2) The dataset Education - Post 12th Standard.csv is a dataset that contains the names of various colleges. This particular case study is based on various parameters of various institutions. You are expected to do Principal Component Analysis for this case study according to the instructions given in the following rubric. The data dictionary of the 'Education - Post 12th Standard.csv' can be found in the following file: Data Dictionary.xlsx

Step 1 - import all the necessary libraries that we think we will requiring to perform the EDA.

Step 2 - Loading the data set

Excel file using pandas and read_excel file.

Step 3 - Basic Data Exploration

In this step, we will perform the below operations to check what the data set comprises of. We will check the below things:

- **head of the dataset**
- **shape of the dataset**
- **info of the dataset**
- **summary of the dataset**

head function will tell you the top records in the data set. By default python shows you only top 5 records.

Shape attribute tells us number of observations and variables we have in the data set. It is used to check the dimension of data. The cars data set has 777 observations and 18 variables in the data set.

info() is used to check the Information about the data and the datatypes of each respective attributes.And it shows no null values *

The describe method will help to see how data has been spread for the numerical values. We can clearly see the minimum value, mean values, different percentile values and maximum values.

Step 4 - Check for Duplicate records

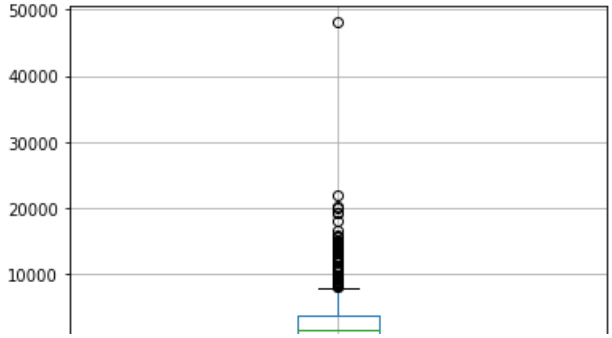
Since we have 0 duplicate records in the data, no need to remove the duplicates.Duplicate records are found using dups()

Step 5 - Outlier Treatment

To check for outliers, we will be plotting the box plots.

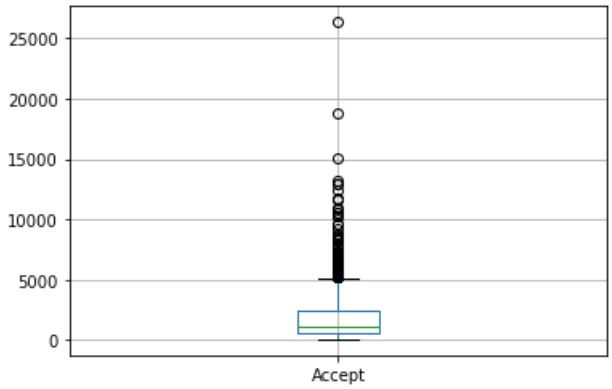
In [27]:

```
df.boxplot(column=['Apps'])
plt.show()
```



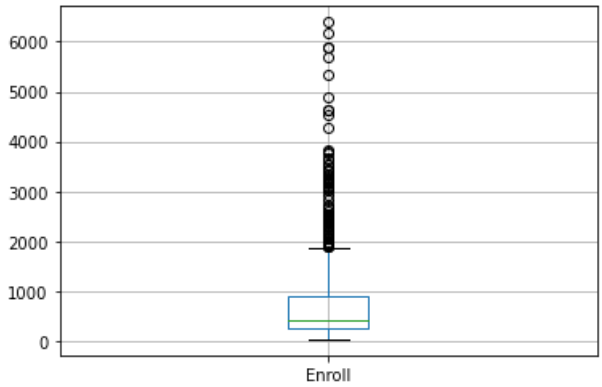
In [28]:

```
df.boxplot(column=['Accept'])
plt.show()
```



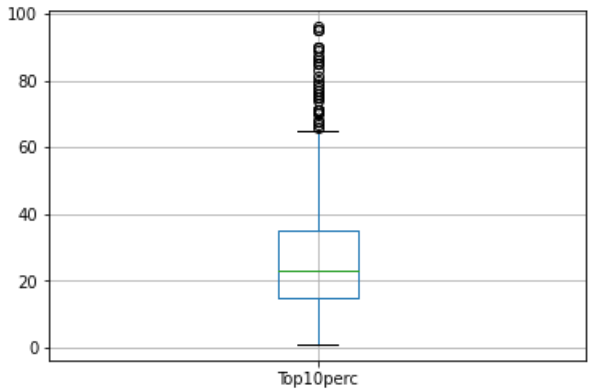
In [29]:

```
df.boxplot(column=['Enroll'])
plt.show()
```



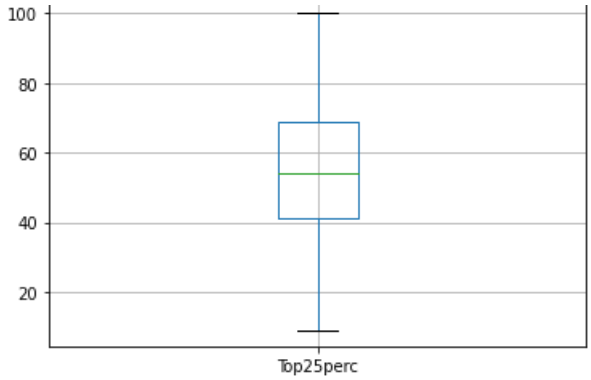
In [30]:

```
df.boxplot(column=['Top10perc'])
plt.show()
```



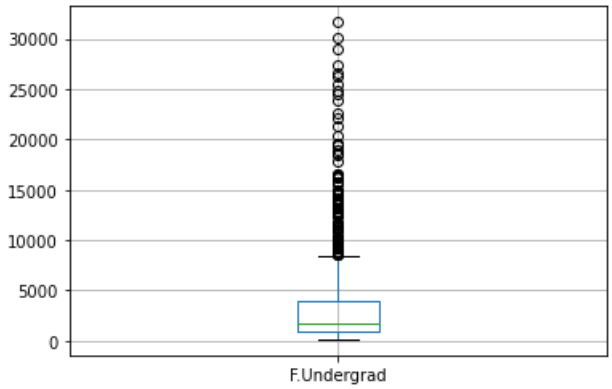
In [31]:

```
df.boxplot(column=['Top25perc'])
plt.show()
```



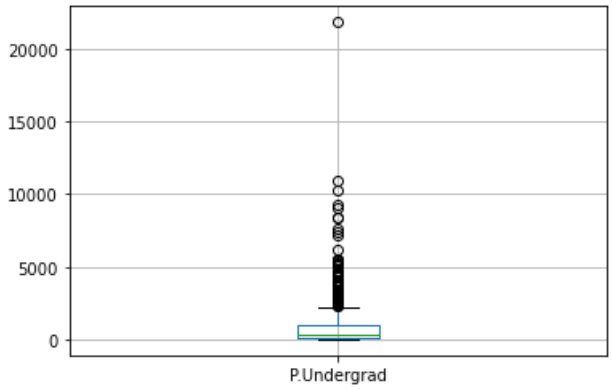
In [32]:

```
df.boxplot(column=['F.Undergrad'])
plt.show()
```



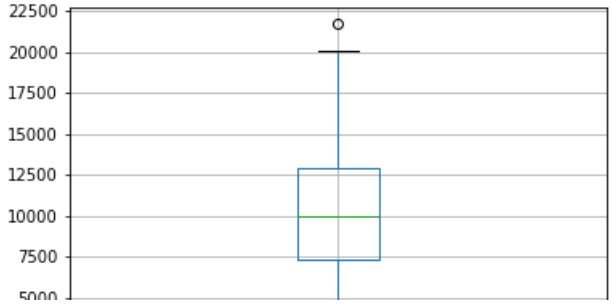
In [33]:

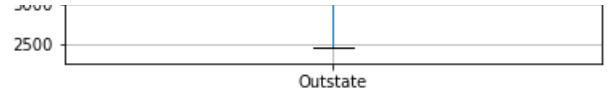
```
df.boxplot(column=['P.Undergrad'])
plt.show()
```



In [34]:

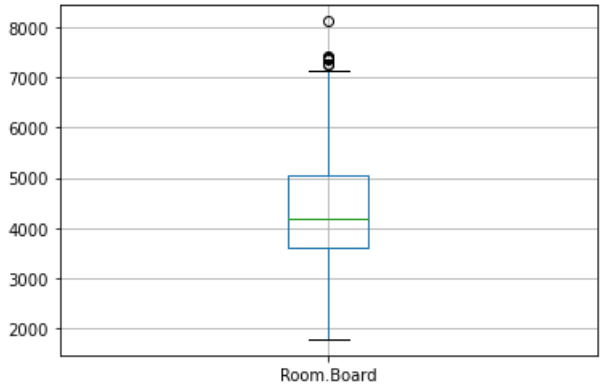
```
df.boxplot(column=['Outstate'])
plt.show()
```





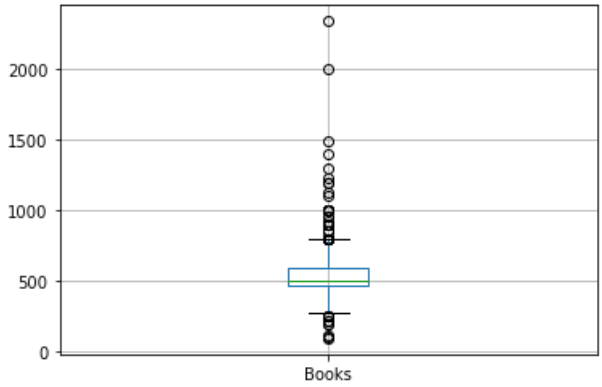
In [35]:

```
df.boxplot(column=['Room.Board'])
plt.show()
```



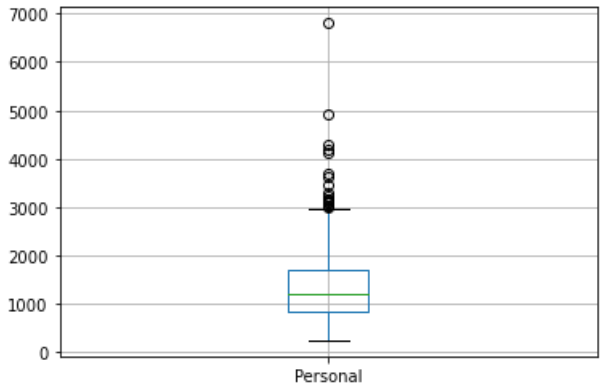
In [36]:

```
df.boxplot(column=['Books'])
plt.show()
```



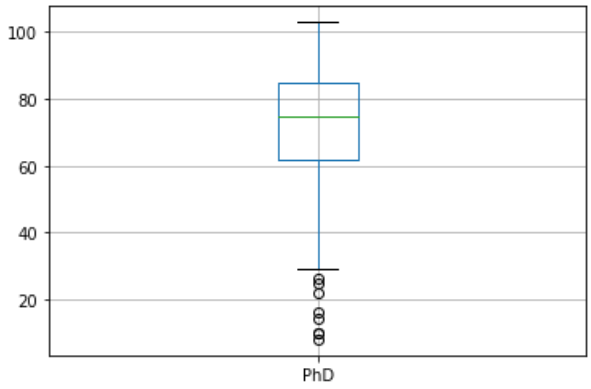
In [37]:

```
df.boxplot(column=['Personal'])
plt.show()
```



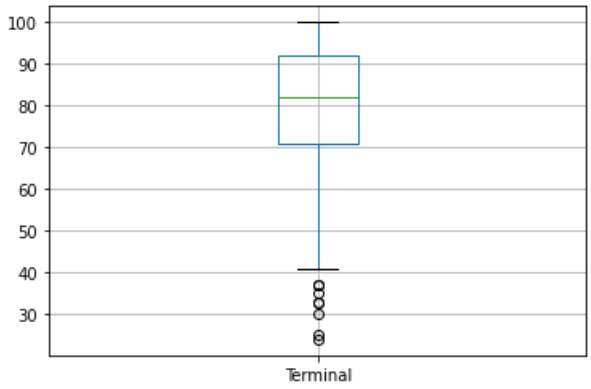
In [38]:

```
df.boxplot(column=['PhD'])
plt.show()
```



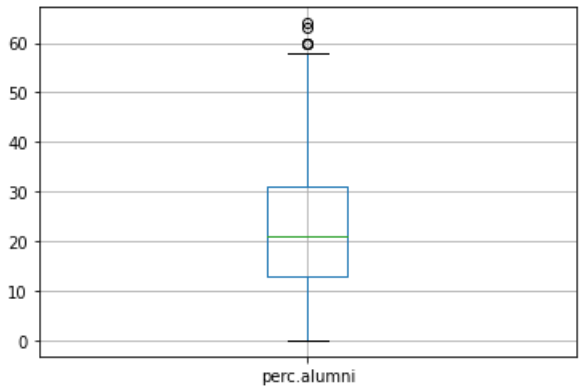
In [39]:

```
df.boxplot(column=['Terminal'])
plt.show()
```



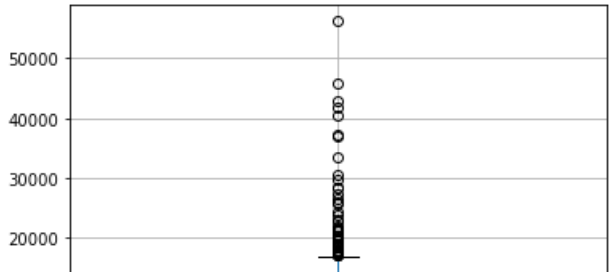
In [40]:

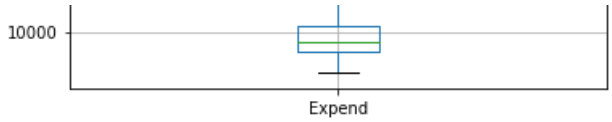
```
df.boxplot(column=['perc.alumni'])
plt.show()
```



In [41]:

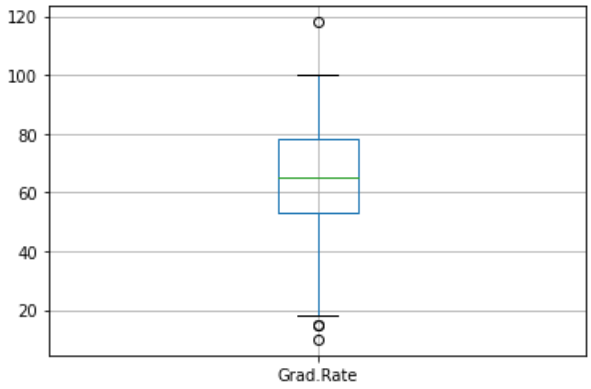
```
df.boxplot(column=['Expend'])
plt.show()
```





In [42]:

```
df.boxplot(column=['Grad.Rate'])
plt.show()
```



Looking at the box plot, it seems that all the variables are having outliers except for Top25perc and Outstate.

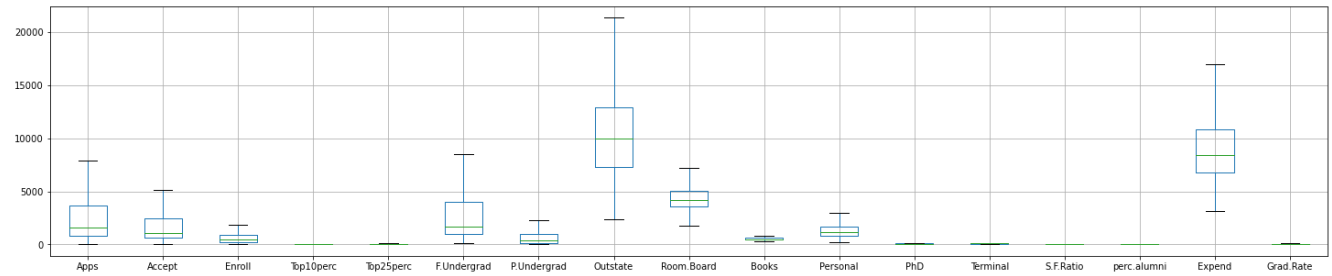
These outliers value needs to be teated and there are several ways of treating them:

- **Drop the outlier value**
- **Replace the outlier value using the IQR**

Created a user definded function for finding the lower and upper range for a variable so that outlier can be treated.

