Manipulating DataFrames with pandas

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1 Manipulating DataFrames with pandas

1.1 Course Description

In this course, you'll learn how to leverage pandas' extremely powerful data manipulation engine to get the most out of your data. It is important to be able to extract, filter, and transform data from DataFrames in order to drill into the data that really matters. The pandas library has many techniques that make this process efficient and intuitive. You will learn how to tidy, rearrange, and restructure your data by pivoting or melting and stacking or unstacking DataFrames. These are all fundamental next steps on the road to becoming a well-rounded Data Scientist, and you will have the chance to apply all the concepts you learn to real-world datasets

1.2 1 Extracting and transforming data

In this chapter, you will learn all about how to index, slice, filter, and transform DataFrames, using a variety of datasets, ranging from 2012 US election data for the state of Pennsylvania to Pittsburgh weather data.

1.2.1 1.1 Index ordering

In this exercise, the DataFrame election is provided for you. It contains the 2012 US election results for the state of Pennsylvania with county names as row indices. Your job is to select 'Bedford' county and the'winner' column. Which method is the preferred way?

Feel free to explore the DataFrame in the IPython Shell.

Instructions

Possible Answers

- election['Bedford', 'winner']
- election['Bedford']['winner']
- election['eggs']['Bedford']
- **election.loc['Bedford', 'winner']**
- election.iloc['Bedford', 'winner']

[1]:
```
import pandas as pd
election = pd.read_csv('./Data/pennsylvania2012_turnout.csv'
                       , index_col='county')
election.head()
```

[1]:
```
              state   total      Obama    Romney  winner  voters   turnout  \
county
Adams            PA   41973  35.482334  63.112001  Romney   61156  68.632677
Allegheny        PA  614671  56.640219  42.185820   Obama  924351  66.497575
Armstrong        PA   28322  30.696985  67.901278  Romney   42147  67.198140
Beaver           PA   80015  46.032619  52.637630  Romney  115157  69.483401
Bedford          PA   21444  22.057452  76.986570  Romney   32189  66.619031

              margin
county
Adams      27.629667
Allegheny  14.454399
Armstrong  37.204293
Beaver      6.605012
Bedford    54.929118
```

[2]:
```python
election.loc['Bedford', 'winner']
```

[2]:
```
'Romney'
```

1.2.2 1.2 Positional and labeled indexing

Given a pair of label-based indices, sometimes it's necessary to find the corresponding positions. In this exercise, you will use the Pennsylvania election results again. The DataFrame is provided for you as `election`.

Find `x` and `y` such that ~~~ election.iloc[x, y] == election.loc['Bedford', 'winner'] ~~~ . That is, what is the row position of `'Bedford'`, and the column position of `'winner'`? Remember that the first position in Python is 0, not 1!

To answer this question, first explore the DataFrame using `election.head()` in the IPython Shell and inspect it with your eyes.

This course introduces a lot of new concepts, so if you ever need a quick refresher, download the Pandas Cheat Sheet and keep it handy!

Instructions

- Explore the DataFrame in the IPython Shell using `election.head()`.
- Assign the row position of `election.loc['Bedford']` to `x`.
- Assign the column position of `election['winner']` to `y`.
- Hit 'Submit Answer' to print the boolean equivalence of the `.loc` and `.iloc` selections.

[3]:
```python
# Assign the row position of election.loc['Bedford']: x
x = 4

# Assign the column position of election['winner']: y
y = 4

# Print the boolean equivalence
```

```python
print(election.iloc[x, y] == election.loc['Bedford', 'winner'])
```

```
True
```

1.2.3 1.3 Indexing and column rearrangement

There are circumstances in which it's useful to modify the order of your DataFrame columns. We do that now by extracting just two columns from the Pennsylvania election results DataFrame.

Your job is to read the CSV file and set the index to `'county'`. You'll then assign a new DataFrame by selecting the list of columns `['winner', 'total', 'voters']`. The CSV file is provided to you in the variable `filename`.

Instructions

- Import pandas as pd.
- Read in `filename` using `pd.read_csv()` and set the index to `'county'` by specifying the `index_col parameter`.
- Create a separate DataFrame `results` with the columns `['winner', 'total', 'voters']`.
- Print the output using `results.head()`. This has been done for you, so hit 'Submit Answer' to see the new DataFrame!

[4]:
```python
# Import pandas
import pandas as ps

# Read in filename and set the index: election
filename = './Data/pennsylvania2012_turnout.csv'
election = pd.read_csv(filename, index_col='county')

# Create a separate dataframe with the columns ['winner', 'total', 'voters']:
↪results
results = election[['winner', 'total', 'voters']]

# Print the output of results.head()
print(results.head())
```

```
           winner   total  voters
county
Adams      Romney   41973   61156
Allegheny   Obama  614671  924351
Armstrong  Romney   28322   42147
Beaver     Romney   80015  115157
Bedford    Romney   21444   32189
```

[5]:
```python
election[['winner']][1:4]
```

[5]:
```
           winner
county
Allegheny   Obama
```

```
Armstrong  Romney
Beaver     Romney
```

1.2.4 1.4 Slicing rows

The Pennsylvania US election results data set that you have been using so far is ordered by county name. This means that county names can be sliced alphabetically. In this exercise, you're going to perform slicing on the county names of the `election` DataFrame from the previous exercises, which has been pre-loaded for you.

Instructions

- Slice the row labels `'Perry'` to `'Potter'` and assign the output to `p_counties`.
- Print the `p_counties` DataFrame. This has been done for you.
- Slice the row labels `'Potter'` to `'Perry'` in reverse order. To do this for hypothetical row labels `'a'` and `'b'`, you could use a stepsize of -1 like so: `df.loc['b':'a':-1]`.
- Print the `p_counties_rev` DataFrame. This has also been done for you, so hit 'Submit Answer' to see the result of your slicing!

[6]:
```python
# Slice the row labels 'Perry' to 'Potter': p_counties
p_counties = election.loc['Perry':'Potter',:]

# Print the p_counties DataFrame
print(p_counties)

# Slice the row labels 'Potter' to 'Perry' in reverse order: p_counties_rev
p_counties_rev = election.loc['Potter':'Perry':-1,:]

# Print the p_counties_rev DataFrame
print(p_counties_rev)
```

```
            state   total      Obama     Romney  winner   voters    turnout  \
county
Perry          PA   18240  29.769737  68.591009  Romney    27245  66.948064
Philadelphia   PA  653598  85.224251  14.051451   Obama  1099197  59.461407
Pike           PA   23164  43.904334  54.882576  Romney    41840  55.363289
Potter         PA    7205  26.259542  72.158223  Romney    10913  66.022175

                margin
county
Perry        38.821272
Philadelphia 71.172800
Pike         10.978242
Potter       45.898681
            state   total      Obama     Romney  winner   voters    turnout  \
county
Potter         PA    7205  26.259542  72.158223  Romney    10913  66.022175
Pike           PA   23164  43.904334  54.882576  Romney    41840  55.363289
Philadelphia   PA  653598  85.224251  14.051451   Obama  1099197  59.461407
```

```
Perry           PA   18240  29.769737  68.591009  Romney    27245  66.948064

                 margin
county
Potter        45.898681
Pike          10.978242
Philadelphia  71.172800
Perry         38.821272
```

1.2.5 1.5 Slicing columns

Similar to row slicing, columns can be sliced by value. In this exercise, your job is to slice column names from the Pennsylvania election results DataFrame using `.loc[]`.

It has been pre-loaded for you as `election`, with the index set to `'county'`.

Instructions

- Slice the columns from the starting column to `'Obama'` and assign the result to `left_columns`
- Slice the columns from `'Obama'` to `'winner'` and assign the result to `middle_columns`
- Slice the columns from `'Romney'` to the end and assign the result to `right_columns`
- The code to print the first 5 rows of `left_columns`, `middle_columns`, and `right_columns` has been written, so hit 'Submit Answer' to see the results!

[7]:
```python
# Slice the columns from the starting column to 'Obama': left_columns
left_columns = election.loc[:,:'Obama']

# Print the output of left_columns.head()
print(left_columns.head())

# Slice the columns from 'Obama' to 'winner': middle_columns
middle_columns = election.loc[:,'Obama':'winner']

# Print the output of middle_columns.head()
print(middle_columns.head())

# Slice the columns from 'Romney' to the end: 'right_columns'
right_columns = election.loc[:,'Romney':]

# Print the output of right_columns.head()
print(right_columns.head())
```

```
          state   total      Obama
county
Adams        PA   41973  35.482334
Allegheny    PA  614671  56.640219
Armstrong    PA   28322  30.696985
Beaver       PA   80015  46.032619
Bedford      PA   21444  22.057452
               Obama     Romney  winner
```

```
county
Adams      35.482334  63.112001  Romney
Allegheny  56.640219  42.185820   Obama
Armstrong  30.696985  67.901278  Romney
Beaver     46.032619  52.637630  Romney
Bedford    22.057452  76.986570  Romney
              Romney  winner  voters    turnout     margin
county
Adams      63.112001  Romney   61156  68.632677  27.629667
Allegheny  42.185820   Obama  924351  66.497575  14.454399
Armstrong  67.901278  Romney   42147  67.198140  37.204293
Beaver     52.637630  Romney  115157  69.483401   6.605012
Bedford    76.986570  Romney   32189  66.619031  54.929118
```

1.2.6 1.6 Subselecting DataFrames with lists

You can use lists to select specific row and column labels with the `.loc[]` accessor. In this exercise, your job is to select the counties `['Philadelphia', 'Centre', 'Fulton']` and the columns `['winner','Obama','Romney']` from the `election` DataFrame, which has been pre-loaded for you with the index set to `'county'`.

Instructions

- Create the list of row labels `['Philadelphia', 'Centre', 'Fulton']` and assign it to `rows`.
- Create the list of column labels `['winner', 'Obama', 'Romney']` and assign it to `cols`.
- Create a new DataFrame by selecting with `rows` and `cols` in `.loc[]` and assign it to `three_counties`.
- Print the `three_counties` DataFrame. This has been done for you, so hit 'Submit Answer' to see your new DataFrame.

[8]:
```python
# Create the list of row labels: rows
rows = ['Philadelphia', 'Centre', 'Fulton']

# Create the list of column labels: cols
cols = ['winner', 'Obama', 'Romney']

# Create the new DataFrame: three_counties
three_counties = election.loc[rows,cols]

# Print the three_counties DataFrame
print(three_counties)
```

```
              winner      Obama     Romney
county
Philadelphia   Obama  85.224251  14.051451
Centre        Romney  48.948416  48.977486
Fulton        Romney  21.096291  77.748861
```

1.2.7 1.7 Thresholding data

In this exercise, we have provided the Pennsylvania election results and included a column called `'turnout'` that contains the percentage of voter turnout per county. Your job is to prepare a boolean array to select all of the rows and columns where voter turnout exceeded 70%.

As before, the DataFrame is available to you as `election` with the index set to `'county'`.

Instructions

- Create a boolean array of the condition where the `'turnout'` column is greater than `70` and assign it to `high_turnout`.
- Filter the `election` DataFrame with the `high_turnout` array and assign it to `high_turnout_df`.
- Print the filtered DataFrame. This has been done for you, so hit 'Submit Answer' to see it!

1.2.8 1.8 Filtering columns using other columns

The election results DataFrame has a column labeled `'margin'` which expresses the number of extra votes the winner received over the losing candidate. This number is given as a percentage of the total votes cast. It is reasonable to assume that in counties where this margin was less than 1%, the results would be too-close-to-call.

Your job is to use boolean selection to filter the rows where the margin was less than 1. You'll then convert these rows of the `'winner'` column to `np.nan` to indicate that these results are too close to declare a winner.

The DataFrame has been pre-loaded for you as `election`.

Instructions

- Import `numpy` as `np`.
- Create a boolean array for the condition where the `'margin'` column is less than 1 and assign it to `too_close`.
- Convert the entries in the `'winner'` column where the result was too close to call to `np.nan`.
- Print the output of `election.info()`. This has been done for you, so hit 'Submit Answer' to see the results.

