Data Wrangling

with pandas Cheat Sheet
http://pandas.pydata.org

Pandas API Reference   Pandas User Guide

Creating DataFrames

	a	b	c
1	4	7	10
2	5	8	11
3	6	9	12

```
df = pd.DataFrame(
          {"a" : [4, 5, 6],
           "b" : [7, 8, 9],
           "c" : [10, 11, 12]},
        index = [1, 2, 3])
```

Specify values for each column.

```
df = pd.DataFrame(
     [[4, 7, 10],
      [5, 8, 11],
      [6, 9, 12]],
     index=[1, 2, 3],
     columns=['a', 'b', 'c'])
```

Specify values for each row.

		a	b	c
N	v			
D	1	4	7	10
	2	5	8	11
e	2	6	9	12

```
df = pd.DataFrame(
          {"a" : [4 ,5, 6],
           "b" : [7, 8, 9],
           "c" : [10, 11, 12]},
index = pd.MultiIndex.from_tuples(
        [('d’, 1), ('d’, 2),
         ('e’, 2)], names=['n’, 'v']))
```

Create DataFrame with a MultiIndex

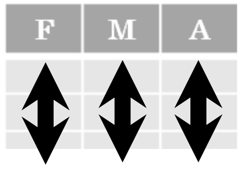
Method Chaining

Most pandas methods return a DataFrame so that another pandas method can be applied to the result. This improves readability of code.

```
df = (pd.melt(df)
        .rename(columns={
               'variable':'var',
               'value':'val'})
        .query('val >= 200')
     )
```

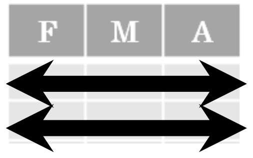
Tidy Data – A foundation for wrangling in pandas

In a tidy data set:



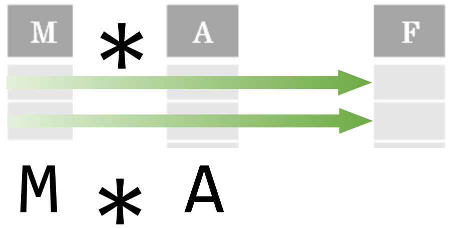
Each **variable** is saved in its own **column**

&

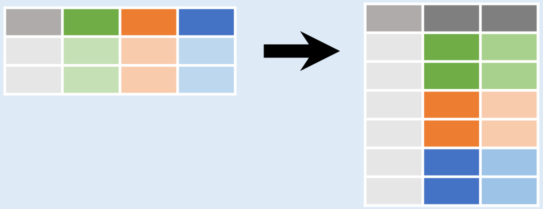


Each **observation** is saved in its own **row**

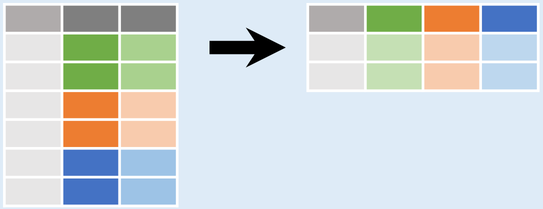
Tidy data complements pandas's **vectorized operations**. pandas will automatically preserve observations as you manipulate variables. No other format works as intuitively with pandas.



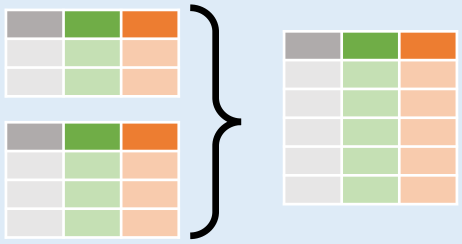
Reshaping Data – Change layout, sorting, reindexing, renaming



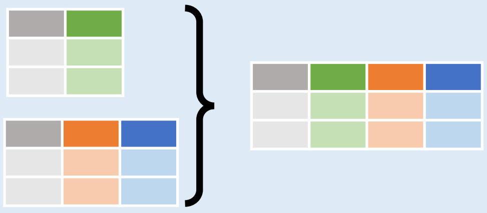
`pd.melt(df)`
Gather columns into rows.



`df.pivot(columns='var', values='val')`
Spread rows into columns.



`pd.concat([df1,df2])`
Append rows of DataFrames



`pd.concat([df1,df2], axis=1)`
Append columns of DataFrames

`df.sort_values('mpg')`
Order rows by values of a column (low to high).

`df.sort_values('mpg’, ascending=False)`
Order rows by values of a column (high to low).

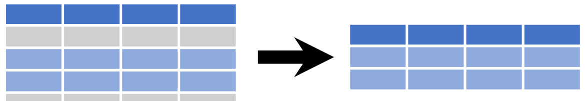
`df.rename(columns = {'y':'year'})`
Rename the columns of a DataFrame

`df.sort_index()`
Sort the index of a DataFrame

`df.reset_index()`
Reset index of DataFrame to row numbers, moving index to columns.

`df.drop(columns=['Length’, 'Height'])`
Drop columns from DataFrame

Subset Observations - rows



`df[df.Length > 7]`
Extract rows that meet logical criteria.

`df.drop_duplicates()`
Remove duplicate rows (only considers columns).

`df.sample(frac=0.5)`
Randomly select fraction of rows.

`df.sample(n=10)` Randomly select n rows.

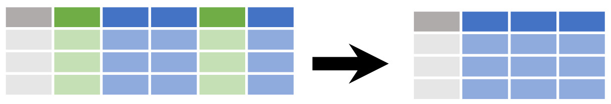
`df.nlargest(n, 'value’)`
Select and order top n entries.

`df.nsmallest(n, 'value')`
Select and order bottom n entries.

`df.head(n)`
Select first n rows.

`df.tail(n)`
Select last n rows.

Subset Variables - columns



`df[['width’, 'length’, 'species']]`
Select multiple columns with specific names.

`df['width']` *or* `df.width`
Select single column with specific name.

`df.filter(regex='`*`regex`*`')`
Select columns whose name matches regular expression *regex*.

Using query

query() allows Boolean expressions for filtering rows.

```
df.query('Length > 7')
df.query('Length > 7 and Width < 8')
df.query('Name.str.startswith("abc")',
                 engine="python")
```

Subsets - rows and columns

Use **df.loc[]** and **df.iloc[]** to select only rows, only columns or both.
Use **df.at[]** and **df.iat[]** to access a single value by row and column.
First index selects rows, second index columns.

`df.iloc[10:20]`
Select rows 10-20.

`df.iloc[:, [1, 2, 5]]`
Select columns in positions 1, 2 and 5 (first column is 0).

`df.loc[:, 'x2':'x4']`
Select all columns between x2 and x4 (inclusive).

`df.loc[df['a'] > 10, ['a’, 'c']]`
Select rows meeting logical condition, and only the specific columns .