In [357]:

```
plt.figure(figsize=(25,5))
df.boxplot()
plt.show()
```



box plots above,post treating the outlier there are no outliers in all these columns.

Step 6 - Check for missing value

Using isnull() funtion and found no null values

2.1) Perform Exploratory Data Analysis [both univariate and multivariate analysis to be performed]. The inferences drawn from this should be properly documented.

Univariate Analysis

Univariate Analysis is done on all the variables

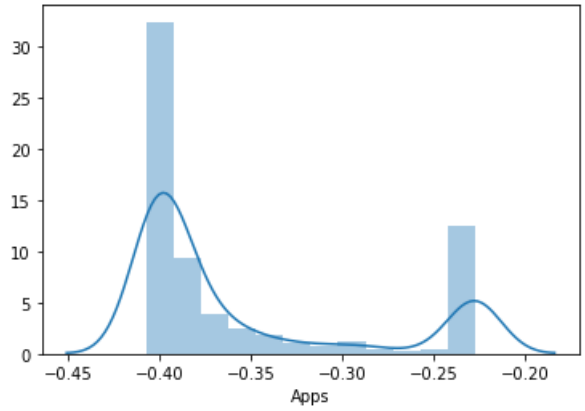
Number of application recieved

In [270]:

```
sns.distplot(df["Apps"])
```

Out[270]:

```
<AxesSubplot:xlabel='Apps'>
```



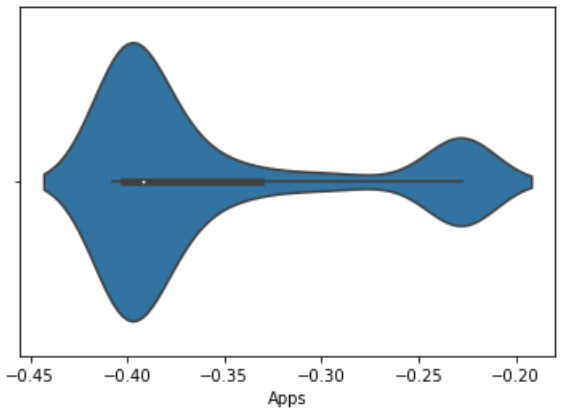
From above figure, we can say that the Apps parameter is highly right skewed

In [271]:

```
sns.violinplot(df['Apps'])
```

Out[271]:

```
<AxesSubplot:xlabel='Apps'>
```



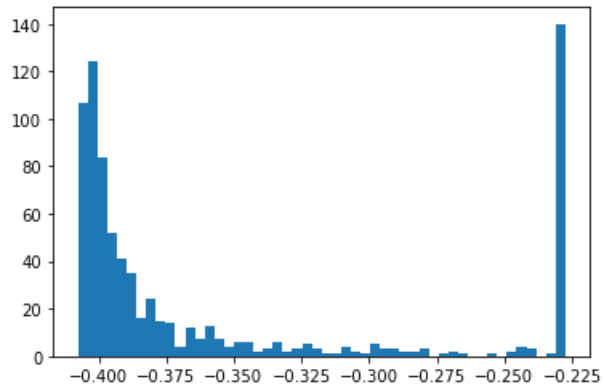
In [272]:

```
plt.hist(df['Apps'], bins=50)
```

Out[272]:

```
(array([107., 124.,  84.,  52.,  41.,  35.,  16.,  24.,  15.,  14.,   4.,
         12.,   7.,  13.,   7.,   4.,   6.,   6.,   2.,   3.,   6.,   2.,
          3.,   5.,   3.,   1.,   1.,   4.,   2.,   1.,   5.,   3.,   3.,
          2.,   2.,   3.,   0.,   1.,   2.,   1.,   0.,   0.,   1.,   0.,
          2.,   4.,   3.,   0.,   1., 140.]),
 array([-0.40768319, -0.40407832, -0.40047345, -0.39686858, -0.39326371,
        -0.38965883, -0.38605396, -0.38244909, -0.37884422, -0.37523935,
        -0.37163447, -0.3680296 , -0.36442473, -0.36081986, -0.35721499,
        -0.35361011, -0.35000524, -0.34640037, -0.3427955 , -0.33919063,
        -0.33558576, -0.33198088, -0.32837601, -0.32477114, -0.32116627,
        -0.3175614 , -0.31395652, -0.31035165, -0.30674678, -0.30314191,
        -0.29953704, -0.29593217, -0.29232729, -0.28872242, -0.28511755,
        -0.28151268, -0.27790781, -0.27430293, -0.27069806, -0.26709319,
```

```
        -0.26348832, -0.25988345, -0.25627857, -0.2526737 , -0.24906883,
        -0.24546396, -0.24185909, -0.23825422, -0.23464934, -0.23104447,
        -0.2274396 ]),
 <BarContainer object of 50 artists>)
```

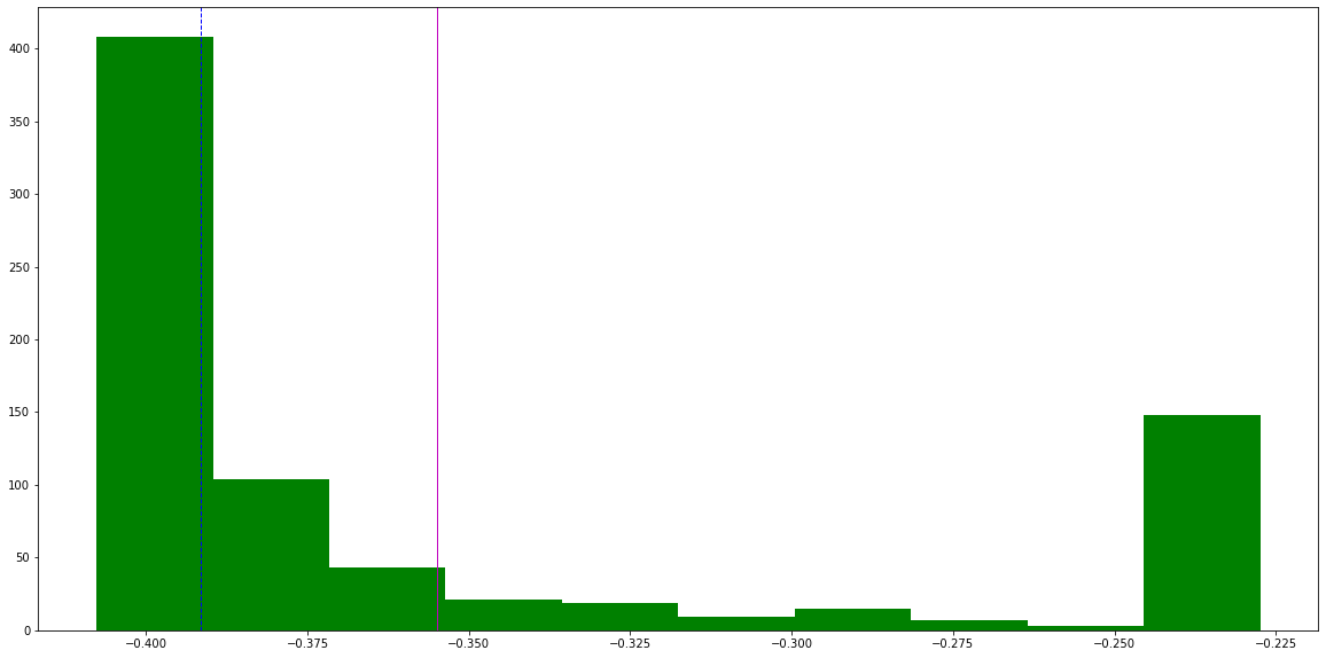


In [273]:

```
plt.figure(figsize=(20,10))
plt.hist(df["Apps"], color='g')
plt.axvline(df['Apps'].mean(), color='m', linewidth=1)
plt.axvline(df['Apps'].median(), color='b', linestyle='dashed', linewidth=1)
plt.axvline(df['Apps'].mode()[0], color='w', linestyle='dashed', linewidth=1)
```

Out[273]:

```
<matplotlib.lines.Line2D at 0x2223fb3a670>
```



In the above histogram the first bin with class limits (1041.26, 6802.82) has the most number of observations. A bulk of the observations lie within the first 2 classes. The rest of the 3 classes contain only a very few observations. In this case we are measuring various parameters. We can say based on visual observation that most of the parameters present on the data are less than 10000.

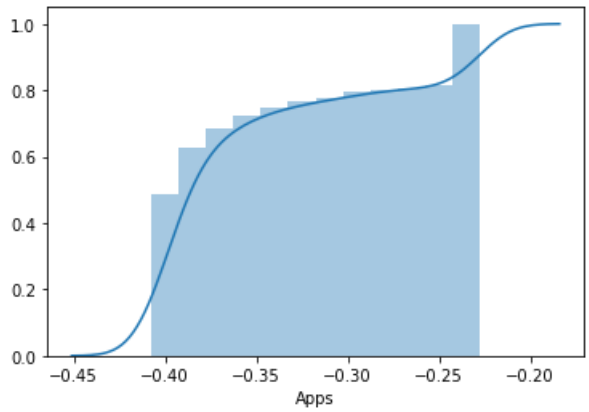
Cumulative distribution

In [274]:

```
sns.distplot(df['Apps'], hist_kws=dict(cumulative=True), kde_kws=dict(cumulative=True))
```

Out[274]:

```
<AxesSubplot:xlabel='Apps'>
```



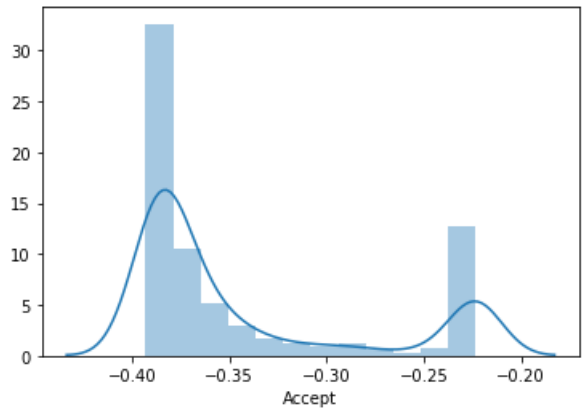
Number of application accepted

In [275]:

```
sns.distplot(df["Accept"])
```

Out[275]:

```
<AxesSubplot:xlabel='Accept'>
```



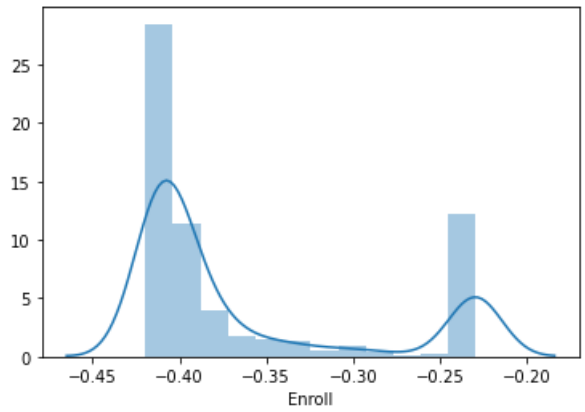
Number of new students enrolled

In [276]:

```
sns.distplot(df["Enroll"])
```

Out[276]:

```
<AxesSubplot:xlabel='Enroll'>
```



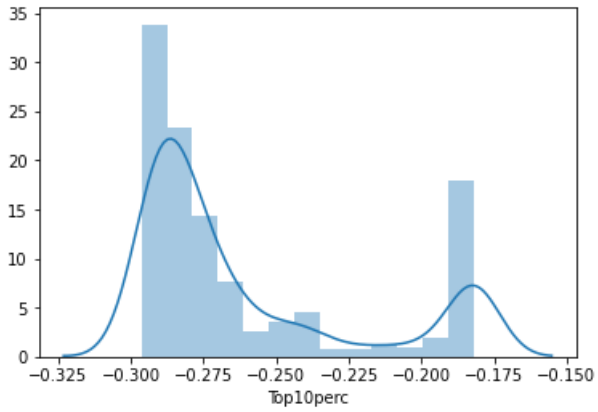
Percentage of new students from top 10% of Higher Secondary class

In [277]:

```
sns.distplot(df["Top10perc"])
```

Out[277]:

```
<AxesSubplot:xlabel='Top10perc'>
```



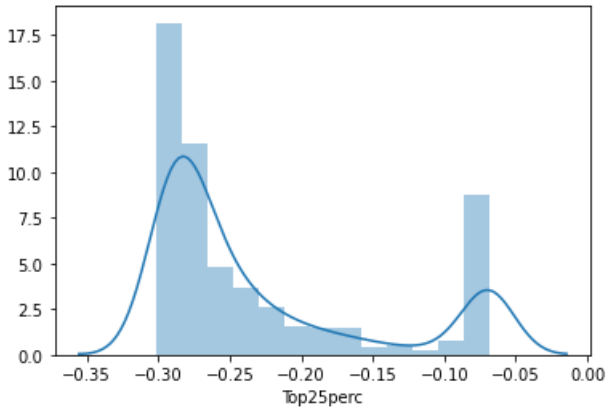
Percentage of new students from top 25% of Higher Secondary class

In [278]:

```
sns.distplot(df["Top25perc"])
```

Out[278]:

```
<AxesSubplot:xlabel='Top25perc'>
```



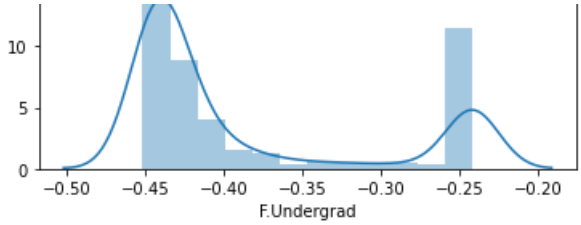
Number of full-time undergraduate students

In [279]:

```
sns.distplot(df["F.Undergrad"])
```

Out[279]:

```
<AxesSubplot:xlabel='F.Undergrad'>
```



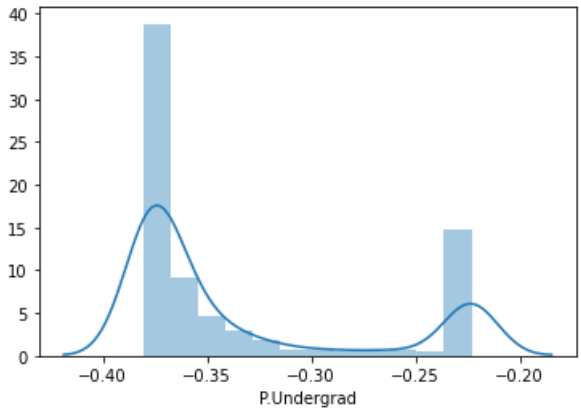
Number of part-time undergraduate students

In [280]:

```
sns.distplot(df["P.Undergrad"])
```

Out[280]:

```
<AxesSubplot:xlabel='P.Undergrad'>
```



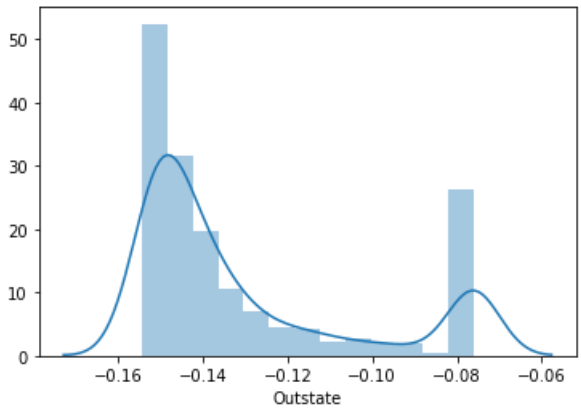
Number of students for whom the particular college or university is Out-of-state tuition

