Pandas

This is the slide version of “3_pandas.html”

Python Overview

In R I Want	In Python I Use
Base R	numpy
dplyr/tidyr	pandas
ggplot2	matplotlib/seaborn

Pandas versus Tidyverse

- These are the equivalencies you should have in mind.

  `<DataFrame>.fun()` means that `fun()` is a method of the `<DataFrame>` object.

  `<Series>.fun()` means that `fun()` is a method of the `<Series>` object.

```
| tidyverse        | pandas |
|----------------|----------|
|`arrange()`     | `<DataFrame>.sort_values()`|
|`bind_rows()`   | `pandas.concat()`|
|`filter()`      | `<DataFrame>.query()`|
|`gather()` and `pivot_longer()` | `<DataFrame>.melt()`|
|`glimpse()`     | `<DataFrame>.info()` and |
|                |                    `<DataFrame>.head()`|
|`group_by()`    | `<DataFrame>.groupby()`|
|`if_else()`     | `numpy.where()`|
|`left_join()`   | `pandas.merge()`|
|`library()`     | `import`|
|`mutate()`      | `<DataFrame>.eval()` and |
|                |                 `<DataFrame>.assign()`|
|`read_csv()`    | `pandas.read_csv()`|
```

```
| tidyverse        | pandas |
|---------------|----------|
|`read_csv()`   | `pandas.read_csv()`|
|`recode()`     | `<DataFrame>.replace()` |
|`rename()`     | `<DataFrame>.rename()`|
|`select()`     | `<DataFrame>.filter()` and|
|               |                 `<DataFrame>.drop()`|
|`separate()`   | `<Series>.str.split()`|
|`slice()`      | `<DataFrame>.iloc()`|
|`spread()` and `pivot_wider()` | |
|            `<DataFrame>.pivot_table().reset_index()`|
|`summarize()`  | `<DataFrame>.agg()`|
|`unite()`      | `<Series>.str.cat()`|
|`%>%`          | Enclose pipeline in `()`|
```

Importing libraries

Python: `import <package> as <alias>`.

Python

```
import numpy as np
import pandas as pd
```

- You can use the alias that you define in place of the package name. In Python we write down the package name a lot, so it is nice for it to be short.

R equivalent

R

```
library(tidyverse)
```

Reading in and Printing Data

- We'll demonstrate most methods with the "estate" data that we've seen before: https://data-science-master.github.io/lectures/data/estate.csv
- You can read about these data here: https://data-science-master.github.io/lectures/data.html
- Python: `pd.read_csv()`. There is a family of reading functions in pandas (fixed width files, e.g.). Use tab-completion to scroll through them.

  Python

```python
estate = pd.read_csv("../data/estate.csv")
```

R equivalent:

R

```r
estate1 <- read_csv("../data/estate.csv")
```

Use the `info()` and `head()` methods to get a view of the data.

Python

```python
estate.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 522 entries, 0 to 521
Data columns (total 12 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Price     522 non-null    int64
 1   Area      522 non-null    int64
 2   Bed       522 non-null    int64
 3   Bath      522 non-null    int64
 4   AC        522 non-null    int64
 5   Garage    522 non-null    int64
```

Python

```
estate.head()
```

```
    Price  Area  Bed  Bath  AC  ...  Year  Quality  Style
0  360000  3032    4     4   1  ...  1972   Medium      1
1  340000  2058    4     2   1  ...  1976   Medium      1
2  250000  1780    4     3   1  ...  1980   Medium      1
3  205500  1638    4     2   1  ...  1963   Medium      1
4  275500  2196    4     3   1  ...  1968   Medium      7

[5 rows x 12 columns]
```

R equivalent:

R

```r
glimpse(estate1)
```

```
Rows: 522
Columns: 12
$ Price   <dbl> 360000, 340000, 250000, 205500, 275500, 248
$ Area    <dbl> 3032, 2058, 1780, 1638, 2196, 1966, 2216, 1
$ Bed     <dbl> 4, 4, 4, 4, 4, 4, 3, 2, 3, 3, 7, 3, 5, 5, 3
$ Bath    <dbl> 4, 2, 3, 2, 3, 3, 2, 1, 2, 3, 5, 4, 4, 4, 3
$ AC      <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1
$ Garage  <dbl> 2, 2, 2, 2, 2, 5, 2, 1, 2, 1, 2, 3, 3, 2, 2
$ Pool    <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0
$ Year    <dbl> 1972, 1976, 1980, 1963, 1968, 1972, 1972, 1
$ Quality <chr> "Medium", "Medium", "Medium", "Medium", "Me
$ Style   <dbl> 1, 1, 1, 1, 7, 1, 7, 1, 1, 1, 7, 1, 7, 5, 1
$ Lot     <dbl> 22221, 22912, 21345, 17342, 21786, 18902, 1
$ Highway <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
```

`DataFrames and Series`

- Pandas reads in tabular data as a `DataFrame` object.
- Just as R's `data.frame` is a list of a bunch of vectors, Panda's `DataFrame` contains a bunch of `Series` objects.

- A `Series` object is a generalization of a numpy array. So you can use numpy functions on it.

Python

```
x = pd.Series([1, 4, 2, 1])
x[2:3]
x[pd.Series([0, 2])]
x[x >= 2]
np.sum(x)
```

Extract Variables

- Python: Use a period. This extracts the column as a Pandas Series.

Python

```
estate.Price
```

- Then you can use all of those numpy functions on the `Series`

Python

```
np.mean(estate.Price)
np.max(estate.Price)
```

R equivalent: Use a $:

R

```
estate1$Price
```

Filtering/Arranging Rows (Observations)

- Filter rows based on booleans (logicals) with `query()`. The queries need to be in quotes.

Python

```
estate.query('(Price > 300000) & (Area < 2500)')
```

Some folks use bracket notation, which is more similar to base R

Python

```
estate[(estate.Price > 300000) & (estate.Area < 2500)]
```

R equivalent:

R

```r
filter(estate1, Price > 300000, Area < 2500)
```

Select rows by numerical indices with `iloc()`

Python

```python
estate.iloc[[1, 4, 10]]
```

```
     Price  Area  Bed  Bath  AC  ...  Year  Quality  Style
1   340000  2058    4     2   1  ...  1976   Medium      1
4   275500  2196    4     3   1  ...  1968   Medium      7
10  190000  2812    7     5   0  ...  1966      Low      7

[3 rows x 12 columns]
```

R equivalent:

R

```r
slice(estate1, 1, 4, 10)
```

```
# A tibble: 3 x 12
   Price  Area   Bed  Bath    AC Garage  Pool  Year Quality
   <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl> <dbl> <dbl> <chr>
1 360000  3032     4     4     1      2     0  1972 Medium
2 205500  1638     4     2     1      2     0  1963 Medium
3 160000  1976     3     3     0      1     0  1918 Low
```

Arrange rows by `sort_values()`.

Python

```
estate.sort_values(by="Price", ascending=False)
```

R equivalent

R

```r
arrange(estate1, desc(Price))
```

Exercise: Use both the tidyverse and pandas to extract all medium

quality homes that have a pool and arrange the rows in increasing order of price.

Selecting Columns (Variables)

- Variables are selected using `filter()`.

Python

```
estate.filter(["Price"])
estate.filter(["Price", "Area"])
```

Some folks use bracket notation, which is more similar to Base R.

Python

```
estate[["Price"]]
```

Python

```
estate[["Price", "Area"]]
```

The inner brackets [] just creates a Python list. The outer brackets []

says that we are subsetting the columns.

R equivalent:

R

```
select(estate1, Price)
```

R

```r
select(estate1, Price, Area)
```

Dropping a column is done by `drop()`. The `axis=1` argument says to drop by

columns (rather than by “`index`”, which is something we haven’t covered).

Python

```
estate.drop(["Price", "Area"], axis=1)
```

R: just use `select()` with a minus sign.

R

```
select(estate1, -Price, -Area)
```

Renaming variables is done with `rename()`.

