pandas

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1 Python Pandas

One of the best options for working with tabular data in Python is to use the **Python Data Analysis Library (Pandas)**. The Pandas library provides data structures, produces high quality plots with matplotlib and integrates nicely with other libraries that use NumPy (which is another Python library) arrays.

[1]:
```
# Load library as a alias
import pandas as pd
```

[2]:
```
# Make sure figures appear inline in Ipython Notebook
%matplotlib inline
```

1.0.1 Read in data comma separated value file into data frame

[3]:
```
# Note that pd.read_csv is used because we imported pandas as pd
pd.read_csv("surveys.csv")
```

[3]:

	record_id	month	day	year	plot_id	species_id	sex	hindfoot_length	weight
0	1	7	16	1977	2	NL	M	32.0	NaN
1	2	7	16	1977	3	NL	M	33.0	NaN
2	3	7	16	1977	2	DM	F	37.0	NaN
3	4	7	16	1977	7	DM	M	36.0	NaN
4	5	7	16	1977	3	DM	M	35.0	NaN
…	…	…	…	…	…	…	…	…	…
35544	35545	12	31	2002	15	AH	NaN	NaN	NaN
35545	35546	12	31	2002	15	AH	NaN	NaN	NaN
35546	35547	12	31	2002	10	RM	F	15.0	NaN
35547	35548	12	31	2002	7	DO	M	36.0	NaN
35548	35549	12	31	2002	5	NaN	NaN	NaN	NaN

```
…       …
35544     NaN
35545     NaN
35546    14.0
35547    51.0
35548     NaN

[35549 rows x 9 columns]
```

1.0.2 What is our data?

[4]:
```
surveys_df = pd.read_csv("surveys.csv")
```

1.1 Useful Ways to View DataFrame objects in Python

Summarize and access the data stored in DataFrames using attributes and methods provided by the DataFrame object.

Attributes are accessed using the DataFrame object name followed by the attribute name `df_object.attribute`

Examples of attributes:

[5]:
```
# List of column names
surveys_df.columns
```

[5]:
```
Index(['record_id', 'month', 'day', 'year', 'plot_id', 'species_id', 'sex',
       'hindfoot_length', 'weight'],
      dtype='object')
```

[6]:
```
# Shape (dimensions) of array
surveys_df.shape
```

[6]:
```
(35549, 9)
```

[7]:
```
# Data types
surveys_df.dtypes
```

[7]:
```
record_id            int64
month                int64
day                  int64
year                 int64
plot_id              int64
species_id          object
sex                 object
hindfoot_length    float64
weight             float64
dtype: object
```

Methods are called using the syntax `df_object.method()`

Examples of methods:

[8]:
```
# Look at the start of the data:
surveys_df.head()
```

[8]:
```
   record_id  month  day  year  plot_id species_id sex  hindfoot_length  \
0          1      7   16  1977        2         NL   M             32.0
1          2      7   16  1977        3         NL   M             33.0
2          3      7   16  1977        2         DM   F             37.0
3          4      7   16  1977        7         DM   M             36.0
4          5      7   16  1977        3         DM   M             35.0

   weight
0     NaN
1     NaN
2     NaN
3     NaN
4     NaN
```

1.2 Quick Statistics in a Pandas DataFrame

Let's get a list of all the species. The `pd.unique` function tells us all of the unique values in the species_id column.

[9]:
```
# Unique list of species
pd.unique(surveys_df['species_id'])
```

[9]:
```
array(['NL', 'DM', 'PF', 'PE', 'DS', 'PP', 'SH', 'OT', 'DO', 'OX', 'SS',
       'OL', 'RM', nan, 'SA', 'PM', 'AH', 'DX', 'AB', 'CB', 'CM', 'CQ',
       'RF', 'PC', 'PG', 'PH', 'PU', 'CV', 'UR', 'UP', 'ZL', 'UL', 'CS',
       'SC', 'BA', 'SF', 'RO', 'AS', 'SO', 'PI', 'ST', 'CU', 'SU', 'RX',
       'PB', 'PL', 'PX', 'CT', 'US'], dtype=object)
```

1.2.1 Groups in Pandas

We often want to calculate summary statistics grouped by subsets or attributes within fields of our data. For example, we might want to calculate the average weight of all individuals per site.