In [281]:

```
sns.distplot(df["Outstate"])
```

Out[281]:

```
<AxesSubplot:xlabel='Outstate'>
```



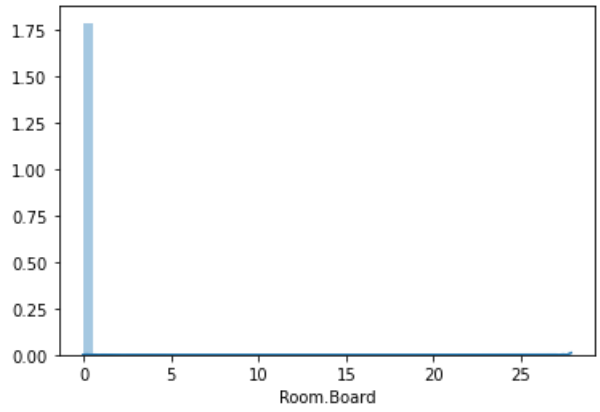
Cost of Room and board

In [282]:

```
sns.distplot(df["Room.Board"])
```

Out[282]:

```
<AxesSubplot:xlabel='Room.Board'>
```



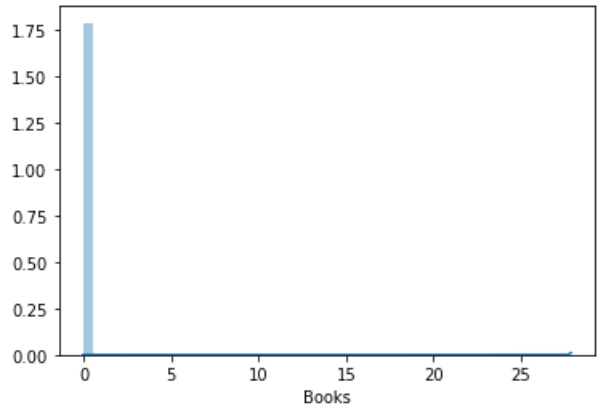
Estimated book costs for a student

In [283]:

```
sns.distplot(df["Books"])
```

Out[283]:

```
<AxesSubplot:xlabel='Books'>
```



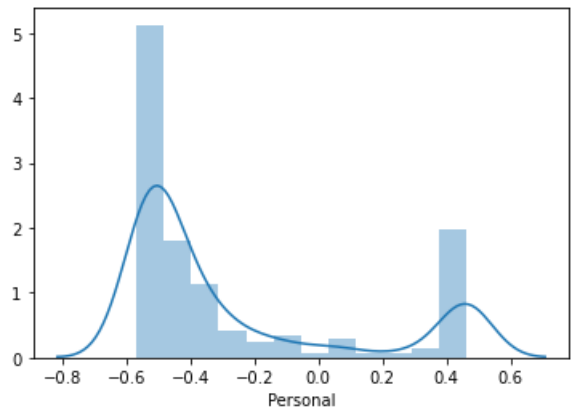
Estimated personal spending for a student

In [284]:

```
sns.distplot(df["Personal"])
```

Out[284]:

```
<AxesSubplot:xlabel='Personal'>
```



Percentage of faculties with Ph.D.'s

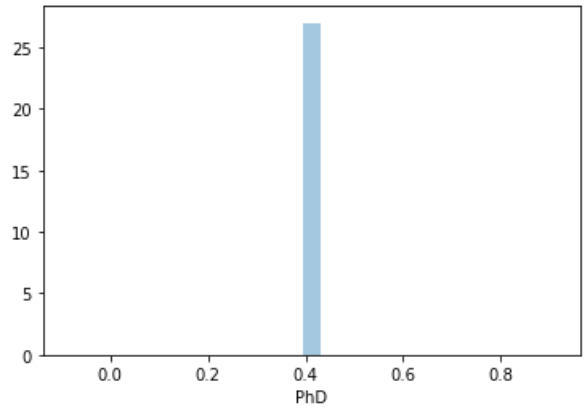
In [285]:

```
sns.distplot(df["PhD"])
```

```
C:\Users\Admin\anaconda4\lib\site-packages\seaborn\distributions.py:369: UserWarning: Default
bandwidth for data is 0; skipping density estimation.
  warnings.warn(msg, UserWarning)
```

Out[285]:

```
<AxesSubplot:xlabel='PhD'>
```



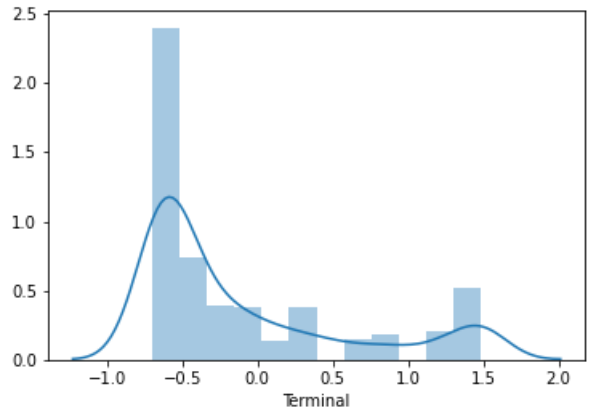
Percentage of faculties with terminal degree

In [286]:

```
sns.distplot(df["Terminal"])
```

Out[286]:

```
<AxesSubplot:xlabel='Terminal'>
```



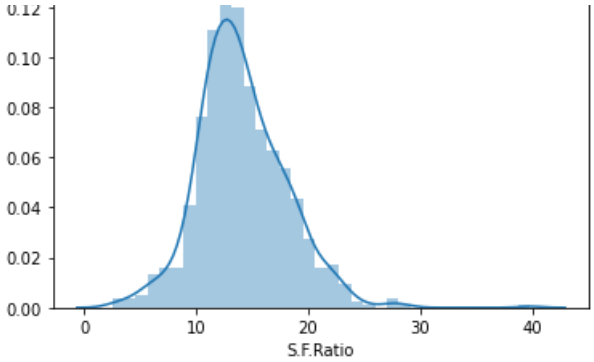
Student/faculty ratio

In [287]:

```
sns.distplot(df["S.F.Ratio"])
```

Out[287]:

```
<AxesSubplot:xlabel='S.F.Ratio'>
```



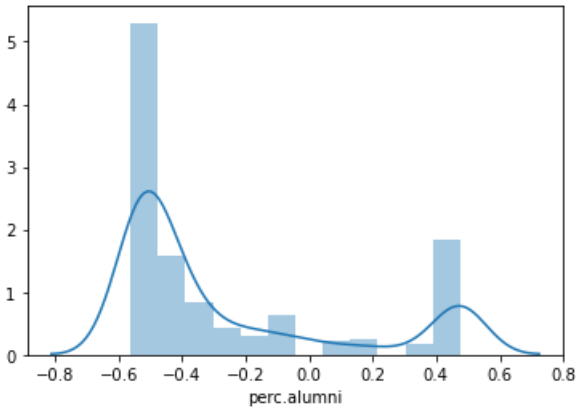
Percentage of alumni who donate

In [288]:

```
sns.distplot(df["perc.alumni"])
```

Out[288]:

```
<AxesSubplot:xlabel='perc.alumni'>
```



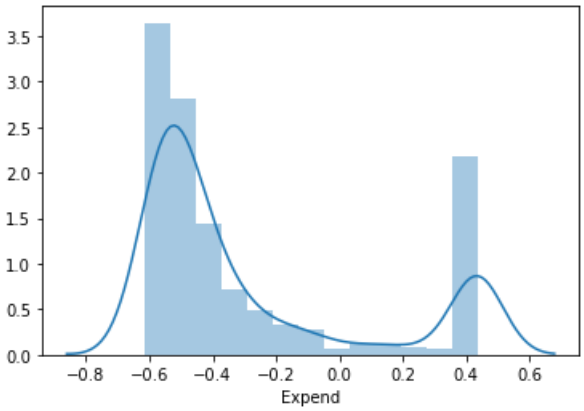
The Instructional expenditure per student

In [289]:

```
sns.distplot(df["Expend"])
```

Out[289]:

```
<AxesSubplot:xlabel='Expend'>
```



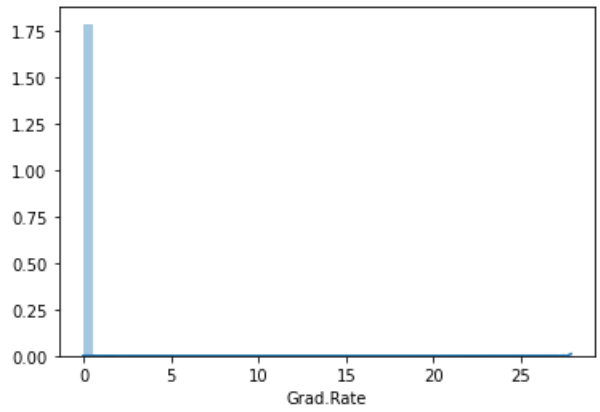
Graduation rate

In [290]:

```
sns.distplot(df["Grad.Rate"])
```

Out[290]:

```
<AxesSubplot:xlabel='Grad.Rate'>
```

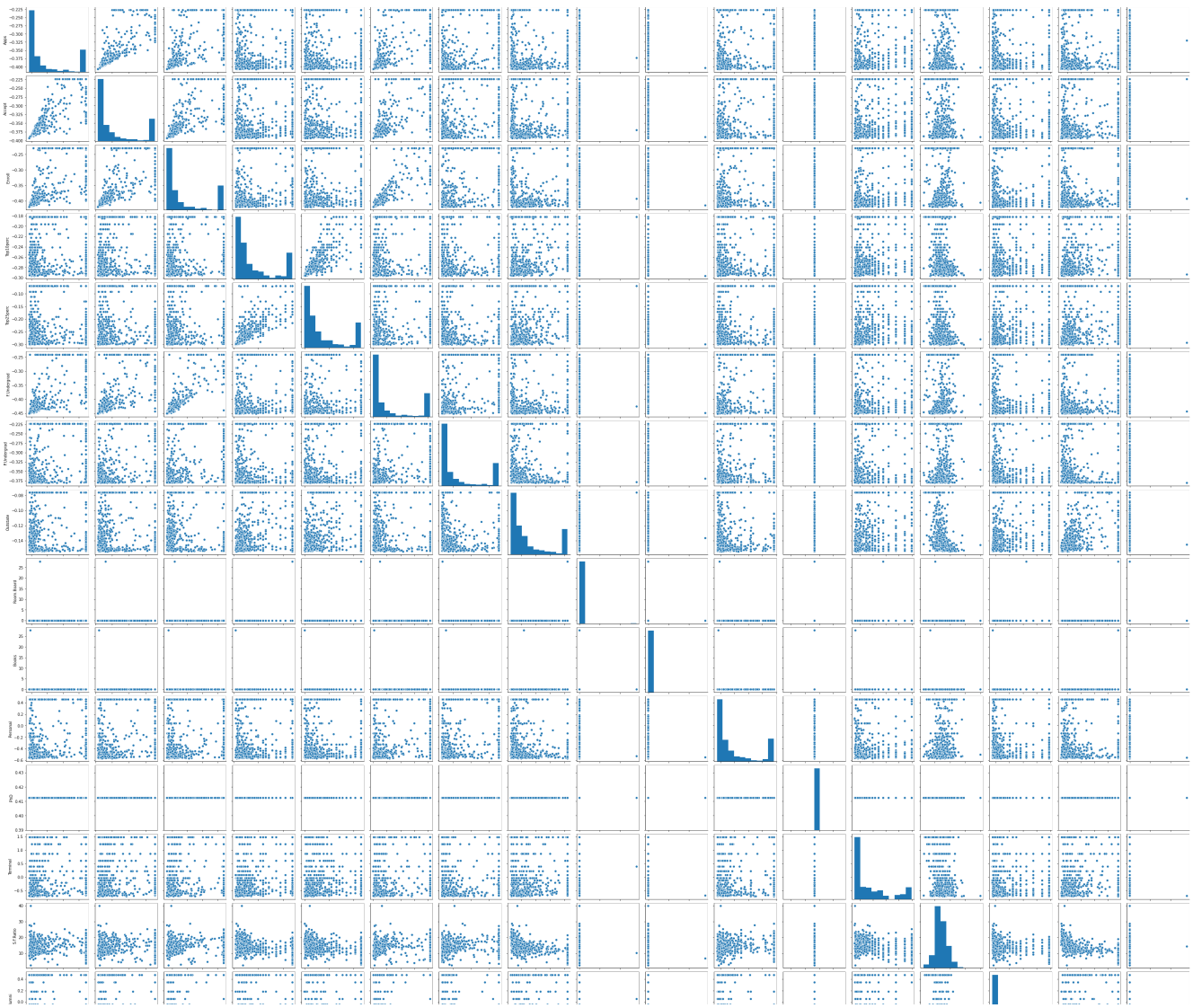


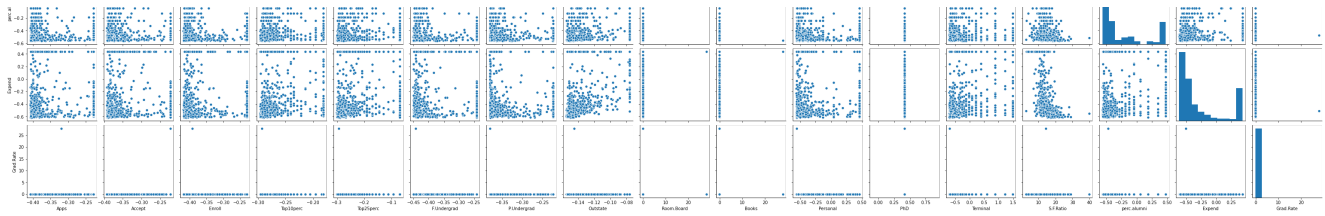
Bivariate Analysis

Bivariate Analysis is done using pairplot of all the variables

In [292]:

```
sns.pairplot(df);     #Pairplot of all variables
```





In the above plot scatter diagrams are plotted for all the numerical columns in the dataset. A scatter plot is a visual representation of the degree of correlation between any two columns. The pair plot function in seaborn makes it very easy to generate joint scatter plots for all the columns in the data.

