Project_Final

October 3, 2017

1 School Finances Dataset

```
In [1]: import missingno as msno
        import seaborn as sns
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        sns.set()
        import math
        import csv
        from scipy import stats

        from sklearn.preprocessing import MinMaxScaler
        import statsmodels.api as sm
        import matplotlib.mlab as mlab
        from sklearn.feature_selection import RFECV
        from sklearn.linear_model import LinearRegression
        from sklearn.model_selection import train_test_split
```

```
/usr/lib/python3.4/importlib/_bootstrap.py:321: FutureWarning: The pandas.core.datetools module
  return f(*args, **kwds)
```

```
In [2]: df = pd.read_csv('elsec15.csv')
```

```
/usr/local/lib/python3.4/dist-packages/IPython/core/interactiveshell.py:2698: DtypeWarning: Colu
  interactivity=interactivity, compiler=compiler, result=result)
```

1.1 Understanding the Data

```
In [3]: df.shape
```

```
Out[3]: (14376, 141)
```

```
In [4]: df.head()
```

Out[4]:
```
   STATE       IDCENSUS                            NAME  CONUM  CSA   CBSA  \
0      1  1500100100000  AUTAUGA COUNTY SCHOOL DISTRICT   1001    N  33860
1      1  1500200100000  BALDWIN COUNTY SCHOOL DISTRICT   1003  380  19300
2      1  1500300100000  BARBOUR COUNTY SCHOOL DISTRICT   1005    N      N
3      1  1500300200000    EUFAULA CITY SCHOOL DISTRICT   1005    N      N
4      1  1500400100000     BIBB COUNTY SCHOOL DISTRICT   1007  142  13820

   SCHLEV   NCESID  YRDATA    V33  ...    V32    _19H   _21F   _31F    _41F  \
0       3  0100240      15   9664  ...      0   49431  16603   2992   63042
1       3  0100270      15  30596  ...      0  337160  99087  13027  423220
2       3  0100300      15    925  ...      0    8024      0    304    7720
3       3  0101410      15   2829  ...      0       0      0      0       0
4       3  0100360      15   3357  ...      0   22155      0   1190   20965

   _61V  _66V   W01    W31    W61
0     0     0  2094    372   8617
1     0     0  5784  50441  71370
2     0     0     0      0    646
3     0     0     0   2054   7478
4     0     0  1397    790   5400

[5 rows x 141 columns]
```

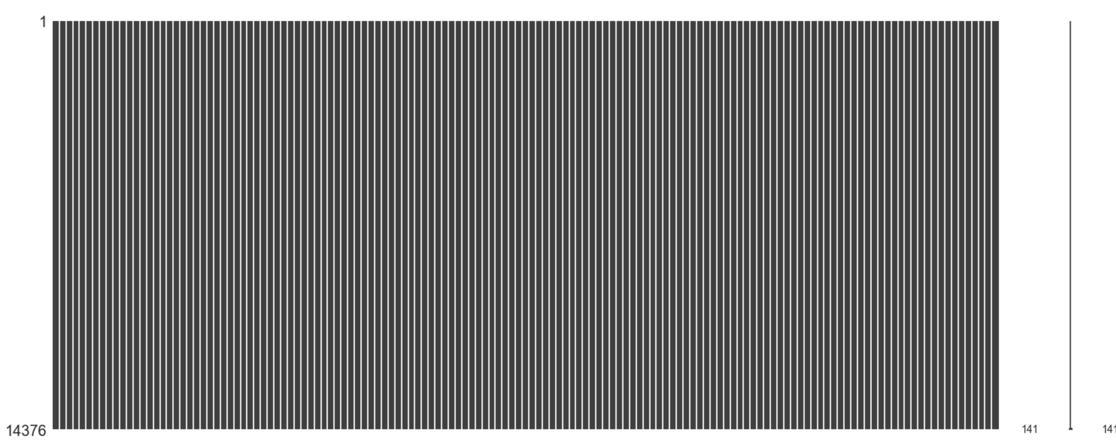
In [5]:
```
df.describe()
```

Out[5]:
```
              STATE      IDCENSUS         CONUM        SCHLEV   YRDATA  \
count  14376.000000  1.437600e+04  14376.000000  14376.000000  14376.0
mean      26.801336  2.728090e+13  29838.158598      2.883139     15.0
std       13.894331  1.389514e+13  14753.492121      1.271649      0.0
min        1.000000  1.500100e+12   1001.000000      1.000000     15.0
25%       15.000000  1.550327e+13  18063.000000      3.000000     15.0
50%       27.000000  2.750320e+13  30063.000000      3.000000     15.0
75%       38.000000  3.850053e+13  41009.000000      3.000000     15.0
max       51.000000  5.150230e+13  56045.000000      7.000000     15.0

                 V33      TOTALREV       TFEDREV            C14  \
count   14376.000000  1.437600e+04  1.437600e+04   14376.000000
mean     3374.682526  4.546951e+04  3.708038e+03     915.914858
std     14419.737037  2.590623e+05  2.021328e+04    5972.748111
min         0.000000  0.000000e+00  0.000000e+00       0.000000
25%       305.000000  5.241500e+03  2.920000e+02      54.000000
50%       979.500000  1.402300e+04  8.470000e+02     180.000000
75%      2744.250000  3.791375e+04  2.433500e+03     545.250000
max    995192.000000  2.543738e+07  1.307783e+06  379531.000000

                 C15      ...                V32          _19H          _21F  \
count   14376.000000      ...       14376.000000  1.437600e+04  1.437600e+04
mean      752.781093      ...           7.318656  2.871850e+04  4.831726e+03
```

```
std      3619.184513     ...        122.649299  1.841763e+05  2.652979e+04
min         0.000000     ...          0.000000  0.000000e+00  0.000000e+00
25%         0.000000     ...          0.000000  8.400000e+01  0.000000e+00
50%       118.000000     ...          0.000000  4.034000e+03  0.000000e+00
75%       532.000000     ...          0.000000  1.866350e+04  3.030000e+02
max    248209.000000     ...       7753.000000  1.372802e+07  1.312286e+06

                _31F          _41F           _61V           _66V  \
count   14376.000000  1.437600e+04   14376.000000   14376.000000
mean     3936.853158  2.957606e+04     487.162354     553.761547
std     20071.591744  1.894224e+05    3555.988118    6968.740454
min         0.000000  0.000000e+00       0.000000       0.000000
25%         5.000000  7.150000e+01       0.000000       0.000000
50%       410.000000  4.143500e+03       0.000000       0.000000
75%      1845.000000  1.912600e+04       0.000000       0.000000
max    731854.000000  1.447108e+07  173300.000000  700000.000000

                 W01            W31           W61
count   14376.000000   14376.000000  1.437600e+04
mean     1335.636825    3710.651920  9.091542e+03
std     10651.097318   20183.852905  3.261580e+04
min         0.000000       0.000000  0.000000e+00
25%         0.000000       0.000000  8.350000e+02
50%         0.000000       0.000000  2.708500e+03
75%       491.000000     626.250000  7.567500e+03
max    869643.000000  885058.000000  2.355662e+06

[8 rows x 137 columns]
```

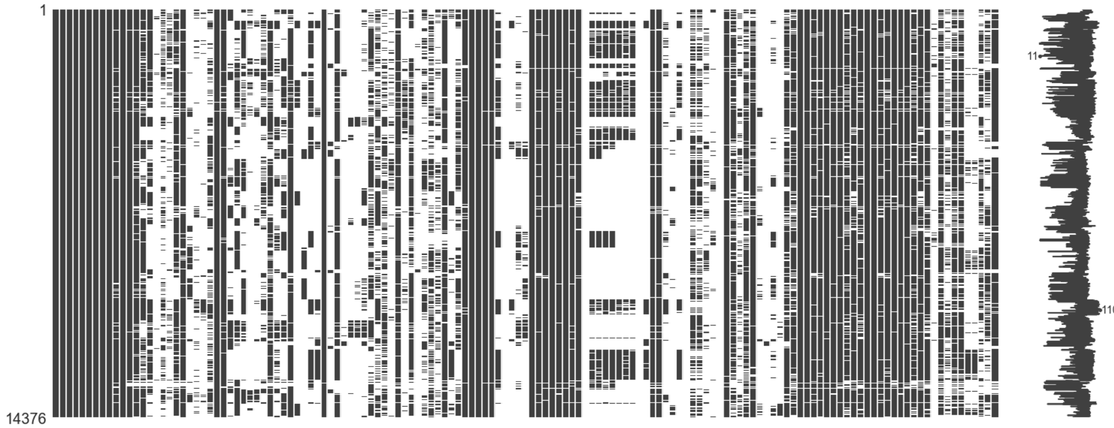
What does our Matrix look like?

```
In [6]: msno.matrix(df)
```



