Intro to pandas data structures

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UPDATE: If you're interested in learning pandas from a SQL perspective and would prefer to watch a video, you can find video of my 2014 PyData NYC talk here.



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However, the other week a couple of coworkers expressed their interest in learning a bit more about it - this seemed like a good reason to revisit the topic.

What follows is a fairly thorough introduction to the library. I chose to break it into three parts as I felt it was too long and daunting as one.

- Part 1: Intro to pandas data structures, covers the basics of the library's two main data structures - Series and DataFrames.
- Part 2: Working with
 DataFrames, dives a bit
 deeper into the functionality
 of DataFrames. It shows how
 to inspect, select, filter,
 merge, combine, and group
 your data.
- Part 3: Using pandas with the MovieLens dataset, applies the learnings of the first two parts in order to answer a few basic analysis questions about the MovieLens ratings data.

If you'd like to follow along, you can find the necessary CSV files here and the MovieLens dataset here.



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always been great for prepping and munging data, but it's never been great for analysis - you'd usually end up using R or loading it into a database and using SQL (or worse, Excel). pandas makes Python great for analysis.

Data Structures

pandas introduces two new data structures to Python - Series and DataFrame, both of which are built on top of NumPy (this means it's fast).

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
pd.set_option('max_columns', 50)
%matplotlib inline
```

Series

A Series is a one-dimensional object similar to an array, list, or column in a table. It will assign a labeled index to each item in the Series. By default, each item will receive an index label from 0 to N, where N is the length of the Series minus one.



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```
0 7
1 Heisenberg
2 3.14
3 -1789710578
4 Happy Eating!
dtype: object
```

Alternatively, you can specify an index to use when creating the Series.

The Series constructor can convert a dictonary as well, using the keys of the dictionary as its index.

```
d = {'Chicago': 1000, 'New York': 1300, 'Portlan
     'Austin': 450, 'Boston': None}
cities = pd.Series(d)
cities
Austin
                  450
                  NaN
Boston
Chicago
                 1000
New York
                 1300
Portland
                 900
San Francisco
                 1100
dtype: float64
```

You can use the index to select specific items from the Series ...

```
cities['Chicago']
1000.0
```





Chicago 1000
Portland 900
San Francisco 1100
dtype: float64

Or you can use boolean indexing for selection.

```
cities[cities < 1000]

Austin 450
Portland 900
dtype: float64
```

That last one might be a little weird, so let's make it more clear - cities < 1000 returns a Series of True/False values, which we then pass to our Series cities, returning the corresponding True items.

```
less_than_1000 = cities < 1000</pre>
print(less_than_1000)
print('\n')
print(cities[less_than_1000])
                  True
Austin
                 False
Boston
Chicago
                 False
New York
                 False
Portland
                 True
San Francisco
                 False
dtype: bool
Austin
            450
Portland
            900
dtype: float64
```

You can also change the values in a Series on the fly.



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```
('Old value:', 1000.0)
('New value:', 1400.0)
# changing values using boolean logic
print(cities[cities < 1000])</pre>
print('\n')
cities[cities < 1000] = 750
print cities[cities < 1000]</pre>
Austin
            450
Portland
            900
dtype: float64
Austin
            750
Portland
            750
dtype: float64
```

What if you aren't sure whether an item is in the Series? You can check using idiomatic Python.

```
print('Seattle' in cities)
print('San Francisco' in cities)

False
True
```

Mathematical operations can be done using scalars and functions.





Austin	562500
Boston	NaN
Chicago	1960000
New York	1690000
Portland	562500
San Francisco	1210000
dtype: float64	

You can add two Series together, which returns a union of the two Series with the addition occurring on the shared index values. Values on either Series that did not have a shared index will produce a NULL/NaN (not a number).

```
print(cities[['Chicago', 'New York', 'Portland']]
print('\n')
print(cities[['Austin', 'New York']])
print('\n')
print(cities[['Chicago', 'New York', 'Portland']
            1400
Chicago
         1300
New York
Portland
            750
dtype: float64
Austin
            750
New York
            1300
dtype: float64
Austin
           NaN
Chicago
            NaN
New York 2600
Portland NaN
dtype: float64
```



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NULL/NaN values.

dtype: float64

NULL checking can be performed with isnull and notnull.

