Linning up my Strategy to Solve this Challenge:

1. Understand the problem by knowing your data
2. Univariate data analysis.
3. Multivariate data analysis.
4. Check for missing data.
5. Finding the outliers in the data.
6. Checking Skewness in the data.
7. Convert Categorical data items into numerical data items.
8. Scaling the data
9. Training Models on this data.

Step 1: Understand the problem by knowing the data.

This Step involves having a look at the shape of the data, the content of the data, different type of datatypes present in the data. Also gathering some knowledge about problem by studies articles, blogs, researches on market trends about this problem.

In [311…
```
#importing useful libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.stats import norm
from sklearn.preprocessing import StandardScaler
from scipy import stats
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
import eli5
from eli5.sklearn import PermutationImportance
from sklearn.linear_model import Ridge
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [312…
```
ScoreData= pd.read_csv('Math_Students_Data_Challenge.csv')
```

In [313…
```
ScoreData.columns.values
```

Out[313…
```
array(['State', 'Avg_Math_Score', 'Avg_English_Score', 'Total_Enrollment',
       'State_Debt', 'State_Revenue', 'Salaries', 'Emp_Benefits',
       'Student_Support', 'Inst_Staff_Support'], dtype=object)
```

In [314…
```
ScoreData.shape
```

Out[314…
```
(51, 10)
```

In [315…
```
ScoreData.head()
```

Out[315…

	State	Avg_Math_Score	Avg_English_Score	Total_Enrollment	State_Debt	State_Revenue	Salaries	Emp_Benefits	Student_Support	Inst_St
0	Alabama	269.1943	257.4278	744548	5116627	3898347	5045	1884	502	
1	Alaska	281.5596	261.2561	131091	1321403	1707449	8151	6110	1497	
2	Arizona	279.7223	260.4483	941726	4270089	2934165	4446	1265	567	
3	Arkansas	277.9148	261.9645	477716	3664741	3847045	5639	1556	484	
4	California	275.9014	261.5025	6208733	54627921	35141208	5567	2085	492	

In [316…
```
ScoreData.dtypes
```

Out[316…
```
State                  object
Avg_Math_Score        float64
Avg_English_Score     float64
Total_Enrollment        int64
State_Debt              int64
State_Revenue           int64
Salaries                int64
Emp_Benefits            int64
Student_Support         int64
Inst_Staff_Support      int64
dtype: object
```

In [317…
```
# Getting a statistical picture of the data items in terms of count, mean, standard deviation, distribution of
ScoreData.describe()
```

Out[317…

	Avg_Math_Score	Avg_English_Score	Total_Enrollment	State_Debt	State_Revenue	Salaries	Emp_Benefits	Student_Support	Inst_S
count	51.000000	51.000000	5.100000e+01	5.100000e+01	5.100000e+01	51.000000	51.000000	51.000000	
mean	283.915004	266.299490	9.470535e+05	8.141933e+06	5.368678e+06	6486.019608	2545.745098	673.254902	
std	7.230598	6.004292	1.133659e+06	1.279279e+07	6.187873e+06	1547.671147	1084.222428	345.795480	
min	265.259400	247.739200	4.417900e+04	0.000000e+00	0.000000e+00	3528.000000	953.000000	230.000000	
25%	279.773450	261.948000	2.771900e+05	1.313020e+06	1.835186e+06	5353.500000	1734.500000	448.500000	
50%	284.897600	267.215000	6.714450e+05	4.270089e+06	3.693829e+06	6156.000000	2282.000000	551.000000	
75%	288.738500	270.133050	1.026836e+06	8.848232e+06	6.975934e+06	7272.500000	3155.500000	790.000000	
max	300.568200	277.009600	6.208733e+06	6.795766e+07	3.514121e+07	10385.000000	6110.000000	1843.000000	

In [318…
```
# Numerical Features
num_feat=ScoreData.select_dtypes(exclude=['object']).columns
print(num_feat)
```

```
Index(['Avg_Math_Score', 'Avg_English_Score', 'Total_Enrollment', 'State_Debt',
       'State_Revenue', 'Salaries', 'Emp_Benefits', 'Student_Support',
       'Inst_Staff_Support'],
      dtype='object')
```

In [319…
```
# Categorical Features
cat_feat=ScoreData.select_dtypes(include=['object']).columns
print(cat_feat)
```

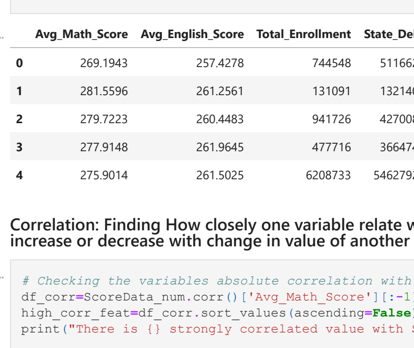
```
Index(['State'], dtype='object')
```

Step 2: Univariate data analysis.

In [320…
```
# For the variable Saleprice, understanding its values using different statistical terms like
# mean, count, standard deviation
ScoreData['Avg_Math_Score'].describe()
```

Out[320…
```
count     51.000000
mean     283.915004
std        7.230598
min      265.259400
25%      279.773450
50%      284.897600
75%      288.738500
max      300.568200
Name: Avg_Math_Score, dtype: float64
```

In [321…
```
#plotting a histogram to check how the different values of saleprice are distributed
sns.distplot(ScoreData['Avg_Math_Score']);
```



Observations drawn looking at the Histogram

- Deviate from the normal distribution.
- Have some negative skewness.
- Show peakedness.

In [322…
```
#skewness and kurtosis
print("Skewness: %f" % ScoreData['Avg_Math_Score'].skew())
print("Kurtosis: %f" % ScoreData['Avg_Math_Score'].kurt())
```