[10]:
```
# We can calculate basic statistics for all records in a single column:
surveys_df['weight'].describe()
```

[10]:
```
count    32283.000000
mean        42.672428
std         36.631259
min          4.000000
25%         20.000000
```

```
50%         37.000000
75%         48.000000
max        280.000000
Name: weight, dtype: float64
```

[11]:
```
# Or all numeric data
surveys_df.describe()
```

[11]:
```
          record_id         month           day          year       plot_id  \
count  35549.000000  35549.000000  35549.000000  35549.000000  35549.000000
mean   17775.000000      6.474022     16.105966   1990.475231     11.397001
std    10262.256696      3.396583      8.256691      7.493355      6.799406
min        1.000000      1.000000      1.000000   1977.000000      1.000000
25%     8888.000000      4.000000      9.000000   1984.000000      5.000000
50%    17775.000000      6.000000     16.000000   1990.000000     11.000000
75%    26662.000000      9.000000     23.000000   1997.000000     17.000000
max    35549.000000     12.000000     31.000000   2002.000000     24.000000

       hindfoot_length        weight
count     31438.000000  32283.000000
mean         29.287932     42.672428
std           9.564759     36.631259
min           2.000000      4.000000
25%          21.000000     20.000000
50%          32.000000     37.000000
75%          36.000000     48.000000
max          70.000000    280.000000
```

But if we want to summarize by one or more variables, for example sex, we can use Pandas `.groupby` method.

[12]:
```
# Group data by sex
grouped_data = surveys_df.groupby('sex')

# Summary statistics for all numeric columns by sex
grouped_data['weight'].describe()
```

[12]:
```
        count       mean        std  min   25%   50%   75%    max
sex
F     15303.0  42.170555  36.847958  4.0  20.0  34.0  46.0  274.0
M     16879.0  42.995379  36.184981  4.0  20.0  39.0  49.0  280.0
```