```
# returns a boolean series indicating which valu
cities.notnull()
                  True
Austin
Boston
                 False
Chicago
                  True
New York
                  True
Portland
                  True
San Francisco
                  True
dtype: bool
# use boolean logic to grab the NULL cities
print(cities.isnull())
print('\n')
print(cities[cities.isnull()])
Austin
                 False
Boston
                 True
Chicago
                 False
New York
                False
Portland
                False
San Francisco
                False
dtype: bool
Boston
        NaN
```



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columns, akin to a spreadsheet, database table, or R's data.frame object. You can also think of a DataFrame as a group of Series objects that share an index (the column names).

For the rest of the tutorial, we'll be primarily working with DataFrames.

Reading Data

To create a DataFrame out of common Python data structures, we can pass a dictionary of lists to the DataFrame constructor.

Using the columns parameter allows us to tell the constructor how we'd like the columns ordered. By default, the DataFrame constructor will order the columns alphabetically (though this isn't the case when reading from a file - more on that next).



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	year	team	wins	losses
0	2010	Bears	11	5
1	2011	Bears	8	8
2	2012	Bears	10	6
3	2011	Packers	15	1
4	2012	Packers	11	5
5	2010	Lions	6	10
6	2011	Lions	10	6
7	2012	Lions	4	12

Much more often, you'll have a dataset you want to read into a DataFrame. Let's go through several common ways of doing so.

CSV

Reading a CSV is as simple as calling the *read_csv* function. By default, the *read_csv* function expects the column separator to be a comma, but you can change that using the sep parameter.

%cd ~/Dropbox/tutorials/pandas/

/Users/gjreda/Dropbox (Personal)/tu





```
Year, Age, Tm, Lg, W, L, W-L%, ERA, G, GS, Gf
1995, 25, NYY, AL, 5, 3, .625, 5.51, 19, 10,
1996, 26, NYY, AL, 8, 3, .727, 2.09, 61, 0, 1
1997, 27, NYY, AL, 6, 4, .600, 1.88, 66, 0, 5
1998, 28, NYY, AL, 3, 0, 1.000, 1.91, 54, 0
```

```
from_csv = pd.read_csv('mariano-rivera.csv')
from_csv.head()
```

	Year	Age	Tm	Lg	W	L	W
0	1995	25	NYY	AL	5	3	0.0
1	1996	26	NYY	AL	8	3	0.
2	1997	27	NYY	AL	6	4	0.0
3	1998	28	NYY	AL	3	0	1.0
4	1999	29	NYY	AL	4	3	0.!

Our file had headers, which the function inferred upon reading in the file. Had we wanted to be more explicit, we could have passed header=None to the function along with a list of column names to use:

```
# Source: pro-football-reference.com/players/M/M!head -n 5 peyton-passing-TDs-2012.csv

1,1,2012-09-09,DEN,,PIT,W 31-19,3,7
2,1,2012-09-09,DEN,,PIT,W 31-19,4,1
3,2,2012-09-17,DEN,@,ATL,L 21-27,2,4,3,2012-09-23,DEN,,HOU,L 25-31,4,5
5,3,2012-09-23,DEN,,HOU,L 25-31,4,6
```



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	num	game	date	tean	
0	1	1	2012-09-09	DEN	
1	2	1	2012-09-09	DEN	
2	3	2 2012		DEN	
3	4	3	2012-09-23	DEN	
4	5	3	2012-09-23	DEN	

pandas' various *reader* functions have many parameters allowing you to do things like skipping lines of the file, parsing dates, or specifying how to handle NA/NULL datapoints.

There's also a set of *writer* functions for writing to a variety of formats (CSVs, HTML tables, JSON). They function exactly as you'd expect and are typically called to_format:

