

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

Loading Other Kinds of Electronic Data Files

- Loading fixed width files

- 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

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- ▶ Defining and working with objects
- ▶ Saving scripts/notebooks
- ▶ Using functions

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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.

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

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

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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

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

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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.

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- ▶ 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.**

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

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- ▶ So many memes:



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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.

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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.

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

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Python's Built-in Help Documentation

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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?

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

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

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import sklearn.linear_model
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Help on class LinearRegression in module
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class LinearRegression(LinearModel,  
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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)
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Some docstrings list the signature, although the signature can be accessed elsewhere. The signature lists all of the **parameters** of a function.

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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.

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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.

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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.])
```

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>>> 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.

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

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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

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

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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

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(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**.

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

Getting Help: Asking a Question on Stack Overflow

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- ▶ 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

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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.

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

Interacting with other Python users on PySlackers

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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**.

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

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

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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.

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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.

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Use a unique, throwaway password!

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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.

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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

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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

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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

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- ▶ 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.

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

Kinds of ASCII files

Our task: to load ASCII data into Python, identify the ways in which it is messy, and create [tidy data](#).

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A comma-separated values (CSV) file:

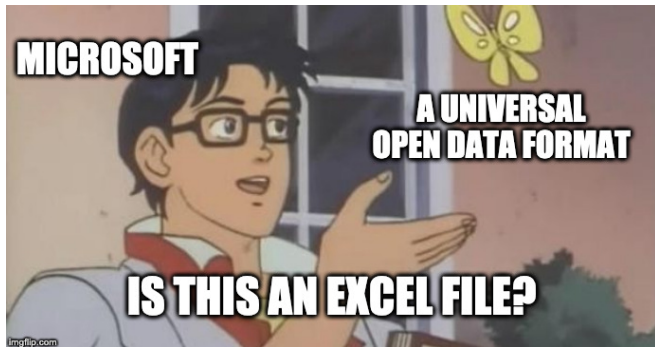
```
sex,race,region,happy,life,sibs,childs,age,educ,paeduc,maeduc,speduc,prestg80,
occcat80,tax,usint1,obey,popular,thnkself,workhard,helpoth,hlth1,hlth2,hlth3,
hlth4,hlth5,hlth6,hlth7,hlth8,hlth9,work1,work2,work3,work4,work5,work6,work7,
work8,work9,prob1,prob2,prob3,prob4
2,1,1,1,1,1,2,61,12,97,12,97,22,3,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0, , , ,
2,1,1,2,1,2,1,32,20,20,18,20,75,1,1,0,5,4,1,2,3,1,1,2,2,2,2,2,2,2,1,2,
2,1,2,1,1,2,4,5,
1,1,1,1,0,2,1,35,20,16,14,17,59,1,0,1,5,4,1,2,3,2,2,2,2,2,2,2,2,2,2,2,
2,2,2,2,2, , , ,
2,1,1,9,2,2,0,26,20,20,20,97,48,1,1,0,4,5,1,3,2,1,2,2,2,2,2,2,2,2,1,2,2,
2,2,2,2,2,2,2, ,
2,2,1,2,1,4,0,25,12,98,98,97,42,3,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0, , , ,
```

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**.

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Kinds of ASCII files

A **tab delimited** file:

sex	race	region	happy	life	sibs	childs	age	educ	paeduc	maeduc	speduc	prestg80	occcat80	tax	usint1	obey									
popular	thnkself	workhard	helptoth	hlth1	hlth2	hlth3	hlth4	hlth5	hlth6	hlth7	hlth8	hlth9	work1	work2	work3	work4	work5	work6	work7	work8	work9	prob1	prob2	prob3	prob4
2	1	1	1	1	1	2	61	12	97	12	97	22	3	1	1	0									
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0									
0	0	0	0	0																					
2	1	1	2	1	2	1	32	20	20	18	20	75	1	1	0	5									
4	1	2	3	1	1	2	2	2	2	2	2	2	2	2	1	2									
2	1	2	1	1	2	4	5																		
1	1	1	1	0	2	1	35	20	16	14	17	59	1	0	1	5									
4	1	2	3	2	2	2	2	2	2	2	2	2	2	2	2	2									
2	2	2	2	2																					
2	1	1	9	2	2	0	26	20	20	20	97	48	1	1	0	4									
5	1	3	2	1	2	2	2	2	2	2	2	2	2	1	2	2									
2	2	2	2	2	2	2																			
2	2	1	2	1	4	0	25	12	98	98	97	42	3	1	1	0									
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0									
0	0	0	0	0																					

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

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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.

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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:

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pd.read_csv(filepath_or_buffer)
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`filepath_or_buffer` – (string) one of three things:

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```

`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/>

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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")
```

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**.

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3. If you catch anything weird, **return to 1. and try different parameters** for `pd.read_csv()`

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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

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3	4.0	1	NaN	2.0	100	5	4	5
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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	
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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
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The columns it skipped (about **148** in this case) are replaced by a **column of dots**.

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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)
```

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

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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**.

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`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, :]
```

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

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

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Replace 10 with however many rows you want to see.

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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)

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`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

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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])
```

Looking at the data to see if it loaded correctly

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```

To see just the int variables, type

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

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

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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

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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.

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- ▶ Are the **variable names** set to what they are supposed to be?

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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.

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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.

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

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- ▶ `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**)

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- ▶ `usecols = ["caseid", "vote12", "meet"]` only loads the variables named “caseid”, “vote12”, and “meet”, as recognized by whatever Python thinks is the header

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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:

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- ▶ **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

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

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

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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**.

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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.

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

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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.

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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="#"`.

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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**.

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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.

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)` .

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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

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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.

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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.

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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**.

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

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'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**.

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

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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.

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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,  
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```

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```
njcc = pd.read_fwf(url, colspecs=datapos,  
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Loading Excel files

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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.

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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:

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pd.read_excel(io, sheet_name)
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- ▶ path and filename,
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- ▶ 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.

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- ▶ 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)
```

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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)
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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

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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

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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

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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:

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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.

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.

Loading SAS, Stata, and SPSS files

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To load the **SAS** inflation data:

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

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 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**.

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- ▶ 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.

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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,birthyr,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
```

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  
}
```

What is JSON?

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```
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  'caseid': 1.0,  
  'fttrump': 1.0,  
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  '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**.

What is JSON?

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}
```

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.

What is JSON?

```
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    '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**.

What is JSON?

```
{  
    'caseid': 1.0,  
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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.

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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',
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```

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.

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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

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

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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)
```

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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

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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.

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'}}
```

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']
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```
{'street': 'Kulas Light',  
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 '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}}'
```

Loading JSON data into Python

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

```
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"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}]
```

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  'birthyr': 1957,  
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```

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'}]
```

Loading JSON data into Python

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  '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.

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First, import the `json_normalize()` function:

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from pandas.io.json import json_normalize
```

Loading JSON data into Python

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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	Roscoevue	-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.

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- ▶ `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**.

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