full_analysis

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1 Dexian Data Analytics Technical Challenge

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1.1 Abstract

This technical challenge aims to provide actionable insights from a dataset containing information on American colleges and universities. By applying advanced data analytics techniques, this project seeks to uncover trends and patterns that could assist a consulting firm in advising institutions of higher learning. Through meticulous data analysis, key insights regarding institutional types, acceptance rates, tuition fees, and graduation rates were discovered, enabling data-driven decision-making.

1.2 Business Problem

The scenario for this technical challenge was as follows:

```
You are working with a firm that provides consulting services for institutions of higher learn
```

1.3 The Data

The dataset for this challenge provides detailed information about various American colleges and universities, including public/private designation, application statistics, tuition fees, and graduation rates. The aim was to analyze this dataset to identify trends and insights that could inform strategic advice for higher education institutions.

The dataset used for this technical challenge can be found at the following: https://docs.google.com/spreadsheets/d/1rThcHm3ZATkhOtsGL6477nQaePrIzcsl/export

While outside resources could have been considered in order to enrich the initial dataset, due to time constraints and a desire to stay within the bounds of the technical challenge, no outside resources were included in the data pool.

1.3.1 Initial Exploration of The Dataset

Here we ingest the dataset using the Pandas library and perform an initial exploration of the dataset using Pandas, Matplotlib, and Seaborn:

[254]:
```
# Imports used in the Analysis
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# Ingest the dataset
filepath = './data/Universities.xlsx'
df = pd.read_excel(filepath,sheet_name='usnews3.data.9 .SS (v5.0)')
```

[255]:
```
# Generate an overview of the data
df.head()
```

[255]:
```
                          College Name State  Public (1)/ Private (2)  \
0           Alaska Pacific University    AK                        2
1  University of Alaska at Fairbanks    AK                        1
2     University of Alaska Southeast    AK                        1
3  University of Alaska at Anchorage    AK                        1
4        Alabama Agri. & Mech. Univ.    AL                        1

   # appli. rec'd  # appl. accepted  # new stud. enrolled  \
0           193.0             146.0                  55.0
1          1852.0            1427.0                 928.0
2           146.0             117.0                  89.0
3          2065.0            1598.0                1162.0
4          2817.0            1920.0                 984.0

   % new stud. from top 10%  % new stud. from top 25%  # FT undergrad  \
0                      16.0                      44.0           249.0
```

```
1                        NaN                       NaN          3885.0
2                        4.0                      24.0           492.0
3                        NaN                       NaN          6209.0
4                        NaN                       NaN          3958.0

   # PT undergrad  in-state tuition  out-of-state tuition    room   board  \
0           869.0            7560.0                7560.0  1620.0  2500.0
1          4519.0            1742.0                5226.0  1800.0  1790.0
2          1849.0            1742.0                5226.0  2514.0  2250.0
3         10537.0            1742.0                5226.0  2600.0  2520.0
4           305.0            1700.0                3400.0  1108.0  1442.0

   add. fees  estim. book costs  estim. personal $  % fac. w/PHD  \
0      130.0              800.0             1500.0          76.0
1      155.0              650.0             2304.0          67.0
2       34.0              500.0             1162.0          39.0
3      114.0              580.0             1260.0          48.0
4      155.0              500.0              850.0          53.0

   stud./fac. ratio  Graduation rate
0              11.9             15.0
1              10.0              NaN
2               9.5             39.0
3              13.7              NaN
4              14.3             40.0
```

[256]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1302 entries, 0 to 1301
Data columns (total 20 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   College Name                1302 non-null   object
 1   State                       1302 non-null   object
 2   Public (1)/ Private (2)     1302 non-null   int64
 3   # appli. rec'd              1292 non-null   float64
 4   # appl. accepted            1291 non-null   float64
 5   # new stud. enrolled        1297 non-null   float64
 6   % new stud. from top 10%    1067 non-null   float64
 7   % new stud. from top 25%    1100 non-null   float64
 8   # FT undergrad              1299 non-null   float64
 9   # PT undergrad              1270 non-null   float64
 10  in-state tuition            1272 non-null   float64
 11  out-of-state tuition        1282 non-null   float64
 12  room                        981 non-null    float64
 13  board                       804 non-null    float64
 14  add. fees                   1028 non-null   float64
```

```
 15  estim. book costs         1254 non-null   float64
 16  estim. personal $         1121 non-null   float64
 17  % fac. w/PHD              1270 non-null   float64
 18  stud./fac. ratio          1300 non-null   float64
 19  Graduation rate           1204 non-null   float64
dtypes: float64(17), int64(1), object(2)
memory usage: 203.6+ KB
```

[257]:

```
df.describe()
```

[257]:

```
       Public (1)/ Private (2)  # appli. rec'd  # appl. accepted  \
count              1302.000000     1292.000000       1291.000000
mean                  1.639017     2752.097523       1870.683191
std                   0.480470     3541.974712       2250.866400
min                   1.000000       35.000000         35.000000
25%                   1.000000      695.750000        554.500000
50%                   2.000000     1470.000000       1095.000000
75%                   2.000000     3314.250000       2303.000000
max                   2.000000    48094.000000      26330.000000

       # new stud. enrolled  % new stud. from top 10%  \
count          1297.000000               1067.000000
mean            778.880493                 25.671978
std             884.578274                 18.312618
min              18.000000                  1.000000
25%             236.000000                 13.000000
50%             447.000000                 21.000000
75%             984.000000                 32.000000
max            7425.000000                 98.000000

       % new stud. from top 25%  # FT undergrad  # PT undergrad  \
count               1100.000000     1299.000000     1270.000000
mean                  52.350000     3692.665127     1081.526772
std                   20.881316     4544.847897     1672.202912
min                    6.000000       59.000000        1.000000
25%                   36.750000      966.000000      131.250000
50%                   50.000000     1812.000000      472.000000
75%                   66.000000     4539.500000     1313.000000
max                  100.000000    31643.000000    21836.000000

       in-state tuition  out-of-state tuition         room        board  \
count       1272.000000           1282.000000   981.000000   804.000000
mean        7897.274371           9276.905616  2514.681957  2060.983831
std         5348.162626           4170.770851  1150.836848   661.742099
min          480.000000           1044.000000   500.000000   531.000000
25%         2580.000000           6111.000000  1710.000000  1619.250000
50%         8050.000000           8670.000000  2200.000000  1980.000000
```

```
75%       11600.000000          11659.000000  3040.000000  2401.500000
max       25750.000000          25750.000000  7400.000000  6250.000000

           add. fees  estim. book costs  estim. personal $  % fac. w/PHD  \
count    1028.000000        1254.000000        1121.000000   1270.000000
mean      392.012646         549.972887        1389.291704     68.645669
std       469.379234         167.355386         714.247857     17.825627
min         9.000000          90.000000          75.000000      8.000000
25%       130.000000         480.000000         900.000000     57.000000
50%       264.500000         502.000000        1250.000000     71.000000
75%       480.000000         600.000000        1794.000000     82.000000
max      4374.000000        2340.000000        6900.000000    105.000000

       stud./fac. ratio  Graduation rate
count       1300.000000      1204.000000
mean          14.858769        60.405316
std            5.186399        18.889058
min            2.300000         8.000000
25%           11.800000        47.000000
50%           14.300000        60.000000
75%           17.600000        74.000000
max           91.800000       118.000000
```

We note a few things here: - Dataset is 1302 rows (excluding headers) by 20 columns - Dataset contains a mixture of data types (categorical and numeric), some of which are improperly formatted upon ingestion. - Dataset contains null values - Column Headers are a bit difficult to read

And from a cursory look at the summary statistics: - Dataset contains illogical/anomalous values (ie. graduation rates, % of faculty with PhDs both contain values over 100%)

We'll address these issues in the cleaning section of this notebook next.

1.4 Data Cleaning

Here we'll begin the process of cleaning the dataset. Issues addressed are as follows:

- Change Column Names to Improve Readability
- Handle Missing Values
- Handle Duplicate Values
- Remove or Correct Misc. Anomalous Data
- Handle Outliers
- Correct Data Types
- Feature Engineering

[258]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1302 entries, 0 to 1301
Data columns (total 20 columns):
 #   Column                    Non-Null Count  Dtype
```

```
---  ------                    --------------  -----
 0   College Name              1302 non-null   object
 1   State                     1302 non-null   object
 2   Public (1)/ Private (2)   1302 non-null   int64
 3   # appli. rec'd            1292 non-null   float64
 4   # appl. accepted          1291 non-null   float64
 5   # new stud. enrolled      1297 non-null   float64
 6   % new stud. from top 10%  1067 non-null   float64
 7   % new stud. from top 25%  1100 non-null   float64
 8   # FT undergrad            1299 non-null   float64
 9   # PT undergrad            1270 non-null   float64
 10  in-state tuition          1272 non-null   float64
 11  out-of-state tuition      1282 non-null   float64
 12  room                      981 non-null    float64
 13  board                     804 non-null    float64
 14  add. fees                 1028 non-null   float64
 15  estim. book costs         1254 non-null   float64
 16  estim. personal $         1121 non-null   float64
 17  % fac. w/PHD              1270 non-null   float64
 18  stud./fac. ratio          1300 non-null   float64
 19  Graduation rate           1204 non-null   float64
dtypes: float64(17), int64(1), object(2)
memory usage: 203.6+ KB
```

1.4.1 Changing Column Names To Improve Readability

Firstly, Column Names have been changed for improved readability

[259]:
```python
# Renaming columns for improved readability
df.rename(columns={
    'College Name': 'college_name',
    'State': 'state',
    'Public (1)/ Private (2)': 'institution_type',
    '# appli. rec\'d': 'applications_received',
    '# appl. accepted': 'applications_accepted',
    '# new stud. enrolled': 'new_students_enrolled',
    '% new stud. from top 10%': 'percent_from_top_10',
    '% new stud. from top 25%': 'percent_from_top_25',
    '# FT undergrad': 'full_time_undergrads',
    '# PT undergrad': 'part_time_undergrads',
    'in-state tuition': 'in_state_tuition',
    'out-of-state tuition': 'out_of_state_tuition',
    'room': 'room_costs',
    'board': 'board_costs',
    'add. fees': 'additional_fees',
    'estim. book costs': 'estimated_book_costs',
    'estim. personal $': 'estimated_personal_expenses',
    '% fac. w/PHD': 'percent_faculty_with_phd',
```

```
    'stud./fac. ratio': 'student_faculty_ratio',
    'Graduation rate': 'graduation_rate',
},inplace=True)
```

[260]:
```
df.columns
```

[260]:
```
Index(['college_name', 'state', 'institution_type', 'applications_received',
       'applications_accepted', 'new_students_enrolled', 'percent_from_top_10',
       'percent_from_top_25', 'full_time_undergrads', 'part_time_undergrads',
       'in_state_tuition', 'out_of_state_tuition', 'room_costs', 'board_costs',
       'additional_fees', 'estimated_book_costs',
       'estimated_personal_expenses', 'percent_faculty_with_phd',
       'student_faculty_ratio', 'graduation_rate'],
      dtype='object')
```

1.4.2 Handling Null Values

Next, here we discuss various strategies for handling missing values in the dataset.