`df.iat[1, 2]` Access single value by index

`df.at[4, 'A']` Access single value by label

Logic in Python (and pandas)

<	Less than	!=	Not equal to
>	Greater than	`df.column.isin(values)`	Group membership
==	Equals	`pd.isnull(obj)`	Is NaN
<=	Less than or equals	`pd.notnull(obj)`	Is not NaN
>=	Greater than or equals	`&,|,~,^,df.any(),df.all()`	Logical and, or, not, xor, any, all

regex (Regular Expressions) Examples

`'\.'`	Matches strings containing a period '.'
`'Length$'`	Matches strings ending with word 'Length'
`'^Sepal'`	Matches strings beginning with the word 'Sepal'
`'^x[1-5]$'`	Matches strings beginning with 'x' and ending with 1,2,3,4,5
`'^(?!Species$).*'`	Matches strings except the string 'Species'

Cheatsheet for pandas (http://pandas.pydata.org/ originally written by Irv Lustig, Princeton Consultants, inspired by Rstudio Data Wrangling Cheatsheet

Summarize Data

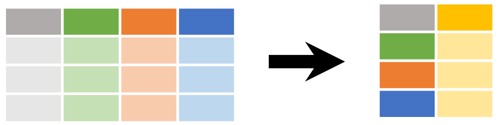
`df['w'].value_counts()`
Count number of rows with each unique value of variable

`len(df)`
# of rows in DataFrame.

`df.shape`
Tuple of # of rows, # of columns in DataFrame.

`df['w'].nunique()`
# of distinct values in a column.

`df.describe()`
Basic descriptive and statistics for each column (or GroupBy).



pandas provides a large set of **summary functions** that operate on different kinds of pandas objects (DataFrame columns, Series, GroupBy, Expanding and Rolling (see below)) and produce single values for each of the groups. When applied to a DataFrame, the result is returned as a pandas Series for each column. Examples:

`sum()`
Sum values of each object.

`count()`
Count non-NA/null values of each object.

`median()`
Median value of each object.

`quantile([0.25,0.75])`
Quantiles of each object.

`apply(`*function*`)`
Apply function to each object.

`min()`
Minimum value in each object.

`max()`
Maximum value in each object.

`mean()`
Mean value of each object.

`var()`
Variance of each object.

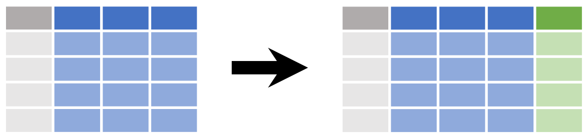
`std()`
Standard deviation of each object.

Handling Missing Data

`df.dropna()`
Drop rows with any column having NA/null data.

`df.fillna(value)`
Replace all NA/null data with value.

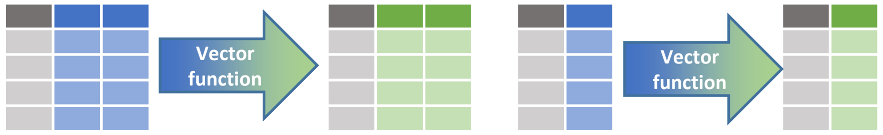
Make New Columns



`df.assign(Area=lambda df: df.Length*df.Height)`
Compute and append one or more new columns.

`df['Volume'] = df.Length*df.Height*df.Depth`
Add single column.

`pd.qcut(df.col, n, labels=False)`
Bin column into n buckets.



pandas provides a large set of **vector functions** that operate on all columns of a DataFrame or a single selected column (a pandas Series). These functions produce vectors of values for each of the columns, or a single Series for the individual Series. Examples:

`max(axis=1)`
Element-wise max.

`clip(lower=-10,upper=10)`
Trim values at input thresholds

`min(axis=1)`
Element-wise min.

`abs()`
Absolute value.

Group Data

`df.groupby(by="col")`
Return a GroupBy object, grouped by values in column named "col".

`df.groupby(level="ind")`
Return a GroupBy object, grouped by values in index level named "ind".

All of the summary functions listed above can be applied to a group. Additional GroupBy functions:

`size()`
Size of each group.

`agg(`*function*`)`
Aggregate group using function.

The examples below can also be applied to groups. In this case, the function is applied on a per-group basis, and the returned vectors are of the length of the original DataFrame.

`shift(1)`
Copy with values shifted by 1.

`rank(method='dense')`
Ranks with no gaps.

`rank(method='min')`
Ranks. Ties get min rank.

`rank(pct=True)`
Ranks rescaled to interval [0, 1].

`rank(method='first')`
Ranks. Ties go to first value.

`shift(-1)`
Copy with values lagged by 1.

`cumsum()`
Cumulative sum.

`cummax()`
Cumulative max.

`cummin()`
Cumulative min.

`cumprod()`
Cumulative product.

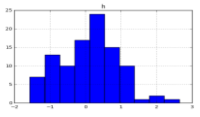
Windows

`df.expanding()`
Return an Expanding object allowing summary functions to be applied cumulatively.

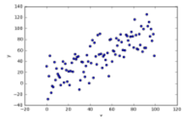
`df.rolling(n)`
Return a Rolling object allowing summary functions to be applied to windows of length n.

Plotting

`df.plot.hist()`
Histogram for each column



`df.plot.scatter(x='w',y='h')`
Scatter chart using pairs of points



Combine Data Sets

adf

x1	x2
A	1
B	2
C	3

+

bdf

x1	x3
A	T
B	F
D	T

=

Standard Joins

x1	x2	x3
A	1	T
B	2	F
C	3	NaN

`pd.merge(adf, bdf,`
`how='left', on='x1')`
Join matching rows from bdf to adf.

x1	x2	x3
A	1.0	T
B	2.0	F
D	NaN	T

`pd.merge(adf, bdf,`
`how='right', on='x1')`
Join matching rows from adf to bdf.

x1	x2	x3
A	1	T
B	2	F

`pd.merge(adf, bdf,`
`how='inner', on='x1')`
Join data. Retain only rows in both sets.

x1	x2	x3
A	1	T
B	2	F
C	3	NaN
D	NaN	T

`pd.merge(adf, bdf,`
`how='outer', on='x1')`
Join data. Retain all values, all rows.

Filtering Joins

x1	x2
A	1
B	2

`adf[adf.x1.isin(bdf.x1)]`
All rows in adf that have a match in bdf.

x1	x2
C	3

`adf[~adf.x1.isin(bdf.x1)]`
All rows in adf that do not have a match in bdf.

ydf

x1	x2
A	1
B	2
C	3

+

zdf

x1	x2
B	2
C	3
D	4

=

Set-like Operations

x1	x2
B	2
C	3

`pd.merge(ydf, zdf)`
Rows that appear in both ydf and zdf (Intersection).

x1	x2
A	1
B	2
C	3
D	4

`pd.merge(ydf, zdf, how='outer')`
Rows that appear in either or both ydf and zdf (Union).

x1	x2
A	1

```
pd.merge(ydf, zdf, how='outer',
             indicator=True)
.query('_merge == "left_only"')
.drop(columns=['_merge'])
```
Rows that appear in ydf but not zdf (Setdiff).

Cheatsheet for pandas (http://pandas.pydata.org/) originally written by Irv Lustig, Princeton Consultants, inspired by Rstudio Data Wrangling Cheatsheet

Pandas cheat sheet

January 30, 2021

1 Pandas cheat sheet

This notebook has some common data manipulations you might do while working in the popular Python data analysis library `pandas`. It assumes you're already are set up to analyze data in pandas using Python 3.

(If you're *not* set up, here's IRE's guide to setting up Python. Hit me up if you get stuck.)

