Module 2: Exploratory Data Analysis

Part 2: Two Dimensional Data

The Data Frame

```
df = pd.DataFrame( <data>, <index>, <column_names> )
```

CSV

```
df = pd.read_csv( <file> )
```

```
df = pd.read_csv( <url> )
```

Excel

```
df = pd.read_excel( <file>, sheetname=<sheetname> )
```

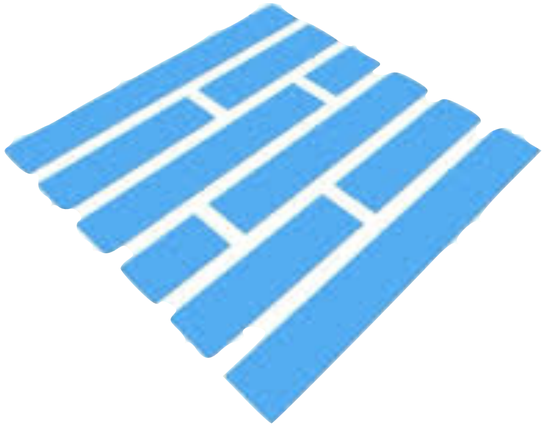
```
[
   {
    “changed":"2015-04-0300:00:00",
    "created":"2014-04-10 00:00:00”,
    “dnssec":"False",
    "expires":"2016-04-10 00:00:00”,
    “isMalicious":0,
    “url":"nuteczki.com"
   },
…
]
```

JSON

```
df = pd.read_json( <file> )
or
df = pd.read_json( <url> )
```

From a Database

```
df = pd.read_sql( <query>, <connection> )
```



Parquet

```
df = pd.read_parquet( <file> )
```

HTML

```
df = pd.read_html( <source> )
```

XML

```
import requests

user_agent_url = 'http://www.user-agents.org/allagents.xml'
xml_data = requests.get(user_agent_url).content
```

http://www.austintaylor.io/lxml/python/pandas/xml/dataframe/2016/07/08/convert-xml-to-pandas-dataframe/

XML

```
import xml.etree.ElementTree as ET

class XML2DataFrame:

    def __init__(self, xml_data):
        self.root = ET.XML(xml_data)

    def parse_root(self, root):
        return [self.parse_element(child) for child in iter(root)]

    def parse_element(self, element, parsed=None):
        if parsed is None:
            parsed = dict()
        for key in element.keys():
            parsed[key] = element.attrib.get(key)
        if element.text:
            parsed[element.tag] = element.text
        for child in list(element):
            self.parse_element(child, parsed)
        return parsed

    def process_data(self):
        structure_data = self.parse_root(self.root)
        return pd.DataFrame(structure_data)

xml2df = XML2DataFrame(xml_data)
xml_dataframe = xml2df.process_data()
```

http://www.austintaylor.io/lxml/python/pandas/xml/dataframe/2016/07/08/convert-xml-to-pandas-dataframe/

Log Files...

```
070823 21:00:32        1 Connect     root@localhost on test1
070823 21:00:48        1 Query       show tables
070823 21:00:56        1 Query       select * from category
070917 16:29:01       21 Query       select * from location
070917 16:29:12       21 Query       select * from location where id = 1 LIMIT 1
```

```
070823 21:00:32       1 Connect     root@localhost on test1
070823 21:00:48       1 Query       show tables
070823 21:00:56       1 Query       select * from category
070917 16:29:01      21 Query       select * from location
070917 16:29:12      21 Query       select * from location where id = 1 LIMIT 1
```

```
logdf = pd.read_table('../data/mysql.log', names=['raw'])
```

	raw
0	070823 21:00:32 1 Connect root@local...
1	070823 21:00:48 1 Query show tables
2	070823 21:00:56 1 Query select * f...
3	070917 16:29:01 21 Query select * f...
4	070917 16:29:12 21 Query select * f...

```
logdf = pd.read_table('../data/mysql.log', names=['raw'])
logdf['raw'].str.extract('(\d{6}\s\d{2}:\d{2}:\d{2})\s+(\d+)\s(\S+)
\s(.+)', expand=False)
```

