Streamlined Data Ingestion with pandas

Thursday, 26 November 2020 7:38 PM

Importing Data from Flat Files

Data Frames

- `pandas` -specific structure for two-dimensional data

	Country	Population	Area (sq. mi.)
0	Afghanistan	31056997	647500
1	Albania	3581655	28748
2	Algeria	32930091	2381740
3	American Samoa	57794	199
4	Andorra	71201	468
5	Angola	12127071	1246700
6	Anguilla	13477	102
7	Antigua & Barbuda	69108	443
8	Argentina	39921833	2766890
9	Armenia	2976372	29800
10	Aruba	71891	193

Column Labels

Row Labels (Index)

Flat Files

- Simple, easy-to-produce format
- Data stored as plain text (no formatting)
- One row per line
- Values for different fields are separated by a delimiter
- Most common flat file type: comma-separated values
- One `pandas` function to load them all: `read_csv()`

Loading CSVs

- Sample of `us_tax_data_2016.csv`

```
STATEFIPS,STATE,zipcode,agi_stub,...,N11901,A11901,N11902,A11902
1,AL,0,1,...,63420,51444,711580,1831661
```

```
import pandas as pd

tax_data = pd.read_csv("us_tax_data_2016.csv")
tax_data.head(4)
```

```
   STATEFIPS STATE  zipcode  agi_stub   ...     N11901  A11901  N11902   A11902
0          1    AL        0         1   ...      63420   51444  711580  1831661
1          1    AL        0         2   ...      74090  110889  416090  1173463
2          1    AL        0         3   ...      64000  143060  195130   543284
3          1    AL        0         4   ...      45020  128920  117410   381329

[4 rows x 147 columns]
```

Loading Other Flat Files

- Specify a different delimiter with `sep`
- Sample of `us_tax_data_2016.tsv`

```
STATEFIPS    STATE    zipcode    agi_stub    ...    N11901    A11901    N11902    A11902
1    AL    0    1    ...    63420    51444    711580    1831661
```

```
import pandas as pd
tax_data = pd.read_csv("us_tax_data_2016.tsv", sep="\t")
tax_data.head(3)
```

```
   STATEFIPS STATE  zipcode  agi_stub   ...     N11901  A11901  N11902   A11902
0          1    AL        0         1   ...      63420   51444  711580  1831661
1          1    AL        0         2   ...      74090  110889  416090  1173463
2          1    AL        0         3   ...      64000  143060  195130   543284

[3 rows x 147 columns]
```

U.S. Tax Data

```
tax_data = pd.read_csv('us_tax_data_2016.csv')

print(tax_data.shape)
```

```
(179796, 147)
```

Limiting Columns

- Choose columns to load with the `usecols` keyword argument
- Accepts a list of column numbers or names, or a function to filter column names

```
col_names = ['STATEFIPS', 'STATE', 'zipcode', 'agi_stub', 'N1']
col_nums = [0, 1, 2, 3, 4]
# Choose columns to load by name
tax_data_v1 = pd.read_csv('us_tax_data_2016.csv',
                          usecols=col_names)
# Choose columns to load by number
tax_data_v2 = pd.read_csv('us_tax_data_2016.csv',
                          usecols=col_nums)
print(tax_data_v1.equals(tax_data_v2))
```

```
True
```

Limiting Rows

- Limit the number of rows loaded with the `nrows` keyword argument

```
tax_data_first1000 = pd.read_csv('us_tax_data_2016.csv', nrows=1000)
print(tax_data_first1000.shape)
```

```
(1000, 147)
```

Limiting Rows

- Use `nrows` and `skiprows` together to process a file in chunks
- `skiprows` accepts a list of row numbers, a number of rows, or a function to filter rows
- Set `header=None` so `pandas` knows there are no column names

```
tax_data_next500 = pd.read_csv('us_tax_data_2016.csv',
                               nrows=500,
                               skiprows=1000,
                               header=None)
```

Limiting Rows

```
print(tax_data_next500.head(1))
```

```
   0   1     2   3    4    5   6   7    8    9    10  ...   136  137   138  139  140  141  142  143
0   1  AL  35565   4  270    0  250   0  210  790  280  ...  1854  260  1978    0    0    0    0   50

[1 rows x 147 columns]
```

Limiting Rows


```
print(tax_data_next500.head(1))
```

```
   0   1     2   3    4    5   6   7    8    9    10  ...   136  137   138  139  140  141  142  143
0   1  AL  35565   4  270    0  250   0  210  790  280  ...  1854  260  1978    0    0    0    0   50

[1 rows x 147 columns]
```

Assigning Column Names

- Supply column names by passing a list to the `names` argument
- The list **MUST** have a name for every column in your data
- **If you only need to rename a few columns, do it after the import!**

Assigning Column Names

```
col_names = list(tax_data_first1000)
tax_data_next500 = pd.read_csv('us_tax_data_2016.csv',
                               nrows=500,
                               skiprows=1000,
                               header=None,
                               names=col_names)

print(tax_data_next500.head(1))
```

```
   STATEFIPS STATE  zipcode  agi_stub   ...  N11901  A11901  N11902  A11902
0          1    AL    35565         4   ...      50     222     210     794

[1 rows x 147 columns]
```

Common Flat File Import Issues

- Column data types are wrong
- Values are missing
- Records that cannot be read by `pandas`

Specifying Data Types

- `pandas` automatically infers column data types

```
print(tax_data.dtypes)
```

```
STATEFIPS      int64
STATE         object
zipcode        int64
agi_stub       int64
N1             int64
               ...
N11902         int64
A11902         int64
Length: 147, dtype: object
```

Specifying Data Types

- Use the `dtype` keyword argument to specify column data types
- `dtype` takes a dictionary of column names and data types

```
tax_data = pd.read_csv("us_tax_data_2016.csv", dtype={"zipcode": str})
print(tax_data.dtypes)
```

```
STATEFIPS      int64
STATE         object
zipcode       object
agi_stub       int64
N1             int64
               ...
N11902         int64
A11902         int64
Length: 147, dtype: object
```

Customizing Missing Data Values

- `pandas` automatically interprets some values as missing or NA

```
print(tax_data.head())
```

```
   STATEFIPS STATE  zipcode  agi_stub      N1  ...  A85300  N11901  A11901  N11902   A11902
0          1    AL        0         1  815440  ...       0   63420   51444  711580  1831661
1          1    AL        0         2  495830  ...       0   74090  110889  416090  1173463
2          1    AL        0         3  263390  ...       0   64000  143060  195130   543284
3          1    AL        0         4  167190  ...       0   45020  128920  117410   381329
4          1    AL        0         5  217440  ...      19   82940  423629  126130   506526

[5 rows x 147 columns]
```