[9]:
```python
import pandas as pd

election = pd.read_csv('./Data/pennsylvania2012_turnout.csv')
```

[10]:
```python
# Import numpy
import numpy as np

# Create the boolean array: too_close
too_close = election.margin < 1

# Assign np.nan to the 'winner' column where the results were too close to call
election.winner[too_close] = np.nan

# Print the output of election.info()
```

```python
print(election.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 67 entries, 0 to 66
Data columns (total 9 columns):
county     67 non-null object
state      67 non-null object
total      67 non-null int64
Obama      67 non-null float64
Romney     67 non-null float64
winner     64 non-null object
voters     67 non-null int64
turnout    67 non-null float64
margin     67 non-null float64
dtypes: float64(4), int64(2), object(3)
memory usage: 4.8+ KB
None
```

```
C:\Users\124501\.conda\envs\datacamp\lib\site-packages\ipykernel_launcher.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
```

1.2.9 1.9 Filtering using NaNs

In certain scenarios, it may be necessary to remove rows and columns with missing data from a DataFrame. The `.dropna()` method is used to perform this action. You'll now practice using this method on a dataset obtained from Vanderbilt University, which consists of data from passengers on the Titanic.

The DataFrame has been pre-loaded for you as `titanic`. Explore it in the IPython Shell and you will note that there are many NaNs. You will focus specifically on the `'age'` and `'cabin'` columns in this exercise. Your job is to use `.dropna()` to remove rows where any of these two columns contains missing data and rows where *all* of these two columns contain missing data.

You'll also use the `.shape` attribute, which returns the number of rows and columns in a tuple from a DataFrame, or the number of rows from a Series, to see the effect of dropping missing values from a DataFrame.

Finally, you'll use the `thresh=` keyword argument to drop columns from the full dataset that have less than 1000 non-missing values.

Instructions

- Select the `'age'` and `'cabin'` columns of `titanic` and create a new DataFrame `df`.
- Print the shape of `df`. This has been done for you.
- Drop rows in `df` with `how='any'` and print the shape.
- Drop rows in `df` with `how='all'` and print the shape.

- Drop columns from the titanic DataFrame that have less than 1000 non-missing values by specifying the thresh and axis keyword arguments. Print the output of .info() from this.

[11]:
```
titanic = pd.read_csv('./Data/titanic.csv')
```

[12]:
```
# Select the 'age' and 'cabin' columns: df
df = titanic[['age','cabin']]

# Print the shape of df
print(df.shape)

# Drop rows in df with how='any' and print the shape
print(df.dropna(how='any').shape)

# Drop rows in df with how='all' and print the shape
print(df.dropna(how='all').shape)

# Drop columns in titanic with less than 1000 non-missing values
print(titanic.dropna(thresh=1000, axis='columns').info())
```

```
(1309, 2)
(272, 2)
(1069, 2)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1309 entries, 0 to 1308
Data columns (total 10 columns):
pclass      1309 non-null int64
survived    1309 non-null int64
name        1309 non-null object
sex         1309 non-null object
age         1046 non-null float64
sibsp       1309 non-null int64
parch       1309 non-null int64
ticket      1309 non-null object
fare        1308 non-null float64
embarked    1307 non-null object
dtypes: float64(2), int64(4), object(4)
memory usage: 102.3+ KB
None
```

1.2.10 1.20 Using apply() to transform a column

The .apply() method can be used on a pandas DataFrame to apply an arbitrary Python function to every element. In this exercise you'll take daily weather data in Pittsburgh in 2013 obtained from Weather Underground.

A function to convert degrees Fahrenheit to degrees Celsius has been written for you. Your job is to use the .apply() method to perform this conversion on the 'Mean TemperatureF' and 'Mean Dew PointF' columns of the weather DataFrame.

Instructions

- Apply the `to_celsius()` function over the `['Mean TemperatureF','Mean Dew PointF']` columns of the `weather` DataFrame.
- Reassign the column labels of `df_celsius` to `['Mean TemperatureC','Mean Dew PointC']` using the `.columns` attribute.
- Hit 'Submit Answer' to see the new DataFrame with the converted units.

[13]:
```
weather = pd.read_csv('./Data/pittsburgh2013.csv')
weather.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 365 entries, 0 to 364
Data columns (total 23 columns):
Date                          365 non-null object
Max TemperatureF              365 non-null int64
Mean TemperatureF             365 non-null int64
Min TemperatureF              365 non-null int64
Max Dew PointF                365 non-null int64
Mean Dew PointF               365 non-null int64
Min DewpointF                 365 non-null int64
Max Humidity                  365 non-null int64
Mean Humidity                 365 non-null int64
Min Humidity                  365 non-null int64
Max Sea Level PressureIn      365 non-null float64
Mean Sea Level PressureIn     365 non-null float64
Min Sea Level PressureIn      365 non-null float64
Max VisibilityMiles           365 non-null int64
Mean VisibilityMiles          365 non-null int64
Min VisibilityMiles           365 non-null int64
Max Wind SpeedMPH             365 non-null int64
Mean Wind SpeedMPH            365 non-null int64
Max Gust SpeedMPH             244 non-null float64
PrecipitationIn               365 non-null float64
 CloudCover                   365 non-null int64
Events                        207 non-null object
WindDirDegrees                365 non-null int64
dtypes: float64(5), int64(16), object(2)
memory usage: 65.7+ KB
```

[14]:
```
# Write a function to convert degrees Fahrenheit to degrees Celsius: to_celsius
def to_celsius(F):
    return 5/9*(F - 32)

# Apply the function over 'Mean TemperatureF' and 'Mean Dew PointF': df_celsius
df_celsius = to_celsius(weather[['Mean TemperatureF','Mean Dew PointF']])

# Reassign the column labels of df_celsius
```

```
df_celsius.columns = ['Mean TemperatureC', 'Mean Dew PointC']

# Print the output of df_celsius.head()
print(df_celsius.head())
```

```
   Mean TemperatureC  Mean Dew PointC
0          -2.222222        -2.777778
1          -6.111111       -11.111111
2          -4.444444        -9.444444
3          -2.222222        -7.222222
4          -1.111111        -6.666667
```

1.2.11 1.21 Using .map() with a dictionary

The `.map()` method is used to transform values according to a Python dictionary look-up. In this exercise you'll practice this method while returning to working with the `election` DataFrame, which has been pre-loaded for you.

Your job is to use a dictionary to map the values `'Obama'` and `'Romney'` in the `'winner'` column to the values `'blue'` and `'red'`, and assign the output to the new column `'color'`.

Instructions

- Create a dictionary with the key:value pairs `'Obama':'blue'` and `'Romney':'red'`.
- Use the `.map()` method on the `'winner'` column using the `red_vs_blue` dictionary you created.
- Print the output of `election.head()`. This has been done for you, so hit 'Submit Answer' to see the new column!

[15]:
```
# Create the dictionary: red_vs_blue
red_vs_blue = {'Obama':'blue', 'Romney':'red'}

# Use the dictionary to map the 'winner' column to the new column:␣
↪election['color']
election['color'] = election.winner.map(red_vs_blue)

# Print the output of election.head()
print(election.head())
```

```
      county state   total      Obama     Romney  winner  voters    turnout  \
0      Adams    PA   41973  35.482334  63.112001  Romney   61156  68.632677
1  Allegheny    PA  614671  56.640219  42.185820   Obama  924351  66.497575
2  Armstrong    PA   28322  30.696985  67.901278  Romney   42147  67.198140
3     Beaver    PA   80015  46.032619  52.637630  Romney  115157  69.483401
4    Bedford    PA   21444  22.057452  76.986570  Romney   32189  66.619031

      margin color
0  27.629667   red
1  14.454399  blue
2  37.204293   red
```

```
3    6.605012   red
4   54.929118   red
```

1.2.12 1.22 Using vectorized functions

When performance is paramount, you should avoid using `.apply()` and `.map()` because those constructs perform Python for-loops over the data stored in a pandas Series or DataFrame. By using vectorized functions instead, you can loop over the data at the same speed as compiled code (C, Fortran, etc.)! NumPy, SciPy and pandas come with a variety of vectorized functions (called Universal Functions or UFuncs in NumPy).

You can even write your own vectorized functions, but for now we will focus on the ones distributed by NumPy and pandas.

In this exercise you're going to import the `zscore` function from `scipy.stats` and use it to compute the deviation in voter turnout in Pennsylvania from the mean in fractions of the standard deviation. In statistics, the z-score is the number of standard deviations by which an observation is above the mean - so if it is negative, it means the observation is below the mean.

Instead of using `.apply()` as you did in the earlier exercises, the `zscore` UFunc will take a pandas Series as input and return a NumPy array. You will then assign the values of the NumPy array to a new column in the DataFrame. You will be working with the `election` DataFrame - it has been pre-loaded for you.

Instructions

- Import `zscore` from `scipy.stats`.
- Call `zscore` with `election['turnout']` as input .
- Print the output of `type(turnout_zscore)`. This has been done for you.
- Assign `turnout_zscore` to a new column in `election` as `'turnout_zscore'`.
- Print the output of `election.head()`. This has been done for you, so hit 'Submit Answer' to view the result.

[16]:
```python
# Import zscore from scipy.stats
from scipy.stats import zscore

# Call zscore with election['turnout'] as input: turnout_zscore
turnout_zscore = zscore(election['turnout'])

# Print the type of turnout_zscore
print(type(turnout_zscore))

# Assign turnout_zscore to a new column: election['turnout_zscore']
election['turnout_zscore'] = turnout_zscore

# Print the output of election.head()
print(election.head())
```

```
<class 'numpy.ndarray'>
      county state   total      Obama     Romney  winner  voters    turnout  \
0      Adams    PA   41973  35.482334  63.112001  Romney   61156  68.632677
```

```
1  Allegheny    PA  614671  56.640219  42.185820   Obama  924351  66.497575
2  Armstrong    PA   28322  30.696985  67.901278  Romney   42147  67.198140
3     Beaver    PA   80015  46.032619  52.637630  Romney  115157  69.483401
4    Bedford    PA   21444  22.057452  76.986570  Romney   32189  66.619031

      margin color  turnout_zscore
0  27.629667   red        0.853734
1  14.454399  blue        0.439846
2  37.204293   red        0.575650
3   6.605012   red        1.018647
4  54.929118   red        0.463391
```

1.3 2. Advanced indexing

Having learned the fundamentals of working with DataFrames, you will now move on to more advanced indexing techniques. You will learn about MultiIndexes, or hierarchical indexes, and learn how to interact with and extract data from them.

1.3.1 2.1 Index values and names

Which one of the following index operations does not raise an error?

The `sales` DataFrame which you have seen in the videos of the previous chapter has been pre-loaded for you and is available for exploration in the IPython Shell. ~~~ eggs salt spam month Jan 47 12.0 17 Feb 110 50.0 31 Mar 221 89.0 72 Apr 77 87.0 20 May 132 NaN 52 Jun 205 60.0 55 ~~~ **Instructions**

Possible Answers - `sales.index[0] = 'JAN'`. - `sales.index[0] = sales.index[0].upper()`. - **`sales.index = range(len(sales))`.**

1.3.2 2.2 Changing index of a DataFrame

As you saw in the previous exercise, indexes are immutable objects. This means that if you want to change or modify the index in a DataFrame, then you need to change the whole index. You will do this now, using a list comprehension to create the new index.

A list comprehension is a succinct way to generate a list in one line. For example, the following list comprehension generates a list that contains the cubes of all numbers from 0 to 9:

`cubes = [i**3 for i in range(10)]`.

This is equivalent to the following code:

```
cubes = []
for i in range(10):
    cubes.append(i**3)
```

Before getting started, print the `sales` DataFrame in the IPython Shell and verify that the index is given by month abbreviations containing lowercase characters.

By the way, if you haven't downloaded it already, check out the Pandas Cheat Sheet. It includes an overview of the most important concepts, functions and methods and might come in handy if you ever need a quick refresher!

Instructions

- Create a list `new_idx` with the same elements as in `sales.index`, but with all characters capitalized.
- Assign `new_idx` to `sales.index`.
- Print the `sales` dataframe. This has been done for you, so hit 'Submit Answer' and to see how the index changed.

