Title: "Elementary and high school students performance and relation to the district education finance " -GA Final Project Research proposal Author: Yu Zhang output:

1. Introduction

In the discussion of K-12 students' success, the issue of financing is prominent from the perspective of various stakeholders. Policymakers are engaged in asking how much public purse should be devoted to elementary and high school students related to competing demands on tuition, expenditure, and transportation. Federal education and census are concerned about the financial capacity to provide quality education and sustain the living hood. Besides, the family and students concerned about how they pay for education can guarantee the students' success beyond elementary and high school.

In observing the NAEP (National Assessment of Educational Progress) data and Educational financing data from the National Finance Census (National Center for Educational Statistics), we have been known the educational finance can be characterized by the goals of students' academic success, and by a strong influence by the financial capacity, by and large, we might predict the elementary and high school students academic success on mathematics and literacy to be influenced by the features of family and federal educational financing, this is for example, highly praise by educational scholar and researcher Joan Herman'description: "the keys resources, educational financing have been imposed the role to expand the enrollment and institutes. On the performance standards, the evaluation can be introduced to predict the student's performance" (2011).

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score
import statsmodels.api as sm
%matplotlib inline

from sklearn.linear_model import Ridge, Lasso, ElasticNet, LinearRegression
from sklearn.model_selection import cross_val_score

plt.rcParams['figure.figsize'] = (8, 6)
plt.rcParams['font.size'] = 14
plt.style.use("fivethirtyeight")


from sklearn.linear_model import LinearRegression
```

In [2]:
```
districts = pd.read_csv("/Users/zhangyu027/Dropbox/Academia/UCI Lecturer/I&
naep = pd.read_csv("/Users/zhangyu027/Dropbox/Academia/UCI Lecturer/I&C_SCI
```

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

Out[3]:

	STATE	ENROLL	NAME	YRDATA	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP
0	Alabama	9609.0	AUTAUGA COUNTY SCHOOL DISTRICT	2016	80867	7447	53842	19578	76672
1	Alabama	30931.0	BALDWIN COUNTY SCHOOL DISTRICT	2016	338236	23710	145180	169346	299880
2	Alabama	912.0	BARBOUR COUNTY SCHOOL DISTRICT	2016	10116	2342	5434	2340	10070
3	Alabama	2842.0	EUFAULA CITY SCHOOL DISTRICT	2016	26182	3558	15900	6724	29843
4	Alabama	3322.0	BIBB COUNTY SCHOOL DISTRICT	2016	32486	3664	21846	6976	31662

In [4]:
```
districts.columns=('state', 'enrollment', 'name', 'year', 'total_revenue','
```

In [5]:
```
districts_new = districts[['state', 'enrollment', 'year', 'total_revenue','
```

In [6]:
```
districts.shape
```

Out[6]: (374161, 13)

In [7]:
```
districts_new1 = districts.dropna()
```

In [8]:
```
districts_new2 = districts_new1.groupby(['year','state','name']).agg(['mean
```

In [9]:
```
districts_new2.shape
```

Out[9]: (356945, 13)

In [10]:
```
districts_new2.head()
```

Out[10]:

	year	state	name	enrollment	total_revenue	federal_revenue	state_revenue	local_rev
				mean	mean	mean	mean	
0	1993	Alabama	ALBERTVILLE CITY SCH DIST	3011.0	11101.0	879.0	7403.0	2
1	1993	Alabama	ALEXANDER CITY SCH DIST	3748.0	14406.0	982.0	8949.0	4
2	1993	Alabama	ANDALUSIA CTY SCH DIST	2136.0	7749.0	949.0	5023.0	1
3	1993	Alabama	ANNISTON CTY SCH DST	4164.0	17714.0	3084.0	10615.0	4
4	1993	Alabama	ARAB CIT SCHOOL DIST	2485.0	8296.0	492.0	5834.0	1

In [11]:
```
districts_new2.columns = ('year','state','name','enrollment', 'total_revenu
```

In [12]:
```
districts_new2.shape
```

Out[12]:
```
(356945, 13)
```

In [13]:
```
districts_new3 = districts_new2[districts_new2.federal_revenue > 50000]
```

In [14]:
```
districts_new3.shape
```

Out[14]:
```
(2123, 13)
```

In [15]:
```
districts_new3.dtypes
```

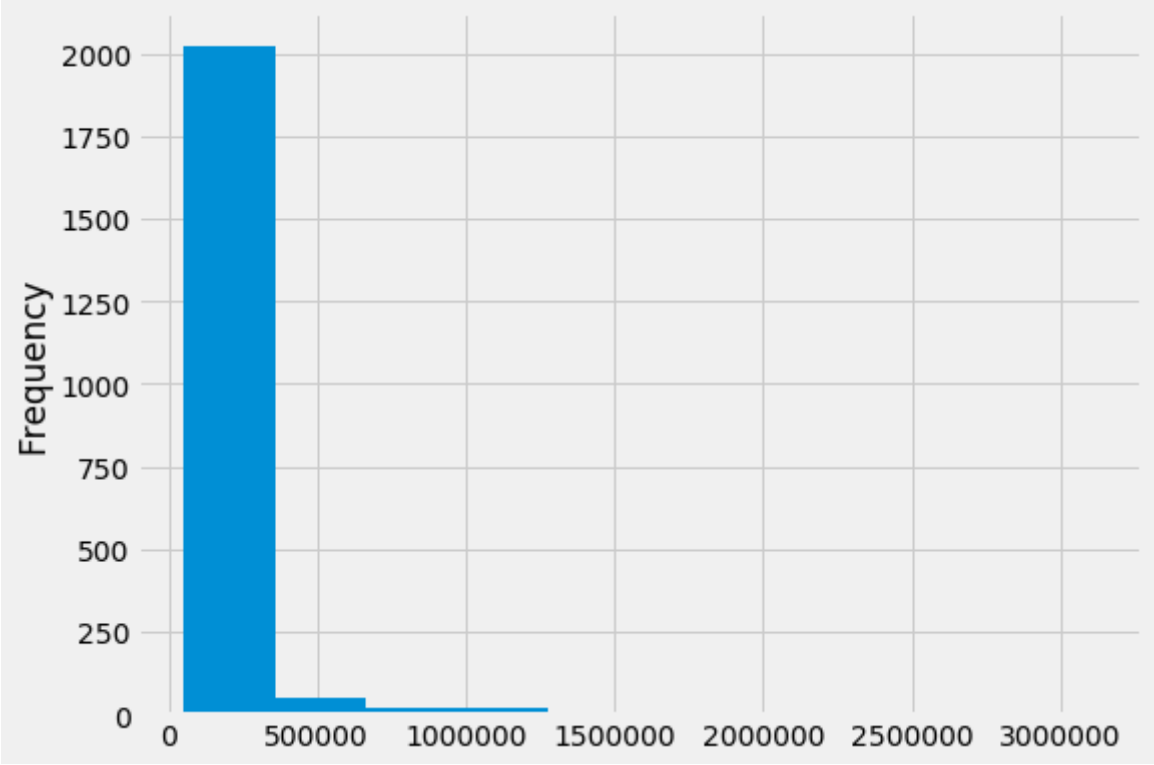
Out[15]:
```
year                              int64
state                            object
name                             object
enrollment                      float64
total_revenue                   float64
federal_revenue                 float64
state_revenue                   float64
local_revenue                   float64
expenditure                     float64
current_spending_instruction    float64
current_spending                float64
other_spending                  float64
total_capital                   float64
dtype: object
```

In [16]:
```
districts_new3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2123 entries, 1059 to 356696
Data columns (total 13 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   year                            2123 non-null   int64  
 1   state                           2123 non-null   object 
 2   name                            2123 non-null   object 
 3   enrollment                      2123 non-null   float64
 4   total_revenue                   2123 non-null   float64
 5   federal_revenue                 2123 non-null   float64
 6   state_revenue                   2123 non-null   float64
 7   local_revenue                   2123 non-null   float64
 8   expenditure                     2123 non-null   float64
 9   current_spending_instruction    2123 non-null   float64
 10  current_spending                2123 non-null   float64
 11  other_spending                  2123 non-null   float64
 12  total_capital                   2123 non-null   float64
dtypes: float64(10), int64(1), object(2)
memory usage: 232.2+ KB
```

In [17]:
```
districts_new3.federal_revenue.plot(kind = 'hist')
```

Out[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f7508f9248>
```