Customizing Missing Data Values

- Use the `na_values` keyword argument to set custom missing values
- Can pass a single value, list, or dictionary of columns and values

```
tax_data = pd.read_csv("us_tax_data_2016.csv",
                       na_values={"zipcode" : 0})
print(tax_data[tax_data.zipcode.isna()])
```

```
        STATEFIPS STATE  zipcode  agi_stub       N1  ...      A85300  N11901    A11901   N11902   A11902
0               1    AL      NaN         1   815440  ...           0   63420     51444   711580  1831661
1               1    AL      NaN         2   495830  ...           0   74090    110889   416090  1173463
2               1    AL      NaN         3   263390  ...           0   64000    143060   195130   543284
...           ...   ...      ...       ...      ...  ...         ...     ...       ...      ...      ...
179034         56    WY      NaN         5    38030  ...         121   13230     73326    22250    99589
179035         56    WY      NaN         6     8480  ...       53835    3630    128149     2250   125557

[306 rows x 147 columns]
```

Lines with Errors

- Set `error_bad_lines=False` to skip unparseable records
- Set `warn_bad_lines=True` to see messages when records are skipped

```
tax_data = pd.read_csv("us_tax_data_2016_corrupt.csv",
                       error_bad_lines=False,
                       warn_bad_lines=True)
```

```
b'Skipping line 3: expected 147 fields, saw 148\n'
```

Spreadsheets

- Also known as Excel files
- Data stored in tabular form, with cells arranged in rows and columns
- Unlike flat files, can have formatting and formulas
- Multiple spreadsheets can exist in a workbook

Loading Spreadsheets

- Spreadsheets have their own loading function in `pandas`: `read_excel()`

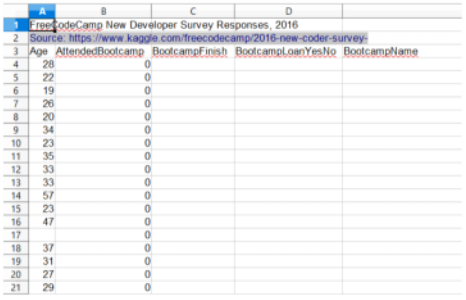
	A	B	C	D	E	F	G	H	I
1	Age	AttendedBootcamp	BootcampFinish	BootcampLoanYesNo	BootcampName	BootcampRecommend	ChildrenNumber	CityPopulation	CodeEventConfere
2	28	0						between 100,000 and 1 million	
3	22	0						between 100,000 and 1 million	
4	19	0						more than 1 million	
5	26	0						more than 1 million	
6	20	0						between 100,000 and 1 million	
7	34	0						more than 1 million	
8	23	0						more than 1 million	
9	35	0						between 100,000 and 1 million	
10	33	0						between 100,000 and 1 million	
11	33	0						more than 1 million	
12	57	0						less than 100,000	
13	23	0						more than 1 million	
14	47	0						more than 1 million	
15		0						between 100,000 and 1 million	
16	37	0						1 between 100,000 and 1 million	
17	31	0						more than 1 million	
18	27	0						more than 1 million	
19	29	0						less than 100,000	
20	30	0						more than 1 million	
21	30	0						less than 100,000	
22	32	0						1 more than 1 million	
23	25	0						between 100,000 and 1 million	
24	29	0						between 100,000 and 1 million	
25	44	0						more than 1 million	
26	21	0						more than 1 million	

Loading Spreadsheets

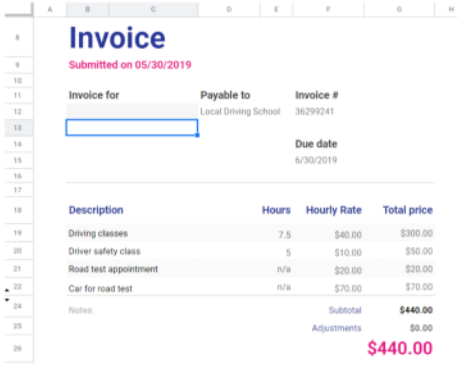
```
import pandas as pd

# Read the Excel file
survey_data = pd.read_excel("fcc_survey.xlsx")

# View the first 5 lines of data
print(survey_data.head())
```

```
    Age  AttendedBootcamp       ...                    SchoolMajor  StudentDebtOwe
0  28.0               0.0       ...                            NaN           20000
1  22.0               0.0       ...                            NaN             NaN
2  19.0               0.0       ...                            NaN             NaN
3  26.0               0.0       ...        Cinematography And Film            7000
4  20.0               0.0       ...                            NaN             NaN

[5 rows x 98 columns]
```

Loading Select Columns and Rows



	A	B	C	D
1	FreeCodeCamp New Developer Survey Responses, 2016			
2	Source: https://www.kaggle.com/freecodecamp/2016-new-coder-survey-			
3	Age	AttendedBootcamp	BootcampFinish	BootcampLoanYesNo	BootcampName
4	28	0			
5	22	0			
6	19	0			
7	26	0			
8	20	0			
9	34	0			
10	23	0			
11	35	0			
12	33	0			
13	33	0			
14	57	0			
15	23	0			
16	47	0			
17		0			
18	37	0			
19	31	0			
20	27	0			
21	29	0			



Invoice

Submitted on 05/30/2019

Invoice for	Payable to	Invoice #
	Local Driving School	36299241

Due date: 6/30/2019

Description	Hours	Hourly Rate	Total price
Driving classes	7.5	$40.00	$300.00
Driver safety class	5	$10.00	$50.00
Road test appointment	n/a	$20.00	$20.00
Car for road test	n/a	$70.00	$70.00
Notes:		Subtotal	$440.00
		Adjustments	$0.00
			$440.00

Loading Select Columns and Rows

- `read_excel()` has many keyword arguments in common with `read_csv()`
  - `nrows` : limit number of rows to load
  - `skiprows` : specify number of rows or row numbers to skip
  - `usecols` : choose columns by name, positional number, or letter (e.g. "A:P")

Loading Select Columns and Rows

	W	X	Y	Z	AA	AB	AR
1							
2							
3	CommuteTime	CountryCitizen	CountryLive	EmploymentField	EmploymentFieldOther	EmploymentStatus	Income
4		35 United States of America	United States of America	office and administrative support		Employed for wages	32000
5		90 United States of America	United States of America	food and beverage		Employed for wages	15000
6		45 United States of America	United States of America	finance		Employed for wages	48000
7		45 United States of America	United States of America	arts, entertainment, sports, or media		Employed for wages	43000
8		10 United States of America	United States of America	education		Employed for wages	6000
9		45 United States of America	United States of America	finance		Self-employed freelancer	40000
10		60 Singapore	Singapore	software development		Employed for wages	32000

Loading Select Columns and Rows

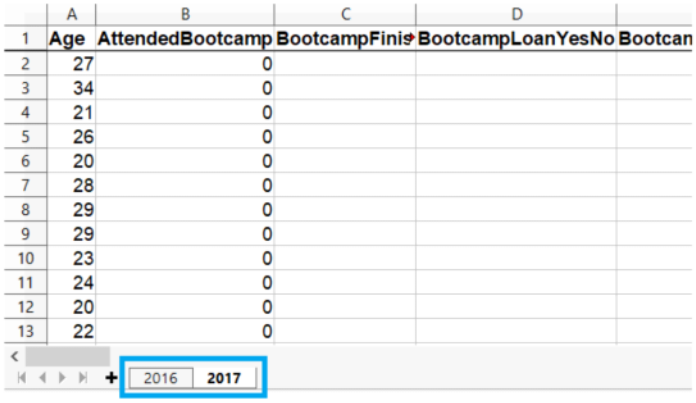
```
# Read columns W-AB and AR of file, skipping metadata header
survey_data = pd.read_excel("fcc_survey_with_headers.xlsx",
                            skiprows=2,
                            usecols="W:AB, AR")

# View data
print(survey_data.head())
```

```
   CommuteTime            CountryCitizen  ...    EmploymentFieldOther    EmploymentStatus   Income
0         35.0  United States of America  ...                     NaN  Employed for wages  32000.0
1         90.0  United States of America  ...                     NaN  Employed for wages  15000.0
2         45.0  United States of America  ...                     NaN  Employed for wages  48000.0
3         45.0  United States of America  ...                     NaN  Employed for wages  43000.0
4         10.0  United States of America  ...                     NaN  Employed for wages   6000.0

[5 rows x 7 columns]
```

