CMSE 381, Fundamental Data Science Methods

September 7, 2025

Homework 1

Lowell Monis

Question 1: ISLP § 2.4.9

[2]:
```
auto = pd.read_csv('../data/Auto.csv')
auto=auto.replace('?', np.nan)
auto=auto.dropna()
auto['horsepower']=auto['horsepower'].astype('int')
auto=auto.reset_index(drop=True)
```

(a) Which of the predictors are quantitative, and which are qualitative? The following predictors are qualitative: `name` and `origin`.

The following predictors are quantitative: `mpg`, `cylinders`, `displacement`, `horsepower`, `weight`, `acceleration`, and `year`.

Why do I think so? For the quantitative predictors, the reasoning is rather simpler. All of them have multiple unique values and are measurable quantities. Even if they are fewer in number, say below 100, they are not really placed equidistantly to be considered discrete. They also have much variation. In the case of `year`, even if it has 13 unique values and they are equidistant from each other, it is a timescale, and timescale values are usually considered quantitative since they do not qualitatively or categorically describe the data in most cases, and time is also a measurable quantity. In the case of `cylinder`, even with 5 unique values, it provides a count of the number of cylinders, thus showing an ability to be measured. There is a limit to the number of cylinders, and cylinders cannot be partial, so even with limited unique values and the appearance of discreteness, it quantitatively describes the data.

Now, even though `name` has the most unique values, being an indication of high variation in the data, it is a text-based variable, thus describing the data qualitatively. It is the name of the automobile, which cannot be used to quantitatively describe the data, and cannot be measured as a quantity. `origin` is the one variable that has the least variation and is discrete, like the perfect categorical variable for clustering or classification. But the primary reasoning for classifying this as qualitative is the fact that it describes where the car was made in three levels. A choice was made to represent these countries using numbers rather than the country name. Origin, like the name, is not a measurable quantity.

[3]:
```
for i in auto.columns:
    print("There are", len(auto[i].unique()), "unique entries in predictor", i)
```

```
There are 127 unique entries in predictor mpg
There are 5 unique entries in predictor cylinders
There are 81 unique entries in predictor displacement
There are 93 unique entries in predictor horsepower
There are 346 unique entries in predictor weight
There are 95 unique entries in predictor acceleration
There are 13 unique entries in predictor year
There are 3 unique entries in predictor origin
There are 301 unique entries in predictor name
```

(b) What is the range of each quantitative predictor? You can answer this using the `min()` and `max()` methods in `numpy`. I used the `describe()` method and selected specific rows rather than repetitively using a command. The range can be read from top to bottom (minimum to maximum).

[4]:
```
auto.drop('origin', axis=1).describe().loc[['min','max']]
```

[4]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	year
min	9.0	3.0	68.0	46.0	1613.0	8.0	70.0
max	46.6	8.0	455.0	230.0	5140.0	24.8	82.0

(c) What is the mean and standard deviation of each quantitative predictor? I used the same technique here as I did in (b).

[5]:
```
auto.drop('origin', axis=1).describe().loc[['mean','std']]
```

[5]:

	mpg	cylinders	displacement	horsepower	weight \
mean	23.445918	5.471939	194.411990	104.469388	2977.584184
std	7.805007	1.705783	104.644004	38.491160	849.402560

	acceleration	year
mean	15.541327	75.979592
std	2.758864	3.683737

(d) Now remove the 10th through 85th observations. What is the range, mean, and standard deviation of each predictor in the subset of the data that remains? The range, once again, is read from minimum to maximum values here.

[6]:
```
auto.drop(range(9,85), axis=0).describe().loc[['min', 'max', 'mean','std']]
```

[6]:

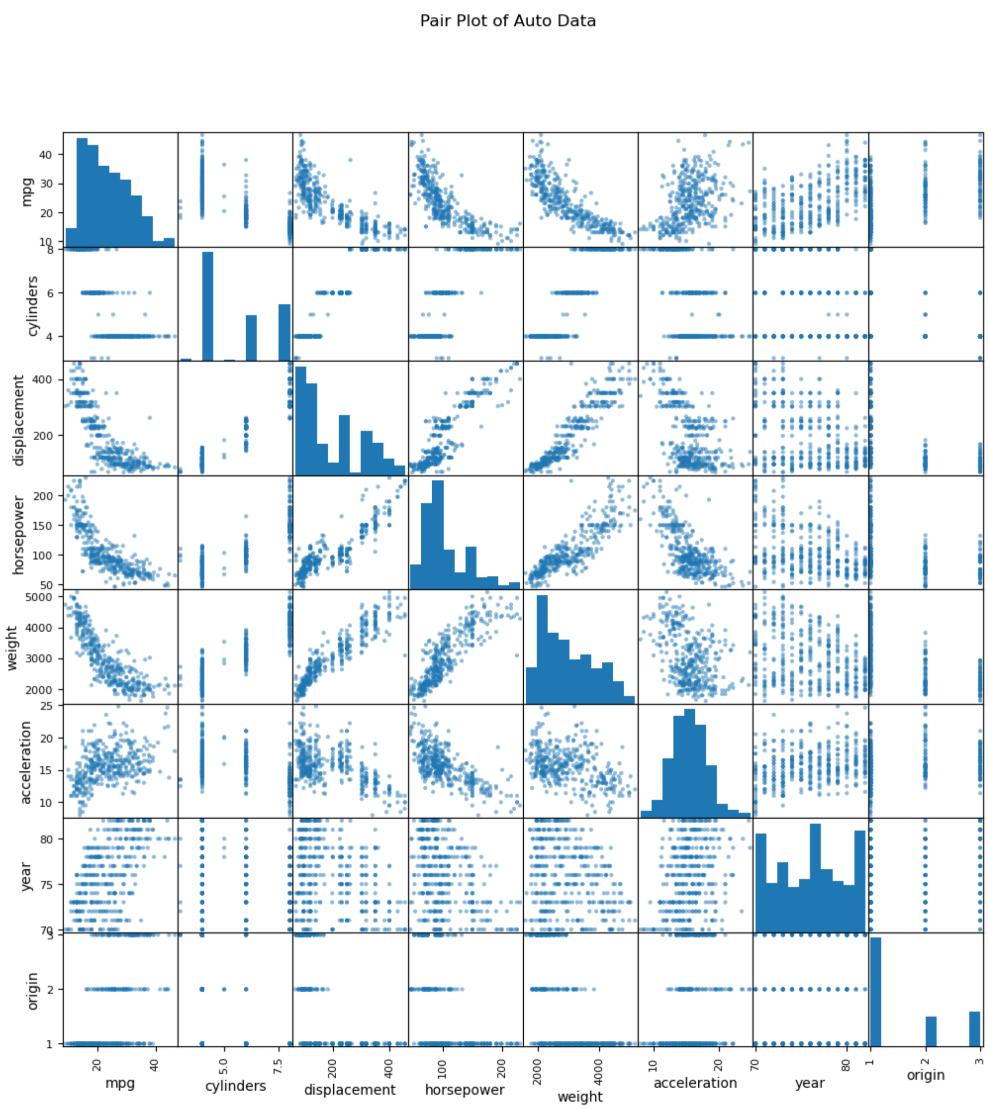
	mpg	cylinders	displacement	horsepower	weight \
min	11.000000	3.000000	68.000000	46.000000	1649.000000
max	46.600000	8.000000	455.000000	230.000000	4997.000000
mean	24.404430	5.373418	187.240506	100.721519	2935.971519
std	7.867283	1.654179	99.678367	35.708853	811.300208

```
      acceleration       year    origin
min       8.500000  70.000000  1.000000
max      24.800000  82.000000  3.000000
mean     15.726899  77.145570  1.601266
std       2.693721   3.106217  0.819910
```

(e) Using the full data set, investigate the predictors graphically, using scatterplots or other tools of your choice. Create some plots highlighting the relationships among the predictors. Comment on your findings.