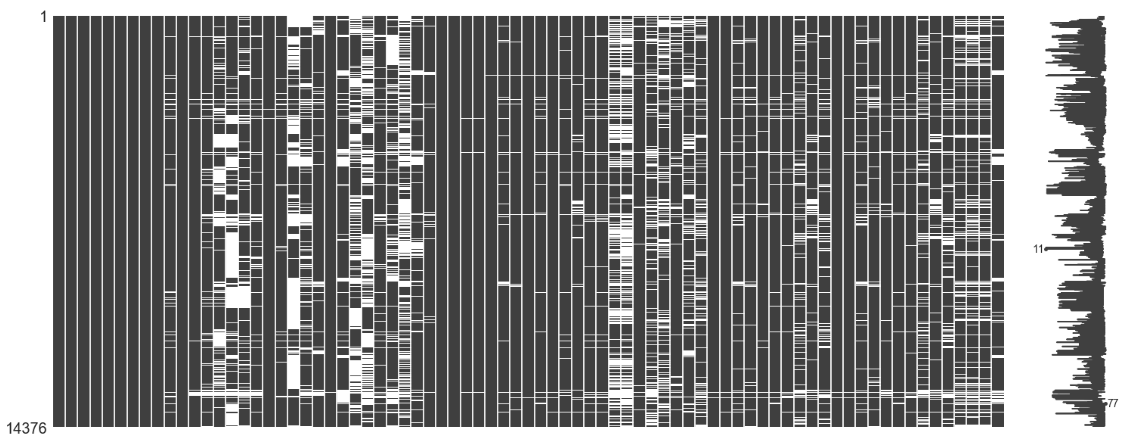
So all the data is here. However some columns have a lot of 0's. Lets see this

```
In [7]: df1 = df.replace(0, float("NAN"))
        msno.matrix(df1)
```



So alot of the data is 0's. Lets see what the data looks like after removing columns have > 50% of their entries as 0's.

```
In [8]: df1 = df1.dropna(axis=1,thresh=math.ceil(df.shape[0]/2), how='all')
        msno.matrix(df1)
        print("%s columns have more than 50%% of their entries as 0's." % str(df.shape[1] - df1.
```




```
64 columns have more than 50% of their entries as 0's.
```

So about half the columns have > 50% of their entries as zeroes.
How many rows have > 50% of their entries as zeroes?

```
In [9]: df1 = df.replace(0, float("NAN"))
        df1 = df1.replace("N", float("NAN"))
        df1 = df1.dropna(axis=0,thresh=math.ceil(df1.shape[1]/2), how='all')
        print("%s rows have more than 50%% of their entries as 0's." % str(df.shape[0] - df1.sha
```

```
2432 rows have more than 50% of their entries as 0's.
```

```
In [10]: df.columns
```

```
Out[10]: Index(['STATE', 'IDCENSUS', 'NAME', 'CONUM', 'CSA', 'CBSA', 'SCHLEV', 'NCESID',
                'YRDATA', 'V33',
                ...
                'V32', '_19H', '_21F', '_31F', '_41F', '_61V', '_66V', 'W01', 'W31',
                'W61'],
               dtype='object', length=141)
```

1.2 Cleaning the Data

We have decided to work only with the columns that have > 50 % of the rows as non-zero entries. We thought that if most of the columns are zero, there is not enough discrepancy in the data to make an interesting analysis.

```
In [11]: df = df.replace(0, float("NAN"))
         df = df.dropna(axis=1,thresh=math.ceil(df.shape[0]/2), how='all')
         df = df.replace(float("NAN"), 0)
```

Additionally some of the data is not very useful to us. For example the census ID's. We have omitted these columns also.

```
In [12]: df.drop("YRDATA", axis=1,inplace=True)     #Its all 2015
         df.drop("IDCENSUS", axis=1, inplace=True)
         df.drop("NCESID", axis=1, inplace=True)
```

No data is missing, so no data needs to be imputed. We made some mappings between column values and human understandable values, for understanding more of the data.

```
In [13]: State_Dict = {1: 'AL', 2: 'AK', 3: 'AZ', 4: 'AR', 5: 'CA', 6: 'CO', 7: 'CT', 8: 'DE', 9

         Col_To_English = {}
         #This is a local file referrenced.
         with open('School Data Labels.csv', 'r') as csvfile:
             csvreader = csv.reader(csvfile, delimiter=',')
             for row in csvreader:
                 Col_To_English[row[0]] = row[1]

         for key in Col_To_English:
             print("Code: ", key, "| Label: ",Col_To_English[key])
```

```
Code:  V29 | Label:  Total salaries and wages - Food services
Code:  D11 | Label:  Revenue from other school systems
Code:  Z34 | Label:  Total employee benefit payments
Code:  TOTALREV | Label:  TOTAL ELEMENTARY-SECONDARY REVENUE
Code:  V10 | Label:  Total employee benefit payments - Instruction
```

```
Code:  Z33 | Label:  Total salaries and wages - Instruction
Code:  TOTALEXP | Label:  TOTAL ELEMENTARY-SECONDARY EXPENDITURE
Code:  U97 | Label:  Miscellaneous other local revenues
Code:  Z32 | Label:  Total salaries and wages
Code:  C13 | Label:  All other revenues from state sources
Code:  E13 | Label:  Current operation expenditure - Instruction
Code:  V13 | Label:  Total salaries and wages - Instructional staff support
Code:  TFEDREV | Label:  TOTAL ELEMENTARY-SECONDARY REVENUE
Code:  TCUROTH | Label:  TOTAL CURRENT SPENDING FOR OTHER ELEMENTARY-SECONDARY PROGRAMS
Code:  K10 | Label:  Other equipment
Code:  C15 | Label:  Federal revenue through the state - Children with disabilities - IDEA
Code:  TCURINST | Label:  TOTAL CURRENT SPENDING FOR INSTRUCTION
Code:  SCHLEV | Label:  School Level Code
Code:  TCAPOUT | Label:  TOTAL CAPITAL OUTLAY EXPENDITURE
Code:  E08 | Label:  Current operation expenditure - General administration
Code:  K09 | Label:  Instructional equipment
Code:  NAME | Label:  School System Name
Code:  TCURELSC | Label:  TOTAL CURRENT SPENDING FOR ELEMENTARY-SECONDARY PROGRAMS
Code:  V16 | Label:  Total employee benefit payments - General administration
Code:  V90 | Label:  Current operation expenditure - Business/central/other support services
Code:  V38 | Label:  Total employee benefit payments - Business/central/other support services
Code:  E11 | Label:  Current operation expenditure - Food services
Code:  V23 | Label:  Total salaries and wages - Student transportation
Code:  C10 | Label:  School lunch programs
Code:  F12 | Label:  Construction
Code:  V11 | Label:  Total salaries and wages - Pupil support
Code:  I86 | Label:  Interest on school system debt
Code:  W61 | Label:  Cash and deposits, held at end of fiscal year - Other funds
Code:  E07 | Label:  Current operation expenditure - Instructional staff support
Code:  V17 | Label:  Total salaries and wages - School administration
Code:  V22 | Label:  Total employee benefit payments - Operation and maintenance of plant
Code:  V15 | Label:  Total salaries and wages - General administration
Code:  A09 | Label:  School lunch revenues
Code:  TSTREV | Label:  Total Revenue from State Sources
Code:  C01 | Label:  General formula assistance
Code:  V18 | Label:  Total employee benefit payments - School administration
Code:  _31F | Label:  Long-term debt retired during the fiscal year
Code:  C20 | Label:  Federal revenue through the state - All other
Code:  Q11 | Label:  Payments to other school systems
Code:  _19H | Label:  Long-term debt outstanding at beginning of the fiscal year
Code:  V40 | Label:  Current operation expenditure - Operation and maintenance of plant
Code:  C16 | Label:  Federal revenue through the state - Math, science, and teacher quality
Code:  TLOCREV | Label:  Total Revenue from Local Sources
Code:  NONELSEC | Label:  TOTAL CURRENT SPENDING FOR NONELEMENTARY-SECONDARY PROGRAMS
Code:  _41F | Label:  Long-term debt outstanding at end of fiscal year
Code:  V37 | Label:  Total salaries and wages - Business/central/other support services
Code:  CONUM | Label:  ANSI State and County Code
Code:  V45 | Label:  Current operation expenditure - Student transportation
```

```
Code:  STATE | Label:  State Identification Number
Code:  T06 | Label:  Property taxes
Code:  V24 | Label:  Total employee benefit payments - Student transportation
Code:  TCURSSVC | Label:  TOTAL CURRENT SPENDING FOR SUPPORT SERVICES
Code:  V33 | Label:  Fall Membership
Code:  CBSA | Label:  Core-Based Statistical Area
Code:  V14 | Label:  Total employee benefit payments - Instructional staff
Code:  E09 | Label:  Current operation expenditure - School administration
Code:  V30 | Label:  Total employee benefit payments - Food services
Code:  V21 | Label:  Total salaries and wages - Operation and maintenance of plant
Code:  C14 | Label:  Federal revenue through the state - Title I
Code:  U22 | Label:  Interest earnings
Code:  V12 | Label:  Total employee benefit payments - Pupil support
Code:  A13 | Label:  District activity receipts
```