The featueres are extremely right skewed; majority fundings are densed on small amount range, set up the data range

In [18]:
```
districts_f = districts_new3[districts_new3.year > 1995 ]
```

In [19]:
```
districts_f.shape
```

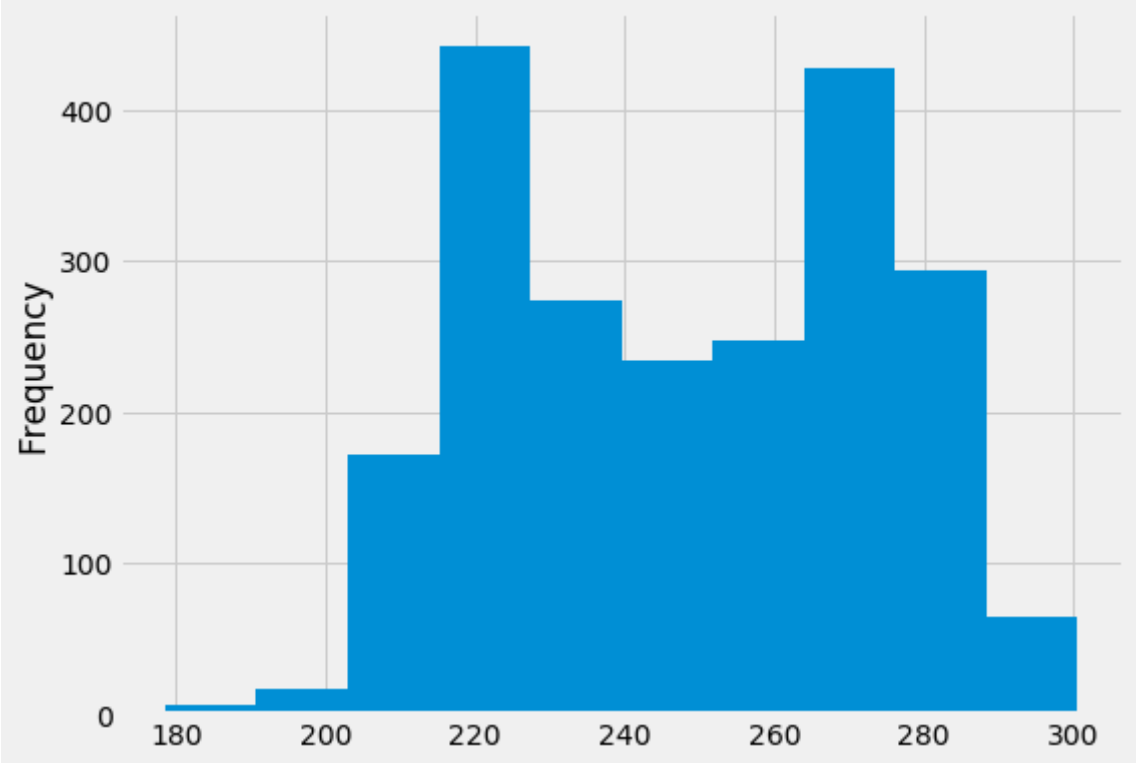
Out[19]:
```
(2057, 13)
```

In [20]:
```
naep.columns=('year', 'state', 'score', 'test_subject','grade')
```

In [21]:
```
naep.score = pd.to_numeric(naep['score'],errors='coerce')
```

In [22]:
```
naep.score.plot(kind = 'hist') ##NAEP data are normaly  distributed
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f7509fdfc8>
```