	0	1	2	3
0	070823 21:00:32	1	Connect	root@localhost on test1
1	070823 21:00:48	1	Query	show tables
2	070823 21:00:56	1	Query	select * from category
3	070917 16:29:01	21	Query	select * from location
4	070917 16:29:12	21	Query	select * from location where id = 1 LIMIT 1

```
logdf = pd.read_table('../data/mysql.log', names=['raw'])
logdf['raw'].str.extract('(?P<date>\d{6}\s\d{2}:\d{2}:\d{2})\s+(?
P<PID>\d+)\s(?P<Action>\S+)\s(?P<Query>.+)', expand=False)
```

	Date	PID	Action	Query
0	070823 21:00:32	1	Connect	root@localhost on test1
1	070823 21:00:48	1	Query	show tables
2	070823 21:00:56	1	Query	select * from category
3	070917 16:29:01	21	Query	select * from location
4	070917 16:29:12	21	Query	select * from location where id = 1 LIMIT 1

Web Server Logs

Web Server Logs

```
195.154.46.135 - - [25/Oct/2015:04:11:25 +0100] "GET /linux/
doing-pxe-without-dhcp-control HTTP/1.1" 200 24323 "http://
howto.basjes.nl/" "Mozilla/5.0 (Windows NT 5.1; rv:35.0)
Gecko/20100101 Firefox/35.0"
```

Web Server Logs

```
195.154.46.135 - - [25/Oct/2015:04:11:25 +0100] "GET /linux/
doing-pxe-without-dhcp-control HTTP/1.1" 200 24323 "http://
howto.basjes.nl/" "Mozilla/5.0 (Windows NT 5.1; rv:35.0)
Gecko/20100101 Firefox/35.0"
```

```
from apachelogs import LogParser
line_parser = LogParser("%h %l %u %t \"%r\" %>s %b
\"{Referer}i\" \"%{User-agent}i\"")
```

Web Server Logs

er	request_first_line	request_header_referer	request_header_user_agent	request_http_ver	request_method	request_url
	GET /linux/doing-pxe-without-dhcp-control HTTP...	http://howto.basjes.nl/	Mozilla/5.0 (Windows NT 5.1; rv:35.0) Gecko/20...	1.1	GET	/linux/doing-pxe-v
	GET /join_form HTTP/1.0	http://howto.basjes.nl/	Mozilla/5.0 (Windows NT 5.1; rv:35.0) Gecko/20...	1.0	GET	/join_form
	POST /join_form HTTP/1.1	http://howto.basjes.nl/join_form	Mozilla/5.0 (Windows NT 5.1; rv:35.0) Gecko/20...	1.1	POST	/join_form
	GET /join_form HTTP/1.0	http://howto.basjes.nl/	Mozilla/5.0 (Windows NT 6.3; WOW64; rv:34.0) G...	1.0	GET	/join_form
	POST /join_form HTTP/1.1	http://howto.basjes.nl/join_form	Mozilla/5.0 (Windows NT 6.3; WOW64; rv:34.0) G...	1.1	POST	/join_form
	GET /acl_users/credentials_cookie_auth/require...	http://howto.basjes.nl/join_form	Mozilla/5.0 (Windows NT 6.3; WOW64; rv:34.0) G...	1.1	GET	/acl_users/creden

Nested Data?

Nested Data?


```
{"time": 1084443427.311224,
 "timestamp": "2004-05-13T10:17:07.311224",
"IP": {
   "version": 4,
   "ttl": 128,
   "proto": 6,
   "options": [],
   "len": 48,
   "dst": "65.208.228.223",
   "frag": 0,
   "flags": 2, "src": “145.254.160.237",
   "chksum": 37355
   },
   "Ethernet": {"src": "00:00:01:00:00:00", "type": 2048, "dst": “fe:ff:20:00:01:00"},
   …
```

Nested Data

```
pd.read_json( 'nested_data.json' )
```

```
pd.read_json( 'nested_data.json' )
```