```
Skewness: -0.262241
Kurtosis: 0.171323
```

3. Bivariate Data Analysis

Analysing all Against Avg Math Score (target)

Part 1: For Numerical Features

In [323…
```
# Filtering out the numerical features in a different data frame
ScoreData_num=ScoreData[num_feat]
ScoreData_num.head(5)
```

Out[323…

	Avg_Math_Score	Avg_English_Score	Total_Enrollment	State_Debt	State_Revenue	Salaries	Emp_Benefits	Student_Support	Inst_Staff_Suppor
0	269.1943	257.4278	744548	5116627	3898347	5045	1884	502	40
1	281.5596	261.2561	131091	1321403	1707449	8151	6110	1497	126
2	279.7223	260.4483	941726	4270089	2934165	4446	1265	567	41
3	277.9148	261.9645	477716	3664741	3847045	5639	1556	484	79
4	275.9014	261.5025	6208733	54627921	35141208	5567	2085	492	51

Correlation: Finding How closely one variable relate with another i.e. How strongly the value of the variable increase or decrease with change in value of another variable

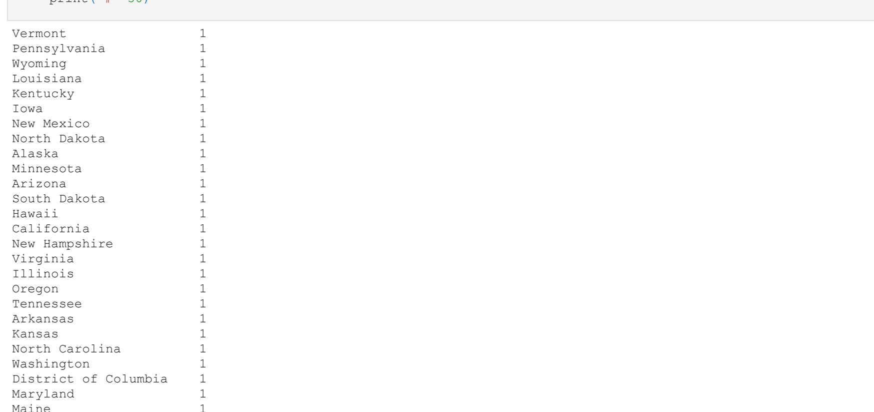
In [324…
```
# Checking the variables absolute correlation with Avg_Math_Score
df_corr=ScoreData_num.corr()['Avg_Math_Score'][:-1]
high_corr_feat=df_corr.sort_values(ascending=False)
print("There is {} strongly correlated value with SalePrice:\n{}".format(len(high_corr_feat), high_corr_feat))
```

```
There is 8 strongly correlated value with SalePrice:
Avg_Math_Score        1.000000
Avg_English_Score     0.889285
Salaries              0.602606
Student_Support       0.341295
Emp_Benefits          0.270238
State_Debt            0.026528
State_Revenue         0.008343
Total_Enrollment     -0.034391
Name: Avg_Math_Score, dtype: float64
```

As Avg_Math_Score value is almost independent of values of State_Debt, State_Revenue, Total_enrollment, they might be excluded from analysis for prediction house prices, but let's look further before making any haste

Plotting all Numerical Columns against Sale Price to get a more clear picture

In [325…
```
for i in range(0, len(ScoreData_num.columns), 5):
    sns.pairplot(data=ScoreData_num,
                x_vars=ScoreData_num.columns[i:i+5],
                y_vars=['Avg_Math_Score'])
```



Looking at scatter plots

I find 'that in first position 'Salaries' is most positively correlated to Avg_Math_Score

I find that in second position 'Student_Support' is positively correlated to Avg_Math_Score

I find that is third position 'Emp_Benefits' is less positively correlated to Avg_Math_Score

I find that is fourth position 'Inst_Staff_Support' is very less positively correlated to Avg_Math_Score

But State_Debt, State_Revenue, Total_enrollment still do not show any relation and are still eligible to be dropped but let's do further analysis

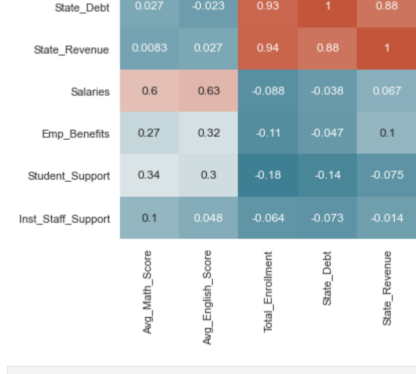
Part 2: For Categorical Features

In [326…
```
# Getting list of different categories which each categorical feature belong too
for catg in list(cat_feat) :
    print(ScoreData[catg].value_counts())
    print('#'*50)
```

