

How to Clean Messy Data in Python



DS 6001: Practice and Applications of
Data Science

Getting Yourself Unstuck

- Online Communities

- Using Python's built-in help documentation

- Good old Google

- Stack Overflow

- Interacting with other Python users on PySlackers

- Live chats with Python users on Freenode

- Python Mailing lists

Loading CSV and ASCII Data into Python

- Electronic data files

- Changing the working directory

- Loading standard CSV files

- Looking at the data to see if it loaded correctly

- Loading messy CSV and other ASCII files

- Writing CSV and ASCII files

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- Loading Excel files

- Loading SAS, Stata, and SPSS files

- Working with JSON files

 - What is JSON?

 - Who uses JSON?

 - Loading JSON data into Python

 - Converting DataFrames/CSVs to JSON

 - Writing JSON files to disk

A note before we begin

We will be **updating these slides over the next several weeks**, and posting the most recent versions on Collab before each class.

These slides are intended to be a **guide on data management in Python**, but not on the basics of Python programming.

We need you to be comfortable with

- ▶ Using a Python interface (Jupyter, Spyder, etc.)
- ▶ Defining and working with objects
- ▶ Saving scripts/notebooks
- ▶ Using functions

If you are not comfortable with these skills, that's fine, but **speak to us after class** so we can help you get these skills.

Managing Data

At most companies, data scientists spend about **80% of their time managing data** (also called wrangling, cleaning, engineering, or organizing data).

If you want to get to the fun stuff, like **visualizing, modeling, and forecasting**, you need to be able to clean data **very quickly and accurately**.

Among other skills, you will need to

- ▶ Load electronic data into Python
- ▶ Store data in a database
- ▶ Query the database
- ▶ Manage the rows and columns of a dataset
- ▶ Reshape and merge datasets

And you need to be able to perform these tasks **instinctively**, without having to think about it too much.

Managing Data

In other words, you will all become Python Ninjas:



But before we can teach you all those ninja skills, we have to talk about the **most important programming skill of all**, which is ...

Getting Yourself Unstuck

The single most important skill to master with a programming language is **knowing what to do when you get stuck**.

Everyone, even people with years of Python programming experience, uses help resources **CONSTANTLY**. So **don't** feel like it is cheating or a judgment on your skills to look for help.

Here are at least **six places** to go for help:

1. Python documentation
2. Google
3. Stack Overflow
4. PySlackers
5. Internet relay chat (IRC) rooms with other Python users
6. Various Python mailing lists

Online Communities

These options involve becoming a responsible, respectful member of the **worldwide community of Python users** (See python.org/community/).

Open-source platforms like Python and R depend on a community of volunteers who **develop and maintain the tools** that we use. All these people working for the common good. That's a beautiful thing.

Slack, Stack Overflow, the Freenode IRC, and mailing lists are also online communities for Python users.

BUT, like any online community, there's the potential for a **toxic culture** to destroy everything.

Toxic Online Communities

What is a toxic culture? How do you know one when you see one?

Toxic cultures are more likely when

- ▶ members are allowed to be **anonymous** ([Lapidot-Lefler and Barak 2011](#)),
- ▶ and members **up-vote and down-vote** and **comment on** each other's contributions ([Massanari 2015](#)).

A culture can be either **actively** or **passively** toxic.

Actively toxic communities are easy to identify. They encourage and are characterized by **overt** sexism, racism, bigotry, and calls for violence or other aggression against individuals.

Toxic Online Communities

Most of the toxicity you will encounter in online programming and data science communities is not actively, but **passively toxic**.

Passive toxicity is characterized by **gate-keeping**. **Subtle behaviors** that discourage people with less experience, or with some social anxiety, from participating.

Stack overflow, IRCs, and mailing lists are notorious for passive toxic behavior.

Passive toxicity is a bigger problem for us than active toxicity because

- ▶ actively toxic behavior is usually explicitly banned by codes of conduct,
- ▶ and **individuals are often unaware of when they are acting in a passively toxic way.**

Toxic Online Communities

Examples of passive toxic behavior:

Condescending language: “obviously”, “clearly”, “actually”, “just”, “that should be easy”, “google it”, “read the manual”, “RTFM”. [An example.](#)

Shaming: implying that the solution is easy and that someone is an idiot for not knowing it.

- ▶ “Learn to debug your own code”
- ▶ “If you don’t get this, you have no business being a data scientist”

Downvotes without explanation: this can be very upsetting to anyone, especially to people with less experience

Toxic Online Communities

Examples of passive toxic behavior:

Virtue signaling: implying that people are superior/inferior because of the language, software, or methods they use.

- ▶ “Real programmers don’t use for loops”
- ▶ “You still use SAS?”
- ▶ So many memes:



Toxic Online Communities

Examples of passive toxic behavior:

Authoritarianism: Abusing people for failing to follow all of a community's rules for asking questions.

- ▶ Ignore the content of the question but comment “provide an example”
- ▶ Editing a user's post to remove where they wrote “Hi everyone” and “thanks”

Overzealous curation: Being very quick to tag a question as a “duplicate” without checking to see nuanced ways in which the question comes from a new situation.

Toxic Online Communities

The result of passive toxicity is that many **potential community members** choose not to participate because

1. Initial experiences made new members feel **ashamed, confused, or belittled**.
2. Other potential new members *observe* negative interactions involving other members, and **choose to disengage**.

Passive toxicity **shrinks** the community and makes it **more homogeneous**.

Across society, small, homogeneous communities are much more likely to exclude or discriminate against people based on **sex, race, class, language** and other factors. And that leads to many ethical problems.

Toxic Online Communities

Under no circumstances are you to contribute to an active or passive toxic culture in any community, online or otherwise.

Please keep the behaviors we discussed in mind when you engage in online communities, and avoid them. Don't be afraid to call out other people who behave in these ways.

Everyone, please **rise**, **raise your right hand**, **place your left hand over your computer**, and repeat after me:

*I promise
not to contribute to the destruction of society
by being an asshole online*

Python's Built-in Help Documentation

Packages, modules, classes and functions in Python have **built-in documentation** that you can display directly in the console or in the output of a notebook.

This is the first place to look for help with specific, pre-built Python code.

There are three parts of Python's documentation for an object:

1. The **signature** – if the object is a function, the complete function syntax, including all arguments and their default values
2. The **docstring** – text explaining how to use the object, in detail (we'll go over this next)
3. The **type** – what kind of object is this?

Python's Built-in Help Documentation

There are a few ways to **display the help documentation** for an object:

`help(x)` – displays the docstring for object `x`

`x?` – displays an **abbreviated** docstring for `x`, as well as the signature and type

`x??` – same as `x?`, but shows the internal code of `x` if `x` is a Python function (not just a call to a C function)

The most important skill is to know **how to read the docstring** to quickly find the information you need.

Python's Built-in Help Documentation

To understand how to read the docstring, call up the docstring for a **linear regression class** object from the sklearn package:

```
import sklearn.linear_model
help(sklearn.linear_model.LinearRegression)
```

Docstrings often have **sections** that convey particular information.

1. The header

Help on class LinearRegression in module
sklearn.linear_model.base:

```
class LinearRegression(LinearModel,  
sklearn.base.RegressorMixin, sklearn.base.MultiOutputMixin)
```

The header tells us that the `LinearRegression` object is a **class**, stored in the `linear_model.base` module within the `sklearn` package.

Python's Built-in Help Documentation

2. The signature

```
LinearRegression(fit_intercept=True, normalize=False,  
copy_X=True, n_jobs=None)
```

Some docstrings list the signature, although the signature can be accessed elsewhere. The signature lists all of the **parameters** of a function.

The value each parameter is set equal to is the **default**. If the user doesn't specify the parameter, it's set to the default.

3. The short description

Ordinary least squares Linear Regression.

A one-or-two sentence summary of what the function does.

