11 Pandas 3: Grouping

Lab Objective: *Many data sets contain categorical values that naturally sort the data into groups. Analyzing and comparing such groups is an important part of data analysis. In this lab we explore pandas tools for grouping data and presenting tabular data more compactly, primarily through groupby and pivot tables.*

Note

This lab will be done using Colab Notebooks. These notebooks are similar to Jupyter Notebooks but run remotely on Google's servers. Open a Google Colab notebook by going to your Google Drive account and creating a new Colaboratory file. If making a Colaboratory file is not an option, download the application Colaboratory onto your Google Drive. Once opening a new Colab Notebook, upload the file `pandas3.ipynb`. To make the data files accessible, run the following at the top of the lab:

```
>>> from google.colab import files

>>> uploaded = files.upload()
```

This will prompt you upload files for this notebook. For this lab, upload `college.csv` and `ohio_1999.csv`.

Once the lab is complete, delete BOTH lines of code used for uploading files (the import statement and the upload statement) and download as a `.py` file to your git repository. Push the newly made `pandas3.py` file.

Groupby

The file `mammal_sleep.csv`[1] contains data on the sleep cycles of different mammals, classified by order, genus, species, and diet (carnivore, herbivore, omnivore, or insectivore). The `"sleep_total"`

[1]Proceedings of the National Academy of Sciences, 104 (3):1051–1056, 2007. Updates from V. M. Savage and G. B. West, with additional variables supplemented by Wikipedia. Available in `pydataset` (with a few more columns) under the key `"msleep"`.

column gives the total number of hours that each animal sleeps (on average) every 24 hours. To get an idea of how many animals sleep for how long, we start off with a histogram of the "sleep_total" column.

```
>>> import pandas as pd
>>> from matplotlib import pyplot as plt

# Read in the data and print a few random entries.
>>> msleep = pd.read_csv("mammal_sleep.csv")
>>> msleep.sample(5)
      name     genus   vore         order  sleep_total  sleep_rem  sleep_cycle
51  Jaguar  Panthera  carni     Carnivora         10.4        NaN          NaN
77  Tenrec    Tenrec   omni  Afrosoricida         15.6        2.3          NaN
10    Goat     Capri  herbi  Artiodactyla          5.3        0.6          NaN
80   Genet   Genetta  carni     Carnivora          6.3        1.3          NaN
33   Human      Homo   omni      Primates          8.0        1.9          1.5

# Plot the distribution of the sleep_total variable.
>>> msleep.plot(kind="hist", y="sleep_total", title="Mammalian Sleep Data")
>>> plt.xlabel("Hours")
```

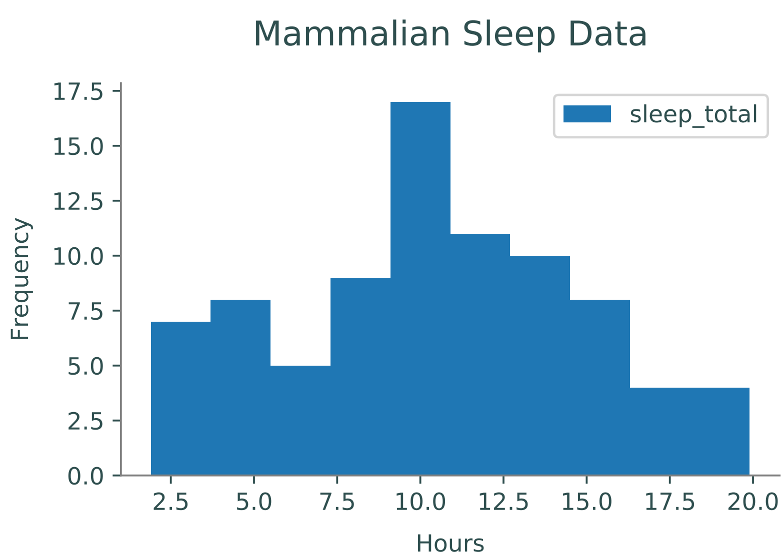


Figure 11.1: "sleep_total" frequencies from the mammalian sleep data set.