1.0.1 Topics

- Importing pandas
- Creating a dataframe from a CSV
- Checking out the data
- Selecting columns of data
- Getting unique values in a column
- Running basic summary stats
- Sorting your data
- Filtering rows of data
- Filtering text columns with string methods
- Filtering against multiple values
- Exclusion filtering
- Adding a calculated column
- Filtering for nulls
- Grouping and aggregating data
- Pivot tables
- Applying a function across rows
- Joining data

1.0.2 Importing pandas

Before we can use pandas, we need to import it. The most common way to do this is:

[81]:

```
import pandas as pd
```

1.0.3 Creating a dataframe from a CSV

To begin with, let's import a CSV of Major League Baseball player salaries on opening day. The file, which is in the same directory as this notebook, is called `mlb.csv`.

Pandas has a `read_csv()` method that we can use to get this data into a dataframe (it has methods to read other file types, too). At minimum, you need to tell this method where the file lives:

```
[82]: mlb = pd.read_csv('mlb.csv')
```

1.0.4 Checking out the data

When you first load up your data, you'll want to get a sense of what's in there. A pandas dataframe has several useful things to help you get a quick read of your data:

- `.head()`: Shows you the first 5 records in the data frame (optionally, if you want to see a different number of records, you can pass in a number)
- `.tail()`: Same as `head()`, but it pull records from the end of the dataframe
- `.sample(n)` will give you a sample of n rows of the data – just pass in a number
- `.info()` will give you a count of non-null values in each column – useful for seeing if any columns have null values
- `.describe()` will compute summary stats for numeric columns
- `.columns` will list the column names
- `.dtypes` will list the data types of each column
- `.shape` will give you a pair of numbers: *(number of rows, number of columns)*

```
[83]: mlb.head()
```

```
[83]:                NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
      0   Clayton Kershaw  LAD  SP  33000000        2014      2020      7
      1      Zack Greinke  ARI  SP  31876966        2016      2021      6
      2       David Price  BOS  SP  30000000        2016      2022      7
      3    Miguel Cabrera  DET  1B  28000000        2014      2023     10
      4  Justin Verlander  DET  SP  28000000        2013      2019      7
```

```
[84]: mlb.tail()
```

```
[84]:                NAME TEAM POS  SALARY  START_YEAR  END_YEAR  YEARS
      863    Steve Selsky  BOS  RF  535000        2017      2017      1
      864   Stuart Turner  CIN   C  535000        2017      2017      1
      865  Vicente Campos  LAA  RP  535000        2017      2017      1
      866   Wandy Peralta  CIN  RP  535000        2017      2017      1
      867      Yandy Diaz  CLE  3B  535000        2017      2017      1
```

```
[85]: mlb.sample(5)
```

[85]:

```
                  NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
784         David Dahl  COL  CF    537000        2017      2017      1
734         Jett Bandy  MIL   C    539800        2017      2017      1
63        Wei-Yin Chen  MIA  SP  15500000        2016      2020      5
665  Kendall Graveman  OAK  SP    545000        2017      2017      1
395         Aaron Hill   SF  2B   2000000        2017      2017      1
```

[86]:

```
mlb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 868 entries, 0 to 867
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   NAME        868 non-null    object
 1   TEAM        868 non-null    object
 2   POS         868 non-null    object
 3   SALARY      868 non-null    int64
 4   START_YEAR  868 non-null    int64
 5   END_YEAR    868 non-null    int64
 6   YEARS       868 non-null    int64
dtypes: int64(4), object(3)
memory usage: 47.6+ KB
```

[87]:

```
mlb.describe()
```

[87]:

```
             SALARY   START_YEAR     END_YEAR       YEARS
count  8.680000e+02   868.000000   868.000000  868.000000
mean   4.468069e+06  2016.486175  2017.430876    1.944700
std    5.948459e+06     1.205923     1.163087    1.916764
min    5.350000e+05  2008.000000  2015.000000    1.000000
25%    5.455000e+05  2017.000000  2017.000000    1.000000
50%    1.562500e+06  2017.000000  2017.000000    1.000000
75%    6.000000e+06  2017.000000  2017.000000    2.000000
max    3.300000e+07  2017.000000  2027.000000   13.000000
```

[88]:

```
mlb.columns
```

[88]:

```
Index(['NAME', 'TEAM', 'POS', 'SALARY', 'START_YEAR', 'END_YEAR', 'YEARS'],
dtype='object')
```

[89]:

```
mlb.dtypes
```

[89]:

```
NAME          object
TEAM          object
POS           object
SALARY         int64
```

```
START_YEAR     int64
END_YEAR       int64
YEARS          int64
dtype: object
```

[90]:
```
mlb.shape
```

[90]:
```
(868, 7)
```

To get the number of records in a dataframe, you can access the first item in the `shape` pair, or you can just use the Python function `len()`:

[91]:
```
len(mlb)
```

[91]:
```
868
```

1.0.5 Selecting columns of data

If you need to select just one column of data, you can use "dot notation" (`mlb.SALARY`) as long as your column name doesn't have spaces and it isn't the name of a dataframe method (e.g., `product`). Otherwise, you can use "bracket notation" (`mlb['SALARY']`).

Selecting one column will return a `Series`.

If you want to select multiple columns of data, use bracket notation and pass in a *list* of columns that you want to select. In Python, a list is a collection of items enclosed in square brackets, separated by commas: `['SALARY', 'NAME']`.

Selecting multiple columns will return a `DataFrame`.

[92]:
```
# select one column of data
teams = mlb.TEAM

# bracket notation would do the same thing -- note the quotes around the column␣
 ↪name
# teams = mlb['TEAM']

teams.head()
```

[92]:
```
0    LAD
1    ARI
2    BOS
3    DET
4    DET
Name: TEAM, dtype: object
```

[93]:
```
type(teams)
```

```
[93]: pandas.core.series.Series
```

```
[94]: # select multiple columns of data
      salaries_and_names = mlb[['SALARY', 'NAME']]
```

```
[95]: salaries_and_names.head()
```

```
[95]:      SALARY               NAME
      0  33000000   Clayton Kershaw
      1  31876966      Zack Greinke
      2  30000000       David Price
      3  28000000    Miguel Cabrera
      4  28000000  Justin Verlander
```

```
[96]: type(salaries_and_names)
```

```
[96]: pandas.core.frame.DataFrame
```

1.0.6 Getting unique values in a column

As you evaluate your data, you'll often want to get a list of unique values in a column (for cleaning, filtering, grouping, etc.).

To do this, you can use the Series method `unique()`. If you wanted to get a list of baseball positions, you could do:

```
[97]: mlb.POS.unique()
```

```
[97]: array(['SP', '1B', 'RF', '2B', 'DH', 'CF', 'C', 'LF', '3B', 'SS', 'OF',
             'RP', 'P'], dtype=object)
```

If useful, you could also sort the results alphabetically with the Python `sorted()` function:

```
[98]: sorted(mlb.POS.unique())
```

```
[98]: ['1B', '2B', '3B', 'C', 'CF', 'DH', 'LF', 'OF', 'P', 'RF', 'RP', 'SP', 'SS']
```

Sometimes you just need the *number* of unique values in a column. To do this, you can use the pandas method `nunique()`:

```
[99]: mlb.POS.nunique()
```

```
[99]: 13
```

(You can also run `nunique()` on an entire dataframe:)

```
[100]: mlb.nunique()
```

```
[100]: NAME          867
       TEAM           30
       POS            13
       SALARY        419
       START_YEAR      8
       END_YEAR       10
       YEARS          11
       dtype: int64
```

If you want to count up the number of times a value appears in a column of data – the equivalent of doing a pivot table in Excel and aggregating by count – you can use the Series method `value_counts()`.