	DNS	Ethernet	IP	TCP	UDP	time	timestamp
0	NaN	{'type': 2048, 'dst': 'fe:ff:20:00:01:00', 'sr...	{'dst': '65.208.228.223', 'len': 48, 'version'...	{'window': 8760, 'chksum': 49932, 'sport': 337...	NaN	1.084443e+09	2004-05-13 10:17:07.311224
1	NaN	{'type': 2048, 'dst': '00:00:01:00:00:00', 'sr...	{'dst': '145.254.160.237', 'len': 48, 'version...	{'window': 5840, 'chksum': 23516, 'sport': 80,...	NaN	1.084443e+09	2004-05-13 10:17:08.222534
2	NaN	{'type': 2048, 'dst': 'fe:ff:20:00:01:00', 'sr...	{'dst': '65.208.228.223', 'len': 40, 'version'...	{'window': 9660, 'chksum': 31076, 'sport': 337...	NaN	1.084443e+09	2004-05-13 10:17:08.222534
3	NaN	{'type': 2048, 'dst': 'fe:ff:20:00:01:00', 'sr...	{'dst': '65.208.228.223', 'len': 519, 'version...	{'window': 9660, 'chksum': 43352, 'sport': 337...	NaN	1.084443e+09	2004-05-13 10:17:08.222534
4	NaN	{'type': 2048, 'dst': '00:00:01:00:00:00', 'sr...	{'dst': '145.254.160.237', 'len': 40, 'version...	{'window': 6432, 'chksum': 33825, 'sport': 80,...	NaN	1.084443e+09	2004-05-13 10:17:08.783340

Nested Data

```
from pandas import json_normalize
import json
import pandas as pd

with open('nested.json') as data_file:
    pcap_data = json.load(data_file)

df = pd.DataFrame(json_normalize(pcap_data))
```

```
df = pd.DataFrame(json_normalize(pcap_data))
```

...	TCP.seq	TCP.sport	TCP.urgptr	TCP.window	L
...	951057939.0	3372.0	0.0	8760.0	
...	290218379.0	80.0	0.0	5840.0	
...	951057940.0	3372.0	0.0	9660.0	
...	951057940.0	3372.0	0.0	9660.0	
...	290218380.0	80.0	0.0	6432.0	

Stop

Manipulating a DataFrame

Creating a new Column

```
df['new_col'] = df['column1'] + 3
```

Two Ways of Accessing Columns

```
my_series = df.loc[:,'column1']
```

Don't use the dots!

```
series = df.column1
```

```
my_series = df.loc[:,'column1']
```

Returns a **series**

```
df = df[['column1','column2','column3']]
```

Returns a DataFrame

Filtering a DataFrame

```
df[<boolean condition>]
```

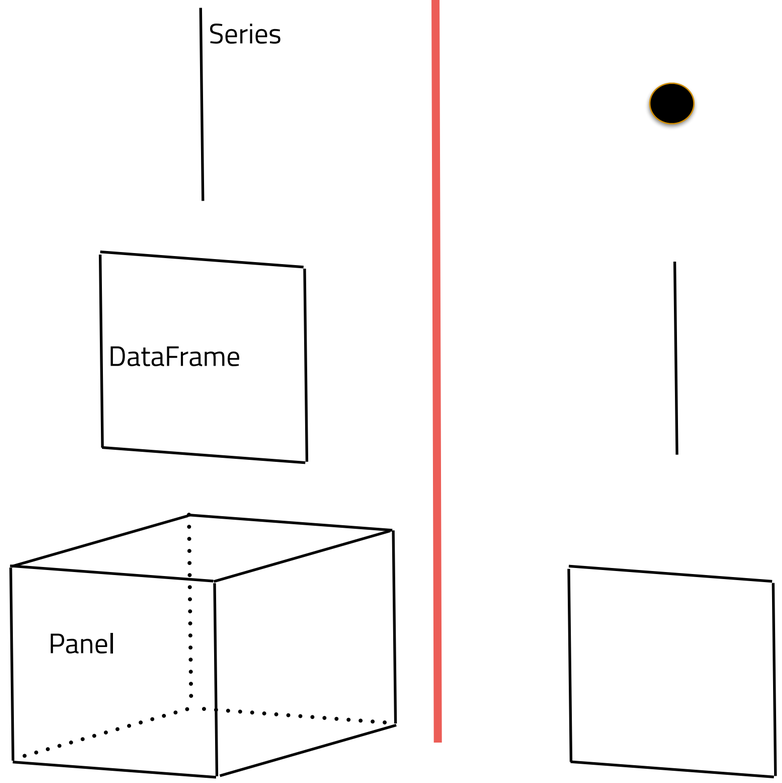
```
df[['col1','col2']][df['col3'] > 5]
```

```
data.loc[<index>]
data.loc[<list of indexes>]
data.sample(<n>)
```

- `data.apply( <function> )`

IF
Call Apply On...

