MACS 30111

M7: Pandas

Announcements

- **Switch to accelerated track: need MPCS exam**
  - https://masters.cs.uchicago.edu/student-resources/placement-exams/
  - Register, take the exam
- **Final exam schedule**
  - Tues, Dec 10th, 10-12pm
- **Review**
  - Textbook
  - Team tutorial
  - Short exercise
  - Programming assignment
  - Extra exercise

Agenda / misc

Topics:

- **Introduction to Pandas**
- Creating DataFrames and Series
- Working with DataFrames and Series
- Applying functions to data
- Group, combine, and pivoting
- Visualizing DataFrames and Series (Probably Thurs)

Data analysis toolkit

Reference: https://pandas.pydata.o

The “*pandas*” name

pan for “Panel”

da for “Data”

Panel data: multidimensional, structured datasets that include observations of something over a number of different time periods.

Use cases for the pandas library

Tabular Data

Time-series Data

Matrix Data

Statistical Datasets

Topics:

- Introduction to Pandas
- **Creating DataFrames and Series**
- Working with DataFrames and Series
- Applying functions to data
- Group, combine, and pivoting
- Visualizing DataFrames and Series

Pandas

Series

In: s
Out:
Rory 90
Lorelai 95
Luke 90
dtype: int64

DataFrame

In: s = pd.DataFrame(data)

In: s
Out:

	PA1	PA2
Rory	90	88
Lorelai	95	90
Luke	90	75

Reference:

- https://pandas.pydata.org/docs/reference/api/pandas.Series.html
- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.html

Importing the Pandas library

Import pandas using the alias “pd”

```
import pandas as pd
```

Series Constructor

Pass in 1-d data (list/np.array), alongside an accompanying (1-d) index:

```
data = [90, 95, 90]


index = ["Rory", "Lorelai", "Luke"]

s = pd.Series(data, index)
```

```
s
Out:
Rory      90
Lorelai    95
Luke      90
dtype: int64
```

Pass in a dictionary, where the keys are inferred to be the indices:

```
data = {"Rory":90, "Lorelai": 95, "Luke": 90}


s = pd.Series(data)
```

DataFrame Constructor

Pass in a dictionary of lists/arrays, alongside an accompanying (1-d) index:

```
data = {"PA1": [90,95,90], "PA2":[88,90,75]}

index = ["Rory", "Lorelai", "Luke"]

df = pd.DataFrame(data, index = index)
```

	PA1	PA2
Rory	90	88
Lorelai	95	90
Luke	90	75

Pass in a **dictionary of dictionaries**

```
data = {"PA1": {"Rory": 90,"Lorelai": 95,"Luke":90}, "PA2": {"Rory":
88,"Lorelai": 90,"Luke": 75}}
```

DataFrame Constructor

Data can also be passed in as an NumPy multidimensional array:

```
In: import numpy as np

In: np.random.seed(13)

In: data = np.random.uniform(0, 1, (3,2))

In: data
Out:
array([[0.77770241, 0.23754122],
       [0.82427853, 0.9657492 ],
       [0.97260111, 0.45344925]])


In: index = ["Rory", "Lorelai", "Luke"]

In: columns = ["pa1", "pa2"]

In: df = pd.DataFrame(data, index, columns)

In: df
Out:
            pa1       pa2
Rory    0.777702  0.237541
Lorelai 0.824279  0.965749
Luke    0.972601  0.453449
```

Read from file

CSV

JSON

HTML

Excel Spreadsheets

And much more...

```
trees =pd.read_csv("2015_Street_Tree_Census_Tree_Data_20231117.csv")
```

Reference: https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html

Key commands

- Loading: read_csv()
- Summarizing:
  - data.head()
  - data.tail()
- Selecting:
  - By index: iloc (e.x. `trees.iloc[:,1]`)
  - By name: loc (e.x. `trees.loc[:,"block_id"]`)

https://www.datacamp.com/cheat-sheet/pandas-cheat-sheet-for-data-science-in-python