To get a list of MLB teams and the number of times each one appears in our salary data – in other words, the roster count for each team – we could do:

```
[101]: mlb.TEAM.value_counts()
```

```
[101]: TEX    34
       COL    32
       TB     32
       NYM    31
       CIN    31
       LAD    31
       BOS    31
       SEA    31
       SD     31
       STL    30
       LAA    30
       OAK    30
       ATL    30
       TOR    29
       MIN    29
       CWS    28
       MIA    28
       BAL    28
       ARI    28
       SF     28
       CLE    28
       KC     28
       HOU    27
       NYY    27
       DET    26
       PIT    26
       WSH    26
       MIL    26
       CHC    26
       PHI    26
```

```
Name: TEAM, dtype: int64
```

1.0.7 Running basic summary stats

Some of this already surfaced with `describe()`, but in some cases you'll want to compute these stats manually: - `sum()` - `mean()` - `median()` - `max()` - `min()`

You can run these on a Series (e.g., a column of data), or on an entire DataFrame.

```
[102]: mlb.SALARY.sum()
```

```
[102]: 3878284045
```

```
[103]: mlb.SALARY.mean()
```

```
[103]: 4468069.176267281
```

```
[104]: mlb.SALARY.median()
```

```
[104]: 1562500.0
```

```
[105]: mlb.SALARY.max()
```

```
[105]: 33000000
```

```
[106]: mlb.SALARY.min()
```

```
[106]: 535000
```

```
[107]: # entire dataframe
       mlb.mean()
```

```
[107]: SALARY        4.468069e+06
       START_YEAR    2.016486e+03
       END_YEAR      2.017431e+03
       YEARS         1.944700e+00
       dtype: float64
```

1.0.8 Sorting your data

You can use the `sort_values()` method to sort a dataframe by one or more columns. The default is to sort the values ascending; if you want your results sorted descending, specify `ascending=False`.

Let's sort our dataframe by `SALARY` descending:

```
[108]: mlb.sort_values('SALARY', ascending=False).head()
```

```
[108]:                NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
       0   Clayton Kershaw  LAD  SP  33000000        2014      2020      7
       1      Zack Greinke  ARI  SP  31876966        2016      2021      6
       2       David Price  BOS  SP  30000000        2016      2022      7
       3   Miguel Cabrera  DET  1B  28000000        2014      2023     10
       4  Justin Verlander  DET  SP  28000000        2013      2019      7
```

To sort by multiple columns, pass a list of columns to the `sort_values()` method – the sorting will happen in the order you specify in the list. You'll also need to pass a list to the `ascending` keyword argument, otherwise both will sort ascending.

Let's sort our dataframe first by `TEAM` ascending, then by `SALARY` descending:

```
[109]: mlb.sort_values(['TEAM', 'SALARY'], ascending=[True, False]).head()
```

```
[109]:                  NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
       1         Zack Greinke  ARI  SP  31876966        2016      2021      6
       137      Yasmany Tomas  ARI  OF   9500000        2015      2020      6
       149  Paul Goldschmidt  ARI  1B   8833333        2014      2018      5
       190       A.J. Pollock  ARI  CF   6750000        2016      2017      2
       262      Shelby Miller  ARI  SP   4700000        2017      2017      1
```

1.0.9 Filtering rows of data

To filter your data by some criteria, you'd pass your filtering condition(s) to a dataframe using bracket notation.

You can use Python's comparison operators in your filters, which include: - `>` greater than - `<` less than - `>=` greater than or equal to - `<=` less than or equal to - `==` equal to - `!=` not equal to

Example: You want to filter your data to keep records where the `TEAM` value is 'ARI':

```
[110]: diamondbacks = mlb[mlb.TEAM == 'ARI']
```

```
[111]: diamondbacks.head()
```

```
[111]:                  NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
       1         Zack Greinke  ARI  SP  31876966        2016      2021      6
       137      Yasmany Tomas  ARI  OF   9500000        2015      2020      6
       149  Paul Goldschmidt  ARI  1B   8833333        2014      2018      5
       190       A.J. Pollock  ARI  CF   6750000        2016      2017      2
       262      Shelby Miller  ARI  SP   4700000        2017      2017      1
```

We could filter to get all records where the `TEAM` value is *not* 'ARI':

```
[112]: non_diamondbacks = mlb[mlb.TEAM != 'ARI']
```

```
[113]: non_diamondbacks.head()
```

```
[113]:                NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
        0   Clayton Kershaw  LAD  SP  33000000        2014      2020      7
        2       David Price  BOS  SP  30000000        2016      2022      7
        3    Miguel Cabrera  DET  1B  28000000        2014      2023     10
        4  Justin Verlander  DET  SP  28000000        2013      2019      7
        5     Jason Heyward  CHC  RF  26055288        2016      2023      8
```

We could filter our data to just grab the players that make at least $1 million:

```
[114]: million_a_year  = mlb[mlb.SALARY >= 1000000]
```

```
[115]: million_a_year.head()
```

```
[115]:                NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
        0   Clayton Kershaw  LAD  SP  33000000        2014      2020      7
        1      Zack Greinke  ARI  SP  31876966        2016      2021      6
        2       David Price  BOS  SP  30000000        2016      2022      7
        3    Miguel Cabrera  DET  1B  28000000        2014      2023     10
        4  Justin Verlander  DET  SP  28000000        2013      2019      7
```

1.0.10 Filtering against multiple values

You can use the `isin()` method to test a value against multiple matches – just hand it a *list* of values to check against.

Example: Let's say we wanted to filter to get just players in Texas (in other words, just the Texas Rangers and the Houston Astros):

```
[116]: tx = mlb[mlb.TEAM.isin(['TEX', 'HOU'])]
```

```
[117]: tx.head()
```

```
[117]:               NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
        11  Prince Fielder  TEX  DH  24000000        2017      2017      1
        15     Cole Hamels  TEX  SP  22500000        2013      2018      6
        35    Shin-Soo Choo  TEX  RF  20000000        2014      2020      7
        45   Adrian Beltre  TEX  3B  18000000        2017      2018      2
        52     Brian McCann  HOU   C  17000000        2014      2018      5
```

1.0.11 Exclusion filtering

Sometimes it's easier to specify what records you *don't* want returned. To flip the meaning of a filter condition, prepend a tilde `~`.

For instance, if we wanted to get all players who are *not* from Texas, we'd use the same filter condition we just used to get the TX players but add a tilde at the beginning:

```
[118]: not_tx = mlb[~mlb.TEAM.isin(['TEX', 'HOU'])]
```

```
[119]: not_tx.head()
```

```
[119]:             NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
       0  Clayton Kershaw  LAD  SP  33000000        2014      2020      7
       1     Zack Greinke  ARI  SP  31876966        2016      2021      6
       2      David Price  BOS  SP  30000000        2016      2022      7
       3   Miguel Cabrera  DET  1B  28000000        2014      2023     10
       4  Justin Verlander  DET  SP  28000000        2013      2019      7
```

1.0.12 Filtering text columns with string methods

You can access the text values in a column with `.str`, and you can use any of Python's native string functions to manipulate them.

For our purposes, though, the pandas `str.contains()` method is useful for filtering data by matching text patterns.