[7]:
```
pd.plotting.scatter_matrix(auto, figsize=(12, 12))
plt.suptitle('Pair Plot of Auto Data')
```

[7]:
```
Text(0.5, 0.98, 'Pair Plot of Auto Data')
```



The pair plot provides a comprehensive visual summary of the relationships between all the variables. The scatter plots reveal several key findings:

- There's a strong positive correlation between several of the quantitative predictors. For example, `horsepower`, `weight`, and `displacement` are all positively related to each other. Cars that have larger engine displacement tend to be heavier and have more horsepower. The relationship appears mostly linear.
- The `cylinders` variable, which is discrete, shows a clear positive relationship with other variables like `displacement`, `horsepower`, and `weight`. Vehicles with more cylinders generally have larger, heavier, and more powerful engines.
- The `acceleration` variable has negative trends with `displacement` (slightly), `horsepower` (fairly), and `weight` (slightly), suggesting that heavier, more powerful cars may not always be the fastest.

(f) Suppose that we wish to predict gas mileage (mpg) on the basis of the other variables. Do your plots suggest that any of the other variables might be useful in predicting mpg? Justify your answer. The plots strongly suggest that many of the other variables will be useful in predicting `mpg`. We can justify this by observing the relationships in the first column of the pair plot, which shows `mpg` plotted against every other variable.

- The scatter plots of `mpg` versus `horsepower`, `weight`, and `displacement` show a strong, clear negative relationship. As `horsepower`, `weight`, or `displacement` increase, `mpg` consistently decreases. The distinct downward slope in these plots indicates that they are highly useful predictors.
- The `mpg` vs. `cylinders` plot shows that the average `mpg` value is significantly lower for cars with more cylinders compared to those with fewer.

In short, any variable that shows a discernible trend (linear or otherwise) with `mpg` is a useful predictor, and the pair plot confirms that most of the variables in this dataset fit that description.

Question 2: ISLP § 2.4.2

Explain whether each scenario is a classification or regression problem, and indicate whether we are most interested in inference or prediction. Finally, provide n and p. In each of these scenarios, we establish that n is the number of data points, and p is the number of predictors, or features.

(a) We collect a set of data on the top 500 firms in the US. For each firm we record profit, number of employees, industry and the CEO salary. We are interested in understanding which factors affect CEO salary.

In this scenario, an attempt is being made to understand the behaviors of the data and its effect on the target variable within the time frame provided, rather than predict behaviors of the target variable in the future. I can thus conclude that we are interested primarily in **inference** here. Considering that salary is a quantitative variable, due to its variability, wide range, and continuous, rather than discrete, numerical nature as a value, I can assume that this analysis would need **regression**, since classification will need a few discrete, and a certain number of groups to classify into. Here, $n = 500$, since the analysis is using data from 500 firms, and $p = 3$, considering the CEO salary is a target variable and won't be counted as a predictor.

(b) We are considering launching a new product and wish to know whether it will be a success or a failure. We collect data on 20 similar products that were previously launched. For each product we have recorded whether it was a success or failure, price charged for the product, marketing budget, competition price, and ten other variables.

In this scenario, an attempt is being made to forecast the outcome of a new product through different market factors of existing products that are similar to the new one. I can thus conclude that we are interested primarily in **prediction** here, rather than understanding what led to the success and failure of the 20 other products that have already been launched. Considering that the target variable, which is the market outcome of the product, has two discrete levels, i.e., success or failure, we assume this variable is of a qualitative nature, and we can further assume that this is a **classification** problem, since we have to use the other factors to classify the new product between one of two levels. Here, $n = 20$, since there are twenty existing data points. $p = 13$ here; this is because there are 4 named variables, and 10 unnamed ones, out of which 1 of the variables is the target variable.

(c) We are interested in predicting the % change in the USD/Euro exchange rate in relation to the weekly changes in the world stock markets. Hence we collect weekly data for all of 2012. For each week we record the % change in the USD/Euro, the % change in the US market, the % change in the British market, and the % change in the German market.

In this scenario, an attempt is being made to forecast the percent change in the exchange rate in relation to the percent change by week in three other markets around the world. I can thus conclude, from just the framing of the question, that this is a **prediction** problem. Considering that percent changes are on a continuous numerical scale and fluctuate between multiple decimal values, this is a quantitative target variable, and thus leads me to conclude that this problem is a **regression** problem. There are weekly values for the year 2012 in the data here, so $n = 52$, since there were 52 weeks in the year 2012. Considering we are using market changes from three markets to predict the exchange rate, we can also conclude that $p = 3$.

Question 3: ISLP § 2.4.4

(a) Describe *one* real-life application in which classification might be useful. Describe the response, as well as the predictors. Is the goal of each application inference or prediction? Explain your answer. Here are three applications of classification I see in real life:

1. While this is a massive oversimplification, the "algorithm" in social media and video-sharing websites can be thought of as a classification model. The response here is a discrete, categorical variable with levels "recommend" and "do not recommend". The predictors could be things like what videos I have watched, for how long, whether I finished them, and if I have watched them again (these apply to video-sharing sites); what posts I have liked, commented on, or shared; the accounts I follow/am subscribed to; my demographic information, like age, gender, region, etc. This is clearly a prediction, by virtue of the fact that the model is predicting what I want to watch or see, as well as the fact that the model can be entirely wrong. An example is when I am recommended posts not in line with my political views, just because I may have searched an account that promotes views to inform myself.
2. I believe one of the most common applications of classification is the spam filter in emails. The response here is a discrete, categorical variable with levels "spam" and "not spam". The

predictors could be things like the occurrence of some common words associated with a spam email (e.g., “free,” “winner,” “urgent”), the sender’s address (this might need NLP, however, if my understanding of NLP is correct), and the number of recipients. This is a prediction, by virtue of the fact that the goal is to automatically sort an email before the user even sees it. The model’s primary task is to make a fast and accurate guess on new emails, and it can be entirely wrong, sometimes sending a legitimate email to the spam folder.

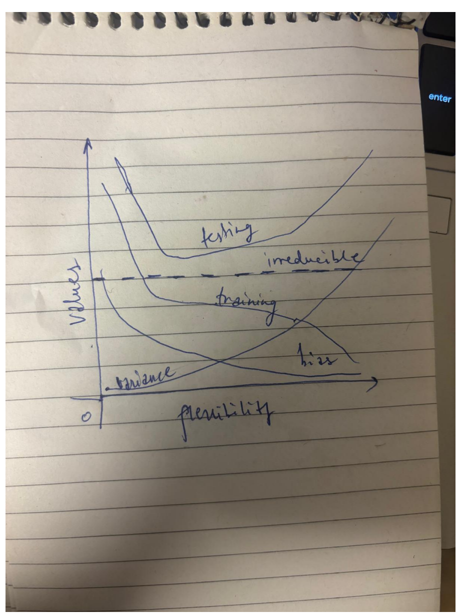
3. Another important application is in loan or credit card applications to analyze risk in lending money to the borrower or approving an applicant for their credit card. The response here is a discrete, categorical variable with levels “risky” and “not risky”, or “approve” and “deny”. The predictors can include credit score, income, past defaults, age, and employment status. While I feel this is obviously a prediction model, a perspective can be provided in terms of inference by virtue of the fact that the model can be used to rewrite lending policies based on past data.

I used Gemini by Google for the first application, since I was a little lost and needed a head start on what were potential predictors for a model like this. My prompt was as follows: > what are examples of predictors for the “algorithm” that recommends content on social media and video-sharing sites, in the context that i am simplifying this model to a simple classification problem?

Note to grader: I just read the question properly, but I feel bad deleting the other responses I wrote, so I am submitting three examples for the first one.