[261]:
```
# Calculate percentage of missing values per column
missing_percentage = (df.isnull().sum() / len(df)) * 100
print(missing_percentage)
```

```
college_name                    0.000000
state                           0.000000
institution_type                0.000000
applications_received           0.768049
applications_accepted           0.844854
new_students_enrolled           0.384025
percent_from_top_10            18.049155
percent_from_top_25            15.514593
full_time_undergrads            0.230415
part_time_undergrads            2.457757
in_state_tuition                2.304147
out_of_state_tuition            1.536098
room_costs                     24.654378
board_costs                    38.248848
additional_fees                21.044547
estimated_book_costs            3.686636
estimated_personal_expenses    13.901690
percent_faculty_with_phd        2.457757
student_faculty_ratio           0.153610
graduation_rate                 7.526882
dtype: float64
```

Possible strategies for handling Null Values in the dataset are as follows: - Removing Null values from the dataset - Filling in Null values (by imputing the mean, median, using KNNImputer, etc.) - Setting Nulls = 0 - De-emphasis or Elimination of Column from Analysis Entirely

Next we'll discuss the pros and cons of each method, and discuss how we'll apply them to the dataset.

1. Removing Null values from the dataset - Pros: - Ensures Data Purity and avoids the introduction of bias - Simplicity - Cons: - Data Loss and Reduction in Statistical Power: Continued removal of data from the dataset can limit the number of overall observations and reduce statistical power

2. Filling in Null Values: - Pros: - Data Preservation: We maximize the preservation of the overall dataset - Cons: - Possible Introduction of Bias: If the imputation method does not align well with the true data distribution or the reason behind the missingness, we risk introducing bias into the dataset. - Reduced variability: Replacing missing values with the median can artificially reduce the variability in the dataset, leading to an underestimate in the observed variance, covariance, etc.

3. Setting Nulls = 0: - Depending on the method of data collection, null values here might be indicating a true value of zero. Because it was unclear from this dataset, the author chose not to use this method when handling null values.

4. De-emphasis or Elimination of Column from Analysis Entirely: - For columns with a high percentage of missing values, it may be wise to eliminate them from the analysis entirely, or simply leave the column as-is and acknowledge a lack of data during the final analysis.

To decide how to apply each strategy to the dataset, we'll categorize each column according to it's percentage of missing values and assign one of the above strategies accordingly. Categories are as follows: - Columns with 0% Missing Values - Columns with a Small Percentage of Missing Values (<5%) - Columns with a Moderate Percentage of Missing Values (5-20%) - Columns with a High Amount of Missing Values (>20%)

Columns with 0% Missing Values - unchanged

```
college_name
state
institution_type
percent_faculty_with_phd
student_faculty_ratio
graduation_rate
```

Columns with a Small Percentage of Missing Values (<5%) - We'll remove these from the dataset to maximize data purity, although filling in null values via imputation would have also been appropriate here.

```
applications_received - 0.511073%
applications_accepted - 0.425894%
new_students_enrolled - 0.170358%
full_time_undergrads - 0.255537%
part_time_undergrads - 2.470187%
in_state_tuition - 2.129472%
out_of_state_tuition - 1.277683%
estimated_book_costs - 2.896082%
percent_faculty_with_phd - 2.457757%
```

Columns with a Moderate Percentage of Missing Values (5-20%) - For percent_from_top_10 and percent_from top_25, we'll make the assumption that missing values should be properly interpreted as 0, meaning no students from the top of high school classes attended these universities, although confirmation of this from an enhanced understanding of the data gathering process would be desirable. For estimate_personal_expenses and additional_fees, we'll impute the median (which is more resistant to skewness in the distribution in the data than the mean), as it's assumed that ever university will have some additional fees associated with a program, and every student will face some out-of-pocket costs to attend a university, even if only minimally. For graduation rate, it's assumed that every accredited university has at level some level of graduation, and so the median will be imputed for missing values rather than setting them to 0.

```
percent_from_top_10 - 15.587734%
percent_from_top_25 - 13.117547%
estimated_personal_expenses - 12.095400%
additional_fees - 20.528109%
graduation_rate - 7.526882%
```

Columns with a High Amount of Missing Values (>20%) - Due to the high number of missing values and data integrity concerns, we'll leave these columns as-is be de-emphasis them from the analysis.

```
room_costs - 23.594549%
board_costs - 37.223169%
```

[262]:
```
# Drop Missing values from columns with small percentage of null values
df.dropna(subset=['applications_received', 'applications_accepted',␣
↪'new_students_enrolled', 'full_time_undergrads', 'part_time_undergrads',␣
↪'in_state_tuition','out_of_state_tuition','estimated_book_costs','percent_faculty_with_phd'],
↪inplace=True)
```

[263]:
```
# Fill percent_from_top_10 and percent_from_top_25 with 0
df['percent_from_top_10'].fillna(0, inplace=True)
df['percent_from_top_25'].fillna(0, inplace=True)
```

[264]:
```
# Fill estimated_personal_expenses and additional_fees with median
df['estimated_personal_expenses'].fillna(df['estimated_personal_expenses'].
↪median(), inplace=True)
df['additional_fees'].fillna(df['additional_fees'].median(), inplace=True)
df['graduation_rate'].fillna(df['graduation_rate'].median(), inplace=True)
```

[265]:
```
# Calculate percentage of missing values per column
missing_percentage = (df.isnull().sum() / len(df)) * 100
print(missing_percentage)
```

```
college_name                   0.000000
state                          0.000000
institution_type               0.000000
applications_received          0.000000
applications_accepted          0.000000
new_students_enrolled          0.000000
percent_from_top_10            0.000000
percent_from_top_25            0.000000
```

```
full_time_undergrads             0.000000
part_time_undergrads             0.000000
in_state_tuition                 0.000000
out_of_state_tuition             0.000000
room_costs                      22.723404
board_costs                     37.191489
additional_fees                  0.000000
estimated_book_costs             0.000000
estimated_personal_expenses      0.000000
percent_faculty_with_phd         0.000000
student_faculty_ratio            0.000000
graduation_rate                  0.000000
dtype: float64
```

1.4.3 Handling Duplicate Data

Next we check for and handle duplicates in the dataset.

[266]:
```python
duplicate_rows = df.duplicated()
print(f"Number of duplicate rows: {duplicate_rows.sum()}")
```

```
Number of duplicate rows: 0
```

After cleaning missing values the dataset appears to have no duplicate values, and so we move on to the next stage of cleaning the dataset.

1.4.4 Removing Misc. Anomalous Data

Upon our initial inspection of the dataset we noted some anomalous data (eg. graduation_rate and percent_faculty_with_phd both contain values over 100%). Anomalous data is expunged from the dataset here. We begin by examining summary statistics to check for illogical or impossible values like those noted above, and then perform some cross-field validation to check for logical inconsistencies (ex. in-state tuitions for a university that are higher than out of state, etc.)

[267]:
```python
df.describe()
```

[267]:
```
       institution_type  applications_received  applications_accepted  \
count       1175.000000            1175.000000            1175.000000
mean           1.651064            2663.513191            1839.102979
std            0.476837            3408.747132            2187.012227
min            1.000000              52.000000              36.000000
25%            1.000000             684.000000             553.000000
50%            2.000000            1450.000000            1086.000000
75%            2.000000            3286.500000            2309.000000
max            2.000000           48094.000000           26330.000000

       new_students_enrolled  percent_from_top_10  percent_from_top_25  \
count            1175.000000          1175.000000          1175.000000
mean              769.183830            20.908936            44.501277
```

```
std          881.649886          18.098567           26.108308
min           18.000000           0.000000            0.000000
25%          234.000000           9.000000           29.000000
50%          444.000000          18.000000           46.000000
75%          945.000000          29.000000           63.000000
max         7425.000000          96.000000          100.000000

       full_time_undergrads  part_time_undergrads  in_state_tuition  \
count           1175.000000           1175.000000       1175.000000
mean            3642.939574           1047.977021       7906.854468
std             4491.340232           1649.297896       5273.593853
min               88.000000              1.000000        480.000000
25%              967.500000            128.000000       2615.500000
50%             1803.000000            442.000000       8190.000000
75%             4475.000000           1283.000000      11515.000000
max            31643.000000          21836.000000      25750.000000

       out_of_state_tuition   room_costs  board_costs  additional_fees  \
count           1175.000000   908.000000   738.000000      1175.000000
mean            9297.880851  2515.396476  2044.966125       339.243404
std             4094.042844  1151.534021   637.178853       301.456287
min             1044.000000   500.000000   531.000000         9.000000
25%             6161.000000  1710.750000  1620.500000       150.000000
50%             8734.000000  2200.000000  1980.000000       260.000000
75%            11652.000000  3000.000000  2392.250000       400.000000
max            25750.000000  7400.000000  6250.000000      3247.000000

       estimated_book_costs  estimated_personal_expenses  \
count           1175.000000                  1175.000000
mean             545.386383                  1370.233191
std              159.317616                   680.727562
min               90.000000                   250.000000
25%              475.500000                   920.000000
50%              500.000000                  1230.000000
75%              600.000000                  1700.000000
max             2340.000000                  6900.000000

       percent_faculty_with_phd  student_faculty_ratio  graduation_rate
count               1175.000000            1175.000000      1175.000000
mean                  68.740426              14.879830        60.549787
std                   17.617501               5.245299        17.965015
min                    8.000000               2.300000         8.000000
25%                   57.000000              11.800000        49.000000
50%                   71.000000              14.300000        60.000000
75%                   82.000000              17.500000        73.000000
max                  103.000000              91.800000       118.000000
```

We note two instancies of anomalies - percent_faculty_with_phd greater than 100%, and graduation_rate over 100%. Because we cannot be certain whether these values were intended 10 be 100% or some other value entirely, we remove them from the dataset here.