```
Vermont                 1
Pennsylvania            1
Wyoming                 1
Louisiana               1
Kentucky                1
Iowa                    1
New Mexico              1
North Dakota            1
Alaska                  1
Minnesota               1
Arizona                 1
South Dakota            1
Hawaii                  1
California              1
New Hampshire           1
Virginia                1
Illinois                1
Oregon                  1
Tennessee               1
Arkansas                1
Kansas                  1
North Carolina          1
Washington              1
District of Columbia    1
Maryland                1
Maine                   1
Missouri                1
Colorado                1
Georgia                 1
South Carolina          1
Massachusetts           1
Alabama                 1
Montana                 1
Connecticut             1
Utah                    1
Indiana                 1
Oklahoma                1
Nebraska                1
West Virginia           1
Florida                 1
Ohio                    1
New Jersey              1
Texas                   1
Nevada                  1
Mississippi             1
Idaho                   1
New York                1
Michigan                1
Wisconsin               1
Delaware                1
Rhode Island            1
Name: State, dtype: int64
##################################################
```

Plotting Box Plots which are Generally Good Visual representation to Observe how categorical values are distributed

In [327…
```
plt.show()
sns.boxplot(x='State', y='Avg_Math_Score', data=ScoreData)
sns.set(rc={"figure.figsize":(20, 5)})
```



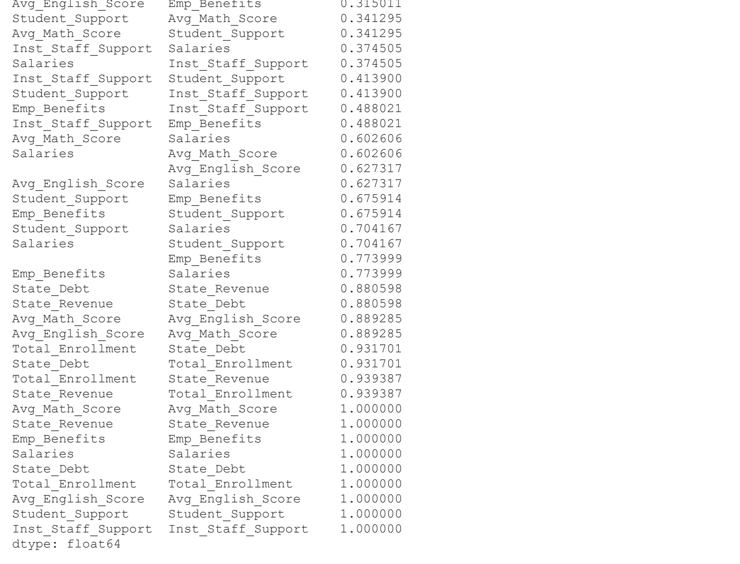
Step 4: Multivariate Data Analysis

This Step involves learning relationships between every pair of variable in the dataset

Best place to start with is to draw a Correlation Matrix (heatmap) filtering pairs which have high absolute correlation

In [328…
```
# plot the heatmap
corr = ScoreData.corr()
plt.figure(figsize=(12,7))
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns, annot=True, cmap=sns.diverging_palette(22
```

Out[328…
```
<AxesSubplot:>
```



In [329…
```
c = corr
s = c.unstack()
so = s.sort_values(kind="quicksort")
so.tail(40)
```

Out[329…
```
Avg_Math_Score      Emp_Benefits          0.270238
Student_Support     Avg_English_Score     0.304263
Avg_English_Score   Student_Support       0.304263
Emp_Benefits        Avg_English_Score     0.315011
Avg_English_Score   Emp_Benefits          0.315011
Student_Support     Avg_Math_Score        0.341295
Avg_Math_Score      Student_Support       0.341295
Inst_Staff_Support  Salaries              0.374505
Salaries            Inst_Staff_Support    0.374505
Inst_Staff_Support  Student_Support       0.413900
Student_Support     Inst_Staff_Support    0.413900
Emp_Benefits        Inst_Staff_Support    0.488021
Inst_Staff_Support  Emp_Benefits          0.488021
Avg_Math_Score      Salaries              0.602606
Salaries            Avg_Math_Score        0.602606
                    Avg_English_Score     0.627317
Avg_English_Score   Salaries              0.627317
Student_Support     Emp_Benefits          0.675914