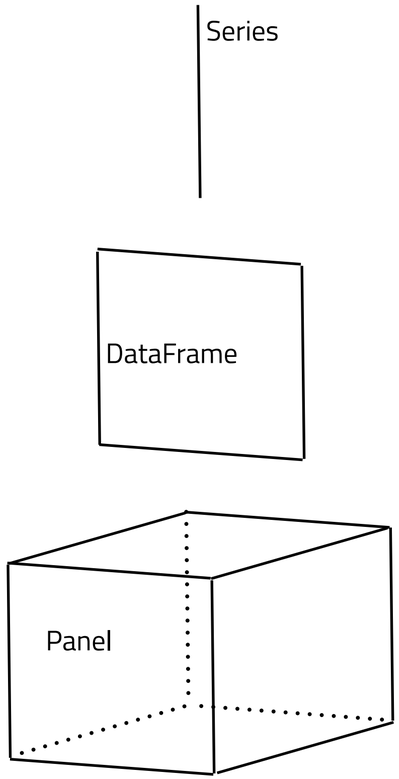
THEN
Function
Receives

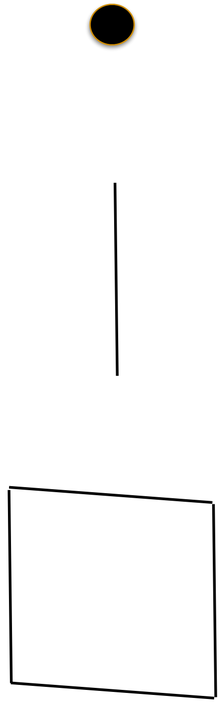


- `data.apply( <function> )`

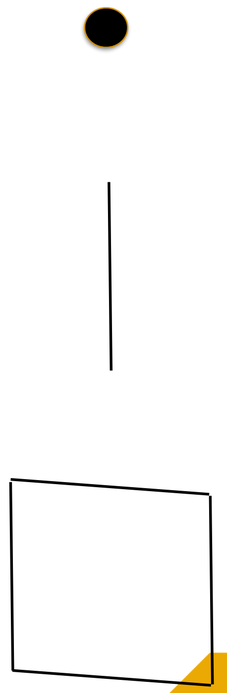
IF
Call Apply On...

THEN
Function
Receives

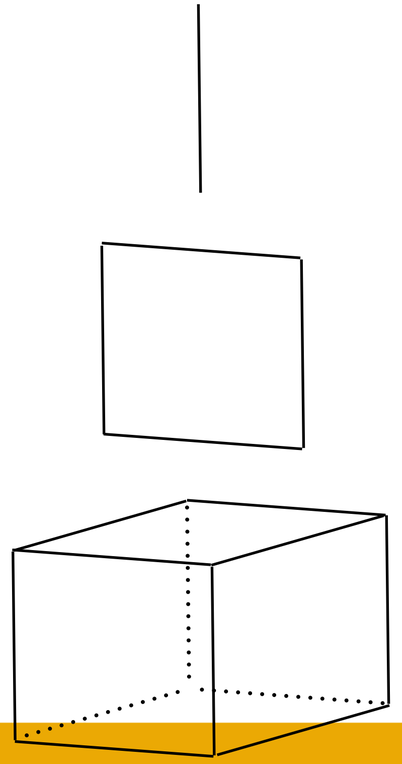




IF
Function
Returns



THEN
Apply Returns...



Questions?

In Class Exercise
Back at xx:xx

Please complete Exercise 5 in Worksheet 2.1: Exploring Two Dimensional Data

Start on Worksheet 2.2

Get Oriented

```
#set the axis to apply the sum
data.sum( axis='index' )
```

OR

```
data.sum( axis='columns' )
```

```
DataFrame.drop(labels,
               axis=0,
               level=None,
               in_place=False,
               errors='raise')
```