Python's Built-in Help Documentation

4. The parameters section is the most useful for learning how to use a function:

Parameters

`fit_intercept` : boolean, optional, default True

whether to calculate the intercept for this model. If set to False, no intercept will be used in calculations (e.g. data is expected to be already centered).

`normalize` : boolean, optional, default False

This parameter is ignored when `fit_intercept` is set to False. If True, the regressors X will be normalized before regression by subtracting the mean and dividing by the l2-norm.

If you wish to standardize, please use

`:class:`sklearn.preprocessing.StandardScaler`` before calling `fit` on an estimator with `normalize=False`.

`copy_X` : boolean, optional, default True

If True, X will be copied; else, it may be overwritten.

`n_jobs` : int or None, optional (default=None)

The number of jobs to use for the computation. This will only provide speedup for `n_targets > 1` and sufficient large problems.

`None` means 1 unless in a `:obj:`joblib.parallel_backend`` context.

`-1` means using all processors. See `:term:`Glossary <n_jobs>` for more details.

Python's Built-in Help Documentation

The parameters section lists the parameters, in the order in which they appear in the signature of the function, along with information about each parameter.

Each parameter has a **type**: in this case, the first three parameters are boolean, which means they can be set to either True or False. The fourth parameter is an integer.

Each parameter is noted as either **required** or **optional** in a call to the function.

Each parameter is **described** in a sentence or two to explain what the parameter does.

Python's Built-in Help Documentation

5. The attributes

Attributes

`coef_` : array, shape (n_features,) or (n_targets, n_features)
Estimated coefficients for the linear regression problem.
If multiple targets are passed during the fit (y 2D), this is a 2D array of shape (n_targets, n_features), while if only one target is passed, this is a 1D array of length n_features.

`intercept_` : array
Independent term in the linear model.

Attributes are components of the the **output of the function**.

If the output is saved in an object named `regress`, to access the coefficients, type `regress.coef_`, and to access the intercept, type `regress.intercept_`.

Python's Built-in Help Documentation

6. The examples

Examples

```
-----  
>>> import numpy as np  
>>> from sklearn.linear_model import LinearRegression  
>>> X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])  
>>> # y = 1 * x_0 + 2 * x_1 + 3  
>>> y = np.dot(X, np.array([1, 2])) + 3  
>>> reg = LinearRegression().fit(X, y)  
>>> reg.score(X, y)  
1.0  
>>> reg.coef_  
array([1., 2.])  
>>> reg.intercept_ # doctest: +ELLIPSIS  
3.0000...  
>>> reg.predict(np.array([[3, 5]]))  
array([16.]
```

Examples are **meant to be run**, not just looked at. Copy-and-paste the examples into your notebook or script, run the code. See if **you can do more things with the given objects** than the examples do.

Python's Built-in Help Documentation

7. The related methods defines methods that **expand the functionality** of the one you are looking at, along with their own documentation:

Methods defined here:

```
__init__(self, fit_intercept=True, normalize=False, copy_X=True, n_jobs=None)  
    Initialize self. See help(type(self)) for accurate signature.
```

```
fit(self, X, y, sample_weight=None)  
    Fit linear model.
```

Parameters

X : array-like or sparse matrix, shape (n_samples, n_features)
 Training data

y : array_like, shape (n_samples, n_targets)
 Target values. Will be cast to X's dtype if necessary

sample_weight : numpy array of shape [n_samples]
 Individual weights for each sample

.. versionadded:: 0.17
 parameter **sample_weight** support to LinearRegression.

Returns

self : returns an instance of self.

Using Google

If you know the functions you need more information about, **using the built-in documentation the best habit.**

Don't go to Google first! There are way too many presentations of any one topic to sift through. **It can take a lot longer** if you use Google primarily.

If the built-in documentation doesn't give you the information you need, the best Google search is

Python *the function you want help with additional details*

Google will often take you to **Stack Overflow**.

Stack Overflow

Stack Overflow is the **most popular and most useful website** for help with programming of all kinds. Google searching a Python problem will usually lead to a Stack Overflow post on the same issue.

Python is now the **most frequent** tag for posts on Stack Overflow: see the video embedded on [this blog post](#).

Finding a Stack Overflow post that's relevant to your problem can give you both the **code** and **intuition** to solve your problem.

Or maybe not! Small differences in the situation can make the solution irrelevant to you. **Be cautious** and don't treat a Stack Overflow post as automatically a definitive answer.

How Stack Overflow Works

1. Someone asks a question
2. Other people comment on and provide answers to the question
3. The person who asked the question replies to the comments, and can choose an answer to mark as “accepted”
4. People with **reputation scores** higher than 15 can **upvote or downvote** questions and answers.
5. Reputation points are awarded for asking questions or giving answers that **other people upvote**, or for having an answer accepted. Points are taken away for **downvotes or spam or offensive posts**.

Going for reputation is an **entirely optional** activity. If you don't want to worry about it, don't.

Asking a Question on Stack Overflow

Okay, so you're stuck. You've combed through the Python documentation, Google, and old Stack Overflow posts, but you **haven't found a solution**.

It's time to consider writing a **new question** on Stack Overflow.



Asking a Question on Stack Overflow

This can be **frightening**. A lot of the time, people answering questions on Stack Overflow can be, well . . . huge assholes that cause **real suffering**.

You might choose to **avoid posting** to Stack Overflow, so as not to support a website that has harbored and even encouraged abuse. That's completely fair.

If you do post to Stack Overflow, you are likely to get some very useful responses if you follow some guidelines. There's **a strategy for getting good responses**: stackoverflow.com/help/how-to-ask

Asking a Question on Stack Overflow

You are more likely to get a **good response** if you follow these steps:

Step 1: Search Stack Overflow and Google to see if the question has **already been answered**. Commenters dislike if the same question is asked repeatedly. This **poor guy** got roasted for posing a “duplicate” question.

(An aside: *Why?* There's an idea that Stack Overflow should be a **central repository of knowledge**. That means there should be one **canonical** answer to one question. But people often take this much too far. There are kinder ways to point to an existing answer.)

So spend a **significant amount of time** digging through the internet. If there's something similar, but not quite what you need, you can **say so in your post**.

Asking a Question on Stack Overflow

Step 2: Write a **good title** for your post.

A good title is **specific** about the problem, and also **succinct**:

Bad: Problem with matplotlib (not specific)

Bad: How do I place the labels of cars in a scatterplot of the weight and miles per gallon of cars onto the points in the scatterplot using matplotlib 3.3.1 on Python 3.7.4 on Mac OSX 10.14.5? (not succinct)

Good: How to place labels on top of points in a matplotlib scatterplot?

Getting Help: Asking a Question on Stack Overflow

Step 3: Start the post with a **paragraph describing the problem** in more detail.

Some good things to include in this paragraph:

- ▶ The **context** of the problem – how did you come across the problem? Describe the **overall goal**, not the just the buggy step
- ▶ What you've already tried to solve the problem, and what happened
- ▶ What is the **expected output**? What do you see instead?
- ▶ You can write the version of Python you are using, the version of the modules, and the operating system on your computer, in case the problem turns out to be specific to one of those

Asking a Question on Stack Overflow

Step 4: If possible, **include code** that reproduces the problem. The code SHOULD NOT simply be the code in your script that isn't working. It needs to be able to **work on someone else's computer**.

That means the code should not depend on any **specific data files**, and should not contain file addresses that refer to a location on your computer. Only use modules that are **easy to get**.

If the code needs to run on data, can you use something **pre-loaded in Python** that everyone can access? (There are example datasets included with `psykitlearn`, for example.)

Make the code as short as possible, and use comments, to help people understand the code more quickly.

A few additional things to keep in mind

Be courteous and respectful. Respond to and thank everyone who comments.

Post a [follow-up once the problem is solved](#) so that people who come across this page in the future with the same problem know the solution.

Don't ask people to write code for you. It's better to request help with code you provide.

Don't claim you **found a bug** in Python or in a module. It's a bit rude to the people who programmed the code (who don't get paid).