Emp_Benefits        Student_Support       0.675914
Student_Support     Salaries              0.704167
Salaries            Student_Support       0.704167
                    Emp_Benefits          0.773999
Emp_Benefits        Salaries              0.773999
State_Debt          State_Revenue         0.880598
State_Revenue       State_Debt            0.880598
Avg_Math_Score      Avg_English_Score     0.889285
Avg_English_Score   Avg_Math_Score        0.889285
Total_Enrollment    State_Debt            0.931701
State_Debt          Total_Enrollment      0.931701
Total_Enrollment    State_Revenue         0.939387
State_Revenue       Total_Enrollment      0.939387
Avg_Math_Score      Avg_Math_Score        1.000000
State_Revenue       State_Revenue         1.000000
Emp_Benefits        Emp_Benefits          1.000000
Salaries            Salaries              1.000000
State_Debt          State_Debt            1.000000
Total_Enrollment    Total_Enrollment      1.000000
Avg_English_Score   Avg_English_Score     1.000000
Student_Support     Student_Support       1.000000
Inst_Staff_Support  Inst_Staff_Support    1.000000
dtype: float64
```

State_Debt is Highly Positively Correlated with Total_Enrollment

State_Revenue is Highly Positively Correlated with Total_Enrollment

Total_Enrollment,State_Dept and State_Revenue are weakly correlated to Avg_Math_Score.

Therefore two of the above three variable can be dropped

Employy_Benefits is Highly Positively Correlated with Salary

Salaries is Highly Positively Correlated with Student_Support

In [330…
```
plt.figure(figsize=(10,4))
ScoreData.corr()['Avg_Math_Score'].sort_values(ascending = False).plot(kind='bar')
```

Out[330…
```
<AxesSubplot:>
```

Therefore Marked for Dropping are:

State Revenue, State Depth

Step 5: Missing Data Analysis

In [331…
```
missing = pd.DataFrame((ScoreData.isnull().sum())*100/ScoreData.shape[0]).reset_index()
plt.figure(figsize=(16,5))
ax = sns.pointplot('index',0,data=missing)
plt.xticks(rotation =90,fontsize =15)
plt.title("Percentage of Missing values")
plt.ylabel("PERCENTAGE")
plt.show()
```

Good News, No missing data found

Step 7: Finding Skewness in Data

We will draw boxplot - Kurtosis and skewness. Normal probability plot - Data distribution should closely follow the diagonal that represents the normal distribution.

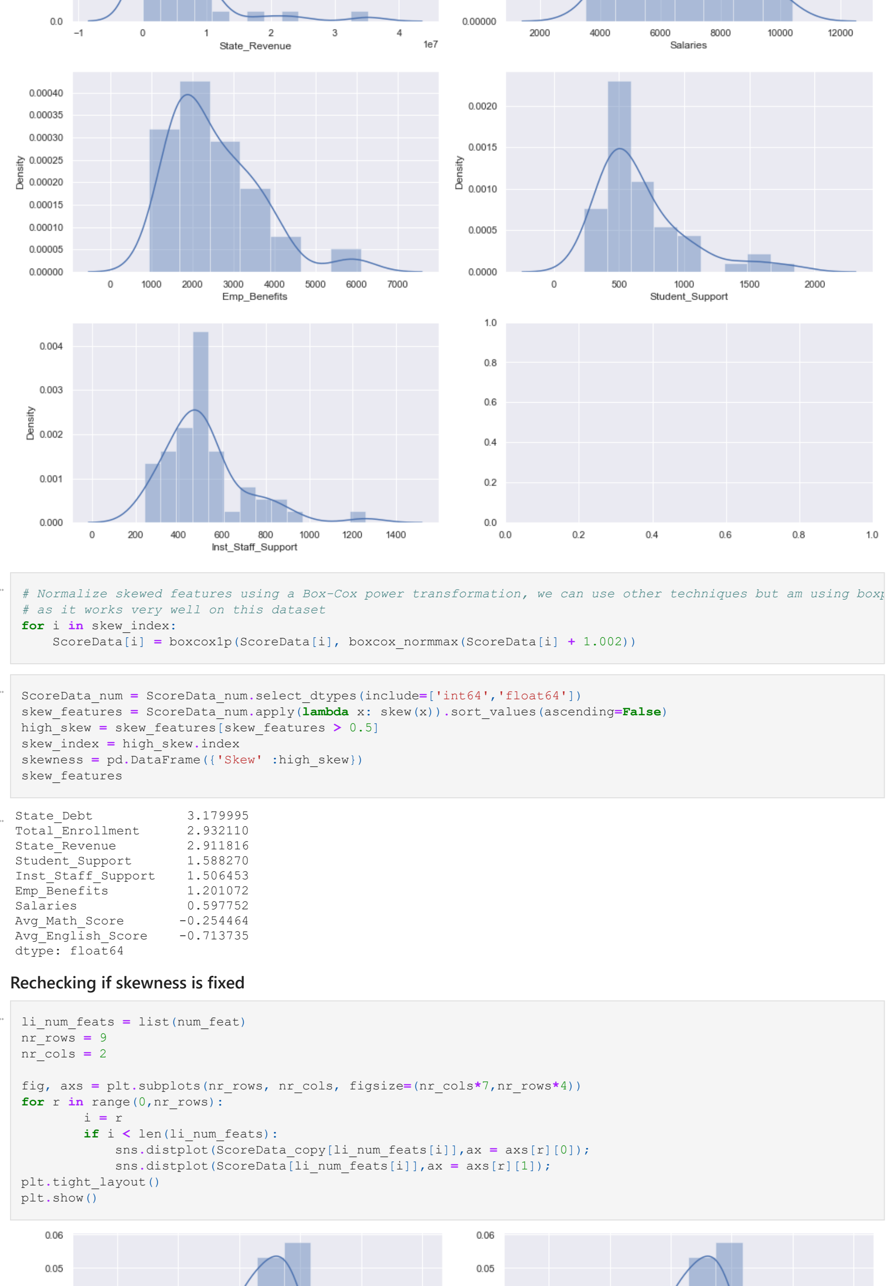
In [332…
```
from scipy.stats import skew,boxcox_normmax
from scipy.special import boxcox1p
ScoreData_num = ScoreData_num.select_dtypes(include=['int64','float64'])
skew_features = ScoreData_num.apply(lambda x: skew(x)).sort_values(ascending=False)
high_skew = skew_features[skew_features > 0.5]
skew_index = high_skew.index
skewness = pd.DataFrame({'Skew' :high_skew})
skew_features
```

Out[332…
```
State_Debt            3.179995
Total_Enrollment      2.932110
State_Revenue         2.911816
Student_Support       1.588270
Inst_Staff_Support    1.506453
Emp_Benefits          1.201072
Salaries              0.597752
Avg_Math_Score       -0.254464
Avg_English_Score    -0.713735
dtype: float64
```

In [333…
```
num_feat=ScoreData.select_dtypes(exclude=['object']).columns
li_num_feats = list(ScoreData_num)
nr_rows = 5
nr_cols = 2