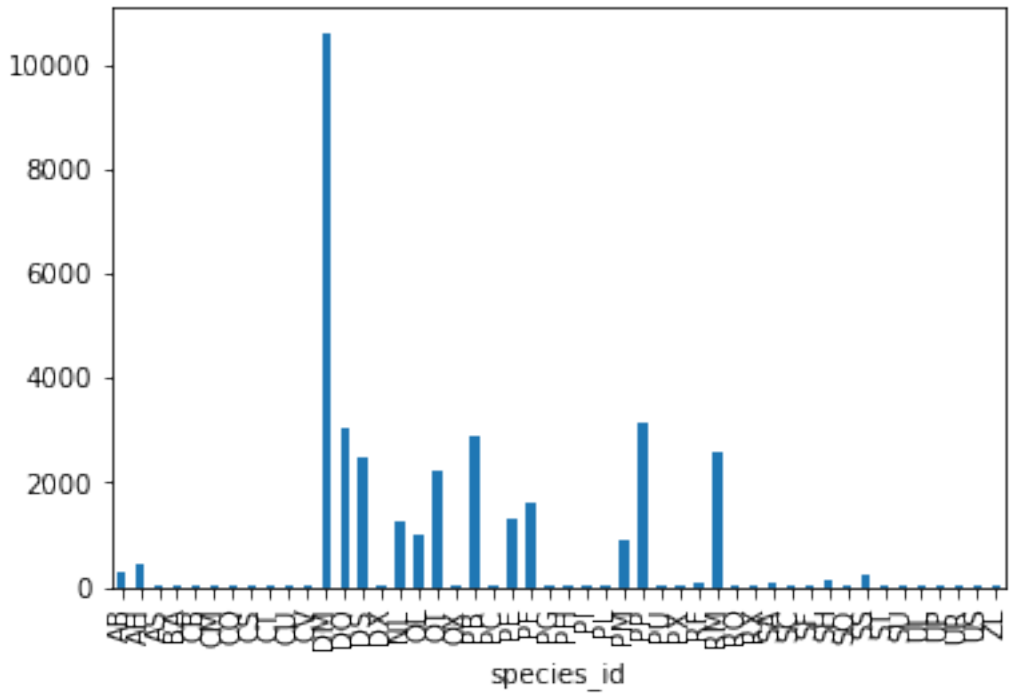
1.2.2 Creating Summary Counts in Pandas

Let's next count the number of samples for each species. Use `groupby` combined with a `count()` method.

[13]:
```
# Count the number of samples by species
species_counts = surveys_df.groupby('species_id')['record_id'].count()
#print(species_counts)

# Create a quick bar chart
species_counts.plot(kind='bar')
```

[13]:
```
<AxesSubplot:xlabel='species_id'>
```



1.2.3 How do I create a new column from existing columns?

If we wanted to, we could perform math on an entire column (or columns) of our data and add it to the dataframe.

[14]:
```
# Example of basic math normalizing weight
(surveys_df['weight'] - surveys_df['weight'].mean()) / surveys_df['weight'].
↪std()
```

[14]:
```
0          NaN
1          NaN
2          NaN
3          NaN
4          NaN
          ...
```

```
35544         NaN
35545         NaN
35546   -0.782731
35547    0.227335
35548         NaN
Name: weight, Length: 35549, dtype: float64
```

To create a new column, use the [] brackets with the new column name at the left side of the assignment.

[15]:
```
surveys_df['normalized_weight'] = (surveys_df['weight'] - surveys_df['weight'].
 ↪mean()) / surveys_df['weight'].std()
#print(surveys_df)
```

2 Indexing, Slicing and Subsetting DataFrames in Python

Selecting data using Labels (Column Headings) We use square brackets [] to select a subset of a Python object.

For example, we can select all data from a column named species_id from the surveys_df DataFrame by name. There are two ways to do this:

[16]:
```
# Method 1: select a 'subset' of the data using the column name
surveys_df['species_id']

# Method 2: use the column name as an 'attribute'; gives the same output
surveys_df.species_id
```

[16]:
```
0         NL
1         NL
2         DM
3         DM
4         DM
        ...
35544     AH
35545     AH
35546     RM
35547     DO
35548    NaN
Name: species_id, Length: 35549, dtype: object
```

We can also create a new object that contains only the data within the species_id column as follows:

[17]:
```
# Creates an object, surveys_species, that only contains the `species_id` column
surveys_species = surveys_df['species_id']
```

[18]:
```
# Select the species and plot columns from the DataFrame
surveys_df[['species_id', 'plot_id']]

# What happens when you flip the order?
```

[18]:
```
      species_id  plot_id
0             NL        2
1             NL        3
2             DM        2
3             DM        7
4             DM        3
…            …        …
35544         AH       15
35545         AH       15
35546         RM       10
35547         DO        7
35548        NaN        5

[35549 rows x 2 columns]
```

2.0.1 Extracting Range based Subsets: Slicing

Slicing using the `[]` operator selects a set of rows and/or columns from a DataFrame. To slice out a set of rows, you use the following syntax: `data[start:stop]`.

When slicing in pandas the start bound is included in the output. The stop bound is one step BEYOND the row you want to select.

[19]:
```
# Select rows 0, 1, 2 (row 3 is not selected)
surveys_df[0:3]
```

[19]:
```
   record_id  month  day  year  plot_id species_id sex  hindfoot_length  \
0          1      7   16  1977        2         NL   M             32.0
1          2      7   16  1977        3         NL   M             33.0
2          3      7   16  1977        2         DM   F             37.0

   weight  normalized_weight
0     NaN                NaN
1     NaN                NaN
2     NaN                NaN
```