In [23]:
```
naep.head()
```

Out[23]:

	year	state	score	test_subject	grade
0	2017	Alabama	232.170688	Mathematics	4
1	2017	Alaska	230.456278	Mathematics	4
2	2017	Arizona	234.435788	Mathematics	4
3	2017	Arkansas	233.848144	Mathematics	4
4	2017	California	232.262941	Mathematics	4

In [24]:
```
eduf = pd.merge(districts_new3, naep, on = ['year','state'])
eduf.head()
```

Out[24]:

	year	state	name	enrollment	total_revenue	federal_revenue	state_revenue	local_reve
0	1994	California	LOS ANGELES CO OFF OF EDUCATION	0.0	329287.0	114874.0	124991.0	894
1	1994	California	LOS ANGELES UNIF SCH DIST	639129.0	3813590.0	475847.0	2428837.0	9089
2	1994	California	SAN DIEGO CITY UNIF SCH DIST	127258.0	735898.0	59809.0	297470.0	3786
3	1994	District of Columbia	DC PUBLIC SCHOOLS	80678.0	735720.0	79432.0	0.0	6562
4	1994	Florida	BROWARD CO SCHOOL DIST	189862.0	1217958.0	73252.0	617046.0	5276

In [25]:
```
eduf.to_csv(r'data/edu_data.csv')
```

In [26]:
```
## total revenue, state revenue, adn expenditure are on odd range
## missing the unit information to transform the data
## suggest drop
```

In [361]:
```
eduf.head()
```

Out[361]:

	year	state	name	enrollment	total_revenue	federal_revenue	state_revenue	local_reve
0	1994	California	LOS ANGELES CO OFF OF EDUCATION	0.0	329287.0	114874.0	124991.0	894
1	1994	California	LOS ANGELES UNIF SCH DIST	639129.0	3813590.0	475847.0	2428837.0	9089
2	1994	California	SAN DIEGO CITY UNIF SCH DIST	127258.0	735898.0	59809.0	297470.0	3786
3	1994	District of Columbia	DC PUBLIC SCHOOLS	80678.0	735720.0	79432.0	0.0	6562
4	1994	Florida	BROWARD CO SCHOOL DIST	189862.0	1217958.0	73252.0	617046.0	5276

##education EDA visualization

In [362]:
```
eduf.corr()
```

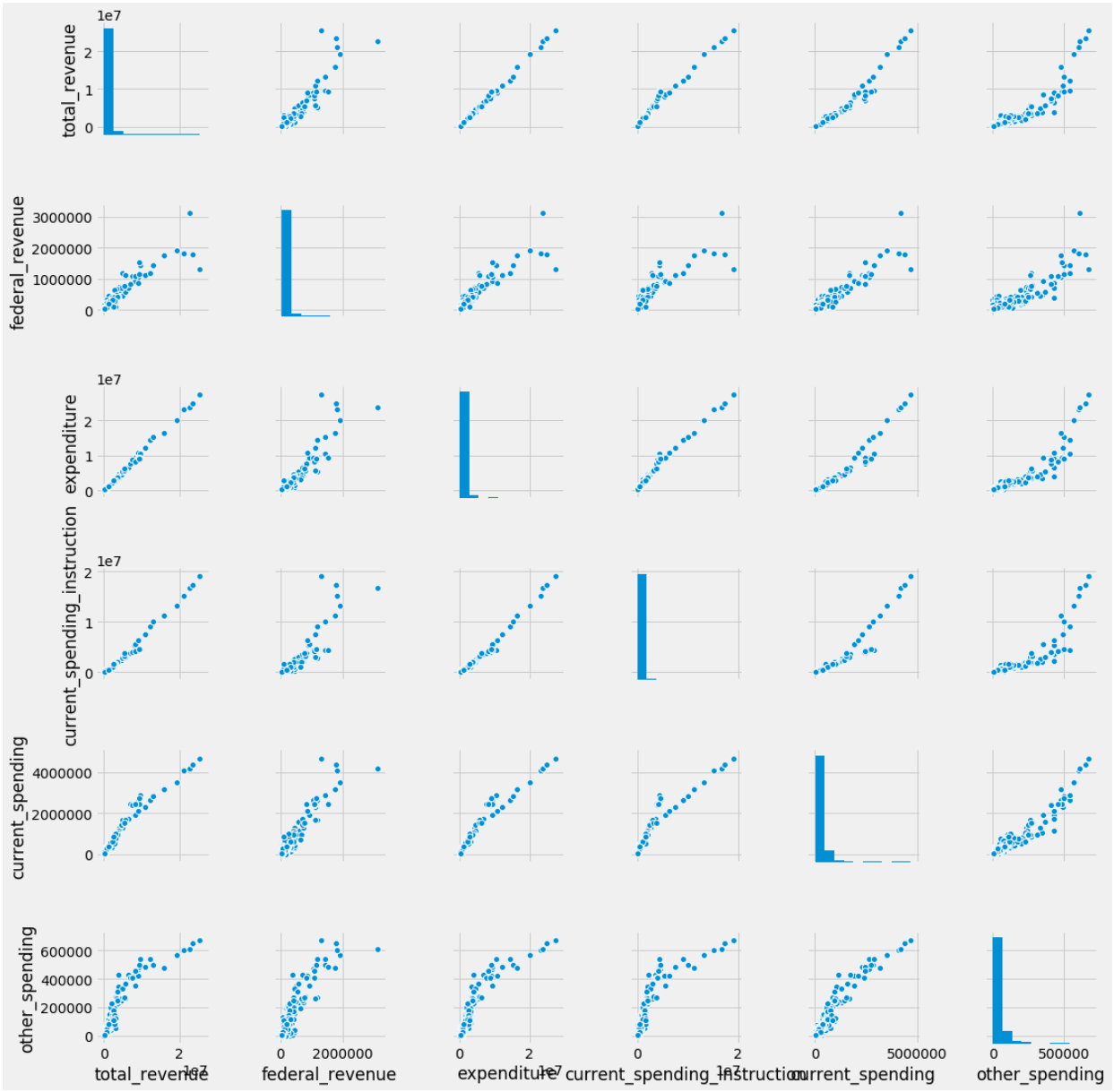
Out[362]:

	year	enrollment	total_revenue	federal_revenue	state_revenue	lo
year	1.000000	-0.176945	-0.039407	-0.024318	-0.058719	
enrollment	-0.176945	1.000000	0.902879	0.868165	0.902086	
total_revenue	-0.039407	0.902879	1.000000	0.917869	0.958876	
federal_revenue	-0.024318	0.868165	0.917869	1.000000	0.903667	
state_revenue	-0.058719	0.902086	0.958876	0.903667	1.000000	
local_revenue	-0.019887	0.815687	0.952118	0.816075	0.829721	
expenditure	-0.042459	0.904216	0.998196	0.914874	0.954947	
current_spending_instruction	-0.027907	0.860274	0.988210	0.884147	0.928328	
current_spending	-0.057108	0.941326	0.971238	0.925755	0.955879	
other_spending	-0.091002	0.951188	0.911038	0.898340	0.918368	
total_capital	-0.079319	0.863639	0.919154	0.853129	0.903232	
score	0.155699	-0.018320	0.007067	-0.002246	-0.002641	
grade	0.019577	-0.005029	-0.000797	-0.000416	-0.000915	

##heat map indicated poor correlation between score and enrollment and features

In [381]:
```
sns.pairplot(eduf[['total_revenue','federal_revenue','expenditure','current
```

Out[381]: <seaborn.axisgrid.PairGrid at 0x183a05b7d08>



In [202]:
```
##feature EDA
```

In [33]:
```
by_year = eduf.groupby('year')['total_revenue','federal_revenue','expenditu
```

```
C:\Users\zhang\anaconda3\lib\site-packages\ipykernel_launcher.py:1: Futur
eWarning: Indexing with multiple keys (implicitly converted to a tuple of
keys) will be deprecated, use a list instead.
  """Entry point for launching an IPython kernel.
```

In [27]:
```
plt.plot(by_year['total_revenue'], color='red')
plt.plot(by_year['federal_revenue'], color='orange', label='federal_revenue
plt.plot(by_year['expenditure'], color='green')
plt.plot(by_year['current_spending_instruction'], color='blue')
plt.plot(by_year['current_spending'], color='grey')
plt.plot(by_year['other_spending'], color='black')
plt.legend(['total_revenue','federal_revenue','expenditure','current_spendi
plt.grid(b=None)
plt.xlabel('year')
plt.ylabel('Revenue')
plt.title('All Features Growth by year')
plt.savefig('data/features_by_year.png', transparent=True,dpi=300, bbox_inc
plt.show()
```

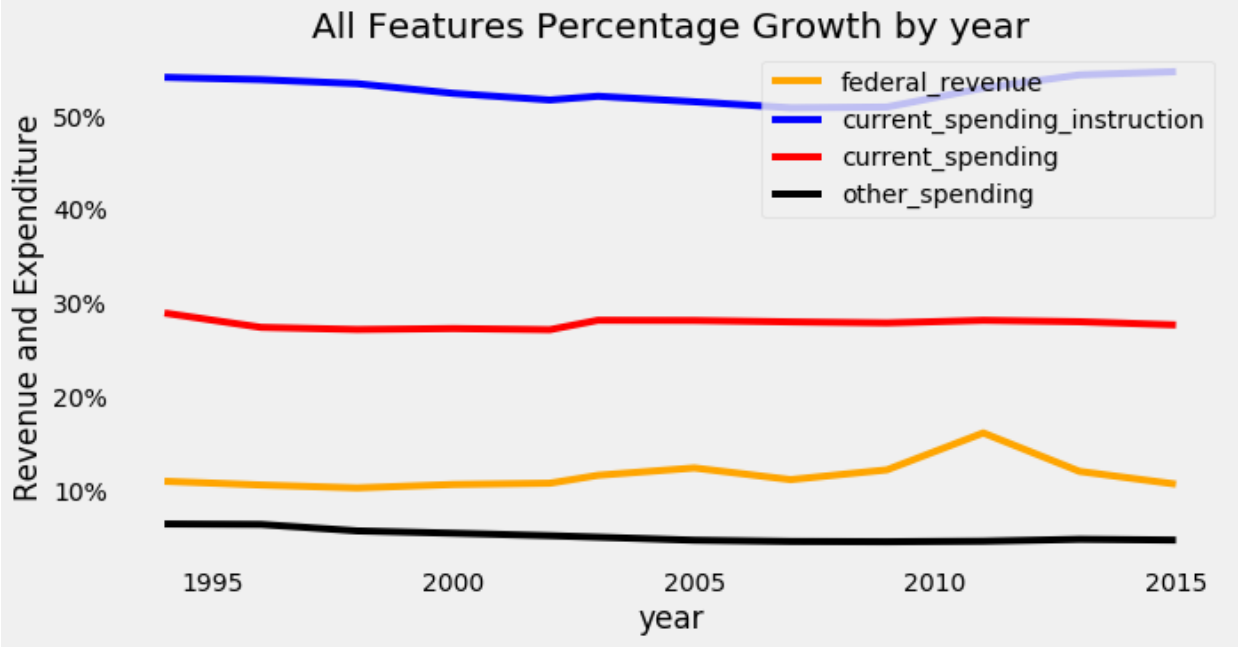
```
---------------------------------------------------------------------------
--
NameError                                 Traceback (most recent call las
t)
<ipython-input-27-4862f67c1388> in <module>
----> 1 plt.plot(by_year['total_revenue'], color='red')
      2 plt.plot(by_year['federal_revenue'], color='orange', label='feder
al_revenue')
      3 plt.plot(by_year['expenditure'], color='green')
      4 plt.plot(by_year['current_spending_instruction'], color='blue')
      5 plt.plot(by_year['current_spending'], color='grey')

NameError: name 'by_year' is not defined
```

