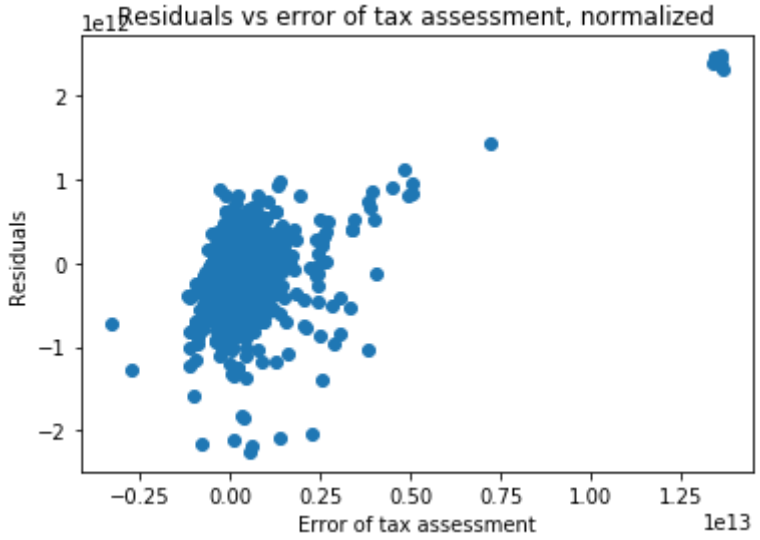



```
print(np.median(y_test))
```

```
0.3073582222790861
```

```
scale_factor = int((max(data['diff']) - min(data['diff'])))

y_test = y_test.reshape(len(y_test),) * scale_factor
y_hat = [x * scale_factor for x in y_hat]
residuals = y_test - y_hat

#print(residuals.shape)
#print(y_test.shape)
#print(scale_factor)
plt.figure()

plt.xlabel('Error of tax assessment')
plt.ylabel('Residuals')
plt.title('Residuals vs error of tax assessment, normalized')

plt.scatter(y_test, residuals)

#print(" RMSE of house value is " +  str(scale_factor * 0.03691012168704651))
```

```
<matplotlib.collections.PathCollection at 0x7f840effec18>
```

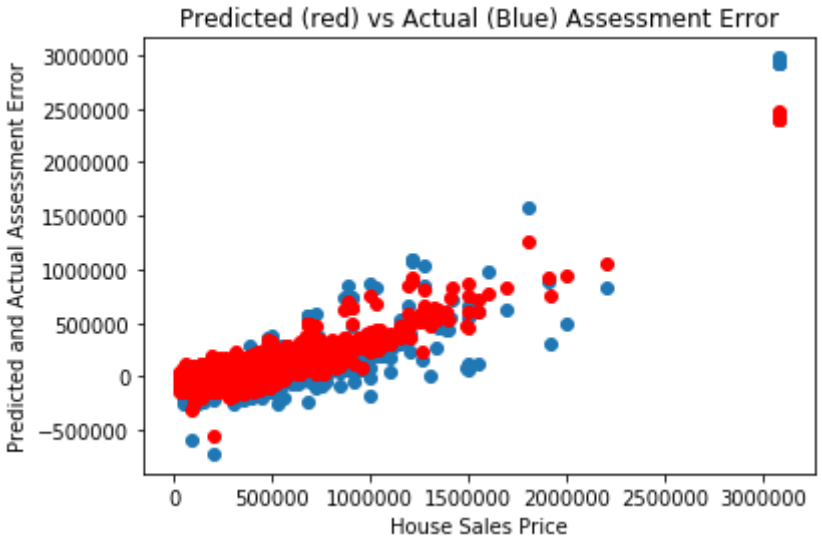



```
# train test split

data_copy = data.copy()
trainData = data_copy.sample(frac=0.8, random_state=0)
testData = data_copy.drop(trainData.index)

X_train = trainData[features].to_numpy().astype(float)
y_train = (trainData['diff']).to_numpy().reshape(len(trainData),1).astype(float)
```

```
X_test = testData[features].to_numpy().astype(float)
y_test = (testData['diff']).to_numpy().reshape(len(testData),1).astype(float)

ols = OrdinaryLeastSquares()

ols.fit(X_train,y_train)
y_hat = ols.predict(X_test)

y_hat = [item for sublist in y_hat for item in sublist]

X_plot = (testData['SalePrice']).to_numpy().reshape(len(testData),1).astype(float)

plt.figure()

plt.xlabel('House Sales Price')
plt.ylabel('Predicted and Actual Assessment Error')
plt.title('Predicted (red) vs Actual (Blue) Assessment Error')

plt.scatter(X_plot,y_test)
plt.scatter(X_plot,y_hat, color='#FF0000')

from sklearn.metrics import r2_score

print(r2_score(y_test, y_hat))
print(rmse(y_test, y_hat))

getImportanceTable(ols, features)
```

```
0.8777362989087802
169237.7188891875
```

	Feature	Importance
0	LAT	-0.2538650895008694
1	isPartialInterest	-0.17812355698527096
2	CLASS	-0.13142421472402277
3	LON	-0.08576271178970861
4	BSRelatedorCorporate	0.07626186629749096
5	isPersonalProperty	0.076142717205788
6	STORIES	0.07611867453217096
7	QUALITY	-0.05051602558156512
8	ROOMS	0.025073917307846406
9	GISACRES	-0.02197862270553631
10	HEAT	-0.012038567038466199
11	BATHFIXTUR	-0.01046223985680548
12	YEAR	0.0010372897411348257
13	p_Cat	-0.0007863180402079631
14	SQFT	-0.00027271887741514334
15	POOLAREA	-6.666173327413906e-05
16	SaleDate	6.630765533463487e-05
17	SalePrice	2.383125060784364e-06
18	LASTACTION	-1.1730203139332165e-07