While this visualization is a good start, it doesn't provide any information about how different kinds of animals have different sleeping habits. How long do carnivores sleep compared to herbivores? Do mammals of the same genus have similar sleep patterns?

A powerful tool for answering these kinds of questions is the `groupby()` method of the pandas `DataFrame` class, which partitions the original `DataFrame` into groups based on the values in one or more columns. The `groupby()` method does **not** return a new `DataFrame`; it returns a pandas `GroupBy` object, an interface for analyzing the original `DataFrame` by groups.

For example, the columns "genus", "vore", and "order" in the mammal sleep data all have a discrete number of categorical values that could be used to group the data. Since the "vore" column has only a few unique values, we start by grouping the animals by diet.

```
# List all of the unique values in the 'vore' column.
>>> set(msleep["vore"])
{nan, 'herbi', 'omni', 'carni', 'insecti'}

# Group the data by the 'vore' column.
>>> vores = msleep.groupby("vore")
>>> list(vores.groups)
['carni', 'herbi', 'insecti', 'omni']       # NaN values for vore were dropped.

# Get a single group and sample a few rows. Note vore='carni' in each entry.
>>> vores.get_group("carni").sample(5)
       name     genus  vore      order  sleep_total  sleep_rem  sleep_cycle
80    Genet   Genetta  carni  Carnivora          6.3        1.3          NaN
50    Tiger  Panthera  carni  Carnivora         15.8        NaN          NaN
8       Dog     Canis  carni  Carnivora         10.1        2.9        0.333
0   Cheetah  Acinonyx  carni  Carnivora         12.1        NaN          NaN
82  Red fox    Vulpes  carni  Carnivora          9.8        2.4        0.350
```

As shown above, `groupby()` is useful for filtering a `DataFrame` by column values; the command `df.groupby(col).get_group(value)` returns the rows of `df` where the entry of the `col` column is `value`. The real advantage of `groupby()`, however, is how easily it compares groups of data. Standard `DataFrame` methods like `describe()`, `mean()`, `std()`, `min()`, and `max()` all work on `GroupBy` objects to produce a new data frame that describes the statistics of each group.

```
# Get averages of the numerical columns for each group.
>>> vores.mean()
         sleep_total  sleep_rem  sleep_cycle
vore
carni         10.379      2.290        0.373
herbi          9.509      1.367        0.418
insecti       14.940      3.525        0.161
omni          10.925      1.956        0.592

# Get more detailed statistics for 'sleep_total' by group.
>>> vores["sleep_total"].describe()
         count    mean    std  min   25%   50%     75%   max
vore
carni     19.0  10.379  4.669  2.7  6.25  10.4  13.000  19.4
herbi     32.0   9.509  4.879  1.9  4.30  10.3  14.225  16.6
insecti    5.0  14.940  5.921  8.4  8.60  18.1  19.700  19.9
omni      20.0  10.925  2.949  8.0  9.10   9.9  10.925  18.0
```

Multiple columns can be used simultaneously for grouping. In this case, the `get_group()` method of the `GroupBy` object requires a tuple specifying the values for each of the grouping columns.

```
>>> msleep_small = msleep.drop(["sleep_rem", "sleep_cycle"], axis=1)
>>> vores_orders = msleep_small.groupby(["vore", "order"])
>>> vores_orders.get_group(("carni", "Cetacea"))
                    name          genus   vore    order  sleep_total
30           Pilot whale  Globicephalus  carni  Cetacea          2.7
59       Common porpoise       Phocoena  carni  Cetacea          5.6
79  Bottle-nosed dolphin       Tursiops  carni  Cetacea          5.2
```

Problem 1. Read in the data `college.csv` containing information on various United States universities in 1995. To access information on variable names, go to `https://cran.r-project.org/web/packages/ISLR/ISLR.pdf`. Use a `groupby` object to group the colleges by private and public universities. Read in the data as a `DataFrame` object and use `groupby` and `describe` to examine the following columns by group:

1. Student to Faculty Ratio,
2. How many students from the top 25% of their high school class,
3. How many students from the top 10% of their high school class.