[268]:
```
# Example: Removing rows where 'Graduation rate' is above 100%
df = df[df['percent_faculty_with_phd'] <= 100]
df = df[df['graduation_rate'] <= 100]
```

[269]:
```
df.describe()
```

[269]:
```
       institution_type  applications_received  applications_accepted  \
count       1173.000000            1173.000000            1173.000000
mean           1.651321            2664.323956            1838.901961
std            0.476755            3410.909317            2188.022662
min            1.000000              52.000000              36.000000
25%            1.000000             686.000000             553.000000
50%            2.000000            1450.000000            1086.000000
75%            2.000000            3281.000000            2306.000000
max            2.000000           48094.000000           26330.000000

       new_students_enrolled  percent_from_top_10  percent_from_top_25  \
count            1173.000000          1173.000000          1173.000000
mean              769.838875            20.918159            44.507246
std               882.239351            18.110632            26.128999
min                18.000000             0.000000             0.000000
25%               233.000000             9.000000            29.000000
50%               444.000000            18.000000            46.000000
75%               946.000000            29.000000            63.000000
max              7425.000000            96.000000           100.000000

       full_time_undergrads  part_time_undergrads  in_state_tuition  \
count           1173.000000           1173.000000       1173.000000
mean            3647.261722           1049.639386       7911.670929
std             4493.947007           1650.210361       5273.805830
min               88.000000              1.000000        480.000000
25%              967.000000            128.000000       2625.000000
50%             1803.000000            446.000000       8190.000000
75%             4481.000000           1283.000000      11520.000000
max            31643.000000          21836.000000      25750.000000

       out_of_state_tuition   room_costs  board_costs  additional_fees  \
count           1173.000000   906.000000   736.000000      1173.000000
mean            9301.590793  2516.556291  2045.112772       339.212276
std             4095.481045  1152.363247   637.646380       301.708472
min             1044.000000   500.000000   531.000000         9.000000
25%             6172.000000  1711.250000  1621.500000       150.000000
50%             8734.000000  2200.000000  1980.000000       260.000000
75%            11656.000000  3000.000000  2390.750000       400.000000
```

```
max           25750.000000  7400.000000  6250.000000      3247.000000

       estimated_book_costs  estimated_personal_expenses  \
count           1173.000000                  1173.000000
mean             545.293265                  1371.589088
std              159.437506                   680.507288
min               90.000000                   250.000000
25%              475.000000                   930.000000
50%              500.000000                  1230.000000
75%              600.000000                  1700.000000
max             2340.000000                  6900.000000

       percent_faculty_with_phd  student_faculty_ratio  graduation_rate
count               1173.000000            1173.000000      1173.000000
mean                  68.751066              14.878176        60.515772
std                   17.551079               5.249229        17.894480
min                    8.000000               2.300000         8.000000
25%                   57.000000              11.800000        49.000000
50%                   71.000000              14.200000        60.000000
75%                   82.000000              17.500000        73.000000
max                  100.000000              91.800000       100.000000
```

[270]:
```python
# Check if in-state tuition is ever higher than out-of-state tuition
inconsistent_tuition = df[df['in_state_tuition'] > df['out_of_state_tuition']]
print(f"Number of records where in-state tuition is higher than out-of-state␣
↪tuition: {len(inconsistent_tuition)}")

# Keep only the records where in-state tuition is less than or equal to␣
↪out-of-state tuition
df = df[df['in_state_tuition'] <= df['out_of_state_tuition']]

# Checking if accepted applications exceed received applications
inconsistent_applications = df[df['applications_received'] <␣
↪df['applications_accepted']]
print(f"Number of records where accepted applications exceed received␣
↪applications: {len(inconsistent_applications)}")
```

```
Number of records where in-state tuition is higher than out-of-state tuition: 2
Number of records where accepted applications exceed received applications: 0
```

1.4.5 Handling Outliers

In this section we identify and discuss strategies for dealing with outliers.

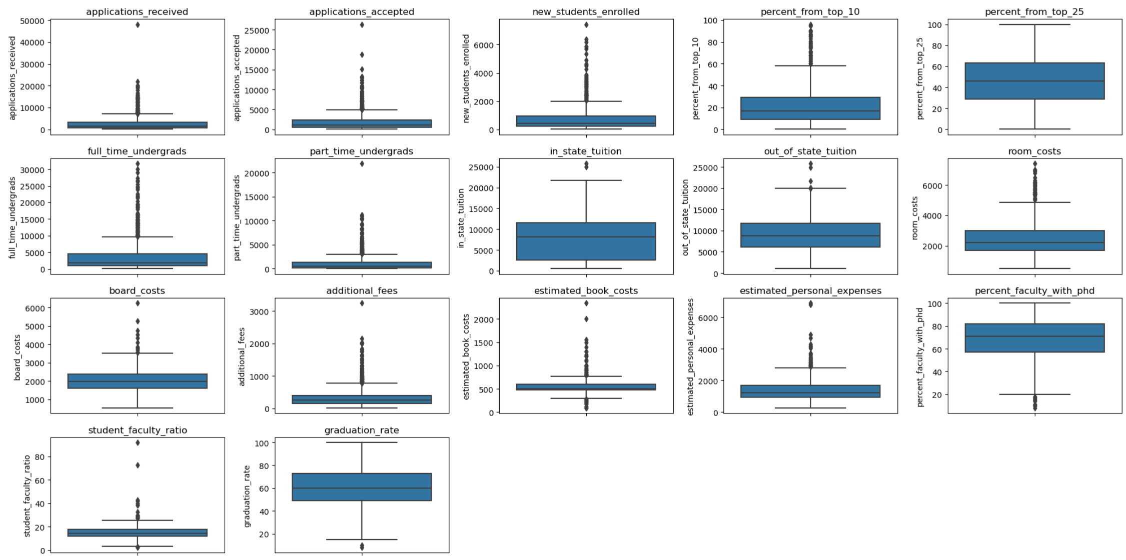
Possible Strategies for Dealing with Outliers - Removal - Capping - Transformation - Leaving as Is

[271]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1171 entries, 0 to 1301
Data columns (total 20 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   college_name                  1171 non-null   object
 1   state                         1171 non-null   object
 2   institution_type              1171 non-null   int64
 3   applications_received         1171 non-null   float64
 4   applications_accepted         1171 non-null   float64
 5   new_students_enrolled         1171 non-null   float64
 6   percent_from_top_10           1171 non-null   float64
 7   percent_from_top_25           1171 non-null   float64
 8   full_time_undergrads          1171 non-null   float64
 9   part_time_undergrads          1171 non-null   float64
 10  in_state_tuition              1171 non-null   float64
 11  out_of_state_tuition          1171 non-null   float64
 12  room_costs                    904 non-null    float64
 13  board_costs                   734 non-null    float64
 14  additional_fees               1171 non-null   float64
 15  estimated_book_costs          1171 non-null   float64
 16  estimated_personal_expenses   1171 non-null   float64
 17  percent_faculty_with_phd      1171 non-null   float64
 18  student_faculty_ratio         1171 non-null   float64
 19  graduation_rate               1171 non-null   float64
dtypes: float64(17), int64(1), object(2)
memory usage: 192.1+ KB
```

[272]:

```python
# Create Visualizations to check for Outliers

# Selecting numeric columns to visualize. Exclude 'institution_type' since it's␣
↪categorical represented as int64.
numeric_cols = df.select_dtypes(include=['float64']).columns

# Create a large figure to accommodate the subplots
plt.figure(figsize=(20, 10))

# Create a boxplot for each numeric column
for index, column in enumerate(numeric_cols, 1):
    plt.subplot(4, 5, index)  # Adjust grid dimensions (4x5) based on the␣
↪number of columns
    sns.boxplot(y=df[column])
    plt.title(column)
    plt.tight_layout()

plt.show()
```



A number of columns appear to have numerous outliers, we attempt to get a value count for each column below:

[273]:
```python
outlier_counts = {}

# Loop through each column in the DataFrame
for column in df.select_dtypes(include=['float64', 'int64']).columns:
    # Calculate Q1 and Q3, and then IQR
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    # Define outliers as values below (Q1 - 1.5 * IQR) or above (Q3 + 1.5 * IQR)
    outliers = df[(df[column] < (Q1 - 1.5 * IQR)) | (df[column] > (Q3 + 1.5 *␣
↪IQR))]
    # Count the number of outliers
    outlier_counts[column] = outliers.shape[0]

# Print the number of outliers in each column
for column, count in outlier_counts.items():
    print(f"{column}: {count} outliers")
```

```
institution_type: 0 outliers
applications_received: 102 outliers
applications_accepted: 92 outliers
new_students_enrolled: 94 outliers
percent_from_top_10: 48 outliers
percent_from_top_25: 0 outliers
full_time_undergrads: 114 outliers
part_time_undergrads: 105 outliers
```