Selecting Sheets to Load

- `read_excel()` loads the first sheet in an Excel file by default
- Use the `sheet_name` keyword argument to load other sheets
- Specify spreadsheets by name and/or (zero-indexed) position number
- Pass a list of names/numbers to load more than one sheet at a time
- Any arguments passed to `read_excel()` apply to all sheets read

Selecting Sheets to Load



Loading Select Sheets

```
# Get the second sheet by position index
survey_data_sheet2 = pd.read_excel('fcc_survey.xlsx',
                                   sheet_name=1)

# Get the second sheet by name
survey_data_2017 = pd.read_excel('fcc_survey.xlsx',
                                 sheet_name='2017')

print(survey_data_sheet2.equals(survey_data_2017))
```

```
True
```

Loading All Sheets

- Passing `sheet_name=None` to `read_excel()` reads all sheets in a workbook

```
survey_responses = pd.read_excel("fcc_survey.xlsx", sheet_name=None)

print(type(survey_responses))
```

```
<class 'collections.OrderedDict'>
```

```
for key, value in survey_responses.items():
    print(key, type(value))
```

```
2016 <class 'pandas.core.frame.DataFrame'>
2017 <class 'pandas.core.frame.DataFrame'>
```

Remember, each value is a data frame corresponding to a worksheet, and each key is a sheet name.

We have one data frame per sheet, which is great if sheets have different columns or describe different subjects.

For the survey data, each sheet has the same columns, just for different years.

Putting It All Together

```
# Create empty data frame to hold all loaded sheets
all_responses = pd.DataFrame()

# Iterate through data frames in dictionary
for sheet_name, frame in survey_responses.items():
    # Add a column so we know which year data is from
    frame["Year"] = sheet_name

    # Add each data frame to all_responses
    all_responses = all_responses.append(frame)

# View years in data
print(all_responses.Year.unique())
```

```
['2016' '2017']
```

For each data frame, we add a column, Year, containing the sheet name, so we know which dataset a record came from.

Boolean Data

- `True` / `False` data

	A	B	C	D	E	F	G
1	ID.x	AttendedBootcamp	AttendedBootCampYesNo	AttendedBootcampTF	BootcampLoan	LoanYesNo	LoanTF
89	6ca993739cf368a8b764ecb355359da2	0	No	FALSE			
90	48439bea8554956d8a577b5ad63f9524	0	No	FALSE			
91	79aebaf36d9ccd10d0f1b2a9dff9543c	0	No	FALSE			
92	ea0319686c422efc9fe9c0364a6fb117	0	No	FALSE			
93	915f2ed898947d610e3b41c10bed72fe	0	No	FALSE			
94	24b64d38e5025f28bd5c0be8fd6ae9be	0	No	FALSE			
95	1a124244c3f5501bc0a5c96ff2387cc0	1	Yes	TRUE		0 No	FALSE
96	fe4b00562e4aaa53b4b6956d0631f021	0	No	FALSE			
97	9cc94bb3a1e6a029c54e1baaad346055	0	No	FALSE			
98	16e7110386a7c024adcb4753cdd042b8	0	No	FALSE			
99	f78cf5785eba1985f5bdb9de8dfdda69	1	Yes	TRUE		0 No	FALSE
100	65bb23364ae1581e38e35b166d47ef1e	0	No	FALSE			
101	ae712b0271669b79479c8051e56956cc	0	No	FALSE			
102	3aaae9b5b7a39f4a6b4febedc5152c2f	0	No	FALSE			
103	50eb0912d0efb00dee1b0590a48c8668	0	No	FALSE			
104	8a4040d2531281194752475dc2c53609	0	No	FALSE			
105	5aaa2d5e9596cccc55ca93a8d7de6127	0	No	FALSE			
106	b20068a41d1199ada2e55b5fdfd254f2	0	No	FALSE			
107	e90cb86f2b59212724bce3b2dad53276	0	No	FALSE			
108	7c196c58dbee549119218158b2b28d8d	0	No	FALSE			
109	bc28535824b91a4a5b7cceb99bfe8d4f	0	No	FALSE			

pandas and Booleans

```
bootcamp_data = pd.read_excel("fcc_survey_booleans.xlsx")
print(bootcamp_data.dtypes)
```

```
ID.x                     object
AttendedBootcamp        float64
AttendedBootCampYesNo    object
AttendedBootcampTF      float64
BootcampLoan            float64
LoanYesNo                object
LoanTF                  float64
dtype: object
```

pandas and Booleans

```
# Count True values
print(bootcamp_data.sum())
```

```
AttendedBootcamp      38
AttendedBootcampTF    38
BootcampLoan          14
LoanTF                14
dtype: object
```

```
# Count NAs
print(bootcamp_data.isna().sum())
```

```
ID.x                    0
AttendedBootcamp        0
AttendedBootCampYesNo   0
AttendedBootcampTF      0
BootcampLoan          964
LoanYesNo             964
LoanTF                964
dtype: int64
```

```
# Load data, casting True/False columns as Boolean
bool_data = pd.read_excel("fcc_survey_booleans.xlsx",
                          dtype={"AttendedBootcamp": bool,
                                 "AttendedBootCampYesNo": bool,
                                 "AttendedBootcampTF":bool,
                                 "BootcampLoan": bool,
                                 "LoanYesNo": bool,
                                 "LoanTF": bool})
print(bool_data.dtypes)
```

```
ID.x                    object
AttendedBootcamp          bool
AttendedBootCampYesNo     bool
AttendedBootcampTF        bool
BootcampLoan              bool
LoanYesNo                 bool
LoanTF                    bool
dtype: object
```

```
# Count True values
print(bool_data.sum())
```

```
AttendedBootcamp          38
AttendedBootCampYesNo    1000
AttendedBootcampTF         38
BootcampLoan              978
LoanYesNo                1000
LoanTF                    978
dtype: object
```

```
# Count NA values
print(bool_data.isna().sum())
```

```
ID.x                    0
AttendedBootcamp        0
AttendedBootCampYesNo   0
AttendedBootcampTF      0
BootcampLoan            0
LoanYesNo               0
LoanTF                  0
dtype: int64
```

pandas and Booleans

- `pandas` loads `True` / `False` columns as float data by default
- Specify a column should be `bool` with `read_excel()` 's `dtype` argument
- Boolean columns can *only* have `True` and `False` values
- **NA/missing values in Boolean columns are changed to `True`**
- `pandas` automatically recognizes some values as `True` / `False` in Boolean columns
- Unrecognized values in a Boolean column are also changed to `True`

We can solve the issue of the yes/no columns being misinterpreted with read Excel's true values and false values arguments.