[17]:
```
sales = pd.read_csv('./Data/sales.csv', index_col = 'month')
print(sales)
```

```
       eggs  salt  spam
month
Jan      47  12.0    17
Feb     110  50.0    31
Mar     221  89.0    72
Apr      77  87.0    20
May     132   NaN    52
Jun     205  60.0    55
```

[18]:
```
# Create the list of new indexes: new_idx
new_idx = [month.upper() for month in sales.index]

# Assign new_idx to sales.index
sales.index = new_idx

# Print the sales DataFrame
print(sales)
```

```
     eggs  salt  spam
JAN    47  12.0    17
FEB   110  50.0    31
MAR   221  89.0    72
APR    77  87.0    20
MAY   132   NaN    52
JUN   205  60.0    55
```

1.3.3 2.3 Changing index name labels

Notice that in the previous exercise, the index was not labeled with a name. In this exercise, you will set its name to `'MONTHS'`.

Similarly, if all the columns are related in some way, you can provide a label for the set of columns.

To get started, print the `sales` DataFrame in the IPython Shell and verify that the index has no name, only its data (the month names).

Instructions

- Assign the string `'MONTHS'` to `sales.index.name` to create a name for the index.
- Print the `sales` dataframe to see the index name you just created.

- Now assign the string 'PRODUCTS' to sales.columns.name to give a name to the set of columns.
- Print the sales dataframe again to see the columns name you just created.

[19]:
```
# Assign the string 'MONTHS' to sales.index.name
sales.index.name = 'MONTHS'

# Print the sales DataFrame
print(sales,'\n')

# Assign the string 'PRODUCTS' to sales.columns.name
sales.columns.name = 'PRODUCTS'

# Print the sales dataframe again
print(sales)
```

```
        eggs  salt  spam
MONTHS
JAN       47  12.0    17
FEB      110  50.0    31
MAR      221  89.0    72
APR       77  87.0    20
MAY      132   NaN    52
JUN      205  60.0    55

PRODUCTS  eggs  salt  spam
MONTHS
JAN         47  12.0    17
FEB        110  50.0    31
MAR        221  89.0    72
APR         77  87.0    20
MAY        132   NaN    52
JUN        205  60.0    55
```

1.3.4 2.4 Building an index, then a DataFrame

You can also build the DataFrame and index independently, and then put them together. If you take this route, be careful, as any mistakes in generating the DataFrame or the index can cause the data and the index to be aligned incorrectly.

In this exercise, the sales DataFrame has been provided for you without the month index. Your job is to build this index separately and then assign it to the sales DataFrame. Before getting started, print the sales DataFrame in the IPython Shell and note that it's missing the month information.

Instructions

- Generate a list months with the data ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun']. This has been done for you.
- Assign months to sales.index.

- Print the modified sales dataframe and verify that you now have month information in the index.

[20]:
```
# Generate the list of months: months
months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun']

# Assign months to sales.index
sales.index = months

# Print the modified sales DataFrame
print(sales)
```

```
PRODUCTS  eggs  salt  spam
Jan         47  12.0    17
Feb        110  50.0    31
Mar        221  89.0    72
Apr         77  87.0    20
May        132   NaN    52
Jun        205  60.0    55
```

1.3.5 2.5 Extracting data with a MultiIndex

In the video, Dhavide explained the concept of a hierarchical index, or a MultiIndex. You will now practice working with these types of indexes.

The sales DataFrame you have been working with has been extended to now include State information as well. In the IPython Shell, print the new sales DataFrame to inspect the data. Take note of the MultiIndex!

Extracting elements from the outermost level of a MultiIndex is just like in the case of a single-level Index. You can use the .loc[] accessor as Dhavide demonstrated in the video.

Instructions

- Print sales.loc[['CA', 'TX']]. Note how New York is excluded.
- Print sales['CA':'TX']. Note how New York is included.

[21]:
```
sales = pd.read_csv('./Data/sales_w_states.csv')
print(sales)
print('\n')
sales = sales.set_index(['state','month'])
sales = sales.sort_index()
print(sales.index.names)
print('\n')
print(sales)
```

```
  state  month  eggs  salt  spam
0    CA      1    47  12.0    17
1    CA      2   110  50.0    31
2    NY      1   221  89.0    72
3    NY      2    77  87.0    20
```

```
4     TX       1    132    NaN     52
5     TX       2    205   60.0     55
```

```
['state', 'month']
```

```
             eggs  salt  spam
state month
CA    1        47  12.0    17
      2       110  50.0    31
NY    1       221  89.0    72
      2        77  87.0    20
TX    1       132   NaN    52
      2       205  60.0    55
```

[22]:

```python
# Print sales.loc[['CA', 'TX']]
print(sales.loc[['CA', 'TX']])

print('\n')

# Print sales['CA':'TX']
print(sales['CA':'TX'])
```

```
             eggs  salt  spam
state month
CA    1        47  12.0    17
      2       110  50.0    31
TX    1       132   NaN    52
      2       205  60.0    55


             eggs  salt  spam
state month
CA    1        47  12.0    17
      2       110  50.0    31
NY    1       221  89.0    72
      2        77  87.0    20
TX    1       132   NaN    52
      2       205  60.0    55
```

1.3.6 2.6 Setting & sorting a MultiIndex

In the previous exercise, the MultiIndex was created and sorted for you. Now, you're going to do this yourself! With a MultiIndex, you should always ensure the index is sorted. You can skip this only if you know the data is already sorted on the index fields.

To get started, print the pre-loaded `sales` DataFrame in the IPython Shell to verify that there is no MultiIndex.

Instructions

- Create a MultiIndex by setting the index to be the columns `['state', 'month']`.
- Sort the MultiIndex using the `.sort_index()` method.
- Print the `sales` DataFrame. This has been done for you, so hit 'Submit Answer' to verify that indeed you have an index with the fields `state` and `month`!

[23]:
```python
sales = pd.read_csv('./Data/sales_w_states.csv')
# Set the index to be the columns ['state', 'month']: sales
sales = sales.set_index(['state','month'])

# Sort the MultiIndex: sales
sales = sales.sort_index()

# Print the sales DataFrame
print(sales)
```

```
             eggs  salt  spam
state month
CA    1        47  12.0    17
      2       110  50.0    31
NY    1       221  89.0    72
      2        77  87.0    20
TX    1       132   NaN    52
      2       205  60.0    55
```

1.3.7 2.7 Using .loc[] with nonunique indexes

As Dhavide mentioned in the video, it is always preferable to have a meaningful index that uniquely identifies each row. Even though pandas does not require unique index values in DataFrames, it works better if the index values are indeed unique. To see an example of this, you will index your `sales` data by `'state'` in this exercise.

As always, begin by printing the `sales` DataFrame in the IPython Shell and inspecting it.

Instructions

- Set the index of `sales` to be the column `'state'`.
- Print the `sales` DataFrame to verify that indeed you have an index with state values.
- Access the data from `'NY'` and print it to verify that you obtain two rows.

[24]:
```python
sales = pd.read_csv('./Data/sales_w_states.csv')
# Set the index to the column 'state': sales
sales = sales.set_index(['state'])

# Print the sales DataFrame
print(sales)

# Access the data from 'NY'
print(sales.loc['NY'])
```

```
       month  eggs  salt  spam
state
CA         1    47  12.0    17
CA         2   110  50.0    31
NY         1   221  89.0    72
NY         2    77  87.0    20
TX         1   132   NaN    52
TX         2   205  60.0    55
       month  eggs  salt  spam
state
NY         1   221  89.0    72
NY         2    77  87.0    20
```

1.3.8 2.8 Indexing multiple levels of a MultiIndex

Looking up indexed data is fast and efficient. And you have already seen that lookups based on the outermost level of a `MultiIndex` work just like lookups on DataFrames that have a single-level `Index`.

Looking up data based on inner levels of a `MultiIndex` can be a bit trickier. In this exercise, you will use your `sales` DataFrame to do some increasingly complex lookups.

The trickiest of all these lookups are when you want to access some inner levels of the index. In this case, you need to use `slice(None)` in the slicing parameter for the outermost dimension(s) instead of the usual `:`, or use `pd.IndexSlice`. You can refer to the pandas documentation for more details. For example, in the video, Dhavide used the following code to extract rows from all Symbols for the dates Oct. 3rd through 4th inclusive:

`stocks.loc[(slice(None), slice('2016-10-03', '2016-10-04')), :]`

Pay particular attention to the tuple

`(slice(None), slice('2016-10-03', '2016-10-04'))`

Instructions

- Look up data for the New York column (`'NY'`) in month `1`.
- Look up data for the California and Texas columns (`'CA'`, `'TX'`) in month `2`.
- Access the inner index `month` and look up data for all states in month `2`. Use `(slice(None), 2)` to extract all rows in month `2`.

[25]:
```
sales = pd.read_csv('./Data/sales_w_states.csv')
sales = sales.set_index(['state','month'])

# Look up data for NY in month 1: NY_month1
NY_month1 = sales.loc[('NY',1)]
# Look up data for CA and TX in month 2: CA_TX_month2
CA_TX_month2 = sales.loc[(['CA','TX'],2),:]
print(CA_TX_month2)
# Access the inner month index and look up data for all states in month 2:
 ↪all_month2
```

```
all_month2 = sales.loc[(slice(None), 2),:]
print(all_month2)
```

```
             eggs  salt  spam
state month
CA    2       110  50.0    31
TX    2       205  60.0    55
             eggs  salt  spam
state month
CA    2       110  50.0    31
NY    2        77  87.0    20
TX    2       205  60.0    55
```

1.4 3. Rearranging and reshaping data

Here, you will learn how to reshape your DataFrames using techniques such as pivoting, melting, stacking, and unstacking. These are powerful techniques that allow you to tidy and rearrange your data into the format that allows you to most easily analyze it for insights.

1.4.1 3.1 Pivoting and the index

Prior to using `.pivot()`, you need to set the index of the DataFrame somehow. Is this statement True or False?

Possible Answers - True - **False**

1.4.2 3.2 Pivoting a single variable

Suppose you started a blog for a band, and you would like to log how many visitors you have had, and how many signed-up for your newsletter. To help design the tours later, you track where the visitors are. A DataFrame called `users` consisting of this information has been pre-loaded for you.

Inspect `users` in the IPython Shell and make a note of which variable you want to use to index the rows (`'weekday'`), which variable you want to use to index the columns (`'city'`), and which variable will populate the values in the cells (`'visitors'`). Try to visualize what the result should be.

For example, in the video, Dhavide used `'treatment'` to index the rows, `'gender'` to index the columns, and `'response'` to populate the cells. Prior to pivoting, the DataFrame looked like this: ~~~ id treatment gender response 0 1 A F 5 1 2 A M 3 2 3 B F 8 3 4 B M 9 ~~~

After pivoting: ~~~ gender F M treatment
A 5 3 B 8 9 ~~~

In this exercise, your job is to pivot `users` so that the focus is on `'visitors'`, with the columns indexed by `'city'` and the rows indexed by `'weekday'`.

Instructions

- Pivot the users DataFrame with the rows indexed by `'weekday'`, the columns indexed by `'city'`, and the values populated with `'visitors'`.

- Print the pivoted DataFrame. This has been done for you, so hit 'Submit Answer' to view the result.

[26]:
```
users = pd.read_csv('./Data/users.csv', index_col = 0)
print(users)
```

```
  weekday    city  visitors  signups
0     Sun  Austin       139        7
1     Sun  Dallas       237       12
2     Mon  Austin       326        3
3     Mon  Dallas       456        5
```

[27]:
```
# Pivot the users DataFrame: visitors_pivot
visitors_pivot = users.pivot(
    index = 'weekday',
    columns = 'city',
    values = 'visitors'
    )

# Print the pivoted DataFrame
print(visitors_pivot)
```

```
city     Austin  Dallas
weekday
Mon         326     456
Sun         139     237
```

1.4.3 3.3 Pivoting all variables

If you do not select any particular variables, all of them will be pivoted. In this case - with the `users` DataFrame - both `'visitors'` and '`signups'` will be pivoted, creating hierarchical column labels.