(b) Describe *one* real-life application in which regression might be useful. Describe the response, as well as the predictors. Is the goal of each application inference or prediction? Explain your answer. I believe fitness apps can use regression to see how their app helps their users’ fitness goals through responses such as a net change in weight, for example, where the user wants to undergo weight loss. Here, predictors can be the frequency of active time, number of workouts, intensity of workouts, original weight, goal weight, etc. This is an inference application, since the app can be tweaked based on the net percent change in weight by the user.

Question 4: ISLP § 2.4.3



(a) Provide a sketch of typical (squared) bias, variance, training error, test error, and irreducible error curves, on a single plot, as we go from less flexible statistical learning methods towards more flexible approaches. The x-axis should represent the amount of flexibility in the method, and the y-axis should represent the values for each curve. There should be five curves. Make sure to label each one.

(b) Explain why each of the five curves has the shape displayed in part (a). As we increase the flexibility of a statistical learning method, there's a trade-off between bias and variance. Less flexible models, such as regression-based models, have high bias because they can't capture the complex patterns in the data; however, they have low variance because their predictions remain consistent even with different training sets. Conversely, highly flexible models, and even black-box models, like deep neural networks, have low bias because they fit the training data extremely well, but they suffer from high variance as they become overly sensitive to noise. Thus, the bias and variance curves are almost opposite to each other, with bias decreasing with nearly, if not exactly, the same magnitude as variance increases.

The bias-variance trade-off impacts the error curves. The training error consistently decreases as flexibility increases because the model can fit the training data more closely. However, the test error, which is what we should care about, follows a near U-shaped curve. This is because it decreases as bias is reduced, but eventually rises again as the model becomes too flexible and suffers from high variance and overfitting. The lowest point on this curve represents the optimal balance. Finally, there is an intrinsic, constant, irreducible error that no model can ever eliminate, as it's caused by the random noise in the data itself, and not the noise that is captured by highly flexible, overfitted models.

Question 5: ISLP § 2.4.8

This exercise relates to the College data set, which can be found in the file `College.csv` on the book website. It contains a number of variables for 777 different universities and colleges in the US. The variables are

- `Private`: Public/private indicator
- `Apps`: Number of applications received
- `Accept`: Number of applicants accepted
- `Enroll`: Number of new students enrolled
- `Top10perc`: New students from top 10% of high school class
- `Top25perc`: New students from top 25% of high school class
- `F.Undergrad`: Number of full-time undergraduates
- `P.Undergrad`: Number of part-time undergraduates
- `Outstate`: Out-of-state tuition
- `Room.Board`: Room and board costs
- `Books`: Estimated book costs
- `Personal`: Estimated personal spending
- `PhD`: Percent of faculty with Ph.D.s
- `Terminal`: Percent of faculty with terminal degree
- `S.F.Ratio`: Student/faculty ratio
- `perc.alumni`: Percent of alumni who donate
- `Expends`: Instructional expenditure per student
- `Grad.Rate`: Graduation rate

Before reading the data into Python, it can be viewed in Excel or a text editor.

(a) Use the `pd.read_csv()` function to read the data into Python. Call the loaded data `college`. Make sure that you have the directory set to the correct location for the data.

[8]:
```
college = pd.read_csv('../data/College.csv')
```

(b) Look at the data used in the notebook by creating and running a new cell with just the code `college` in it.

[9]:
```
college
```

[9]:
```
                       Unnamed: 0 Private   Apps  Accept  Enroll  Top10perc  \
0    Abilene Christian University     Yes   1660    1232     721         23
1              Adelphi University     Yes   2186    1924     512         16
2                  Adrian College     Yes   1428    1097     336         22
3             Agnes Scott College     Yes    417     349     137         60
4       Alaska Pacific University     Yes    193     146      55         16
..                            ...     ...    ...     ...     ...        ...
772       Worcester State College      No   2197    1515     543          4
773             Xavier University     Yes   1959    1805     695         24
774  Xavier University of Louisiana     Yes   2097    1915     695         34
775               Yale University     Yes  10705    2453    1317         95
776   York College of Pennsylvania     Yes   2989    1855     691         28

     Top25perc  F.Undergrad  P.Undergrad  Outstate  Room.Board  Books  \
0           52         2885          537      7440        3300    450
1           29         2683         1227     12280        6450    750
2           50         1036           99     11250        3750    400
3           89          510           63     12960        5450    450
4           44          249          869      7560        4120    800
..         ...          ...          ...       ...         ...    ...
772         26         3089         2029      6797        3900    500
773         47         2849         1107     11520        4960    600
774         61         2793          166      6900        4200    617
775         99         5217           83     19840        6510    630
776         63         2988         1726      4990        3560    500

     Personal  PhD  Terminal  S.F.Ratio  perc.alumni  Expend  Grad.Rate
0        2200   70        78       18.1           12    7041         60
1        1500   29        30       12.2           16   10527         56
2        1165   53        66       12.9           30    8735         54
3         875   92        97        7.7           37   19016         59
4        1500   76        72       11.9            2   10922         15
..        ...  ...       ...        ...          ...     ...        ...
772      1200   60        60       21.0           14    4469         40
773      1250   73        75       13.3           31    9189         83
774       781   67        75       14.4           20    8323         49
775      2115   96        96        5.8           49   40386         99
```

```
776      1250   75         75       18.1           28    4509          99

[777 rows x 19 columns]
```

You should notice that the first column is just the name of each university in a column named something like `Unnamed: 0`. We don't really want pandas to treat this as data. However, it may be handy to have these names for later. Try the following commands and similarly look at the resulting data frames.

[10]:
```
college2 = pd.read_csv('../data/College.csv', index_col=0)
college3 = college.rename({'Unnamed: 0': 'College'}, axis=1)
college3 = college3.set_index('College')
college2
```

[10]:
```
                              Private   Apps  Accept  Enroll  Top10perc  \
Abilene Christian University      Yes   1660    1232     721         23
Adelphi University                Yes   2186    1924     512         16
Adrian College                    Yes   1428    1097     336         22
Agnes Scott College               Yes    417     349     137         60
Alaska Pacific University         Yes    193     146      55         16
...                               ...    ...     ...     ...        ...
Worcester State College            No   2197    1515     543          4
Xavier University                 Yes   1959    1805     695         24
Xavier University of Louisiana    Yes   2097    1915     695         34
Yale University                   Yes  10705    2453    1317         95
York College of Pennsylvania      Yes   2989    1855     691         28

                                Top25perc  F.Undergrad  P.Undergrad  Outstate  \
Abilene Christian University           52         2885          537      7440
Adelphi University                     29         2683         1227     12280
Adrian College                         50         1036           99     11250
Agnes Scott College                    89          510           63     12960
Alaska Pacific University              44          249          869      7560
...                                   ...          ...          ...       ...
Worcester State College                26         3089         2029      6797
Xavier University                      47         2849         1107     11520
Xavier University of Louisiana         61         2793          166      6900
Yale University                        99         5217           83     19840
York College of Pennsylvania           63         2988         1726      4990

                                Room.Board  Books  Personal  PhD  Terminal  \
Abilene Christian University          3300    450      2200   70        78
Adelphi University                    6450    750      1500   29        30
Adrian College                        3750    400      1165   53        66
Agnes Scott College                   5450    450       875   92        97
Alaska Pacific University             4120    800      1500   76        72
...                                    ...    ...       ...  ...       ...
Worcester State College               3900    500      1200   60        60
```

```
Xavier University                     4960     600      1250    73          75
Xavier University of Louisiana        4200     617       781    67          75
Yale University                       6510     630      2115    96          96
York College of Pennsylvania          3560     500      1250    75          75

                                S.F.Ratio  perc.alumni  Expend  Grad.Rate
Abilene Christian University         18.1           12    7041         60
Adelphi University                   12.2           16   10527         56
Adrian College                       12.9           30    8735         54
Agnes Scott College                   7.7           37   19016         59
Alaska Pacific University            11.9            2   10922         15
...                                   ...          ...     ...        ...
Worcester State College              21.0           14    4469         40
Xavier University                    13.3           31    9189         83
Xavier University of Louisiana       14.4           20    8323         49
Yale University                       5.8           49   40386         99
York College of Pennsylvania         18.1           28    4509         99

[777 rows x 18 columns]
```