In [163]:

```
df.corr()
```

Out[163]:

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Perso
Apps	1.000000	0.905832	0.821709	0.341434	0.374126	0.762954	0.445846	0.132916	0.171813	-0.019822	0.2042
Accept	0.905832	1.000000	0.891860	0.171606	0.216153	0.836145	0.511618	0.004480	0.102521	-0.017775	0.2433
Enroll	0.821709	0.891860	1.000000	0.133346	0.183667	0.950968	0.618496	-0.092102	0.014764	-0.019541	0.3513
Top10perc	0.341434	0.171606	0.133346	1.000000	0.911219	0.078718	-0.108971	0.576708	0.332950	-0.021818	0.1085
Top25perc	0.374126	0.216153	0.183667	0.911219	1.000000	0.128763	-0.051297	0.554635	0.327937	-0.028204	0.0812
F.Undergrad	0.762954	0.836145	0.950968	0.078718	0.128763	1.000000	0.657372	-0.145010	-0.017834	-0.020972	0.3699
P.Undergrad	0.445846	0.511618	0.618496	-0.108971	-0.051297	0.657372	1.000000	-0.211103	-0.032876	-0.018422	0.3126
Outstate	0.132916	0.004480	-0.092102	0.576708	0.554635	-0.145010	-0.211103	1.000000	0.459474	-0.008593	0.2485
Room.Board	0.171813	0.102521	0.014764	0.332950	0.327937	-0.017834	-0.032876	0.459474	1.000000	0.089755	0.1372
Books	-0.019822	-0.017775	-0.019541	-0.021818	-0.028204	-0.020972	-0.018422	-0.008593	0.089755	1.000000	0.0312
Personal	0.204271	0.243302	0.351389	-0.108558	-0.081242	0.369988	0.312653	-0.248589	-0.137235	-0.031268	1.0000
PhD	0.384999	0.302116	0.268291	0.559219	0.565023	0.245846	0.119797	0.532856	0.312936	-0.042809	0.0417
Terminal	0.367588	0.304608	0.267850	0.533230	0.551476	0.254479	0.126406	0.509026	0.318393	-0.041805	0.0527
perc.alumni	-0.097793	-0.172961	-0.203800	0.377161	0.367680	-0.249811	-0.309651	0.509342	0.185261	-0.035152	0.2833
Expend	0.230684	0.146255	0.048412	0.606885	0.579190	-0.001391	-0.100884	0.760554	0.440715	0.050903	0.1625
Grad.Rate	0.125807	0.008189	-0.057899	0.447156	0.435555	-0.109682	-0.198985	0.456804	0.284866	-0.021122	0.2260

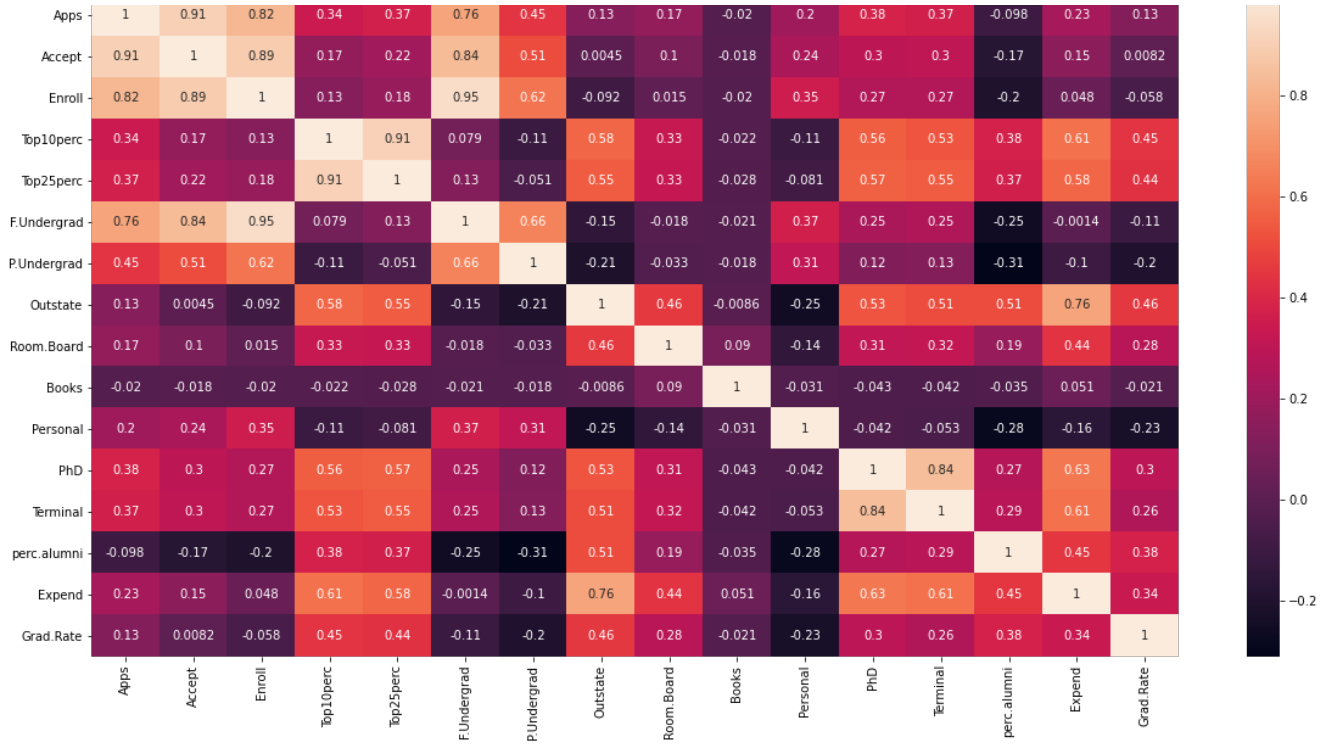
Correlation Heatmap

In [164]:

```
plt.figure(figsize=(20,10))
sns.heatmap(df.corr(), annot=True)
```

Out[164]:

```
<AxesSubplot:>
```



2.2) Scale the variables and write the inference for using the type of scaling function for this case study.

Normalizing and Scaling

Often the variables of the data set are of different scales i.e. one variable is in millions and other in only 100. For e.g. in our data set Income is having values in thousands and age in just two digits. Since the data in these variables are of different scales, it is tough to compare these variables.

Feature scaling (also known as data normalization) is the method used to standardize the range of features of data. Since, the range of values of data may vary widely, it becomes a necessary step in data preprocessing while using machine learning algorithms.

In this method, we convert variables with different scales of measurements into a single scale.

StandardScaler normalizes the data using the formula (x-mean)/standard deviation.

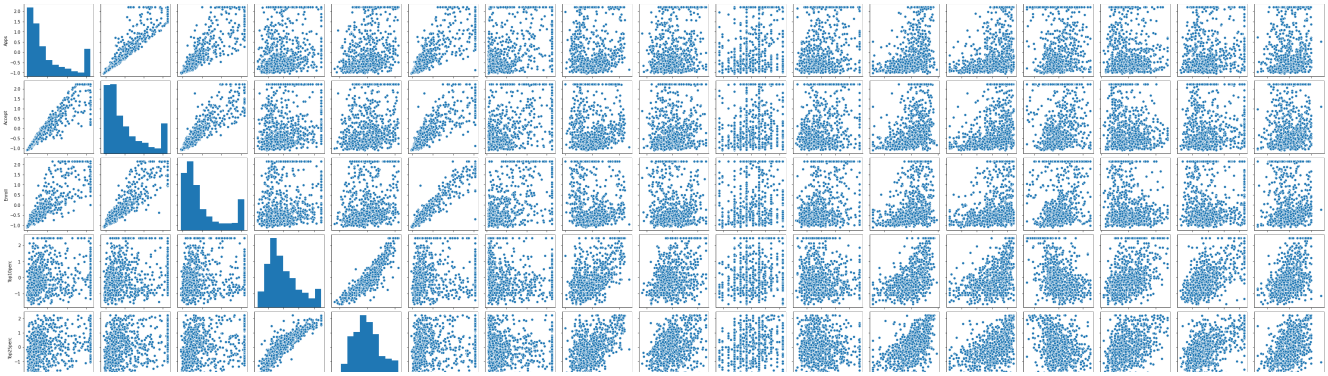
Scales the data. Essentially returns the z-scores of every attribute

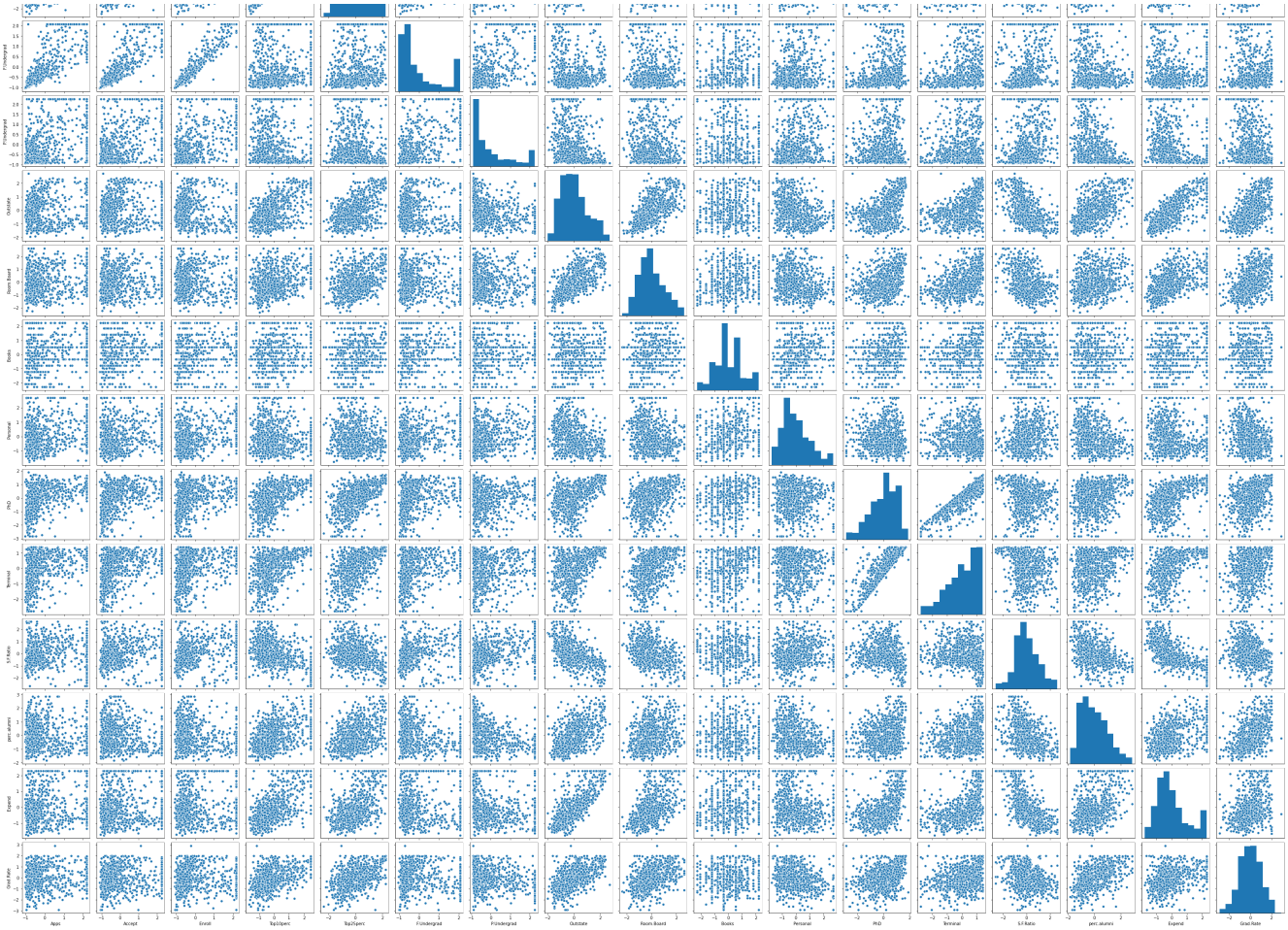
In [406]:

```
sns.pairplot(df)
```

Out[406]:

```
<seaborn.axisgrid.PairGrid at 0x2225835b850>
```





In [407]:

```
using corr() correlation is found out
```

Out[407]:

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Perso
Apps	1.000000	0.955307	0.896883	0.321342	0.364491	0.861002	0.519823	0.065337	0.187475	0.236138	0.2299
Accept	0.955307	1.000000	0.935277	0.223298	0.273681	0.897034	0.572691	-0.005002	0.119586	0.208705	0.2563
Enroll	0.896883	0.935277	1.000000	0.171756	0.230434	0.967302	0.641595	-0.155655	-0.023846	0.202057	0.3393
Top10perc	0.321342	0.223298	0.171756	1.000000	0.913875	0.111215	-0.180009	0.562160	0.357366	0.153452	0.1167
Top25perc	0.364491	0.273681	0.230434	0.913875	1.000000	0.181196	-0.099295	0.489569	0.330987	0.169761	0.0868
F.Undergrad	0.861002	0.897034	0.967302	0.111215	0.181196	1.000000	0.696130	-0.226166	-0.054476	0.207879	0.3597
P.Undergrad	0.519823	0.572691	0.641595	-0.180009	-0.099295	0.696130	1.000000	-0.354216	-0.067638	0.122529	0.3440
Outstate	0.065337	-0.005002	-0.155655	0.562160	0.489569	-0.226166	-0.354216	1.000000	0.655489	0.005110	0.3256
Room.Board	0.187475	0.119586	-0.023846	0.357366	0.330987	-0.054476	-0.067638	0.655489	1.000000	0.108924	0.2195
Books	0.236138	0.208705	0.202057	0.153452	0.169761	0.207879	0.122529	0.005110	0.108924	1.000000	0.2398
Personal	0.229948	0.256346	0.339348	-0.116730	-0.086810	0.359783	0.344053	-0.325609	-0.219554	0.239863	1.0000
PhD	0.463924	0.427341	0.381540	0.544048	0.551461	0.361564	0.127663	0.391321	0.341469	0.136390	0.0116
Terminal	0.434478	0.403409	0.354379	0.506748	0.527654	0.335054	0.122152	0.412579	0.379270	0.159318	0.0319
S.F.Ratio	0.126411	0.188506	0.274269	-0.387926	-0.297233	0.324504	0.370607	-0.573683	-0.376430	-0.008536	0.1739

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Perso
perc.alumni	0.101158	0.165516	0.222723	0.455797	0.416832	-0.285457	-0.419334	0.565736	0.272393	0.042832	0.3057
Expend	0.242935	0.161808	0.054221	0.657039	0.572905	0.000371	-0.201929	0.775328	0.580622	0.149983	0.1632
Grad.Rate	0.150803	0.078982	-0.023251	0.493670	0.478985	-0.082239	-0.265158	0.572458	0.425790	-0.008051	0.2908

Exponential Transformation

In [410]:

```
df.corr()
```

Out[410]:

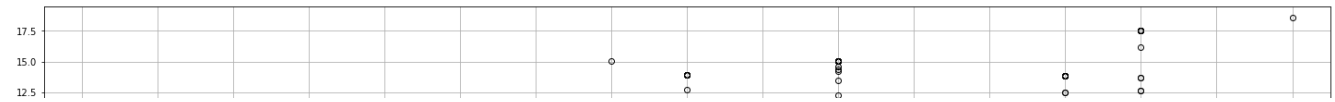
	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Perso
Apps	1.000000	0.905832	0.821709	0.341434	0.374126	0.762954	0.445846	0.132916	0.192476	0.148029	0.1339
Accept	0.905832	1.000000	0.891860	0.171606	0.216153	0.836145	0.511618	0.004480	0.115243	0.147019	0.1814
Enroll	0.821709	0.891860	1.000000	0.133346	0.183667	0.950968	0.618496	-0.092102	0.017649	0.142501	0.2624
Top10perc	0.341434	0.171606	0.133346	1.000000	0.911219	0.078718	-0.108971	0.576708	0.357313	0.103459	0.0857
Top25perc	0.374126	0.216153	0.183667	0.911219	1.000000	0.128763	-0.051297	0.554635	0.336911	0.142225	0.0689
F.Undergrad	0.762954	0.836145	0.950968	0.078718	0.128763	1.000000	0.657372	-0.145010	-0.018062	0.139734	0.2958
P.Undergrad	0.445846	0.511618	0.618496	-0.108971	-0.051297	0.657372	1.000000	-0.211103	-0.034702	0.073980	0.3030
Outstate	0.132916	0.004480	-0.092102	0.576708	0.554635	-0.145010	-0.211103	1.000000	0.490571	0.060151	0.1830
Room.Board	0.192476	0.115243	0.017649	0.357313	0.336911	-0.018062	-0.034702	0.490571	1.000000	0.045903	0.1258
Books	0.148029	0.147019	0.142501	0.103459	0.142225	0.139734	0.073980	0.060151	0.045903	1.000000	0.2358
Personal	0.133968	0.181456	0.262421	-0.085780	-0.068912	0.295893	0.303030	-0.183001	-0.125876	0.235880	1.0000
PhD	0.384999	0.302116	0.268291	0.559219	0.565023	0.245846	0.119797	0.532856	0.346271	0.142493	0.0118
Terminal	0.367062	0.303764	0.266823	0.534287	0.552265	0.253421	0.125533	0.509828	0.345099	0.150356	0.0108
S.F.Ratio	0.119816	0.146627	0.227474	-0.189006	-0.165043	0.273443	0.319609	-0.285454	-0.194603	0.014711	0.0813
perc.alumni	-0.055582	-0.138333	-0.147226	0.420168	0.405392	-0.180146	-0.225461	0.503739	0.159349	-0.027670	0.1572
Expend	0.265421	0.146660	0.061760	0.687139	0.627762	0.015255	-0.089111	0.773491	0.488331	0.128784	0.0789
Grad.Rate	0.128861	0.007452	-0.058226	0.458544	0.446950	-0.110923	-0.202168	0.468043	0.307899	0.036480	0.1603

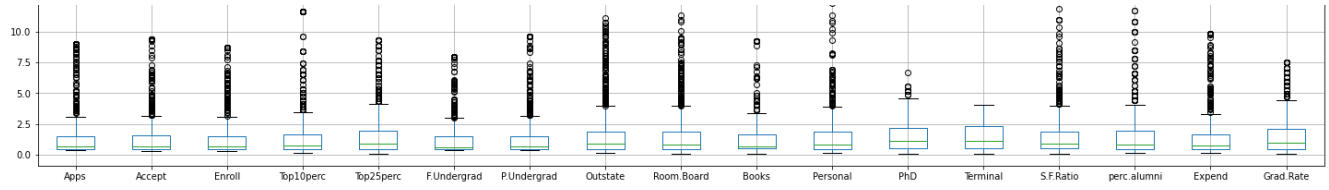
The data above shows that the Exponential transformation is best suited for scaling for the given data as data after exponential transformation appear to be range and intepration becomes feasible.