Setting Custom True/False Values

- Use `read_excel()` 's `true_values` argument to set custom `True` values
- Use `false_values` to set custom `False` values
- Each takes a list of values to treat as `True` / `False` , respectively
- Custom `True` / `False` values are only applied to columns set as Boolean

Setting Custom True/False Values


```
# Load data with Boolean dtypes and custom T/F values
bool_data = pd.read_excel("fcc_survey_booleans.xlsx",
                          dtype={"AttendedBootcamp": bool,
                                 "AttendedBootCampYesNo": bool,
                                 "AttendedBootcampTF":bool,
                                 "BootcampLoan": bool,
                                 "LoanYesNo": bool,
                                 "LoanTF": bool},
                          true_values=["Yes"],
                          false_values=["No"])
```


Setting Custom True/False Values


```
print(bool_data.sum())
```

```
AttendedBootcamp                    38
AttendedBootCampYesNo               38
AttendedBootcampTF                  38
BootcampLoan                       978
LoanYesNo                          978
LoanTF                             978
dtype: object
```

But there is still the issue of NA's being coded as True

Boolean Considerations

- Are there missing values, or could there be in the future?
- How will this column be used in analysis?
- What would happen if a value were incorrectly coded as `True` ?
- Could the data be modeled another way (e.g., as floats or integers)?

Date and Time Data

- Dates and times have their own data type and internal representation
- Datetime values can be translated into string representations
- Common set of codes to describe datetime string formatting

pandas and Datetimes

- Datetime columns are loaded as objects (strings) by default
- Specify that columns have datetimes with the `parse_dates` argument (not `dtype` !)
- `parse_dates` can accept:
  - a list of column names or numbers to parse
  - a list containing lists of columns to combine and parse
  - a dictionary where keys are new column names and values are lists of columns to parse together

pandas and Datetimes

	BG	BH	BI	BJ	BK
1	Part1StartTime	Part1EndTime	Part2StartDate	Part2StartTime	Part2EndTime
2	2016-03-29 21:23:13	2016-03-29 21:24:53	2016-03-29	21:24:57	03292016 21:27:25
3	2016-03-29 21:24:59	2016-03-29 21:27:09	2016-03-29	21:27:14	03292016 21:29:10
4	2016-03-29 21:25:37	2016-03-29 21:27:11	2016-03-29	21:27:13	03292016 21:28:21
5	2016-03-29 21:21:37	2016-03-29 21:28:47	2016-03-29	21:28:51	03292016 21:30:51
6	2016-03-29 21:26:22	2016-03-29 21:29:27	2016-03-29	21:29:32	03292016 21:31:54
7	2016-03-29 21:29:33	2016-03-29 21:30:40	2016-03-29	21:30:44	03292016 21:32:19
8	2016-03-29 21:24:58	2016-03-29 21:31:49	2016-03-29	21:31:51	03292016 21:33:08
9	2016-03-29 21:30:44	2016-03-29 21:33:58	2016-03-29	21:34:04	03292016 21:37:32
10	2016-03-29 21:33:05	2016-03-29 21:34:21	2016-03-29	21:34:25	03292016 21:35:40
11	2016-03-29 21:34:52	2016-03-29 21:36:17	2016-03-29	21:36:23	03292016 21:39:18
12	2016-03-29 21:32:59	2016-03-29 21:36:26	2016-03-29	21:36:29	03292016 21:39:27

Parsing Dates

```
# List columns of dates to parse
date_cols = ["Part1StartTime", "Part1EndTime"]

# Load file, parsing standard datetime columns
survey_df = pd.read_excel("fcc_survey.xlsx",
                          parse_dates=date_cols)
```

Parsing Dates

```
# Check data types of timestamp columns
print(survey_df[["Part1StartTime",
                 "Part1EndTime",
                 "Part2StartDate",
                 "Part2StartTime",
                 "Part2EndTime"]].dtypes)
```

```
Part1StartTime    datetime64[ns]
Part1EndTime      datetime64[ns]
Part2StartDate            object
Part2StartTime            object
Part2EndTime              object
dtype: object
```

Parsing Dates

```
# List columns of dates to parse
date_cols = ["Part1StartTime",
             "Part1EndTime",
             [["Part2StartDate", "Part2StartTime"]]]

# Load file, parsing standard and split datetime columns
survey_df = pd.read_excel("fcc_survey.xlsx",
                          parse_dates=date_cols)
print(survey_df.head(3))
```

```
  Part2StartDate_Part2StartTime   Age       ...    SchoolMajor  StudentDebtOwe
0           2016-03-29 21:24:57  28.0       ...            NaN           20000
1           2016-03-29 21:27:14  22.0       ...            NaN             NaN
2           2016-03-29 21:27:13  19.0       ...            NaN             NaN

[3 rows x 98 columns]
```

Parsing Dates

```
# List columns of dates to parse
date_cols = {"Part1Start": "Part1StartTime",
             "Part1End": "Part1EndTime",
             "Part2Start": ["Part2StartDate",
                            "Part2StartTime"]}

# Load file, parsing standard and split datetime columns
survey_df = pd.read_excel("fcc_survey.xlsx",
                          parse_dates=date_cols)

print(survey_df.Part2Start.head(3))
```

```
0   2016-03-29 21:24:57
1   2016-03-29 21:27:14
2   2016-03-29 21:27:13
Name: Part2Start, dtype: datetime64[ns]
```

Non-Standard Dates

- `parse_dates` doesn't work with non-standard datetime formats
- Use `pd.to_datetime()` after loading data if `parse_dates` won't work
- `to_datetime()` arguments:
  - Data frame and column to convert
  - `format` : string representation of datetime format

Datetime Formatting

Code	Meaning	Example
%Y	Year (4-digit)	1999
%m	Month (zero-padded)	03
%d	Day (zero-padded)	01
%H	Hour (24-hour clock)	21
%M	Minute (zero-padded)	09
%S	Second (zero-padded)	05

Parsing Non-Standard Dates

	BG	BH	BI	BJ	BK
1	Part1StartTime	Part1EndTime	Part2StartDate	Part2StartTime	Part2EndTime
2	2016-03-29 21:23:13	2016-03-29 21:24:53	2016-03-29	21:24:57	03292016 21:27:25
3	2016-03-29 21:24:59	2016-03-29 21:27:09	2016-03-29	21:27:14	03292016 21:29:10
4	2016-03-29 21:25:37	2016-03-29 21:27:11	2016-03-29	21:27:13	03292016 21:28:21
5	2016-03-29 21:21:37	2016-03-29 21:28:47	2016-03-29	21:28:51	03292016 21:30:51
6	2016-03-29 21:26:22	2016-03-29 21:29:27	2016-03-29	21:29:32	03292016 21:31:54
7	2016-03-29 21:29:33	2016-03-29 21:30:40	2016-03-29	21:30:44	03292016 21:32:19
8	2016-03-29 21:24:58	2016-03-29 21:31:49	2016-03-29	21:31:51	03292016 21:33:08
9	2016-03-29 21:30:44	2016-03-29 21:33:58	2016-03-29	21:34:04	03292016 21:37:32
10	2016-03-29 21:33:05	2016-03-29 21:34:21	2016-03-29	21:34:25	03292016 21:35:40
11	2016-03-29 21:34:52	2016-03-29 21:36:17	2016-03-29	21:36:23	03292016 21:39:18
12	2016-03-29 21:32:59	2016-03-29 21:36:26	2016-03-29	21:36:29	03292016 21:39:27

```
format_string = "%m%d%Y %H:%M:%S"
survey_df["Part2EndTime"] = pd.to_datetime(survey_df["Part2EndTime"],
                                           format=format_string)
```