[20]:
```
# Select the first 5 rows (rows 0, 1, 2, 3, 4)
surveys_df[:5]
```

[20]:
```
   record_id  month  day  year  plot_id species_id sex  hindfoot_length  \
0          1      7   16  1977        2         NL   M             32.0
1          2      7   16  1977        3         NL   M             33.0
2          3      7   16  1977        2         DM   F             37.0
```

```
3          4      7   16  1977        7         DM   M             36.0
4          5      7   16  1977        3         DM   M             35.0

   weight  normalized_weight
0     NaN                NaN
1     NaN                NaN
2     NaN                NaN
3     NaN                NaN
4     NaN                NaN
```

[21]:
```
# Select the last element in the list
# (the slice starts at the last element, and ends at the end of the list)
surveys_df[-1:]
```

[21]:
```
       record_id  month  day  year  plot_id species_id  sex  hindfoot_length  \
35548      35549     12   31  2002        5        NaN  NaN              NaN

       weight  normalized_weight
35548     NaN                NaN
```

2.0.2 Slicing Subsets of Rows and Columns in Python

We can select specific ranges of our data in both the row and column directions using either label or integer-based indexing.

- loc is primarily label based indexing. Integers may be used but they are interpreted as a label.
- iloc is primarily integer based indexing

To select a subset of rows and columns from our DataFrame, we can use the iloc method.

[22]:
```
# iloc[row slicing, column slicing]
surveys_df.iloc[0:3, 1:4]
```

[22]:
```
   month  day  year
0      7   16  1977
1      7   16  1977
2      7   16  1977
```

Let's explore some other ways to index and select subsets of data:

[23]:
```
# Select all columns for rows of index values 0 and 10
surveys_df.loc[[0, 10], :]
```

[23]:
```
    record_id  month  day  year  plot_id species_id sex  hindfoot_length  \
0           1      7   16  1977        2         NL   M             32.0
10         11      7   16  1977        5         DS   F             53.0

    weight  normalized_weight
```

```
0      NaN                 NaN
10     NaN                 NaN
```

[24]:
```
# What does this do?
surveys_df.loc[0, ['species_id', 'plot_id', 'weight']]
```

[24]:
```
species_id     NL
plot_id         2
weight        NaN
Name: 0, dtype: object
```

[25]:
```
# What happens when you type the code below?
#surveys_df.loc[[0, 10, 35549], :]
```

2.0.3 Subsetting Data using Criteria

We can use the syntax below when querying data by criteria from a DataFrame.

- Equals: `==`
- Not equals: `!=`
- Greater than, less than: `>` or `<`
- Greater than or equal to `>=`
- Less than or equal to `<=`

[26]:
```
# Select all rows that have a year value of 2002
surveys_df[surveys_df.year == 2002]
```

[26]:

	record_id	month	day	year	plot_id	species_id	sex	hindfoot_length	\
33320	33321	1	12	2002	1	DM	M	38.0	
33321	33322	1	12	2002	1	DO	M	37.0	
33322	33323	1	12	2002	1	PB	M	28.0	
33323	33324	1	12	2002	1	AB	NaN	NaN	
33324	33325	1	12	2002	1	DO	M	35.0	
…	…	…	…	…	…	…	…	…	
35544	35545	12	31	2002	15	AH	NaN	NaN	
35545	35546	12	31	2002	15	AH	NaN	NaN	
35546	35547	12	31	2002	10	RM	F	15.0	
35547	35548	12	31	2002	7	DO	M	36.0	
35548	35549	12	31	2002	5	NaN	NaN	NaN	

	weight	normalized_weight
33320	44.0	0.036241
33321	58.0	0.418429
33322	45.0	0.063541
33323	NaN	NaN
33324	29.0	-0.373245
…	…	…
35544	NaN	NaN

```
35545     NaN                NaN
35546    14.0          -0.782731
35547    51.0           0.227335
35548     NaN                NaN

[2229 rows x 10 columns]
```

[27]:
```
#We can define sets of criteria too:
surveys_df[(surveys_df.year >= 1980) & (surveys_df.year <= 1985)]
```