Merging Data Sets

Union

Union

Series 1

Index	Value
0	6
1	4
2	2
3	3

Union

Series 1

Index	Value
0	6
1	4
2	2
3	3

Series 2

Index	Value
0	7
1	5
2	3
3	4

Union

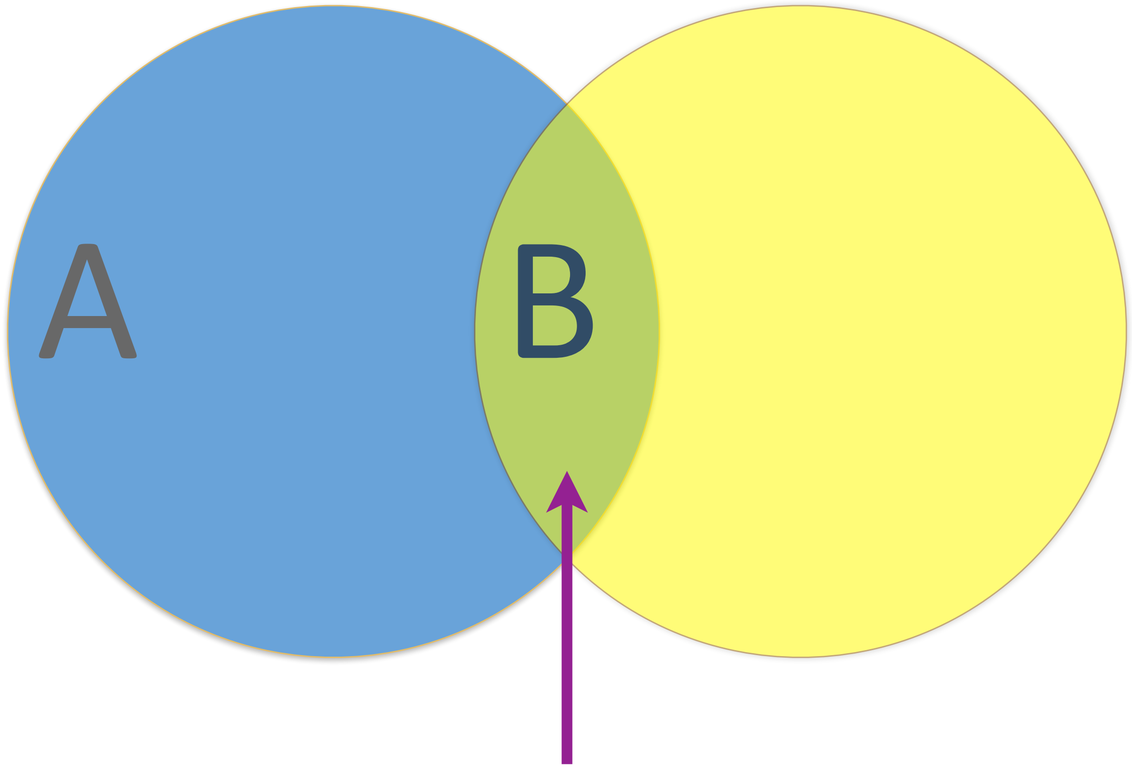
combinedSeries

Index	Value
0	6
1	4
2	2
3	3
4	7
5	5
6	3
7	4

```
combinedSeries = pd.concat(
                     [series1, series2])
```