[11]:
```
college3
```

[11]:
```
                               Private   Apps  Accept  Enroll  Top10perc  \
College
Abilene Christian University       Yes   1660    1232     721         23
Adelphi University                 Yes   2186    1924     512         16
Adrian College                     Yes   1428    1097     336         22
Agnes Scott College                Yes    417     349     137         60
Alaska Pacific University          Yes    193     146      55         16
...                                ...    ...     ...     ...        ...
Worcester State College             No   2197    1515     543          4
Xavier University                  Yes   1959    1805     695         24
Xavier University of Louisiana     Yes   2097    1915     695         34
Yale University                    Yes  10705    2453    1317         95
York College of Pennsylvania       Yes   2989    1855     691         28

                                Top25perc  F.Undergrad  P.Undergrad  Outstate  \
College
Abilene Christian University           52         2885          537      7440
Adelphi University                     29         2683         1227     12280
Adrian College                         50         1036           99     11250
Agnes Scott College                    89          510           63     12960
Alaska Pacific University              44          249          869      7560
...                                   ...          ...          ...       ...
Worcester State College                26         3089         2029      6797
Xavier University                      47         2849         1107     11520
Xavier University of Louisiana         61         2793          166      6900
```

```
Yale University                      99         5217          83      19840
York College of Pennsylvania         63         2988        1726       4990

                                Room.Board  Books  Personal  PhD  Terminal  \
College
Abilene Christian University          3300    450      2200   70        78
Adelphi University                    6450    750      1500   29        30
Adrian College                        3750    400      1165   53        66
Agnes Scott College                   5450    450       875   92        97
Alaska Pacific University             4120    800      1500   76        72
...                                    ...    ...       ...  ...       ...
Worcester State College               3900    500      1200   60        60
Xavier University                     4960    600      1250   73        75
Xavier University of Louisiana        4200    617       781   67        75
Yale University                       6510    630      2115   96        96
York College of Pennsylvania          3560    500      1250   75        75

                                S.F.Ratio  perc.alumni  Expend  Grad.Rate
College
Abilene Christian University         18.1           12    7041         60
Adelphi University                   12.2           16   10527         56
Adrian College                       12.9           30    8735         54
Agnes Scott College                   7.7           37   19016         59
Alaska Pacific University            11.9            2   10922         15
...                                   ...          ...     ...        ...
Worcester State College              21.0           14    4469         40
Xavier University                    13.3           31    9189         83
Xavier University of Louisiana       14.4           20    8323         49
Yale University                       5.8           49   40386         99
York College of Pennsylvania         18.1           28    4509         99

[777 rows x 18 columns]
```

This has used the first column in the file as an index for the data frame. This means that pandas has given each row a name corresponding to the appropriate university. Now you should see that the first data column is `Private`. Note that the names of the colleges appear on the left of the table. We also introduced a new Python object above: a dictionary, which is specified by (key, value) pairs. Keep your modified version of the data with the following:

[12]:
```
college = college3
```

(c) Use the `describe()` method of to produce a numerical summary of the variables in the data set.

[13]:
```
college.describe()
```

[13]:
```
             Apps       Accept       Enroll    Top10perc    Top25perc  \
count  777.000000   777.000000   777.000000   777.000000   777.000000
```

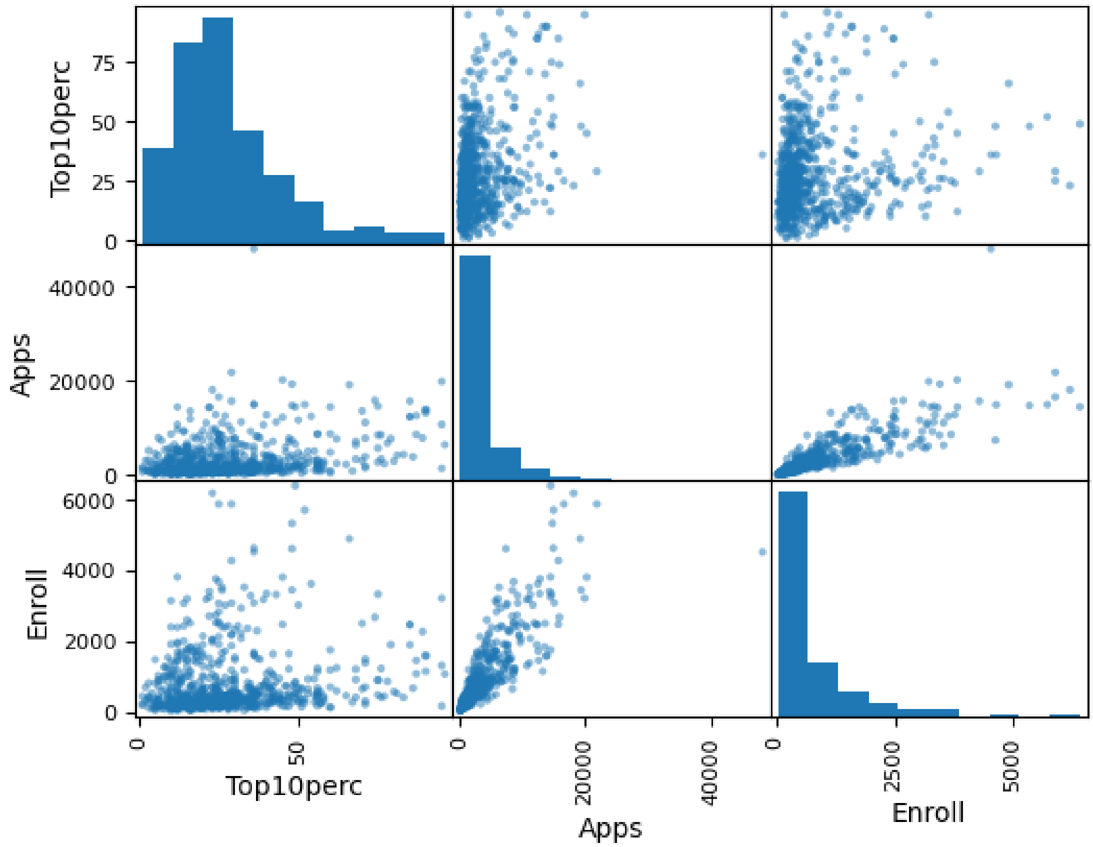
```
mean     3001.638353   2018.804376   779.972973   27.558559    55.796654
std      3870.201484   2451.113971   929.176190   17.640364    19.804778
min        81.000000     72.000000    35.000000    1.000000     9.000000
25%       776.000000    604.000000   242.000000   15.000000    41.000000
50%      1558.000000   1110.000000   434.000000   23.000000    54.000000
75%      3624.000000   2424.000000   902.000000   35.000000    69.000000
max     48094.000000  26330.000000  6392.000000   96.000000   100.000000

         F.Undergrad   P.Undergrad      Outstate   Room.Board        Books  \
count     777.000000    777.000000    777.000000   777.000000   777.000000
mean     3699.907336    855.298584  10440.669241  4357.526384   549.380952
std      4850.420531   1522.431887   4023.016484  1096.696416   165.105360
min       139.000000      1.000000   2340.000000  1780.000000    96.000000
25%       992.000000     95.000000   7320.000000  3597.000000   470.000000
50%      1707.000000    353.000000   9990.000000  4200.000000   500.000000
75%      4005.000000    967.000000  12925.000000  5050.000000   600.000000
max     31643.000000  21836.000000  21700.000000  8124.000000  2340.000000

           Personal         PhD    Terminal   S.F.Ratio  perc.alumni  \
count    777.000000  777.000000  777.000000  777.000000   777.000000
mean    1340.642214   72.660232   79.702703   14.089704    22.743887
std      677.071454   16.328155   14.722359    3.958349    12.391801
min      250.000000    8.000000   24.000000    2.500000     0.000000
25%      850.000000   62.000000   71.000000   11.500000    13.000000
50%     1200.000000   75.000000   82.000000   13.600000    21.000000
75%     1700.000000   85.000000   92.000000   16.500000    31.000000
max     6800.000000  103.000000  100.000000   39.800000    64.000000

             Expend  Grad.Rate
count    777.000000  777.00000
mean    9660.171171   65.46332
std     5221.768440   17.17771
min     3186.000000   10.00000
25%     6751.000000   53.00000
50%     8377.000000   65.00000
75%    10830.000000   78.00000
max    56233.000000  118.00000
```

(d) Use the `pd.plotting.scatter_matrix()` function to produce a scatterplot matrix of the first columns `[Top10perc, Apps, Enroll]`. Recall that you can reference a list `C` of columns of a data frame `A` using `A[C]`.