2.4) Check the dataset for outliers before and after scaling. Draw your inferences from this exercise.

In [413]:

```
plt.figure(figsize=(25,5))
df.boxplot()
plt.show()
```





In [ ]:

```
The above graph shows that after scaling there are many outliers in the given data set
```

Again the below operations to check what the data set comprises of. We will check the below things after loading the data set again:

- **head of the dataset**
- **shape of the dataset**
- **info of the dataset**
- **summary of the dataset**

Check for any null values

In [305]:

```
data_df.isnull().sum()
```

Out[305]:

```
Names          0
Apps           0
Accept         0
Enroll         0
Top10perc      0
Top25perc      0
F.Undergrad    0
P.Undergrad    0
Outstate       0
Room.Board     0
Books          0
Personal       0
PhD            0
Terminal       0
S.F.Ratio      0
perc.alumni    0
Expend         0
Grad.Rate      0
dtype: int64
```

There are no null values

There are no duplicate values

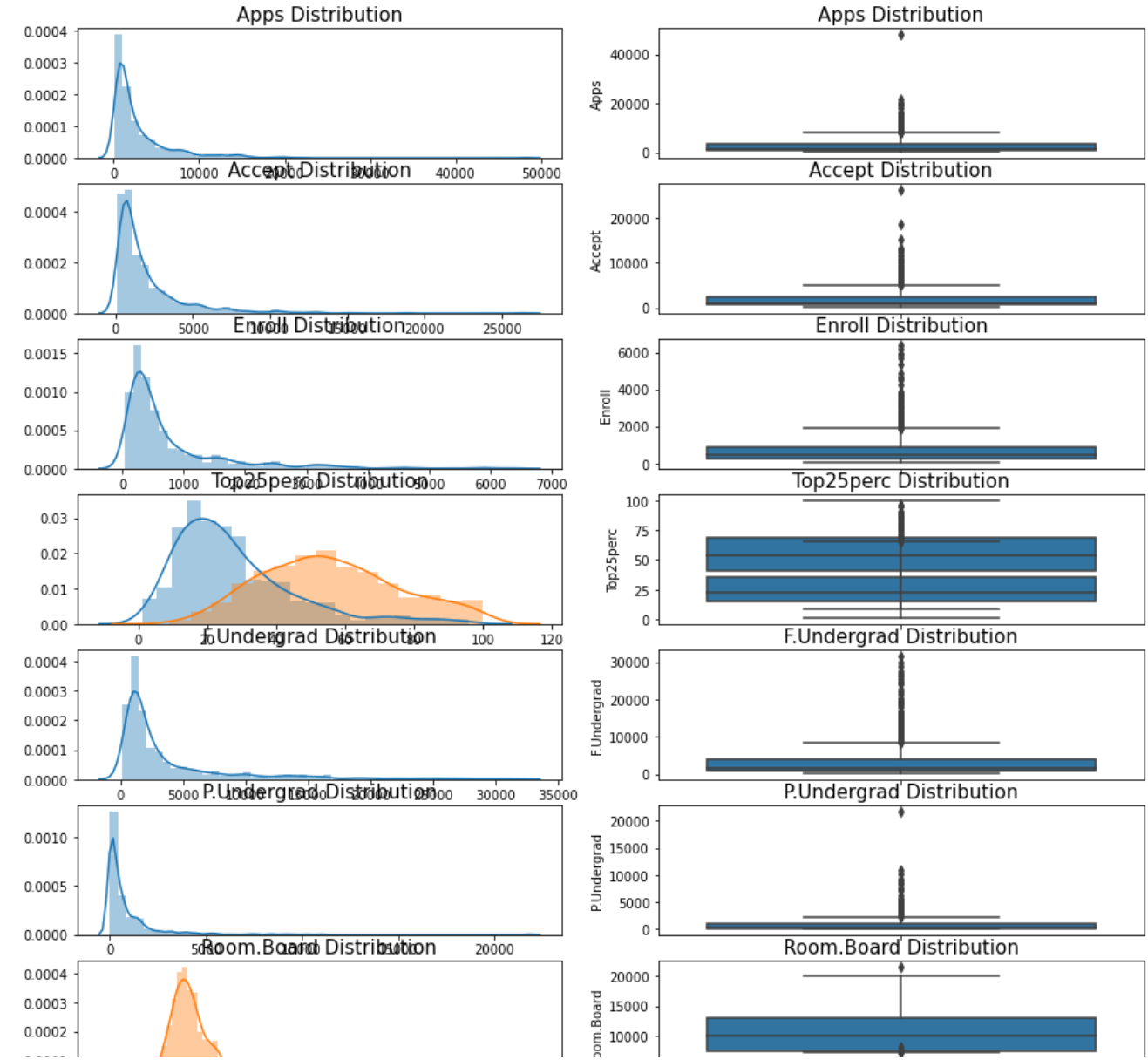
Univariate Analysis is done

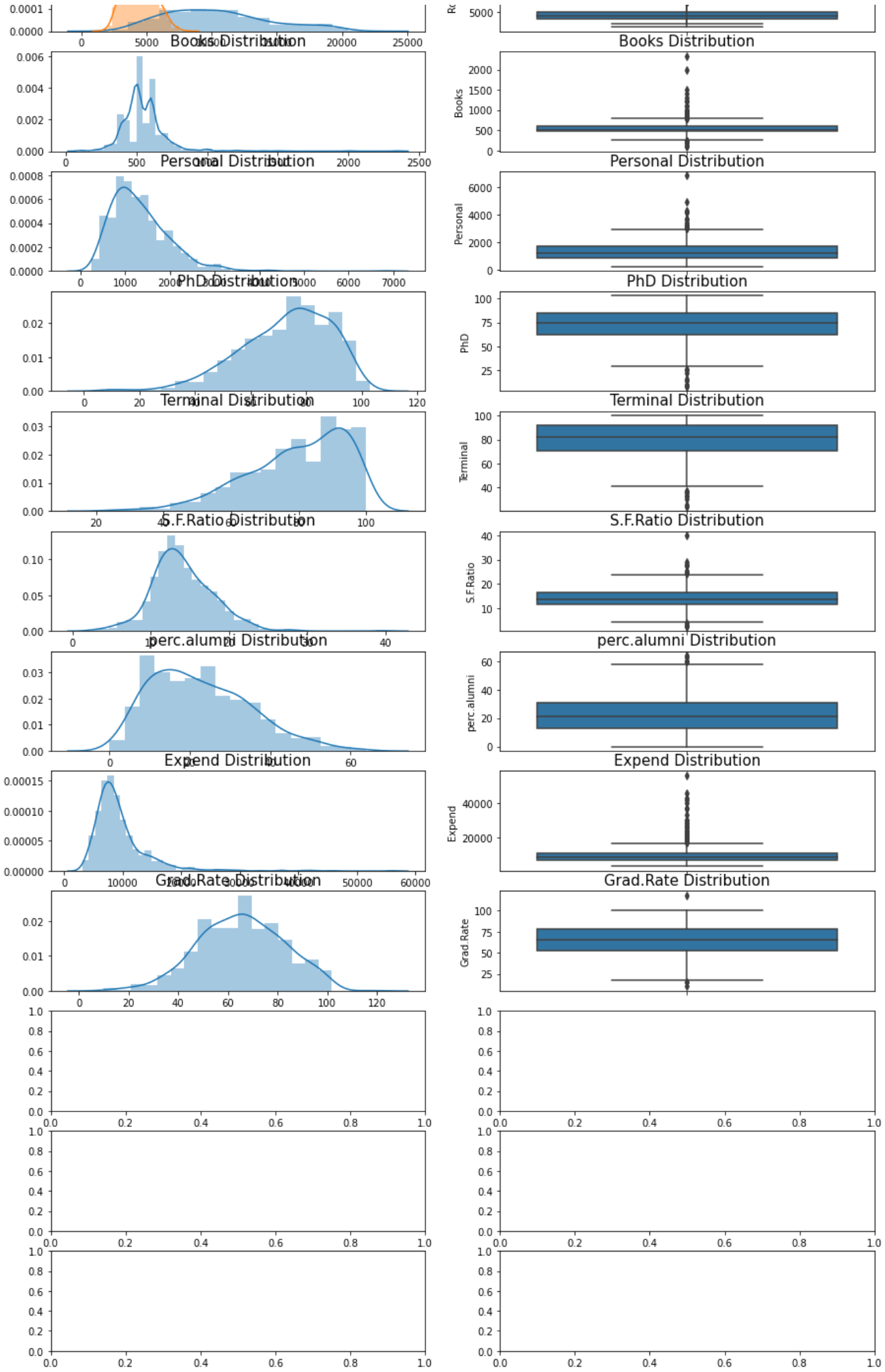
In [323]:

```
fig,axes = plt.subplots(nrows=18,ncols=2)
fig.set_size_inches(15,40)

a= sns.distplot(data_df['Apps'], ax=axes[0][0])
a.set_title('Apps Distribution',fontsize =15)

a= sns.boxplot(data_df['Apps'], orient = 'v', ax=axes[0][1])
a.set_title('Apps Distribution', fontsize =15)

a= sns.distplot(data_df['Accept'], ax=axes[1][0])
a.set_title('Accept Distribution', fontsize =15)

a= sns.boxplot(data_df['Accept'], orient = 'v', ax=axes[1][1])
```

```
a.set_title('Accept Distribution', fontsize =15)


a= sns.distplot(data_df['Enroll'], ax=axes[2][0])
a.set_title('Enroll Distribution', fontsize =15)

a= sns.boxplot(data_df['Enroll'], orient = 'v', ax=axes[2][1])
a.set_title('Enroll Distribution', fontsize =15)


a= sns.distplot(data_df['Top10perc'], ax=axes[3][0])
a.set_title('Top10perc Distribution', fontsize =15)

a= sns.boxplot(data_df['Top10perc'], orient = 'v', ax=axes[3][1])
a.set_title('Top10perc Distribution', fontsize =15)


a= sns.distplot(data_df['Top25perc'], ax=axes[3][0])
a.set_title('Top25perc Distribution', fontsize =15)

a= sns.boxplot(data_df['Top25perc'], orient = 'v', ax=axes[3][1])
a.set_title('Top25perc Distribution', fontsize =15)


a= sns.distplot(data_df['F.Undergrad'], ax=axes[4][0])
a.set_title('F.Undergrad Distribution', fontsize =15)

a= sns.boxplot(data_df['F.Undergrad'], orient = 'v', ax=axes[4][1])
a.set_title('F.Undergrad Distribution', fontsize =15)


a= sns.distplot(data_df['P.Undergrad'], ax=axes[5][0])
a.set_title('P.Undergrad Distribution', fontsize =15)

a= sns.boxplot(data_df['P.Undergrad'], orient = 'v', ax=axes[5][1])
a.set_title('P.Undergrad Distribution', fontsize =15)


a= sns.distplot(data_df['Outstate'], ax=axes[6][0])
a.set_title('Outstate Distribution', fontsize =15)

a= sns.boxplot(data_df['Outstate'], orient = 'v', ax=axes[6][1])
a.set_title('Outstate Distribution', fontsize =15)


a= sns.distplot(data_df['Room.Board'], ax=axes[6][0])
a.set_title('Room.Board Distribution', fontsize =15)

a= sns.boxplot(data_df['Room.Board'], orient = 'v', ax=axes[6][1])
a.set_title('Room.Board Distribution', fontsize =15)


a= sns.distplot(data_df['Books'], ax=axes[7][0])
a.set_title('Books Distribution', fontsize =15)

a= sns.boxplot(data_df['Books'], orient = 'v', ax=axes[7][1])
a.set_title('Books Distribution', fontsize =15)


a= sns.distplot(data_df['Personal'], ax=axes[8][0])
a.set_title('Personal Distribution', fontsize =15)

a= sns.boxplot(data_df['Personal'], orient = 'v', ax=axes[8][1])
a.set_title('Personal Distribution', fontsize =15)

a= sns.distplot(data_df['PhD'], ax=axes[9][0])
a.set_title('PhD Distribution', fontsize =15)

a= sns.boxplot(data_df['PhD'], orient = 'v', ax=axes[9][1])
a.set_title('PhD Distribution', fontsize =15)


a= sns.distplot(data_df['Terminal'], ax=axes[10][0])
a.set_title('Terminal Distribution', fontsize =15)

a= sns.boxplot(data_df['Terminal'], orient = 'v', ax=axes[10][1])
a.set_title('Terminal Distribution', fontsize =15)
```

```
a= sns.distplot(data_df['S.F.Ratio'], ax=axes[11][0])
a.set_title('S.F.Ratio Distribution', fontsize =15)

a= sns.boxplot(data_df['S.F.Ratio'], orient = 'v', ax=axes[11][1])
a.set_title('S.F.Ratio Distribution', fontsize =15)


a= sns.distplot(data_df['perc.alumni'], ax=axes[12][0])
a.set_title('perc.alumni Distribution', fontsize =15)

a= sns.boxplot(data_df['perc.alumni'], orient = 'v', ax=axes[12][1])
a.set_title('perc.alumni Distribution', fontsize =15)


a= sns.distplot(data_df['Expend'], ax=axes[13][0])
a.set_title('Expend Distribution', fontsize =15)

a= sns.boxplot(data_df['Expend'], orient = 'v', ax=axes[13][1])
a.set_title('Expend Distribution', fontsize =15)


a= sns.distplot(data_df['Grad.Rate'], ax=axes[14][0])
a.set_title('Grad.Rate Distribution', fontsize =15)

a= sns.boxplot(data_df['Grad.Rate'], orient = 'v', ax=axes[14][1])
a.set_title('Grad.Rate Distribution', fontsize =15)


plt.show()
```




Books Distribution
Personal Distribution
PhD Distribution
Terminal Distribution
S.F.Ratio Distribution
perc.alumni Distribution
Expend Distribution
Grad.Rate Distribution
Books
Personal
PhD
Terminal
S.F.Ratio
perc.alumni
Expend
Grad.Rate

Bi variate Analysis

In [324]:

```
data_df.corr()
```

Out[324]:

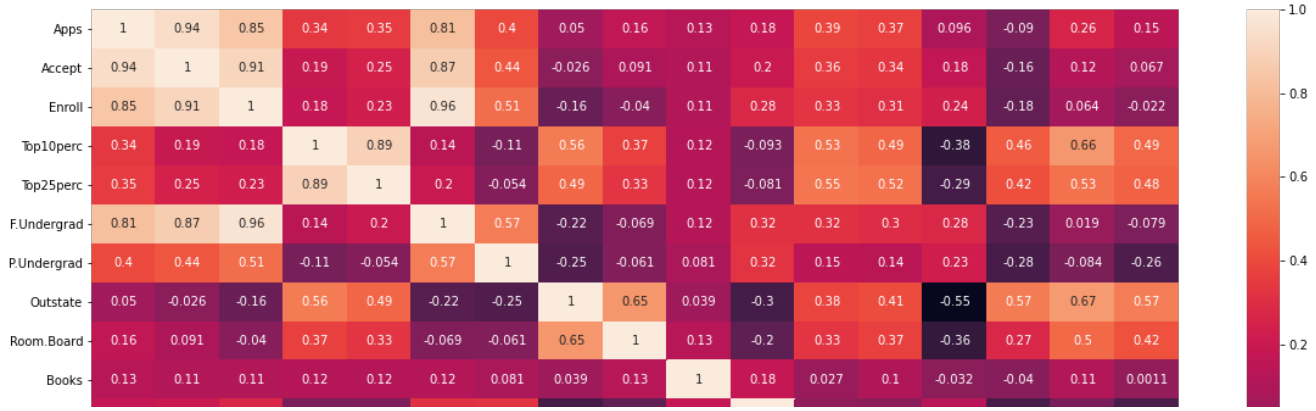
	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Perso
Apps	1.000000	0.943451	0.846822	0.338834	0.351640	0.814491	0.398264	0.050159	0.164939	0.132559	0.1787
Accept	0.943451	1.000000	0.911637	0.192447	0.247476	0.874223	0.441271	-0.025755	0.090899	0.113525	0.2009
Enroll	0.846822	0.911637	1.000000	0.181294	0.226745	0.964640	0.513069	-0.155477	-0.040232	0.112711	0.2809
Top10perc	0.338834	0.192447	0.181294	1.000000	0.891995	0.141289	-0.105356	0.562331	0.371480	0.118858	0.0933
Top25perc	0.351640	0.247476	0.226745	0.891995	1.000000	0.199445	-0.053577	0.489394	0.331490	0.115527	0.0808
F.Undergrad	0.814491	0.874223	0.964640	0.141289	0.199445	1.000000	0.570512	-0.215742	-0.068890	0.115550	0.3172
P.Undergrad	0.398264	0.441271	0.513069	-0.105356	-0.053577	0.570512	1.000000	-0.253512	-0.061326	0.081200	0.3198
Outstate	0.050159	-0.025755	-0.155477	0.562331	0.489394	-0.215742	-0.253512	1.000000	0.654256	0.038855	0.2990
Room.Board	0.164939	0.090899	-0.040232	0.371480	0.331490	-0.068890	-0.061326	0.654256	1.000000	0.127963	0.1994
Books	0.132559	0.113525	0.112711	0.118858	0.115527	0.115550	0.081200	0.038855	0.127963	1.000000	0.1792
Personal	0.178731	0.200989	0.280929	-0.093316	-0.080810	0.317200	0.319882	-0.299087	-0.199428	0.179295	1.0000
PhD	0.390697	0.355758	0.331469	0.531828	0.545862	0.318337	0.149114	0.382982	0.329202	0.026906	0.0109
Terminal	0.369491	0.337583	0.308274	0.491135	0.524749	0.300019	0.141904	0.407983	0.374540	0.099955	0.0306
S.F.Ratio	0.095633	0.176229	0.237271	-0.384875	-0.294629	0.279703	0.232531	-0.554821	-0.362628	-0.031929	0.1363
perc.alumni	-0.090226	-0.159990	-0.180794	0.455485	0.417864	-0.229462	-0.280792	0.566262	0.272363	-0.040208	0.2859
Expend	0.259592	0.124717	0.064169	0.660913	0.527447	0.018652	-0.083568	0.672779	0.501739	0.112409	0.0978
Grad.Rate	0.146755	0.067313	-0.022341	0.494989	0.477281	-0.078773	-0.257001	0.571290	0.424942	0.001061	0.2693

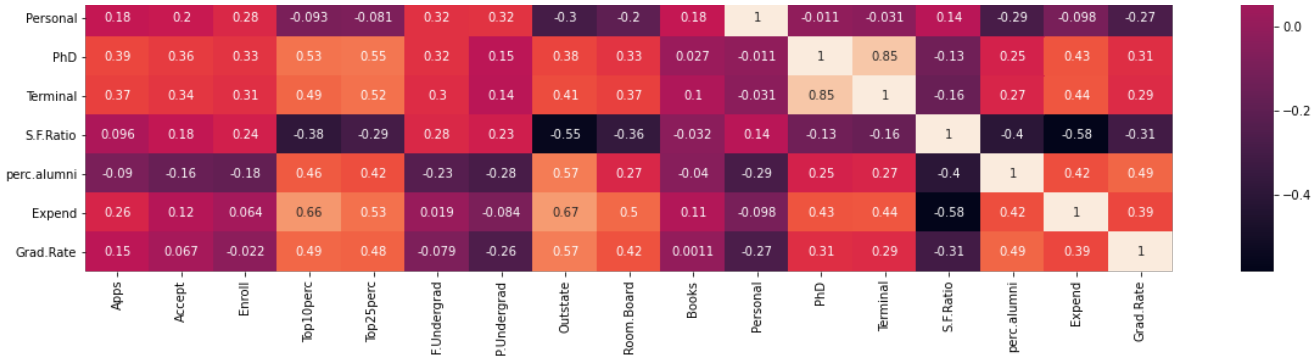
In [327]:

```
plt.figure(figsize=(20,10))
sns.heatmap(data_df.corr(), annot=True)
```

Out[327]:

```
<AxesSubplot:>
```





Lighter the color , it is highly corelated. Hence we need to perform PCA

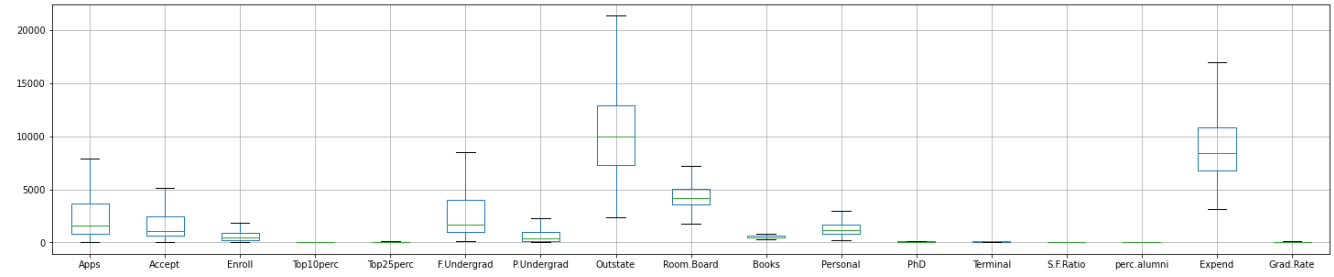
In [361]:

```
lrapps,urapps = remove_outliers(data_df['Apps'])
data_df['Apps'] = np.where(data_df['Apps'] > urapps, urapps, data_df['Apps'])


lraccept,uraccept = remove_outliers(data_df['Accept'])
data_df['Accept'] = np.where(data_df['Accept'] > uraccept, uraccept, data_df['Accept'])

lrenroll,urenroll = remove_outliers(data_df['Enroll'])
data_df['Enroll'] = np.where(data_df['Enroll'] > urenroll, urenroll, data_df['Enroll'])

lrTop10perc,urTop10perc = remove_outliers(data_df['Top10perc'])
data_df['Top10perc'] = np.where(data_df['Top10perc'] > urTop10perc, urTop10perc, data_df['Top10perc
'])

lrTop25perc,urTop25perc = remove_outliers(data_df['Top25perc'])
data_df['Top25perc'] = np.where(data_df['Top25perc'] > urTop25perc, urTop25perc, data_df['Top25perc
'])

lrFUndergrad,urFUndergrad = remove_outliers(data_df['F.Undergrad'])
data_df['F.Undergrad'] = np.where(data_df['F.Undergrad'] > urFUndergrad, urFUndergrad, data_df['F.U
ndergrad'])

lrPUndergrad,urPUndergrad = remove_outliers(data_df['P.Undergrad'])
data_df['P.Undergrad'] = np.where(data_df['P.Undergrad'] > urPUndergrad, urPUndergrad, data_df['P.U
ndergrad'])

lrOutstate,urOutstate = remove_outliers(data_df['Outstate'])
data_df['Outstate'] = np.where(data_df['Outstate'] > urOutstate, urOutstate, data_df['Outstate'])

lrRoomBoard,urRoomBoard = remove_outliers(data_df['Room.Board'])
data_df['Room.Board'] = np.where(data_df['Room.Board'] > urRoomBoard, urRoomBoard, data_df['Room.Bo
ard'])

lrBooks,urBooks = remove_outliers(data_df['Books'])
data_df['Books'] = np.where(data_df['Books'] > urBooks, urBooks, data_df['Books'])
data_df['Books'] = np.where(data_df['Books'] < lrBooks, lrBooks, data_df['Books'])



lrPersonal,urPersonal = remove_outliers(data_df['Personal'])
data_df['Personal'] = np.where(data_df['Personal'] > urPersonal, urPersonal, data_df['Personal'])

lrPhD,urPhD = remove_outliers(data_df['PhD'])
data_df['PhD'] = np.where(data_df['PhD'] > urPhD, urPhD, data_df['PhD'])
data_df['PhD'] = np.where(data_df['PhD'] < lrPhD, lrPhD, data_df['PhD'])

lrTerminal,urTerminal = remove_outliers(data_df['Terminal'])
data_df['Terminal'] = np.where(data_df['Terminal'] > urTerminal, urTerminal, data_df['Terminal'])
data_df['Terminal'] = np.where(data_df['Terminal'] < lrTerminal, lrTerminal, data_df['Terminal'])

lrSFRatio,urSFRatio = remove_outliers(data_df['S.F.Ratio'])
data_df['S.F.Ratio'] = np.where(data_df['S.F.Ratio'] > urSFRatio, urSFRatio, data_df['S.F.Ratio'])
data_df['S.F.Ratio'] = np.where(data_df['S.F.Ratio'] < lrSFRatio, lrSFRatio, data_df['S.F.Ratio'])


lrpercalumni,urpercalumni = remove_outliers(data_df['perc.alumni'])
data_df['perc.alumni'] = np.where(data_df['perc.alumni'] > urpercalumni, urpercalumni, data_df['per
```

```
c.alumni'])

lrExpend,urExpend = remove_outliers(data_df['Expend'])
data_df['Expend'] = np.where(data_df['Expend'] > urExpend, urExpend, data_df['Expend'])

lrGradRate,urGradRate = remove_outliers(data_df['Grad.Rate'])
data_df['Grad.Rate'] = np.where(data_df['Grad.Rate'] < lrGradRate, lrGradRate, data_df['Grad.Rate']
)
data_df['Grad.Rate'] = np.where(data_df['Grad.Rate'] > urGradRate, urGradRate, data_df['Grad.Rate']
)
```

In [362]:

```
plt.figure(figsize=(25,5))
data_df.boxplot()
plt.show()
```



Drop Class column

In [365]:

```
# Since Names column has unique values , so will remove it from the dataset.More over there is no
point in adding ID for PCA.
data_df = data_df.drop(['Names'], axis =1)
```

In [366]:

```
data_df.head()
```

Out[366]:

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Personal	PhD	Terminal
0	1660.0	1232.0	721.0	23.0	52.0	2885.0	537.0	7440.0	3300.0	450.0	2200.0	70.0	78.0
1	2186.0	1924.0	512.0	16.0	29.0	2683.0	1227.0	12280.0	6450.0	750.0	1500.0	29.0	39.5
2	1428.0	1097.0	336.0	22.0	50.0	1036.0	99.0	11250.0	3750.0	400.0	1165.0	53.0	66.0
3	417.0	349.0	137.0	60.0	89.0	510.0	63.0	12960.0	5450.0	450.0	875.0	92.0	97.0
4	193.0	146.0	55.0	16.0	44.0	249.0	869.0	7560.0	4120.0	795.0	1500.0	76.0	72.0

Standardising before processing PCA

In [370]:

```
# All variables must be on same scale, hence we can omit scaling.
# Standardization
from scipy.stats import zscore
data_new = data_df.apply(zscore)
data_new.head()
```

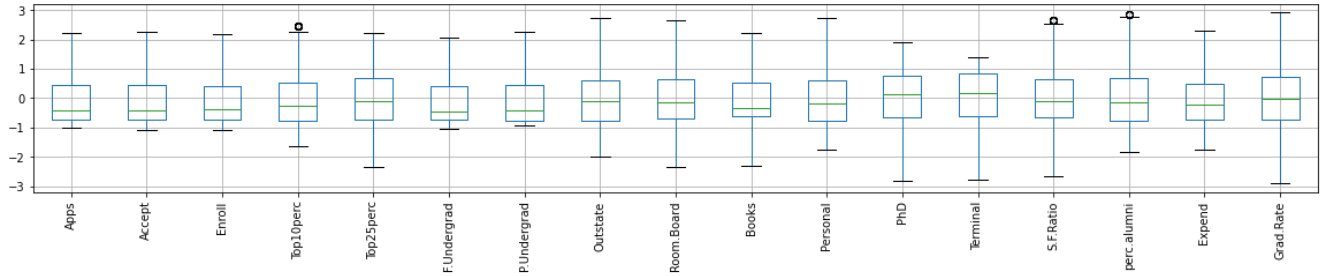
Out[370]:

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Personal	Ph
0	-0.376493	-0.337830	0.106380	-0.246780	-0.191827	-0.018769	-0.166083	-0.746480	-0.968324	-0.776567	1.438500	0.1740

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Personal	Ph
1	0.159195	0.116744	0.260441	-0.696290	-1.353911	-0.093626	0.797856	0.457762	1.921680	1.828605	0.289289	2.7457
2	-0.472336	-0.426511	-0.569343	-0.310996	-0.292878	-0.703966	-0.777974	0.201488	-0.555466	-1.210762	-0.260691	1.2403
3	-0.889994	-0.917871	-0.918613	2.129202	1.677612	-0.898889	-0.828267	0.626954	1.004218	-0.776567	-0.736792	1.2058
4	-0.982532	-1.051221	-1.062533	-0.696290	-0.596031	-0.995610	0.297726	-0.716623	-0.216006	2.219381	0.289289	0.2022

In [371]:

```
data_new.boxplot(figsize=(20,3))
plt.xticks(rotation=90)
plt.show()
```