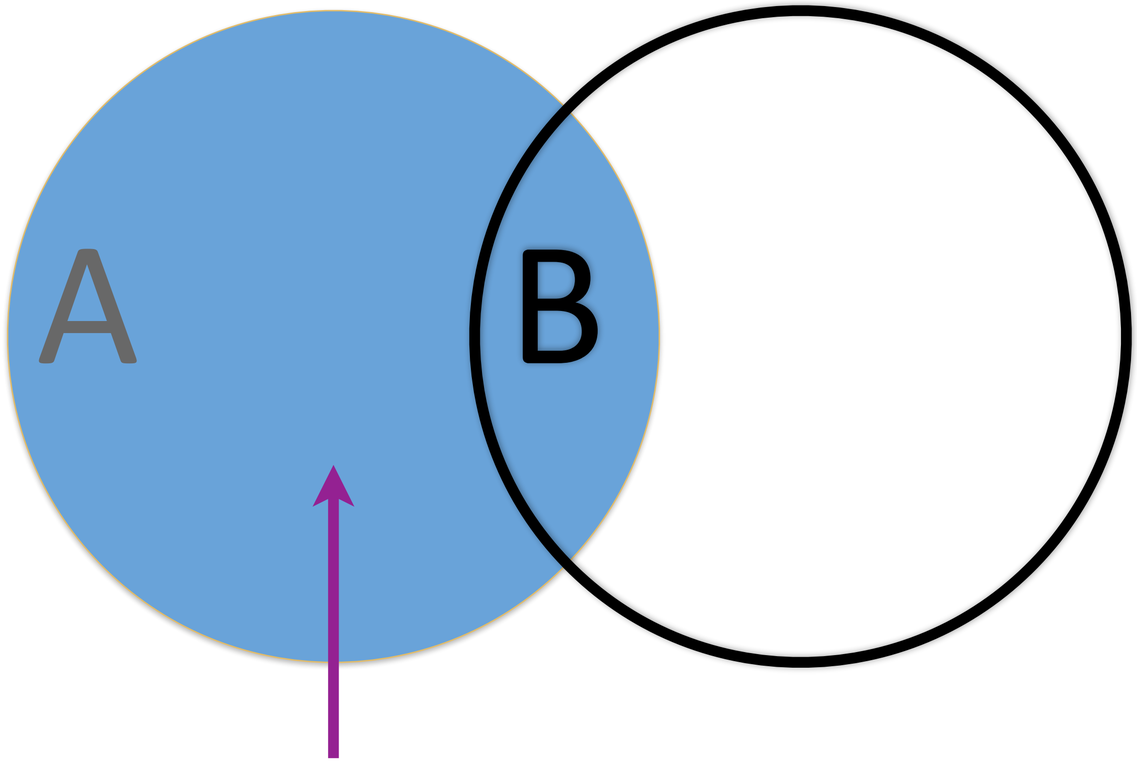
Joins

Inner Join (Intersection)



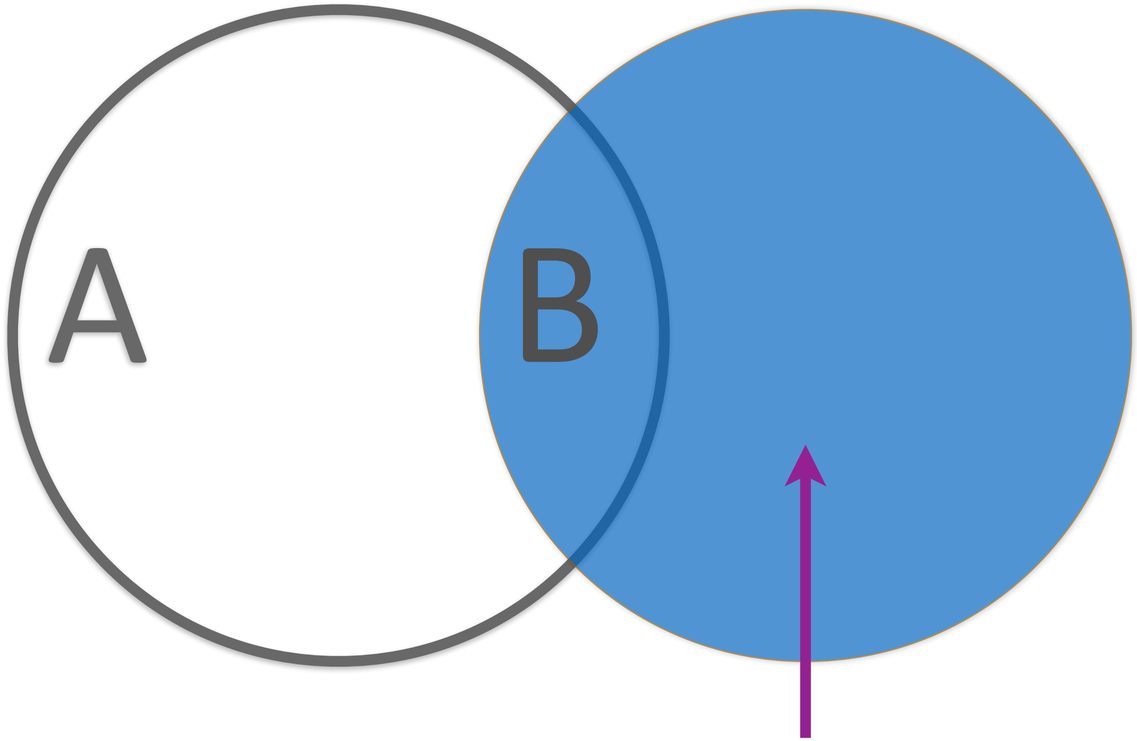
Inner Join

Left Join



Left Join

Right Join



Right Join

```
pd.merge( leftData, rightData )
```

```
pd.merge( leftData,
          rightData,
          how="<join type>" )
```

```
pd.merge( leftData, rightData,
how="<join type>" )
```