Python

```
estate.rename({'Price': 'price', 'Area': 'area'},
axis = 'columns')
```

R equivalence:

R

```r
rename(estate1, price = Price, area = Area)
```

```
# A tibble: 522 x 12
    price  area   Bed  Bath    AC Garage  Pool  Year Qualit
    <dbl> <dbl> <dbl> <dbl> <dbl>  <dbl> <dbl> <dbl> <chr>
 1 360000  3032     4     4     1      2     0  1972 Mediun
 2 340000  2058     4     2     1      2     0  1976 Mediun
 3 250000  1780     4     3     1      2     0  1980 Mediun
 4 205500  1638     4     2     1      2     0  1963 Mediun
 5 275500  2196     4     3     1      2     0  1968 Mediun
 6 248000  1966     4     3     1      5     1  1972 Mediun
 7 229900  2216     3     2     1      2     0  1972 Mediun
 8 150000  1597     2     1     1      1     0  1955 Mediun
 9 195000  1622     3     2     1      2     0  1975 Low
10 160000  1976     3     3     0      1     0  1918 Low
# i 512 more rows
```

Exercise:

Use the tidyverse and pandas to select year, price, and area.

Creating New Variables (Mutate)

- New variables are created in Python using `eval()`. Note that we need to place the expression in quotes.

Python

```
estate.eval('age = 2013 - Year')
```

You can use `assign()`, but then you need to reference the `DataFrame`

as you extract variables:

Python

```
estate.assign(age = 2013 - estate.Year)
```

R equivalent:

R

```r
mutate(estate1, age = 2013 - Year)
```

Exercise:

Use the tidyverse and pandas to calculate the price per unit area.

Piping

- All of these pandas functions return `DataFrames`. So, we can apply methods to these `DataFrames` by just appending methods to the end.
- E.g., suppose we want to find the total number of beds/baths and only select the price and this total number to print. Then the following code would work.

Python

```
estate.eval('tot = Bed + Bath').filter(["Price", "tot"])
```

If you want to place these operations on different lines, then just place

the whole operation within parentheses.

Python

```
(
estate.eval('tot = Bed + Bath')
.filter(["Price", "tot"])
)
```

This looks similar to piping in the tidyverse

R

```
estate1 %>%
  mutate(tot = Bed + Bath) %>%
  select(Price, tot)
```

Exercise:

Use pandas to extract all medium quality homes that have a pool and arrange the rows in increasing order of price. Use piping.

Group Summaries

- Summaries can be calculated by the agg() method. You usually first select the columns whose summaries you want before running agg().

Python

```
(
estate.filter(["Price", "Area"])
.agg(np.mean)
)
```

```
Price    277894.147510
Area       2260.626437
dtype: float64
```

R equivalent

R

```r
summarize(estate1, Price = mean(Price), Area = mean(Area))
```

```
# A tibble: 1 x 2
    Price  Area
    <dbl> <dbl>
1 277894. 2261.
```

Use `groupby()` to create group summaries.

Python

```python
(
estate.filter(["Price", "Area", "Bed", "Bath"])
  .groupby(["Bed", "Bath"])
  .agg(np.mean)
)
```

R equivalent

R

```
estate1 %>%
  group_by(Bed, Bath) %>%
  summarize(Price = mean(Price), Area = mean(Area))
```

You can get multiple summaries out by passing a list of functions:

Python

```
(
estate.filter(["Price", "Area", "Quality"])
  .groupby("Quality")
  .agg([np.mean, np.var])
)
```

You can create your own functions and pass those

Python

```
def cv(x):
  """Calculate coefficient of variation"""
  return(np.sqrt(np.var(x)) / np.mean(x))

(
estate.filter(["Price", "Area"])
  .agg(cv)
)
```

```
Price    0.495841
Area     0.314242
dtype: float64
```

Recoding

- Use `replace()` with a `dict` object to recode variable values.