Series VS DataFrame

- Series:
  - One-dimensional ndarray with axis labels

Rory	90
Lorelai	95
Luke	90

- DataFrame
  - Two-dimensional tabular data with labeled row and column axes

	PA1	PA2
Rory	90	88
Lorelai	95	90
Luke	90	75

Reference:

- Series: https://pandas.pydata.org/docs/reference/api/pandas.Series.html
- DataFrame: https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.html

Approaching the Series / DataFrame

Size, column names and data types: *dtype*, *shape*

```
In [34]: s
Out[34]:
Rory      90
Lorelai   95
Luke      90
dtype: int64
```

```
In [35]: s.dtype
Out[35]: dtype('int64')
```

```
In [36]: s.shape
Out[36]: (3,)
```

```
In [37]:
```

```
In [37]: df
Out[37]:
         PA1  PA2
Rory      90   88
Lorelai   95   90
Luke      90   75
```

```
In [38]: df.dtypes
Out[38]:
PA1    int64
PA2    int64
dtype: object
```

```
In [39]: df.shape
Out[39]: (3, 2)
```

Approaching the Series / DataFrame

What does the data look like? *df.head(), df.tail()*

```
In [40]: s.head(n=2)
Out[40]:
Rory      90
Lorelai   95
dtype: int64
```

```
In [41]: s.tail(n=1)
Out[41]:
Luke    90
dtype: int64
```

Motivating example

- Data exploration for the 2015 New York City Street Tree Survey
- Data: https://data.cityofnewyork.us/Environment/2015-Street-Tree-Census-Tree-Data/uvpi-gqnh
  - CSV, 683,789 lines

1. How many different species are planted as street trees in New York?
2. What are the five most common street tree species in New York?
3. What is the most common street tree species in Brooklyn?
4. What percentage of the street trees in Queens are dead or in poor health?
5. How does street tree health differ by borough?

https://github.com/computer-science-with-applications/examples/tree/main/working_with_data/pandas

Coding practice: 4.3.1

Missing Data

Identifying missing data in Series and DataFrames:

```
s.isna(); s.notna()
df.isna(); df.notna()
```

We can drop rows or columns with missing data:

```
df_drop_byrow = df.dropna()
df_drop_bycol = df.dropna(axis = 1)
```

We can also fill missing values:

```
df.col.fillna(np.mean(df.col))
```

```
In [42]: s.isna()
Out[42]:
Rory      False
Lorelai   False
Luke      False
dtype: bool
```

```
In [43]: s.notna()
Out[43]:
Rory      True
Lorelai   True
Luke      True
dtype: bool
```

```
In [44]: df.isna()
Out[44]:
         PA1    PA2
Rory     False  False
Lorelai  False  False
Luke     False  False
```

```
In [45]: df.notna()
Out[45]:
         PA1   PA2
Rory     True  True
Lorelai  True  True
Luke     True  True
```

Coding practice: 4.3.2

Selecting rows (indexing)

```
In [6]: trees.head()
Out[6]:
   tree_id  block_id  created_at  tree_dbh  ...  council district census tract       bin         bbl
0   180683    348711  08/27/2015         3  ...              29.0         739.0  4052307.0  4.022210e+09
1   200540    315986  09/03/2015        21  ...              19.0         973.0  4101931.0  4.044750e+09
2   204026    218365  09/05/2015         3  ...              34.0         449.0  3338310.0  3.028870e+09
3   204337    217969  09/05/2015        10  ...              34.0         449.0  3338342.0  3.029250e+09
4   189565    223043  08/30/2015        21  ...              39.0         165.0  3025654.0  3.010850e+09
```

Row label-based indexing

```
In [7]: trees.loc[180683]
Out[7]:
tree_id        362889
block_id        209521
created_at     10/22/2015
tree_dbh        6
...
```

Position-based indexing

```
In [8]: trees.iloc[0]
Out[8]:
tree_id                 180683
block_id                 348711
created_at             08/27/2015
tree_dbh                    3
stump_diam                  0
curb_loc                OnCurb
status                  Alive
health                   Fair
spc_latin            Acer rubrum
...
```