You will explore this for yourself now in this exercise.

Instructions

- Pivot the `users` DataFrame with the `'signups'` indexed by `'weekday'` in the rows and `'city'` in the columns.
- Print the new DataFrame. This has been done for you.
- Pivot the `users` DataFrame with both `'signups'` and `'visitors'` pivoted - that is, all the variables. This will happen automatically if you do not specify an argument for the `values` parameter of `.pivot()`.
- Print the pivoted DataFrame. This has been done for you, so hit 'Submit Answer' to see the result.

[28]:
```
# Pivot users with signups indexed by weekday and city: signups_pivot
signups_pivot = users.pivot(
    index = 'weekday',
    columns = 'city',
```

```
    values = 'signups'
    )

# Print signups_pivot
print(signups_pivot)

# Pivot users pivoted by both signups and visitors: pivot
pivot = users.pivot(
    index = 'weekday',
    columns = 'city'
    )

# Print the pivoted DataFrame
print(pivot)
```

```
city     Austin  Dallas
weekday
Mon           3       5
Sun           7      12
        visitors        signups
city      Austin Dallas  Austin Dallas
weekday
Mon          326    456       3      5
Sun          139    237       7     12
```

1.4.4 3.4 Stacking & unstacking I

You are now going to practice stacking and unstacking DataFrames. The `users` DataFrame you have been working with in this chapter has been pre-loaded for you, this time with a MultiIndex. Explore it in the IPython Shell to see the data layout. Pay attention to the index, and notice that the index levels are `['city', 'weekday']`. So `'weekday'` - the second entry - has position 1. This position is what corresponds to the `level` parameter in `.stack()` and `.unstack()` calls. Alternatively, you can specify `'weekday'` as the level instead of its position.

Your job in this exercise is to unstack users by `'weekday'`. You will then use `.stack()` on the unstacked DataFrame to see if you get back the original layout of `users`.

Instructions

- Define a DataFrame `byweekday` with the `'weekday'` level of `users` unstacked.
- Print the `byweekday` DataFrame to see the new data layout. This has been done for you.
- Stack `byweekday` by `'weekday'` and print it to check if you get the same layout as the original `users` DataFrame.

[29]:
```
users = pd.read_csv('./Data/users.csv', index_col = 0)
users = users.set_index(['city','weekday'])
users = users.sort_index()
print(users,'\n')
```

```
# Unstack users by 'weekday': byweekday
byweekday = users.unstack(level='weekday')

# Print the byweekday DataFrame
print(byweekday)

# Stack byweekday by 'weekday' and print it
print(byweekday.stack(level='weekday'))
```

```
                visitors  signups
city   weekday
Austin Mon           326        3
       Sun           139        7
Dallas Mon           456        5
       Sun           237       12

        visitors      signups
weekday      Mon  Sun     Mon Sun
city
Austin       326  139       3   7
Dallas       456  237       5  12
                visitors  signups
city   weekday
Austin Mon           326        3
       Sun           139        7
Dallas Mon           456        5
       Sun           237       12
```

1.4.5 3.5 Stacking & unstacking II

You are now going to continue working with the `users` DataFrame. As always, first explore it in the IPython Shell to see the layout and note the index.

Your job in this exercise is to unstack and then stack the `'city'` level, as you did previously for `'weekday'`. Note that you won't get the same DataFrame.

Instructions

- Define a DataFrame `bycity` with the `'city'` level of users unstacked.
- Print the `bycity` DataFrame to see the new data layout. This has been done for you.
- Stack `bycity` by `'city'` and print it to check if you get the same layout as the original `users` DataFrame.

[30]:
```
# Unstack users by 'city': bycity
bycity = users.unstack(level='city')

# Print the bycity DataFrame
print(bycity)
```

```python
# Stack bycity by 'city' and print it
print(bycity.stack(level='city'))
```

```
        visitors        signups
city      Austin Dallas  Austin Dallas
weekday
Mon          326    456       3      5
Sun          139    237       7     12
                visitors  signups
weekday city
Mon     Austin       326        3
        Dallas       456        5
Sun     Austin       139        7
        Dallas       237       12
```

1.4.6 3.6 Restoring the index order

Continuing from the previous exercise, you will now use `.swaplevel(0, 1)` to flip the index levels. Note they won't be sorted. To sort them, you will have to follow up with a `.sort_index()`. You will then obtain the original DataFrame. Note that an unsorted index leads to slicing failures.

To begin, print both `users` and `bycity` in the IPython Shell. The goal here is to convert `bycity` back to something that looks like `users`.

Instructions

- Define a DataFrame `newusers` with the `'city'` level stacked back into the index of `bycity`.
- Swap the levels of the index of `newusers`.
- Print `newusers` and verify that the index is not sorted. This has been done for you.
- Sort the index of `newusers`.
- Print `newusers` and verify that the index is now sorted. This has been done for you.
- Assert that `newusers` equals `users`. This has been done for you, so hit 'Submit Answer' to see the result.

[31]:
```python
# Stack 'city' back into the index of bycity: newusers
newusers = bycity.stack(level='city')

# Swap the levels of the index of newusers: newusers
newusers = newusers.swaplevel(0,1)

# Print newusers and verify that the index is not sorted
print(newusers)

# Sort the index of newusers: newusers
newusers = newusers.sort_index()

# Print newusers and verify that the index is now sorted
print(newusers)
```

```python
# Verify that the new DataFrame is equal to the original
print(newusers.equals(users))
```

```
               visitors  signups
city   weekday
Austin Mon          326        3
Dallas Mon          456        5
Austin Sun          139        7
Dallas Sun          237       12
               visitors  signups
city   weekday
Austin Mon          326        3
       Sun          139        7
Dallas Mon          456        5
       Sun          237       12
True
```

1.4.7 3.7 Adding names for readability

You are now going to practice melting DataFrames. A DataFrame called `visitors_by_city_weekday` has been pre-loaded for you. Explore it in the IPython Shell and see that it is the `users` DataFrame from previous exercises with the rows indexed by `'weekday'`, columns indexed by `'city'`, and values populated with `'visitors'`.

Recall from the video that the goal of melting is to restore a pivoted DataFrame to its original form, or to change it from a wide shape to a long shape. You can explicitly specify the columns that should remain in the reshaped DataFrame with `id_vars`, and list which columns to convert into values with `value_vars`. As Dhavide demonstrated, if you don't pass a name to the values in `pd.melt()`, you will lose the name of your variable. You can fix this by using the `value_name` keyword argument.

Your job in this exercise is to melt `visitors_by_city_weekday` to move the city names from the column labels to values in a single column called `'city'`. If you were to use just `pd.melt(visitors_by_city_weekday)`, you would obtain the following result: ~~~ city value 0 weekday Mon 1 weekday Sun 2 Austin 326 3 Austin 139 4 Dallas 456 5 Dallas 237 ~~~

Therefore, you have to specify the `id_vars` keyword argument to ensure that `'weekday'` is retained in the reshaped DataFrame, and the `value_name` keyword argument to change the name of `value` to `visitors`.

Instructions

- Reset the index of `visitors_by_city_weekday` with `.reset_index()`.
- Print `visitors_by_city_weekday` and verify that you have just a range index, 0, 1, 2, 3. This has been done for you.
- Melt `visitors_by_city_weekday` to move the city names from the column labels to values in a single column called `visitors`.
- Print `visitors` to check that the city values are in a single column now and that the dataframe is longer and skinnier.

[32]:
```
users = pd.read_csv('./Data/users.csv', index_col = 0)
visitors_by_city_weekday = users.pivot(
    index = 'weekday',
    columns = 'city',
    values = 'visitors'
    )
visitors_by_city_weekday
```

[32]:
```
city     Austin  Dallas
weekday
Mon         326     456
Sun         139     237
```

[33]:
```
# Reset the index: visitors_by_city_weekday
visitors_by_city_weekday = visitors_by_city_weekday.reset_index()

# Print visitors_by_city_weekday
print(visitors_by_city_weekday)

# Melt visitors_by_city_weekday: visitors
visitors = pd.melt(visitors_by_city_weekday, id_vars='weekday',␣
 ↪value_name='visitors')

# Print visitors
print(visitors)
```

```
city weekday  Austin  Dallas
0        Mon     326     456
1        Sun     139     237
  weekday    city  visitors
0     Mon  Austin       326
1     Sun  Austin       139
2     Mon  Dallas       456
3     Sun  Dallas       237
```

1.4.8 3.8 Going from wide to long

You can move multiple columns into a single column (making the data long and skinny) by "melting" multiple columns. In this exercise, you will practice doing this.

The `users` DataFrame has been pre-loaded for you. As always, explore it in the IPython Shell and note the index.

Instructions

- Define a DataFrame `skinny` where you melt the `'visitors'` and `'signups'` columns of `users` into a single column.
- Print `skinny` to verify the results. Note the `value` column that had the cell values in `users`.

[34]:
```
# Melt users: skinny
skinny = pd.melt(users, id_vars = ['weekday','city']     )

# Print skinny
print(skinny)
```

```
  weekday    city  variable  value
0     Sun  Austin  visitors    139
1     Sun  Dallas  visitors    237
2     Mon  Austin  visitors    326
3     Mon  Dallas  visitors    456
4     Sun  Austin   signups      7
5     Sun  Dallas   signups     12
6     Mon  Austin   signups      3
7     Mon  Dallas   signups      5
```

1.4.9 3.9 Obtaining key-value pairs with melt()

Sometimes, all you need is some key-value pairs, and the context does not matter. If said context is in the index, you can easily obtain what you want. For example, in the `users` DataFrame, the `visitors` and `signups` columns lend themselves well to being represented as key-value pairs. So if you created a hierarchical index with `'city'` and `'weekday'` columns as the index, you can easily extract key-value pairs for the `'visitors'` and `'signups'` columns by melting `users` and specifying `col_level=0`.

Instructions

- Set the index of `users` to `['city', 'weekday']`.
- Print the DataFrame `users_idx` to see the new index.
- Obtain the key-value pairs corresponding to visitors and signups by melting `users_idx` with the keyword argument `col_level=0`.

[35]:
```
users
```

[35]:
```
  weekday    city  visitors  signups
0     Sun  Austin       139        7
1     Sun  Dallas       237       12
2     Mon  Austin       326        3
3     Mon  Dallas       456        5
```

[36]:
```
# Set the new index: users_idx
users_idx = users.set_index(['city', 'weekday'])

# Print the users_idx DataFrame
print(users_idx)

# Obtain the key-value pairs: kv_pairs
kv_pairs = users_idx.melt(col_level=0)
```

```python
# Print the key-value pairs
print(kv_pairs)
```

```
                visitors  signups
city   weekday
Austin Sun           139        7
Dallas Sun           237       12
Austin Mon           326        3
Dallas Mon           456        5
   variable  value
0  visitors    139
1  visitors    237
2  visitors    326
3  visitors    456
4   signups      7
5   signups     12
6   signups      3
7   signups      5
```

1.4.10 3.10 Setting up a pivot table

Recall from the video that a pivot table allows you to see all of your variables as a function of two other variables. In this exercise, you will use the `.pivot_table()` method to see how the `users` DataFrame entries appear when presented as functions of the `'weekday'` and `'city'` columns. That is, with the rows `indexed` by `'weekday'` and the columns indexed by `'city'`.

Before using the pivot table, print the `users` DataFrame in the IPython Shell and observe the layout.

Instructions

- Use a pivot table to index the rows of `users` by `'weekday'` and the columns of `users` by `'city'`. These correspond to the `index` and `columns` parameters of `.pivot_table()`.
- Print `by_city_day`. This has been done for you, so hit 'Submit Answer' to see the result.

[37]:
```python
# Create the DataFrame with the appropriate pivot table: by_city_day
by_city_day = users.pivot_table(
    index = 'weekday',
    columns = 'city')

# Print by_city_day
print(by_city_day)
```

```
        signups        visitors
city     Austin Dallas   Austin Dallas
weekday
Mon           3      5      326    456
Sun           7     12      139    237
```

1.4.11 3.11 Using other aggregations in pivot tables

You can also use aggregation functions within a pivot table by specifying the `aggfunc` parameter. In this exercise, you will practice using the `'count'` and `len` aggregation functions - which produce the same result - on the `users` DataFrame.