  Python

```
estate.replace({'AC' : {0: "No AC", 1: "AC"}})
```

R equivalent:

R

```r
estate1 %>%
  mutate(AC = recode(AC,
                     "0" = "No AC",
                     "1" = "AC"))
```

To recode values based on logical conditions, use `np.where()`.

Python

```
estate.assign(isbig = np.where(estate.Price > 300000,
"expensive", "cheap"))
```

R equivalence:

R

```
mutate(estate1, isbig = if_else(Price > 300000,
                                "expensive", "cheap"))
```

Gathering

- Problem: One variable spread across multiple columns.
- Column names are actually *values* of a variable
- Recall `table4a` from the tidyr package

R

```r
data("table4a")
```

Python

```
table4a = pd.DataFrame({'country': ['Afghanistan',
'Brazil', 'China'],
                        '1999': [745, 37737, 212258],
                        '2000': [2666, 80488, 213766]})
table4a
```

```
       country    1999    2000
0  Afghanistan     745    2666
1       Brazil   37737   80488
2        China  212258  213766
```

Solution: `melt()`.

Python

```
table4a.melt(id_vars='country',
value_vars=['1999', '2000'])
```

```
       country variable   value
0  Afghanistan     1999     745
1       Brazil     1999   37737
2        China     1999  212258
3  Afghanistan     2000    2666
4       Brazil     2000   80488
5        China     2000  213766
```

R equivalences:

R

```r
gather(table4a, key = "variable", value = "value",
       `1999`, `2000`)
```

```
# A tibble: 6 x 3
  country     variable  value
  <chr>       <chr>     <dbl>
1 Afghanistan 1999        745
2 Brazil      1999      37737
3 China       1999     212258
4 Afghanistan 2000       2666
5 Brazil      2000      80488
6 China       2000     213766
```

R

```r
pivot_longer(table4a, cols = c("1999", "2000"),
             names_to = "variable",
             values_to = "value")
```

RDS visualization:

`![](../graphix/tidy-9.png)\`

Exercise: Use pandas to gather the `monkeymem` data frame (available at

https://data-science-master.github.io/lectures/data/tidy_exercise/monkeymem.csv). The cell values represent identification accuracy of some objects (in percent of 20 trials).

Spreading

- Problem: One observation is spread across multiple rows.
- One column contains variable names. One column contains values for the different variables.
- Recall `table2` from the tidyr package

R

```r
data("table2")
```

Python

```
table2 = pd.DataFrame({'country': ['Afghanis
                                   'Afghanistan', 'Afghanis
                                   'Brazil', 'Brazil', 'Bra
                                   'Brazil', 'China', 'Chin
                                   'China', 'China'],
                       'year': [1999, 1999, 2000, 2000, 199
                                2000, 2000, 1999, 1999, 200
                       'type': ['cases', 'population', 'cas
                                'population', 'cases', 'pop
                                'cases', 'population', 'cas
                                'population', 'cases', 'pop
                                'count':
                                  [745, 19987071, 2666, 205
                                   172006362, 80488, 174504
                                   1272915272, 213766, 1280
```

Python

```python
table2
```

	country	year	type	count
0	Afghanistan	1999	cases	745
1	Afghanistan	1999	population	19987071
2	Afghanistan	2000	cases	2666
3	Afghanistan	2000	population	20595360
4	Brazil	1999	cases	37737
5	Brazil	1999	population	172006362
6	Brazil	2000	cases	80488
7	Brazil	2000	population	174504898
8	China	1999	cases	212258
9	China	1999	population	1272915272
10	China	2000	cases	213766
11	China	2000	population	1280428583

Solution: `pivot_table()` followed by `reset_index()`.

Python

```
(
table2.pivot_table(index=['country', 'year'],
columns='type', values='count')
  .reset_index()
)
```

```
type       country  year     cases    population
0      Afghanistan  1999     745.0  1.998707e+07
1      Afghanistan  2000    2666.0  2.059536e+07
2           Brazil  1999   37737.0  1.720064e+08
3           Brazil  2000   80488.0  1.745049e+08
4            China  1999  212258.0  1.272915e+09
5            China  2000  213766.0  1.280429e+09
```

- `pivot_table()` creates a table with an `index` attribute defined by the columns you pass to the `index` argument. The `reset_index()` converts that attribute to columns and changes the `index` attribute to a sequence `[0, 1, ..., n-1]`.