```
in_state_tuition: 2 outliers
out_of_state_tuition: 6 outliers
room_costs: 44 outliers
board_costs: 11 outliers
additional_fees: 93 outliers
estimated_book_costs: 81 outliers
estimated_personal_expenses: 41 outliers
percent_faculty_with_phd: 10 outliers
student_faculty_ratio: 21 outliers
graduation_rate: 2 outliers
```

While handling of outliers should ordinarily be done with great care and attention paid to the goals of the analysis and their affect on the data's distribution, due to the time constraints of this analysis we will retain them in the dataset and discuss them as they come up in the analysis section of this notebook.

1.4.6 Correcting Data Types

Here we improve the formatting of several columns. For increased readability, we'll first convert the institution type (Public/Private) from a numeric representation to "Public" or "Private". Additionally, several columns referencing number of students, faculty, and applications, where decimal values don't make sense, are changed to integer data type here as well.

[274]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1171 entries, 0 to 1301
Data columns (total 20 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   college_name                 1171 non-null   object
 1   state                        1171 non-null   object
 2   institution_type             1171 non-null   int64
 3   applications_received        1171 non-null   float64
 4   applications_accepted        1171 non-null   float64
 5   new_students_enrolled        1171 non-null   float64
 6   percent_from_top_10          1171 non-null   float64
 7   percent_from_top_25          1171 non-null   float64
 8   full_time_undergrads         1171 non-null   float64
 9   part_time_undergrads         1171 non-null   float64
 10  in_state_tuition             1171 non-null   float64
 11  out_of_state_tuition         1171 non-null   float64
 12  room_costs                   904 non-null    float64
 13  board_costs                  734 non-null    float64
 14  additional_fees              1171 non-null   float64
 15  estimated_book_costs         1171 non-null   float64
 16  estimated_personal_expenses  1171 non-null   float64
 17  percent_faculty_with_phd     1171 non-null   float64
 18  student_faculty_ratio        1171 non-null   float64
```

```
 19  graduation_rate              1171 non-null   float64
dtypes: float64(17), int64(1), object(2)
memory usage: 192.1+ KB
```

[275]:
```
# Define a mapping dictionary to translate 1 to 'Public' and 2 to 'Private'
institution_type_map = {1: 'Public', 2: 'Private'}

# Use the map function to apply this translation to the 'Public (1)/ Private␣
↪(2)' column
df['institution_type'] = df['institution_type'].map(institution_type_map)
```

[276]:
```
# Correcting Data Types
data_types = {
    'institution_type' : 'object',
    'applications_received': 'int64',
    'applications_accepted': 'int64',
    'new_students_enrolled' : 'int64',
    'full_time_undergrads' : 'int64',
    'part_time_undergrads' : 'int64',
}

# Apply the data type changes to your DataFrame
df = df.astype(data_types)
```

[277]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1171 entries, 0 to 1301
Data columns (total 20 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   college_name                 1171 non-null   object
 1   state                        1171 non-null   object
 2   institution_type             1171 non-null   object
 3   applications_received        1171 non-null   int64
 4   applications_accepted        1171 non-null   int64
 5   new_students_enrolled        1171 non-null   int64
 6   percent_from_top_10          1171 non-null   float64
 7   percent_from_top_25          1171 non-null   float64
 8   full_time_undergrads         1171 non-null   int64
 9   part_time_undergrads         1171 non-null   int64
 10  in_state_tuition             1171 non-null   float64
 11  out_of_state_tuition         1171 non-null   float64
 12  room_costs                   904 non-null    float64
 13  board_costs                  734 non-null    float64
 14  additional_fees              1171 non-null   float64
 15  estimated_book_costs         1171 non-null   float64
 16  estimated_personal_expenses  1171 non-null   float64
```

```
 17  percent_faculty_with_phd     1171 non-null   float64
 18  student_faculty_ratio        1171 non-null   float64
 19  graduation_rate              1171 non-null   float64
dtypes: float64(12), int64(5), object(3)
memory usage: 192.1+ KB
```

1.4.7 Feature Engineering

Here we create a few columns containing metrics helpful to our analysis, namely Acceptance Rate, Yield Rate, Total Cost of Attendance, Total Enrollment

[278]:
```python
# Create Aforementioned Columns
df['acceptance_rate'] = (df['applications_accepted'] /␣
 ↪df['applications_received']) * 100
df['yield_rate'] = (df['new_students_enrolled'] / df['applications_accepted'])␣
 ↪* 100
df['total_cost_in_state'] = df['in_state_tuition'] + df['room_costs'].fillna(0)␣
 ↪+ df['board_costs'].fillna(0) + df['additional_fees'] +␣
 ↪df['estimated_book_costs'] + df['estimated_personal_expenses']
df['total_enrollment'] = df['full_time_undergrads'] + df['part_time_undergrads']
```

[279]:
```python
df.info()
```

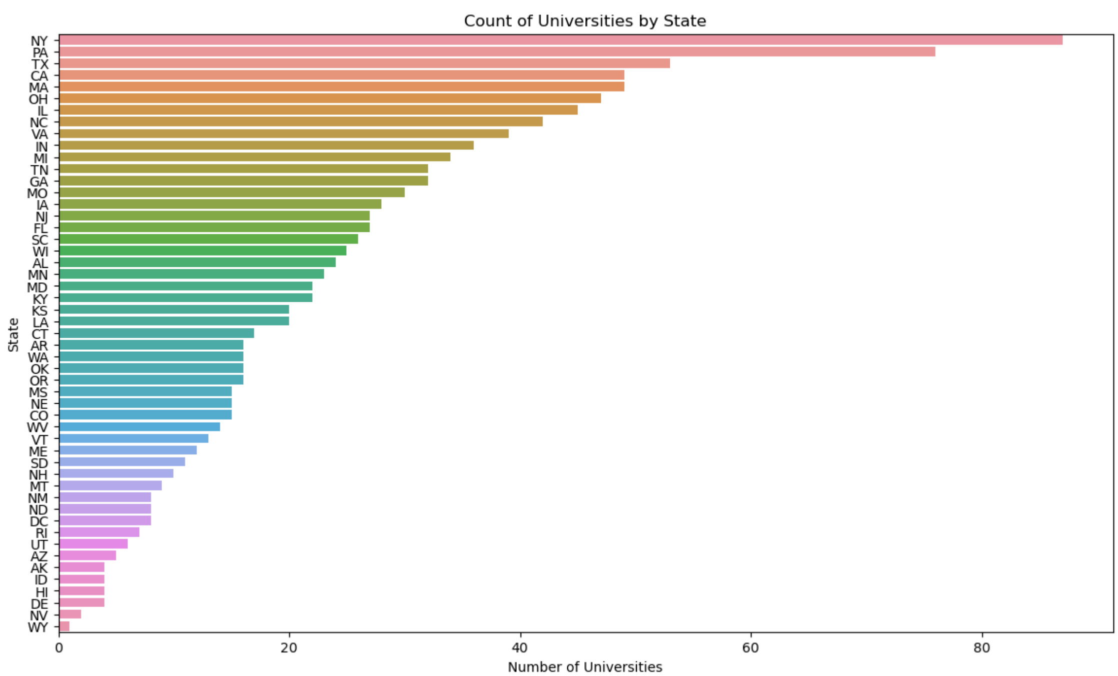
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1171 entries, 0 to 1301
Data columns (total 24 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   college_name                 1171 non-null   object
 1   state                        1171 non-null   object
 2   institution_type             1171 non-null   object
 3   applications_received        1171 non-null   int64
 4   applications_accepted        1171 non-null   int64
 5   new_students_enrolled        1171 non-null   int64
 6   percent_from_top_10          1171 non-null   float64
 7   percent_from_top_25          1171 non-null   float64
 8   full_time_undergrads         1171 non-null   int64
 9   part_time_undergrads         1171 non-null   int64
 10  in_state_tuition             1171 non-null   float64
 11  out_of_state_tuition         1171 non-null   float64
 12  room_costs                   904 non-null    float64
 13  board_costs                  734 non-null    float64
 14  additional_fees              1171 non-null   float64
 15  estimated_book_costs         1171 non-null   float64
 16  estimated_personal_expenses  1171 non-null   float64
 17  percent_faculty_with_phd     1171 non-null   float64
 18  student_faculty_ratio        1171 non-null   float64
 19  graduation_rate              1171 non-null   float64
```

```
 20   acceptance_rate              1171 non-null   float64
 21   yield_rate                   1171 non-null   float64
 22   total_cost_in_state          1171 non-null   float64
 23   total_enrollment             1171 non-null   int64
dtypes: float64(15), int64(6), object(3)
memory usage: 228.7+ KB
```