Instructions

- Define a DataFrame `count_by_weekday1` that shows the count of each column with the parameter `aggfunc='count'`. The index here is `'weekday'`.
- Print `count_by_weekday1`. This has been done for you.
- Replace `aggfunc='count'` with `aggfunc=len` and verify you obtain the same result.

[38]:
```
# Use a pivot table to display the count of each column: count_by_weekday1
count_by_weekday1 = users.pivot_table(
    index = 'weekday',
    aggfunc='count')



# Print count_by_weekday
print(count_by_weekday1)

# Replace 'aggfunc='count'' with 'aggfunc=len': count_by_weekday2
count_by_weekday2 = users.pivot_table(
    index = 'weekday',
    aggfunc=len)

# Verify that the same result is obtained
print('==========================================')
print(count_by_weekday1.equals(count_by_weekday2))
```

```
         city  signups  visitors
weekday
Mon         2        2         2
Sun         2        2         2
==========================================
True
```

1.4.12 3.12 Using margins in pivot tables

Sometimes it's useful to add totals in the margins of a pivot table. You can do this with the argument `margins=True`. In this exercise, you will practice using margins in a pivot table along with a new aggregation function: `sum`.

The `users` DataFrame, which you are now probably very familiar with, has been pre-loaded for you.

Instructions

- Define a DataFrame `signups_and_visitors` that shows the breakdown of signups and visitors by day.

  - You will need to use `aggfunc=sum` to do this.
- Print `signups_and_visitors`. This has been done for you.
- Now pass the additional argument `margins=True` to the `.pivot_table()` method to obtain the totals.
- Print `signups_and_visitors_total`. This has been done for you, so hit 'Submit Answer' to see the result.

[39]:
```
# Create the DataFrame with the appropriate pivot table: signups_and_visitors
signups_and_visitors = users.pivot_table(
    index = 'weekday',
    aggfunc='sum')

# Print signups_and_visitors
print(signups_and_visitors)

# Add in the margins: signups_and_visitors_total
signups_and_visitors_total = users.pivot_table(
    index = 'weekday',
    aggfunc ='sum',
    margins = True)

# Print signups_and_visitors_total
print(signups_and_visitors_total)
```

```
         signups  visitors
weekday
Mon            8       782
Sun           19       376
         signups  visitors
weekday
Mon            8       782
Sun           19       376
All           27      1158
```

1.5 4. Grouping data

In this chapter, you'll learn how to identify and split DataFrames by groups or categories for further aggregation or analysis. You'll also learn how to transform and filter your data, including how to detect outliers and impute missing values. Knowing how to effectively group data in pandas can be a seriously powerful addition to your data science toolbox.

4.1 Advantages of categorical data types What are the main advantages of storing data explicitly as categorical types instead of object types?

Answer the question

Possible Answers

- Computations are faster.
- Categorical data require less space in memory.

- **All of the above.**
- None of the above.

1.5.1 4.1 Grouping by multiple columns

In this exercise, you will return to working with the Titanic dataset from Chapter 1 and use `.groupby()` to analyze the distribution of passengers who boarded the Titanic.

The `'pclass'` column identifies which class of ticket was purchased by the passenger and the `'embarked'` column indicates at which of the three ports the passenger boarded the Titanic. `'S'` stands for Southampton, England, `'C'` for Cherbourg, France and `'Q'` for Queenstown, Ireland.

Your job is to first group by the `'pclass'` column and count the number of rows in each class using the `'survived'` column. You will then group by the `'embarked'` and `'pclass'` columns and count the number of passengers.

The DataFrame has been pre-loaded as `titanic`.

Instructions

- Group by the `'pclass'` column and save the result as `by_class`.
- Aggregate the `'survived'` column of `by_class` using `.count()`. Save the result as `count_by_class`.
- Print `count_by_class`. This has been done for you.

[40]:
```
titanic = pd.read_csv('./Data/titanic.csv')
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1309 entries, 0 to 1308
Data columns (total 14 columns):
pclass       1309 non-null int64
survived     1309 non-null int64
name         1309 non-null object
sex          1309 non-null object
age          1046 non-null float64
sibsp        1309 non-null int64
parch        1309 non-null int64
ticket       1309 non-null object
fare         1308 non-null float64
cabin        295 non-null object
embarked     1307 non-null object
boat         486 non-null object
body         121 non-null float64
home.dest    745 non-null object
dtypes: float64(3), int64(4), object(7)
memory usage: 143.2+ KB
```

[41]:
```
# Group titanic by 'pclass'
by_class = titanic.groupby('pclass')
```

```
# Aggregate 'survived' column of by_class by count
count_by_class = by_class['survived'].count()

# Print count_by_class
print(count_by_class)

# Group titanic by 'embarked' and 'pclass'
by_mult =  titanic.groupby(['embarked','pclass'])

# Aggregate 'survived' column of by_mult by count
count_mult = by_mult['survived'].count()

# Print count_mult
print(count_mult)
```

```
pclass
1    323
2    277
3    709
Name: survived, dtype: int64
embarked  pclass
C         1         141
          2          28
          3         101
Q         1           3
          2           7
          3         113
S         1         177
          2         242
          3         495
Name: survived, dtype: int64
```

1.5.2 4.2 Grouping by another series

In this exercise, you'll use two data sets from Gapminder.org to investigate the average life expectancy (in years) at birth in 2010 for the 6 continental regions. To do this you'll read the life expectancy data per country into one pandas DataFrame and the association between country and region into another.

By setting the index of both DataFrames to the country name, you'll then use the region information to group the countries in the life expectancy DataFrame and compute the mean value for 2010.

The life expectancy CSV file is available to you in the variable `life_fname` and the regions filename is available in the variable `regions_fname`.

Instructions

- Read `life_fname` into a DataFrame called `life` and set the index to `'Country'`.
- Read `regions_fname` into a DataFrame called `regions` and set the index to `'Country'`.

- Group life by the region column of regions and store the result in life_by_region.
- Print the mean over the 2010 column of life_by_region.

[42]:
```
life_fname = 'https://s3.amazonaws.com/assets.datacamp.com/production/
↪course_1650/datasets/life_expectancy.csv'
regions_fname = 'https://s3.amazonaws.com/assets.datacamp.com/production/
↪course_1650/datasets/regions.csv'
# Read life_fname into a DataFrame: life
life = pd.read_csv(life_fname, index_col='Country')

# Read regions_fname into a DataFrame: regions
regions = pd.read_csv(regions_fname, index_col='Country')

# Group life by regions['region']: life_by_region
life_by_region = life.groupby(regions['region'])

# Print the mean over the '2010' column of life_by_region
print(life_by_region['2010'].mean())
```

```
region
America                       74.037350
East Asia & Pacific           73.405750
Europe & Central Asia         75.656387
Middle East & North Africa    72.805333
South Asia                    68.189750
Sub-Saharan Africa            57.575080
Name: 2010, dtype: float64
```

Great work! It looks like the average life expectancy (in years) at birth in 2010 was highest in `Europe & Central Asia` *and lowest in* `Sub-Saharan Africa`.

1.5.3 4.3 Computing multiple aggregates of multiple columns

The .agg() method can be used with a tuple or list of aggregations as input. When applying multiple aggregations on multiple columns, the aggregated DataFrame has a multi-level column index.

In this exercise, you're going to group passengers on the Titanic by 'pclass' and aggregate the 'age' and 'fare' columns by the functions 'max' and 'median'. You'll then use multi-level selection to find the oldest passenger per class and the median fare price per class.

The DataFrame has been pre-loaded as titanic.

Instructions

- Group titanic by 'pclass' and save the result as by_class.
- Select the 'age' and 'fare' columns from by_class and save the result as by_class_sub.
- Aggregate by_class_sub using 'max' and 'median'. You'll have to pass 'max' and 'median' in the form of a list to .agg().
- Use .loc[] to print all of the rows and the column specification ('age','max'). This has been done for you.

- Use `.loc[]` to print all of the rows and the column specification `('fare','median')`.

[43]:
```
# Group titanic by 'pclass': by_class
by_class = titanic.groupby(['pclass'])

# Select 'age' and 'fare'
by_class_sub = by_class[['age','fare']]

# Aggregate by_class_sub by 'max' and 'median': aggregated
aggregated = by_class_sub.agg(['max','median'])

# Print the maximum age in each class
print(aggregated.loc[:, ('age','max')])

# Print the median fare in each class
print(aggregated.loc[:, ('fare','median')])
```

```
pclass
1    80.0
2    70.0
3    74.0
Name: (age, max), dtype: float64
pclass
1    60.0000
2    15.0458
3     8.0500
Name: (fare, median), dtype: float64
```

1.5.4 4.4 Aggregating on index levels/fields

If you have a DataFrame with a multi-level row index, the individual levels can be used to perform the groupby. This allows advanced aggregation techniques to be applied along one or more levels in the index and across one or more columns.

In this exercise you'll use the full Gapminder dataset which contains yearly values of life expectancy, population, child mortality (per 1,000) and per capita gross domestic product (GDP) for every country in the world from 1964 to 2013.

Your job is to create a multi-level DataFrame of the columns `'Year'`, `'Region'` and `'Country'`. Next you'll group the DataFrame by the `'Year'` and `'Region'` levels. Finally, you'll apply a dictionary aggregation to compute the total population, spread of per capita GDP values and average child mortality rate.

The Gapminder CSV file is available as `'gapminder.csv'`.

Instructions

- Read 'gapminder.csv' into a DataFrame with

`index_col=['Year','region','Country']`

. Sort the index. - Group gapminder with a level of ['Year','region'] using its level parameter. Save the result as by_year_region. - Define the function spread which returns the maximum and minimum of an input series. This has been done for you. - Create a dictionary with 'population':'sum', 'child_mortality':'mean' and 'gdp':spread as aggregator. This has been done for you. - Use the aggregator dictionary to aggregate by_year_region. Save the result as aggregated. - Print the last 6 entries of aggregated. This has been done for you, so hit 'Submit Answer' to view the result.

[44]:
```
# Read the CSV file into a DataFrame and sort the index: gapminder
gapminder = pd.read_csv('./Data/gapminder.csv',␣
↪index_col=['Year','region','Country']).sort_index()

# Group gapminder by 'Year' and 'region': by_year_region
by_year_region = gapminder.groupby(level = ['Year','region'])

# Define the function to compute spread: spread
def spread(series):
    return series.max() - series.min()

# Create the dictionary: aggregator
aggregator = {'population':'sum', 'child_mortality':'mean', 'gdp':spread}

# Aggregate by_year_region using the dictionary: aggregated
aggregated = by_year_region.agg(aggregator)

# Print the last 6 entries of aggregated
print(aggregated.tail(6))
```

```
                                population  child_mortality       gdp
Year region
2013 America                  9.629087e+08        17.745833   49634.0
     East Asia & Pacific      2.244209e+09        22.285714  134744.0
     Europe & Central Asia    8.968788e+08         9.831875   86418.0
     Middle East & North Africa 4.030504e+08      20.221500  128676.0
     South Asia               1.701241e+09        46.287500   11469.0
     Sub-Saharan Africa       9.205996e+08        76.944490   32035.0
```

[45]:
```
gapminder.head()
```

[45]:
```
                                  fertility    life  population  \
Year region  Country
1964 America Antigua and Barbuda      4.250  63.775     58653.0
             Argentina                3.068  65.388  21966478.0
             Aruba                    4.059  67.113     57031.0
             Bahamas                  4.220  64.189    133709.0
             Barbados                 4.094  62.819    234455.0

                                  child_mortality      gdp
```

```
Year region  Country
1964 America Antigua and Barbuda            72.78   5008.0
             Argentina                      57.43   8227.0
             Aruba                            NaN   5505.0
             Bahamas                        48.56  18160.0
             Barbados                       64.70   5681.0
```

1.5.5 4.5 Grouping on a function of the index

Groupby operations can also be performed on transformations of the index values. In the case of a DateTimeIndex, we can extract portions of the datetime over which to group.