Naming columns

- If you want to explore the column names that were imported, you can use: trees.columns

```
Index(['tree_id', 'block_id', 'created_at', 'tree_dbh', 'stump_diam',
       'curb_loc', 'status', 'health', 'spc_latin', 'spc_common', 'steward',
       'guards', 'sidewalk', 'user_type', 'problems', 'root_stone',
       'root_grate', 'root_other', 'trunk_wire', 'trnk_light', 'trnk_other',
       'brch_light', 'brch_shoe', 'brch_other', 'address', 'postcode',
       'zip_city', 'community board', 'borocode', 'borough', 'cncldist',
       'st_assem', 'st_senate', 'nta', 'nta_name', 'boro_ct', 'state',
       'latitude', 'longitude', 'x_sp', 'y_sp', 'council district',
       'census tract', 'bin', 'bbl'],
      dtype='object')
```

Selecting columns

Note: depending on data, might have 'boronar

```
1 type(trees['health'])
```

```
pandas.core.series.Series
```

```
In [16]: trees["health"]
Out[16]:
0       Fair
1       Fair
2       Good
3       Good
4       Good
        ...
683783  Good
683784  Good
683785  Good
683786  Good
683787  Fair
Name: health, Length: 683788, dtype: object
```

```
1 type(trees[['health']])
```

```
pandas.core.frame.DataFrame
```

```
In [17]: trees[["health"]]
Out[17]:
        health
0         Fair
1         Fair
2         Good
3         Good
4         Good
...        ...
683783    Good
683784    Good
683785    Good
683786    Good
683787    Fair

[683788 rows x 1 columns]
```

```
1 type(trees[['health','borough']])
```

```
pandas.core.frame.DataFrame
```

```
In [18]: trees[["health", "borough"]]
Out[18]:
        health      borough
0         Fair       Queens
1         Fair       Queens
2         Good     Brooklyn
3         Good     Brooklyn
4         Good     Brooklyn
...        ...          ...
683783    Good     Brooklyn
683784    Good       Queens
683785    Good  Staten Island
683786    Good        Bronx
683787    Fair       Queens

[683788 rows x 2 columns]
```

Selecting rows and columns

Note: depending on data, might have 'boroname'

```
In [19]: trees.iloc[:5][["health", "borough"]]
Out[19]:
  health   borough
0   Fair    Queens
1   Fair    Queens
2   Good  Brooklyn
3   Good  Brooklyn
4   Good  Brooklyn
```

```
In [20]: trees.loc[[180683, 200540, 204026], ["health",
   ...: "borough"]]
Out[20]:
        health       borough
180683   Good      Brooklyn
200540    NaN  Staten Island
204026   Good  Staten Island
```

Filtering

- Boolean masks
- Logical operations

```
filter = (trees. borough== "Queens") & ((trees.status == "Dead") | (trees.health == "Poor"))
trees[filter]
```

- Remove rows where trees.status is Dead
- Select rows where trees.status is not Dead

```
trees[trees.status != "Dead"]
```

```
0       False
1       False
2       False
3       False
4       False
        ...
683783  False
683784  False
683785  False
683786  False
683787  False
Name: status, Length: 683788, dtype: bool
```

Coding practice: 4.3.4

Agenda / misc

- Applied practice
- Room reservation: final exam
- Deadlines/grading/etc.
- Anything else?

Topics:

- Introduction to Pandas
- Creating DataFrames and Series
- **Working with DataFrames and Series**
- Applying functions to data
- Group, combine, and pivoting
- Visualizing DataFrames and Series (Probably Thurs)

Review: load in data + add row names

- How to load data?
- How to set row names? (and why)
  - Hint: index_col
- **Application**: find tree at index 9 and tree_id of 192755

Practice Task: answer a research question

- **Suppose we have the following question:** how do tree health indicators vary by borough? **GIVEN THE CURRENT SKILLS / TOOLS WE HAVE DISCUSSED SO FAR**
- **In groups:**
  - Determine how you will measure this. (which column)
  - What tools do you currently have to do this?
  - What do you want to be able to do?