ScoreData_copy=ScoreData.copy()

fig, axs = plt.subplots(nr_rows, nr_cols, figsize=(nr_cols*7,nr_rows*4))
for r in range(0,nr_rows):
    for c in range(0,nr_cols):
        i = r*nr_cols+c
        if i < len(li_num_feats):
            sns.distplot(ScoreData[li_num_feats[i]],ax = axs[r][c]);
plt.tight_layout()
plt.show()
```



In [334…
```
# Normalize skewed features using a Box-Cox power transformation, we can use other techniques but am using boxp
# as it works very well on this dataset
for i in skew_index:
    ScoreData[i] = boxcox1p(ScoreData[i], boxcox_normmax(ScoreData[i] + 1.002))
```

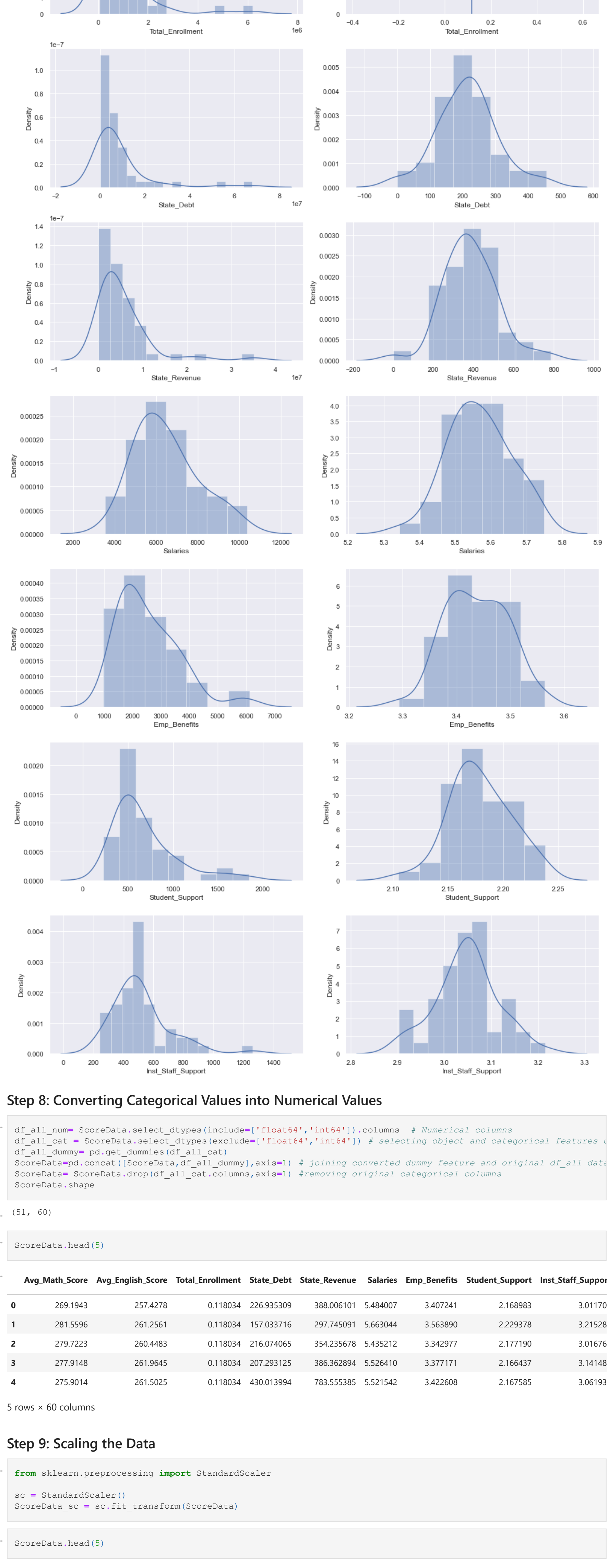
In [335…
```
ScoreData_num = ScoreData_num.select_dtypes(include=['int64','float64'])
skew_features = ScoreData_num.apply(lambda x: skew(x)).sort_values(ascending=False)
high_skew = skew_features[skew_features > 0.5]
skew_index = high_skew.index
skewness = pd.DataFrame({'Skew' :high_skew})
skew_features
```

Out[335…
```
State_Debt            3.179995
Total_Enrollment      2.932110
State_Revenue         2.911816
Student_Support       1.588270
Inst_Staff_Support    1.506453
Emp_Benefits          1.201072
Salaries              0.597752
Avg_Math_Score       -0.254464
Avg_English_Score    -0.713735
dtype: float64
```

Rechecking if skewness is fixed

In [336…
```
li_num_feats = list(num_feat)
nr_rows = 9
nr_cols = 2