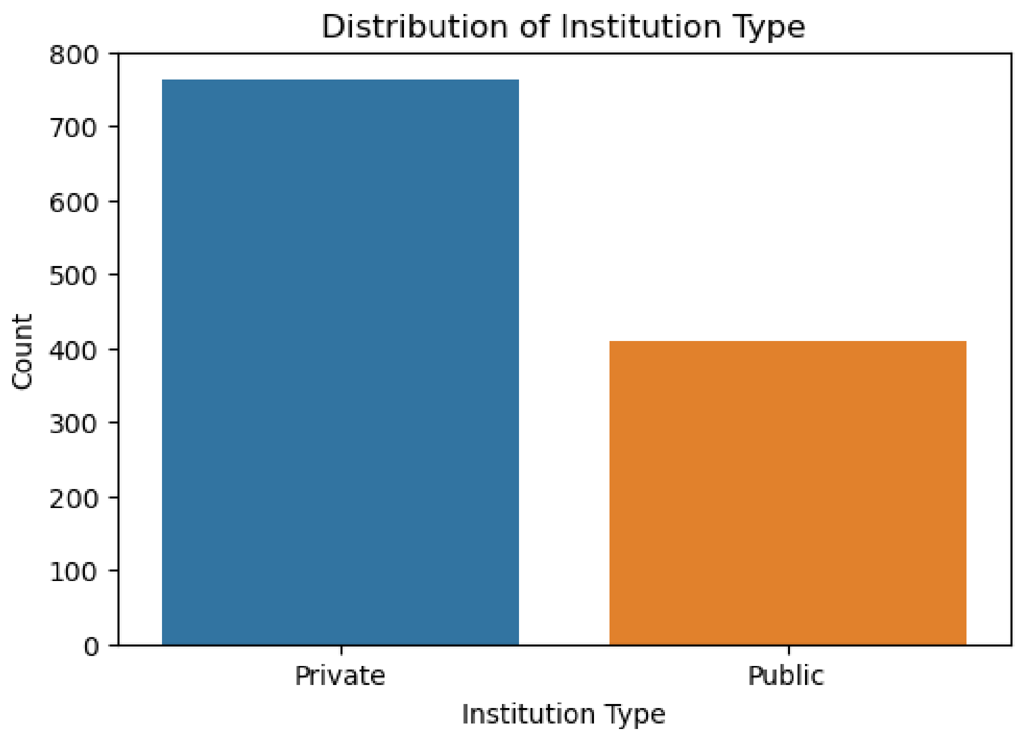
1.5 Exploratory Data Analysis/Results

In this section, we analyze our cleaned prepared dataset

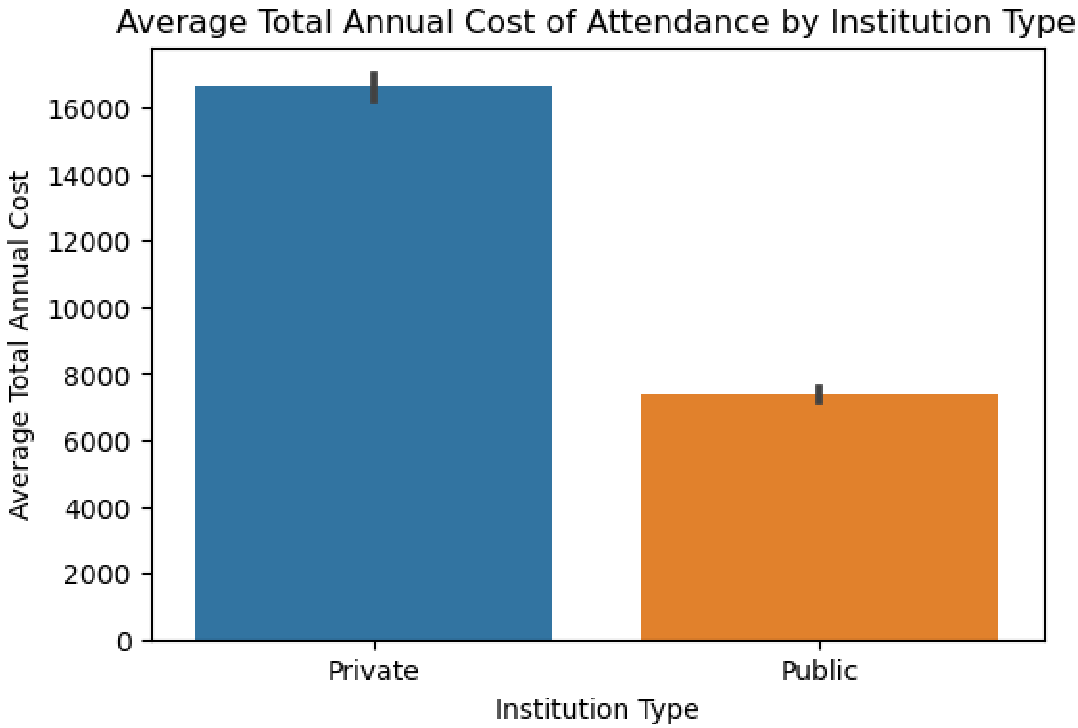
[280]:
```
# Visualization: Distribution of Universities by State
plt.figure(figsize=(14, 8))
sns.countplot(y='state', data=df, order = df['state'].value_counts().index)
plt.title('Count of Universities by State')
plt.xlabel('Number of Universities')
plt.ylabel('State')
plt.show()
```



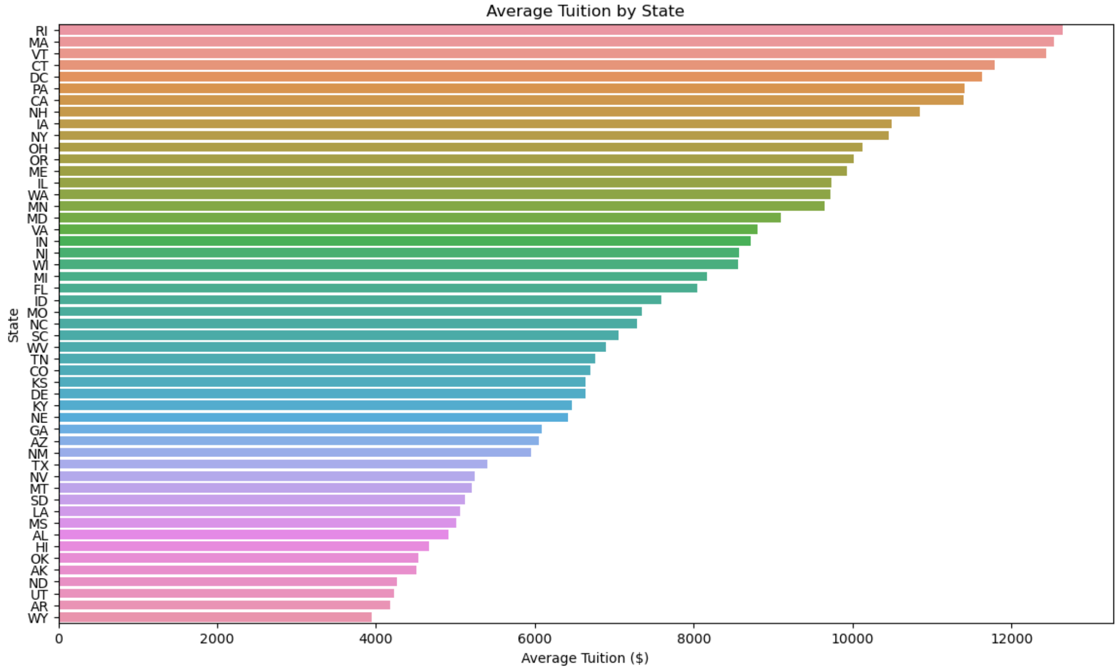
[281]:
```
# Visualization: Distribution of public vs. private institutions
plt.figure(figsize=(6, 4))
sns.countplot(x='institution_type', data=df)
plt.title('Distribution of Institution Type')
plt.xlabel('Institution Type')
plt.ylabel('Count')
plt.show()
```



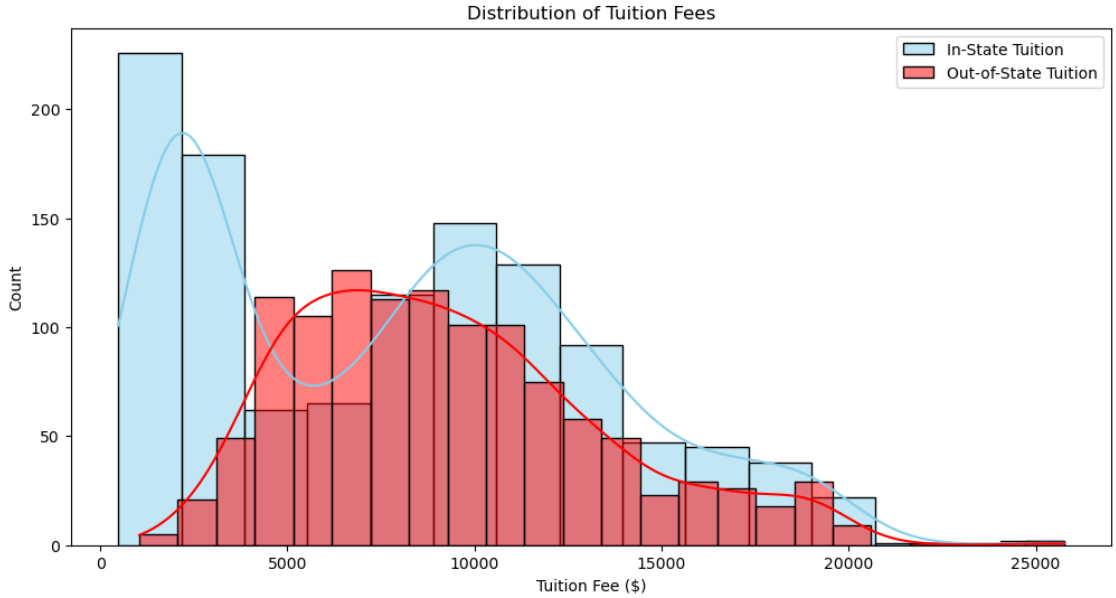
[282]:
```
# Visualization: Average Total Annual Cost of Attendance for Public vs Private
  ↪Institutions
df['total_cost'] = df['total_cost_in_state']
plt.figure(figsize=(6, 4))
sns.barplot(x='institution_type', y='total_cost', data=df, estimator=np.mean)
plt.title('Average Total Annual Cost of Attendance by Institution Type')
plt.xlabel('Institution Type')
plt.ylabel('Average Total Annual Cost')
plt.show()
```



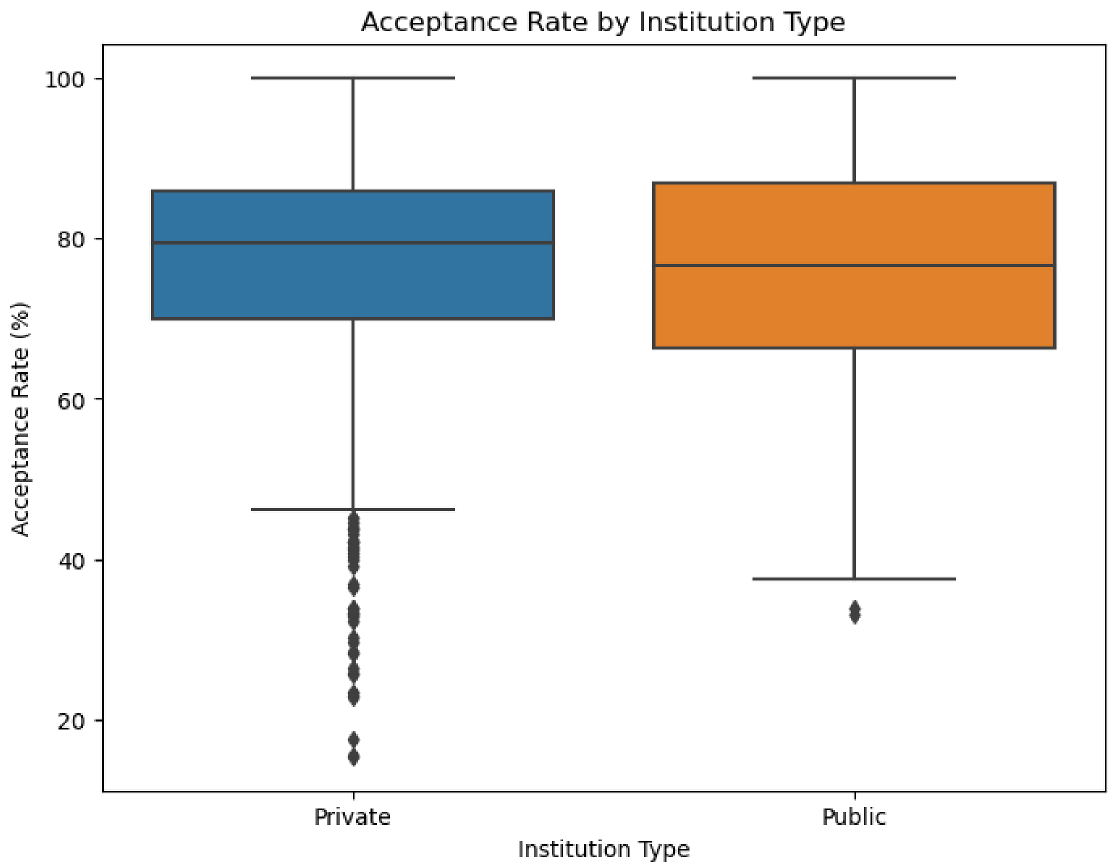
[ ]:
```
# Visualization: Average Total Tuition Cost by State
plt.figure(figsize=(14, 8))
df['average_tuition'] = (df['in-state tuition'] + df['out-of-state tuition']) /␣
↪2
state_tuition = df.groupby('State')['average_tuition'].mean().
↪sort_values(ascending=False)
sns.barplot(x=state_tuition.values, y=state_tuition.index)
plt.title('Average Tuition by State')
plt.xlabel('Average Tuition ($)')
plt.ylabel('State')
plt.show()
```