If we wanted to get every player with 'John' in their name, we could do something like this:

```
[120]: johns = mlb[mlb.NAME.str.contains('John', case=False)]
```

```
[121]: johns.head()
```

```
[121]:             NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
       12   Johnny Cueto   SF  SP  23500000        2016      2021      6
       60    John Lackey  CHC  SP  16000000        2016      2017      2
       237   John Axford  OAK  RP   5500000        2016      2017      2
       255   Jim Johnson  ATL  RP   5000000        2017      2018      2
       295     John Jaso  PIT  1B   4000000        2016      2017      2
```

Note the `case=False` keyword argument – we're telling pandas to match case-insensitive. And if the pattern you're trying to match is more complex, the method is set up to support regular expressions by default.

1.0.13 Multiple filters

Sometimes you have multiple filters to apply to your data. Lots of the time, it makes sense to break the filters out into separate statements.

For instance, if you wanted to get all Texas players who make at least $1 million, I might do this:

```
[122]: tx = mlb[mlb.TEAM.isin(['TEX', 'HOU'])]

       # note that I'm filtering the dataframe I just created,  not the original `mlb`␣
        ↪dataframe
```

```
tx_million_a_year = tx[tx.SALARY >= 1000000]
```

```
[123]: tx_million_a_year.head()
```

```
[123]:               NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
       11  Prince Fielder  TEX  DH  24000000        2017      2017      1
       15     Cole Hamels  TEX  SP  22500000        2013      2018      6
       35   Shin-Soo Choo  TEX  RF  20000000        2014      2020      7
       45   Adrian Beltre  TEX  3B  18000000        2017      2018      2
       52    Brian McCann  HOU   C  17000000        2014      2018      5
```

But sometimes you want to chain your filters together into one statement. Use `|` for "or" and `&` for "and" rather than Python's built-in `or` and `and` statements, and use grouping parentheses around each statement.

The same filter in one statement:

```
[124]: tx_million_a_year = mlb[(mlb.TEAM.isin(['TEX', 'HOU'])) & (mlb.SALARY >␣
        ↪1000000)]
```

```
[125]: tx_million_a_year.head()
```

```
[125]:               NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS
       11  Prince Fielder  TEX  DH  24000000        2017      2017      1
       15     Cole Hamels  TEX  SP  22500000        2013      2018      6
       35   Shin-Soo Choo  TEX  RF  20000000        2014      2020      7
       45   Adrian Beltre  TEX  3B  18000000        2017      2018      2
       52    Brian McCann  HOU   C  17000000        2014      2018      5
```

Do what works for you and makes sense in context, but I find the first version a little easier to read.

1.0.14 Adding a calculated column

To add a new column to a dataframe, use bracket notation to supply the name of the new column (in quotes, or apostrophes, as long as they match), then set it equal to a value – maybe a calculation derived from other data in your dataframe.

For example, let's create a new column, `contract_total`, that multiplies the annual salary by the number of contract years:

```
[126]: mlb['contract_total'] = mlb['SALARY'] * mlb['YEARS']
```

```
[127]: mlb.head()
```

```
[127]:               NAME TEAM POS    SALARY  START_YEAR  END_YEAR  YEARS  \
       0  Clayton Kershaw  LAD  SP  33000000        2014      2020      7
       1     Zack Greinke  ARI  SP  31876966        2016      2021      6
```

```
2       David Price  BOS  SP  30000000        2016      2022       7
3    Miguel Cabrera  DET  1B  28000000        2014      2023      10
4  Justin Verlander  DET  SP  28000000        2013      2019       7

   contract_total
0       231000000
1       191261796
2       210000000
3       280000000
4       196000000
```

1.0.15 Filtering for nulls

You can use the `isnull()` method to get records that are null, or `notnull()` to get records that aren't. The most common use I've seen for these methods is during filtering to see how many records you're missing (and, therefore, how that affects your analysis).

The MLB data is complete, so to demonstrate this, let's load up a new data set: A cut of the National Inventory of Dams database, courtesy of the NICAR data library. (We'll need to specify the `encoding` on this CSV because it's not UTF-8.)

[128]:

```
dams = pd.read_csv('dams.csv',
                   encoding='latin-1')
```

[129]:

```
dams.head()
```

[129]:

```
     NIDID                        Dam_Name   Insp_Date Submit_Date  \
0  VA16104  CLIFFORD D. CRAIG MEMORIAL DAM  2007-09-06  2013-03-12
1  VA07915        GREENE MOUNTAIN LAKE DAM  2008-07-14  2013-03-12
2  VA06906                     LEHMANS DAM         NaN  2013-03-12
3  VA13905                           LURAY  2010-12-22  2013-02-28
4  VA06106                     MATHEWS DAM         NaN  2013-03-12

                         River        City_02      County State Cong_Dist  \
0       TRIB. TO ROANOKE RIVER          SALEM  ROANOKE CO    VA      VA09
1                     BLUE RUN  ADVANCE MILLS      GREENE    VA      VA05
2                    GOUGH RUN       MARLBORO   FREDERICK    VA      VA10
3  SOUTH FORK SHENANDOAH RIVER     RILEYVILLE        PAGE    VA      VA06
4                   TR-GAP RUN     RECTORTOWN    FAUQUIER    VA      VA05

                 Cong_Rep  … Fed_Fund Fed_Design Fed_Con  Fed_Reg Fed_Insp  \
0  H. MORGAN GRIFFITH (R)  …      NaN        NaN     NaN      NaN      NaN
1         ROBERT HURT (R)  …      NaN        NaN     NaN      NaN      NaN
2       FRANK R. WOLF (R)  …      NaN        NaN     NaN      NaN      NaN
3       BOB GOODLATTE (R)  …      NaN        NaN     NaN     FERC     FERC
4         ROBERT HURT (R)  …      NaN        NaN     NaN      NaN      NaN
```

```
  Srce_Agncy Oth_StrucID Num_Struc Longitude Latitude
0         VA         NaN         0  -80.1750  37.2250
1         VA         NaN         0  -78.4366  38.2700
2         VA         NaN         0  -78.3083  39.1516
3       FERC         NaN         1  -78.4999  38.6774
4         VA         NaN         0  -77.9600  38.9800

[5 rows x 42 columns]
```

Maybe we're interested in looking at the year the dam was completed (the `Year_Comp`) column. Running `.info()` on the dataframe shows that we're missing some values:

[130]:
```
dams.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2482 entries, 0 to 2481
Data columns (total 42 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   NIDID          2482 non-null   object
 1   Dam_Name       2480 non-null   object
 2   Insp_Date      1093 non-null   object
 3   Submit_Date    2482 non-null   object
 4   River          2264 non-null   object
 5   City_02        1407 non-null   object
 6   County         2477 non-null   object
 7   State          2482 non-null   object
 8   Cong_Dist      2445 non-null   object
 9   Cong_Rep       2445 non-null   object
 10  Party          2445 non-null   object
 11  Owner_Type     2482 non-null   object
 12  Owner_Name     2199 non-null   object
 13  Year_Comp      1663 non-null   float64
 14  Year_Mod       438 non-null    object
 15  Private_Dam    2482 non-null   object
 16  NPDP_Hazard    1487 non-null   object
 17  Permit_Auth    2482 non-null   object
 18  Insp_Auth      2482 non-null   object
 19  Enfrc_Auth     2482 non-null   object
 20  Juris_Dam      2482 non-null   object
 21  NID_Height     2468 non-null   float64
 22  NID_Storage    2453 non-null   float64
 23  Dam_Length     1813 non-null   float64
 24  Max_Discharge  831 non-null    float64
 25  Drain_Area     1188 non-null   float64
 26  Dam_Designer   831 non-null    object
 27  EAP            2482 non-null   object
 28  Insp_Freq      2482 non-null   int64
 29  St_Reg_Dam     2482 non-null   object
 30  St_Reg_Agncy   2374 non-null   object
 31  Volume         530 non-null    float64
 32  Fed_Fund       219 non-null    object
 33  Fed_Design     578 non-null    object
 34  Fed_Con        221 non-null    object
 35  Fed_Reg        132 non-null    object
 36  Fed_Insp       146 non-null    object
 37  Srce_Agncy     2482 non-null   object
 38  Oth_StrucID    17 non-null     object
 39  Num_Struc      2482 non-null   int64
 40  Longitude      2482 non-null   float64
 41  Latitude       2482 non-null   float64
dtypes: float64(9), int64(2), object(31)
memory usage: 814.5+ KB
```

We can filter for isnull() to take a closer look:

[131]:

```
no_year_comp = dams[dams.Year_Comp.isnull()]
```

[132]:

```
no_year_comp.head()
```

[132]:

```
       NIDID                Dam_Name   Insp_Date Submit_Date  \
43   DE00095         WAPLES POND DAM         NaN  2013-02-04
114  VA17710            LEE LAKE DAM  2003-09-08  2013-03-12
152  VA19104  HIDDEN VALLEY LAKE DAM  2004-12-31  2013-03-12
212  MD00018          EMMITSBURG DAM  2012-08-30  2013-02-04
263  DE00070         BLAIRS POND DAM  2011-07-26  2013-02-04

                River             City_02        County State Cong_Dist  \
43    PRIMEHOOK CREEK  BROADKILL BEACH  E        SUSSEX    DE      DE00
114    WILDERNESS RUN            MINE RUN  SPOTSYLVANIA    VA      VA07
152     BRUMLEY CREEK         DUNCANVILLE    WASHINGTON    VA      VA09
212      TURKEY CREEK          EMMITSBURG     FREDERICK    MD      MD08
263  BEAVERDAM BRANCH             HOUSTON          KENT    DE      DE00

                   Cong_Rep  … Fed_Fund Fed_Design Fed_Con  Fed_Reg  \
43   JOHN C. CARNEY JR. (D)  …      NaN        NaN     NaN      NaN
114         ERIC CANTOR (R)  …      NaN        NaN     NaN      NaN
152  H. MORGAN GRIFFITH (R)  …      NaN        NaN     NaN      NaN
212    CHRIS VAN HOLLEN (D)  …      NaN        NaN     NaN      NaN
263  JOHN C. CARNEY JR. (D)  …      NaN        NaN     NaN      NaN

    Fed_Insp Srce_Agncy Oth_StrucID Num_Struc Longitude Latitude
43       NaN         DE         NaN         0  -75.3087  38.8240
114      NaN         VA         NaN         0  -77.7400  38.3033
152      NaN         VA         NaN         0  -82.0733  36.8500
212      NaN         MD         NaN         0  -77.3885  39.6959
```

```
263      NaN         DE         NaN         0  -75.4848  38.9039

[5 rows x 42 columns]
```

How many are we missing? That will help us determine whether the analysis would be valid:

[133]:
```
# calculate the percentage of records with no Year_Comp value
# (part / whole) * 100

(len(no_year_comp) / len(dams)) * 100
```

[133]:
```
32.99758259468171
```

So this piece of our analysis would exclude one-third of our records – something you'd need to explain to your audience, if indeed your reporting showed that the results of your analysis would still be meaningful.

To get records where the `Year_Comp` is not null, we'd use `notnull()`:

[134]:
```
has_year_comp = dams[dams.Year_Comp.notnull()]
```

[135]:
```
has_year_comp.head()
```

[135]:
```
     NIDID                        Dam_Name   Insp_Date Submit_Date  \
0  VA16104  CLIFFORD D. CRAIG MEMORIAL DAM  2007-09-06  2013-03-12
1  VA07915        GREENE MOUNTAIN LAKE DAM  2008-07-14  2013-03-12
2  VA06906                     LEHMANS DAM         NaN  2013-03-12
3  VA13905                           LURAY  2010-12-22  2013-02-28
4  VA06106                     MATHEWS DAM         NaN  2013-03-12

                         River        City_02      County State Cong_Dist  \
0       TRIB. TO ROANOKE RIVER          SALEM  ROANOKE CO    VA      VA09
1                     BLUE RUN  ADVANCE MILLS      GREENE    VA      VA05
2                    GOUGH RUN       MARLBORO   FREDERICK    VA      VA10
3  SOUTH FORK SHENANDOAH RIVER     RILEYVILLE        PAGE    VA      VA06
4                   TR-GAP RUN     RECTORTOWN    FAUQUIER    VA      VA05

                 Cong_Rep  … Fed_Fund Fed_Design Fed_Con  Fed_Reg Fed_Insp  \
0  H. MORGAN GRIFFITH (R)  …      NaN        NaN     NaN      NaN      NaN
1         ROBERT HURT (R)  …      NaN        NaN     NaN      NaN      NaN
2       FRANK R. WOLF (R)  …      NaN        NaN     NaN      NaN      NaN
3       BOB GOODLATTE (R)  …      NaN        NaN     NaN     FERC     FERC
4         ROBERT HURT (R)  …      NaN        NaN     NaN      NaN      NaN

  Srce_Agncy Oth_StrucID Num_Struc Longitude Latitude
0         VA         NaN         0  -80.1750  37.2250
1         VA         NaN         0  -78.4366  38.2700
2         VA         NaN         0  -78.3083  39.1516
```

```
3       FERC          NaN         1  -78.4999  38.6774
4         VA          NaN         0  -77.9600  38.9800

[5 rows x 42 columns]
```

What years remain? Let's use `value_counts()` to find out:

```
[136]: has_year_comp.Year_Comp.value_counts()
```

```
[136]: 1960.0    86
       1965.0    56
       1974.0    54
       1955.0    52
       1967.0    51
                 ..
       1832.0     1
       1914.0     1
       1682.0     1
       1922.0     1
       1881.0     1
       Name: Year_Comp, Length: 142, dtype: int64
```

(To sort by year, not count, we could tack on a `sort_index()`:

```
[137]: has_year_comp.Year_Comp.value_counts().sort_index()
```

```
[137]: 1682.0     1
       1694.0     1
       1780.0     2
       1800.0    11
       1801.0     1
                 ..
       2008.0     7
       2009.0     6
       2010.0     2
       2011.0     1
       2012.0     1
       Name: Year_Comp, Length: 142, dtype: int64
```

1.0.16 Grouping and aggregating data

You can use the `groupby()` method to group and aggregate data in pandas, similar to what you'd get by running a pivot table in Excel or a `GROUP BY` query in SQL. We'll also provide the aggregate function to use.