R equivalences

R

```r
spread(table2, key = "type", value = "count")
```

```
# A tibble: 6 x 4
  country      year  cases population
  <chr>       <dbl>  <dbl>      <dbl>
1 Afghanistan  1999    745   19987071
2 Afghanistan  2000   2666   20595360
3 Brazil       1999  37737  172006362
4 Brazil       2000  80488  174504898
5 China        1999 212258 1272915272
6 China        2000 213766 1280428583
```

R

```r
pivot_wider(table2, id_cols = c("country", "year"),
            names_from = "type",
            values_from = "count")
```

```
# A tibble: 6 x 4
  country      year  cases population
  <chr>       <dbl>  <dbl>      <dbl>
1 Afghanistan  1999    745   19987071
2 Afghanistan  2000   2666   20595360
3 Brazil       1999  37737  172006362
4 Brazil       2000  80488  174504898
5 China        1999 212258 1272915272
6 China        2000 213766 1280428583
```

RDS visualization:

`![](../graphix/tidy-8.png)\`

Exercise:

Use pandas to spread the `flowers1` data frame (available at https://data-science-master.github.io/lectures/data/tidy_exercise/flowers1.csv).

Separating

- Sometimes we want to split a column based on a delimiter:

R

```
data("table3")
```

Python

```
table3 = pd.DataFrame({'country': ['Afghanistan', 'Afghanis
                                   'Brazil', 'China', 'Chi
                       'year': [1999, 2000, 1999, 2000, 19
                       'rate': ['745/19987071', '2666/20595
                                '37737/172006362', '80488/1
                                '212258/1272915272', '2137
table3
```

```
       country  year               rate
0  Afghanistan  1999       745/19987071
1  Afghanistan  2000      2666/20595360
2       Brazil  1999    37737/172006362
3       Brazil  2000    80488/174504898
```

Python

```
table3[['cases', 'population']] = table3.rate.str.split(pat
table3.drop('rate', axis=1)
```

```
       country  year   cases  population
0  Afghanistan  1999     745    19987071
1  Afghanistan  2000    2666    20595360
2       Brazil  1999   37737   172006362
3       Brazil  2000   80488   174504898
4        China  1999  212258  1272915272
5        China  2000  213766  1280428583
```

R equivalence

R

```
separate(table3, col = "rate", sep = "/",
         into = c("cases", "population"))
```

```
# A tibble: 6 x 4
  country      year cases  population
  <chr>       <dbl> <chr>  <chr>
1 Afghanistan  1999 745    19987071
2 Afghanistan  2000 2666   20595360
3 Brazil       1999 37737  172006362
4 Brazil       2000 80488  174504898
5 China        1999 212258 1272915272
6 China        2000 213766 1280428583
```

Exercise:

Use pandas to separate the `flowers2` data frame (available at https://data-science-master.github.io/lectures/data/tidy_exercise/flowers2.csv).

Uniting

- Sometimes we want to combine two columns of strings into one column.

R

```r
data("table5")
```

Python

```
table5 = pd.DataFrame({'country': ['Afghanistan', 'Afghanis
                                    'Brazil', 'China', 'Chin
                       'century': ['19', '20', '19', '20',
                       'year': ['99', '00', '99', '00', '99
                       'rate': ['745/19987071', '2666/20595
                                 '37737/172006362', '80488/1
                                 '212258/1272915272', '21376
table5
```

```
       country century year               rate
0  Afghanistan      19   99       745/19987071
1  Afghanistan      20   00      2666/20595360
2       Brazil      19   99    37737/172006362
3       Brazil      20   00    80488/174504898
4        China      19   99  212258/1272915272
5        China      20   00  213766/1280428583
```

You can use `str.cat()` to combine two columns.