[14]:
```python
pd.plotting.scatter_matrix(college[['Top10perc', 'Apps', 'Enroll']])
```

[14]:
```
array([[<Axes: xlabel='Top10perc', ylabel='Top10perc'>,
        <Axes: xlabel='Apps', ylabel='Top10perc'>,
        <Axes: xlabel='Enroll', ylabel='Top10perc'>],
       [<Axes: xlabel='Top10perc', ylabel='Apps'>,
```

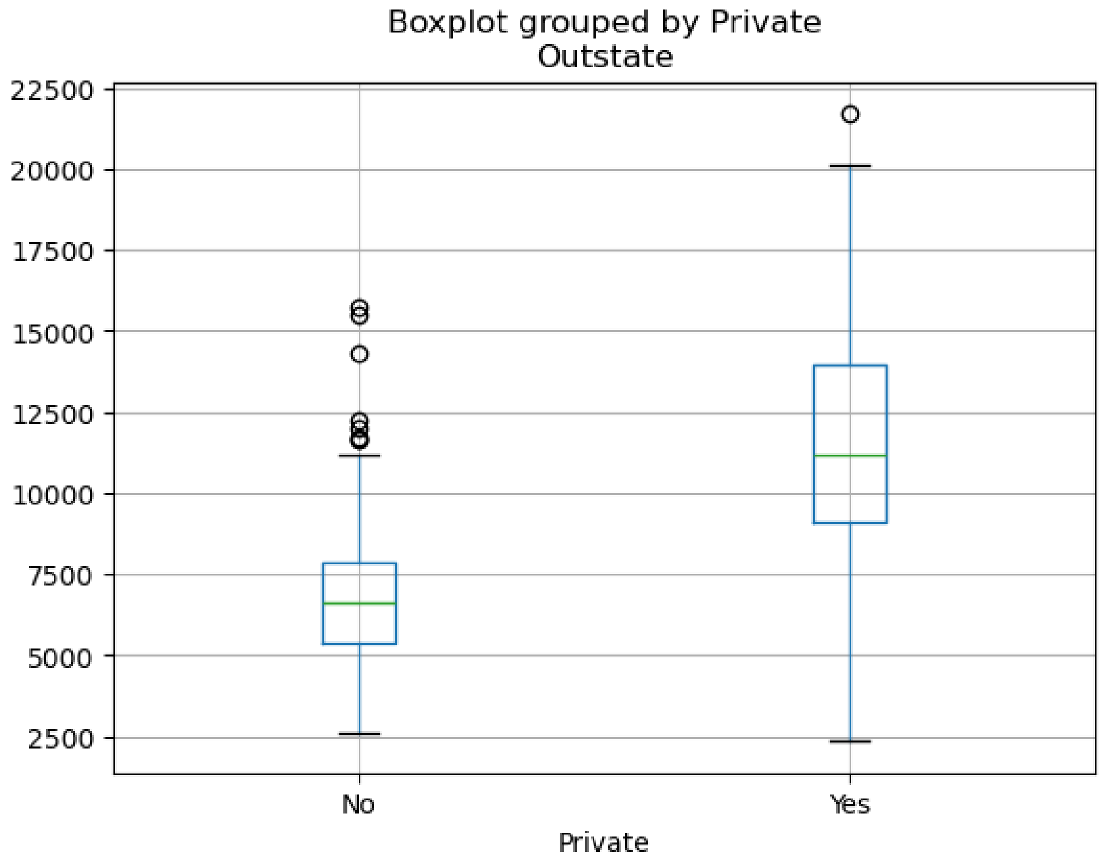
```
 <Axes: xlabel='Apps', ylabel='Apps'>,
 <Axes: xlabel='Enroll', ylabel='Apps'>],
[<Axes: xlabel='Top10perc', ylabel='Enroll'>,
 <Axes: xlabel='Apps', ylabel='Enroll'>,
 <Axes: xlabel='Enroll', ylabel='Enroll'>]], dtype=object)
```



(e) **Use the** `boxplot()` **method of** `college` **to produce side-by-side boxplots of** `Outstate` **versus** `Private`**.**

[15]:
```
college.boxplot(column='Outstate', by='Private')
```

[15]:
```
<Axes: title={'center': 'Outstate'}, xlabel='Private'>
```



(f) Create a new qualitative variable, called `Elite`, by binning the `Top10perc` variable into two groups based on whether or not the proportion of students coming from the top 10% of their high school classes exceeds 50%.

[16]:
```
college['Elite'] = pd.cut(college['Top10perc'],
                          [0,50,100],
                          labels=['No', 'Yes'])
```

Use the `value_counts()` method of `college['Elite']` to see how many elite universities there are.

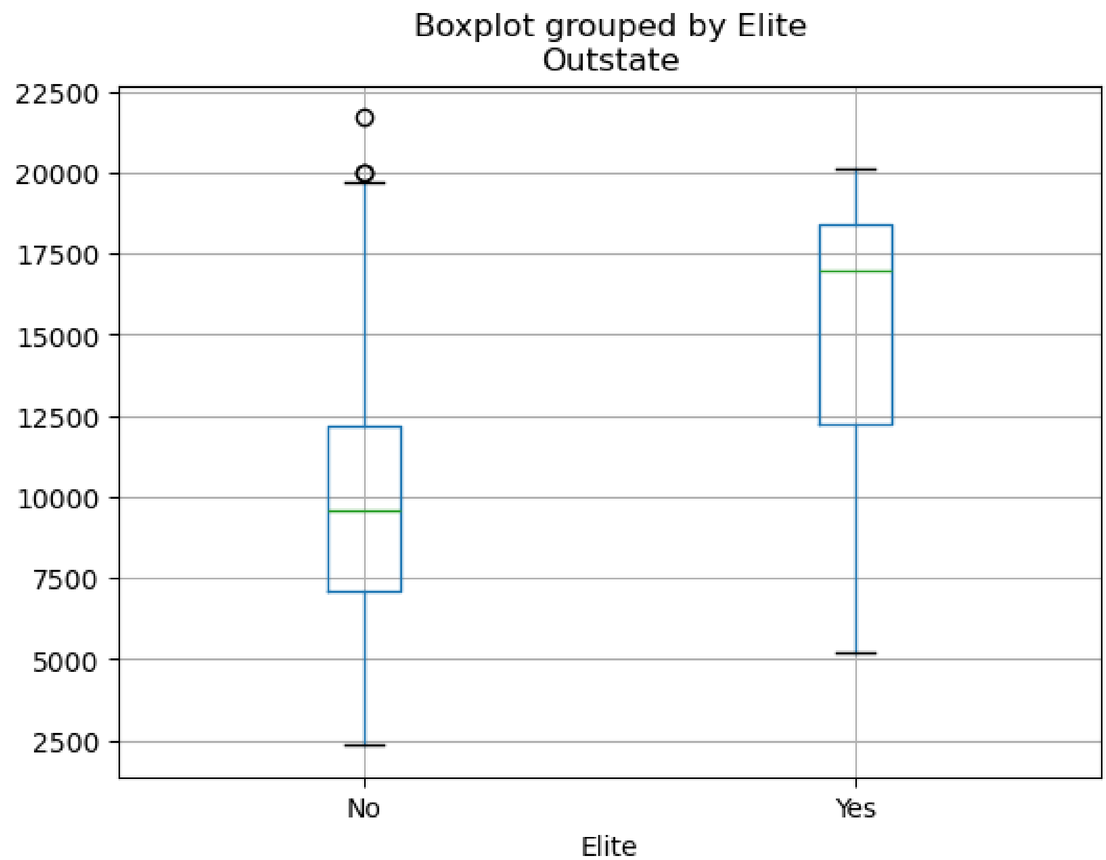
[17]:
```
college['Elite'].value_counts()
```

[17]:
```
Elite
No     699
Yes     78
Name: count, dtype: int64
```

Finally, use the `boxplot()` method again to produce side-by-side boxplots of `Outstate` versus `Elite`.