Parsing Non-Standard Dates

```
print(survey_df.Part2EndTime.head())
```

```
0   2016-03-29 21:27:25
1   2016-03-29 21:29:10
2   2016-03-29 21:28:21
3   2016-03-29 21:30:51
4   2016-03-29 21:31:54
Name: Part2EndTime, dtype: datetime64[ns]
```

Importing Data from Databases

Relational Databases

- Data about entities is organized into tables
- Each row or record is an instance of an entity
- Each column has information about an attribute
- Tables can be linked to each other via unique keys
- Support more data, multiple simultaneous users, and data quality controls
- Data types are specified for each column
- SQL (Structured Query Language) to interact with databases

Common Relational Databases

- SQLite databases are computer files

Connecting to Databases

- Two-step process:
  1. Create way to connect to database
  2. Query database

Creating a Database Engine

SQLAlchemy

- `sqlalchemy` 's `create_engine()` makes an engine to handle database connections
  - Needs string URL of database to connect to
  - SQLite URL format: `sqlite:///filename.db`

Querying Databases

- `pd.read_sql(query, engine)` to load in data from a database
- Arguments
  - `query` : String containing SQL query to run or table to load
  - `engine` : Connection/database engine object

SQL Review: SELECT

- Used to query data from a database
- Basic syntax:

```
SELECT [column_names] FROM [table_name];
```

- To get all data in a table:

```
SELECT * FROM [table_name];
```

- Code style: keywords in ALL CAPS, semicolon (;) to end a statement

Getting Data from a Database

```
# Load pandas and sqlalchemy's create_engine
import pandas as pd
from sqlalchemy import create_engine

# Create database engine to manage connections
engine = create_engine("sqlite:///data.db")

# Load entire weather table by table name
weather = pd.read_sql("weather", engine)
```

```
# Create database engine to manage connections
engine = create_engine("sqlite:///data.db")

# Load entire weather table with SQL
weather = pd.read_sql("SELECT * FROM weather", engine)

print(weather.head())
```

```
      station                      name  latitude  ...   prcp  snow  tavg tmax  tmin
0  USW00094728  NY CITY CENTRAL PARK, NY US  40.77898  ...   0.00   0.0         52    42
1  USW00094728  NY CITY CENTRAL PARK, NY US  40.77898  ...   0.00   0.0         48    39
2  USW00094728  NY CITY CENTRAL PARK, NY US  40.77898  ...   0.00   0.0         48    42
3  USW00094728  NY CITY CENTRAL PARK, NY US  40.77898  ...   0.00   0.0         51    40
4  USW00094728  NY CITY CENTRAL PARK, NY US  40.77898  ...   0.75   0.0         61    50

[5 rows x 13 columns]
```

SELECTing Columns

- `SELECT [column names] FROM [table name];`
- Example:

```
SELECT date, tavg
FROM weather;
```

WHERE Clauses

- Use a `WHERE` clause to selectively import records

```
SELECT [column_names]
  FROM [table_name]
 WHERE [condition];
```

Filtering by Numbers

- Compare numbers with mathematical operators
  - `=`
  - `>` and `>=`
  - `<` and `<=`
  - `<>` (not equal to)

- Example:

```
SELECT *
FROM weather
WHERE tmax > 32;
```

Filtering Text

- Match exact strings with the `=` sign and the text to match
- String matching is case-sensitive
- Example:

```
/* Get records about incidents in Brooklyn */
SELECT *
FROM hpd311calls
WHERE borough = 'BROOKLYN';
```

SQL and pandas

```
# Load libraries
import pandas as pd
from sqlalchemy import create_engine
# Create database engine
engine = create_engine("sqlite:///data.db")
# Write query to get records from Brooklyn
query = """SELECT *
             FROM hpd311calls
            WHERE borough = 'BROOKLYN';"""
# Query the database
brooklyn_calls = pd.read_sql(query, engine)
print(brookyn_calls.borough.unique())
```

```
['BROOKLYN']
```

Combining Conditions: AND

- `WHERE` clauses with `AND` return records that meet all conditions

```
# Write query to get records about plumbing in the Bronx
and_query = """SELECT *
                FROM hpd311calls
               WHERE borough = 'BRONX'
                 AND complaint_type = 'PLUMBING';"""
# Get calls about plumbing issues in the Bronx
bx_plumbing_calls = pd.read_sql(and_query, engine)

# Check record count
print(bx_plumbing_calls.shape)
```

```
(2016, 8)
```

Combining Conditions: OR

- `WHERE` clauses with `OR` return records that meet at least one condition

```
# Write query to get records about water leaks or plumbing
or_query = """SELECT *
                FROM hpd311calls
               WHERE complaint_type = 'WATER LEAK'
                  OR complaint_type = 'PLUMBING';"""
# Get calls that are about plumbing or water leaks
leaks_or_plumbing = pd.read_sql(or_query, engine)

# Check record count
print(leaks_or_plumbing.shape)
```

```
(10684, 8)
```

Getting DISTINCT Values

- Get unique values for one or more columns with `SELECT DISTINCT`
- Syntax:

```
SELECT DISTINCT [column names] FROM [table];
```

- Remove duplicate records:

```
SELECT DISTINCT * FROM [table];
```

```
/* Get unique street addresses and boroughs */
SELECT DISTINCT incident_address,
       borough
  FROM hpd311calls;
```

Aggregate Functions

- Query a database directly for descriptive statistics
- Aggregate functions
  - `SUM`
  - `AVG`
  - `MAX`
  - `MIN`

Aggregate Functions

- `SUM` , `AVG` , `MAX` , `MIN`
  - Each takes a single column name

```
SELECT AVG(tmax) FROM weather;
```

- `COUNT`
  - Get number of rows that meet query conditions

```
SELECT COUNT(*) FROM [table_name];
```

  - Get number of unique values in a column

```
SELECT COUNT(DISTINCT [column_names]) FROM [table_name];
```

GROUP BY

- Aggregate functions calculate a single summary statistic by default
- Summarize data by categories with `GROUP BY` statements
- Remember to also select the column you're grouping by!