1.3 Visualizations

First lets look at the geographic distribution of our data

In [14]:
```python
State_Dict = {1: 'AL', 2: 'AK', 3: 'AZ', 4: 'AR', 5: 'CA', 6: 'CO', 7: 'CT', 8: 'DE', 9
State_Rows = []
for key in State_Dict:
    mask = (df["STATE"] == key)
    States_Values = df[mask]
    count = mask.sum()
    # Corruption is a data value dealt with later
    corruption = (States_Values["V15"].sum() + States_Values["V16"].sum() + States_Valu

    mydict = {"State": State_Dict[key], "Count": count, "Corruption":corruption}
    State_Rows.append(mydict)
States = pd.DataFrame(State_Rows)
```

In [15]:
```python
# GENERATES OUR NUMBER OF SCHOOLS PER STATE CHLOROPLETH
import plotly.plotly as py # Note you need to setup an API key for this to work.
from plotly.graph_objs import *

scl = [[0.0, 'rgb(252,240,247)'],[0.2, 'rgb(218,218,235)'],[0.4, 'rgb(188,189,220)'],\
            [0.6, 'rgb(158,154,200)'],[0.8, 'rgb(117,107,177)'],[1.0, 'rgb(84,39,143)']
data = [ dict(
        type='choropleth',
        colorscale = scl,
        autocolorscale = False,
        locations = States['State'],
        z = States['Count'].astype(float),
        locationmode = 'USA-states',
        marker = dict(
            line = dict (
```

```
                color = 'rgb(255,255,255)',
                width = 2
            ) ),
        colorbar = dict(
            title = "Number of Schools")
        ) ]
layout = Layout(
    autosize=False,
    geo=dict(
        countrycolor='rgb(102, 102, 102)',
        countrywidth=0.1,
        lakecolor='rgb(255, 255, 255)',
        landcolor='rgba(237, 247, 138, 0.28)',
        lonaxis=dict(
            gridwidth=1.5999999999999999,
            range=[-180, -50],
            showgrid=False
        ),
        projection=dict(
            type='albers usa'
        ),
        scope='usa',
        showland=True,
        showrivers=False,
        showsubunits=True,
        subunitcolor='rgb(102, 102, 102)',
        subunitwidth=0.5
    ),
    hovermode='closest',
    images=list([
        dict(
            x=1,
            y=0.6,
            sizex=0.155,
            sizey=0.4,
            source='http://i.imgur.com/Xe3f1zg.png',
            xanchor='right',
            xref='paper',
            yanchor='bottom',
            yref='paper'
        )
    ]),
    showlegend=True,
    title='<b>Number of Schools per State</b>',
    width= 800,
    margin = dict(
        l=0,
        r=50,
```

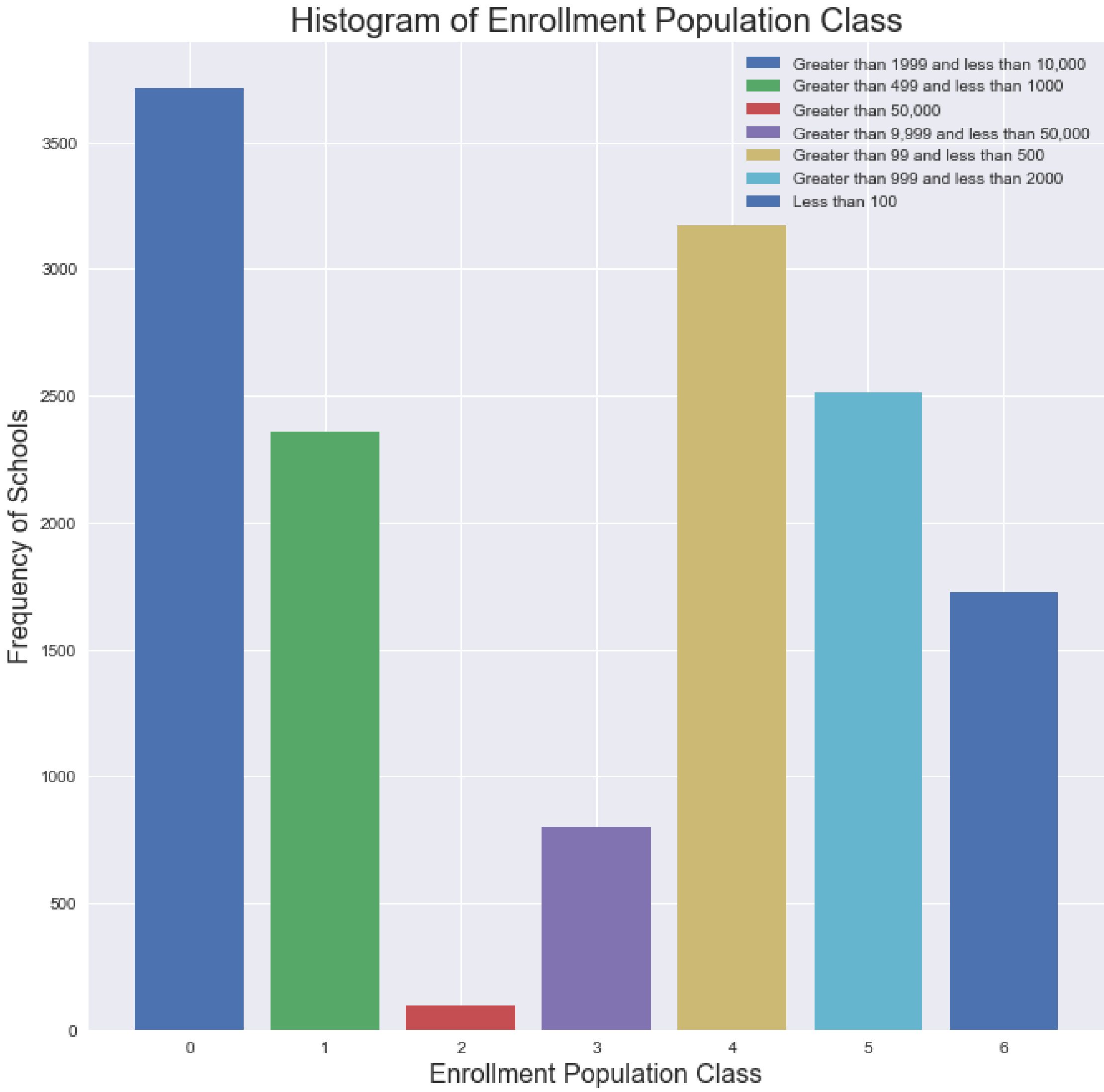
```
            b=100,
            t=100,
            pad=4)
    )
    fig = Figure(data=data, layout=layout)
    py.iplot(fig, filename='DSD_1')
```

Out[15]: <plotly.tools.PlotlyDisplay object>

Now we are going to add a column which converts enrollment size to a categorical data type. Note that the average enrollment size is 693, according to https://nces.ed.gov/pubs2012/2012001.pdf, Page 170.