fig, axs = plt.subplots(nr_rows, nr_cols, figsize=(nr_cols*7,nr_rows*4))
for r in range(0,nr_rows):
        i = r
        if i < len(li_num_feats):
            sns.distplot(ScoreData_copy[li_num_feats[i]],ax = axs[r][0]);
            sns.distplot(ScoreData[li_num_feats[i]],ax = axs[r][1]);
plt.tight_layout()
plt.show()
```



Step 8: Converting Categorical Values into Numerical Values

In [337…
```
df_all_num= ScoreData.select_dtypes(include=['float64','int64']).columns  # Numerical columns
df_all_cat = ScoreData.select_dtypes(exclude=['float64','int64']) # selecting object and categorical features o
df_all_dummy= pd.get_dummies(df_all_cat)
ScoreData=pd.concat([ScoreData,df_all_dummy],axis=1) # joining converted dummy feature and original df_all data
ScoreData= ScoreData.drop(df_all_cat.columns,axis=1) #removing original categorical columns
ScoreData.shape
```

Out[337…
```
(51, 60)
```

In [338…
```
ScoreData.head(5)
```

Out[338…

	Avg_Math_Score	Avg_English_Score	Total_Enrollment	State_Debt	State_Revenue	Salaries	Emp_Benefits	Student_Support	Inst_Staff_Suppor
0	269.1943	257.4278	0.118034	226.935309	388.006101	5.484007	3.407241	2.168983	3.01170
1	281.5596	261.2561	0.118034	157.033716	297.745091	5.663044	3.563890	2.229378	3.21528
2	279.7223	260.4483	0.118034	216.074065	354.235678	5.435212	3.342977	2.177190	3.01676
3	277.9148	261.9645	0.118034	207.293125	386.362894	5.526410	3.377171	2.166437	3.14148
4	275.9014	261.5025	0.118034	430.013994	783.555385	5.521542	3.422608	2.167585	3.06193

5 rows × 60 columns

Step 9: Scaling the Data

In [339…
```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
ScoreData_sc = sc.fit_transform(ScoreData)
```

In [340…
```
ScoreData.head(5)
```

Out[340…

	Avg_Math_Score	Avg_English_Score	Total_Enrollment	State_Debt	State_Revenue	Salaries	Emp_Benefits	Student_Support	Inst_Staff_Suppor
0	269.1943	257.4278	0.118034	226.935309	388.006101	5.484007	3.407241	2.168983	3.01170
1	281.5596	261.2561	0.118034	157.033716	297.745091	5.663044	3.563890	2.229378	3.21528
2	279.7223	260.4483	0.118034	216.074065	354.235678	5.435212	3.342977	2.177190	3.01676
3	277.9148	261.9645	0.118034	207.293125	386.362894	5.526410	3.377171	2.166437	3.14148
4	275.9014	261.5025	0.118034	430.013994	783.555385	5.521542	3.422608	2.167585	3.06193

5 rows × 60 columns

Step 10: Training Models on this data.

We will test simple sklearn models and compare by metrics

We test the following Regressors from scikit-learn:

LinearRegression

In [341…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData.drop(['Avg_Math_Score','Avg_English_Score'],axis=1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=42)
model = LinearRegression().fit(x_train, y_train)
r_sq = model.score(x_train, y_train)
print('coefficient of determination training:', r_sq)
r_sq = model.score(x_test, y_test)
print('coefficient of determination testing:', r_sq)
```

```
coefficient of determination training: 1.0
coefficient of determination testing: -0.07755520757453449
```