In [44]:
```
import matplotlib.ticker as mtick
```

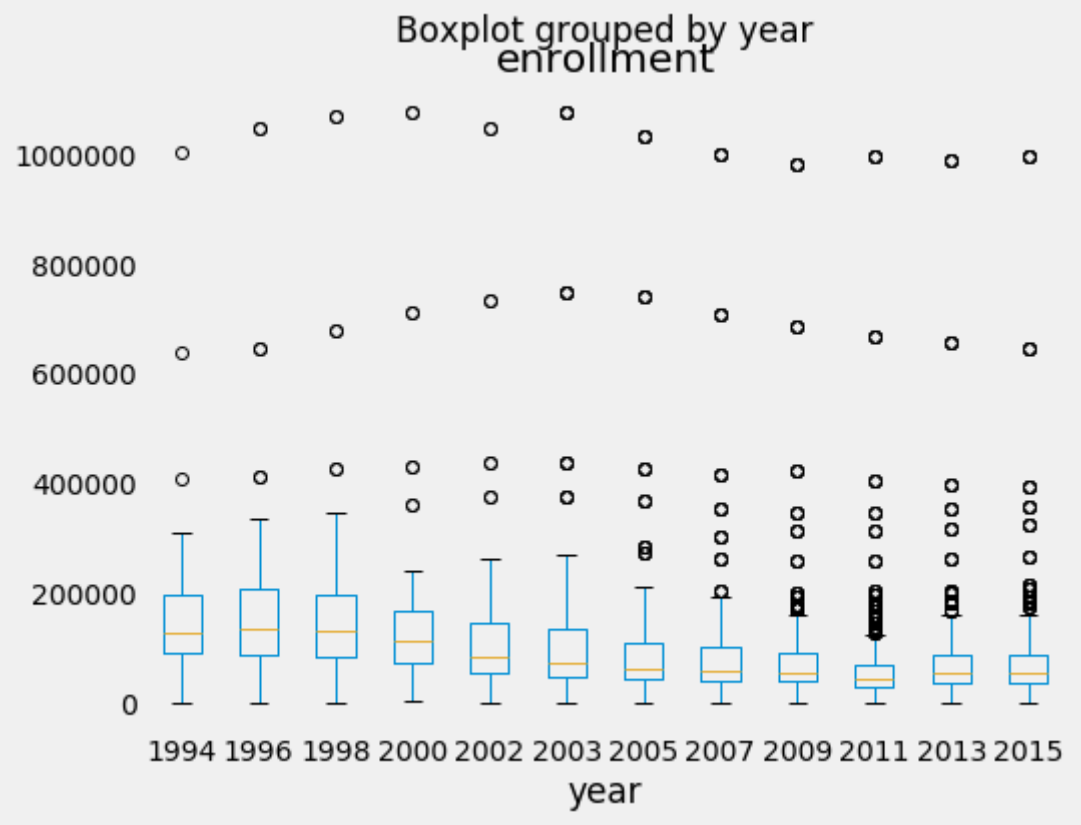
In [48]:

```
##percentage break down
by_year['current_spending_percentage'] = by_year['current_spending'] / by_y
by_year['federal_revenue_percentage'] = by_year['federal_revenue'] / by_yea
by_year['current_spending_instruction_percentage'] = by_year['current_spend
by_year['other_spending_percentage'] = by_year['other_spending'] / by_year[
ax = plt.subplots(1, 1, figsize=(10,5))
p1 = plt.plot(by_year['federal_revenue_percentage'], color='orange', label=
p2 = plt.plot(by_year['current_spending_instruction_percentage'], color='bl
p3 = plt.plot(by_year['current_spending_percentage'], color='red')
p4 = plt.plot(by_year['other_spending_percentage'], color='black')
plt.legend(['federal_revenue','current_spending_instruction','current_spend
plt.grid(b=None)
plt.gca().yaxis.set_major_formatter(mtick.PercentFormatter(1.0))
plt.xlabel('year')
plt.ylabel('Revenue and Expenditure')
plt.title('All Features Percentage Growth by year')
plt.savefig('data/feature_pct.png', dpi=300, bbox_inches='tight')
plt.show()
```



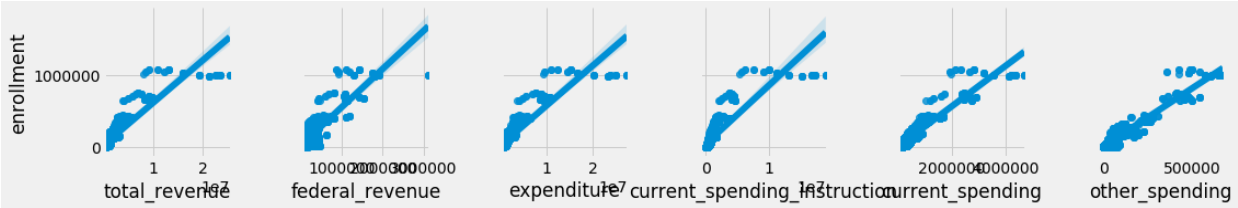
In [30]:
```
# Box plot of score, grouped by season
eduf.boxplot(column='enrollment', by='year')
plt.grid(b=None)
plt.savefig('data/enrollment_box.png', transparent=True,dpi=300, bbox_inche
plt.show()
```

```
C:\Users\zhang\anaconda3\lib\site-packages\numpy\core\_asarray.py:83: Vis
ibleDeprecationWarning: Creating an ndarray from ragged nested sequences
(which is a list-or-tuple of lists-or-tuples-or ndarrays with different l
engths or shapes) is deprecated. If you meant to do this, you must specif
y 'dtype=object' when creating the ndarray
  return array(a, dtype, copy=False, order=order)
```