Create a covariance matrix for identifying Principal components

In [ ]:

```
```

In [372]:

```
# PCA
# Step 1 - Create covariance matrix

cov_matrix = np.cov(data_new.T)
print('Covariance Matrix \n%s', cov_matrix)
```

```
Covariance Matrix
%s [[ 1.00128866e+00  9.56537704e-01  8.98039052e-01  3.21756324e-01
   3.64960691e-01  8.62111140e-01  5.20492952e-01  6.54209711e-02
   1.87717056e-01  2.36441941e-01  2.30243993e-01  4.64521757e-01
   4.35037784e-01  1.26573895e-01 -1.01288006e-01  2.43248206e-01
   1.50997775e-01]
 [ 9.56537704e-01  1.00128866e+00  9.36482483e-01  2.23586208e-01
   2.74033187e-01  8.98189799e-01  5.73428908e-01 -5.00874847e-03
   1.19740419e-01  2.08974091e-01  2.56676290e-01  4.27891234e-01
   4.03929238e-01  1.88748711e-01 -1.65728801e-01  1.62016688e-01
   7.90839722e-02]
 [ 8.98039052e-01  9.36482483e-01  1.00128866e+00  1.71977357e-01
   2.30730728e-01  9.68548601e-01  6.42421828e-01 -1.55856056e-01
  -2.38762560e-02  2.02317274e-01  3.39785395e-01  3.82031198e-01
   3.54835877e-01  2.74622251e-01 -2.23009677e-01  5.42906862e-02
  -2.32810071e-02]
 [ 3.21756324e-01  2.23586208e-01  1.71977357e-01  1.00128866e+00
   9.15052977e-01  1.11358019e-01 -1.80240778e-01  5.62884044e-01
   3.57826139e-01  1.53650150e-01 -1.16880152e-01  5.44748764e-01
   5.07401238e-01 -3.88425719e-01  4.56384036e-01  6.57885921e-01
   4.94306540e-01]
 [ 3.64960691e-01  2.74033187e-01  2.30730728e-01  9.15052977e-01
   1.00128866e+00  1.81429267e-01 -9.94231153e-02  4.90200034e-01
   3.31413314e-01  1.69979808e-01 -8.69219644e-02  5.52172085e-01
   5.28333659e-01 -2.97616423e-01  4.17369123e-01  5.73643193e-01
   4.79601950e-01]
 [ 8.62111140e-01  8.98189799e-01  9.68548601e-01  1.11358019e-01
   1.81429267e-01  1.00128866e+00  6.97027420e-01 -2.26457040e-01
```

```
  -5.45459528e-02  2.08147257e-01  3.60246460e-01  3.62030390e-01
   3.35485771e-01  3.24921933e-01 -2.85825062e-01  3.71119607e-04
  -8.23447851e-02]
 [ 5.20492952e-01  5.73428908e-01  6.42421828e-01 -1.80240778e-01
  -9.94231153e-02  6.97027420e-01  1.00128866e+00 -3.54672874e-01
  -6.77252009e-02  1.22686416e-01  3.44495974e-01  1.27827147e-01
   1.22309141e-01  3.71084841e-01 -4.19874031e-01 -2.02189396e-01
  -2.65499420e-01]
 [ 6.54209711e-02 -5.00874847e-03 -1.55856056e-01  5.62884044e-01
   4.90200034e-01 -2.26457040e-01 -3.54672874e-01  1.00128866e+00
   6.56333564e-01  5.11656377e-03 -3.26028927e-01  3.91824814e-01
   4.13110264e-01 -5.74421963e-01  5.66465309e-01  7.76326650e-01
   5.73195743e-01]
 [ 1.87717056e-01  1.19740419e-01 -2.38762560e-02  3.57826139e-01
   3.31413314e-01 -5.45459528e-02 -6.77252009e-02  6.56333564e-01
   1.00128866e+00  1.09064551e-01 -2.19837042e-01  3.41908577e-01
   3.79759015e-01 -3.76915472e-01  2.72743761e-01  5.81370284e-01
   4.26338910e-01]
 [ 2.36441941e-01  2.08974091e-01  2.02317274e-01  1.53650150e-01
   1.69979808e-01  2.08147257e-01  1.22686416e-01  5.11656377e-03
   1.09064551e-01  1.00128866e+00  2.40172145e-01  1.36566243e-01
   1.59523091e-01 -8.54689129e-03 -4.28870629e-02  1.50176551e-01
  -8.06107505e-03]
 [ 2.30243993e-01  2.56676290e-01  3.39785395e-01 -1.16880152e-01
  -8.69219644e-02  3.60246460e-01  3.44495974e-01 -3.26028927e-01
  -2.19837042e-01  2.40172145e-01  1.00128866e+00 -1.16986124e-02
  -3.20117803e-02  1.74136664e-01 -3.06146886e-01 -1.63481407e-01
  -2.91268705e-01]
 [ 4.64521757e-01  4.27891234e-01  3.82031198e-01  5.44748764e-01
   5.52172085e-01  3.62030390e-01  1.27827147e-01  3.91824814e-01
   3.41908577e-01  1.36566243e-01 -1.16986124e-02  1.00128866e+00
   8.64040263e-01 -1.29556494e-01  2.49197779e-01  5.11186852e-01
   3.10418895e-01]
 [ 4.35037784e-01  4.03929238e-01  3.54835877e-01  5.07401238e-01
   5.28333659e-01  3.35485771e-01  1.22309141e-01  4.13110264e-01
   3.79759015e-01  1.59523091e-01 -3.20117803e-02  8.64040263e-01
   1.00128866e+00 -1.51187934e-01  2.66375402e-01  5.24743500e-01
   2.93180212e-01]
 [ 1.26573895e-01  1.88748711e-01  2.74622251e-01 -3.88425719e-01
  -2.97616423e-01  3.24921933e-01  3.71084841e-01 -5.74421963e-01
  -3.76915472e-01 -8.54689129e-03  1.74136664e-01 -1.29556494e-01
  -1.51187934e-01  1.00128866e+00 -4.12632056e-01 -6.55219504e-01
  -3.08922187e-01]
 [-1.01288006e-01 -1.65728801e-01 -2.23009677e-01  4.56384036e-01
   4.17369123e-01 -2.85825062e-01 -4.19874031e-01  5.66465309e-01
   2.72743761e-01 -4.28870629e-02 -3.06146886e-01  2.49197779e-01
   2.66375402e-01 -4.12632056e-01  1.00128866e+00  4.63518674e-01
   4.92040760e-01]
 [ 2.43248206e-01  1.62016688e-01  5.42906862e-02  6.57885921e-01
   5.73643193e-01  3.71119607e-04 -2.02189396e-01  7.76326650e-01
   5.81370284e-01  1.50176551e-01 -1.63481407e-01  5.11186852e-01
   5.24743500e-01 -6.55219504e-01  4.63518674e-01  1.00128866e+00
   4.15826026e-01]
 [ 1.50997775e-01  7.90839722e-02 -2.32810071e-02  4.94306540e-01
   4.79601950e-01 -8.23447851e-02 -2.65499420e-01  5.73195743e-01
   4.26338910e-01 -8.06107505e-03 -2.91268705e-01  3.10418895e-01
   2.93180212e-01 -3.08922187e-01  4.92040760e-01  4.15826026e-01
   1.00128866e+00]]
```

In [ ]:

```
#Even if we take the transpose of the covariance matrix it results in same value as that of the ab
ove
#Covariance is less than the correlation
```

Comparing Correlation and Covariance Matrix

In [373]:

```
df_corr = data_df.copy()
df_corr.corr()
```

Out[373]:

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Perso
Apps	1.000000	0.955307	0.896883	0.321342	0.364491	0.861002	0.519823	0.065337	0.187475	0.236138	0.2299
Accept	0.955307	1.000000	0.935277	0.223298	0.273681	0.897034	0.572691	-0.005002	0.119586	0.208705	0.2563
Enroll	0.896883	0.935277	1.000000	0.171756	0.230434	0.967302	0.641595	-0.155655	-0.023846	0.202057	0.3393
Top10perc	0.321342	0.223298	0.171756	1.000000	0.913875	0.111215	-0.180009	0.562160	0.357366	0.153452	0.1167
Top25perc	0.364491	0.273681	0.230434	0.913875	1.000000	0.181196	-0.099295	0.489569	0.330987	0.169761	0.0868
F.Undergrad	0.861002	0.897034	0.967302	0.111215	0.181196	1.000000	0.696130	-0.226166	-0.054476	0.207879	0.3597
P.Undergrad	0.519823	0.572691	0.641595	-0.180009	-0.099295	0.696130	1.000000	-0.354216	-0.067638	0.122529	0.3440
Outstate	0.065337	-0.005002	-0.155655	0.562160	0.489569	-0.226166	-0.354216	1.000000	0.655489	0.005110	0.3256
Room.Board	0.187475	0.119586	-0.023846	0.357366	0.330987	-0.054476	-0.067638	0.655489	1.000000	0.108924	0.2195
Books	0.236138	0.208705	0.202057	0.153452	0.169761	0.207879	0.122529	0.005110	0.108924	1.000000	0.2398
Personal	0.229948	0.256346	0.339348	-0.116730	-0.086810	0.359783	0.344053	-0.325609	-0.219554	0.239863	1.0000
PhD	0.463924	0.427341	0.381540	0.544048	0.551461	0.361564	0.127663	0.391321	0.341469	0.136390	0.0116
Terminal	0.434478	0.403409	0.354379	0.506748	0.527654	0.335054	0.122152	0.412579	0.379270	0.159318	0.0319
S.F.Ratio	0.126411	0.188506	0.274269	-0.387926	-0.297233	0.324504	0.370607	-0.573683	-0.376430	-0.008536	0.1739
perc.alumni	-0.101158	-0.165516	-0.222723	0.455797	0.416832	-0.285457	-0.419334	0.565736	0.272393	-0.042832	0.3057
Expend	0.242935	0.161808	0.054221	0.657039	0.572905	0.000371	-0.201929	0.775328	0.580622	0.149983	0.1632
Grad.Rate	0.150803	0.078982	-0.023251	0.493670	0.478985	-0.082239	-0.265158	0.572458	0.425790	-0.008051	0.2908

In [374]:

```
data_new.corr() #with scaled data
```

Out[374]:

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Perso
Apps	1.000000	0.955307	0.896883	0.321342	0.364491	0.861002	0.519823	0.065337	0.187475	0.236138	0.2299
Accept	0.955307	1.000000	0.935277	0.223298	0.273681	0.897034	0.572691	-0.005002	0.119586	0.208705	0.2563
Enroll	0.896883	0.935277	1.000000	0.171756	0.230434	0.967302	0.641595	-0.155655	-0.023846	0.202057	0.3393
Top10perc	0.321342	0.223298	0.171756	1.000000	0.913875	0.111215	-0.180009	0.562160	0.357366	0.153452	0.1167
Top25perc	0.364491	0.273681	0.230434	0.913875	1.000000	0.181196	-0.099295	0.489569	0.330987	0.169761	0.0868
F.Undergrad	0.861002	0.897034	0.967302	0.111215	0.181196	1.000000	0.696130	-0.226166	-0.054476	0.207879	0.3597
P.Undergrad	0.519823	0.572691	0.641595	-0.180009	-0.099295	0.696130	1.000000	-0.354216	-0.067638	0.122529	0.3440
Outstate	0.065337	-0.005002	-0.155655	0.562160	0.489569	-0.226166	-0.354216	1.000000	0.655489	0.005110	0.3256
Room.Board	0.187475	0.119586	-0.023846	0.357366	0.330987	-0.054476	-0.067638	0.655489	1.000000	0.108924	0.2195
Books	0.236138	0.208705	0.202057	0.153452	0.169761	0.207879	0.122529	0.005110	0.108924	1.000000	0.2398
Personal	0.229948	0.256346	0.339348	-0.116730	-0.086810	0.359783	0.344053	-0.325609	-0.219554	0.239863	1.0000

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Perso
PhD	0.463924	0.427341	0.381540	0.544048	0.551461	0.361564	0.127663	0.391321	0.341469	0.136390	0.0116
Terminal	0.434478	0.403409	0.354379	0.506748	0.527654	0.335054	0.122152	0.412579	0.379270	0.159318	0.0319
S.F.Ratio	0.126411	0.188506	0.274269	-0.387926	-0.297233	0.324504	0.370607	-0.573683	-0.376430	-0.008536	0.1739
perc.alumni	-0.101158	-0.165516	-0.222723	0.455797	0.416832	-0.285457	-0.419334	0.565736	0.272393	-0.042832	0.3057
Expend	0.242935	0.161808	0.054221	0.657039	0.572905	0.000371	-0.201929	0.775328	0.580622	0.149983	0.1632
Grad.Rate	0.150803	0.078982	-0.023251	0.493670	0.478985	-0.082239	-0.265158	0.572458	0.425790	-0.008051	0.2908

Correlation is same for both scaled and non scaled data “Covariance” indicates the direction of the linear relationship between variables. “Correlation” on the other hand measures both the strength and direction of the linear relationship between two variables.Correlation is a function of the covariance. You can obtain the correlation coefficient of two variables by dividing the covariance of these variables by the product of the standard deviations of the same values.

2.5) Build the covariance matrix, eigenvalues, and eigenvector.

Identify eigen values and eigen vector

In [376]:

```
# Step 2- Get eigen values and eigen vector
eig_vals, eig_vecs = np.linalg.eig(cov_matrix)
```

In [377]:

```
eig_vals
```

Out[377]:

```
array([5.6625219 , 4.89470815, 1.12636744, 1.00397659, 0.87218426,
       0.7657541 , 0.58491404, 0.5445048 , 0.42352336, 0.38101777,
       0.24701456, 0.02239369, 0.03789395, 0.14726392, 0.13434483,
       0.09883384, 0.07469003])
```

In [378]:

```
eig_vecs
```

Out[378]:

```
array([[-2.62171542e-01,  3.14136258e-01,  8.10177245e-02,
         -9.87761685e-02, -2.19898081e-01,  2.18800617e-03,
         -2.83715076e-02, -8.99498102e-02,  1.30566998e-01,
         -1.56464458e-01, -8.62132843e-02,  1.82169814e-01,
         -5.99137640e-01,  8.99775288e-02,  8.88697944e-02,
          5.49428396e-01,  5.41453698e-03],
        [-2.30562461e-01,  3.44623583e-01,  1.07658626e-01,
         -1.18140437e-01, -1.89634940e-01, -1.65212882e-02,
         -1.29584896e-02, -1.37606312e-01,  1.42275847e-01,
         -1.49209799e-01, -4.25899061e-02, -3.91041719e-01,
          6.61496927e-01,  1.58861886e-01,  4.37945938e-02,
          2.91572312e-01,  1.44582845e-02],
        [-1.89276397e-01,  3.82813322e-01,  8.55296892e-02,
         -9.30717094e-03, -1.62314818e-01, -6.80794143e-02,
         -1.52403625e-02, -1.44216938e-01,  5.08712481e-02,
         -6.48997860e-02, -4.38408622e-02,  7.16684935e-01,
          2.33235272e-01, -3.53988202e-02, -6.19241658e-02,
         -4.17001280e-01, -4.97908902e-02],
        [-3.38874521e-01, -9.93191661e-02, -7.88293849e-02,
          3.69115031e-01, -1.57211016e-01, -8.88656824e-02,
         -2.57455284e-01,  2.89538833e-01, -1.22467790e-01,
         -3.58776186e-02,  1.77837341e-03, -5.62053913e-02,
          2.21448729e-02, -3.92277722e-02,  6.99599977e-02,
          8.79767299e-03,  7.23645373e-01]
```

```
  8.79767299e-03, -7.23645373e-01],
 [-3.34690532e-01, -5.95055011e-02, -5.07938247e-02,
   4.16824361e-01, -1.44449474e-01, -2.76268979e-02,
  -2.39038849e-01,  3.45643551e-01, -1.93936316e-01,
   6.41786425e-03, -1.02127328e-01,  1.96735274e-02,
   3.22646978e-02,  1.45621999e-01, -9.70282598e-02,
  -1.07779150e-02,  6.55464648e-01],
 [-1.63293010e-01,  3.98636372e-01,  7.37077827e-02,
  -1.39504424e-02, -1.02728468e-01, -5.16468727e-02,
  -3.11751439e-02, -1.08748900e-01,  1.45452749e-03,
  -1.63981359e-04, -3.49993487e-02, -5.42774834e-01,
  -3.67681187e-01, -1.33555923e-01, -8.71753137e-02,
  -5.70683843e-01,  2.53059904e-02],
 [-2.24797091e-02,  3.57550046e-01,  4.03568700e-02,
  -2.25351078e-01,  9.56790178e-02, -2.45375721e-02,
  -1.00138971e-02,  1.23841696e-01, -6.34774326e-01,
   5.46346279e-01,  2.52107094e-01,  2.95029745e-02,
   2.62494456e-02,  5.02487566e-02,  4.45537493e-02,
   1.46321060e-01, -3.97146972e-02],
 [-2.83547285e-01, -2.51863617e-01,  1.49394795e-02,
  -2.62975384e-01, -3.72750885e-02, -2.03860462e-02,
   9.45370782e-02,  1.12721477e-02, -8.36648339e-03,
  -2.31799759e-01,  5.93433149e-01,  1.03393587e-03,
  -8.14247697e-02,  5.60392799e-01,  6.72405494e-02,
  -2.11561014e-01, -1.59275617e-03],
 [-2.44186588e-01, -1.31909124e-01, -2.11379165e-02,
  -5.80894132e-01,  6.91080879e-02,  2.37267409e-01,
   9.45210745e-02,  3.89639465e-01, -2.20526518e-01,
  -2.55107620e-01, -4.75297296e-01,  9.85725168e-03,
   2.67779296e-02, -1.07365653e-01,  1.77715010e-02,
  -1.00935084e-01, -2.82578388e-02],
 [-9.67082754e-02,  9.39739472e-02, -6.97121128e-01,
   3.61562884e-02, -3.54056654e-02,  6.38604997e-01,
  -1.11193334e-01, -2.39817267e-01,  2.10246624e-02,
   9.11624912e-02,  4.35697999e-02,  4.36086500e-03,
   1.04624246e-02,  5.16224550e-02,  3.54343707e-02,
  -2.86384228e-02, -8.06259380e-03],
 [ 3.52299594e-02,  2.32439594e-01, -5.30972806e-01,
   1.14982973e-01,  4.75358244e-04, -3.81495854e-01,
   6.39418106e-01,  2.77206569e-01,  1.73715184e-02,
  -1.27647512e-01,  1.51627393e-02, -1.08725257e-02,
   4.54572099e-03,  9.39409228e-03, -1.18604404e-02,
   3.38197909e-02,  1.42590097e-03],
 [-3.26410696e-01,  5.51390195e-02,  8.11134044e-02,
   1.47260891e-01,  5.50786546e-01,  3.34444832e-03,
   8.92320786e-02, -3.42628480e-02,  1.66510079e-01,
   1.00975002e-01, -3.91865961e-02,  1.33146759e-02,
   1.25137966e-02, -7.16590441e-02,  7.02656469e-01,
  -6.38096394e-02,  8.31471932e-02],
 [-3.23115980e-01,  4.30332048e-02,  5.89785929e-02,
   8.90079921e-02,  5.90407136e-01,  3.54121294e-02,
   9.16985445e-02, -9.03076644e-02,  1.12609034e-01,
   8.60363025e-02, -8.48575651e-02,  7.38135022e-03,
  -1.79275275e-02,  1.63820871e-01, -6.62488717e-01,
   9.85019644e-02, -1.13374007e-01],
 [ 1.63151642e-01,  2.59804556e-01,  2.74150657e-01,
   2.59486122e-01,  1.42842546e-01,  4.68752604e-01,
   1.52864837e-01,  2.42807562e-01, -1.53685343e-01,
  -4.70527925e-01,  3.63042716e-01,  8.85797314e-03,
   1.83059753e-02, -2.39902591e-01, -4.79006197e-02,
   6.19970446e-02,  3.83160891e-03],
 [-1.86610828e-01, -2.57092552e-01,  1.03715887e-01,
   2.23982467e-01, -1.28215768e-01,  1.25669415e-02,
   3.91400512e-01, -5.66073056e-01, -5.39235753e-01,
  -1.47628917e-01, -1.73918533e-01, -2.40534190e-02,
  -8.03169296e-05, -4.89753356e-02,  3.58875507e-02,
   2.80805469e-02, -7.32598621e-03],
 [-3.28955847e-01, -1.60008951e-01, -1.84205687e-01,
  -2.13756140e-01,  2.24240837e-02, -2.31562325e-01,
  -1.50501305e-01, -1.18823549e-01,  2.42371616e-02,
  -8.04154875e-02,  3.93722676e-01,  1.05658769e-02,
   5.60069250e-02, -6.90417042e-01, -1.26667522e-01,
   1.28739213e-01,  1.45099786e-01],
 [-2.38822447e-01, -1.67523664e-01,  2.45335837e-01,
   3.61915064e-02, -3.56843227e-01,  3.13556243e-01,
   4.68641965e-01,  1.80458508e-01,  3.15812873e-01,
   4.88415259e-01,  8.72638706e-02, -2.51028410e-03,
```

```
 1.48410810e-02, -1.59332164e-01, -6.30737002e-02,
-7.09643331e-03, -3.29024228e-03]])
```