In this exercise you'll read in a set of sample sales data from February 2015 and assign the `'Date'` column as the index. Your job is to group the sales data by the day of the week and aggregate the sum of the `'Units'` column.

Is there a day of the week that is more popular for customers? To find out, you're going to use `.strftime('%a')` to transform the index datetime values to abbreviated days of the week.

The sales data CSV file is available to you as `'sales.csv'`.

Instructions

- Read `'sales.csv'` into a DataFrame with `index_col='Date'` and `parse_dates=True`.
- Create a groupby object with `sales.index.strftime('%a')` as input and assign it to `by_day`.
- Aggregate the `'Units'` column of by_day with the `.sum()` method. Save the result as `units_sum`.
- Print `units_sum`. This has been done for you, so hit 'Submit Answer' to see the result.

[46]:
```
# Read file: sales
sales = pd.read_csv('./Data/sales-feb-2015.csv', index_col='Date', parse_dates=True)

# Create a groupby object: by_day
by_day = sales.groupby(sales.index.strftime('%a'))

# Create sum: units_sum
units_sum = by_day['Units'].sum()

# Print units_sum
print(units_sum)
```

```
Mon    48
Sat     7
Thu    59
Tue    13
Wed    48
Name: Units, dtype: int64
```

1.5.6 4.6 Detecting outliers with Z-Scores

As Dhavide demonstrated in the video using the `zscore` function, you can apply a `.transform()` method after grouping to apply a function to groups of data independently. The z-score is also useful to find outliers: a z-score value of +/- 3 is generally considered to be an outlier.

In this example, you're going to normalize the Gapminder data in 2010 for life expectancy and fertility by the z-score per region. Using boolean indexing, you will filter for countries that have high fertility rates and low life expectancy for their region.

The Gapminder DataFrame for 2010 indexed by `'Country'` is provided for you as `gapminder_2010`.

Instructions

- Import `zscore` from `scipy.stats`.
- Group `gapminder_2010` by `'region'` and transform the `['life','fertility']` columns by `zscore`.
- Construct a boolean Series of the bitwise `or` between `standardized['life'] < -3` and `standardized['fertility'] > 3`.
- Filter `gapminder_2010` using `.loc[]` and the outliers Boolean Series. Save the result as `gm_outliers`.
- Print `gm_outliers`. This has been done for you, so hit 'Submit Answer' to see the results.

[47]:
```python
gapminder = pd.read_csv('./Data/gapminder.csv', index_col=['Country']).
↪sort_index()
gapminder_2010 = gapminder[gapminder['Year']==2010]

# Import zscore
from scipy.stats import zscore

# Group gapminder_2010: standardized
standardized = gapminder_2010.groupby('region')[['life','fertility']].
↪transform(zscore)

# Construct a Boolean Series to identify outliers: outliers
outliers = (standardized['life'] < -3) | (standardized['fertility'] > 3)

# Filter gapminder_2010 by the outliers: gm_outliers
gm_outliers = gapminder_2010.loc[outliers]

# Print gm_outliers
print(gm_outliers)
```

```
             Year  fertility    life  population  child_mortality     gdp  \
Country
Guatemala    2010      3.974  71.100  14388929.0             34.5  6849.0
Haiti        2010      3.350  45.000   9993247.0            208.8  1518.0
Tajikistan   2010      3.780  66.830   6878637.0             52.6  2110.0
Timor-Leste  2010      6.237  65.952   1124355.0             63.8  1777.0
```

```
                            region
Country
Guatemala                  America
Haiti                      America
Tajikistan   Europe & Central Asia
Timor-Leste    East Asia & Pacific
```

1.5.7 4.7 Filling missing data (imputation) by group

Many statistical and machine learning packages cannot determine the best action to take when missing data entries are encountered. Dealing with missing data is natural in pandas (both in using the default behavior and in defining a custom behavior). In Chapter 1, you practiced using the `.dropna()` method to drop missing values. Now, you will practice imputing missing values. You can use `.groupby()` and `.transform()` to fill missing data appropriately for each group.

Your job is to fill in missing `'age'` values for passengers on the Titanic with the median age from their `'gender'` and `'pclass'`. To do this, you'll group by the `'sex'` and `'pclass'` columns and transform each group with a custom function to call `.fillna()` and impute the median value.

The DataFrame has been pre-loaded as `titanic`. Explore it in the IPython Shell by printing the output of `titanic.tail(10)`. Notice in particular the NaNs in the 'age' column.

Instructions

- Group `titanic` by `'sex'` and `'pclass'`. Save the result as `by_sex_class`.
- Write a function called `impute_median()` that fills missing values with the median of a series. This has been done for you.
- Call `.transform()` with `impute_median` on the `'age'` column of `by_sex_class`.
- Print the output of `titanic.tail(10)`. This has been done for you - hit 'Submit Answer' to see how the missing values have now been imputed.

[48]:
```python
# Create a groupby object: by_sex_class
by_sex_class = titanic.groupby(['sex','pclass'])

# Write a function that imputes median
def impute_median(series):
    return series.fillna(series.median())

# Impute age and assign to titanic['age']
titanic.age = by_sex_class['age'].transform(impute_median)

# Print the output of titanic.tail(10)
print(titanic.tail(10))
```

```
      pclass  survived                                     name     sex   age  \
1299       3         0                      Yasbeck, Mr. Antoni    male  27.0
1300       3         1  Yasbeck, Mrs. Antoni (Selini Alexander)  female  15.0
1301       3         0                     Youseff, Mr. Gerious    male  45.5
1302       3         0                        Yousif, Mr. Wazli    male  25.0
1303       3         0                    Yousseff, Mr. Gerious    male  25.0
```

```
1304       3       0                  Zabour, Miss. Hileni  female  14.5
1305       3       0                 Zabour, Miss. Thamine  female  22.0
1306       3       0             Zakarian, Mr. Mapriededer    male  26.5
1307       3       0                   Zakarian, Mr. Ortin    male  27.0
1308       3       0                    Zimmerman, Mr. Leo    male  29.0

      sibsp  parch  ticket     fare cabin embarked boat   body home.dest
1299      1      0    2659  14.4542   NaN        C    C    NaN       NaN
1300      1      0    2659  14.4542   NaN        C  NaN    NaN       NaN
1301      0      0    2628   7.2250   NaN        C  NaN  312.0       NaN
1302      0      0    2647   7.2250   NaN        C  NaN    NaN       NaN
1303      0      0    2627  14.4583   NaN        C  NaN    NaN       NaN
1304      1      0    2665  14.4542   NaN        C  NaN  328.0       NaN
1305      1      0    2665  14.4542   NaN        C  NaN    NaN       NaN
1306      0      0    2656   7.2250   NaN        C  NaN  304.0       NaN
1307      0      0    2670   7.2250   NaN        C  NaN    NaN       NaN
1308      0      0  315082   7.8750   NaN        S  NaN    NaN       NaN
```

1.5.8 4.8 Other transformations with .apply

The `.apply()` method when used on a groupby object performs an arbitrary function on each of the groups. These functions can be aggregations, transformations or more complex workflows. The `.apply()` method will then combine the results in an intelligent way.

In this exercise, you're going to analyze economic disparity within regions of the world using the Gapminder data set for 2010. To do this you'll define a function to compute the aggregate spread of per capita GDP in each region and the individual country's z-score of the regional per capita GDP. You'll then select three countries - United States, Great Britain and China - to see a summary of the regional GDP and that country's z-score against the regional mean.

The 2010 Gapminder DataFrame is provided for you as `gapminder_2010`. Pandas has been imported as `pd`.

The following function has been defined for your use:

[49]:
```python
def disparity(gr):
    # Compute the spread of gr['gdp']: s
    s = gr['gdp'].max() - gr['gdp'].min()
    # Compute the z-score of gr['gdp'] as (gr['gdp']-gr['gdp'].mean())/
 ↪gr['gdp'].std(): z
    z = (gr['gdp'] - gr['gdp'].mean())/gr['gdp'].std()
    # Return a DataFrame with the inputs {'z(gdp)':z, 'regional spread(gdp)':s}
    return pd.DataFrame({'z(gdp)':z , 'regional spread(gdp)':s})
```

Instructions

- Group `gapminder_2010` by `'region'`. Save the result as `regional`.
- Apply the provided `disparity` function on `regional`, and save the result as `reg_disp`.
- Use `.loc[]` to select `['United States','United Kingdom','China']` from `reg_disp` and print the results.

[50]:
```
# Group gapminder_2010 by 'region': regional
regional = gapminder_2010.groupby('region')

# Apply the disparity function on regional: reg_disp
reg_disp = regional.apply(disparity)

# Print the disparity of 'United States', 'United Kingdom', and 'China'
print(reg_disp.loc[['United States','United Kingdom','China']])
```

```
                  z(gdp)  regional spread(gdp)
Country
United States   3.013374               47855.0
United Kingdom  0.572873               89037.0
China          -0.432756               96993.0
```

1.5.9 4.9 Grouping and filtering with .apply()

By using `.apply()`, you can write functions that filter rows within groups. The `.apply()` method will handle the iteration over individual groups and then re-combine them back into a Series or DataFrame.

In this exercise you'll take the Titanic data set and analyze survival rates from the `'C'` deck, which contained the most passengers. To do this you'll group the dataset by `'sex'` and then use the `.apply()` method on a provided user defined function which calculates the mean survival rates on the `'C'` deck:

[52]:
```
def c_deck_survival(gr):

    c_passengers = gr['cabin'].str.startswith('C').fillna(False)

    return gr.loc[c_passengers, 'survived'].mean()
```

The DataFrame has been pre-loaded as titanic.

Instructions

- Group titanic by `'sex'`. Save the result as `by_sex`.
- Apply the provided `c_deck_survival` function on the `by_sex` DataFrame. Save the result as `c_surv_by_sex`.
- Print `c_surv_by_sex`.

[54]:
```
# Create a groupby object using titanic over the 'sex' column: by_sex
by_sex = titanic.groupby('sex')

# Call by_sex.apply with the function c_deck_survival
c_surv_by_sex = by_sex.apply(c_deck_survival)

# Print the survival rates
print(c_surv_by_sex)
```

```
sex
female    0.913043
male      0.312500
dtype: float64
```

1.5.10 4.10 Grouping and filtering with .filter()

You can use groupby with the `.filter()` method to remove whole groups of rows from a DataFrame based on a boolean condition.

In this exercise, you'll take the February sales data and remove entries from companies that purchased less than or equal to 35 Units in the whole month.

First, you'll identify how many units each company bought for verification. Next you'll use the `.filter()` method after grouping by `'Company'` to remove all rows belonging to companies whose sum over the `'Units'` column was less than or equal to 35. Finally, verify that the three companies whose total Units purchased were less than or equal to 35 have been filtered out from the DataFrame.

Instructions

- Group `sales` by `'Company'`. Save the result as `by_company`.
- Compute and print the sum of the `'Units'` column of `by_company`.
- Call `.filter()` on `by_company` with

```
lambda g:g['Units'].sum() > 35
```

```
as input and print the result.
```

[61]:
```
# Read the CSV file into a DataFrame: sales
sales = pd.read_csv('./Data/sales-feb-2015.csv', index_col='Date',␣
↪parse_dates=True)

# Group sales by 'Company': by_company
by_company = sales.groupby('Company')

# Compute the sum of the 'Units' of by_company: by_com_sum
by_com_sum = by_company['Units'].sum()
print(by_com_sum)

# Filter 'Units' where the sum is > 35: by_com_filt
by_com_filt =  by_company.filter(lambda g:g['Units'].sum() > 35)
print(by_com_filt)
```

```
Company
Acme Coporation    34
Hooli              30
Initech            30
Mediacore          45
Streeplex          36
Name: Units, dtype: int64
                       Company   Product  Units
```

```
Date
2015-02-02 21:00:00  Mediacore  Hardware      9
2015-02-04 15:30:00  Streeplex  Software     13
2015-02-09 09:00:00  Streeplex   Service     19
2015-02-09 13:00:00  Mediacore  Software      7
2015-02-19 11:00:00  Mediacore  Hardware     16
2015-02-19 16:00:00  Mediacore   Service     10
2015-02-21 05:00:00  Mediacore  Software      3
2015-02-26 09:00:00  Streeplex   Service      4
```

4.11 Filtering and grouping with .map() You have seen how to group by a column, or by multiple columns. Sometimes, you may instead want to group by a function/transformation of a column. The key here is that the Series is indexed the same way as the DataFrame. You can also mix and match column grouping with Series grouping.