Remember to select the column you're grouping by as well as the aggregate

```
/* Get counts of plumbing calls by borough */
SELECT borough,
       COUNT(*)
  FROM hpd311calls
 WHERE complaint_type = 'PLUMBING'
 GROUP BY borough;
```

Counting by Groups

```
# Create database engine
engine = create_engine("sqlite:///data.db")

# Write query to get plumbing call counts by borough
query = """SELECT borough, COUNT(*)
             FROM hpd311calls
            WHERE complaint_type = 'PLUMBING'
            GROUP BY borough;"""

# Query databse and create data frame
plumbing_call_counts = pd.read_sql(query, engine)
```

Counting by Groups

```
print(plumbing_call_counts)
```

```
         borough  COUNT(*)
0          BRONX      2016
1       BROOKLYN      2702
2      MANHATTAN      1413
3         QUEENS       808
4  STATEN ISLAND       178
```

Keys

- Database records have unique identifiers, or keys

unique_key	created_date	agency	complaint_type	incident_zip	incident_address	community_board	borough
Filter	Filter	Fi...	Filter	Filter	Filter	Filter	Filter
38070822	01/01/2018	HPD	HEAT/HOT WATER	10468	2786 JEROME AVEN...	07 BRONX	BRONX
38065299	01/01/2018	HPD	PLUMBING	10003	323 EAST 12 STRE...	03 MANHATTAN	MANHA...
38066653	01/01/2018	HPD	HEAT/HOT WATER	10452	1235 GRAND CONC...	04 BRONX	BRONX
38070264	01/01/2018	HPD	HEAT/HOT WATER	10032	656 WEST 171 STR...	12 MANHATTAN	MANHA...
38072466	01/01/2018	HPD	HEAT/HOT WATER	11213	1030 PARK PLACE	08 BROOKLYN	BROOK...

Joining Tables

station	name	latitude	longitude	elevation	date	month	awnd	prcp	snow	tavg	tmax	tmin
USW00094728	NY CITY CEN...	40.77898	-73.96925	42.7	01/01/2018	January	7.83	0	0		19	7
USW00094728	NY CITY CEN...	40.77898	-73.96925	42.7	01/02/2018	January	8.05	0	0		26	13
USW00094728	NY CITY CEN...	40.77898	-73.96925	42.7	01/03/2018	January	3.13	0	0		30	16
USW00094728	NY CITY CEN...	40.77898	-73.96925	42.7	01/04/2018	January	12.53	0.76	9.8		29	19
USW00094728	NY CITY CEN...	40.77898	-73.96925	42.7	01/05/2018	January	12.97	0	0		19	9
USW00094728	NY CITY CEN...	40.77898	-73.96925	42.7	01/06/2018	January	10.96	0	0		13	6
USW00094728	NY CITY CEN...	40.77898	-73.96925	42.7	01/07/2018	January	6.49	0	0		18	5

unique_key	created_date	agency	complaint_type	incident_zip	incident_address	community_board	borough
38070822	01/01/2018	HPD	HEAT/HOT WATER	10468	2786 JEROME AVEN...	07 BRONX	BRONX
38065299	01/01/2018	HPD	PLUMBING	10003	323 EAST 12 STRE...	03 MANHATTAN	MANHATTAN
38066653	01/01/2018	HPD	HEAT/HOT WATER	10452	1235 GRAND CONC...	04 BRONX	BRONX
38070264	01/01/2018	HPD	HEAT/HOT WATER	10032	656 WEST 171 STR...	12 MANHATTAN	MANHATTAN
38072466	01/01/2018	HPD	HEAT/HOT WATER	11213	1030 PARK PLACE	08 BROOKLYN	BROOKLYN

Joining Tables

```
SELECT *
  FROM hpd311calls
       JOIN weather
       ON hpd311calls.created_date = weather.date;
```

- Use dot notation (`table.column`) when working with multiple tables
- Default join only returns records whose key values appear in both tables
- Make sure join keys are the same data type or nothing will match

Joining and Filtering

```
/* Get only heat/hot water calls and join in weather data */
SELECT *
  FROM hpd311calls
       JOIN weather
       ON hpd311calls.created_date = weather.date
 WHERE hpd311calls.complaint_type = 'HEAT/HOT WATER';
```

Joining and Aggregating

```
/* Get call counts by borough */
SELECT hpd311calls.borough,
          COUNT(*)
  FROM hpd311calls
 GROUP BY hpd311calls.borough;
```

Joining and Aggregating

```
/* Get call counts by borough
   and join in population and housing counts */
SELECT hpd311calls.borough,
       COUNT(*),
       boro_census.total_population,
       boro_census.housing_units
  FROM hpd311calls
 GROUP BY hpd311calls.borough
```

Joining and Aggregating

```
/* Get call counts by borough
   and join in population and housing counts */
SELECT hpd311calls.borough,
       COUNT(*),
       boro_census.total_population,
       boro_census.housing_units
  FROM hpd311calls
       JOIN boro_census
       ON hpd311calls.borough = boro_census.borough
 GROUP BY hpd311calls.borough;
```

```
query = """SELECT hpd311calls.borough,
                  COUNT(*),
                  boro_census.total_population,
                  boro_census.housing_units
             FROM hpd311calls
                  JOIN boro_census
                  ON hpd311calls.borough = boro_census.borough
            GROUP BY hpd311calls.borough;"""

call_counts = pd.read_sql(query, engine)
print(call_counts)
```

	borough	COUNT(*)	total_population	housing_units
0	BRONX	29874	1455846	524488
1	BROOKLYN	31722	2635121	1028383
2	MANHATTAN	20196	1653877	872645
3	QUEENS	11384	2339280	850422
4	STATEN ISLAND	1322	475948	179179

Review

- SQL order of keywords
  - `SELECT`
  - `FROM`
  - `JOIN`
  - `WHERE`
  - `GROUP BY`

Importing JSON Data and Working with APIs

Javascript Object Notation (JSON)

- Common web data format
- Not tabular
  - Records don't have to all have the same set of attributes
- Data organized into collections of objects
- Objects are collections of attribute-value pairs
- Nested JSON: objects within objects

Reading JSON Data

- `read_json()`
  - Takes a string path to JSON _or_ JSON data as a string
  - Specify data types with `dtype` keyword argument
  - `orient` keyword argument to flag uncommon JSON data layouts
    - possible values in `pandas` documentation

Data Orientation

- JSON data isn't tabular
  - `pandas` guesses how to arrange it in a table
- `pandas` can automatically handle common orientations

Record Orientation

- Most common JSON arrangement

```
[
  {
      "age_adjusted_death_rate": "7.6",
      "death_rate": "6.2",
      "deaths": "32",
      "leading_cause": "Accidents Except Drug Posioning (V01-X39, X43, X45-X59, Y85-Y86)",
      "race_ethnicity": "Asian and Pacific Islander",
      "sex": "F",
      "year": "2007"
  },
  {
      "age_adjusted_death_rate": "8.1",
      "death_rate": "8.3",
      "deaths": "87",
      ...
```

Column Orientation

- More space-efficient than record-oriented JSON


```
{
  "age_adjusted_death_rate": {
      "0": "7.6",
      "1": "8.1",
      "2": "7.1",
      "3": ".",
      "4": ".",
      "5": "7.3",
      "6": "13",
      "7": "20.6",
      "8": "17.4",
      "9": ".",
      "10": ".",
      "11": "19.8",
      ...
```