In [342…

```
coeff_df = pd.DataFrame(model.coef_, x.columns, columns=['Coefficient'])
coeff_df
```

Out[342…

	Coefficient
Total_Enrollment	-0.170770
State_Debt	0.011005
State_Revenue	-0.010249
Salaries	7.606103
Emp_Benefits	1.517856
Student_Support	0.823267
Inst_Staff_Support	1.817843
State_Alabama	-15.091717
State_Alaska	-4.901563
State_Arizona	-4.337565
State_Arkansas	-0.000096
State_California	-0.000417
State_Colorado	4.793808
State_Connecticut	-0.000615
State_Delaware	-3.272969
State_District of Columbia	-0.000465
State_Florida	-2.935744
State_Georgia	-4.930674
State_Hawaii	-2.033930
State_Idaho	-0.000214
State_Illinois	-0.000457
State_Indiana	3.585774
State_Iowa	-0.069170
State_Kansas	4.250715
State_Kentucky	-0.000440
State_Louisiana	-12.128351
State_Maine	2.679472
State_Maryland	1.370202
State_Massachusetts	14.967232
State_Michigan	-4.416959
State_Minnesota	9.498649
State_Mississippi	-0.000018
State_Missouri	-1.892877
State_Montana	3.918158
State_Nebraska	-0.765796
State_Nevada	-6.414091
State_New Hampshire	9.592803
State_New Jersey	0.000000
State_New Mexico	0.000000
State_New York	0.000000
State_North Carolina	2.072648
State_North Dakota	4.745532
State_Ohio	4.888019
State_Oklahoma	0.000000
State_Oregon	-1.270887
State_Pennsylvania	3.784013
State_Rhode Island	-2.635013
State_South Carolina	0.000000
State_South Dakota	2.042535
State_Tennessee	-6.630785
State_Texas	0.000000
State_Utah	0.552916
State_Vermont	9.230271
State_Virginia	0.000000
State_Washington	0.000000
State_West Virginia	-10.116302
State_Wisconsin	0.000000
State_Wyoming	1.868936

Model is getting Overfit

Dropping some Redundant Columns we earlier marked for deletion can trying to fit model again

In [378…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Salaries','Emp_Benefits','Student_Support','Inst_Staff_Support']]
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.27, random_state=42)
model = LinearRegression().fit(x_train, y_train)
r_sq = model.score(x_train, y_train)
print('coefficient of determination during training:', r_sq)
r_sq = model.score(x_test, y_test)
print('coefficient of determination during testing:', r_sq)
y_pred=model.predict(x_test)
print('Mean Absolute error during testing:',mean_absolute_error(y_test, y_pred))
```

```
coefficient of determination during training: 0.4025648056104084
coefficient of determination during testing: 0.43462324599957924
Mean Absolute error during testing: 5.005719973499936
```

In [379…

```
coeff_df = pd.DataFrame(model.coef_, x.columns, columns=['Coefficient'])
coeff_df
```

Out[379…

	Coefficient
Salaries	83.043883
Emp_Benefits	-53.155303
Student_Support	-20.328592
Inst_Staff_Support	-11.215740

Due to less data this might not be good fit, but as per this, the linear regression equation will be

Avg_Math_Score = 83(Salaries) -53(Emp_Benefits) -20(Student_Support)-11(Inst_Staff_Support)

Interpreting Permutation Importances The values towards the top are the most important features, and those towards the bottom matter least.

The first number in each row shows how much model performance decreased with a random shuffling (in this case, using "accuracy" as the performance metric).

Like most things in data science, there is some randomness to the exact performance change from a shuffling a column. We measure the amount of randomness in our permutation importance calculation by repeating the process with multiple shuffles. The number after the ± measures how performance varied from one-reshuffling to the next.

You'll occasionally see negative values for permutation importances. In those cases, the predictions on the shuffled (or noisy) data happened to be more accurate than the real data. This happens when the feature didn't matter (should have had an importance close to 0), but random chance caused the predictions on shuffled data to be more accurate. This is more common with small datasets, like the one in this example, because there is more room for luck/chance.

In our example, the most important feature was Salaries. That seems sensible

In [380…

```
perm = PermutationImportance(model, random_state=1).fit(x_train, y_train)
eli5.show_weights(perm, feature_names = x_train.columns.tolist())
```

Out[380…

Weight	Feature
1.8590 ± 0.8542	Salaries
0.3873 ± 0.2155	Emp_Benefits
0.0346 ± 0.0420	Inst_Staff_Support
0.0180 ± 0.0239	Student_Support

In [381…

```
model = Ridge(alpha=1e-2).fit(x_train, y_train)
model.score(x_test, y_test)

perm = PermutationImportance(model, random_state=1).fit(x_train, y_train)
eli5.show_weights(perm, feature_names = x_train.columns.tolist())
```

Out[381…

Weight	Feature
1.3267 ± 0.6398	Salaries
0.2076 ± 0.1325	Emp_Benefits
0.0278 ± 0.0332	Inst_Staff_Support
0.0103 ± 0.0166	Student_Support

According to the concept of permutation Feature the following is order of imponce of feature

1. Salaries
2. Emp_Benefits
3. Inst_Staff_Support
4. Student_Support

Finding Feature Importance by adding Feature one by one and Checking r2 score

In [382…