[18]:
```
college.boxplot(column='Outstate', by='Elite')
```

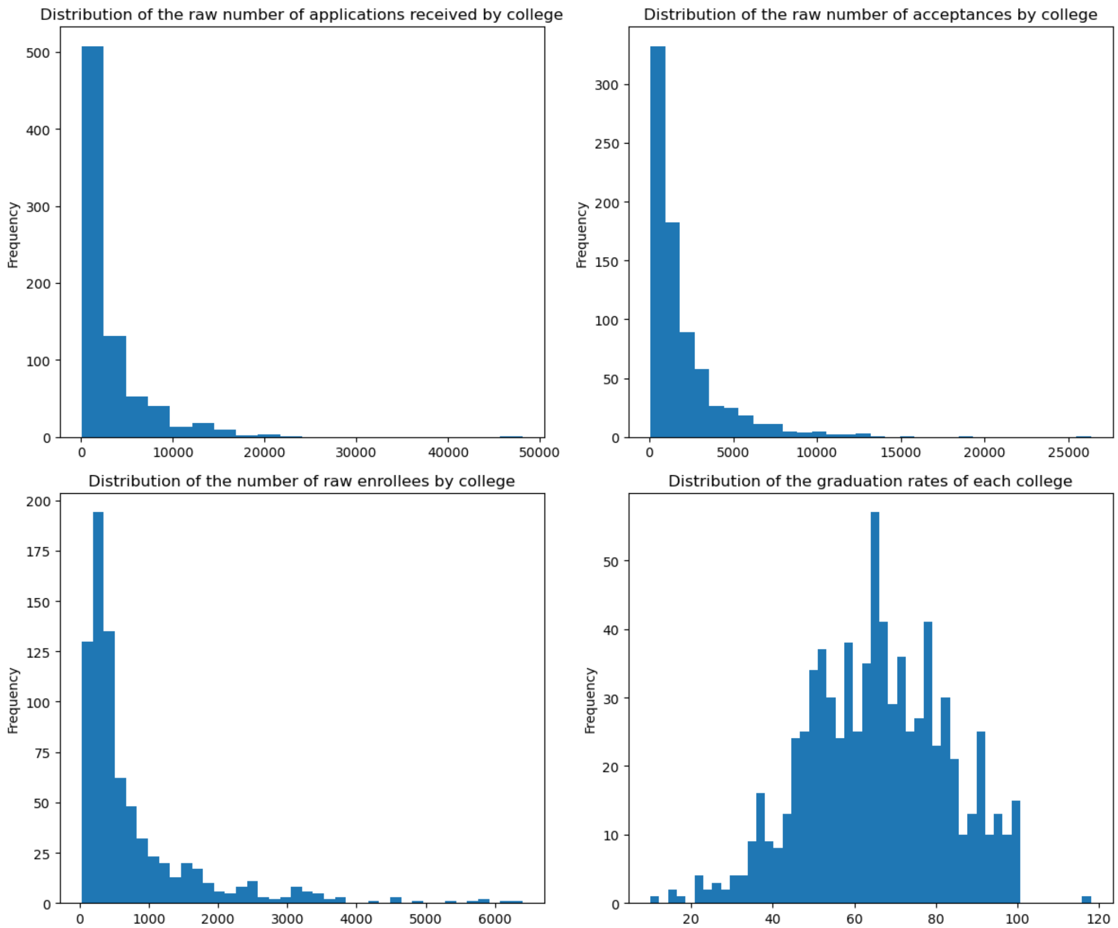
```
[18]: <Axes: title={'center': 'Outstate'}, xlabel='Elite'>
```



(g) Use the `plot.hist()` method of `college` to produce some histograms with differing numbers of bins for a few of the quantitative variables. The command `plt.subplots(2, 2)` may be useful: it will divide the plot window into four regions so that four plots can be made simultaneously. By changing the arguments you can divide the screen up in other combinations.

```
[19]: fig, axes = plt.subplots(2, 2, figsize=(12, 10))
ax1, ax2, ax3, ax4 = axes.flatten()

college['Apps'].plot.hist(ax=ax1, bins=20, title='Distribution of the raw number of applications received by college')
college['Accept'].plot.hist(ax=ax2, bins=30, title='Distribution of the raw number of acceptances by college')
college['Enroll'].plot.hist(ax=ax3, bins=40, title='Distribution of the number of raw enrollees by college')
college['Grad.Rate'].plot.hist(ax=ax4, bins=50, title='Distribution of the graduation rates of each college')
```

```
plt.tight_layout()
```