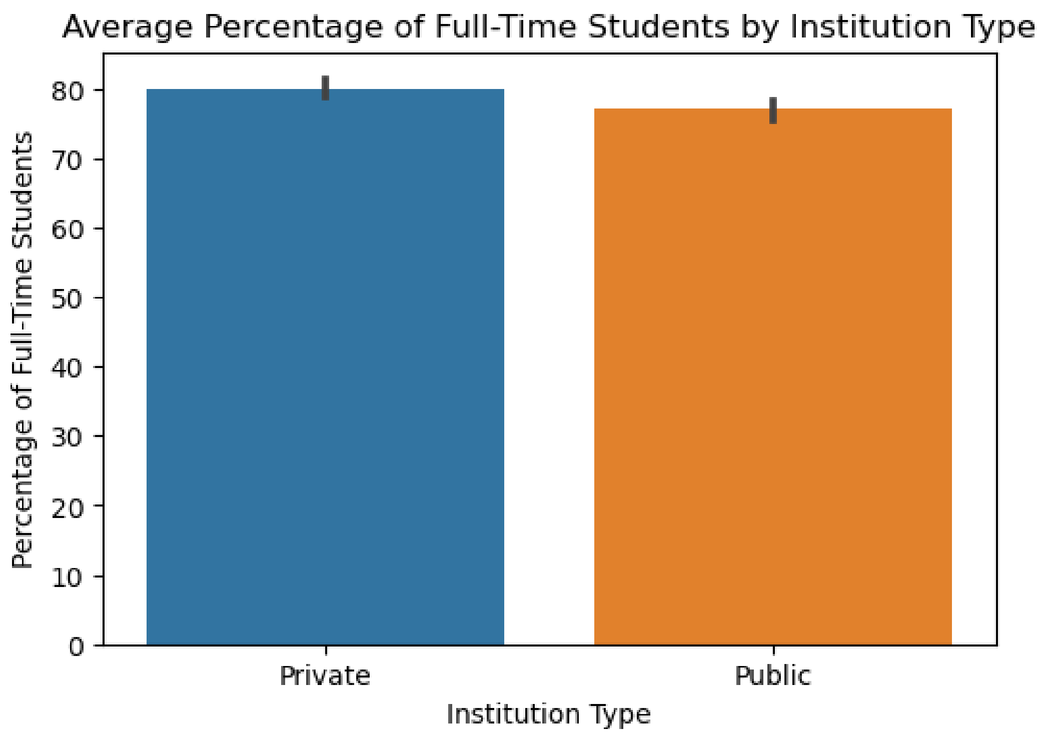
[287]:
```
# Visualization: Distribution of Tuition Fees
plt.figure(figsize=(12, 6))
sns.histplot(df['in_state_tuition'], kde=True, color='skyblue', label='In-State␣
 ↪Tuition')
sns.histplot(df['out_of_state_tuition'], kde=True, color='red',␣
 ↪label='Out-of-State Tuition')
plt.title('Distribution of Tuition Fees')
plt.xlabel('Tuition Fee ($)')
plt.ylabel('Count')
plt.legend()
plt.show()
```



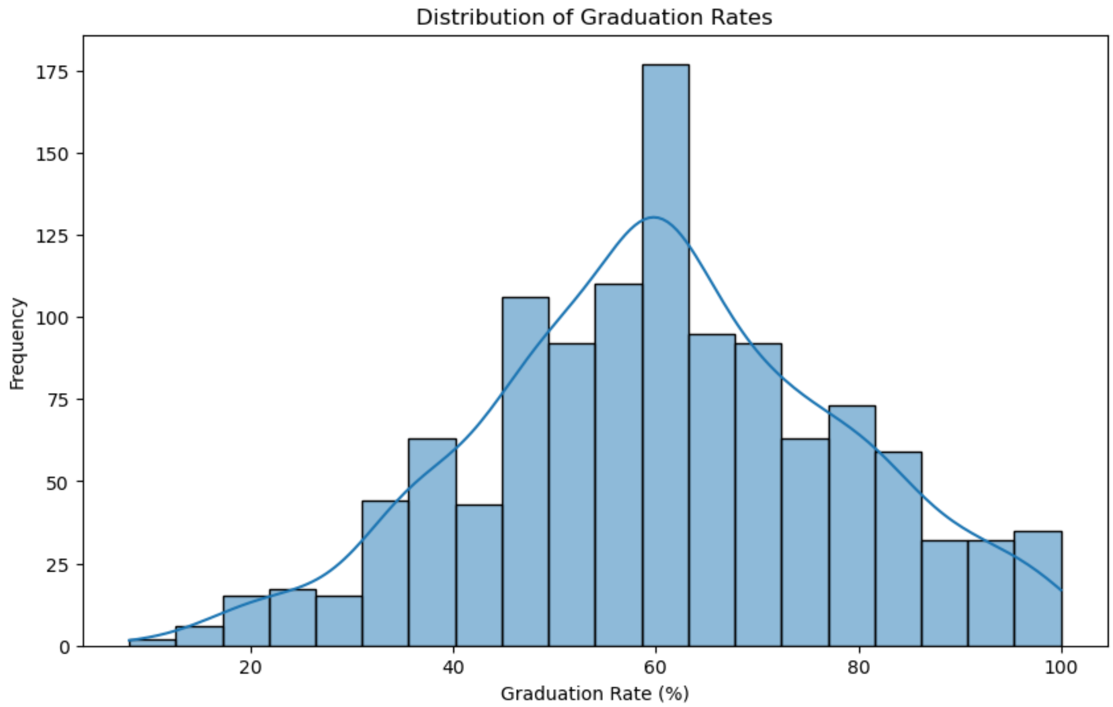
[291]:
```
# Visualization: Distribution of Acceptance Rates by Institution Type
plt.figure(figsize=(8, 6))
sns.boxplot(x='institution_type', y='acceptance_rate', data=df)
plt.title('Acceptance Rate by Institution Type')
plt.xlabel('Institution Type')
plt.ylabel('Acceptance Rate (%)')
plt.show()
```



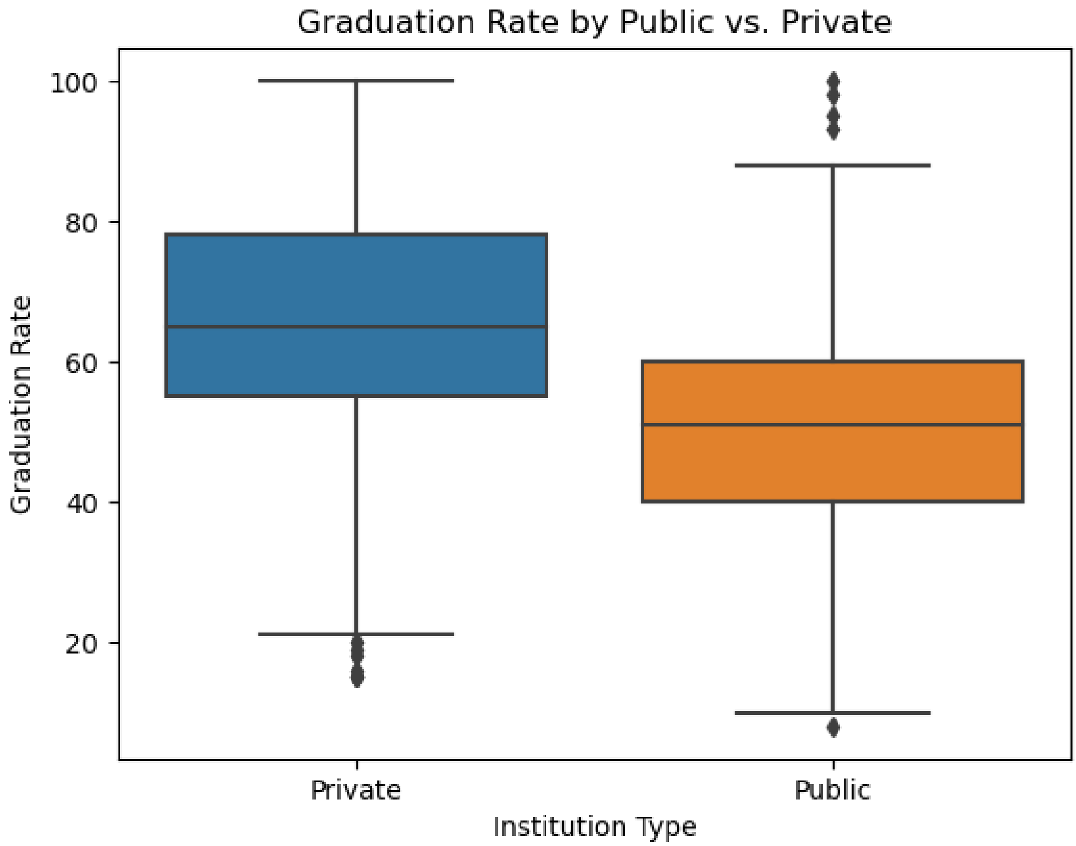
[283]:
```
# Visualization: Average Student Body Composition (Full-time vs. Part-time)
df['total_students'] = df['full_time_undergrads'] + df['part_time_undergrads']
df['percent_full_time'] = (df['full_time_undergrads'] / df['total_students']) *␣
↪100

plt.figure(figsize=(6, 4))
sns.barplot(x='institution_type', y='percent_full_time', data=df, estimator=np.
↪mean)
plt.title('Average Percentage of Full-Time Students by Institution Type')
plt.xlabel('Institution Type')
plt.ylabel('Percentage of Full-Time Students')
plt.show()
```