Don't ask about **homework problems**. ([Here's an example](#) of someone getting called out on this)

Interacting with other Python users on PySlackers

The main slack page for the global community of Python users is **Pyslackers**: <https://pyslackers.com/web>

To join, just go to the URL and click "join the community".

Some useful channels:

- ▶ data_science
- ▶ python_
- ▶ job_advice

Live chats with Python users on Freenode

The Python user community is world-wide, and for the most part, very supportive. There are active **internet relay chat** (IRC) networks where you can post a question to members who are also logged in, to possibly **get an answer right away**.

The most active Python IRC is the **#python** channel on Freenode (<https://webchat.freenode.net/>). When I logged in while writing this slide, there were 1,778 people logged on.

Internet chatrooms can be rough places, but the **#python** channel claims to enforce this Code of Conduct:

<https://www.python.org/psf/codeofconduct/>.

Live chats with Python users on Freenode

Getting started on Freenode can be tricky, but it's easier if follow these steps:

1. Go to (<https://webchat.freenode.net/>). Choose a **nickname**. Make it **professional** (you're a UVA student after all!) and **unique**.
2. Don't write anything under channel. Prove you are not a robot by selecting pictures of motorcycles or something. Then, once your humanity has been established, click **Start**.
3. To use the #python channel, you need to register your nickname. To check if your nickname is **unique**, click on the "freenode" tab on the left-hand sidebar. A text box will appear on the bottom of the screen. Type:

```
/msg NickServ info
```

Live chats with Python users on Freenode

4. Step 3 will open a new tab. Switch to that tab. If no one else already has your nickname, you will see

```
NickServ: (notice) <nickname> is not registered.
```

If you see something else, it means someone **already has your nickname**. You can change your nickname right here by typing `/nick` followed by another nickname. Then type `/msg NickServ info` again. Repeat until you see the message listed above.

Live chats with Python users on Freenode

Important note: DON'T use a password here that you use for important things like **email, bank accounts, etc.**

We shouldn't have the same faith in the security of Freenode's servers as we can have in Google's.

Also, this is the kind of platform that tends to attract hackers. And for people used to a graphical user interface, it might be easy to mistype in a way that **accidentally displays your password** in the chat.

Use a unique, throwaway password!

Live chats with Python users on Freenode

5. To register this nickname, type

```
/msg NickServ register <password> <email-address>
```

where `<password>` is a password you will use in the future, and `<email address>` is the email you want associated with this account.

Live chats with Python users on Freenode

6. Check your email for a confirmation code. **Be patient**. It can take up to 20 minutes for the email to go through.
7. Once you have the code, paste it and your nickname into this code, and submit it:

```
/msg NickServ VERIFY REGISTER <nickname> <secret-code>
```

8. You are now registered! Return to <https://webchat.freenode.net/> and log-in with your nickname and password. Type `#python` under channel.

You are free to chat away. Pay attention to the guidelines that appear as links on the top of the screen.

Python mailing lists and message boards

Usenet – a distributed discussion system (no central server) – was invented in 1979, and is still in use today. The Python Usenet message boards are at <https://mail.python.org/archives>. The `comp.lang.python` board is for general discussions and questions about Python.

The tutor mailing list (<https://mail.python.org/mailman/listinfo/tutor>) is for users who want to ask questions about learning computer programming with Python.

If you have a question for the Python core development team, send an email to help@python.org. The team is pretty busy, so be sure to check other resources and lists for an answer first.

Many ways to do the same thing in Python

Stata, SAS, SPSS, and Excel are **carefully curated** software. There is often **only one way** to perform a task. It's easier to memorize how to do a task.

In Python (and R), there are usually **many, many ways** to do the same thing using different functions and packages.

What follows is a set of *guidelines and suggestions*. NOT a definitive list of how to do things.

It's OKAY to **mix styles, packages, and approaches**. Use whatever works, but **keep track of what you do**.

Electronic Data Files

In the late 1970s and through the 1980s, it became possible to store data **directly** on a computer hard drive. But space was very limited.

In order to store data as efficiently as possible, **universal standards** were adopted.

ASCII – American Standard Code for Information Interchange
pronounced “As-Key”

- ▶ Defined 128 characters to be “legal” in data files
- ▶ **Text files**. Messy, but we can deal with them.
- ▶ Designed to be as small and as universally portable as possible.
- ▶ Data points usually **delimited by commas, spaces, or tabs**. Might require a data dictionary to read.

Electronic Data Files

Today there are two common ways to access electronic data.

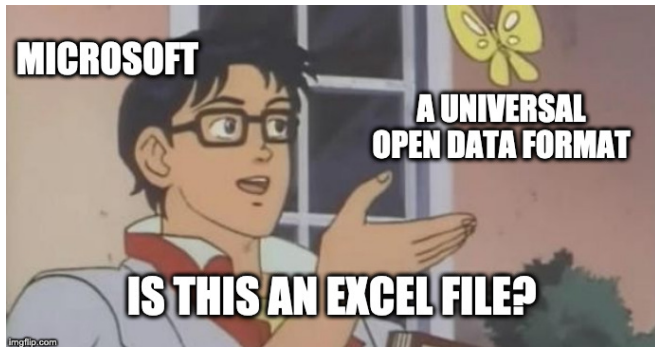
1. People can share **individual data files** through websites, email, or hard storage. These files are often in **ASCII format**, but can be stored in other (sometimes proprietary) formats.
2. Through a local or remote **relational database** – a collection of many individual datasets – managed using SQL.

It's important to be very comfortable **working with both** methods of sharing data. To build a database, we often have to **collect and clean individual data files**.

We will go over individual data files today, and databases soon.

Kinds of ASCII files

Note: Although the CSV format is universal, Excel sometimes opens by default when you double-click on the CSV file. But, **CSV files are NOT exclusive to Excel**.



Kinds of ASCII files

A fixed-width ASCII file with **no delimitation**. Files like these minimize memory (no need to store a bunch of commas), but require a dictionary file to read them.

```
2111112611297129722311000000000000000000000...  
21121213220201820751105412311222222221221211245  
1111021352016141759101541232222222222222222...  
2119220262020209748110451321222222221222222222...  
2212140251298989742311000000000000000000000...
```

Dictionary:

- ▶ Variable 1: sex, column 1
- ▶ Variable 2: race, column 2
- ▶ ...
- ▶ Variable 8: age, columns 8-9

Changing the working directory

Before we go over the functions, it is useful to **set the working directory** at the start of your script or notebook.

This **sets the default folder** where Python looks for files. If all of your files are in the same folder, setting the working directory means you **don't have to write out the paths** each time you load or save a file.

To set the working directory:

- ▶ Load the os package: `import os`
- ▶ Type the folder's address into `os.chdir("folder")`

Changing the working directory

To **check** on the path Python is currently using as a default, type `os.getcwd()` into the console.

If you want to **change the working directory** back after you've run the relevant code:

```
import os
oldpath = os.getcwd()
os.chdir("folder")

#(Your code goes here)

os.chdir(oldpath)
```

Loading CSV files

We will be using the Pandas package:

```
import pandas as pd
```

The main function for loading an ASCII data file is `pd.read_csv()`. There are lots of parameters, and we'll go over a few important ones, starting with this one:

```
pd.read_csv(filepath_or_buffer)
```

filepath_or_buffer – (string) one of three things:

1. The **full file address and file name** of the data file
2. **Just the file name** of the data file if you've already set the working directory to the folder where the file exist
3. The **URL** of a data file that's accessible online

Example: 2016 American National Election Study (ANES)

The ANES is a large survey, conducted every 4 years after the presidential election, that has 1000s of variables on topics no poll gets into. See <https://electionstudies.org/>

I put several versions of the ANES data on [our class GitHub page](#).