Specifying Orientation

- Split oriented data - `nyc_death_causes.json`


```
{
  "columns": [
      "age_adjusted_death_rate",
      "death_rate",
      "deaths",
      "leading_cause",
      "race_ethnicity",
      "sex",
      "year"
  ],
  "index": [...],
  "data": [
      [
          "7.6",
```

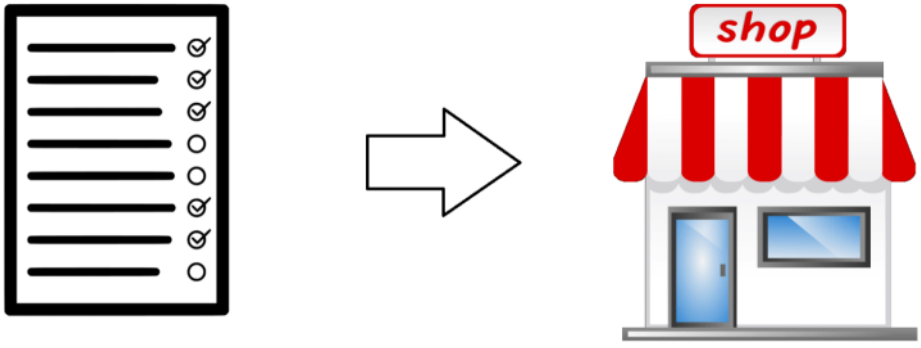
Specifying Orientation

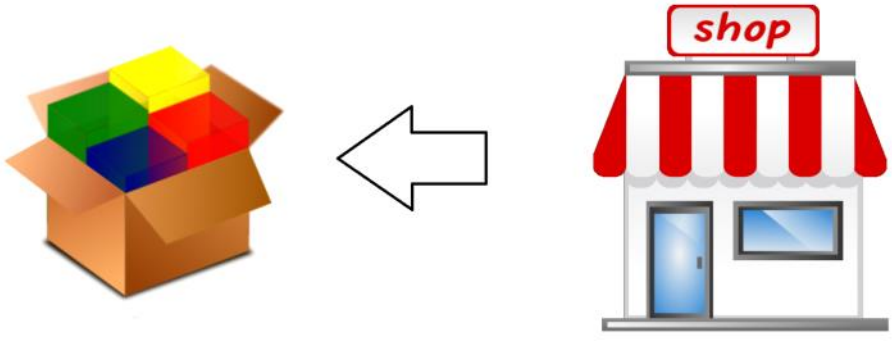
```
import pandas as pd
death_causes = pd.read_json("nyc_death_causes.json",
                            orient="split")
print(death_causes.head())
```

```
   age_adjusted_death_rate death_rate deaths             leading_cause              race_ethnicity sex  year
0                      7.6        6.2     32  Accidents Except Drug...  Asian and Pacific Islander   F  2007
1                      8.1        8.3     87  Accidents Except Drug...          Black Non-Hispanic   F  2007
2                      7.1        6.1     71  Accidents Except Drug...                    Hispanic   F  2007
3                        .          .      .  Accidents Except Drug...          Not Stated/Unknown   F  2007
4                        .          .      .  Accidents Except Drug...       Other Race/ Ethnicity   F  2007

[5 rows x 7 columns]
```

Application Programming Interfaces

- Defines how a application communicates with other programs
- Way to get data from an application without knowing database details





Requests

- Send and get data from websites
- Not tied to a particular API
- `requests.get()` to get data from a URL

requests.get()

- `requests.get(url_string)` to get data from a URL
- Keyword arguments
  - `params` keyword: takes a dictionary of parameters and values to customize API request
  - `headers` keyword: takes a dictionary, can be used to provide user authentication to API
- Result: a `response` object, containing data and metadata
  - `response.json()` will return just the JSON data

response.json() and pandas

- `response.json()` returns a dictionary
- `read_json()` expects strings, not dictionaries
- Load the response JSON to a data frame with `pd.DataFrame()`
  - `read_json()` will give an error!

Yelp Business Search API

Yelp Business Search API

Request

```
GET https://api.yelp.com/v3/businesses/search
```

Parameters

These parameters should be in the query string.

Name	Type	Description
term	string	Optional. Search term, for example "food" or "restaurants". The term may also be business names, such as "Starbucks". If term is not included the endpoint will default to searching across businesses from a small number of popular categories.
location	string	Required if either latitude or longitude is not provided. This string indicates the geographic area to be used when searching for businesses. Examples: "New York City", "NYC", "350 5th Ave, New York, NY 10118". Businesses returned in the response may not be strictly within the specified location.
latitude	decimal	Required if location is not provided. Latitude of the location you want to search nearby.

Yelp Business Search API

Response Body


```
{
  "total": 8228,
  "businesses": [
    {
      "rating": 4,
      "price": "$",
      "phone": "+14152520800",
      "id": "E8RJkjfdcwgtyoPMjQ_Olg",
      "alias": "four-barrel-coffee-san-francisco",
      "is_closed": false,
      "categories": [
        {
          "alias": "coffee",
          "title": "Coffee & Tea"
        }
      ],
      "review_count": 1738,
      "name": "Four Barrel Coffee",
      "url": "https://www.yelp.com/biz/four-barrel-coffee-san-francisco",
      "coordinates": {
        "latitude": 37.7670169511878,
```


Making Requests

```
import requests
import pandas as pd

api_url = "https://api.yelp.com/v3/businesses/search"
# Set up parameter dictionary according to documentation
params = {"term": "bookstore",
          "location": "San Francisco"}
# Set up header dictionary w/ API key according to documentation
headers = {"Authorization": "Bearer {}".format(api_key)}
```

API keys are strings used to identify the program calling the API and confirm it can make the call.

They are sensitive information, so it's hidden behind the API key variable here.

```
# Call the API
response = requests.get(api_url,
                        params=params,
                        headers=headers)
```

Since responses contain data and metadata, we use the JSON method to isolate the data.

Parsing Responses

```
# Isolate the JSON data from the response object
data = response.json()
print(data)
```

```
{'businesses': [{'id': '_rbF2ooLcMRA7Kh8neIr4g', 'alias': 'city-lights-bookstore-san-francisco', 'name': 'City L
```

```
# Load businesses data to a data frame
bookstores = pd.DataFrame(data["businesses"])
print(bookstores.head(2))
```

```
                            alias  ...                                                url
0   city-lights-bookstore-san-francisco  ...      https://www.yelp.com/biz/city-lights-bookstore...
1  alexander-book-company-san-francisco  ...      https://www.yelp.com/biz/alexander-book-compan...

[2 rows x 16 columns]
```

Nested JSONs

- JSONs contain objects with attribute-value pairs
- A JSON is nested when the value itself is an object

Response Body


```
{
  "total": 8228,
  "businesses": [
    {
      "rating": 4,
      "price": "$",
      "phone": "+14152520800",
      "id": "E8RJkjfdcwgtyoPMjQ_Olg",
      "alias": "four-barrel-coffee-san-francisco",
      "is_closed": false,
      "categories": [
        {
          "alias": "coffee",
          "title": "Coffee & Tea"
        }
      ],
      "review_count": 1738,
      "name": "Four Barrel Coffee",
      "url": "https://www.yelp.com/biz/four-barrel-coffee-san-francisco",
      "coordinates": {
        "latitude": 37.7670169511878,
        "longitude": -122.42184275
      },
      "image_url": "http://s3-media2.fl.yelpcdn.com/bphoto/MmgtASP3l_t4tPCL1iAsCg/o.jpg",
      "location": {
        "city": "San Francisco",
        "country": "US",
        "address2": "",
        "address3": "",
        "state": "CA",
        "address1": "375 Valencia St",
        "zip_code": "94103"
      },
      "distance": 1604.23
```