Python

```
(
table5.assign(year = table5.century.str.cat(table5.year))
  .drop('century', axis = 1)
)
```

```
       country  year                  rate
0  Afghanistan  1999          745/19987071
1  Afghanistan  2000         2666/20595360
2       Brazil  1999       37737/172006362
3       Brazil  2000       80488/174504898
4        China  1999    212258/1272915272
5        China  2000    213766/1280428583
```

R equivalence:

R

```r
unite(table5, century, year, col = "year", sep = "")
```

```
# A tibble: 6 x 3
  country     year  rate
  <chr>       <chr> <chr>
1 Afghanistan 1999  745/19987071
2 Afghanistan 2000  2666/20595360
3 Brazil      1999  37737/172006362
4 Brazil      2000  80488/174504898
5 China       1999  212258/1272915272
6 China       2000  213766/1280428583
```

Exercise:

Use pandas to re-unite the data frame you separated from the flowers2 exercise. Use a comma for the separator.

Joining

- We will use these `DataFrames` for the examples below.

Python

```
xdf = pd.DataFrame({"mykey": np.array([1, 2, 3]),
                    "x": np.array(["x1", "x2", "x3"])})
ydf = pd.DataFrame({"mykey": np.array([1, 2, 4]),
                    "y": np.array(["y1", "y2", "y3"])})
xdf
ydf
```

R

```
xdf <- tibble(mykey = c("1", "2", "3"),
              x_val = c("x1", "x2", "x3"))
ydf <- tibble(mykey = c("1", "2", "4"),
              y_val = c("y1", "y2", "y3"))
xdf
ydf
```

Binding rows is done with `pd.concat()`.

Python

```
pd.concat([xdf, ydf])
```

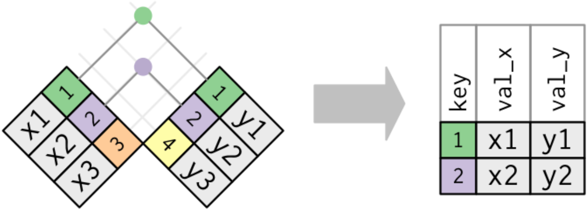
R equivalence:

R

```r
bind_rows(xdf, ydf)
```

All joins use `pd.merge()`.

- Inner Join (visualization from RDS):



Python

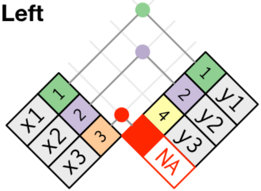
```
pd.merge(left=xdf, right=ydf, how="inner", on="mykey")
```

R

```r
inner_join(xdf, ydf, by = "mykey")
```

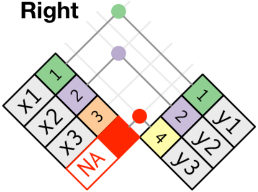
Outer Joins (visualization from RDS):

Left



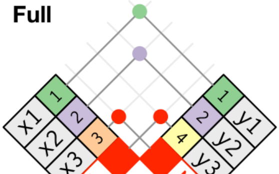
key	val_x	val_y
1	x1	y1
2	x2	y2
3	x3	NA

Right



key	val_x	val_y
1	x1	y1
2	x2	y2
4	NA	y3

Full



key	val_x	val_y
1	x1	y1
2	x2	y2

Left Join

Python

```
pd.merge(left=xdf, right=ydf, how="left", on="mykey")
```

R

```r
left_join(xdf, ydf, by = "mykey")
```

Right Join

Python

```
pd.merge(left=xdf, right=ydf, how="right", on="mykey")
```

R

```r
right_join(xdf, ydf, by = "mykey")
```

Full Join

Python

```
pd.merge(left=xdf, right=ydf, how="outer", on="mykey")
```

R

```r
full_join(xdf, ydf, by = "mykey")
```

Use the `left_on` and `right_on` arguments if the keys are named differently.

- The `on` argument can take a list of key names if your key is multiple columns.

Extra Resources

Here are some resources if you want to learn more:

- Python Data Science Handbook
- Python for Data Analysis
- Another Book on Data Science