You can load the `anes_example.csv` data by either **downloading and unzipping** the file, or by using the URL:

[https://raw.githubusercontent.com/NovaVolunteer/
Practice_Application_DS/master/Week%205/anes_example.csv](https://raw.githubusercontent.com/NovaVolunteer/Practice_Application_DS/master/Week%205/anes_example.csv)

Example: 2016 American National Election Study (ANES)

If you **download and unzip** the ANES data, and you've already changed your working directory, then to load the ANES data, type

```
anes = pd.read_csv("anes_example.csv")
```

If you want to load the data **directly from the URL**, save the URL as a separate object, then pass this to the function:

```
url = "https://raw.githubusercontent.com/NovaVolunteer/  
Practice_Application_DS/master/Week%205/  
anes_example.csv"  
anes = pd.read_csv(url)
```

Looking at the data to see if it loaded correctly

Before we get to the other parameters of the `pd.read_csv()` function, let's talk about the **workflow of loading data**.

The steps are

1. Run code to load a data file
2. **Examine the loaded dataframe** object to make sure the data was correctly read
3. If you catch anything weird, **return to 1. and try different parameters** for `pd.read_csv()`

There's an important set of functions in Python that let you quickly explore a dataframe.

Looking at the data to see if it loaded correctly

If you are using a Jupyter Notebook, typing the name of the data frame **in its own cell** will produce a **good-looking HTML table** illustrating the data frame.

```
[3]: anes
```

```
[3]:
```

	caseid	turnout12	turnout12b	vote12	percent16	meet	givefut	info
0	1.0	1	NaN	2.0	100	1	3	4
1	2.0	2	NaN	NaN	50	4	5	4
2	3.0	1	NaN	1.0	100	1	1	1
3	4.0	1	NaN	2.0	100	5	4	5
4	5.0	1	NaN	1.0	100	2	1	3

If you are using Spyder, look in the **upper-right window** and select the “Variable explorer” tab. Clicking on the data frame will open a separate window for viewing the data.

Looking at the data to see if it loaded correctly

One annoying thing about Jupyter's interactive viewer is that it **omits the columns in the middle** for data frames with more than about 20 columns:

```
[3]: anes
```

```
[3]:
```

	caseid	turnout12	turnout12b	vote12	percent16	meet	givefut	info	march	sign	...	votereg	pid3
0	1.0	1	NaN	2.0	100	1	3	4	1	2	...	1	1
1	2.0	2	NaN	NaN	50	4	5	4	2	2	...	2	3
2	3.0	1	NaN	1.0	100	1	1	1	1	1	...	1	2
3	4.0	1	NaN	2.0	100	5	4	5	2	2	...	1	1
4	5.0	1	NaN	1.0	100	2	1	3	1	2	...	1	4
5	6.0	1	NaN	3.0	100	3	3	2	2	1	...	1	3

The columns it skipped (about **148** in this case) are replaced by a **column of dots**.

To keep Python from skipping columns, you can change this behavior **globally** (for all subsequent code) or **locally** (for each line of code individually).

Looking at the data to see if it loaded correctly

To always display all of the columns, type

```
pd.set_option('display.max_columns', None)
```

To always display all of the rows, type

```
pd.set_option('display.max_rows', None)
```

Caution: If you are working with large dataframes, it's probably not a good idea to always display ALL of the rows and columns.

To keep a [specific line of code](#) from skipping variables, use the `anes.loc` and `anes.iloc` functions. (Replace “anes” with the name of your dataframe object.)

Looking at the data to see if it loaded correctly

`anes.loc` allows you to select columns of a data frame **by name**, and `anes.iloc` allows you to select columns by **column number**.

To see the “sign”, “give12mo”, and “ftobama” variables, type

```
anes.loc[:, ['sign', 'give12mo', 'ftobama']]
```

	sign	give12mo	ftobama
0	2	2	100.0
1	2	2	39.0
2	1	1	1.0
3	2	2	89.0
4	2	1	1.0
5	1	1	0.0
6	2	1	73.0
7	1	2	0.0
8	2	1	12.0

Looking at the data to see if it loaded correctly

To see all variables in between “sign”, and “fthisp”, type

```
anes.loc[:, 'sign':'fthisp']
```

	sign	give12mo	compromise	ftobama	ftblack	ftwhite	fthisp
0	2	2	1	100.0	100.0	100	100.0
1	2	2	1	39.0	6.0	74	6.0
2	1	1	2	1.0	50.0	50	50.0
3	2	2	1	89.0	61.0	64	61.0
4	2	1	2	1.0	61.0	58	71.0
5	1	1	2	0.0	50.0	51	51.0
6	2	1	1	73.0	100.0	70	100.0
7	1	2	1	0.0	70.0	70	69.0
8	2	1	2	12.0	50.0	50	50.0

Looking at the data to see if it loaded correctly

To select columns and rows numerically, use `anes.iloc`. To see **rows 254 through 262 and all columns**, type

```
anes.iloc[254:262, :]
```

To see **all rows, columns 21 through 30**, type

```
anes.iloc[:, 21:30]
```

To see **rows 254 through 262 , columns 21 through 30**, type

```
anes.iloc[254:262, 21:30]
```

Looking at the data to see if it loaded correctly

To see only the **first 10 rows** of the data, type `anes.head(10)` .
Replace 10 with however many rows you want to see.

To see only the **last 10 rows** of the data, type `anes.tail(10)` .

Typing `anes.info()` tells us the **dimensions of the data**, the number of variables of each type, and the size of the dataframe in memory:

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 1200 entries, 0 to 1199  
Columns: 168 entries, caseid to ever_vs_12mo_rand  
dtypes: float64(76), int64(86), object(6)  
memory usage: 1.5+ MB
```

Looking at the data to see if it loaded correctly

`anes.columns` lists **all the variable names**.

If there are **too many variables**, Python will abbreviate the list with "...". To see the omitted items, change the maximum number of items that can display in a list with:

```
pd.set_option('display.max_seq_items', None)
```

(Again, be careful about removing this limit for data frames with a large number of columns)

`anes.dtypes` lists the variables along with their types (**int64** for integers, **float64** for numbers with decimals, **object** for variables that might be either categorical or string).

Looking at the data to see if it loaded correctly

`anes.describe()` shows basic summary statistics for every variable in the dataframe.

There are **different summary statistics for different types of variables**. By default, `anes.describe()` displays stats only for the float and int types:

- ▶ `count` – number of non-missing observations
- ▶ `mean` – the sample mean
- ▶ `std` – the sample standard deviation
- ▶ `min` – the minimum value
- ▶ `25%` – the 25th percentile
- ▶ `50%` – the median value
- ▶ `75%` – the 75th percentile
- ▶ `max` – the maximum value

Looking at the data to see if it loaded correctly

Use the percentiles argument to display different percentiles.

To see the 20th, 37.5th, and 74.23th percentiles, type

```
anes.describe(percentiles = [.20, .375, .7423])
```

To see just the int variables, type

`anes.describe(include = "int")`, and to see just the float variables, type `anes.describe(include = "float")`.

To see object variables, type

`anes.describe(include = "object")`. These variables have different stats:

- ▶ count – number of non-missing observations
- ▶ unique – number of unique observations
- ▶ top – the most frequent value
- ▶ freq – the frequency of the top value

Looking at the data to see if it loaded correctly

To see **all of the variables**, type

`anes.describe(include = "all")` , but this will result in NA values for stats that aren't relevant to the variable.

Use these tools a lot! After loading the data, you need to quickly be able to see if there were any problems with loading the data. Ask:

- ▶ Are the **dimensions** what I expect?
- ▶ Are the **variable names** set to what they are supposed to be?
- ▶ Are there any **bizarrely high/low means** or other stats?

There are many reasons why a load might have failed. Fortunately, there are parameters within the `pd.read_csv()` function to deal with many of these issues.

Loading messy CSV and other ASCII files