Let's group our baseball salary data by team to see which teams have the biggest payrolls – in other words, we want to use `sum()` as our aggregate function:

```
[138]: grouped_mlb = mlb.groupby('TEAM').sum()
```

```
[139]: grouped_mlb.head()
```

```
[139]:          SALARY  START_YEAR  END_YEAR  YEARS  contract_total
       TEAM
       ARI     90730499       56469     56485     44       341698661
       ATL    137339527       60491     60525     64       593579662
       BAL    161684185       56460     56485     53       510234644
       BOS    174287098       62510     62541     62       749308534
       CHC    170088502       52429     52456     53       648189802
```

If you don't specify what columns you want, it will run `sum()` on every numeric column. Typically I select just the grouping column and the column I'm running the aggregation on:

```
[140]: grouped_mlb = mlb[['TEAM', 'SALARY']].groupby('TEAM').sum()
```

```
[141]: grouped_mlb.head()
```

```
[141]:          SALARY
       TEAM
       ARI     90730499
       ATL    137339527
       BAL    161684185
       BOS    174287098
       CHC    170088502
```

… and we can sort descending, with `head()` to get the top payrolls:

```
[142]: grouped_mlb.sort_values('SALARY', ascending=False).head(10)
```

```
[142]:          SALARY
       TEAM
       LAD    187989811
       DET    180250600
       TEX    178431396
       SF     176531278
       NYM    176284679
       BOS    174287098
       NYY    170389199
       CHC    170088502
       WSH    162742157
       TOR    162353367
```

You can use different aggregate functions, too. Let's say we wanted to get the top median salaries by team:

```
[143]: mlb[['TEAM', 'SALARY']].groupby('TEAM').median().sort_values('SALARY',␣
        ↪ascending=False).head(10)
```

```
[143]:         SALARY
       TEAM
       WSH   4000000
       KC    4000000
       HOU   3725000
       BAL   3462500
       PIT   2962500
       CLE   2950000
       TOR   2887500
       STL   2762500
       MIA   2762500
       CHC   2750000
```

You can group by multiple columns by passing a list. Here, we'll select our columns of interest and group by TEAM, then by POS, using sum() as our aggregate function:

```
[144]: mlb[['TEAM', 'POS', 'SALARY']].groupby(['TEAM', 'POS']).sum()
```

```
[144]:             SALARY
       TEAM POS
       ARI  1B   10183333
            3B    1127200
            C     4437500
            CF    7289500
            LF     542500
       …             …
       WSH  LF   22971429
            RF   13625000
            RP   15698700
            SP   54886428
            SS     537800

       [306 rows x 1 columns]
```

1.0.17 Pivot tables

Sometimes you need a full-blown pivot table, and pandas has a function to make one.

For this example, we'll look at some foreign trade data – specifically, eel product imports from 2010 to mid-2017:

```
[145]: eels = pd.read_csv('eels.csv')
```

```
[146]: eels.head()
```

```
[146]:    year  month  country       product  kilos  dollars
       0  2010      1    CHINA  EELS FROZEN  49087   393583
       1  2010      1    JAPAN   EELS FRESH    263     7651
       2  2010      1   TAIWAN  EELS FROZEN   9979   116359
       3  2010      1  VIETNAM   EELS FRESH   1938    10851
       4  2010      1  VIETNAM  EELS FROZEN  21851    69955
```

Let's run a pivot table where the grouping column is `country`, the values are the sum of `kilos`, and the columns are the year:

```
[147]: pivoted_sums = pd.pivot_table(eels,
                                     index='country',
                                     columns='year',
                                     values='kilos',
                                     aggfunc=sum)
```

```
[148]: pivoted_sums.head()
```

```
[148]: year             2010      2011       2012       2013       2014       2015  \
       country
       BANGLADESH        NaN       NaN       13.0        NaN        NaN      600.0
       BURMA             NaN       NaN        NaN        NaN        NaN        NaN
       CANADA        13552.0   24968.0   110796.0    44455.0    31546.0    28619.0
       CHILE             NaN       NaN        NaN        NaN     6185.0        NaN
       CHINA        372397.0  249232.0  1437392.0  1090135.0  1753140.0  4713882.0

       year              2016       2017
       country
       BANGLADESH         NaN        NaN
       BURMA            699.0        NaN
       CANADA         68568.0    23571.0
       CHILE              NaN        NaN
       CHINA        4578546.0  1771272.0
```

Let's sort by the 2017 value. While we're at it, let's fill in null values (`NaN`) with zeroes using the `fillna()` method.

```
[149]: pivoted_sums.sort_values(2017, ascending=False).fillna(0)
```

```
[149]: year                    2010      2011       2012       2013       2014  \
       country
       CHINA               372397.0  249232.0  1437392.0  1090135.0  1753140.0
       TAIWAN               73842.0       0.0    53774.0    39752.0    83478.0
       SOUTH KOREA          42929.0   41385.0    28146.0    27353.0    37708.0
       JAPAN                 1326.0    2509.0    32255.0   105758.0    40177.0
       THAILAND              2866.0    5018.0     9488.0     4488.0    15110.0
       VIETNAM              63718.0  155488.0   118063.0   100828.0    38112.0
       CANADA               13552.0   24968.0   110796.0    44455.0    31546.0
```

```
PORTUGAL             2081.0    3672.0     2579.0     2041.0     7215.0
PANAMA                  0.0       0.0        0.0    11849.0        0.0
BANGLADESH              0.0       0.0       13.0        0.0        0.0
BURMA                   0.0       0.0        0.0        0.0        0.0
CHILE                   0.0       0.0        0.0        0.0     6185.0
CHINA - HONG KONG       0.0       0.0        0.0        0.0        0.0
COSTA RICA              0.0       0.0        0.0        0.0        0.0
INDIA                   0.0       0.0        0.0        0.0        0.0
MEXICO                  0.0       0.0        0.0     4000.0        0.0
NEW ZEALAND             0.0    2652.0      900.0      270.0        0.0
NORWAY                  0.0       0.0        0.0    17391.0        0.0
PAKISTAN                0.0       0.0        0.0    22453.0        0.0
PHILIPPINES             0.0       0.0        0.0      610.0        0.0
POLAND                  0.0       0.0     1296.0        0.0      864.0
SENEGAL                 0.0    1350.0        0.0        0.0        0.0
SPAIN                   0.0       0.0      977.0      275.0     1019.0
UKRAINE                 0.0       0.0        0.0        0.0        0.0

year                    2015       2016       2017
country
CHINA              4713882.0  4578546.0  1771272.0
TAIWAN               48272.0    99535.0    44087.0
SOUTH KOREA           8386.0    14729.0    42904.0
JAPAN                69699.0    71748.0    37892.0
THAILAND             41771.0    26931.0    31884.0
VIETNAM              36859.0    96179.0    28490.0
CANADA               28619.0    68568.0    23571.0
PORTUGAL              8013.0     9105.0     6747.0
PANAMA                   0.0        0.0      974.0
BANGLADESH             600.0        0.0        0.0
BURMA                    0.0      699.0        0.0
CHILE                    0.0        0.0        0.0
CHINA - HONG KONG        0.0      735.0        0.0
COSTA RICA               0.0      563.0        0.0
INDIA                    0.0     2200.0        0.0
MEXICO               16860.0        0.0        0.0
NEW ZEALAND              0.0        0.0        0.0
NORWAY                   0.0        0.0        0.0
PAKISTAN                 0.0        0.0        0.0
PHILIPPINES              0.0        0.0        0.0
POLAND                   0.0        0.0        0.0
SENEGAL                  0.0        0.0        0.0
SPAIN                  719.0     1008.0        0.0
UKRAINE                  0.0    11414.0        0.0
```

1.0.18 Applying a function across rows

Often, you'll want to calculate a value for every column but it won't be that simple, and you'll write a separate function that accepts one row of data, does some calculations and returns a value. We'll use the `apply()` method to accomplish this.