Determine whether private or public universities have a higher mean for each of these columns. For the type of university with the higher mean, save the values of the describe function on said column as an array using `.values`. Return a tuple with these arrays in the order described above.

For example, if I were comparing whether the number of professors with PhDs was higher at private or public universities, I would return the following array:

```
array([212., 76.83490566, 12.31752531, 33., 71., 78.5 , 86., 103.])
```

Visualizing Groups

There are a few ways that `groupby()` can simplify the process of visualizing groups of data. First of all, `groupby()` makes it easy to visualize one group at a time using the `plot` method. The following visualization improves on Figure 11.1 by grouping mammals by their diets.

```
# Plot histograms of 'sleep_total' for two separate groups.
>>> vores.get_group("carni").plot(kind="hist", y="sleep_total", legend="False",
                                                title="Carnivore Sleep Data")
>>> plt.xlabel("Hours")
>>> vores.get_group("herbi").plot(kind="hist", y="sleep_total", legend="False",
                                                title="Herbivore Sleep Data")
>>> plt.xlabel("Hours")
```

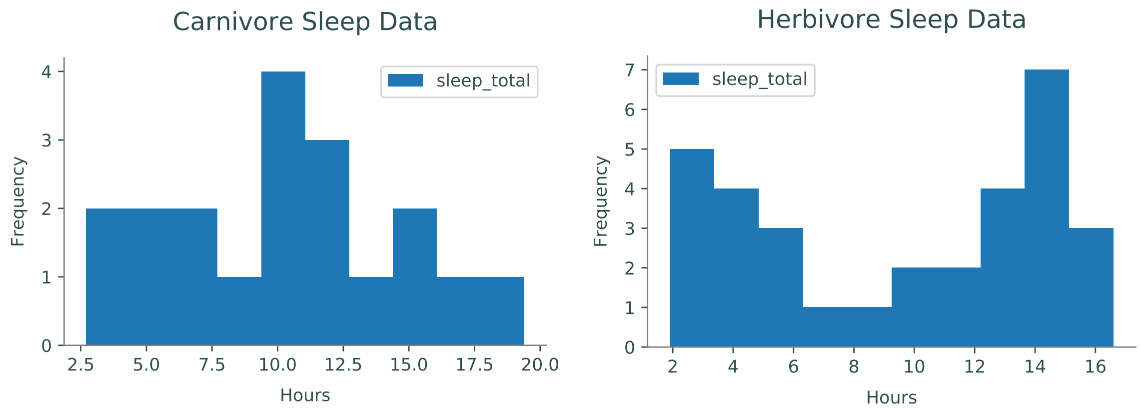
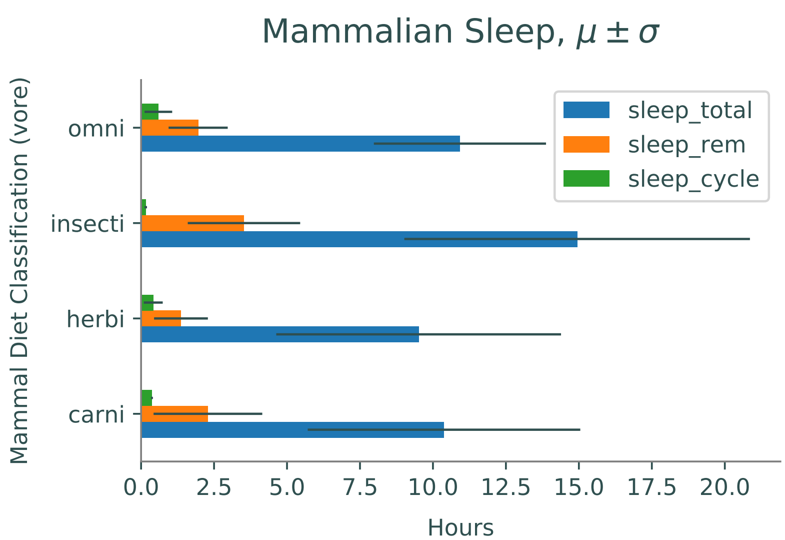


Figure 11.2: "sleep_total" histograms for two groups in the mammalian sleep data set.