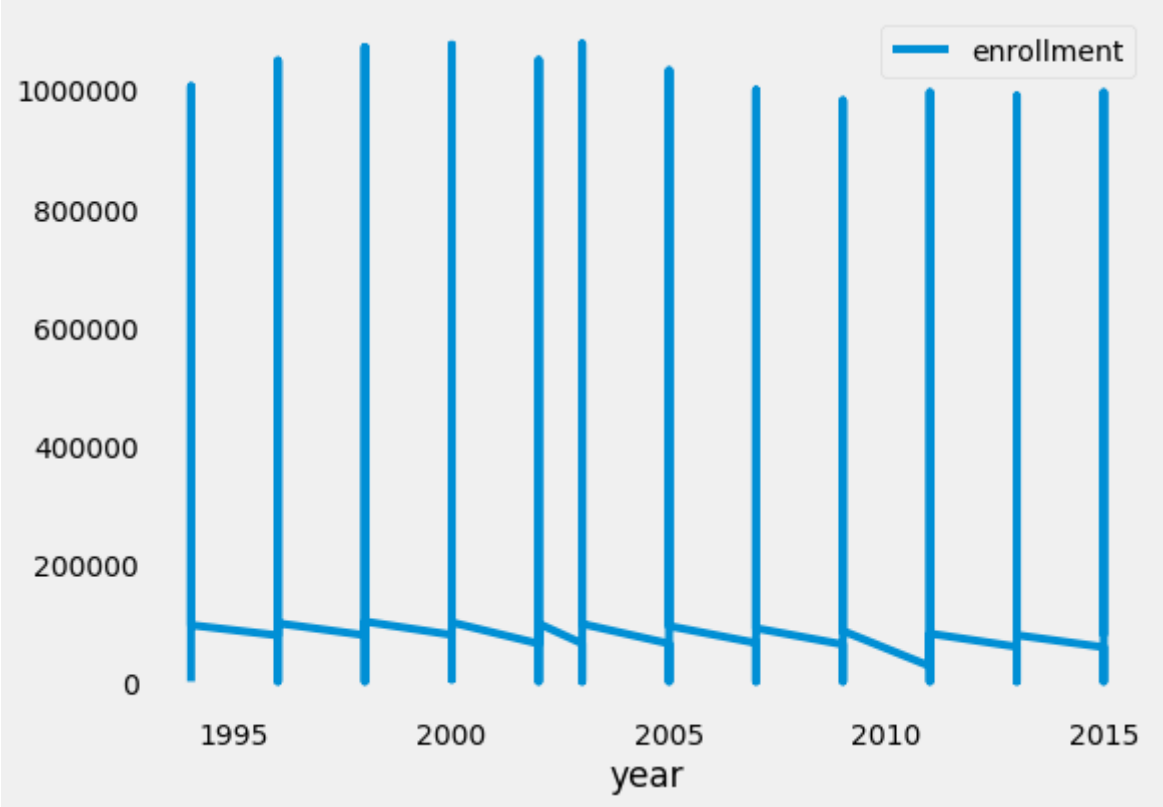


In [74]:
```
##scatter plots of all correlation
feature_cols =['total_revenue','federal_revenue','state_revenue','expenditu
```

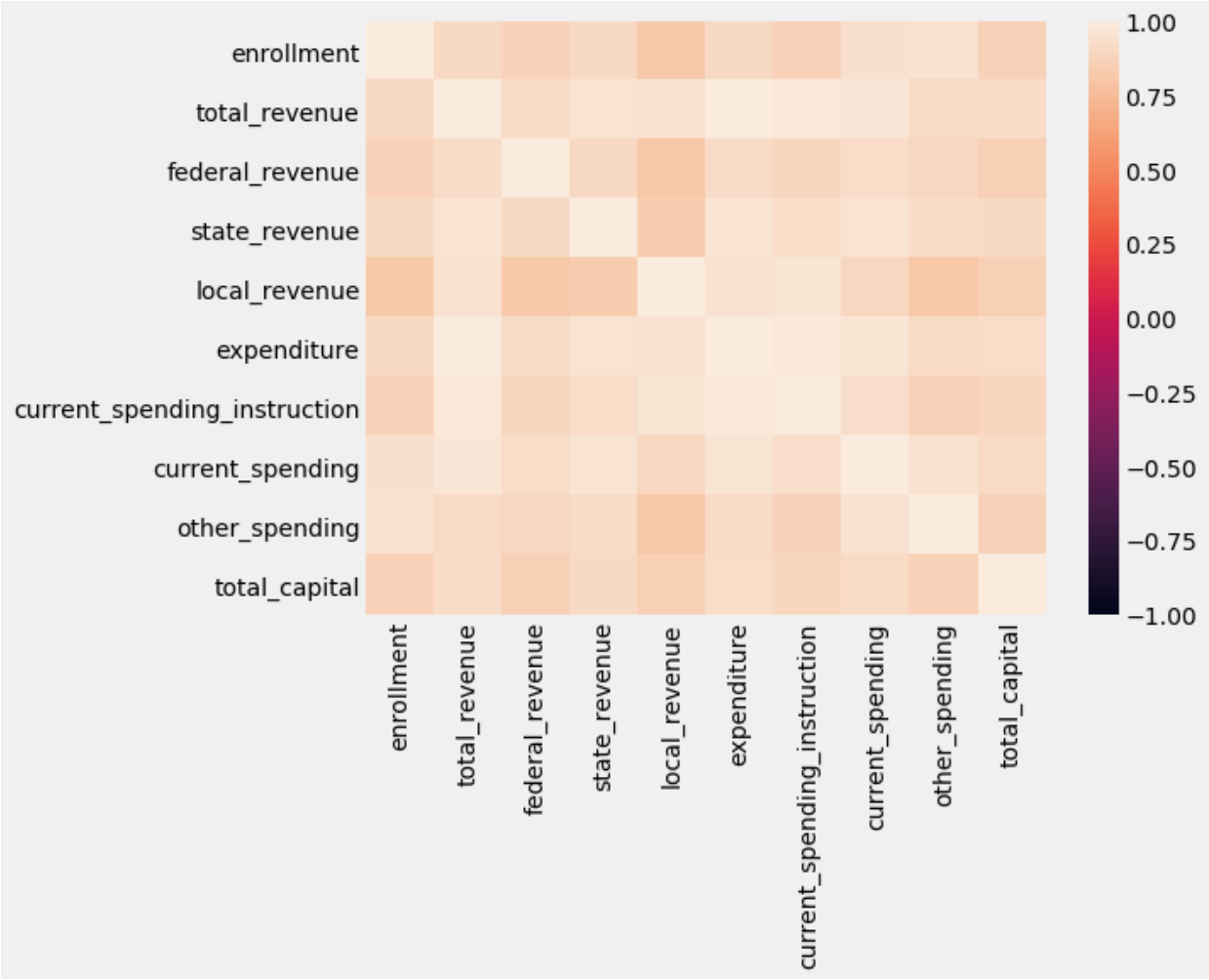
In [383]:
```
sns.pairplot(eduf, x_vars=feature_cols, y_vars='enrollment', kind='reg');
plt.grid(b=None)
plt.savefig('data/enrollment_corr.png', transparent=True,dpi=300, bbox_inch
plt.show()
```