2.7) Discuss the cumulative values of the eigenvalues. How does it help you to decide on the optimum number of principal components? What do the eigenvectors indicate? Perform PCA and export the data of the Principal Component scores into a data frame.

Cummulative Distribution of Eigen values

In [379]:

```
tot = sum(eig_vals)
var_exp = [( i /tot ) * 100 for i in sorted(eig_vals, reverse=True)]
cum_var_exp = np.cumsum(var_exp)
print("Cumulative Variance Explained", cum_var_exp)
```

```
Cumulative Variance Explained [ 33.26608367  62.02142867  68.63859223  74.53673619  79.66062886
  84.15926753  87.59551019  90.79435736  93.28246491  95.52086136
  96.97201814  97.83716159  98.62640821  99.20703552  99.64582321
  99.86844192 100.        ]
```

In [ ]:

```

```

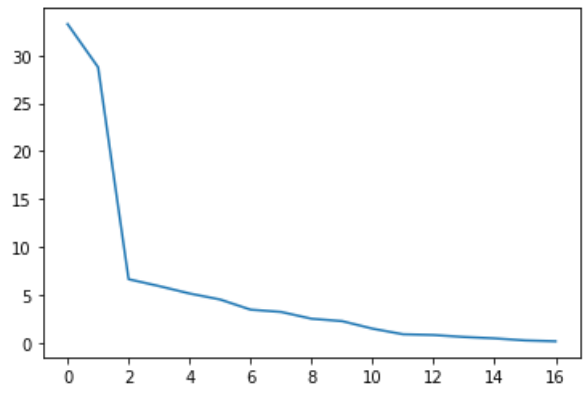
Scree plot

In [380]:

```
plt.plot(var_exp)
```

Out[380]:

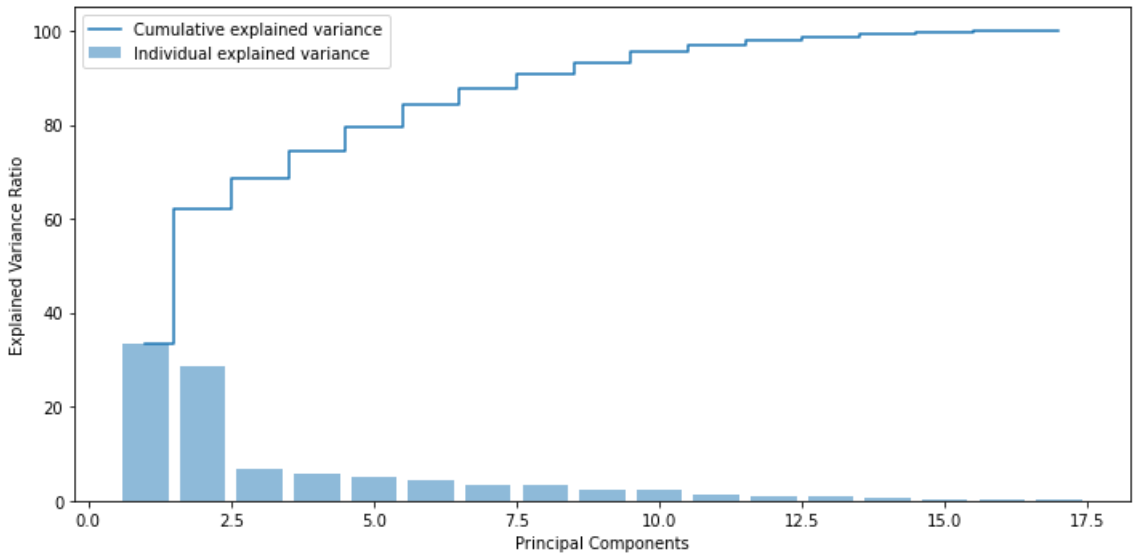
```
[<matplotlib.lines.Line2D at 0x222511acc10>]
```



Visually we can observe that their is steep drop in variance explained with increase in number of PC's. We will proceed with 4 components here. But depending on requirement 90% variation or 5 components will also do good

In [381]:

```
# Ploting
plt.figure(figsize=(10 , 5))
plt.bar(range(1, eig_vals.size + 1), var_exp, alpha = 0.5, align = 'center', label = 'Individual ex
plained variance')
plt.step(range(1, eig_vals.size + 1), cum_var_exp, where='mid', label = 'Cumulative explained varia
nce')
plt.ylabel('Explained Variance Ratio')
plt.xlabel('Principal Components')
plt.legend(loc = 'best')
plt.tight_layout()
plt.show()
```



Use PCA command from sklearn and find Principal Components

In [384]:

```
# Using scikit learn PCA here. It does all the above steps and maps data to PCA dimensions in one shot
from sklearn.decomposition import PCA
# NOTE - we are generating only 4 PCA dimensions (dimensionality reduction from 18 to 4)

pca = PCA(n_components = 4)
data_reduced = pca.fit_transform(data_new)
data_reduced.T
```

Out[384]:

```
array([[-1.60249937, -1.80467547, -1.60828258, ..., -0.57688269,
         6.57095201, -0.4773931 ],
       [ 0.99368301, -0.07041499, -1.38279212, ...,  0.01779846,
        -1.18493014,  1.04394673],
       [ 0.03004373,  2.12213212, -0.5015119 , ...,  0.32216376,
         1.32596316, -1.42543193],
       [-1.0084203 ,  3.13893281, -0.03637465, ..., -0.58726445,
         0.07770845, -1.30028602]])
```

In [401]:

```
pca.components_
```

Out[401]:

```
array([[ 0.26217154,  0.23056246,  0.1892764 ,  0.33887452,  0.33469053,
         0.16329301,  0.02247971,  0.28354729,  0.24418659,  0.09670828,
        -0.03522996,  0.3264107 ,  0.32311598, -0.16315164,  0.18661083,
         0.32895585,  0.23882245],
       [ 0.31413626,  0.34462358,  0.38281332, -0.09931917, -0.0595055 ,
         0.39863637,  0.35755005, -0.25186362, -0.13190912,  0.09397395,
         0.23243959,  0.05513902,  0.0430332 ,  0.25980456, -0.25709255,
        -0.16000895, -0.16752366],
       [-0.08101716, -0.10765826, -0.08553006,  0.07883042,  0.0507929 ,
        -0.07370849, -0.04035666, -0.0149397 ,  0.02113785,  0.69712111,
         0.53097284, -0.08111366, -0.05897824, -0.27415063, -0.10371585,
         0.18420555, -0.24533585],
       [ 0.09877485,  0.11813972,  0.00930802, -0.3691173 , -0.41682234,
         0.01395194,  0.22535062,  0.26297585,  0.58089427, -0.03615625,
        -0.11498306, -0.14726034, -0.08900876, -0.25948617, -0.22398255,
         0.21375646, -0.03619149]])
```

In [385]:

```
pca.explained_variance_ratio_
```

Out[385]:

```
array([0.33266084, 0.28755345, 0.06617164, 0.05898144])
```

In [386]:

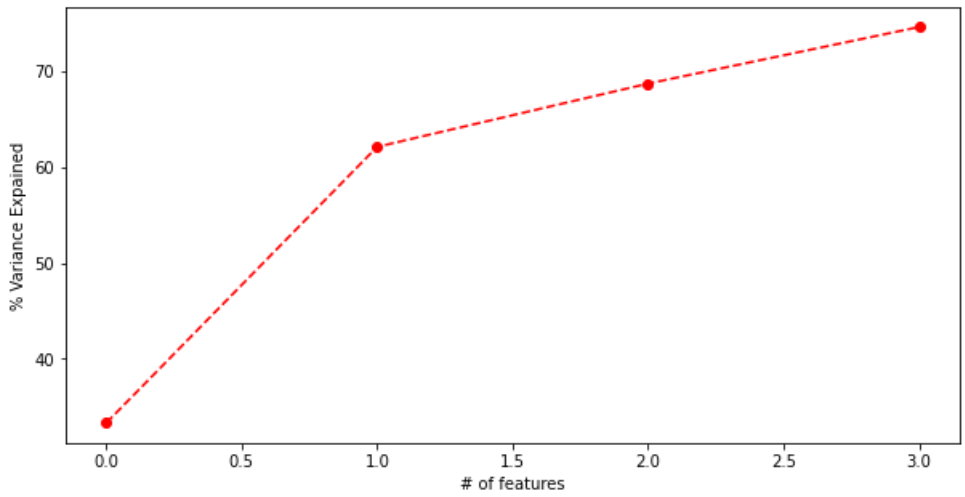
```
var=np.cumsum(np.round(pca.explained_variance_ratio_, decimals=3)*100)
var #cumulative sum of variance explained with [n] features
```

Out[386]:

```
array([33.3, 62.1, 68.7, 74.6])
```

In [389]:

```
plt.figure(figsize=(10 , 5))
plt.plot(var,marker='o',linestyle ='--',color='red')
plt.ylabel('% Variance Expained')
plt.xlabel('# of features')
plt.show()
```



The Cumulative % gives the percentage of variance accounted for by the n components. For example, the cumulative percentage for the second component is the sum of the percentage of variance for the first and second components. It helps in deciding the number of components by selecting the components which explained the high variance

In the above array we see that the first feature explains 33.26% of the variance within our data set while the first two explain 62.02 and so on. If we employ 4 features we capture ~ 74% of the variance within the dataset, thus we gain very little by implementing an additional feature (think of this as diminishing marginal return on total variance explained)

In [ ]:

```
# Correlation between components and features
```

In [390]:

```
df_comp =pd.DataFrame(pca.components_,columns=list(data_new))
df_comp.head()
```

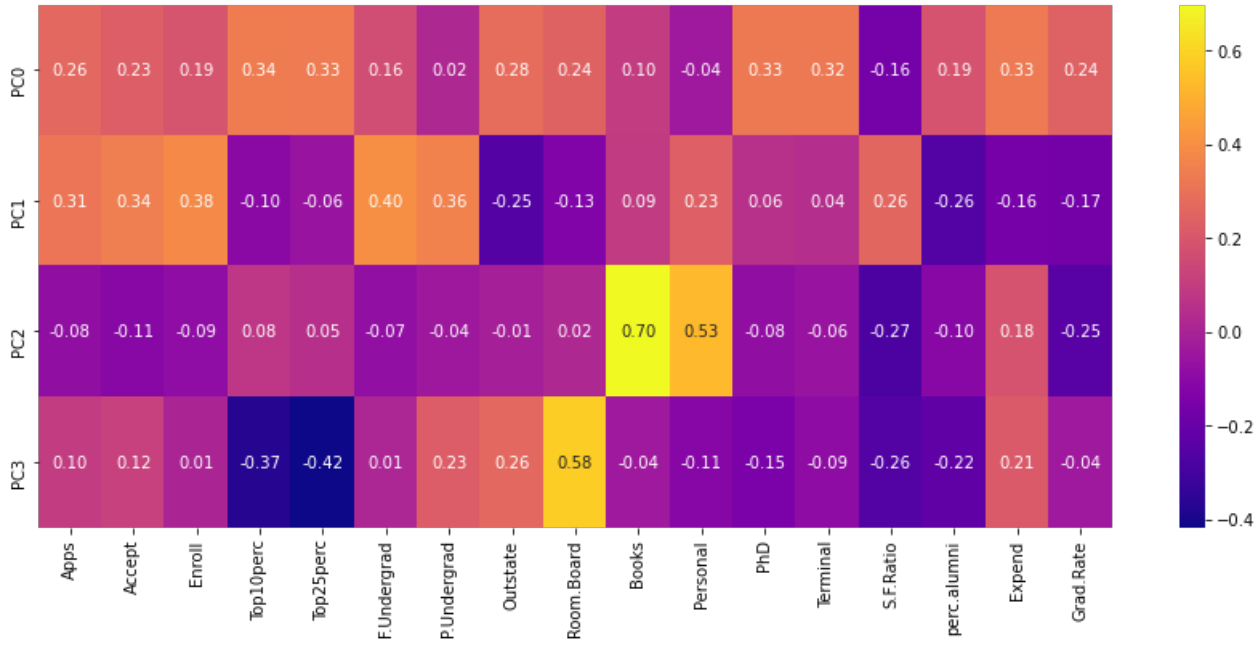
Out[390]:

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Personal	Ph
0	0.262172	0.230562	0.189276	0.338875	0.334691	0.163293	0.022480	0.283547	0.244187	0.096708	-0.035230	0.3264
1	0.314136	0.344624	0.382813	-0.099319	-0.059506	0.398636	0.357550	-0.251864	-0.131909	0.093974	0.232440	0.0551

	Apps	Accept	Enroll	Top10perc	Top25perc	F.Undergrad	P.Undergrad	Outstate	Room.Board	Books	Personal	Ph
2	0.081017	0.107658	0.085530	0.078830	0.050793	-0.073708	-0.040357	0.014940	0.021138	0.697121	0.530973	0.0811
3	0.098775	0.118140	0.009308	-0.369117	-0.416822	0.013952	0.225351	0.262976	0.580894	0.036156	0.114983	0.1472

In [400]:

```
plt.figure(figsize=(15,6))
sns.heatmap(df_comp,cmap='plasma',annot= True,fmt='.2f',yticklabels=['PC0', 'PC1','PC2','PC3'])
plt.show()
```



In [382]:

```
# This heatmap and the color bar basically represent the correlation between the various feature
# and the principal component itself
# Component 2 looks more related to aspect  - We can label it as aspect property
# Depending on relations ship, we could go ahead and label relationship with features
```

PCA is a statistical technique and uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. PCA also is a tool to reduce multidimensional data to lower dimensions while retaining most of the information. Principal Component Analysis (PCA) is a well-established mathematical technique for reducing the dimensionality of data, while keeping as much variation as possible.

This PCA can only be done on continous variables

In [ ]:

```

```