[288]:
```
# Visualization: Distribution of Graduation Rates
plt.figure(figsize=(10, 6))
sns.histplot(df['graduation_rate'], bins=20, kde=True)
plt.title('Distribution of Graduation Rates')
plt.xlabel('Graduation Rate (%)')
plt.ylabel('Frequency')
plt.show()
```

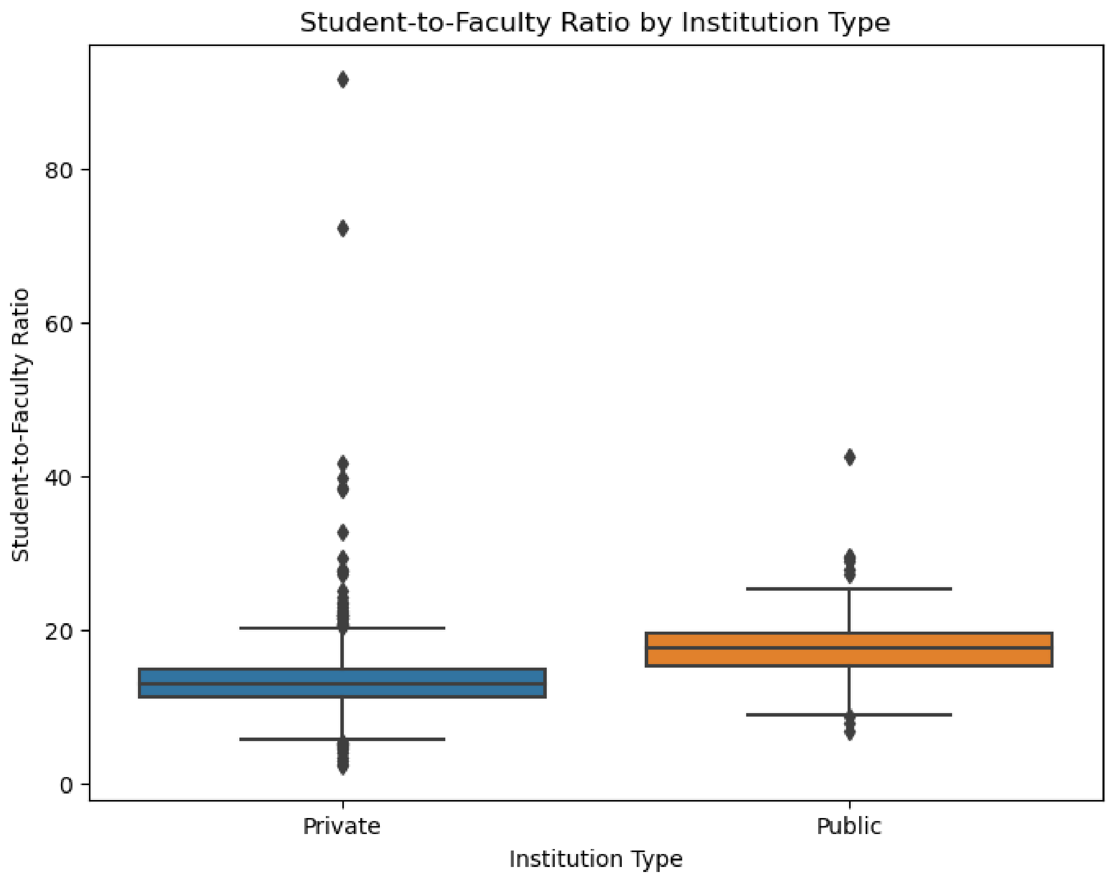


[284]:
```
# Visualization: Average Student Body Composition (Full-time vs. Part-time)
sns.boxplot(x='institution_type', y='graduation_rate', data=df)
plt.title('Graduation Rate by Public vs. Private')
plt.xlabel('Institution Type')
plt.ylabel('Graduation Rate')
plt.show()
```



[290]:
```
# Visualization: Student-to-Faculty Ratio by Institution Type
plt.figure(figsize=(8, 6))
sns.boxplot(x='institution_type', y='student_faculty_ratio', data=df)
plt.title('Student-to-Faculty Ratio by Institution Type')
plt.xlabel('Institution Type')
plt.ylabel('Student-to-Faculty Ratio')
plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```



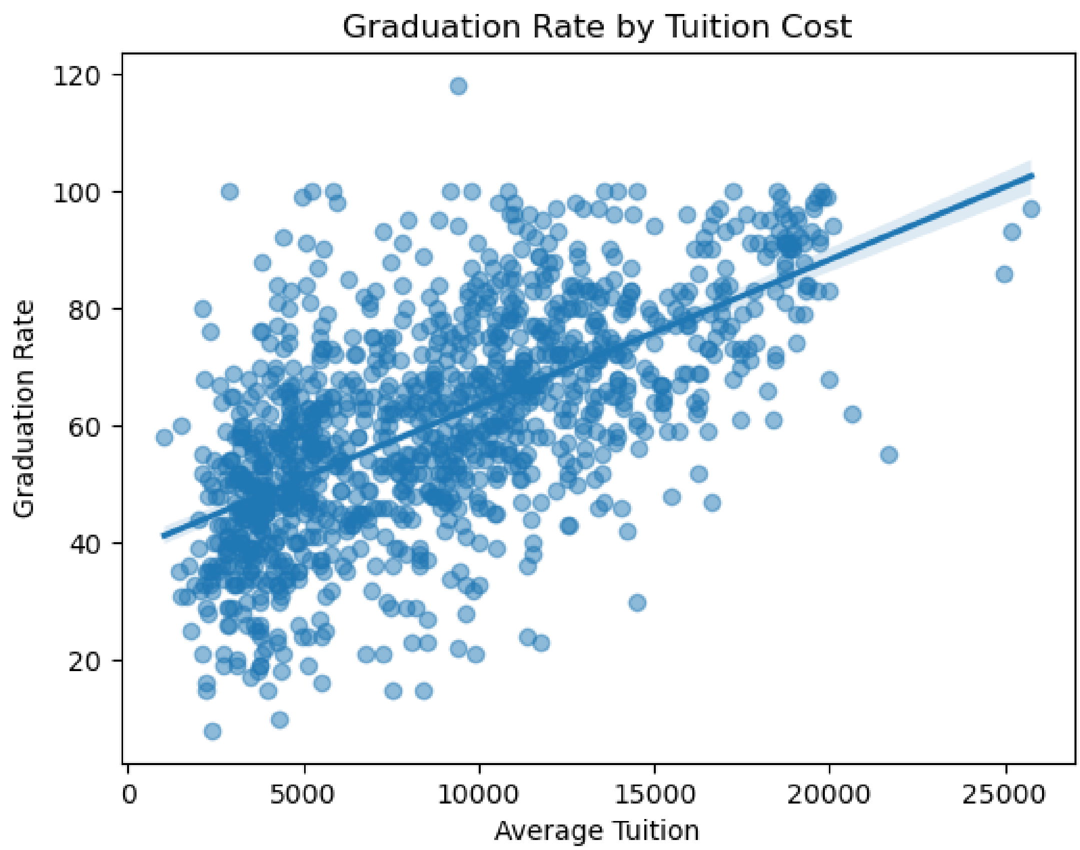
[212]:
```
# Calculate the correlation between 'graduation_rate' and variables in the
↪dataset

# Calculate the correlation matrix for the dataframe
correlation_matrix = df.corr()

# Extract the 'graduation_rate' column to see correlations with other variables
graduation_rate_correlation = correlation_matrix['graduation_rate'].
↪sort_values(ascending=False)

# Print the correlations
print(graduation_rate_correlation)
```

```
graduation_rate                1.000000
out_of_state_tuition           0.596518
in_state_tuition               0.580855
total_cost_in_state            0.574065
percent_from_top_10            0.539111
percent_from_top_25            0.498203
board_costs                    0.390641
```

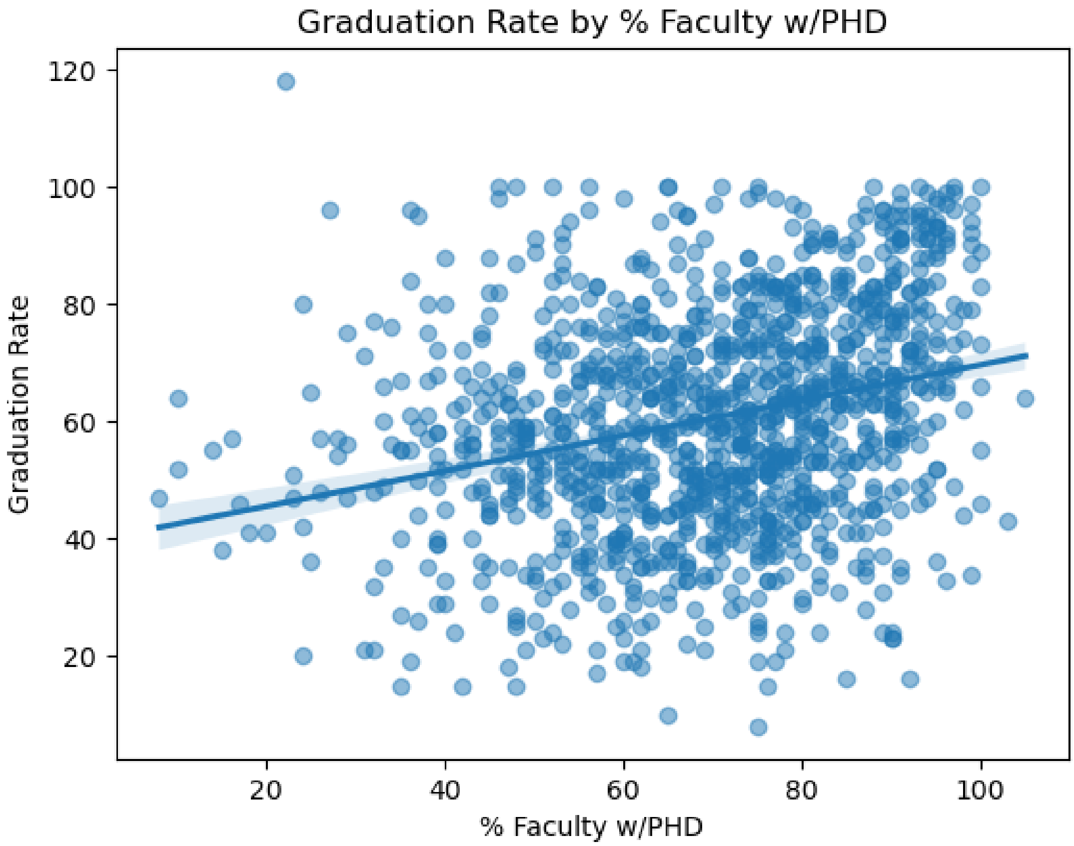
```
percent_faculty_with_phd       0.287155
room_costs                     0.243991
applications_received          0.137240
applications_accepted          0.063971
additional_fees                0.050750
estimated_book_costs           0.005696
new_students_enrolled         -0.059394
full_time_undergrads          -0.096151
total_enrollment              -0.164624
estimated_personal_expenses   -0.197224
acceptance_rate               -0.236663
student_faculty_ratio         -0.284587
part_time_undergrads          -0.297154
yield_rate                    -0.318371
Name: graduation_rate, dtype: float64
```