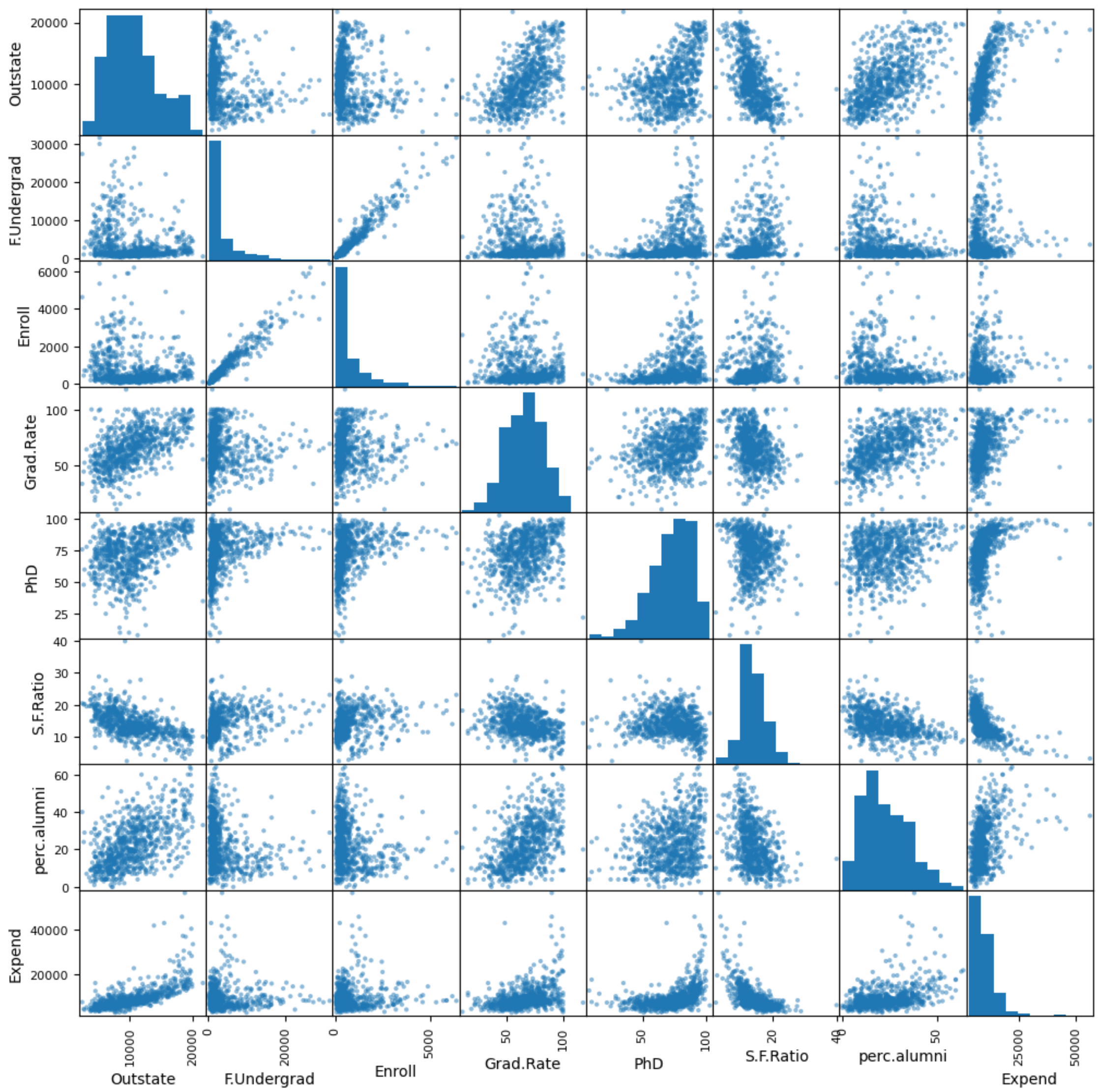


(h) Continue exploring the data and provide a brief summary of what you discover.

[20]:
```
select = ['Outstate', 'F.Undergrad', 'Enroll', 'Grad.Rate', 'PhD', 'S.F.Ratio',␣
 ↪'perc.alumni', 'Expend']
pd.plotting.scatter_matrix(college[select], figsize=(12, 12))
plt.suptitle('Pair Plot of College Data')
```

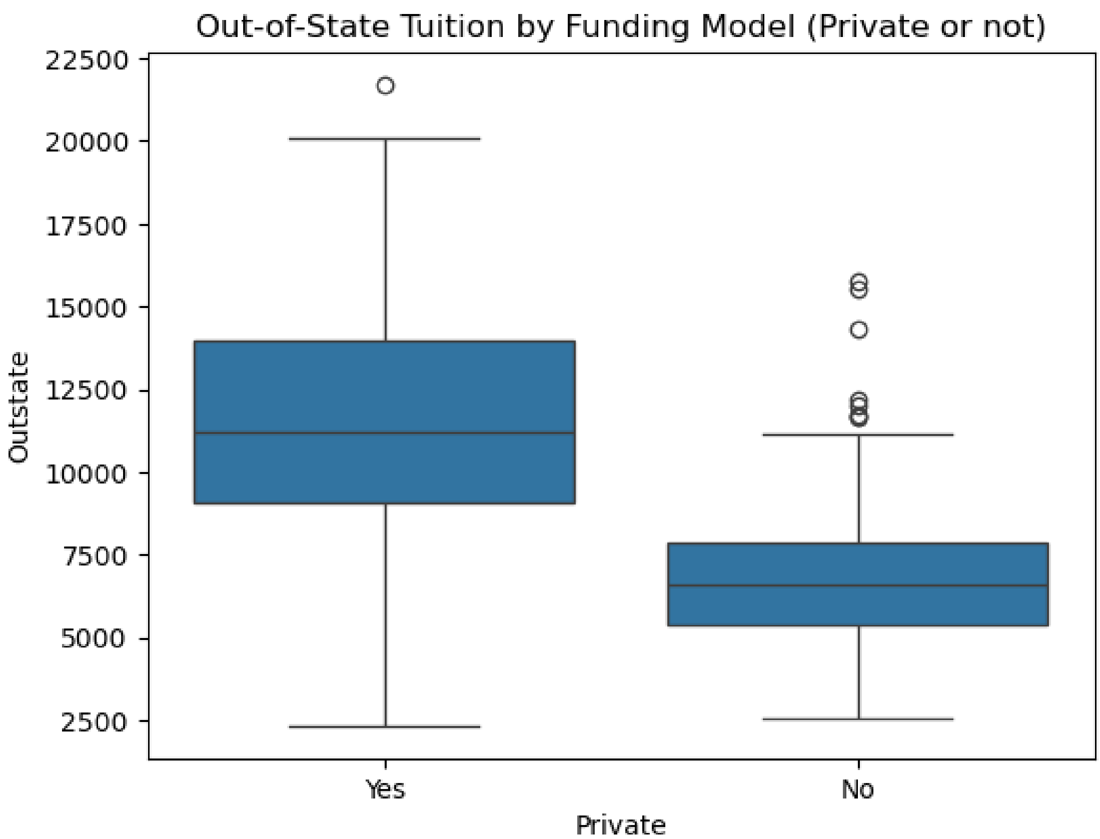
[20]:
```
Text(0.5, 0.98, 'Pair Plot of College Data')
```

Pair Plot of College Data



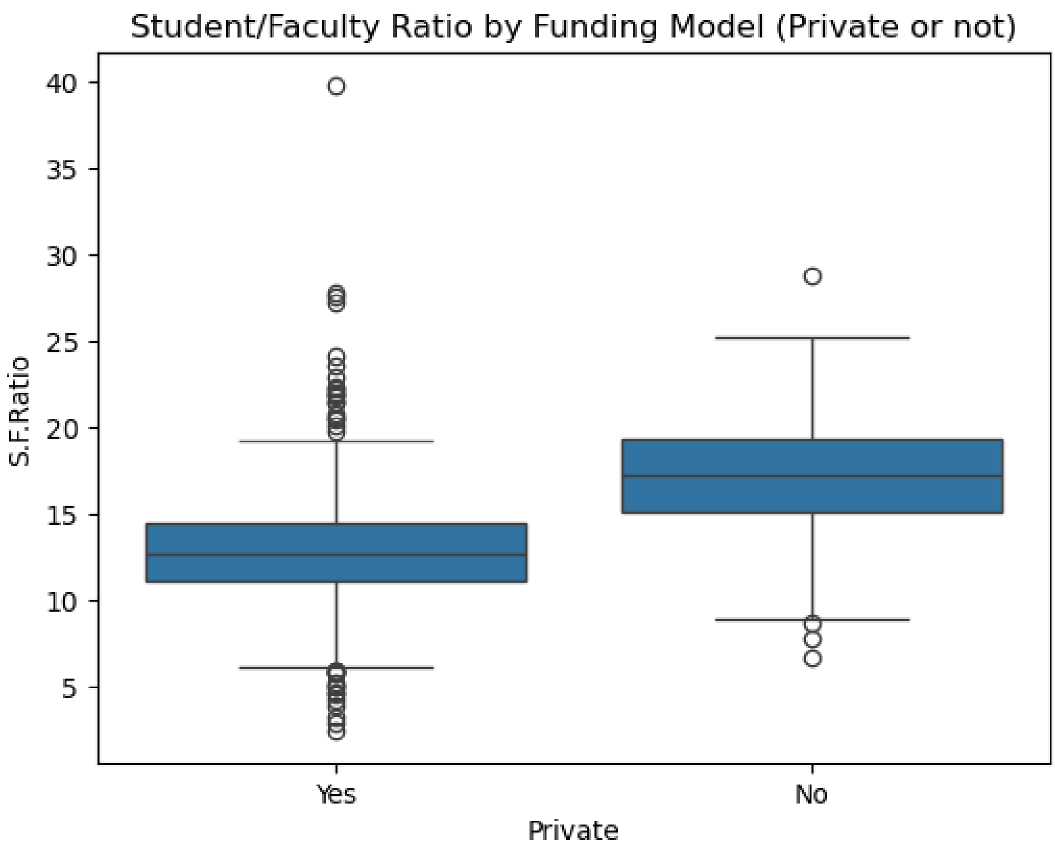
[21]:
```
sns.boxplot(data=college, x='Private', y='Outstate')
plt.title('Out-of-State Tuition by Funding Model (Private or not)')
```