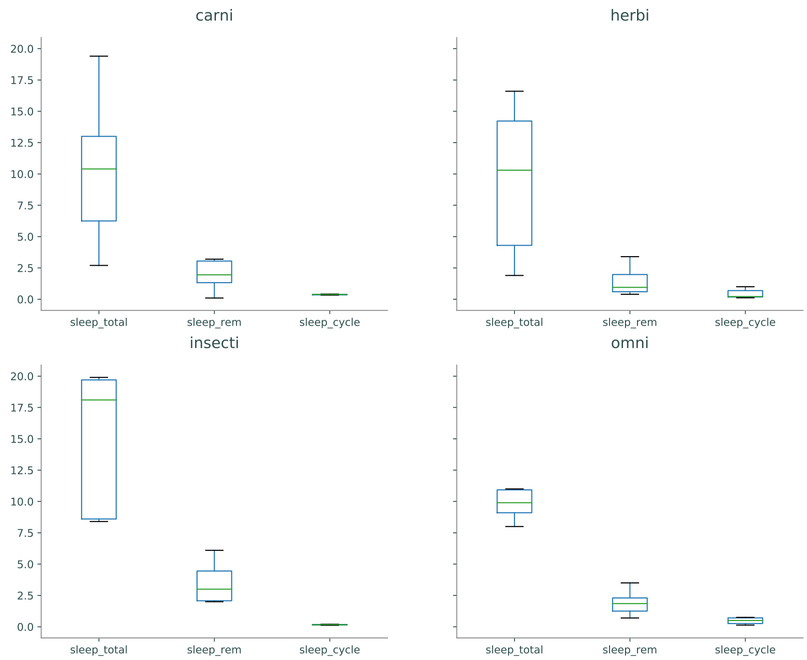
The statistical summaries from the GroupBy object's mean(), std(), or describe() methods also lend themselves well to certain visualizations for comparing groups.

```
>>> vores[["sleep_total", "sleep_rem", "sleep_cycle"]].mean().plot(kind="barh",
                xerr=vores.std(), title=r"Mammallian Sleep, $\mu\pm\sigma$")
>>> plt.xlabel("Hours")
>>> plt.ylabel("Mammal Diet Classification (vore)")
```



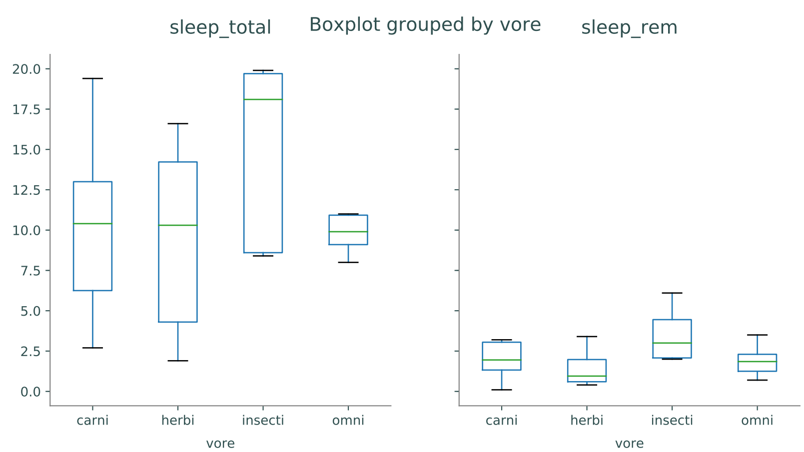
Box plots are well suited for comparing similar distributions. The boxplot() method of the GroupBy class creates one subplot **per group**, plotting each of the columns as a box plot.

```
# Use GroupBy.boxplot() to generate one box plot per group.
>>> vores.boxplot(grid=False)
>>> plt.tight_layout()
```