```
pd.read_csv(filepath_or_buffer, sep, header)
```

sep or **delimiter** – (string) The **symbol** that is used in the file to separate one datapoint from the next on the same row. By default, it looks for commas.

- ▶ For tab-delimited, use `sep="\t"`
- ▶ For semi-colon delimited, use `sep=";"`

header – (integer or string) Where to look for **variable names**.

- ▶ The default is `header=0`, which uses the first row as variable names
- ▶ `header=None` assumes there are no variable names and that the first row is data. It labels the columns with numbers, but if you also type `prefix="X"` the variables will be X0, X1, ...
- ▶ `header=j` uses the j_{th} row for variable names, and deletes all higher rows

Loading messy CSV and other ASCII files

```
pd.read_csv(filepath_or_buffer, sep, header, usecols)
```

usecols – (a list of strings or integers) Use this if you only want some of the columns to be loaded from the outset:

- ▶ `usecols = [0, 3, 5]` only loads the 1st, 4th, and 6th columns (**note that Python always starts at 0, making all indices off-by-one**)
- ▶ `usecols = ["caseid", "vote12", "meet"]` only loads the variables named “caseid”, “vote12”, and “meet”, as recognized by whatever Python thinks is the header

In general, don't use this parameter unless the data file is **too large to load** in its entirety. You can delete columns later.

Loading messy CSV and other ASCII files

```
pd.read_csv(filepath_or_buffer, sep, header, usecols,  
skiprows, skipfooter, nrows)
```

skiprows – (integer, or a list of integers) Likewise, which rows to skip when loading the data:

- ▶ **skiprows=3** skips the first three rows of the data. If **header** is left to its default, the 4th row is assumed to contain the variable names
- ▶ **skiprows=[0,3,5]** skips the 1st, 4th, and 6th rows

skipfooter – same as **skiprows** but counts up from the bottom row

nrows – (integer) only loads the first several rows, as specified by the user

Loading messy CSV and other ASCII files

```
pd.read_csv(filepath_or_buffer, sep, header, usecols,  
skiprows, skipfooter, nrows, na_values)
```

na_values – (list of strings or numeric) Sometimes data authors use codes other than NA to indicate a **missing value**.

Example: the American National Election Study (ANES) data uses -7, -8, -9, and 998, as well as blank cells and NA to represent missing values.

To replace all these values with NA across the whole data frame, type `na_values = [-7, -8, -9, 998]`.

Caution: Only specify missing codes in the `pd.read_csv()` function if the code ALWAYS means a missing value. If 998 is a valid datapoint for some variables, you can replace the missing codes for relevant variables later.

Loading messy CSV and other ASCII files

```
pd.read_csv(filepath_or_buffer, sep, header, usecols,  
skiprows, skipfooter, nrows, na_values, comment )
```

comment – (string) If there are comments in the data file itself (it shouldn't happen but **it does!**), what character to read as indicating a commented-out row.

If the data authors wrote “# Collected on Mon 9/23” before some rows, then “# Collected on Tues 9/24” further down, you can ignore these by typing `comment="#"`.

Careful: if the comment-symbol appears ANYWHERE on the row, the remainder of the row is not read. That's a problem if, for example, the data contain tweets and one tweet reads “UVA is #1!”.

Writing CSV and ASCII files

Once the data are loaded into Python, there are **many tools, techniques, and functions** to know to get the data into a **clean state**.

We'll go over all of that in detail soon. But after having cleaned the data, you might want to **save the cleaned dataframe as a CSV** or as a different ASCII file.

Suppose the `anes` object contains a cleaned dataframe. To save it as a CSV, use `anes.to_csv()`. There are several parameters, you can see with `help(anes.to_csv)`.

Let's talk about two important parameters:

```
anes.to_csv(path_or_buf, sep)
```

Writing CSV and ASCII files

```
anes.to_csv(path_or_buf, sep)
```

path_or_buf – (string) the name of the file to save, with the appropriate file extension (.csv, .txt, etc.)

You can write an entire file path here if you want. But if you **set the working directory**, and write the file name alone, it will save in the working directory.

sep – (string) the character to use as a delimiter. A comma by default. Use `sep="\t"` for a tab-delimited file.

To save the `anes` dataframe as a standard CSV file, type:

```
anes.to_csv("anes_cleaned.csv", sep=",")
```

Loading fixed width files

A fixed-width file contains **no delimiters**. Instead, it aligns all of the data for one variable in the **same position** on each row. These files might use less memory than CSV.

But that makes the data impossible to parse without an external list of which variable is stored where. The first and most important step is to **get this list**.

Example: the National Journal conducted a public opinion poll and saved the data in fixed-width format. I saved the codebook on GitHub, and the data here:

[https://raw.githubusercontent.com/NovaVolunteer/
Practice_Application_DS/master/Week%205/njcc33850.dat](https://raw.githubusercontent.com/NovaVolunteer/Practice_Application_DS/master/Week%205/njcc33850.dat)

Loading fixed width files

In this codebook, [find the variable names](#) and save them in a list, for example:

```
datanames = ['psraid', 'sample', 'int_date', 'area',  
'state', 'cregion', 'density', 'usr', 'cc1', 'cc1a',  
'cc2', 'cc3', 'cc4', 'cc5', 'cc6', 'cc7', 'ql1', 'ql1a',  
'qc1', 'hh1', 'employ', 'par', 'sex', 'age', 'educ2',  
'hisp', 'race', 'inc', 'income', 'reg', 'party',  
'partyln', 'iphoneus', 'hphoneus', 'recage', 'receduc',  
'racethn', 'standwt', 'raceos']
```

There are **two ways** to proceed next:

Method 1: If you know **how many characters each variable takes**, at maximum, save these widths as a list:

```
datawidths = [6, 1, 6, 3, 2, 1, 1, 3, 1, 1,  
              1, 1, 1, 1, 1, 1, 1, 1, 1, 1,  
              1, 1, 1, 2, 1, 1, 1, 2, 1, 1,  
              1, 1, 1, 1, 1, 1, 1, 4, 30]
```

Loading fixed width files

Method 2: if you know the **starting and ending position** of each variable, create a **list of length 2** for each variable, where

- ▶ the first element is the **column the previous variable ends on** (or 0 for the first variable)
- ▶ and the second element is the **column the current variable ends on**.

For example, if a variable occupies columns 34, 35, and 36, its list of length 2 is `[33,36]`.

Create a **list-of-lists**, which can look like:

```
datapos = [[0,6], [6,7], [7,13], [13,16], [16,18],  
           [18,19], [19,20], [20,23], [23,24], [24,25],  
           [25,26], [26,27], [27,28], [28,29], [29,30],  
           [30,31], [31,32], [32,33], [33,34], [34,35],  
           [35,36], [36,37], [37,38], [38,40], [40,41],  
           [41,42], [42,43], [43,45], [45,46], [46,47],  
           [47,48], [48,49], [49,50], [50,51], [51,52],  
           [52,53], [53,54], [54,58], [58,88]]
```

Loading fixed width files

To read the fixed-width file, use the `pd.read_fwf()` function.

To parse the data using **variable widths**, save the URL, the variable names, and widths in separate objects (as on the previous slides), and type:

```
njcc = pd.read_fwf(url, widths=datawidths,  
                  header=None, names=datanames)
```

To parse the data using **variable positions**, save the URL, the variable names, and positions in separate objects, and type:

```
njcc = pd.read_fwf(url, colspecs=datapos,  
                  header=None, names=datanames)
```

Loading Excel files

Like it or not, you will be **working with Excel files** as a professional data scientist. Excel is **ubiquitous**, and at some point, you will have to load Excel cleanly into Python.

My usual strategy: Open Excel, select the sheet I want, and **save it as a CSV** before loading it in Python.

But that's not a good strategy because it requires me to have access to Excel. To work entirely with Python, use the `pd.read_excel()` function.

Many of the parameters that work for `pd.read_csv()` work for `pd.read_excel()` too, including: **header**, **names**, **usecols**, **skiprows**, **skipfooter**, **nrows**, **na_values**, and **comment**.

Loading Excel files

There are two arguments we should go over:

```
pd.read_excel(io, sheet_name)
```

io – (string) This argument is the same as the **filepath_or_buffer** parameter for `pd.read_csv()`. It can be a

- ▶ path and filename,
- ▶ filename alone (if you've set the working directory),
- ▶ or a URL where the Excel file is stored online.

sheet_name – (string, int, or list) If the Excel file has **sheets with names**, you can type the name of the sheet here. Or type a number: **0 refers to the first sheet, 1 to the second**, etc.

If you specify a list, `pd.read_excel()` will produce a list of dataframes, one for each sheet you specify. Typing `sheet_name = None` produces a list with all of the sheets.

Loading Excel files

Example: I saved an Excel sheet on GitHub with NBA statistics, here:

[https://github.com/NovaVolunteer/
Practice_Application_DS/blob/master/Week%205/
NBA-Team-Sample-BoxScore-Dataset.xlsx?raw=true](https://github.com/NovaVolunteer/Practice_Application_DS/blob/master/Week%205/NBA-Team-Sample-BoxScore-Dataset.xlsx?raw=true)

This Excel file has four sheets:

- ▶ **NBA-TEAM-SAMPLE** has team stats for every game last season;
- ▶ **METADATA** defines variables;
- ▶ **TEAMS** provides team names and locations;
- ▶ **PROVIDE DATE FORMAT** has information about date formats.

Loading Excel files

I save the **URL as an object**. Then, to load the **NBA-TEAM-SAMPLE** sheet, I type one of these lines:

```
nba = pd.read_excel(url, sheet_name="NBA-TEAM-SAMPLE")  
nba = pd.read_excel(url, sheet_name=0)
```

To load the **TEAMS** sheet, I type one of these lines:

```
nba = pd.read_excel(url, sheet_name="TEAMS")  
nba = pd.read_excel(url, sheet_name=2)
```

To load both sheets:

```
nba = pd.read_excel(url,  
                    sheet_name=["NBA-TEAM-SAMPLE", "TEAMS"])  
nba = pd.read_excel(url, sheet_name=[0, 2])
```

Loading SAS, Stata, and SPSS files

We're living in a moment when **open-source** programming has become the standard for data science.

BUT until recently most data science was conducted using **proprietary software**: SAS, Stata, or SPSS. Many researchers still use these platforms. So **you will likely have to work with these files.**

Like with Excel, opening SAS/Stata/SPSS and saving as CSV is a bad solution because you need the software to do that, and **the software is expensive.**

Loading SAS, Stata, and SPSS files

Regular **SAS** files have the extension **.sas7bdat**, and compressed SAS files (“transport files”) have the extension **.xport**. We’ll work with a dataset on inflation, here:

https://github.com/NovaVolunteer/Practice_Application_DS/blob/master/Week%205/inflation.sas7bdat?raw=true

Stata files all have the extension **.dta**. We’ll work with a CBS news poll, here:

https://github.com/NovaVolunteer/Practice_Application_DS/blob/master/Week%205/cbspoll.dta?raw=true

SPSS files have the extension **.sav**, or **.zsav** for compressed files. We’ll work with the ANES in SPSS format:

https://github.com/NovaVolunteer/Practice_Application_DS/blob/master/Week%205/anes_timeseries_2016.sav?raw=true

Loading SAS, Stata, and SPSS files

You can load **SAS** and **Stata** files with Pandas using the `pd.read_sas()` and `pd.read_stata()` functions.

To load an **SPSS** file, you need to install the pyreadstat package,

```
pip install pyreadstat
```

and import this package

```
import pyreadstat
```

Then you can use the `pyreadstat.read_sav()` function.

Loading SAS, Stata, and SPSS files

These functions are very similar to `pd.read_csv()`, but one important difference is **they can't read a URL**. So you have to download a **local copy** of the files.

To load the **SAS** inflation data:

```
inflation = pd.read_sas("inflation.sas7bdat")
```

To load the **Stata** CBS poll data:

```
cbspoll = pd.read_stata("cbspoll.dta")
```

Loading **SPSS** data is trickier. You have to define **two objects**, separated by a comma. **The first object will contain the dataframe, and the second object will contain the SPSS metadata:**

```
anes_spss, anes_spss_meta =  
    pyreadstat.read_sav("anes_timeseries_2016.sav")
```

Flat files

All of the electronic data files we've discussed so far are sometimes called **flat files** or **rectangular files**.

CSV and other ASCII, Excel, Stata, SAS, and SPSS are all built around the idea of a **rectangular spreadsheet**:

- ▶ On each row, there's an entry for every field (column), even if that entry is a missing value.
- ▶ All entries in a column have the **same type** (all string, for example, or all numeric, but not a mix of string and numeric)

But what if we had non-rectangular data, where every record might have different fields, or a different data type for a field than another record? **A JSON file is designed for this situation.**

What is JSON?

JSON = **J**ava**S**cript **O**bject **N**otation

Although JSON notation is based on JavaScript, it's **portable** to many other programming languages, like Python and R.

CSV/ASCII is a **text file with specific rules** about how datapoints are typed into the file (i.e. separated by commas, column names on the first row, rows separated by carriage returns.)

JSON is just another text file, with a **different method for writing the data**.

What is JSON?

If this is our **CSV** file:

```
caseid,fttrump,fthrc,birthy,gender
1,1.0,76.0,1960,1
2,28.0,52.0,1957,2
3,100.0,1.0,1963,1
4,0.0,69.0,1980,1
5,13.0,1.0,1974,1
```

We can represent the same data using the **JSON** format:

```
[{'caseid': 1.0, 'fttrump': 1.0, 'fthrc': 76.0,
  'birthy': 1960, 'gender': 1},
 {'caseid': 2.0, 'fttrump': 28.0, 'fthrc': 52.0,
  'birthy': 1957, 'gender': 2},
 {'caseid': 3.0, 'fttrump': 100.0, 'fthrc': 1.0,
  'birthy': 1963, 'gender': 1},
 {'caseid': 4.0, 'fttrump': 0.0, 'fthrc': 69.0,
  'birthy': 1980, 'gender': 1},
 {'caseid': 5.0, 'fttrump': 13.0, 'fthrc': 1.0,
  'birthy': 1974, 'gender': 1}]
```

What is JSON?

Let's look at just the first observation (in JSON-lingo, observations are called **records**):

```
{  
  'caseid': 1.0,  
  'fttrump': 1.0,  
  'fthrc': 76.0,  
  'birthyr': 1960,  
  'gender': 1  
}
```

This style is called **object literal syntax**. In Python, the curly braces { and } represent a **set**. A set is like a list (which we create using square braces [and]) with two differences: **elements cannot be repeated**, and there's no **ordering of the elements**.

Typing [1,2,3] and {1,2,3} return the same output. But [3,3,2,1] and {3,3,2,1} do not, because the {set} removes the extra 3 and sorts the elements.

What is JSON?