In [380]:
```
fig = eduf.plot(x ='year', y = 'enrollment', kind = 'line', markerfacecolor
plt.grid(b=None)
plt.savefig('data/enrollment_by_year.png', transparent=True, dpi=300, bbox_
plt.show()
```



In [372]:
```
sns.heatmap(eduf.drop(['year', 'score','grade'],axis = 1).corr(), vmin=-1,
plt.savefig('data/heatmap.png', transparent=True,dpi=300, bbox_inches='tigh
plt.grid(b=None)
plt.show()
```



In [75]:
```
# Create X and y.
X = eduf[feature_cols]
y = eduf.enrollment
```

In [390]:
```
X2 = sm.add_constant(X)
est = sm.OLS(y, X2)
est2 = est.fit()
print(est2.summary())
pdf.output("data/regression.pdf")
```

```
                            OLS Regression Results
==============================================================================
=====
Dep. Variable:              enrollment   R-squared:
0.924
Model:                             OLS   Adj. R-squared:
0.924
Method:                  Least Squares   F-statistic:
7784.
Date:                 Sat, 13 Feb 2021   Prob (F-statistic):
0.00
Time:                         18:41:33   Log-Likelihood:                -4
5890.
No. Observations:                3855   AIC:                          9.17
9e+04
Df Residuals:                    3848   BIC:                          9.18
4e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
=======================
                                   coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
-----------------------
const                         4230.3263    814.701      5.192      0.000
2633.039    5827.613
total_revenue                   -0.0724      0.005    -13.166      0.000
-0.083      -0.062
federal_revenue                 -0.0502      0.008     -6.654      0.000
-0.065      -0.035
expenditure                      0.0493      0.006      8.693      0.000
0.038       0.060
current_spending_instruction     0.0159      0.006      2.781      0.005
0.005       0.027
current_spending                 0.1727      0.010     16.700      0.000
0.152       0.193
other_spending                   1.0255      0.027     38.685      0.000
0.974       1.077
==============================================================================
=====
Omnibus:                     2230.006   Durbin-Watson:
0.582
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           13607
1.575
Skew:                           1.988   Prob(JB):
0.00
Kurtosis:                      31.833   Cond. No.                     5.1
7e+06
==============================================================================
=====
```

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is co
rrectly specified.
[2] The condition number is large, 5.17e+06. This might indicate that the
re are
strong multicollinearity or other numerical problems.
```

```
---------------------------------------------------------------------------
--
NameError                                 Traceback (most recent call las
t)
<ipython-input-390-c8bad0a8b594> in <module>
      3 est2 = est.fit()
      4 print(est2.summary())
----> 5 pdf.output("data/regression.pdf")

NameError: name 'pdf' is not defined
```

In [77]:
```
##scatter plots of all correlation
feature_cols1 =['total_revenue','federal_revenue','expenditure','current_sp
```

In [78]:
```
##build linear regression for prediction
```

In [79]:
```
X = eduf[feature_cols1]
y = eduf.enrollment
```

In [268]:
```
X.describe()
```

Out[268]:

	total_revenue	federal_revenue	expenditure	current_spending_instruction	current_spending
count	3.855000e+03	3.855000e+03	3.855000e+03	3.855000e+03	3.855000e+03
mean	1.079346e+06	1.325096e+05	1.107774e+06	5.827077e+05	3.089959e+05
std	1.989207e+06	2.122858e+05	2.131881e+06	1.375229e+06	4.353089e+05
min	7.708900e+04	5.001900e+04	3.525100e+04	8.220000e+02	1.801900e+04
25%	4.392340e+05	6.074900e+04	4.355470e+05	2.242330e+05	1.318020e+05
50%	6.131440e+05	7.725900e+04	6.211730e+05	3.122830e+05	1.921970e+05
75%	1.065630e+06	1.138840e+05	1.062236e+06	5.418120e+05	3.224060e+05
max	2.543738e+07	3.120314e+06	2.747789e+07	1.903582e+07	4.694906e+06

In [269]:
```
y.isnull().sum()
```

Out[269]:
```
0
```

In [270]:
```
y.fillna(0, inplace=True)
```

In [271]:
```
X.isnull().sum()
```

Out[271]:
```
total_revenue                   0
federal_revenue                 0
expenditure                     0
current_spending_instruction    0
current_spending                0
other_spending                  0
dtype: int64
```

In [272]:
```
print((X.dtypes))
```

```
total_revenue                   float64
federal_revenue                 float64
expenditure                     float64
current_spending_instruction    float64
current_spending                float64
other_spending                  float64
dtype: object
```

In [273]:
```
print((X.shape))
```