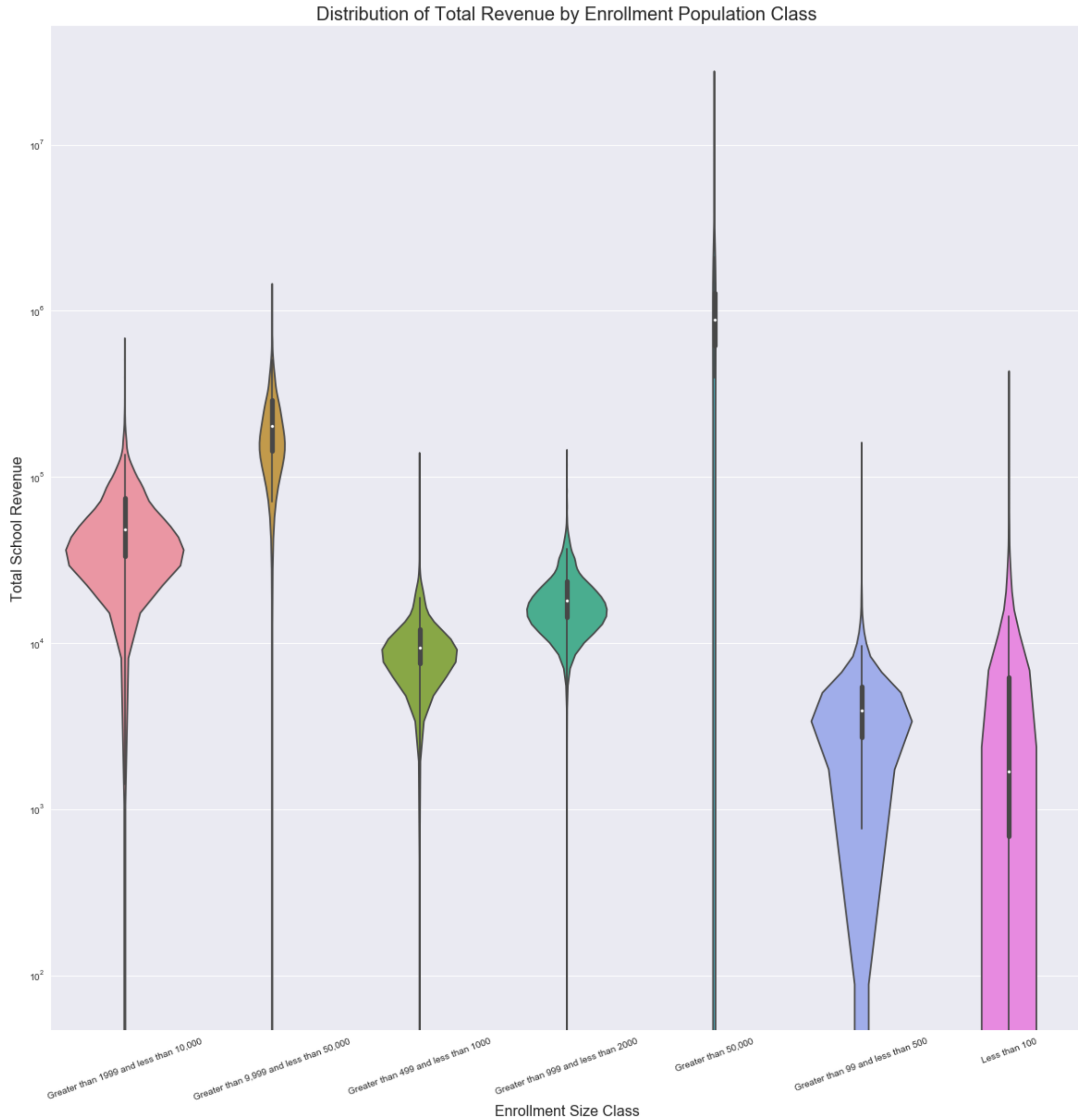
```
In [16]: def group_pop(x):
             if x >= 50000:
                 return "Greater than 50,000"
             elif x < 50000 and x >= 10000:
                 return "Greater than 9,999 and less than 50,000"
             elif x < 10000 and x >= 2000:
                 return "Greater than 1999 and less than 10,000"
             elif x < 2000 and x >= 999:
                 return "Greater than 999 and less than 2000"
             elif x < 1000 and x >= 499:
                 return "Greater than 499 and less than 1000"
             elif x < 500 and x >= 99:
                 return "Greater than 99 and less than 500"
             else:
                 return "Less than 100"

         df["Enrollment Size Class"] = df['V33'].map(group_pop)
         df_pop_mean = df.groupby(df["Enrollment Size Class"]).count()
         df_pop_sum = df.groupby(df["Enrollment Size Class"]).sum()
         df_pop_count= df.sort_values("V33", ascending=True).groupby(df["Enrollment Size Class"]
```

```
In [17]: plt.figure(figsize=(11,11))


         plt.xlabel('Enrollment Population Class', fontsize=16)
         plt.ylabel('Frequency of Schools', fontsize=16)
         plt.title('Histogram of Enrollment Population Class', fontsize=20)


         for i in range(0,7):
             plt.bar(i, df_pop_count["Enrollment Size Class"][i], label = list(df_pop_sum.index)
         plt.legend()
         plt.show()
         plt.close()
```



It would be interesting to compare the enrollment population class to the distribution of total revenue for schools in that class, so that is shown in the following Violin Plot

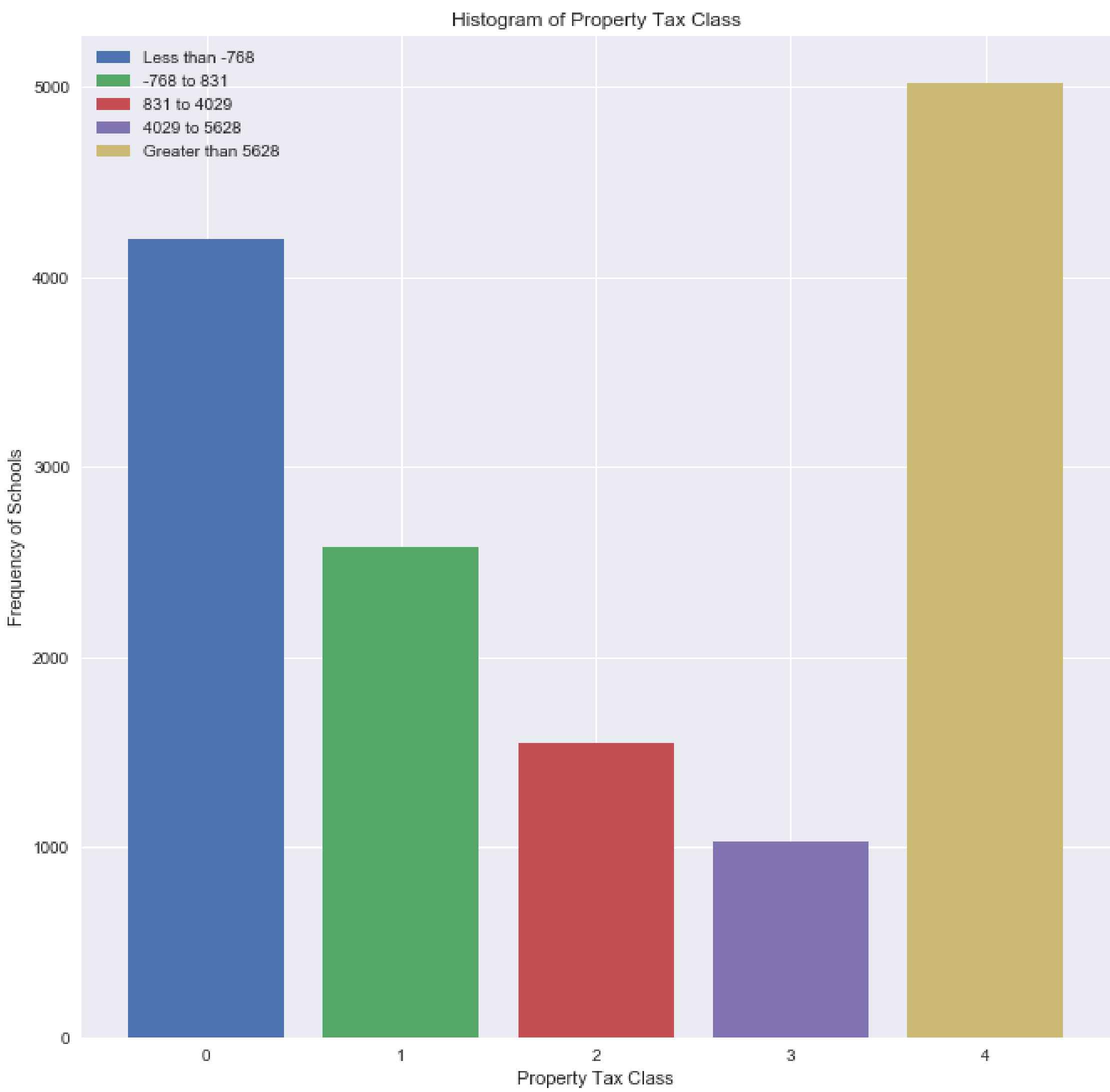
```
In [18]: plt.figure(figsize=(20,20))
         violinplot = sns.violinplot(x="Enrollment Size Class", y="TOTALREV", data=df,scale="cou
         violinplot.axes.set_yscale('log') #Make axis readable
         plt.title("Distribution of Total Revenue by Enrollment Population Class", fontsize=20)
         plt.xticks(rotation=20)
         plt.ylabel('Total School Revenue',fontsize= 16)
         plt.xlabel('Enrollment Size Class',fontsize= 16)
         plt.show()
```



Another aspect of the dataset that could be explored is property tax revenue. It might be of interest to see how much property tax revenue schools in our dataset received. Here we see the frequency of schools within particular property tax revenue brackets.