Alternatively, the `boxplot()` method of the `DataFrame` class creates one subplot **per column**, plotting each of the columns as a box plot. Specify the `by` keyword to group the data appropriately.

```
# Use DataFrame.boxplot() to generate one box plot per column.
>>> msleep.boxplot(["sleep_total", "sleep_rem"], by="vore", grid=False)
```



Like `groupby()`, the `by` argument can be a single column label or a list of column labels. Similar methods exist for creating histograms (`GroupBy.hist()` and `DataFrame.hist()` with `by` keyword), but generally box plots are better for comparing multiple distributions.

Problem 2. Create visualizations that give relevant information answering the following questions (using `college.csv`):

1. How do the number of applicants, number of accepted students, and number of enrolled students compare between private and public universities?
2. How wide is the range of money spent on room and board at both private and public universities?

Pivot Tables

One of the downfalls of `groupby()` is that a typical `GroupBy` object has too much information to display coherently. A *pivot table* intelligently summarizes the results of a `groupby()` operation by aggregating the data in a specified way. The standard tool for making a pivot table is the `pivot_table()` method of the `DataFrame` class. As an example, consider the `"HairEyeColor"` data set from `pydataset`.

```
>>> from pydataset import data
>>> hec = data("HairEyeColor")             # Load and preview the data.
>>> hec.sample(5)
     Hair    Eye     Sex  Freq
3     Red  Brown    Male    10
1   Black  Brown    Male    32
14  Brown  Green    Male    15
31    Red  Green  Female     7
21  Black   Blue  Female     9

>>> for col in ["Hair", "Eye", "Sex"]:      # Get unique values per column.
...     print("{}: {}".format(col, ", ".join(set(str(x) for x in hec[col]))))
...
Hair: Brown, Black, Blond, Red
Eye: Brown, Blue, Hazel, Green
Sex: Male, Female
```

There are several ways to group this data with `groupby()`. However, since there is only one entry per unique hair-eye-sex combination, the data can be completely presented in a pivot table.

```
>>> hec.pivot_table(values="Freq", index=["Hair", "Eye"], columns="Sex")
Sex          Female  Male
Hair  Eye
Black Blue        9    11
      Brown      36    32
      Green       2     3
      Hazel       5    10
Blond Blue       64    30
      Brown       4     3
      Green       8     8
      Hazel       5     5
```

```
Brown Blue      34   50
      Brown     66   53
      Green     14   15
      Hazel     29   25
Red   Blue       7   10
      Brown     16   10
      Green      7    7
      Hazel      7    7
```

Listing the data in this way makes it easy to locate data and compare the female and male groups. For example, it is easy to see that brown hair is more common than red hair and that about twice as many females have blond hair and blue eyes than males.

Unlike "HairEyeColor", many data sets have more than one entry in the data for each grouping. An example in the previous dataset would be if there were two or more rows in the original data for females with blond hair and blue eyes. To construct a pivot table, data of similar groups must be *aggregated* together in some way. By default entries are aggregated by averaging the non-null values. Other options include taking the min, max, standard deviation, or just counting the number of occurrences.

Consider the Titanic data set found in titanic.csv[2]. For this analysis, take only the "Survived", "Pclass", "Sex", "Age", "Fare", and "Embarked" columns, replace null age values with the average age, then drop any rows that are missing data. To begin, we examine the average survival rate grouped by sex and passenger class.

```
>>> titanic = pd.read_csv("titanic.csv")
>>> titanic = titanic[["Survived", "Pclass", "Sex", "Age", "Fare", "Embarked"]]
>>> titanic["Age"].fillna(titanic["Age"].mean(),)

>>> titanic.pivot_table(values="Survived", index="Sex", columns="Pclass")
Pclass    1.0    2.0    3.0
Sex
female  0.965  0.887  0.491
male    0.341  0.146  0.152
```

Note

The pivot_table() method is a convenient way of performing a potentially complicated groupby() operation with aggregation and some reshaping. The following code is equivalent to the previous example.

```
>>> titanic.groupby(["Sex", "Pclass"])["Survived"].mean().unstack()
Pclass    1.0    2.0    3.0
Sex
female  0.965  0.887  0.491
male    0.341  0.146  0.152
```

[2]There is a "Titanic" data set in pydataset, but it does not contain as much information as the data in titanic.csv.