In this exercise your job is to investigate survival rates of passengers on the Titanic by 'age' and 'pclass'. In particular, the goal is to find out what fraction of children under 10 survived in each 'pclass'. You'll do this by first creating a boolean array where True is passengers under 10 years old and False is passengers over 10. You'll use .map() to change these values to strings.

Finally, you'll group by the under 10 series and the 'pclass' column and aggregate the 'survived' column. The 'survived' column has the value 1 if the passenger survived and 0 otherwise. The mean of the 'survived' column is the fraction of passengers who lived.

The DataFrame has been pre-loaded for you as titanic.

Instructions 100 XP Instructions 100 XP Create a Boolean Series of titanic['age'] < 10 and call .map with {True:'under 10', False:'over 10'}. Group titanic by the under10 Series and then compute and print the mean of the 'survived' column. Group titanic by the under10 Series as well as the 'pclass' column and then compute and print the mean of the 'survived' column.

[62]:
```python
# Create the Boolean Series: under10
under10 =  (titanic['age'] < 10).map({True:'under 10', False:'over 10'})


# Group by under10 and compute the survival rate
survived_mean_1 = titanic.groupby(under10)['survived'].mean()
print(survived_mean_1)

# Group by under10 and pclass and compute the survival rate
survived_mean_2 = titanic.groupby([under10, 'pclass'])['survived'].mean()
print(survived_mean_2)
```

```
age
over 10     0.366748
under 10    0.609756
Name: survived, dtype: float64
age       pclass
over 10   1         0.617555
          2         0.380392
```

```
          3         0.238897
under 10  1         0.750000
          2         1.000000
          3         0.446429
Name: survived, dtype: float64
```

1.6 5 Bringing it all together

We'll bring together everything you have learned in this course while working with data recorded from the Summer Olympic games that goes as far back as 1896! This is a rich dataset that will allow you to fully apply the data manipulation techniques you have learned. You will pivot, unstack, group, slice, and reshape your data as you explore this dataset and uncover some truly fascinating insights.

1.6.1 5.1 Grouping and aggregating

The Olympic medal data for the following exercises comes from The Guardian. It comprises records of all events held at the Olympic games between 1896 and 2012.

Suppose you have loaded the data into a DataFrame medals. You now want to find the total number of medals awarded to the USA per edition. To do this, filter the 'USA' rows and use the groupby() function to put the 'Edition' column on the index:

USA_edition_grouped = medals.loc[medals.NOC == 'USA'].groupby('Edition') Given the goal of finding the total number of USA medals awarded per edition, what column should you select and which aggregation method should you use?

Instructions

Possible Answers

USA_edition_grouped['City'].mean()
USA_edition_grouped['Athlete'].sum()
USA_edition_grouped['Medal'].count()
USA_edition_grouped['Gender'].first()

1.6.2 5.2 Using .value_counts() for ranking

For this exercise, you will use the pandas Series method .value_counts() to determine the top 15 countries ranked by total number of medals.

Notice that .value_counts() sorts by values by default. The result is returned as a Series of counts indexed by unique entries from the original Series with values (counts) ranked in descending order.

The DataFrame has been pre-loaded for you as medals.

Instructions

- Extract the 'NOC' column from the DataFrame medals and assign the result to country_names. Notice that this Series has repeated entries for every medal (of any type) a country has won in any Edition of the Olympics.
- Create a Series medal_counts by applying .value_counts() to the Series country_names.

- Print the top 15 countries ranked by total number of medals won. This has been done for you, so hit 'Submit Answer' to see the result.

[65]:
```python
medals = pd.read_csv('./Data/all_medalists.csv')

# Select the 'NOC' column of medals: country_names
country_names = medals['NOC']

# Count the number of medals won by each country: medal_counts
medal_counts = country_names.value_counts()

# Print top 15 countries ranked by medals
print(medal_counts.head(15))
```

```
USA    4335
URS    2049
GBR    1594
FRA    1314
ITA    1228
GER    1211
AUS    1075
HUN    1053
SWE    1021
GDR     825
NED     782
JPN     704
CHN     679
RUS     638
ROU     624
Name: NOC, dtype: int64
```

1.6.3 5.3 Using .pivot_table() to count medals by type

Rather than ranking countries by total medals won and showing that list, you may want to see a bit more detail. You can use a pivot table to compute how many separate bronze, silver and gold medals each country won. That pivot table can then be used to repeat the previous computation to rank by total medals won.

In this exercise, you will use .pivot_table() first to aggregate the total medals by type. Then, you can use .sum() along the columns of the pivot table to produce a new column. When the modified pivot table is sorted by the total medals column, you can display the results from the last exercise with a bit more detail.

Instructions

- Construct a pivot table counted from the DataFrame medals, aggregating by 'count'. Use 'NOC' as the index, 'Athlete' for the values, and 'Medal' for the columns.
- Modify the DataFrame counted by adding a column counted['totals']. The new column 'totals' should contain the result of taking the sum along the columns (i.e., use .sum(axis='columns')).

- Overwrite the DataFrame counted by sorting it with the .sort_values() method. Specify the keyword argument ascending=False.
- Print the first 15 rows of counted using .head(15). This has been done for you, so hit 'Submit Answer' to see the result.

[66]:
```
# Construct the pivot table: counted
counted = medals.pivot_table(index='NOC', values='Athlete', columns='Medal',␣
↪aggfunc='count')

# Create the new column: counted['totals']
counted['totals'] = counted.sum(axis='columns')

# Sort counted by the 'totals' column
counted = counted.sort_values('totals', ascending=False)

# Print the top 15 rows of counted
print(counted.head(15))
```

```
Medal  Bronze    Gold  Silver  totals
NOC
USA    1052.0  2088.0  1195.0  4335.0
URS     584.0   838.0   627.0  2049.0
GBR     505.0   498.0   591.0  1594.0
FRA     475.0   378.0   461.0  1314.0
ITA     374.0   460.0   394.0  1228.0
GER     454.0   407.0   350.0  1211.0
AUS     413.0   293.0   369.0  1075.0
HUN     345.0   400.0   308.0  1053.0
SWE     325.0   347.0   349.0  1021.0
GDR     225.0   329.0   271.0   825.0
NED     320.0   212.0   250.0   782.0
JPN     270.0   206.0   228.0   704.0
CHN     193.0   234.0   252.0   679.0
RUS     240.0   192.0   206.0   638.0
ROU     282.0   155.0   187.0   624.0
```

1.6.4 5.4 Applying .drop_duplicates()

What could be the difference between the 'Event_gender' and 'Gender' columns? You should be able to evaluate your guess by looking at the unique values of the pairs (Event_gender, Gender) in the data. In particular, you should not see something like (Event_gender='M', Gender='Women'). However, you will see that, strangely enough, there is an observation with (Event_gender='W', Gender='Men').

The duplicates can be dropped using the .drop_duplicates() method, leaving behind the unique observations. The DataFrame has been loaded as medals.

Instructions

- Select the columns 'Event_gender' and 'Gender'.

- Create a dataframe ev_gen_uniques containing the unique pairs contained in ev_gen.
- Print ev_gen_uniques. This has been done for you, so hit 'Submit Answer' to see the result.

[67]:
```
# Select columns: ev_gen
ev_gen = medals[['Event_gender', 'Gender']]

# Drop duplicate pairs: ev_gen_uniques
ev_gen_uniques = ev_gen.drop_duplicates()

# Print ev_gen_uniques
print(ev_gen_uniques)
```

```
      Event_gender Gender
0                M    Men
348              X    Men
416              W  Women
639              X  Women
23675            W    Men
```

1.6.5 5.5 Finding possible errors with .groupby()

You will now use .groupby() to continue your exploration. Your job is to group by 'Event_gender' and 'Gender' and count the rows.

You will see that there is only one suspicious row: This is likely a data error.

The DataFrame is available to you as medals.

Instructions

- Group medals by 'Event_gender' and 'Gender'.
- Create a medal_count_by_gender DataFrame with a group count using the .count() method.
- Print medal_count_by_gender. This has been done for you, so hit 'Submit Answer' to view the result.

[69]:
```
# Group medals by the two columns: medals_by_gender
medals_by_gender = medals.groupby(['Event_gender', 'Gender'])

# Create a DataFrame with a group count: medal_count_by_gender
medal_count_by_gender = medals_by_gender.count()

# Print medal_count_by_gender
print(medal_count_by_gender)
```

```
                      City  Edition  Sport  Discipline  Athlete    NOC  Event  \
Event_gender Gender
M            Men     20067    20067  20067       20067    20067  20067  20067
W            Men         1        1      1           1        1      1      1
             Women    7277     7277   7277        7277     7277   7277   7277
X            Men      1653     1653   1653        1653     1653   1653   1653
             Women     218      218    218         218      218    218    218
```

```
                     Medal
Event_gender Gender
M            Men     20067
W            Men         1
             Women    7277
X            Men      1653
             Women     218
```

1.6.6 5.6 Locating suspicious data

You will now inspect the suspect record by locating the offending row.

You will see that, according to the data, Joyce Chepchumba was a man that won a medal in a women's event. That is a data error as you can confirm with a web search.

Instructions

- Create a Boolean Series with a condition that captures the only row that has medals.Event_gender == 'W' and medals.Gender == 'Men'. Be sure to use the & operator.
- Use the Boolean Series to create a DataFrame called suspect with the suspicious row.
- Print suspect. This has been done for you, so hit 'Submit Answer' to see the result.

[71]:
```python
# Create the Boolean Series: sus
sus = (medals.Event_gender == 'W') & (medals.Gender == 'Men')

# Create a DataFrame with the suspicious row: suspect
suspect = medals[sus]

# Print suspect
print(suspect)
```

```
        City  Edition      Sport Discipline            Athlete  NOC Gender  \
23675  Sydney     2000  Athletics  Athletics  CHEPCHUMBA, Joyce  KEN    Men

          Event Event_gender   Medal
23675  marathon            W  Bronze
```

1.6.7 5.7 Using .nunique() to rank by distinct sports

You may want to know which countries won medals in the most distinct sports. The .nunique() method is the principal aggregation here. Given a categorical Series S, S.nunique() returns the number of distinct categories.

Instructions

- Group medals by 'NOC'.
- Compute the number of distinct sports in which each country won medals. To do this, select the 'Sport' column from country_grouped and apply .nunique().
- Sort Nsports in descending order with .sort_values() and ascending=False.

- Print the first 15 rows of Nsports. This has been done for you, so hit 'Submit Answer' to see the result.

[72]:
```python
# Group medals by 'NOC': country_grouped
country_grouped = medals.groupby('NOC')

# Compute the number of distinct sports in which each country won medals:␣
↪Nsports
Nsports = country_grouped.Sport.nunique()

# Sort the values of Nsports in descending order
Nsports = Nsports.sort_values(ascending=False)

# Print the top 15 rows of Nsports
print(Nsports.head(15))
```

```
NOC
USA    34
GBR    31
FRA    28
GER    26
CHN    24
AUS    22
ESP    22
CAN    22
SWE    21
URS    21
ITA    21
NED    20
RUS    20
JPN    20
DEN    19
Name: Sport, dtype: int64
```

1.6.8 5.8 Counting USA vs. USSR Cold War Olympic Sports

The Olympic competitions between 1952 and 1988 took place during the height of the Cold War between the United States of America (USA) & the Union of Soviet Socialist Republics (USSR). Your goal in this exercise is to aggregate the number of distinct sports in which the USA and the USSR won medals during the Cold War years.