Topics:

- Introduction to Pandas
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- Working with DataFrames and Series
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Differences: help me understand

```
In : trees.count()
Out :
tree_id          683788
block_id         683788
created_at       683788
tree_dbh         683788
stump_diam       683788
curb_loc         683788
status           683788
health           652172
spc_latin        652169
spc_common       652169
```

```
In : trees.status.value_counts()
Out :
status
Alive    652173
Stump     17654
Dead      13961
Name: count, dtype: int64
```

```
In : trees.count()
Out :
block_id         683788
created_at       683788
tree_dbh         683788
stump_diam       683788
curb_loc         683788
status           683788
health           652172
spc_latin        652169
spc_common       652169
```

```
In : trees.status.value_counts()
Out:
status
Alive    652173
Stump     17654
Dead      13961
Name: count, dtype: int64
```

Reference: https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.describe.html

Common Summary Statistics

`DataFrame.count`

Count number of non-NA/null observations.

`DataFrame.max`

Maximum of the values in the object.

`DataFrame.min`

Minimum of the values in the object.

`DataFrame.mean`

Mean of the values.

`DataFrame.std`

Standard deviation of the observations.

`DataFrame.select_dtypes`

Subset of a DataFrame including/excluding columns based on their dtype.

```
In : trees.count()
Out :
block_id        683788
created_at      683788
tree_dbh        683788
stump_diam      683788
curb_loc        683788
status          683788
health          652172
spc_latin       652169
spc_common      652169
```

Summary statistics for each column: df.describe()

Summary of categorical values: df.value_counts()

Pairwise correlation of columns: df.corr()

```
In : trees.status.value_counts()
Out:
status
Alive   652173
Stump    17654
Dead     13961
Name: count, dtype: int64
```

Reference: https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.describe.html

Good exam question: Programming practice

- **CLOSED NOTE**

- **Suppose you have a dataframe with 20 rows and 10 columns.**
  - **DF name: albums**
  - **Column names: title, num_songs, year, genre, length, billboard, weeks_on_charts, label, avg_bpm, number_sold**
- **From the above dataframe, write the following code on your paper:**
  - **Get the shape of the dataframe**
  - **Print the information for the album in the 10th row**
  - **Print the information for the "genre" column**
  - **(bonus) Select albums that have have been in the top 100 on billboard (e.g. have a value less than or equal to 100)**

Applying Functions to Data

`Series.apply`

For applying more complex functions on a Series.

`DataFrame.apply`

Apply a function row-/column-wise.

`DataFrame.applymap`

Apply a function elementwise on a whole DataFrame.

Reference: https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.apply.html

Topics:

- Introduction to Pandas
- Creating DataFrames and Series
- Working with DataFrames and Series
- Applying functions to data
- **Group, combine, and pivoting**
- Visualizing DataFrames and Series

Grouping

```
In: trees.groupby("borough")[["tree_dbh"]].mean()
Out:
                tree_dbh
borough
Bronx          9.693649
Brooklyn      11.738884
Manhattan      8.473641
Queens        12.557870
Staten Island 10.492746
```

Coding practice: 4.3.5

Grouping

```
In : trees.groupby(["borough", "status"]).size()
Out :
borough       status
Bronx         Alive     80585
              Dead       2530
              Stump      2088
Brooklyn      Alive     169744
              Dead       3319
              Stump      4230
Manhattan     Alive     62427
              Dead       1802
              Stump      1194
Queens        Alive     237974
              Dead       4440
              Stump      8137
Staten Island  Alive    101443
              Dead       1870
              Stump      2005
dtype: int64
```

Coding practice: 4.3.5

Reshaping: Stacking / Unstacking

- Think about maneuvering your data around – what do you want your rows and columns to be – what is the observation?
- Do you want an indicator variable, a count variable, etc?