```
(3855, 6)
```

In [274]:
```
y.describe
```

Out[274]:
```
<bound method NDFrame.describe of 0            0.0
1       639129.0
2       127258.0
3        80678.0
4       189862.0
           ...
3850     12650.0
3851     77316.0
3852     77316.0
3853     77316.0
3854     77316.0
Name: enrollment, Length: 3855, dtype: float64>
```

In [275]:
```
X.corr()
```

Out[275]:

	total_revenue	federal_revenue	expenditure	current_spending_instructio
total_revenue	1.000000	0.917869	0.998196	0.98821
federal_revenue	0.917869	1.000000	0.914874	0.88414
expenditure	0.998196	0.914874	1.000000	0.99015
current_spending_instruction	0.988210	0.884147	0.990151	1.00000
current_spending	0.971238	0.925755	0.968666	0.93129
other_spending	0.911038	0.898340	0.909028	0.86000

In [276]:
```
# Check y's type.
print(type(y))
```

```
<class 'pandas.core.series.Series'>
```

In [277]:
```
print((y.shape))
```

```
(3855,)
```

In [278]:
```
## 4 steps
## initiate
## training
## predict
## evaluate
```

In [93]:
```
Xs = eduf[['total_revenue','federal_revenue','expenditure','current_spendin
y = eduf['enrollment']
lr = LinearRegression()
lr.fit(Xs, y)
```

Out[93]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=
False)
```

In [279]:
```
from sklearn.linear_model import LinearRegression
```

In [92]:
```
print(lr.intercept_)
print(lr.coef_)
```

```
4230.326308517164
[-0.07238651 -0.0502455   0.04932558  0.01592084  0.17267962  1.02548782]
```

In [125]:
```
x_train, x_test,y_train,y_test = train_test_split(X,y,random_state = 123)
y_pred = lr.predict(X)
X_pred = lr.predict(X)
```

In [109]:
```
lr.fit(x_train,y_train)
```

Out[109]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=
False)
```

In [133]:
```
## calcuate the accuracy
lr.score(x_test,y_test)
```

Out[133]:
```
0.900831053664841
```

In [141]:
```
from sklearn.model_selection import train_test_split

# Define a function that accepts a list of features and returns testing RMS
def train_test_rmse(eduf, feature_cols1):
    X = gpa1[feature_cols]
    y = gpa1.gpa

    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=

    linreg = LinearRegression()
    linreg.fit(X_train, y_train)

    y_pred = linreg.predict(X_test)
    return np.sqrt(metrics.mean_squared_error(true, pred))
```

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

# Define a function that accepts a list of features and returns testing RMS
def train_test_mae(eduf, feature_cols1):
    X = gpa1[feature_cols]
    y = gpa1.gpa

    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=

    linreg = LinearRegression()
    linreg.fit(X_train, y_train)

    y_pred = linreg.predict(X_test)
    return metrics.mean_absolute_error(y_test, y_pred)
```

In [140]:
```
# Compare different sets of features.
print(train_test_rmse(eduf, ['total_revenue','federal_revenue','expenditure
print(train_test_rmse(eduf, ['total_revenue', 'federal_revenue','current_sp
print(train_test_rmse(eduf, ['total_revenue', 'current_spending', 'expendit
```

```
30726.187375168993
30554.656132892174
34903.17143826005
```

In [150]:
```
print(train_test_mae(eduf, ['total_revenue','federal_revenue','expenditure'
print(train_test_mae(eduf, ['total_revenue', 'federal_revenue','current_spe
print(train_test_mae(eduf, ['total_revenue', 'current_spending', 'expenditu
```

```
19979.203553974072
20158.043316193853
22607.78278364976
```

In [305]:
```
## RMSEA reduced wtih more features
```

In [114]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=123)

y_null = np.zeros_like(y_test, dtype=float)

y_null.fill(y_test.mean())
y_null
```

Out[114]:
```
array([83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
       83227.40975104, 83227.40975104, 83227.40975104, 83227.40975104,
```

In [115]:
```
np.sqrt(metrics.mean_squared_error(y_test, y_null))
```

Out[115]:
```
97571.0155302958
```

Ridge Regression

In [423]:
```
revenue_dummies = pd.get_dummies(districts_f.total_revenue)
```

In [424]:
```
districts_dummies = pd.concat([districts_f, revenue_dummies], axis=1)
```

In [425]:
```
X = districts_dummies[feature_cols]
y = districts_dummies.enrollment

linreg = LinearRegression()
linreg.fit(X, y)

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
```

ridge regression

In [ ]:
```
from sklearn.linear_model import Ridge

ridgereg = Ridge(alpha=0, normalize=True)
ridgereg.fit(X_train, y_train)
y_pred = ridgereg.predict(X_test)
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

In [430]:
```
y_pred = ridgereg.predict(X)
```

In [435]:
```
print(ridgereg.intercept_)
```

```
10886.08329776775
```

In [298]:
```
list(zip(feature_cols, ridgereg.coef_))
```

Out[298]:
```
[('total_revenue', -0.07844183321424758),
 ('federal_revenue', -0.06983128027489204),
 ('expenditure', 0.074294423126399),
 ('current_spending_instruction', -0.0047588651012720655),
 ('current_spending', 0.14513856086261095),
 ('other_spending', 1.0430108861542022)]
```

In [433]:
```
ridgereg = Ridge(alpha=0.1, normalize=True)
ridgereg.fit(X_train, y_train)
y_pred = ridgereg.predict(X_test)
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
41640.4232288643
```

In [126]:
```
list(zip(feature_cols, ridgereg.coef_))
```

Out[126]:
```
[('total_revenue', 0.002614288254853433),
 ('federal_revenue', 0.0172038925711048),
 ('state_revenue', 0.014514305171092002),
 ('expenditure', 0.004149895352522794),
 ('current_spending_instruction', -0.0017976188683634198),
 ('current_spending', 0.06633619271346432),
 ('other_spending', 0.6739851697829419),
 ('total_capital', 0.06761253149194939)]
```

Conclusion The total revenue,state_revenue,federal_revenue, enrollment, current_spending, and expenditure are the strong predictors for enrollments. The multicolinearity are also detected on the heatmap. Tuning the KNN model help improve the model evaluation and reduce the testing error. By scale the training and testing data, the testing error reduced although the overall model fits not actually improved.