The construction is mostly the same as in the preceding exercise. There is an additional filtering stage beforehand in which you reduce the original DataFrame medals by extracting data from the Cold War period that applies only to the US or to the USSR. The relevant country codes in the DataFrame, which has been pre-loaded as medals, are 'USA' & 'URS'.

Instructions

- Using medals, create a Boolean Series called during_cold_war that is True when 'Edition' is >= 1952 and <= 1988.

- Using medals, create a Boolean Series called is_usa_urs that is True when 'NOC' is either 'USA' or 'URS'.
- Filter the medals DataFrame using during_cold_war and is_usa_urs to create a new DataFrame called cold_war_medals.
- Group cold_war_medals by 'NOC'.
- Create a Series Nsports from country_grouped using indexing & chained methods:
- Extract the column 'Sport'.
- Use .nunique() to get the number of unique elements in each group;
- Apply .sort_values(ascending=False) to rearrange the Series.
- Print the final Series Nsports. This has been done for you, so hit 'Submit Answer' to see the result!

[74]:
```
# Create a Boolean Series that is True when 'Edition' is between 1952 and 1988:␣
↪during_cold_war
during_cold_war = (medals['Edition'] >= 1952) & (medals['Edition'] <= 1988)

# Extract rows for which 'NOC' is either 'USA' or 'URS': is_usa_urs
is_usa_urs = medals.NOC.isin(['USA', 'URS'])

# Use during_cold_war and is_usa_urs to create the DataFrame: cold_war_medals
cold_war_medals = medals.loc[during_cold_war & is_usa_urs]

# Group cold_war_medals by 'NOC'
country_grouped = cold_war_medals.groupby('NOC')

# Create Nsports
Nsports = country_grouped['Sport'].nunique().sort_values(ascending=False)

# Print Nsports
print(Nsports)
```

```
NOC
URS    21
USA    20
Name: Sport, dtype: int64
```

1.6.9 5.9 Counting USA vs. USSR Cold War Olympic Medals

For this exercise, you want to see which country, the USA or the USSR, won the most medals consistently over the Cold War period.

There are several steps involved in carrying out this computation.

You'll need a pivot table with years ('Edition') on the index and countries ('NOC') on the columns. The entries will be the total number of medals each country won that year. If the country won no medals in a given edition, expect a NaN in that entry of the pivot table. You'll need to slice the Cold War period and subset the 'USA' and 'URS' columns. You'll need to make a Series from this slice of the pivot table that tells which country won the most medals in that edition using .idxmax(axis='columns'). If .max() returns the maximum value of Series or 1D array, .idxmax()

returns the index of the maximizing element. The argument axis=columns or axis=1 is required because, by default, this aggregation would be done along columns for a DataFrame. The final Series contains either 'USA' or 'URS' according to which country won the most medals in each Olympic edition. You can use .value_counts() to count the number of occurrences of each.

Instructions

- Construct medals_won_by_country using medals.pivot_table().
- The index should be the years ('Edition') & the columns should be country ('NOC')
- The values should be 'Athlete' (which captures every medal regardless of kind) & the aggregation method should be 'count' (which captures the total number of medals won).
- Create cold_war_usa_urs_medals by slicing the pivot table medals_won_by_country. Your slice should contain the editions from years 1952:1988 and only the columns 'USA' & 'URS' from the pivot table.
- Create the Series most_medals by applying the .idxmax() method to cold_war_usa_urs_medals. Be sure to use axis='columns'.
- Print the result of applying .value_counts() to most_medals. The result reported gives the number of times each of the USA or the USSR won more Olympic medals in total than the other between 1952 and 1988.

[76]:
```
# Create the pivot table: medals_won_by_country
medals_won_by_country =  medals.pivot_table(index='Edition', columns='NOC',␣
 ↪values='Athlete', aggfunc='count')

# Slice medals_won_by_country: cold_war_usa_urs_medals
cold_war_usa_urs_medals = medals_won_by_country.loc[1952:1988, ['USA','URS']]

# Create most_medals
most_medals = cold_war_usa_urs_medals.idxmax(axis='columns')

# Print most_medals.value_counts()
print(most_medals.value_counts())
```

```
URS    8
USA    2
dtype: int64
```

1.6.10 5.10 Visualizing USA Medal Counts by Edition: Line Plot

Your job in this exercise is to visualize the medal counts by 'Edition' for the USA. The DataFrame has been pre-loaded for you as medals.

Instructions

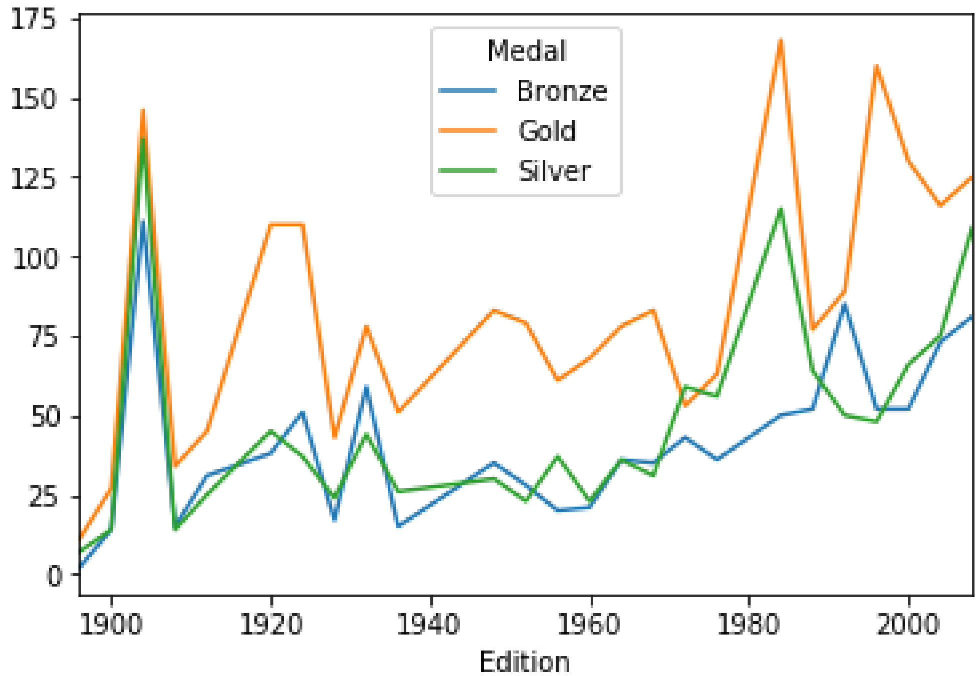
- Create a DataFrame usa with data only for the USA.
- Group usa such that ['Edition', 'Medal'] is the index. Aggregate the count over 'Athlete'.
- Use .unstack() with level='Medal' to reshape the DataFrame usa_medals_by_year.
- Construct a line plot from the final DataFrame usa_medals_by_year. This has been done for you, so hit 'Submit Answer' to see the plot!

[78]:
```python
import matplotlib.pyplot as plt
# Create the DataFrame: usa
usa = medals[medals.NOC == 'USA']

# Group usa by ['Edition', 'Medal'] and aggregate over 'Athlete'
usa_medals_by_year = usa.groupby(['Edition', 'Medal'])['Athlete'].count()

# Reshape usa_medals_by_year by unstacking
usa_medals_by_year = usa_medals_by_year.unstack(level='Medal')

# Plot the DataFrame usa_medals_by_year
usa_medals_by_year.plot()
plt.show()
```



1.6.11 5.11 Visualizing USA Medal Counts by Edition: Area Plot

As in the previous exercise, your job in this exercise is to visualize the medal counts by 'Edition' for the USA. This time, you will use an area plot to see the breakdown better. The usa DataFrame has been created and all reshaping from the previous exercise has been done. You need to write the plotting command.

Instructions

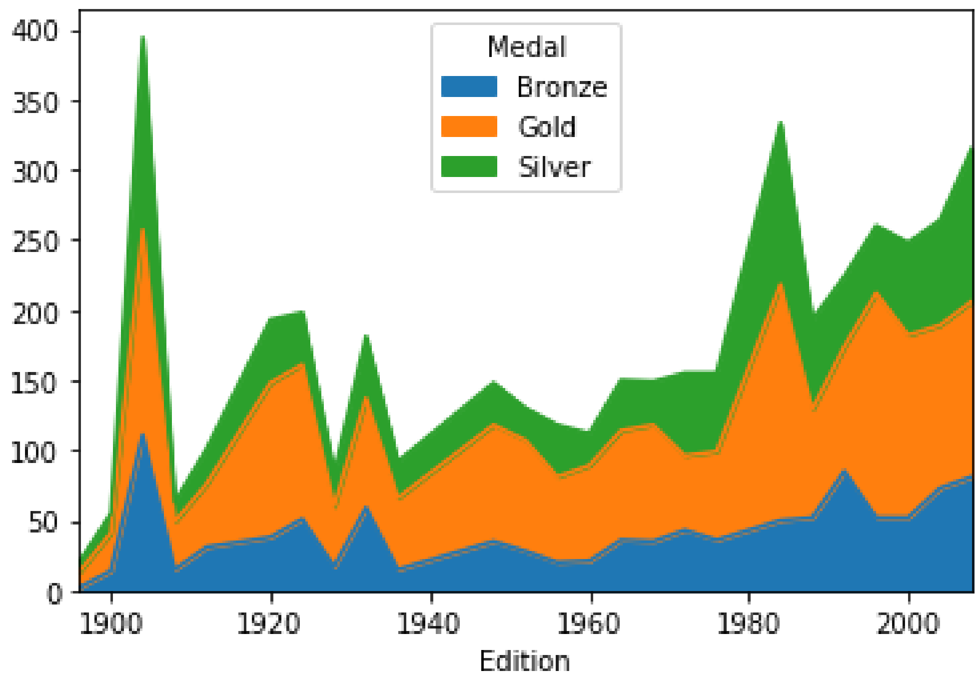
- Create an area plot of usa_medals_by_year. This can be done by using .plot.area().

```
[79]: # Create the DataFrame: usa
usa = medals[medals.NOC == 'USA']

# Group usa by 'Edition', 'Medal', and 'Athlete'
usa_medals_by_year = usa.groupby(['Edition', 'Medal'])['Athlete'].count()

# Reshape usa_medals_by_year by unstacking
usa_medals_by_year = usa_medals_by_year.unstack(level='Medal')

# Create an area plot of usa_medals_by_year
usa_medals_by_year.plot.area()
plt.show()
```



1.6.12 5.12 Visualizing USA Medal Counts by Edition: Area Plot with Ordered Medals

You may have noticed that the medals are ordered according to a lexicographic (dictionary) ordering: Bronze < Gold < Silver. However, you would prefer an ordering consistent with the Olympic rules: Bronze < Silver < Gold.

You can achieve this using Categorical types. In this final exercise, after redefining the 'Medal' column of the DataFrame medals, you will repeat the area plot from the previous exercise to see the new ordering.

Instructions

- Redefine the 'Medal' column of the DataFrame medals as an ordered categorical. To do this, use pd.Categorical() with three keyword arguments:
  - values = medals.Medal.
  - categories=['Bronze', 'Silver', 'Gold'].
  - ordered=True.
- After this, you can verify that the type has changed using medals.info().
- Plot the final DataFrame usa_medals_by_year as an area plot. This has been done for you, so hit 'Submit Answer' to see how the plot has changed!

[80]:
```
# Redefine 'Medal' as an ordered categorical
medals.Medal = pd.Categorical(values=medals.
↪Medal,categories=['Bronze','Silver','Gold'],ordered=True)

# Create the DataFrame: usa
usa = medals[medals.NOC == 'USA']

# Group usa by 'Edition', 'Medal', and 'Athlete'
usa_medals_by_year = usa.groupby(['Edition', 'Medal'])['Athlete'].count()

# Reshape usa_medals_by_year by unstacking
usa_medals_by_year = usa_medals_by_year.unstack(level='Medal')

# Create an area plot of usa_medals_by_year
usa_medals_by_year.plot.area()
plt.show()
```