Unstack: converts series with hierarchical index into a DataFrame

Coding practice: 4.3.5

Unstacking

By default, **unstack** will order the columns by value

```
In : trees.groupby(["borough", "status"]).size()
Out :
borough       status
Bronx         Alive     80585
              Dead       2530
              Stump      2088
Brooklyn      Alive     169744
...
```

```
In : trees.groupby(["borough", "status"]).size().unstack()
Out:
status         Alive  Dead  Stump
borough
Bronx          80585  2530   2088
Brooklyn      169744  3319   4230
Manhattan      62427  1802   1194
Queens        237974  4440   8137
Staten Island 101443  1870   2005
```

TASK: develop a research question

- In your groups, develop a research question you can answer with the **trees dataset**.
- Your question needs to use **ALL of** the following:
  - **Filtering**
  - **Applying a Boolean criterion**
  - **Label-based indexing**
  - **Calculating a numerical value (e.g. mean/min/max/std/corr)**
  - **Exporting the text file (documentation!)**

Using functions

What does this do/mean? Why and how would we do this?

```
for col_name in ["boroname", "health", "spc_common", "status"]:
    trees[col_name] = trees[col_name].astype("category")
```

Using functions

- What does this do/mean? Why and how would we do this?

```
def tree_health_by_boro(trees):
    combined_status = trees.status.where(trees.status != "Alive", trees.health)
    num_per_boro = trees.groupby("borough").size()
    combined_per_boro = trees.groupby(["borough",combined_status]).size()
    pct_per_boro = combined_per_boro/num_per_boro*100.0
    pct_per_boro_df = pct_per_boro.unstack()

    return pct_per_boro_df[["Good", "Fair", "Poor", "Dead", "Stump"]]

tree_health_by_boro(trees)
```

Unstacking

By default, **unstack** will order the columns by value

```
In : trees.groupby(["borough", "status"]).size()
Out :
borough       status
Bronx         Alive     80585
              Dead       2530
              Stump      2088
Brooklyn      Alive     169744
...
```

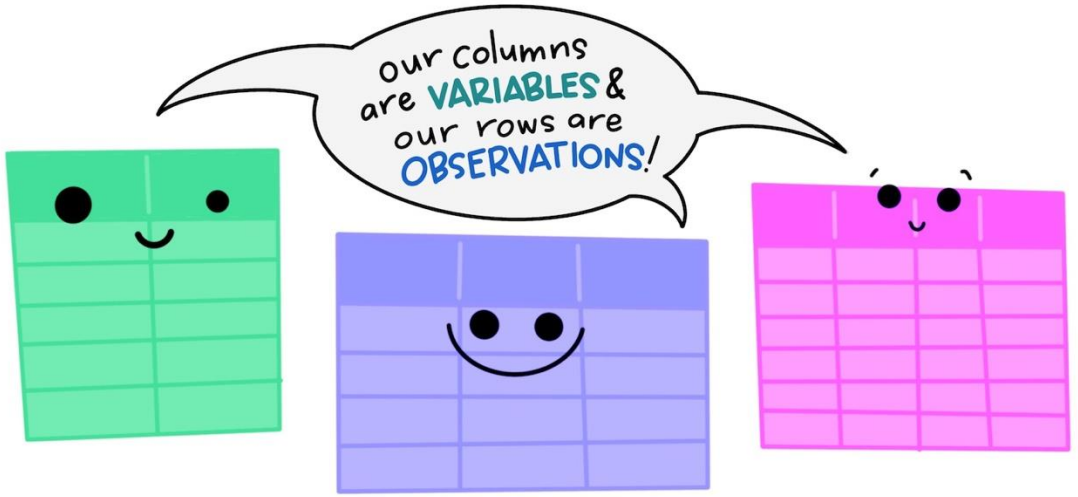
```
In : trees.groupby(["borough", "status"]).size().unstack()
Out:
status         Alive  Dead  Stump
borough
Bronx          80585  2530   2088
Brooklyn      169744  3319   4230
Manhattan      62427  1802   1194
Queens        237974  4440   8137
Staten Island 101443  1870   2005
```

“Happy families are all alike; every unhappy family is unhappy in its own way.” -- Leo Tolstoy

“Tidy datasets are all alike, but every messy dataset is messy in its own way.” -- Hadley Wickham