[27]:
```
       record_id  month  day  year  plot_id species_id  sex  hindfoot_length  \
2270        2271      1   15  1980        8         DO    M             35.0
2271        2272      1   15  1980       11         PF    F             16.0
2272        2273      1   15  1980       18         DM    F             34.0
2273        2274      1   15  1980       11         DM    M             38.0
2274        2275      1   15  1980        8         DO    F             33.0
…            …    …   …    …          …        …  …                …
11222      11223     12    8  1985        4         DM    M             36.0
11223      11224     12    8  1985       11         DM    M             37.0
11224      11225     12    8  1985        7         PE    M             20.0
11225      11226     12    8  1985        1         DM    M             38.0
11226      11227     12    8  1985       15        NaN  NaN              NaN

       weight  normalized_weight
2270     53.0           0.281933
2271     10.0          -0.891928
2272     33.0          -0.264048
2273     37.0          -0.154852
2274     29.0          -0.373245
…         …                …
11222    40.0          -0.072955
11223    49.0           0.172737
11224    18.0          -0.673535
11225    47.0           0.118139
11226     NaN                NaN

[8957 rows x 10 columns]
```

2.1 Export a dataframe to a file

Next, let's drop all the rows that contain missing values using `dropna`. By default, dropna removes rows that contain missing data for even just one column.

[28]:
```
df_na = surveys_df.dropna()
```

We can now use the to_csv command to export a DataFrame in CSV format. Note that the code below will by default save the data into the current working directory.

[29]:
```
# Write DataFrame to CSV
df_na.to_csv('surveys_complete.csv', index=False)
```

3 Combining DataFrames with Pandas

In many research situations, the data that we want to use come in multiple files. We often need to combine these files into a single DataFrame to analyze the data. The pandas package provides various methods for combining DataFrames including `merge` and `concat`.

Load the species and surveys files into pandas DataFrames.

[30]:
```
surveys_df = pd.read_csv("surveys.csv", keep_default_na=False, na_values=[""])
```

[31]:
```
species_df = pd.read_csv("species.csv", keep_default_na=False, na_values=[""])
```

3.0.1 Concatenating DataFrames

Use the `concat` function in pandas to append either columns or rows from one DataFrame to another.

[32]:
```
# Read in first 10 lines of surveys table
survey_sub = surveys_df.head(10)

# Grab the last 10 rows
survey_sub_last10 = surveys_df.tail(10)

# Reset the index values to the second dataframe appends properly
survey_sub_last10 = survey_sub_last10.reset_index(drop=True)
     # drop=True option avoids adding new index column with old index values
```

When we concatenate DataFrames, we need to specify the axis.

- axis=0 tells pandas to stack the second DataFrame UNDER the first one. It will automatically detect whether the column names are the same and will stack accordingly.
- axis=1 will stack the columns in the second DataFrame to the RIGHT of the first DataFrame.

[33]:
```
# Stack the DataFrames on top of each other
vertical_stack = pd.concat([survey_sub, survey_sub_last10], axis=0)
#print(vertical_stack)
```

[34]:
```
# Place the DataFrames side by side
horizontal_stack = pd.concat([survey_sub, survey_sub_last10], axis=1)
#print(horizontal_stack)
```

3.1 Joining Two DataFrames

Combine or **join** DataFrames using columns in each dataset that contain common values.

The columns containing the common values are called **join key(s)**.

[35]:
```
### Identifying join keys
# To identify appropriate join keys we first need to know
# which field(s) are shared between the files (DataFrames).

print(species_df.columns)

print(surveys_df.columns)
```

```
Index(['species_id', 'genus', 'species', 'taxa'], dtype='object')
Index(['record_id', 'month', 'day', 'year', 'plot_id', 'species_id', 'sex',
       'hindfoot_length', 'weight'],
      dtype='object')
```

Join key is the column containing the two-letter species identifier, which is called `species_id`.

There are different types of joins, so we need to decide which type of join makes sense for our analysis.