Categories' values are lists of objects.

```
# Print columns containing nested data
print(bookstores[["categories", "coordinates", "location"]].head(3))
```

```
                                      categories  \
0   [{'alias': 'bookstores', 'title': 'Bookstores'}]
1  [{'alias': 'bookstores', 'title': 'Bookstores'...
2   [{'alias': 'bookstores', 'title': 'Bookstores'}]

                                     coordinates  \
0  {'latitude': 37.7975997924805, 'longitude': -1...
1  {'latitude': 37.7885846793652, 'longitude': -1...
2  {'latitude': 37.7589836120605, 'longitude': -1...

                                            location
0  {'address1': '261 Columbus Ave', 'address2': '...
1  {'address1': '50 2nd St', 'address2': '', 'add...
2  {'address1': '866 Valencia St', 'address2': ''...
```

pandas.io.json

- `pandas.io.json` submodule has tools for reading and writing JSON
  - Needs its own `import` statement
- `json_normalize()`
  - Takes a dictionary/list of dictionaries (like `pd.DataFrame()` does)
  - Returns a flattened data frame
  - Default flattened column name pattern: `attribute.nestedattribute`
  - Choose a different separator with the `sep` argument

Loading Nested JSON Data

```
import pandas as pd
import requests
from pandas.io.json import json_normalize


# Set up headers, parameters, and API endpoint
api_url = "https://api.yelp.com/v3/businesses/search"
headers = {"Authorization": "Bearer {}".format(api_key)}
params = {"term": "bookstore",
          "location": "San Francisco"}

# Make the API call and extract the JSON data
response = requests.get(api_url,
                        headers=headers,
                        params=params)
data = response.json()
```

```
# Flatten data and load to data frame, with _ separators
bookstores = json_normalize(data["businesses"], sep="_")
print(list(bookstores))
```

```
['alias',
 'categories',
 'coordinates_latitude',
 'coordinates_longitude',
 ...
 'location_address1',
 'location_address2',
 'location_address3',
 'location_city',
 'location_country',
 'location_display_address',
 'location_state',
 'location_zip_code',
 ...
 'url']
```

Deeply Nested Data

```
print(bookstores.categories.head())
```

```
0     [{'alias': 'bookstores', 'title': 'Bookstores'}]
1    [{'alias': 'bookstores', 'title': 'Bookstores'...
2     [{'alias': 'bookstores', 'title': 'Bookstores'}]
3     [{'alias': 'bookstores', 'title': 'Bookstores'}]
4    [{'alias': 'bookstores', 'title': 'Bookstores'...
Name: categories, dtype: object
```

Deeply Nested Data

- `json_normalize()`
  - `record_path` : string/list of string attributes to nested data
  - `meta` : list of other attributes to load to data frame
  - `meta_prefix` : string to prefix to meta column names

Deeply Nested Data

```
# Flatten categories data, bring in business details
df = json_normalize(data["businesses"],
                    sep="_",
                    record_path="categories",
                    meta=["name",
                          "alias",
                          "rating",
                          ["coordinates", "latitude"],
                          ["coordinates", "longitude"]],
                    meta_prefix="biz_")
```

```
print(df.head(4))
```

```
        alias              title               biz_name  \
0  bookstores          Bookstores   City Lights Bookstore
1  bookstores          Bookstores  Alexander Book Company
2  stationery  Cards & Stationery  Alexander Book Company
3  bookstores          Bookstores       Borderlands Books

                           biz_alias  biz_rating  biz_coordinates_latitude  \
0   city-lights-bookstore-san-francisco         4.5                 37.797600
1  alexander-book-company-san-francisco         4.5                 37.788585
2  alexander-book-company-san-francisco         4.5                 37.788585
3       borderlands-books-san-francisco         5.0                 37.758984

   biz_coordinates_longitude
0               -122.406578
1               -122.400631
2               -122.400631
3               -122.421638
```

Appending

- Use case: adding rows from one data frame to another
- `append()`
  - Data frame method
  - Syntax: `df1.append(df2)`
  - Set `ignore_index` to `True` to renumber rows

Appending

```
# Get first 20 bookstore results
params = {"term": "bookstore",
          "location": "San Francisco"}
first_results = requests.get(api_url,
                             headers=headers
                             params=params).json()

first_20_bookstores = json_normalize(first_results["businesses"],
                                     sep="_")

print(first_20_bookstores.shape)
```

```
(20, 24)
```

```
# Put bookstore datasets together, renumber rows
bookstores = first_20_bookstores.append(next_20_bookstores,
                                        ignore_index=True)
print(bookstores.name)
```

```
0                             City Lights Bookstore
1                           Alexander Book Company
2                                Borderlands Books
3                                  Alley Cat Books
4                                  Dog Eared Books
...                                              ...
35                                   Forest Books
36                San Francisco Center For The Book
37                          KingSpoke - Book Store
38                           Eastwind Books & Arts
39                                     My Favorite
Name: name, dtype: object
```

Merging

- Use case: combining datasets to add related columns
- Datasets have key column(s) with common values
- `merge()` : `pandas` version of a SQL join

Merging

- `merge()`
  - Both a `pandas` function and a data frame method
- `df.merge()` arguments
  - Second data frame to merge
  - Columns to merge on
    - `on` if names are the same in both data frames
    - `left_on` and `right_on` if key names differ
    - Key columns should be the same data type

```
call_counts.head()
```

```
  created_date  call_counts
0   01/01/2018         4597
1   01/02/2018         4362
2   01/03/2018         3045
3   01/04/2018         3374
4   01/05/2018         4333
```

```
weather.head()
```

```
         date    tmax  tmin
0  12/01/2017      52    42
1  12/02/2017      48    39
2  12/03/2017      48    42
3  12/04/2017      51    40
4  12/05/2017      61    50
```

Merging

```
# Merge weather into call counts on date columns
merged = call_counts.merge(weather,
                           left_on="created_date",
                           right_on="date")
print(merged.head())
```

```
  created_date  call_counts        date  tmax  tmin
0   01/01/2018         4597  01/01/2018    19     7
1   01/02/2018         4362  01/02/2018    26    13
2   01/03/2018         3045  01/03/2018    30    16
3   01/04/2018         3374  01/04/2018    29    19
4   01/05/2018         4333  01/05/2018    19     9
```

Merging

```
  created_date  call_counts        date  tmax  tmin
0   01/01/2018         4597  01/01/2018    19     7
1   01/02/2018         4362  01/02/2018    26    13
2   01/03/2018         3045  01/03/2018    30    16
3   01/04/2018         3374  01/04/2018    29    19
4   01/05/2018         4333  01/05/2018    19     9
```

- Default `merge()` behavior: return only values that are in both datasets
- One record for each value match between data frames
  - Multiple matches = multiple records