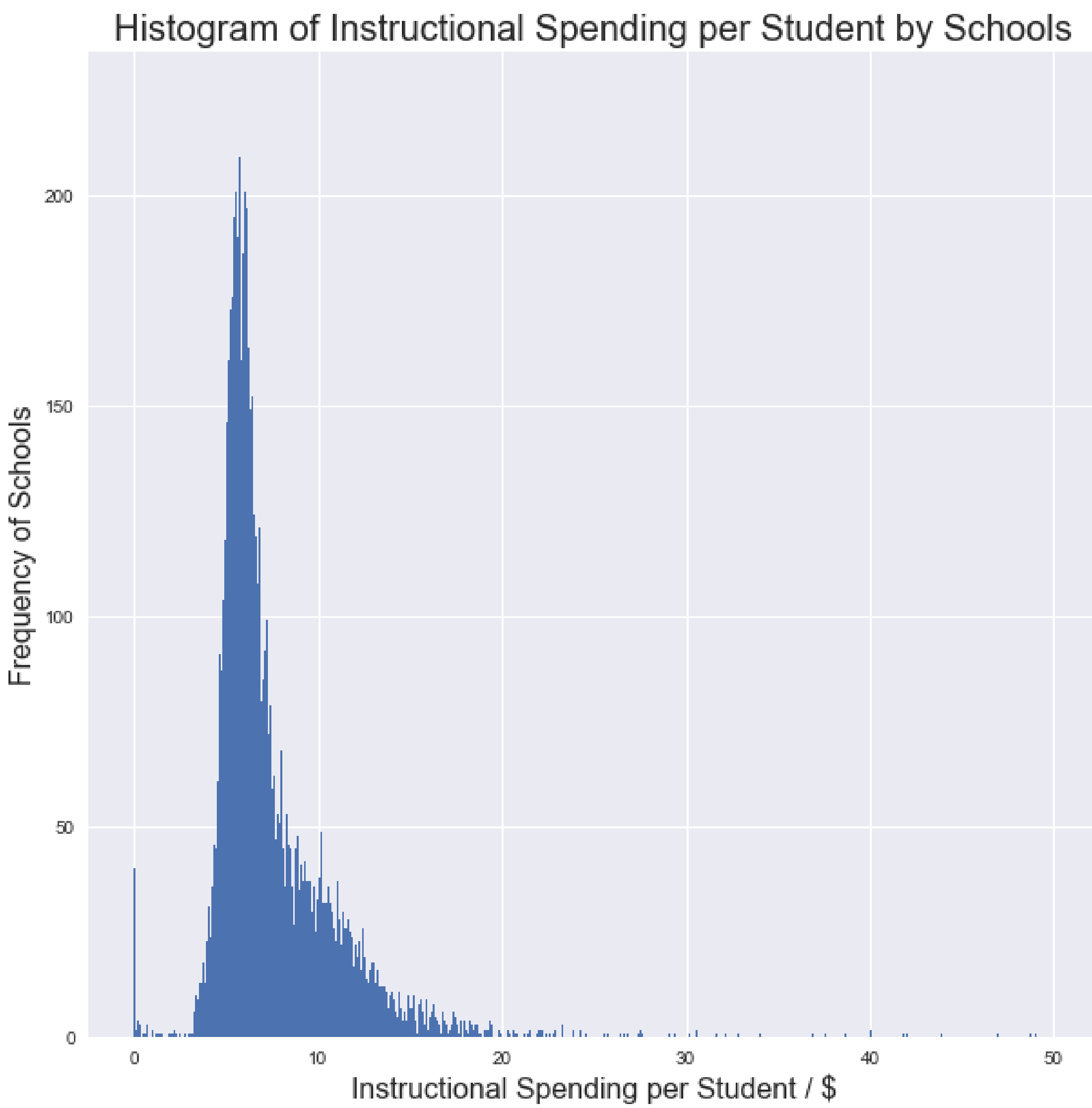
```
In [19]: pt_mean = 2430 # Data obtained from https://www.urban.org/sites/default/files/publicati
         pt_sd = 1599

         property_taxes = df["T06"].dropna()
         bin_names = ["Less than " + str(pt_mean - 2*pt_sd), str(pt_mean - 2*pt_sd) + " to " + s
         pt_bins = pd.cut(property_taxes, [pt_mean-2*pt_sd, pt_mean-1*pt_sd, pt_mean, pt_mean+1*

         pt_taxes = pd.DataFrame(property_taxes.groupby(pt_bins).count())
         df["Property Tax Class"] = pt_bins
```

```
plt.figure(figsize=(11,11))

plt.xlabel('Property Tax Class')
plt.ylabel('Frequency of Schools')
plt.title('Histogram of Property Tax Class')

for i in range(0,5):
    plt.bar(i, pt_taxes["T06"][i], label = list(pt_taxes.index)[i])
plt.legend()
plt.show()
plt.close()
```



But perhaps the schools property tax revenue is not realy indicative of very much the school could serve a lot of students or be in richer in poor communities. Perhaps a better aspect to look at is is instructional spending per fall enrollment. Let's create a new column "Instructional spending per student" and get a histogram for that!

```
In [20]: df["Instructional spending per student"] = df["TCURINST"]/df[df["V33"] != 0]['V33']
         plt.figure(1, figsize=(10,10))
         plt.xlabel('Instructional Spending per Student / $', fontsize = 16)
         plt.ylabel('Frequency of Schools', fontsize = 16)
         plt.title('Histogram of Instructional Spending per Student by Schools', fontsize = 20)
         df["Instructional spending per student"].hist(range=[0, 50], bins = 1000)
         plt.show()
         plt.close()
```



2 Linear Regression!

That was fun! Now lets perfrom some regression. We'll perform regression using property tax to predict federal revenue for disadvantaged students, instructional spending, and school debt.

We'll build 3 models using simple linear regression

Model 1: Regressing on Property Taxes vs Federal Title 1 Funding (Disadvantaged Students)

Model 2: Regressing on Property Taxes vs Instructional Spending

Model 3: Regressing on Property Taxes vs Outstanding Debt at the start of the fiscal year

But before we train our model, we will remove outliers and zero value data in our property tax columns, as it's believed that they do not add the training of the model.