The `stack()`, `unstack()`, and `pivot()` methods provide more advanced shaping options.

Among other things, this pivot table clearly shows how much more likely females were to survive than males. To see how many entries fall into each category, or how many survived in each category, aggregate by counting or summing instead of taking the mean.

```
# See how many entries are in each category.
>>> titanic.pivot_table(values="Survived", index="Sex", columns="Pclass",
...                     aggfunc="count")
Pclass  1.0  2.0  3.0
Sex
female  144  106  216
male    179  171  493

# See how many people from each category survived.
>>> titanic.pivot_table(values="Survived", index="Sex", columns="Pclass",
...                     aggfunc="sum")
Pclass    1.0   2.0    3.0
Sex
female  137.0  94.0  106.0
male     61.0  25.0   75.0
```

Problem 3. The file `ohio_1999.csv` contains data on workers in Ohio in the year 1999. Use pivot tables to answer the following questions:

1. What was the highest paid race/sex combination?
2. What race/sex combination worked the least amount of hours?
3. What race/sex combination worked the most hours per week per person?

Return a tuple for each question (in order of the questions) where the first entry is the numerical code corresponding to the race and the second entry is corresponding to the sex.

Some useful keys in understand the data are as follows:

1. In column `Sex`, {1: `male`, 2: `female`}.
2. In column `Race`, {1: `White`, 2: `African-American`, 3: `Native American/Eskimo`, 4: `Asian`}.

Discretizing Continuous Data

In the Titanic data, we examined survival rates based on sex and passenger class. Another factor that could have played into survival is age. Were male children as likely to die as females in general? We can investigate this question by *multi-indexing*, or pivoting, on more than just two variables, by adding in another index.

In the original dataset, the "Age" column has a floating point value for the age of each passenger. If we add "Age" as another pivot, then the table would create a new row for **each** age present. Instead, we partition the "Age" column into intervals with `pd.cut()`, thus creating a categorical that can be used for grouping. Notice that when creating the pivot table, the index uses the categorical `age` instead of the column name "Age".

```
# pd.cut() maps continuous entries to discrete intervals.
>>> pd.cut([1, 2, 3, 4, 5, 6, 7], [0, 4, 8])
[(4, 8], (0, 4], (0, 4], (0,4], (0, 4], (4, 8], (4, 8], (4, 8]]
Categories (2, interval[int64]): [(0, 4] < (4, 8]]

# Partition the passengers into 3 categories based on age.
>>> age = pd.cut(titanic['Age'], [0, 12, 18, 80])

>>> titanic.pivot_table(values="Survived", index=["Sex", age],
                        columns="Pclass", aggfunc="mean")
Pclass            1.0    2.0    3.0
Sex    Age
female (0, 12]   0.000  1.000  0.467
       (12, 18]  1.000  0.875  0.607
       (18, 80]  0.969  0.871  0.475
male   (0, 12]   1.000  1.000  0.343
       (12, 18]  0.500  0.000  0.081
       (18, 80]  0.322  0.093  0.143
```

From this table, it appears that male children (ages 0 to 12) in the 1st and 2nd class were very likely to survive, whereas those in 3rd class were much less likely to. This clarifies the claim that males were less likely to survive than females. However, there are a few oddities in this table: zero percent of the female children in 1st class survived, and zero percent of teenage males in second class survived. To further investigate, count the number of entries in each group.

```
>>> titanic.pivot_table(values="Survived", index=["Sex", age],
                        columns="Pclass", aggfunc="count")
Pclass          1.0  2.0  3.0
Sex    Age
female (0, 12]    1   13   30
       (12, 18]  12    8   28
       (18, 80] 129   85  158
male   (0, 12]    4   11   35
       (12, 18]   4   10   37
       (18, 80] 171  150  420
```

This table shows that there was only 1 female child in first class and only 10 male teenagers in second class, which sheds light on the previous table.