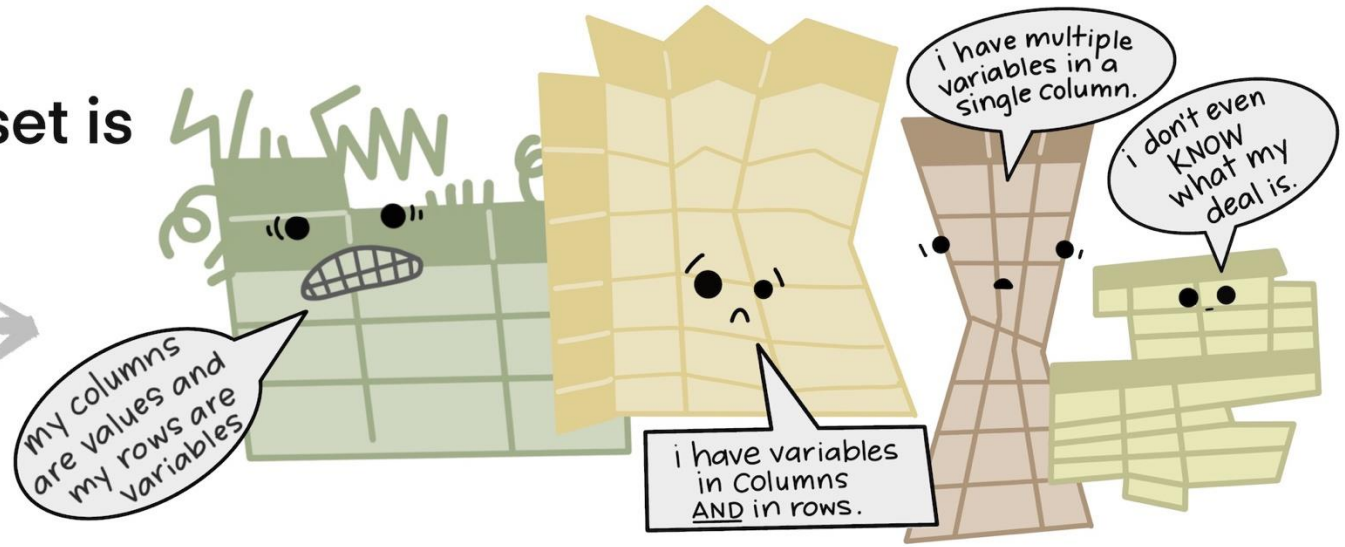
https://allisonhorst.com/other-r-fun

The standard structure of tidy data means that "tidy datasets are all alike..."



"...but every messy dataset is messy in its own way."

–HADLEY WICKHAM

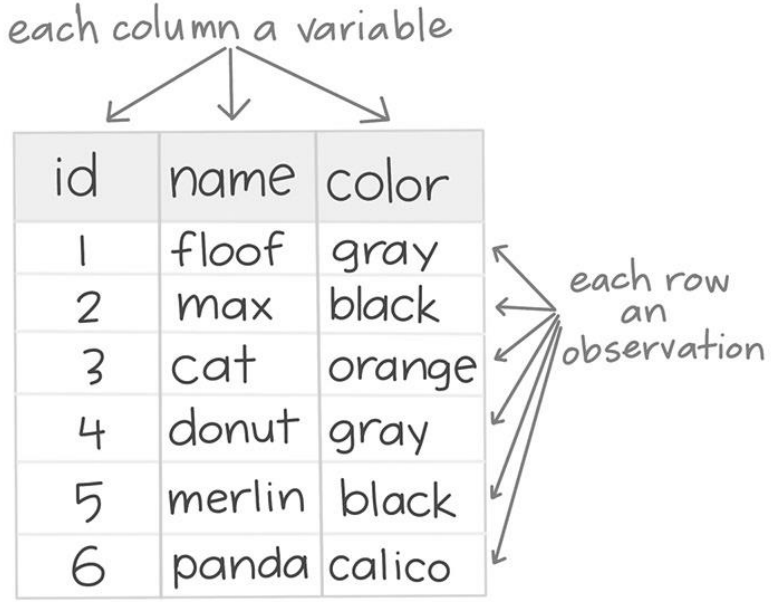


"TIDY DATA is a standard way of mapping the meaning of a dataset to its structure."