```
my_dataframe.to_csv('path_to_file.csv')
```

Take a look at the IO documentation to familiarize yourself with file reading/writing functionality.



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to read and write Excel files, so you can easily read from Excel, write your code in Python, and then write back out to Excel - no need for VBA.

Reading Excel files requires the xlrd library. You can install it via pip (*pip install xlrd*).

Let's first write a DataFrame to Excel.

this is the DataFrame we created from a dictio
football.head()

	year	team	wins	losses
0	2010	Bears	11	5
1	2011	Bears	8	8
2	2012	Bears	10	6
3	2011	Packers	15	1
4	2012	Packers	11	5

since our index on the football DataFrame is
football.to_excel('football.xlsx', index=False)

!ls -l *.xlsx
-rw-r--r-@ 1 gjreda staff 5665 N

delete the DataFrame
del football



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	year	team	wins	losses
0	2010	Bears	11	5
1	2011	Bears	8	8
2	2012	Bears	10	6
3	2011	Packers	15	1
4	2012	Packers	11	5
5	2010	Lions	6	10
6	2011	Lions	10	6
7	2012	Lions	4	12

Database

pandas also has some support for reading/writing DataFrames directly from/to a database [docs]. You'll typically just need to pass a connection object or sqlalchemy engine to the read_sql or to_sql functions within the pandas.io module.

Note that to_sql executes as a series of INSERT INTO statements and thus trades speed for simplicity. If you're writing a large DataFrame to a database, it might be quicker to write the DataFrame to CSV and load that directly using the database's file import arguments.



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results = sql.read_sql(query, con=conn)
results.head()

	tow_date	make	style	mod
0	01/19/2013	FORD	LL	
1	01/19/2013	FORD	4D	
2	01/19/2013	FORD	4D	
3	01/19/2013	FORD	LL	
4	01/19/2013	FORD	LL	



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prefer to read the results directly from the clipboard. I'm often tweaking queries in my SQL client (Sequel Pro), so I would rather see the results *before* I read it into pandas. Once I'm confident I have the data I want, then I'll read it into a DataFrame.

This works just as well with any type of delimited data you've copied to your clipboard. The function does a good job of inferring the delimiter, but you can also use the sep parameter to be explicit.

Hank Aaron

1	linors	G	am	ie L	ogs		Splits	V HR	Log	vs. Pit	cher	н	nders	2М																	
98 14 15 15 15 15 15 15 15	ar Age	ŀ	Tm	Lg			PA	AB	R	н	28	38	HR	RBI	SB	cs	88	so	BA	OBP	SLG	OPS	OPS+	TB	GDP	HBP	SH	SF	188	Pos	Awards
5 1 1 1 2 3 3 4 4 4 4 4 4 4 4	54 20	H	MUN	NL		Cop	v													322	.447	.769	104	209	13	3	6	4		*79	RoY-4
18	55 21	1 15	MUN	NL		car	ch Go	agle fo	r 'Yea	r Age	Tm l	q (PA	AB R H	1 2B	3B I	HR RB	I SB C	S'	366	.540	.906	141	325	20	3	7	4	5	*974	AS,MVP-9
1	56 22	2 11	MUN	N.								-								365	.558	.923	151	340	21	2	5	7	- 6	*9	AS,MVP-3
1	57 23	3 15	MLN	M.																378	.600	.978	166	369	13	0	0	3	15	-98	AS, MVP-1
1	58 24	4 19	MUN	M.															•	386	.546	.931	152	328	21	1	0	3	16	-98	AS,MVP-3,GI