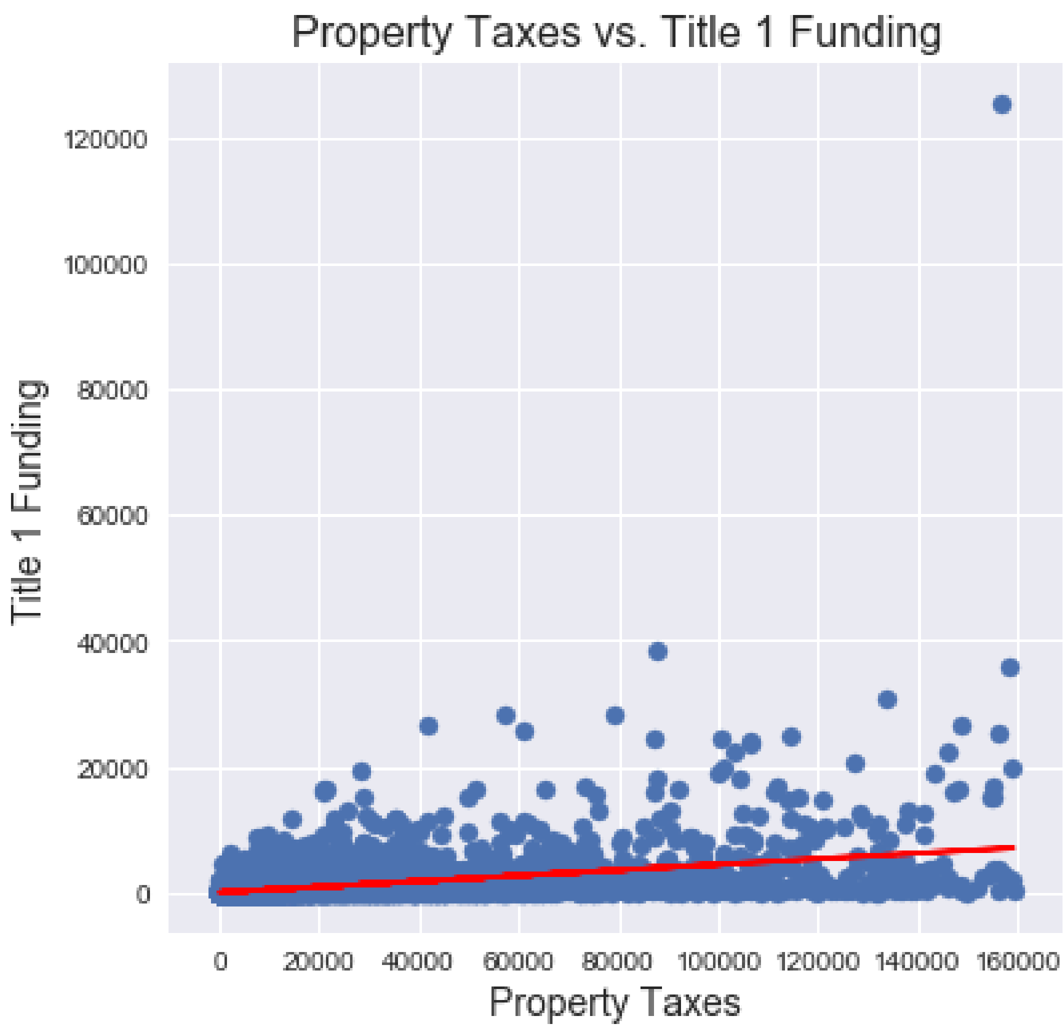
```
In [21]: # Remove outlier property taxes and 0 property taxes.
         df_reg = df.copy()
         df_reg = df_reg[(np.abs(stats.zscore(df_reg["T06"])) < 3) & (df_reg["T06"] != 0)]

         taxes = df_reg["T06"]
         title1 = df_reg["C14"]
         spending = df_reg["TCURINST"]
         debt = df_reg["_19H"]
```

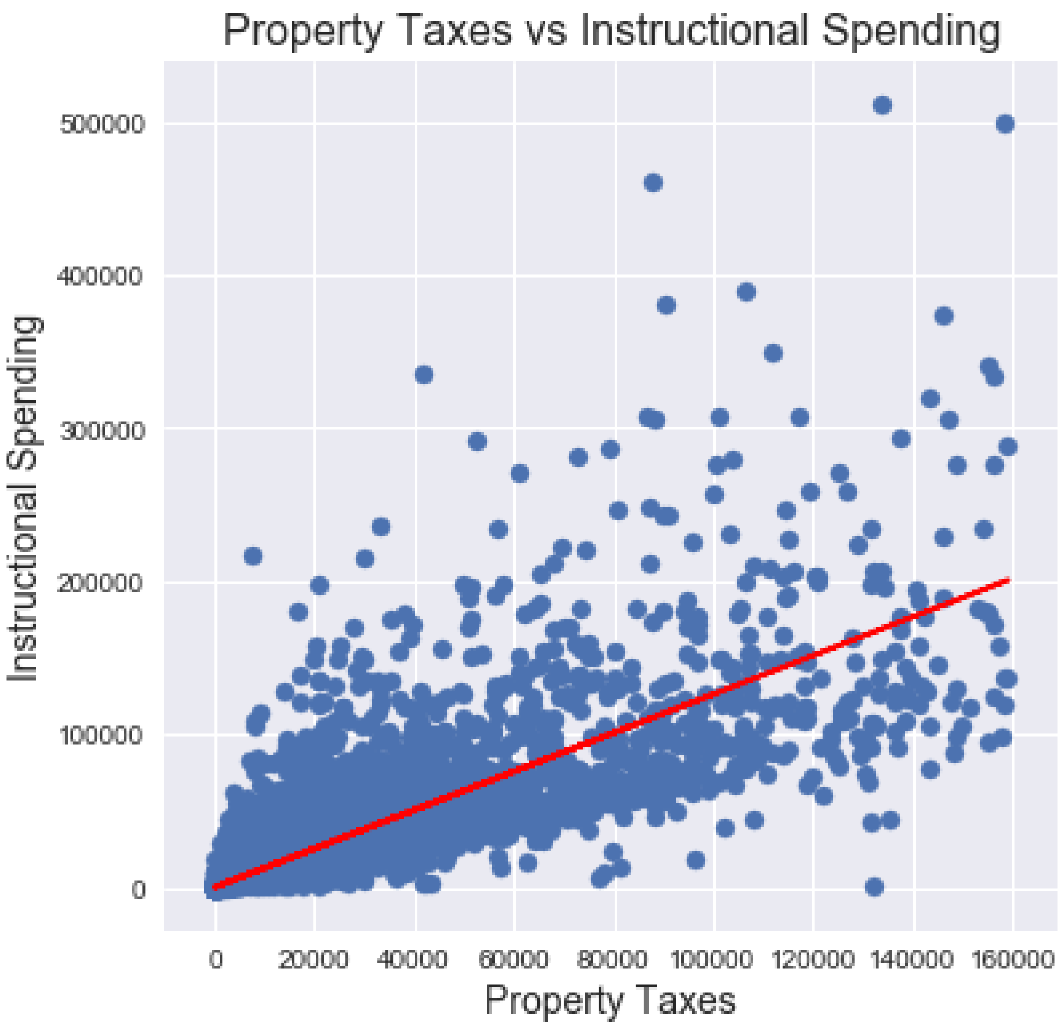
Additionaly, let us partition the data into training and validation sets, so we can see check how our models perform.