–HADLEY WICKHAM

In tidy data:

- each variable forms a column
- each observation forms a row
- each cell is a single measurement



Wickham, H. (2014). Tidy Data. Journal of Statistical Software *59* (10). DOI: 10.18637/jss.v059.i10

Long vs wide

`wide`

id	x	y	z
1	a	c	e
2	b	d	f

`long`

id	key	val
1	x	a
2	x	b
1	y	c
2	y	d
1	z	e
2	z	f

Benefits: long vs wide

- ‘Long’ data: better for analysis
- ‘Wide’ data: can be helpful for visualization

Long vs wide

Common Name	lifespan_cat_eq_Short	lifespan_cat_eq_Medium	lifespan_cat_eq_Long	lifespan_cat_eq_ExtraLong
Ash, Green	0	1	0	0
Ash, White	0	0	0	1
Basswood	1	0	0	0
Beech, American	0	0	0	1
Birch, Gray	1	0	0	0

Common Name	lifespan_cat	value
Ash, Green	lifespan_cat_eq_Short	0
Ash, Green	lifespan_cat_eq_Medium	1
Ash, Green	lifespan_cat_eq_ExtraLong	0
Ash, Green	lifespan_cat_eq_Long	0
Ash, White	lifespan_cat_eq_ExtraLong	1

Pivoting

Convert a long and thin DataFrame into a short and wide DataFrame

- A column for index
- A column to supply column names for the new DataFrame
- A column to fill the new DataFrame

Options: pivot, melt, wide_to_long

Coding practice: 4.3.6

Pivot example

```
pd.melt(trees_life,value_vars=filter_col,
id_vars= ["Common Name", "Scientific Name"],
var_name='lifespan_cat’)
```

```
pd.wide_to_long(trees_life, stubnames="lifespan_cat_eq",
i="Common Name",
j="lifespan_cat", suffix='\\w+')
```

```
trees_life.pivot(index='Common Name', columns='lifespan_cat',
values='Average_lifespan’)
```

*(**bonus**) pd.get_dummies(trees_life, columns=['lifespan_cat_eq'], dtype=int)*

Combining DataFrames

- **concat( )**
  - perform concatenation along an axis
  - while performing set logic of the indexes on other axes
  - make a full copy of the data

- **merge( )**
  - Standard database join operations between DataFrame or Series objects

- **join( )**
  - join on index
  - combine columns of two differently indexed DataFrames into a single one

Reference: https://pandas.pydata.org/docs/user_guide/merging.html

Join vs merge

- Merge is the ‘big picture’ for things
  - Can have more freedom with indices / how you merge
- ‘join’ is like a subset of merge --

Merge: syntax

- **DataFrame.merge(*right*, *how*='inner', *on*=None, *left_on*=None, *right_on*=None, *left_index*=False, *right_index*=False, *sort*=False, *suffixes*=('_x', '_y'), *copy*=None, *indicator*=False, *validate*=None)**

Parameters:

- **how**{*‘left’*, *‘right’*, *‘outer’*, *‘inner’*, *‘cross’*}, *default ‘inner’*Type of merge to be performed.
  - •left: use only keys from left frame, similar to a SQL left outer join; preserve key order.
  - •right: use only keys from right frame, similar to a SQL right outer join; preserve key order.
  - •outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically.
  - •inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys.
  - •cross: creates the cartesian product from both frames, preserves the order of the left keys.

•**On** *label or list*Column or index level names to join on. These must be found in both DataFrames. If *on* is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.

https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.merge.html#pandas.DataFrame.merge

Syntax: is it df.merge or pd.merge?

Similar across circumstances but just depends on how you want to call it…when you look at the documentation, you'll see this trend consistently.

If you call pd.function, you will need to specify the data frame(s).

If you df.function, you no longer need to specify the data frame.

TASK: ADVENTURE TIME (cont'd)

1. Get to know your second dataset
2. Merge the dataframes
3. Think about a question you could ask and give it a go