```
{  
    'caseid': 1.0,  
    'fttrump': 1.0,  
    'fthrc': 76.0,  
    'birthyr': 1960,  
    'gender': 1  
}
```

Also, elements of a list **cannot be named**, but elements of a set **can** be given names: `caseid` is the name, `1.0` is the element.

A Python set that contains variable names and data points is called a **dictionary**. The fact that the dictionary is a set means that **variable names cannot be repeated**, and the **order the variables are entered doesn't matter**.

A JSON file is a list of dictionaries: one dictionary for every record.

What is JSON?

JSON and CSV are just two ways to save data in a text file. There are **pros and cons** to each method.

CSV takes up less space in memory than JSON, usually, because JSON rewrites the variable names for each record.

But JSON is more flexible, and can store data structures that are awkward or impossible for CSV, such as:

- ▶ Data in which variables are stored with different **data types** from record to record
- ▶ Data in which **different records have different variables**
- ▶ Data with a **tree-based** nesting structure

What is JSON?

JSON can store data in which variables are stored with different **data types** from record to record:

```
[{'caseid': 1.0,  
  'fttrump': 'Awful',  
  'fthrc': 'Pretty good',  
  'birthyr': 1960,  
  'gender': 1},  
{ 'caseid': 2.0,  
  'fttrump': 28.0,  
  'fthrc': 52.0,  
  'birthyr': 1957,  
  'gender': 2}]
```

What is JSON?

JSON can store data in which **different records have different variables**:

```
[{'caseid': 1.0, 'fttrump': 1.0, 'turnout': 1.0,  
  'vote': 1.0},  
{ 'caseid': 2.0, 'fttrump': 28.0, 'turnout': 0.0},  
{ 'caseid': 3.0,  
  'fttrump': 100.0,  
  'turnout': 1.0,  
  'vote': 0.0,  
  'comment': 'big fan of Trump'}]
```

What is JSON?

JSON can store data with a **tree-based** nesting structure:

```
[{'id': 1,
  'name': 'Leanne Graham',
  'username': 'Bret',
  'email': 'Sincere@april.biz',
  'address': {'street': 'Kulas Light',
    'suite': 'Apt. 556',
    'city': 'Gwenborough',
    'zipcode': '92998-3874',
    'geo': {'lat': '-37.3159', 'lng': '81.1496'}},
  'phone': '1-770-736-8031 x56442',
  'website': 'hildegard.org',
  'company': {'name': 'Romaguera-Crona',
    'catchPhrase': 'Multi-layered client-server neural-net',
    'bs': 'harness real-time e-markets'}}]
```

What is JSON?

In a tree-based nesting structure, **individual fields can themselves contain dictionaries**. Nested parts of the JSON are highlighted below:

```
[{'id': 1,  
  'name': 'Leanne Graham',  
  'username': 'Bret',  
  'email': 'Sincere@april.biz',  
  'address': {'street': 'Kulas Light',  
               'suite': 'Apt. 556',  
               'city': 'Gwenborough',  
               'zipcode': '92998-3874',  
               'geo': {'lat': '-37.3159', 'lng': '81.1496'}}},  
  'phone': '1-770-736-8031 x56442',  
  'website': 'hildegard.org',  
  'company': {'name': 'Romaguera-Crona',  
               'catchPhrase': 'Multi-layered client-server neural-net',  
               'bs': 'harness real-time e-markets'}}]
```


Who uses JSON?

You are most likely to encounter JSON files when working with **APIs** (Application Programming Interface), which are servers that you can use to retrieve and send data to using code (more on that soon). Many APIs find it convenient to send data in this format.

Some databases (especially “NoSQL” types such as MongoDB) work best with JSON formatted data.

JSON is sometimes referred to as a “readable” or “lightweight” **version** of other structured data formats: XML (Extensible Markup Language) and YAML (Yet Another Markup Language)

Loading JSON data into Python

JSON files are just **text files**, with the **list-of-sets style** encoding we've seen to organize data.

The trick is getting Python to **recognize the data** organized in the file, instead of reading the file as one long string.

There are two methods to loading JSON data into Python:

1. If the data contain **no nesting structure**, then read the file **directly to a data frame** with `pd.read_json()`.
2. If the data **contain nested structures**, use `json_normalize()` from the `pandas.io.json` module to create a data frame.

Loading JSON data into Python

1. If the data contain **no nesting structure**, then read the file **directly to a data frame** with `pd.read_json()`.

```
df = pd.read_json(path_or_buf, orient, typ)
```

path_or_buf – (str) Either an existing string object with JSON-formatted data, the filename (if the working directory is set), the filename and path, or the URL that stores the data

orient – (str) how is the JSON data organized? There are five options: **records**, **columns**, **split**, **index**, and **values**.

typ – (str) what kind of output to produce?

- ▶ A dataframe: `typ="frame"`
- ▶ Or a list of dictionaries: `typ="series"`

Loading JSON data into Python

If `typ = "series"`, then `pd.read_json()` stores the output as a list of dictionaries – and we can call specific elements of that list.

This example JSON contains data on 10 users:

```
data_json = pd.read_json("https://jsonplaceholder.typicode.com/users", typ="series")
data_json
```

```
0    {'id': 1, 'name': 'Leanne Graham', 'username': ...
1    {'id': 2, 'name': 'Ervin Howell', 'username': ...
2    {'id': 3, 'name': 'Clementine Bauch', 'usernam...
3    {'id': 4, 'name': 'Patricia Lebsack', 'usernam...
4    {'id': 5, 'name': 'Chelsey Dietrich', 'usernam...
5    {'id': 6, 'name': 'Mrs. Dennis Schulist', 'use...
6    {'id': 7, 'name': 'Kurtis Weissnat', 'username...
7    {'id': 8, 'name': 'Nicholas Runolfsdottir V', ...
8    {'id': 9, 'name': 'Glenna Reichert', 'username...
9    {'id': 10, 'name': 'Clementina DuBuque', 'user...
dtype: object
```

Loading JSON data into Python

We can look at **just the first dictionary** by calling element 0:

```
data_json[0]
```

```
{'id': 1,  
 'name': 'Leanne Graham',  
 'username': 'Bret',  
 'email': 'Sincere@april.biz',  
 'address': {'street': 'Kulas Light',  
             'suite': 'Apt. 556',  
             'city': 'Gwenborough',  
             'zipcode': '92998-3874',  
             'geo': {'lat': '-37.3159', 'lng': '81.1496'}}},  
 'phone': '1-770-736-8031 x56442',  
 'website': 'hildegard.org',  
 'company': {'name': 'Romaguera-Crona',  
             'catchPhrase': 'Multi-layered client-server neural-net',  
             'bs': 'harness real-time e-markets'}}
```

Loading JSON data into Python

Or we can look at elements [within this dictionary](#) by calling the name of the element we want:

```
data_json[0]['address']
```

```
{'street': 'Kulas Light',  
 'suite': 'Apt. 556',  
 'city': 'Gwenborough',  
 'zipcode': '92998-3874',  
 'geo': {'lat': '-37.3159', 'lng': '81.1496'}}
```

```
data_json[0]['address']['city']
```

```
'Gwenborough'
```

Loading JSON data into Python

orient – (str) how is the JSON data organized? There are five options: **records**, **columns**, **split**, **index**, and **values**.

`orient="records"` works with JSON files organized as a list-of-sets, where each set is an entire record (or a row in flat data):

```
'[{"caseid":1.0,"fttrump":1.0,"fthrc":76.0,"birthyr":1960,"gender":1},  
{"caseid":2.0,"fttrump":28.0,"fthrc":52.0,"birthyr":1957,"gender":2},  
{"caseid":3.0,"fttrump":100.0,"fthrc":1.0,"birthyr":1963,"gender":1},  
{"caseid":4.0,"fttrump":0.0,"fthrc":69.0,"birthyr":1980,"gender":1},  
{"caseid":5.0,"fttrump":13.0,"fthrc":1.0,"birthyr":1974,"gender":1}]'
```

Loading JSON data into Python

orient – (str) how is the JSON data organized? There are five options: **records**, **columns**, **split**, **index**, and **values**.

`orient="columns"` works with JSON files organized as a list-of-sets, where each set is an entire column (the names are the row-names in the flat data):

```
'{"caseid":{"0":1.0,"1":2.0,"2":3.0,"3":4.0,"4":5.0},  
"fttrump":{"0":1.0,"1":28.0,"2":100.0,"3":0.0,"4":13.0},  
"fthrc":{"0":76.0,"1":52.0,"2":1.0,"3":69.0,"4":1.0},  
"birthyr":{"0":1960,"1":1957,"2":1963,"3":1980,"4":1974},  
"gender":{"0":1,"1":2,"2":1,"3":1,"4":1}}'
```


Loading JSON data into Python

orient – (str) how is the JSON data organized? There are five options: **records**, **columns**, **split**, **index**, and **values**.

`orient="split"` works with JSON files organized as set with three lists: **columns** lists the column names, **index** lists the row names, and **data** is a list-of-lists of data points, one list for each row.