[21]: Text(0.5, 1.0, 'Out-of-State Tuition by Funding Model (Private or not)')



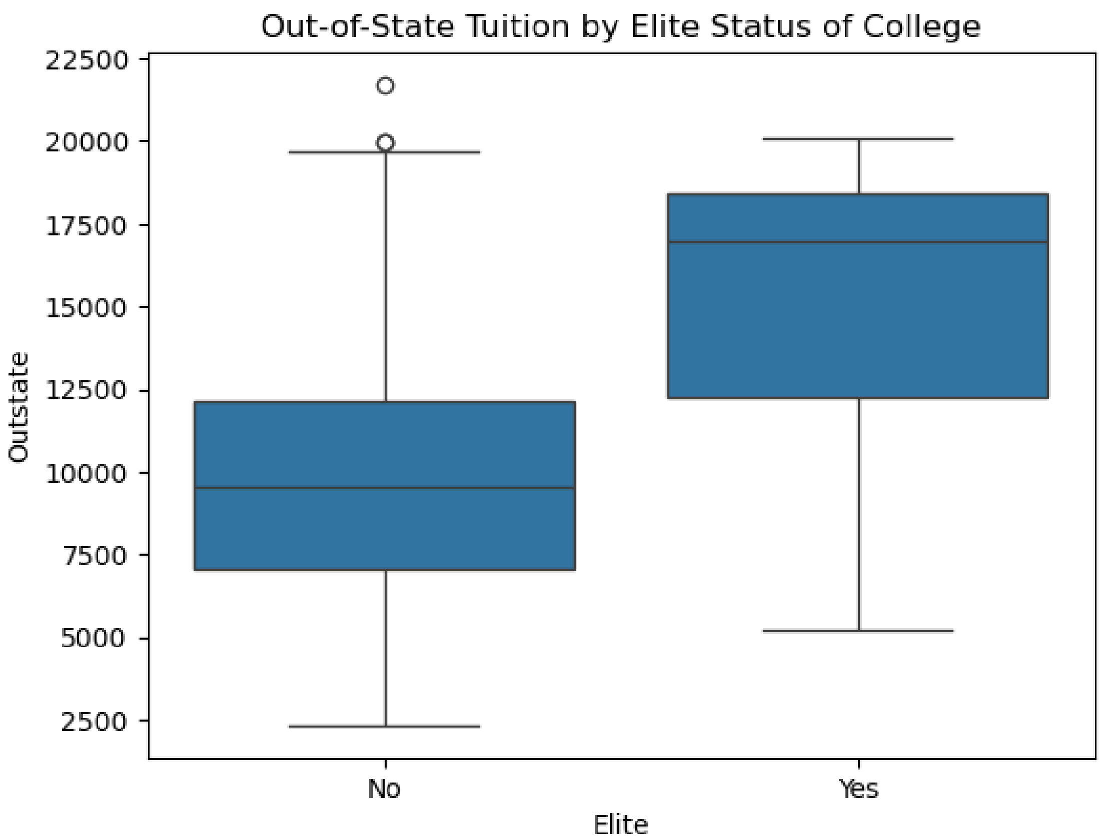
[22]:
```
sns.boxplot(data=college, x='Private', y='S.F.Ratio')
plt.title('Student/Faculty Ratio by Funding Model (Private or not)')
```

[22]: Text(0.5, 1.0, 'Student/Faculty Ratio by Funding Model (Private or not)')



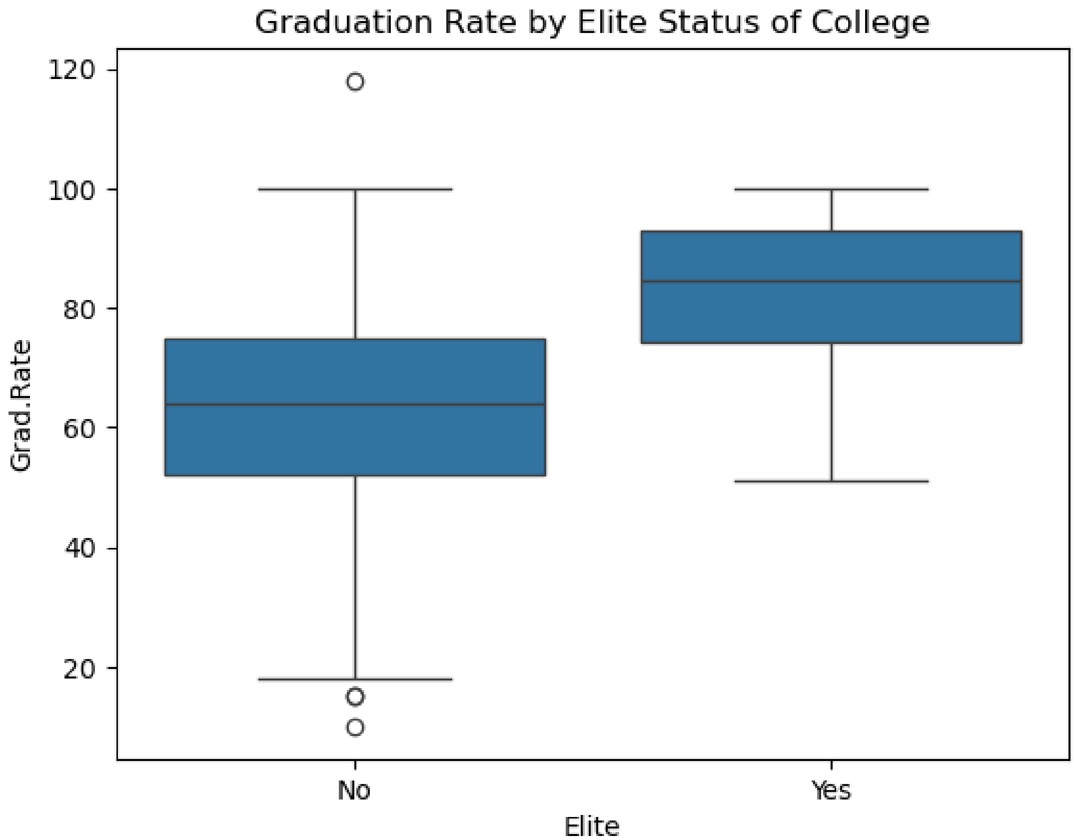
[23]:
```
sns.boxplot(data=college, x='Elite', y='Outstate')
plt.title('Out-of-State Tuition by Elite Status of College')
```

[23]:
```
Text(0.5, 1.0, 'Out-of-State Tuition by Elite Status of College')
```



[24]:
```
sns.boxplot(x='Elite', y='Grad.Rate', data=college)
plt.title('Graduation Rate by Elite Status of College')
```

[24]: Text(0.5, 1.0, 'Graduation Rate by Elite Status of College')



The pair plot matrix provides a visual representation of the relationships between several key quantitative variables. There is a strong positive correlation between per-student instructional expenditure and the out-of-state tuition of colleges. Generally, universities with higher out-of-state tuition typically spend more money to teach the average student at their institution. While there is an almost linear relationship between total full-time undergraduate enrollment and enrollment for the year, this could be attributed to multicollinearity since most colleges typically have some relationship between students enrolled in a year and the total undergraduate class size. I can also observe a strong negative correlation between student/faculty ratio and out-of-state tuition, indicating that schools with fewer students per faculty member charge higher tuition for out-of-state students.

Private schools tend to have higher out-of-state tuition and lower student/faculty ratios. On the other hand “elite” colleges tend to have a higher graduation rate, and a higher out-of-state tuition.