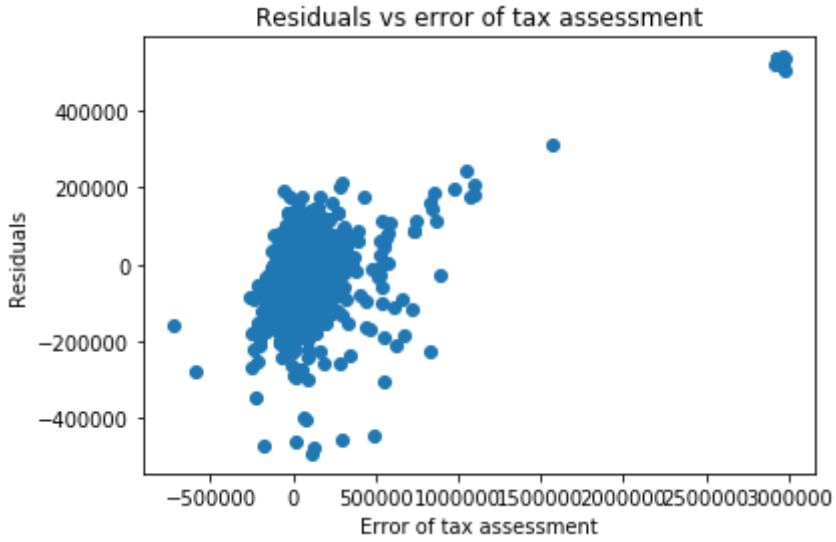



```
y_test = y_test.reshape(len(y_test),)
residuals = y_test - y_hat
```



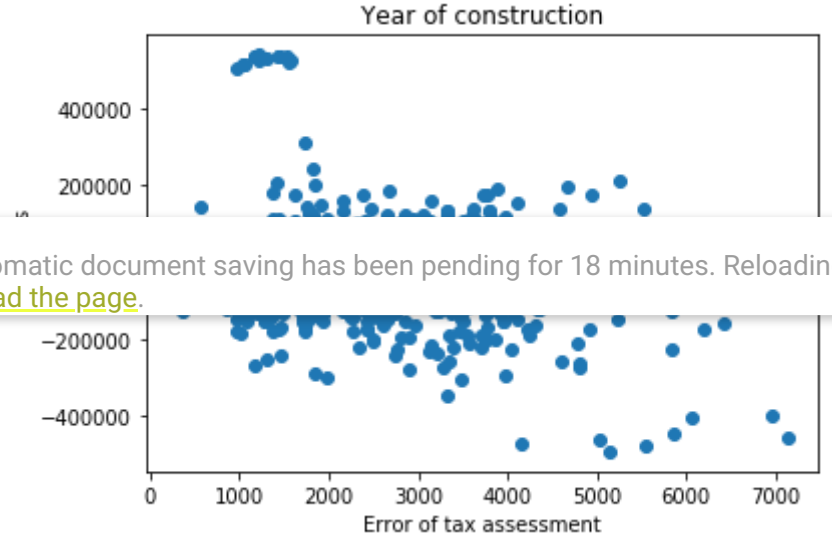
```
#print(scale_factor)
plt.figure()

plt.xlabel('Error of tax assessment')
plt.ylabel('Residuals')
plt.title('Residuals vs error of tax assessment')

plt.scatter((y_test), (residuals))
```

```
<matplotlib.collections.PathCollection at 0x7f840b43ba90>
```




```
y_test = y_test.reshape(len(y_test),)
residuals = y_test - y_hat

#print(residuals.shape)
#print(y_test.shape)
#print(scale_factor)
plt.figure()

plt.xlabel('Error of tax assessment')
plt.ylabel('Residuals')
plt.title('Year of construction')
X_axis = X_test[:,9]
y_axis = residuals
plt.scatter(X_axis, y_axis)
```

```
<matplotlib.collections.PathCollection at 0x7f840a3a5518>
```




```
y_test = y_test.reshape(len(y_test),)
```

```
residuals = y_test - y_nat

#print(residuals.shape)
#print(y_test.shape)
#print(scale_factor)
plt.figure()

plt.xlabel('Error of tax assessment')
plt.ylabel('Residuals')
plt.title('Year of construction')
X_axis = X_test[:,0]
y_axis = residuals
plt.scatter(X_axis, y_axis)
```

```
<matplotlib.collections.PathCollection at 0x7f840f0c0668>
```


```
plt.figure()

plt.xlabel('Error of tax assessment')
plt.ylabel('Residuals')
plt.title('Year of construction')
X_axis = X_test[:,0]
y_axis = residuals
plt.scatter(X_axis, y_axis)
```

```
<matplotlib.collections.PathCollection at 0x7f840f46edd8>
```


```
print("Mean diff is:" + str(np.median(y_test)))
print("Mean house is is:" + str(np.median(X_test[:,1])))

print(np.median(y_test) / np.median(X_test[:,1]))
```

```
Mean diff is:152909061510.66672
Mean house is is:210000.0
728138.388146032
```

```
print((data['TaxEval']).median())
print((data['SalePrice']).median())
```

```
176805.66666666666
210000.0
```