3.1.1 Inner Join (default)

The pandas function for performing joins is called `merge` and an Inner join is the default option:

[36]:
```
merged_inner = pd.merge(left=surveys_df, right=species_df,␣
↪left_on='species_id', right_on='species_id')

# In this case `species_id` is the only column name in  both dataframes, so if␣
↪we skipped `left_on`
# And `right_on` arguments we would still get the same result

# What's the size of the output data?
print(merged_inner.shape)
merged_inner
```

```
(34786, 12)
```

[36]:

	record_id	month	day	year	plot_id	species_id	sex	hindfoot_length	weight	genus	species	taxa
0	1	7	16	1977	2	NL	M	32.0				
1	2	7	16	1977	3	NL	M	33.0				
2	22	7	17	1977	15	NL	F	31.0				
3	38	7	17	1977	17	NL	M	33.0				
4	72	8	19	1977	2	NL	M	31.0				
…	…	…	…	…	…	…	…	…	…	…	…	…
34781	28988	12	23	1998	6	CT	NaN	NaN				
34782	35512	12	31	2002	11	US	NaN	NaN				
34783	35513	12	31	2002	11	US	NaN	NaN				
34784	35528	12	31	2002	13	US	NaN	NaN				
34785	35544	12	31	2002	15	US	NaN	NaN				

```
0          NaN         Neotoma  albigula   Rodent
1          NaN         Neotoma  albigula   Rodent
2          NaN         Neotoma  albigula   Rodent
3          NaN         Neotoma  albigula   Rodent
4          NaN         Neotoma  albigula   Rodent
…        …             …        …      …
34781      NaN  Cnemidophorus    tigris  Reptile
34782      NaN         Sparrow       sp.     Bird
34783      NaN         Sparrow       sp.     Bird
34784      NaN         Sparrow       sp.     Bird
34785      NaN         Sparrow       sp.     Bird

[34786 rows x 12 columns]
```

The result `merged_inner` DataFrame contains all of the columns from `surveys_df` (record id, month, day, etc.) as well as all the columns from `species_df` (species_id, genus, species, and taxa).

3.1.2 Left joins

What if we want to add information from `species_df` to `surveys_df` without losing any of the information from `surveys_df`? In this case, we use a different type of join called a **left join**.

A left join is performed in pandas by calling the same `merge` function used for inner join, but using the `how='left'` argument:

[37]:
```
merged_left = pd.merge(left=surveys_df, right=species_df, how='left',␣
↪left_on='species_id', right_on='species_id')
merged_left
```

[37]:
```
       record_id  month  day  year  plot_id species_id  sex  hindfoot_length  \
0              1      7   16  1977        2         NL    M             32.0
1              2      7   16  1977        3         NL    M             33.0
2              3      7   16  1977        2         DM    F             37.0
3              4      7   16  1977        7         DM    M             36.0
4              5      7   16  1977        3         DM    M             35.0
…            …    …  …   …      …        …       …  …              …
35544      35545     12   31  2002       15         AH  NaN              NaN
35545      35546     12   31  2002       15         AH  NaN              NaN
35546      35547     12   31  2002       10         RM    F             15.0
35547      35548     12   31  2002        7         DO    M             36.0
35548      35549     12   31  2002        5        NaN  NaN              NaN

       weight            genus    species    taxa
0         NaN          Neotoma   albigula  Rodent
1         NaN          Neotoma   albigula  Rodent
2         NaN        Dipodomys   merriami  Rodent
3         NaN        Dipodomys   merriami  Rodent
```

```
4          NaN         Dipodomys   merriami  Rodent
…        …               …        …     …
35544      NaN  Ammospermophilus    harrisi  Rodent
35545      NaN  Ammospermophilus    harrisi  Rodent
35546     14.0   Reithrodontomys  megalotis  Rodent
35547     51.0         Dipodomys      ordii  Rodent
35548      NaN               NaN        NaN     NaN

[35549 rows x 12 columns]
```

3.1.3 References and Image Sources

This lesson is based on the Data Carpentry curriculum "Data Analysis and Visualization in Python for Ecologists" and the Pandas Getting Started introductory tutorials.