```
'{"columns":["caseid","fttrump","fthrc","birthyr","gender"],  
  "index":[0,1,2,3,4],  
  "data":[[1.0,1.0,76.0,1960,1],  
           [2.0,28.0,52.0,1957,2],  
           [3.0,100.0,1.0,1963,1],  
           [4.0,0.0,69.0,1980,1],  
           [5.0,13.0,1.0,1974,1]]}'
```

Loading JSON data into Python

orient – (str) how is the JSON data organized? There are five options: **records**, **columns**, **split**, **index**, and **values**.

`orient="index"` is like `orient="records"` but includes the name of each row in the data:

```
'{"0":{"caseid":1.0,"fttrump":1.0,"fthrc":76.0,"birthyr":1960,"gender":1},  
"1":{"caseid":2.0,"fttrump":28.0,"fthrc":52.0,"birthyr":1957,"gender":2},  
"2":{"caseid":3.0,"fttrump":100.0,"fthrc":1.0,"birthyr":1963,"gender":1},  
"3":{"caseid":4.0,"fttrump":0.0,"fthrc":69.0,"birthyr":1980,"gender":1},  
"4":{"caseid":5.0,"fttrump":13.0,"fthrc":1.0,"birthyr":1974,"gender":1}}'
```

`orient="values"` only contains the datapoints:

```
[[1.0,1.0,76.0,1960,1],  
 [2.0,28.0,52.0,1957,2],  
 [3.0,100.0,1.0,1963,1],  
 [4.0,0.0,69.0,1980,1],  
 [5.0,13.0,1.0,1974,1]]'
```

Loading JSON data into Python

If the JSON data contains different data types for the same variable in different records, such as:

```
[{'caseid': 1.0,  
  'fttrump': 'Awful',  
  'fthrc': 'Pretty good',  
  'birthyr': 1960,  
  'gender': 1},  
 {'caseid': 2.0,  
  'fttrump': 28.0,  
  'fthrc': 52.0,  
  'birthyr': 1957,  
  'gender': 2}]
```

then the `pd.read_json()` function stores the variables (`fttrump` and `fthrc` in this case) as “object” type data – meaning that it is agnostic about whether the variable contains strings or categories.

Loading JSON data into Python

If different JSON records contain data on different variables:

```
[{'caseid': 1.0, 'fttrump': 1.0, 'turnout': 1.0,  
  'vote': 1.0},  
{ 'caseid': 2.0, 'fttrump': 28.0, 'turnout': 0.0},  
{ 'caseid': 3.0,  
  'fttrump': 100.0,  
  'turnout': 1.0,  
  'vote': 0.0,  
  'comment': 'big fan of Trump'}]
```

then the `pd.read_json()` function creates columns for every variable that appears even once, and places NaN values for records that do not address these variables.

	caseid	comment	fttrump	turnout	vote
0	1	NaN	1	1	1.0
1	2	NaN	28	0	NaN
2	3	big fan of Trump	100	1	0.0

Loading JSON data into Python

2. If the data contain nested structures, use `json_normalize()` from the `pandas.io.json` module to create a data frame.

First, import the `json_normalize()` function:

```
from pandas.io.json import json_normalize
```

Second, load the data into Python using `pd.read_json()` as a **list, not a dataframe**. For example:

```
url = "https://jsonplaceholder.typicode.com/users"  
users = pd.read_json(url, typ="series")
```

Loading JSON data into Python

If you load the data directly as a data frame using `pd.read_json()`, and there is nesting in the data, the data frame will **keep these structures as strings** in the output data:

	address	company	email
0	{'street': 'Kulas Light', 'suite': 'Apt. 556',...	{'name': 'Romaguera-Crona', 'catchPhrase': 'Mu...	Sincere@april.biz
1	{'street': 'Victor Plains', 'suite': 'Suite 87...	{'name': 'Deckow-Crist', 'catchPhrase': 'Proac...	Shanna@melissa.tv
2	{'street': 'Douglas Extension', 'suite': 'Suit...	{'name': 'Romaguera-Jacobson', 'catchPhrase': '...	Nathan@yesenia.net
3	{'street': 'Hoeger Mall', 'suite': 'Apt. 692',...	{'name': 'Robel-Corkery', 'catchPhrase': 'Mult...	Julianne.OConner@kory.org
4	{'street': 'Skiles Walks', 'suite': 'Suite 351...	{'name': 'Keebler LLC', 'catchPhrase': 'User-c...	Lucio_Hettinger@annie.ca
5	{'street': 'Norberto Crossing', 'suite': 'Apt....	{'name': 'Considine-Lockman', 'catchPhrase': '...	Karley_Dach@jasper.info
6	{'street': 'Rex Trail', 'suite': 'Suite 280', ...	{'name': 'Johns Group', 'catchPhrase': 'Config...	Telly.Hoeger@billy.biz
7	{'street': 'Ellsworth Summit', 'suite': 'Suite...	{'name': 'Abernathy Group', 'catchPhrase': 'Im...	Sherwood@rosamond.me
8	{'street': 'Dayna Park', 'suite': 'Suite 449',...	{'name': 'Yost and Sons', 'catchPhrase': 'Swit...	Chaim_McDermott@dana.io
9	{'street': 'Kattie Turnpike', 'suite': 'Suite ...	{'name': 'Hoeger LLC', 'catchPhrase': 'Central...	Rey.Padberg@karina.biz

This makes it **hard to access the data** inside the address or company columns, for example.

Loading JSON data into Python

Instead, use `json_normalize()` like this:

```
url = "https://jsonplaceholder.typicode.com/users"
users = pd.read_json(url, typ="series")
users = json_normalize(users)
users
```

	address.city	address.geo.lat	address.geo.lng	address.street	address.suite	address.zipcode	company.bs	company.catchPhrase	company.name
0	Gwenborough	-37.3159	81.1496	Kulas Light	Apt. 556	92998-3874	harness real-time e-markets	Multi-layered client- server neural-net	Romaguera- Crona
1	Wisokyburgh	-43.9509	-34.4618	Victor Plains	Suite 879	90566-7771	synergize scalable supply- chains	Proactive didactic contingency	Deckow-Crist
2	McKenziehaven	-68.6102	-47.0653	Douglas Extension	Suite 847	59590-4157	e-enable strategic applications	Face to face bifurcated interface	Romaguera- Jacobson
3	South Elvis	29.4572	-164.2990	Hoeger Mall	Apt. 692	53919-4257	transition cutting- edge web services	Multi-tiered zero tolerance productivity	Robel-Corkery
4	Roscoeview	-31.8129	62.5342	Skiles Walks	Suite 351	33263	revolutionize end-to-end systems	User-centric fault- tolerant solution	Keebler LLC

The column names are fairly ugly, but **every variable is now stored in a separate column.**

Converting DataFrames/CSVs to JSON

To convert a dataframe to a JSON file, use:

```
df2 = df.to_json(orient)
```

Replace `df` with the name of the dataframe object you are converting, and replace `df2` with object you are creating.

orient – (str) Just like with `pd.read_json()`, the `orient` parameter can be set to

- ▶ `orient="records"` – a list of sets, each one referring to one record
- ▶ `orient="columns"` – a list of sets, each one referring to one column
- ▶ `orient="split"` – three lists, one for column names, one for row names, one for data
- ▶ `orient="index"` – like “records” but including row names
- ▶ `orient="values"` – just data in a list-of-lists

Writing JSON files to disk

To write a JSON file to disk, use:

```
df.to_json(path_or_buf, orient)
```

Replace `df` with the object you want to save as a JSON-encoded text file. If `df` is a dataframe, then this function **both converts it to JSON and writes it to disk**.

path_or_buf – (str) a filename, or a filename with a path.

If you type a **compressed file extension** to end your file name (`.gzip`, `.bz2`, `.zip`, or `.xz`), then this function saves a **compressed version of the data file**.

orient – (str) Works the same as with reading JSON, or converting a dataframe to JSON.