```
initial_r_sq=0
def linearregrun(x,y) :
    global initial_r_sq
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
    model = LinearRegression().fit(x_train, y_train)
    r_sq = model.score(x_train, y_train)
    print('coefficient of determination during training:', r_sq)
    r_sq = model.score(x_test, y_test)
    print('coefficient of determination during testing:', r_sq)
    y_pred=model.predict(x_test)
    print('Mean Absolute error during testing:',mean_absolute_error(y_test, y_pred))
    if initial_r_sq!=0:
      print('Percentage Improvement in r2 square ',(r_sq-initial_r_sq)*100/initial_r_sq)
    initial_r_sq=r_sq
```

Using Only Inst_Staff_Support

In [383…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Inst_Staff_Support']]
linearregrun(x,y)
```

```
coefficient of determination during training: 0.006627860444701872
coefficient of determination during testing: -0.016407464472375954
Mean Absolute error during testing: 5.797814639019603
```

Using Only Inst_Staff_Support and Emp_Benefits

In [384…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Inst_Staff_Support','Emp_Benefits']]
linearregrun(x,y)
```

```
coefficient of determination during training: 0.09332896800014145
coefficient of determination during testing: -0.003961804123792545
Mean Absolute error during testing: 6.0084224583251595
Percentage Improvement in r2 square  -75.85364801208166
```

In [385…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Inst_Staff_Support','Emp_Benefits','Student_Support']]
linearregrun(x,y)
```

```
coefficient of determination during training: 0.11475761164340914
coefficient of determination during testing: 0.011073088839129164
Mean Absolute error during testing: 5.909161721995986
Percentage Improvement in r2 square  -379.496120785728
```

In [386…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Inst_Staff_Support','Emp_Benefits','Student_Support','Salaries']]
linearregrun(x,y)
```

```
coefficient of determination during training: 0.46461423428855964
coefficient of determination during testing: 0.27270492811177816
Mean Absolute error during testing: 4.823957267797926
Percentage Improvement in r2 square  2362.771969715587
```

In [387…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Inst_Staff_Support','Emp_Benefits','Student_Support','Salaries','Total_Enrollment']]
linearregrun(x,y)
```

```
coefficient of determination during training: 0.4646142342885611
coefficient of determination during testing: 0.27270492811177804
Mean Absolute error during testing: 4.823957267797916
Percentage Improvement in r2 square  -4.071151307431052e-14
```

In [388…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Inst_Staff_Support','Emp_Benefits','Student_Support','Salaries','State_Debt']]
linearregrun(x,y)
```

```
coefficient of determination during training: 0.47619189473874457
coefficient of determination during testing: 0.23494984354169723
Mean Absolute error during testing: 5.096402360341312
Percentage Improvement in r2 square  -13.844665306013654
```

In [354…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Inst_Staff_Support','Emp_Benefits','Student_Support','Salaries','State_Revenue']]
linearregrun(x,y)
```

```
coefficient of determination during training: 0.46570490543070786
coefficient of determination during testing: 0.2666569509848099
Mean Absolute error during testing: 4.830097775028445
Percentage Improvement in r2 square  13.495266464174307
```

In [355…

```
ScoreData['Total_Benefit']=ScoreData['Emp_Benefits']+ScoreData['Salaries']
```

In [389…

```
y=ScoreData['Avg_Math_Score']
x=ScoreData[['Inst_Staff_Support','Student_Support','Total_Benefit']]
linearregrun(x,y)
```

```
coefficient of determination during training: 0.30722784609259013
coefficient of determination during testing: 0.17115263778109346
Mean Absolute error during testing: 4.838842276518836
Percentage Improvement in r2 square  -27.15354255993854
```

Using Different Methods of relating 'Inst_Staff_Support','Emp_Benefits','Student_Support','Salaries' to Avg_Math_Score, I observed that:

1) Salaries is highest positively Correlared to Avg_Math_Score which means increase in salaries increase the Avg_Math_Score most.

2) When Tried to create a equation relating all 4 budget sections to the Avg_Math_Score, using linear regression fit, I arrived at equation

Avg_Math_Score = 83(Salaries) -53(Emp_Benefits) -20(Student_Support)-11(Inst_Staff_Support)

This equation also says increasing salary will increase Avg Math score the most while increase in other variables as per this equation won't necessarily increase salary.

3) Using the concept of Permutation Importance, when we tried to put random shuffled variable in place of each column and checked if output is affected, the output was effected most by Salaries establishing the importance of salaries.

4) Method of estimating importance of features by adding features one by one and checking if r2 score increases also shows an improvement of 2000% when salary column gets added in feature slit.

Therefore, An increase in Salaries is most likely to cause highest increase in the average Math score of the students, therefore If I am given 1000 dollars, I will invest that in salaries