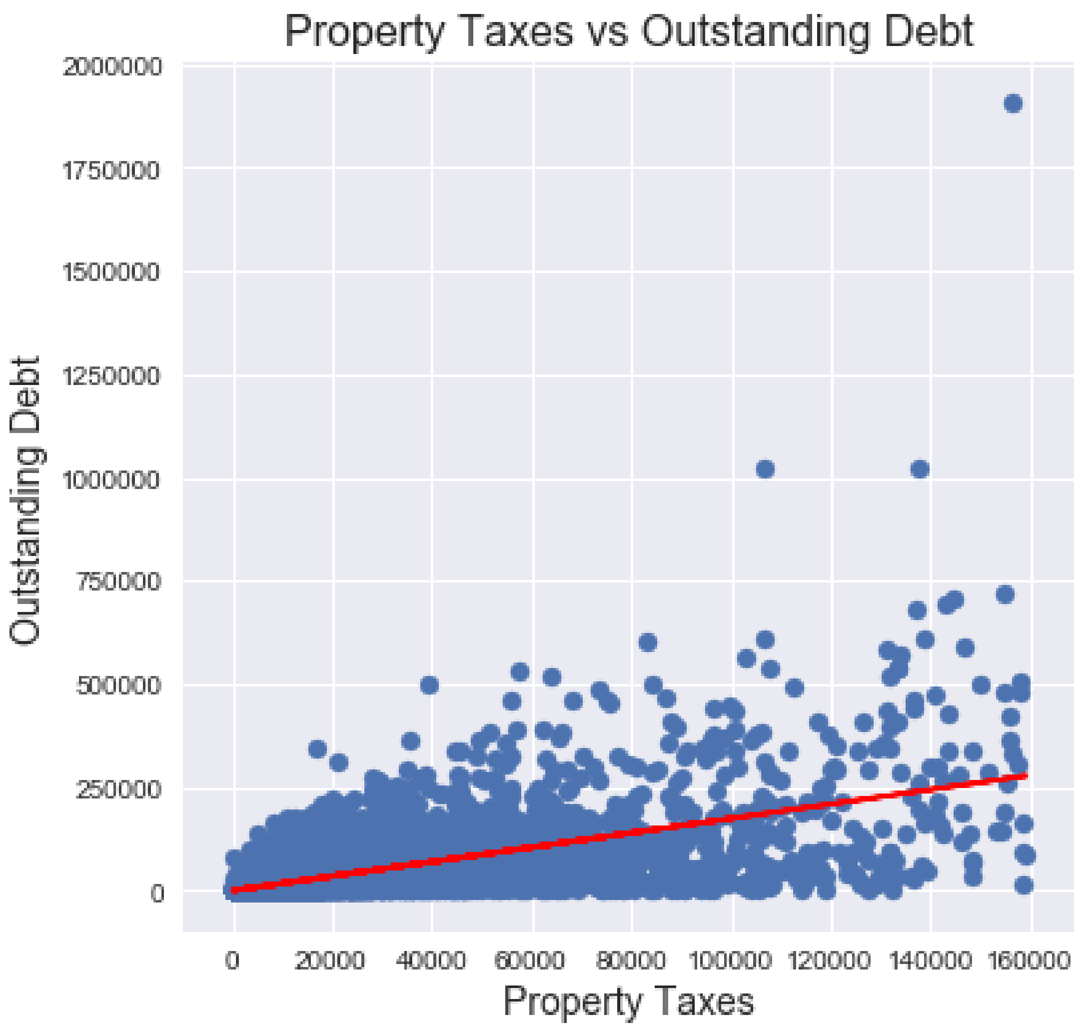
```
In [22]: # Partitioning validation and training data


         taxes.shape
         train_num = int(np.round(taxes.shape[0]*.8))

         taxes_train = taxes[0:train_num]
         taxes_valid = taxes[train_num:]
         title1_train = title1[0:train_num]
         title1_valid = title1[train_num:]
         spending_train = spending[0:train_num]
         spending_valid = spending[train_num:]
         debt_train = debt[0:train_num]
         debt_valid = debt[train_num:]
```

```
In [23]: plt.figure(1, figsize=(6,6))
         myOLS_title1 = sm.OLS(title1,taxes).fit()
         plt.plot(taxes, myOLS_title1.predict(taxes), color = 'red')
         plt.scatter(taxes,title1)
         plt.title("Property Taxes vs. Title 1 Funding", fontsize= 16)
         plt.xlabel("Property Taxes", fontsize= 14)
         plt.ylabel("Title 1 Funding", fontsize= 14)
         plt.show()
         plt.close()

         plt.figure(2, figsize=(6,6))
         myOLS_spending = sm.OLS(spending,taxes).fit()
```

```
plt.plot(taxes, myOLS_spending.predict(taxes), color = 'red')
plt.scatter(taxes,spending)
plt.title("Property Taxes vs Instructional Spending", fontsize= 16)
plt.xlabel("Property Taxes", fontsize= 14)
plt.ylabel("Instructional Spending", fontsize= 14)
plt.show()
plt.close()

plt.figure(3, figsize = (6,6))
myOLS_debt = sm.OLS(debt, taxes).fit()
plt.plot(taxes, myOLS_debt.predict(taxes), color = 'red')
plt.scatter(taxes,debt)
plt.title("Property Taxes vs Outstanding Debt", fontsize= 16)
plt.xlabel("Property Taxes", fontsize= 14)
plt.ylabel("Outstanding Debt", fontsize= 14)
plt.show()
plt.close()
```




Property Taxes vs Instructional Spending
Instructional Spending
Property Taxes
500000
400000
300000
200000
100000
0
0
20000
40000
60000
80000
100000
120000
140000
160000



It looks as if property tax revenue best predicts instructional spending! Let's take a better look by calculating the mean sqaured errors.

```
In [24]: myOLS = sm.OLS(title1_train,taxes_train).fit()
         title1_hat = myOLS.predict(taxes_valid)
         title1_mse = 1/len(title1_valid)*np.dot((title1_valid - title1_hat),(title1_valid - tit
         print("The MSE for the model taxes~title1 is:", title1_mse)
         myOLS = sm.OLS(spending_train,taxes_train).fit()
         spending_hat = myOLS.predict(taxes_valid)
         spending_mse = 1/len(spending_valid)*np.dot((spending_valid - spending_hat),(spending_v
         print("The MSE for the model taxes~spending is:", spending_mse)
         myOLS = sm.OLS(debt_train,taxes_train).fit()
         debt_hat = myOLS.predict(taxes_valid)
         debt_mse = 1/len(debt_valid)*np.dot((debt_valid - debt_hat),(debt_valid - debt_hat))
         print("The MSE for the model taxes~debt is:", debt_mse)
         # Compare MSE
         print(min(title1_mse, spending_mse, debt_mse))
```

```
The MSE for the model taxes~title1 is: 2050414.15614
The MSE for the model taxes~spending is: 282908769.491
The MSE for the model taxes~debt is: 2616542250.57
2050414.15614
```

```
In [25]: myOLS = sm.OLS(title1_train,taxes_train).fit()
         title1_hat = myOLS.predict(taxes_valid)
         title1_mse = 1/len(title1_valid)*np.dot((title1_valid - title1_hat),(title1_valid - tit
         print("The MSE for the model taxes~title1 is:  ", title1_mse)
         myOLS = sm.OLS(spending_train,taxes_train).fit()
         spending_hat = myOLS.predict(taxes_valid)
         spending_mse = 1/len(spending_valid)*np.dot((spending_valid - spending_hat),(spending_v
         print("The MSE for the model taxes~spending is:", spending_mse)
         myOLS = sm.OLS(debt_train,taxes_train).fit()
         debt_hat = myOLS.predict(taxes_valid)
         debt_mse = 1/len(debt_valid)*np.dot((debt_valid - debt_hat),(debt_valid - debt_hat))
         print("The MSE for the model taxes~debt is:    ", debt_mse)
```

```
The MSE for the model taxes~title1 is:   2050414.15614
The MSE for the model taxes~spending is: 282908769.491
The MSE for the model taxes~debt is:     2616542250.57
```

The mean squared error for title 1 and taxes is most minimum, however the best line fit looks best for debt and taxes

3 Logistic Regression!

Let's try logistic regression now! Perhaps it'll be intresting to see if property taxes, title 1 funding, funding for disabled students, funding for "math, science" teacher quality, and other forms of federal revenue-- are all predictors of whether a school is in debt or not.

Because logistic regression performs classification towards categorical data, let's create a categorical column debt/no debt.

```
In [26]: df["Debt Class"] = df["_19H"] ==  0
         print("Percentage of schools with no debt: ", df[df["Debt Class"] == True]["_19H"].coun
         print("percentage of schools with debt: ", 1 -  df[df["Debt Class"] == True]["_19H"].co
```

```
Percentage of schools with no debt:  0.225792988314
percentage of schools with debt:  0.774207011686
```

```
In [27]: #Preprocess columns
         taxes = df["T06"]
         spending = df["TOTALEXP"]
         title1 = df["C14"]
         idea = df["C15"]
```

```
mstq = df["C16"]
fedrev = df["C20"]
debt = df["Debt Class"]


# Originally no normalization was performed, over flow occured when exponentiating.
# Then a mean normalization was performed, resulting in many negative entries, which ca
# Finally, a min-max normalization was tried and worked.

scaler = MinMaxScaler()
categories = [taxes, spending, title1, idea, mstq, fedrev, debt]
scaler.fit(categories)
MinMaxScaler(copy=True, feature_range=(0, 1))

# We'll need to preprocess the columns we want to look at and partition the training an
data_x = np.column_stack(scaler.transform(categories))
data_y = np.reshape(debt, (data_x.shape[0], 1))

train_x, valid_x, train_y, valid_y = train_test_split(data_x, data_y, test_size=0.10, r
```

```
/usr/local/lib/python3.4/dist-packages/numpy/core/fromnumeric.py:57: FutureWarning:

reshape is deprecated and will raise in a subsequent release. Please use .values.reshape(...) in
```

We'll need to borrow the implmentation of the logistic regression given to us in lecture