For this example, we're going to load up a CSV of gators killed by hunters in Florida:

```
[150]: gators = pd.read_csv('gators.csv')
```

```
[151]: gators.head()
```

```
[151]:    Year  Area Number    Area Name  Carcass Size Harvest Date Location
       0  2000          101  LAKE PIERCE  11 ft. 5 in.    09-22-2000
       1  2000          101  LAKE PIERCE   9 ft. 0 in.    10-02-2000
       2  2000          101  LAKE PIERCE  8 ft. 10 in.    10-06-2000
       3  2000          101  LAKE PIERCE   8 ft. 0 in.    09-25-2000
       4  2000          101  LAKE PIERCE   8 ft. 0 in.    10-07-2000
```

We want to find the longest gator in our data, of course, but there's a problem: right now, the caracass size value is being stored as text: `{} ft. {} in.`. The pattern is predicatable, though, and we can use some Python to turn those values into constant numbers – inches – that we can then sort on. Here's our function:

```
[152]: def get_inches(row):
           '''Accepts a row from our dataframe, calculates carcass length in inches␣
        ↪and returns that value'''

           # get the value in the 'Carcass Size' column
           carcass_size = row['Carcass Size']

           # split the text on 'ft.'
           # the result is a list
           size_split = carcass_size.split('ft.')

           # strip whitespace from the first item ([0]) in the resulting list -- the␣
        ↪feet --
           # and coerce it to an integer with the Python `int()` function
           feet = int(size_split[0].strip())

           # in the second item ([1]) in the resulting list -- the inches -- replace␣
        ↪'in.' with nothing,
           # strip whitespace and coerce to an integer
           inches = int(size_split[1].replace('in.', '').strip())

           # add the feet times 12 plus the inches and return that value
           return inches + (feet * 12)
```

Now we're going to create a new column, `length_in` and use the `apply()` method to apply our function to every row. The axis=1 keyword argument means that we're applying our function row-wise, not column-wise.

```
[153]: gators['length_in'] = gators.apply(get_inches, axis=1)
```

```
[154]: gators.sort_values('length_in', ascending=False).head()
```

```
[154]:        Year  Area Number                       Area Name  Carcass Size  \
       44996  2010          502  ST. JOHNS RIVER (LAKE POINSETT)  14 ft. 3 in.
       78315  2014          828                 HIGHLANDS COUNTY  14 ft. 3 in.
       31961  2008          510                      LAKE JESUP  14 ft. 1 in.
       70005  2013          733                    LAKE TALQUIN  14 ft. 1 in.
       63077  2012          828                 HIGHLANDS COUNTY  14 ft. 0 in.

             Harvest Date                        Location  length_in
       44996   10-31-2010                                        171
       78315   10-28-2014            LITTLE RED WATER LAKE       171
       31961   08-26-2008                                        169
       70005   09-02-2013                                        169
       63077   10-31-2012  boat ramp north of boat ramp road     168
```

1.0.19 Joining data

You can use merge() to join data in pandas.

In this simple example, we're going to take a CSV of country population data in which each country is represented by an ISO 3166-1 numeric country code and join it to a CSV that's basically a lookup table with the ISO codes and the names of the countries to which they refer.

Some of the country codes have leading zeroes, so we're going to use the dtype keyword when we import each CSV to specify that the 'code' column in each dataset should be treated as a string (text), not a number.

```
[155]: pop_csv = pd.read_csv('country-population.csv', dtype={'code': str})
```

```
[156]: pop_csv.head()
```

```
[156]:   code  pop2000  pop2001  pop2002  pop2003  pop2004  pop2005  pop2006  \
       0  108   6401.0   6556.0   6742.0   6953.0   7182.0   7423.0   7675.0
       1  174    542.0    556.0    569.0    583.0    597.0    612.0    626.0
       2  262    718.0    733.0    746.0    759.0    771.0    783.0    796.0
       3  232   3393.0   3497.0   3615.0   3738.0   3859.0   3969.0   4067.0
       4  231  66537.0  68492.0  70497.0  72545.0  74624.0  76727.0  78851.0

           pop2007  pop2008  pop2009  pop2010  pop2011  pop2012  pop2013  pop2014  \
       0    7940.0   8212.0   8489.0   8767.0   9044.0   9320.0   9600.0   9892.0
       1     642.0    657.0    673.0    690.0    707.0    724.0    742.0    759.0
       2     809.0    823.0    837.0    851.0    866.0    881.0    897.0    912.0
```

```
3   4153.0   4233.0   4310.0   4391.0   4475.0   4561.0   4651.0   4746.0
4  81000.0  83185.0  85416.0  87703.0  90047.0  92444.0  94888.0  97367.0

   pop2015
0  10199.0
1    777.0
2    927.0
3   4847.0
4  99873.0
```

```
[157]: code_csv = pd.read_csv('country-codes.csv', dtype={'code': str})
```

```
[158]: code_csv.head()
```

```
[158]:   code   country
       0  108   Burundi
       1  174   Comoros
       2  262  Djibouti
       3  232   Eritrea
       4  231  Ethiopia
```

Now we'll use `merge()` to join them.

The `on` keyword argument tells the method what column to join on. If the names of the columns were different, you'd use `left_on` and `right_on`, with the "left" dataframe being the first one you hand to the `merge()` function.

The `how` keyword argument tells the method what type of join to use – the default is `'inner'`.

```
[159]: joined_data = pd.merge(pop_csv,
                              code_csv,
                              on='code',
                              how='left')
```

```
[160]: joined_data.head()
```

```
[160]:   code  pop2000  pop2001  pop2002  pop2003  pop2004  pop2005  pop2006  \
       0  108   6401.0   6556.0   6742.0   6953.0   7182.0   7423.0   7675.0
       1  174    542.0    556.0    569.0    583.0    597.0    612.0    626.0
       2  262    718.0    733.0    746.0    759.0    771.0    783.0    796.0
       3  232   3393.0   3497.0   3615.0   3738.0   3859.0   3969.0   4067.0
       4  231  66537.0  68492.0  70497.0  72545.0  74624.0  76727.0  78851.0

          pop2007  pop2008  pop2009  pop2010  pop2011  pop2012  pop2013  pop2014  \
       0   7940.0   8212.0   8489.0   8767.0   9044.0   9320.0   9600.0   9892.0
       1    642.0    657.0    673.0    690.0    707.0    724.0    742.0    759.0
       2    809.0    823.0    837.0    851.0    866.0    881.0    897.0    912.0
       3   4153.0   4233.0   4310.0   4391.0   4475.0   4561.0   4651.0   4746.0
```

```
4  81000.0  83185.0  85416.0  87703.0  90047.0  92444.0  94888.0  97367.0

   pop2015   country
0  10199.0   Burundi
1    777.0   Comoros
2    927.0  Djibouti
3   4847.0   Eritrea
4  99873.0  Ethiopia
```