Achtung!

The previous pivot table brings up an important point about partitioning datasets. The Titanic dataset includes data for about 1300 passengers, which is a somewhat reasonable sample size, but half of the groupings include less than 30 entries, which is **not** a healthy sample size for statistical analysis. Always carefully question the numbers from pivot tables before making any conclusions.

Pandas also supports multi-indexing on the columns. As an example, consider the price of a passenger tickets. This is another continuous feature that can be discretized with `pd.cut()`. Instead, we use `pd.qcut()` to split the prices into 2 equal quantiles. Some of the resulting groups are empty; to improve readability, specify `fill_value` as the empty string or a dash.

```
# pd.qcut() partitions entries into equally populated intervals.
>>> pd.qcut([1, 2, 5, 6, 8, 3], 2)
[(0.999, 4.0], (0.999, 4.0], (4.0, 8.0], (4.0, 8.0], (4.0, 8.0], (0.999, 4.0]]
Categories (2, interval[float64]): [(0.999, 4.0] < (4.0, 8.0]]

# Cut the ticket price into two intervals (cheap vs expensive).
>>> fare = pd.qcut(titanic["Fare"], 2)
>>> titanic.pivot_table(values="Survived",
                        index=["Sex", age], columns=[fare, "Pclass"],
                        aggfunc="count", fill_value='-')
Fare            (-0.001, 14.454]          (14.454, 512.329]
Pclass                       1.0 2.0  3.0              1.0 2.0 3.0
Sex    Age
female (0, 12]                 -   -    7                1  13  23
       (12, 18]                -   4   23               12   4   5
       (18, 80]                -  31  101              129  54  57
male   (0, 12]                 -   -    8                4  11  27
       (12, 18]                -   5   26                4   5  11
       (18, 80]                8  94  350              163  56  70
```

Not surprisingly, most of the cheap tickets went to passengers in 3rd class.

Problem 4. Use the employment data from Ohio in 1999 to answer the following questions:

1. The column `Educational Attainment` contains numbers 0-46. Any number less than 39 means the person did not get any form of degree. 39-42 refers to either a high-school or associate's degree. A number greater than 43 means the person got at least a bachelor's degree. What is the most common degree among workers?

2. Partition the `Age` column into 4 equally populated intervals. What is the most common age range among workers?

3. What age/degree combination has the smallest yearly salary on average?

Return the answer to each question (in order) as an `Interval`. For part three, the answer should be a tuple where the first entry in the `Interval` of the age and the second is the `Interval` of the degree.

An `Interval` is the object returned by `pd.cut` and `pd.qcut`. An example of getting an `Interval` from a pivot table is shown below.

```
>>> # Create pivot table used in last example with titanic dataset
>>> table = titanic.pivot_table(values="Survived",
                                index=[age], columns=[fare, "Pclass"],
                                aggfunc="count")
>>> # Get index of maximum interval
>>> table.sum(axis=1).idxmax()
Interval(0, 12, closed='right')
```

Problem 5. Examine the college dataset using pivot tables and groupby objects. Determine the answer to the following questions. If the answer is yes, save the answer as `True`. If the answer the no, save the answer as `False`. For the last question, save the answer as a string giving your explanation. Return a tuple containing your answers to the questions in order.

1. Is there a correlation between percent of alumni that donate and the amount the school spends per student in BOTH private and public universities?
2. Partition `Grad.Rate` into intervals of 20%. Is the partition with the greatest number of schools the same for private and public universities?
3. Divide the acceptance rate into partitions of 25%. Does having a lower acceptance rate correlate with having more students from the top 10 percent of their high school class being admitted on average for BOTH private and public universities?
4. Why is the average percentage of students admitted from the top 10 percent of their high school class so high in private universities with very low acceptance rates?