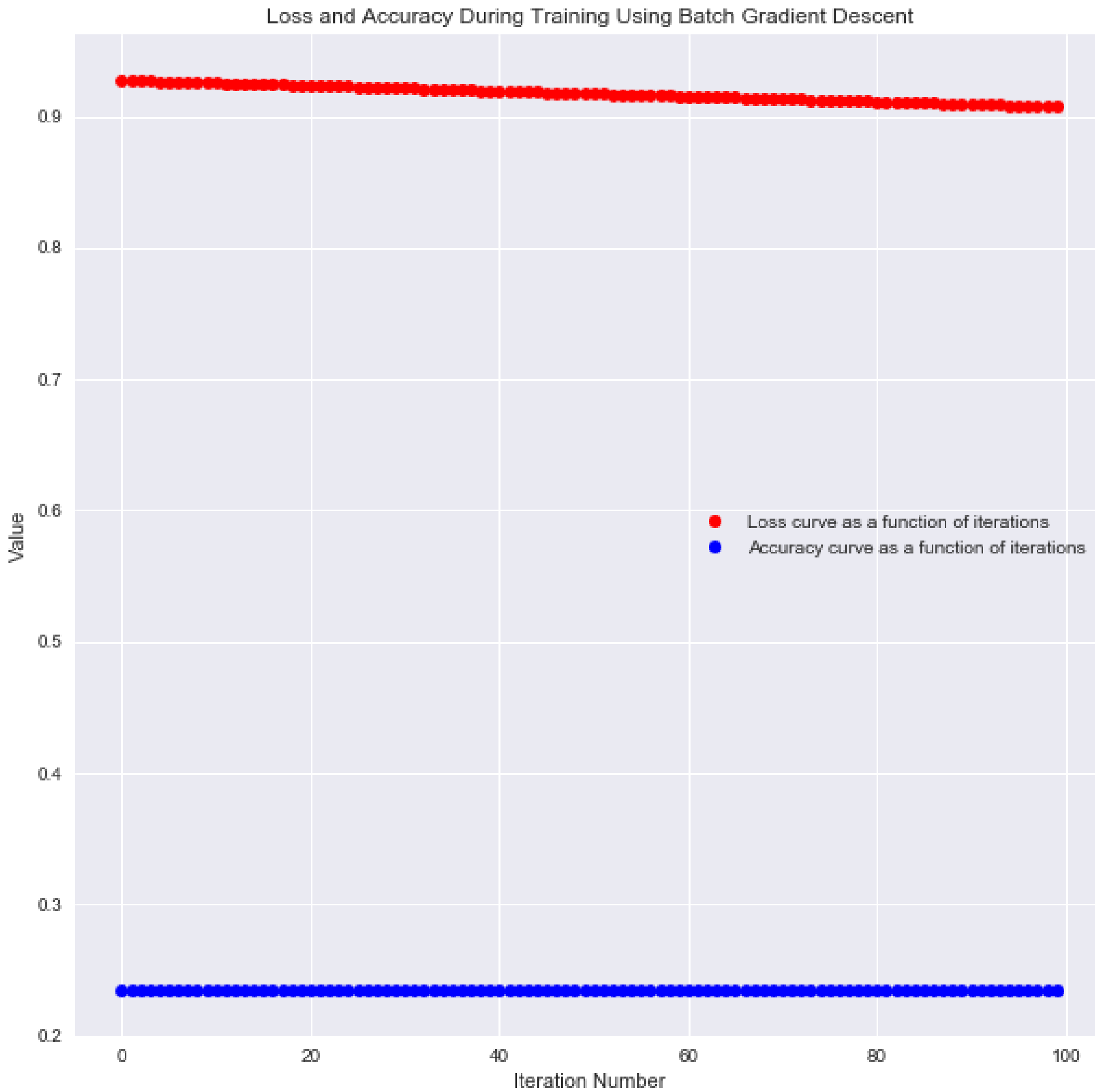
In [28]:
```
def sigmoid(X, w):
    """
    Compute the elementwise sigmoid of the product Xw
    Data in X should be rows, weights are a column.
    """
    return 1 / (1 + np.exp(-np.dot(X, w)))

def gradient(X, y, w, onept, lamb=0):
    """
    Compute gradient of regularized loss function.
    Accomodate for if X is just one data point.
    """
    if onept:
        return 2 * lamb * w - ((y - sigmoid(X, w)) * X).reshape(w.size, 1)
    return 2 * lamb * w - np.dot(X.T, y - sigmoid(X, w)) / y.size

def loss(X, y, w, lamb=0):
    """
    Compute total loss for the data in X, labels in y, params w
    """
```

```
    sumcost = 0
    for i in range(X.shape[0]):
        sumcost += y[i] * np.log(sigmoid(X[i], w)) + (1 - y[i]) * np.log(1 - sigmoid(X[
    return lamb * np.linalg.norm(w)**2 - sumcost / y.size

def accuracy(X, y, w):
    """
    Compute accuracy for data in X, labels in y, params w
    """
    results = np.round(sigmoid(X, w))
    score = sum([results[i] == y[i] for i in range(y.size)]) / y.size
    return score[0]
```

Training the model:

```
In [29]: weights = np.asarray([np.random.rand() for i in range(train_x.shape[1])]).reshape(train
         weights /= np.linalg.norm(weights)
         losses = []
         accuracies = []
         epsilon = 0.001
         num_iterations = 100

         for i in range(100):
             diff = epsilon * gradient(train_x, train_y, weights, False)
             weights = weights - diff
             losses.append(loss(train_x, train_y, weights))
             accuracies.append(accuracy(valid_x, valid_y, weights))
```

```
In [30]: plt.figure(figsize=[10,10])
         loss_line = plt.plot(np.arange(num_iterations), losses, 'ro', label="Loss curve as a fu
         accuracy_line = plt.plot(np.arange(num_iterations), accuracies, 'bo', label = "Accuracy
         plt.legend()
         plt.title('Loss and Accuracy During Training Using Batch Gradient Descent')
         plt.ylabel('Value')
         plt.xlabel('Iteration Number')

         plt.show()
         plt.close()
         print(accuracy(valid_x, valid_y, weights))
```




```
0.234353268428
```

4 Concluding visualization

As a fun conclusion, we made a corruption index, which is defined for a set of data as:

$$\frac{\sum_{i=0}^{\#rows} "Salaries\ and\ employee\ benefits\ for\ general\ and\ school\ administration"}{\sum_{i=0}^{\#rows} "Total\ Revenue"}$$

This is defined as corruption as this money is going into to the pockets of the school administrators, and not the school teachers or students.

```
In [31]: # GENERATES OUR CORRUPTION INDEX PER STATE CHLOROPETH
         import plotly.plotly as py
         from plotly.graph_objs import *

         scl = [[0.0, 'rgb(0,255,0)'],[1.0, 'rgb(188,0,0)']]
         data = [ dict(
                 type='choropleth',
                 colorscale = scl,
                 autocolorscale = False,
                 locations = States['State'],
                 z = States['Corruption'].astype(float),
                 locationmode = 'USA-states',
                 marker = dict(
                     line = dict (
                         color = 'rgb(255,255,255)',
                         width = 2
                     ) ),
                 colorbar = dict(
                     title = "Corruption Index")
                 ) ]
         layout = Layout(
             autosize=False,
             geo=dict(
                 countrycolor='rgb(102, 102, 102)',
                 countrywidth=0.1,
                 lakecolor='rgb(255, 255, 255)',
                 landcolor='rgba(237, 247, 138, 0.28)',
                 lonaxis=dict(
                     gridwidth=1.5999999999999999,
                     range=[-180, -50],
                     showgrid=False
                 ),
                 projection=dict(
                     type='albers usa'
                 ),
                 scope='usa',
                 showland=True,
                 showrivers=False,
                 showsubunits=True,
                 subunitcolor='rgb(102, 102, 102)',
                 subunitwidth=0.5
             ),
             hovermode='closest',
             images=list([
                 dict(
                     x=1,
                     y=0.6,
                     sizex=0.155,
```

```
                sizey=0.4,
                source='http://i.imgur.com/Xe3f1zg.png',
                xanchor='right',
                xref='paper',
                yanchor='bottom',
                yref='paper'
            )
        ]),
        showlegend=True,
        title='<b>Corruption Index per state</b>',
        width= 800,
        margin = dict(
            l=0,
            r=50,
            b=100,
            t=100,
            pad=4)
    )
    fig = Figure(data=data, layout=layout)
    py.iplot(fig, filename='DSD_2')
```

```
Out[31]: <plotly.tools.PlotlyDisplay object>
```

It appears that Missisippi and Oklahoma have the most corruption in their school boards. 10% of their revenue is going towards the school administrators. *Please note that this metric is just for fun and should not be taken seriously. There are issues in measuring corruption this way, since schools need administrators in order to run.*