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83 34 10 10 10 10 10 10 10 1	63 29	9 1	MUN	NL		pe	ech												•	391	.586	.977	179	370	11	0	0	5	18	*9	AS,MVP-3
85 18 18 40 18 40 18 40 18 40 18 40 18 40 18 40 18 40 40 40 40 40 40 40 4	64 30	H	MUN	N,		Inle	and and	th Clau	dAnn											393	.514	.907	153	293	22	0	0	2	9	*94	AS,MVP-14
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88 9 4 16 17 18 18 18 18 18 18 18 18 18 18 18 18 18	166 32	2 A	ATL	M.	_	-		ines as	u 5pc	JAC III	-	-	-	-	-	-	-	_		.356	.539	.895	142	325	14	1	0	8	15	*9/84	AS,MVP-8
84 9 3 6 10 1 2 1 2 2 2 2 3 3 4 2 2 2 2 3 3 4 2 2 2 3 3 4 2 2 3 3 4 2 2 3 3 4 2 3 3 4 2 3 3 4 2 3 3 4 3 4	67 33	3 <u>A</u>	ATL	NI.	1	55	669	600	113	184	37	3	39	109	17	6	63	97	.307	.369	.573	.943	168	344	11	0	0	- 6	19	*98/4	AS,MVP-S
10 10 11 12 13 14 15 15 15 15 15 15 15	68 34	4 <u>A</u>	ATL	NI,	1	60	676	606	84	174	33	4	29	86	28	5	64	62	.287	.354	.498	.852		302	21	1	0	5	23	*93	AS,MVP-12
	69 35	S A	ATL	M.	1	47	639	547	100	164	30	3	44	97	9	10	87	47	.300	.396	.607	1.003	177	332	14	2	0	3	19	*9/3	AS,MVP-3
777 38 AT 18 129 545 449 75 119 10 0 34 77 4 0 52 55 265 390 514 504 127 232 17 1 0 2 1 5 39 ASSAULT 78 AT 18 12 32 32 32 32 32 32 32 32 32 32 32 32 32	70 36	S A	ATL	M.	1	50	598	516	103	154	26	1	38	118	9	0	74	63	.298	.385	.574	.958	149	296	13	2	0	6	15	-93	AS,MVP-17
777 39 ATL M, 120 465 392 84 118 12 1 40 96 1 1 68 51 301 402 643 1.045 177 252 7 1 0 4 13 79 AS_ANNE 774 40 ATL M, 112 382 340 47 91 16 0 20 69 1 0 39 29 268 341 491 832 128 167 6 0 1 2 6 7 AS_	71 37	7 A	ATL	NL	1	39	573	495	95	162	22	3	47	118	1	1	71	58	.327	.410	.669	1.079	194	331	9	2	0	5	21	39	AS,MVP-3
974 40 ATL No. 112 382 340 47 91 16 0 20 69 1 0 39 29 268 341 491 832 128 167 6 0 1 2 6 7 85	72 38	3 4	ATL	NI.	1	29	545	449	75	119	10	0	34	77	4	0	92	55	.265	.390	.514	.904	147	231	17	- 1	0	2	15	*39	AS,MVP-16
	73 39	A	ATL	M.	1	20	465	392	84	118	12	1	40	95	1	1	68	51	.301	.402	.643	1.045	177	252	7	- 1	0	- 4	13	79	AS,MVP-12
75 41 <u>HIL AL</u> 137 543 465 45 109 16 2 12 60 0 1 70 51 .234 .332 .355 .687 95 165 15 1 1 6 3 *D ₂ /7 <u>AS</u>	74 40	A	ATL	M.	1	12	382	340	47	91	16	0	20	69	1	0	39	29	.268	.341	.491	.832	128	167	6	0	1	2	- 6	7	AS
	75 41	B	MIL	AL.	1	37	543	465	45	109	16	2	12	60	0	1	70	51	.234	.332	.355	.687	95	165	15	1	1	6	3	*D/7	AS



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	Year	Age	Tm	Lg	G	PA
	1954		MLN	ΣL	122	509
1	1955 ★	21	MLN	NL	153	665
2	1956 ★	22	MLN	NL	153	660
3	1957 ★	23	MLN	NL	151	675
4	1958 ★	24	MLN	NL	153	664

URL

With read_table, we can also read directly from a URL.

Let's use the best sandwiches data that I wrote about scraping a while back.



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	rank	sandwich	restaurant	ľ
0	1	BLT	Old Oak Tap	- :: ::
1	2	Fried Bologna	Au Cheval	-
2	3	Woodland Mushroom	Xoco	

Google Analytics

pandas also has some integration with the Google Analytics API, though there is some setup required. I won't be covering it, but you can read more about it here and here.

Move onto the next section, which covers working with DataFrames.





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