```
C:\Users\James\AppData\Local\Temp\ipykernel_29048\2859158846.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  correlation_matrix = df.corr()
```

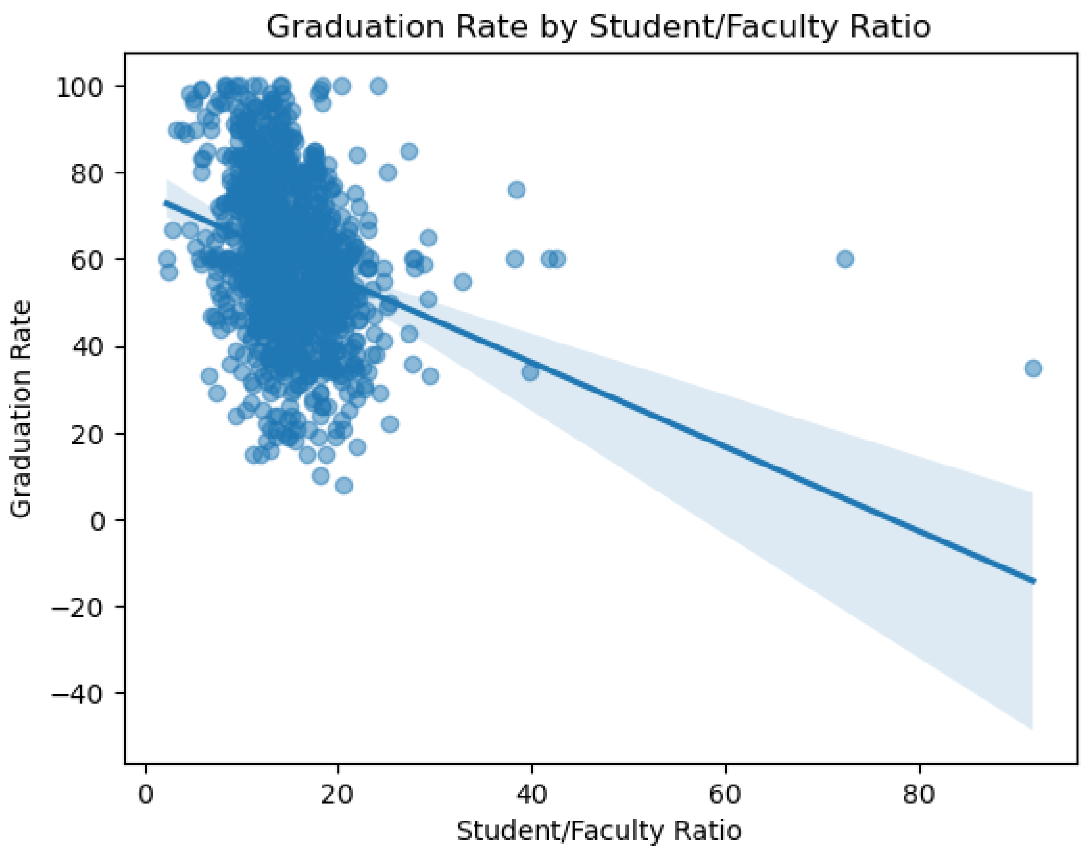
[ ]:
```
sns.regplot(x='average_tuition', y='Graduation rate', data=df,␣
  ↪scatter_kws={'alpha':0.5})
plt.title('Graduation Rate by Tuition Cost')
plt.xlabel('Average Tuition')
plt.ylabel('Graduation Rate')
plt.show()
```




```
[ ]: sns.regplot(x='% fac. w/PHD', y='Graduation rate', data=df,␣
       ↪scatter_kws={'alpha':0.5})
     plt.title('Graduation Rate by % Faculty w/PHD')
     plt.xlabel('% Faculty w/PHD')
     plt.ylabel('Graduation Rate')
     plt.show()
```



[292]:
```
sns.regplot(x='student_faculty_ratio', y='graduation_rate', data=df,␣
 ↪scatter_kws={'alpha':0.5})
plt.title('Graduation Rate by Student/Faculty Ratio')
plt.xlabel('Student/Faculty Ratio')
plt.ylabel('Graduation Rate')
plt.show()
```



[295]:
```
# Generate Summary Statistics
df.describe()
```

[295]:
```
       applications_received  applications_accepted  new_students_enrolled  \
count            1171.000000            1171.000000            1171.000000
mean             2661.401366            1838.443211             769.619129
std              3409.315991            2188.810559             882.600645
min                52.000000              36.000000              18.000000
25%               687.000000             553.500000             233.000000
50%              1450.000000            1086.000000             444.000000
75%              3280.500000            2303.000000             945.000000
max             48094.000000           26330.000000            7425.000000

       percent_from_top_10  percent_from_top_25  full_time_undergrads  \
count          1171.000000          1171.000000           1171.000000
mean             20.906917            44.493595           3647.936806
std              18.119802            26.139218           4496.513985
min               0.000000             0.000000             88.000000
25%               9.000000            29.000000            967.500000
50%              17.000000            46.000000           1803.000000
```

```
75%              29.000000            63.000000           4475.000000
max              96.000000           100.000000          31643.000000

       part_time_undergrads  in_state_tuition  out_of_state_tuition  \
count           1171.000000       1171.000000           1171.000000
mean            1047.527754       7909.197267           9301.883860
std             1648.558020       5277.480869           4098.244588
min                1.000000        480.000000           1044.000000
25%              128.000000       2615.500000           6161.000000
50%              446.000000       8190.000000           8734.000000
75%             1283.000000      11535.000000          11658.000000
max            21836.000000      25750.000000          25750.000000

        room_costs  …  percent_faculty_with_phd  student_faculty_ratio  \
count   904.000000  …               1171.000000            1171.000000
mean   2519.537611  …                 68.756618              14.881981
std    1151.862241  …                 17.536327               5.252689
min     500.000000  …                  8.000000               2.300000
25%    1714.250000  …                 57.000000              11.800000
50%    2200.000000  …                 71.000000              14.300000
75%    3010.000000  …                 82.000000              17.500000
max    7400.000000  …                100.000000              91.800000

       graduation_rate  acceptance_rate   yield_rate  total_cost_in_state  \
count      1171.000000      1171.000000  1171.000000          1171.000000
mean         60.513237        76.088792    45.041695         13391.611443
std          17.909663        14.911831    16.425049          6136.324488
min           8.000000        15.448631     9.975397          2521.000000
25%          49.000000        68.689057    33.477811          8411.000000
50%          60.000000        78.516903    42.250000         12906.000000
75%          73.000000        86.136346    53.475960         17875.500000
max         100.000000       100.000000   244.243421         29355.000000

       total_enrollment    total_cost  total_students  percent_full_time
count       1171.000000   1171.000000     1171.000000        1171.000000
mean        4695.464560  13391.611443     4695.464560          78.954166
std         5602.006605   6136.324488     5602.006605          16.390979
min          100.000000   2521.000000      100.000000          11.431412
25%         1229.500000   8411.000000     1229.500000          68.666242
50%         2323.000000  12906.000000     2323.000000          83.503836
75%         5730.000000  17875.500000     5730.000000          91.899260
max        38338.000000  29355.000000    38338.000000          99.941349

[8 rows x 24 columns]
```

1.6 Discussion:

Summary Statistics for the datasets were as follows (see table above): - Average applications received: 2661.4 - Average acceptance rate: 76% - Average total enrollment (full and part-time): 4,695.4 - Average total annual cost of attendance: $13391.61

Analysis of the data revealed the following insights: - The Greatest number of universities were located in New York, Pennsylvania, and Texas. - The Average Total Annual Cost of Private Universities was OVER DOUBLE that of Public Universities, despite Public and Private Institutions being roughly just as selective. Despite this Graduation Rates at Private Universities are higher than Public (though this finding was not confirmed to be statistically significant using a hypothesis test, a task for further study). - Roughly 80% of the average student body are full-time students - Factors that most predicted high graduation rates were: - Tuition cost - Percent from Top 10%,25% of their High School Class - Low Student-Faculty Ratios - Regarding graduation rates, percent of Faculty with PhD only showed a moderate effect on graduation rates, suggesting a potential cost-saving measure.

1.7 Conclusion:

This project demonstrates the power of data analytics in uncovering meaningful insights from complex datasets. By applying a range of data analysis techniques, it was possible to provide the consulting firm with a comprehensive understanding of the higher education landscape, enabling informed strategic advice for their clients.

Future directions for this work could involve deeper analysis with larger datasets, the integration of external data sources for richer insights, and the application of machine learning models to predict trends and outcomes in the education sector.