Option	SQL Equivalent	Description
inner	INNER JOIN	Intersection
left	LEFT OUTER JOIN	Returns items in Set A, but not in Set B
right	RIGHT OUTER JOIN	Returns items in Set B, but not in Set A
outer	FULL OUTER JOIN	Returns the union of both sets

```
pd.merge( leftData, rightData,
     how="<join type>",
     on=<field list> )
```

Stop

In-Class Exercise
Back at xx:xx

Please complete Worksheet 2.2: Exploratory Data Analysis

Grouping and Aggregating Data

Grouping and Aggregating Data

date	src_ip	dst_ip	port
2018-06-21	192.168.20.2	10.10.4.1	80
2018-06-21	192.168.20.1	10.10.4.2	443
2018-06-21	192.168.20.2	10.10.5.1	80
2018-06-22	192.168.20.2	10.10.4.1	80

```
df.groupby(field or list of fields)
```

Grouping and Aggregating Data

date	src_ip	dst_ip	port
2018-06-21	192.168.20.2	10.10.4.1	80
2018-06-21	192.168.20.1	10.10.4.2	443
2018-06-21	192.168.20.2	10.10.5.1	80
2018-06-22	192.168.20.2	10.10.4.1	80

```
df.groupby('src_ip')['port'].count()
```

src_ip	count
192.168.20.1	1
192.168.20.2	3

Grouping and Aggregating Data

date	src_ip	dst_ip	port
2018-06-21	192.168.20.2	10.10.4.1	80
2018-06-21	192.168.20.1	10.10.4.2	443
2018-06-21	192.168.20.2	10.10.5.1	80
2018-06-22	192.168.20.2	10.10.4.1	80

```
df.groupby(['date','src_ip'])['port'].count()
```

Multi-Index

```
date          src_ip
2018-06-21    192.168.20.1    1
              192.168.20.2    2
2018-06-22    192.168.20.2    1
```

Grouping and Aggregating Data

date	src_ip	dst_ip	port
2018-06-21	192.168.20.2	10.10.4.1	80
2018-06-21	192.168.20.1	10.10.4.2	443
2018-06-21	192.168.20.2	10.10.5.1	80
2018-06-22	192.168.20.2	10.10.4.1	80

```
df.groupby(['date','src_ip'], as_index=False)
['port'].count()
```

	date	src_ip	port
0	2018-06-21	192.168.20.1	1
1	2018-06-21	192.168.20.2	2
2	2018-06-22	192.168.20.2	1

Grouping Functions

Pivot

```
df.pivot(index='foo',
         columns='bar',
         values='baz')
```

df

	foo	bar	baz	zoo
0	one	A	1	x
1	one	B	2	y
2	one	C	3	z
3	two	A	4	q
4	two	B	5	w
5	two	C	6	t

bar	A	B	C
foo			
one	1	2	3
two	4	5	6

http://jalammar.github.io/visualizing-pandas-pivoting-and-reshaping/

Grouping Functions

Melt

df3

	first	last	height	weight
0	John	Doe	5.5	130
1	Mary	Bo	6.0	150

```
df3.melt(id_vars=['first', 'last'])
```

	first	last	variable	value
0	John	Doe	height	5.5
1	Mary	Bo	height	6.0
2	John	Doe	weight	130
3	Mary	Bo	weight	150

http://jalammar.github.io/visualizing-pandas-pivoting-and-reshaping/

Grouping Functions

Stack

df2

		A	B
first	second		
bar	one	1	2
	two	3	4
baz	one	5	6
	two	7	8

MultiIndex

stacked = df2.stack()

first	second		
bar	one	A	1
		B	2
	two	A	3
		B	4
baz	one	A	5
		B	6
	two	A	7
		B	8

MultiIndex

http://jalammar.github.io/visualizing-pandas-pivoting-and-reshaping/

Grouping Functions

Unstack

stacked

first	second		
bar	one	A	1
		B	2
	two	A	3
		B	4
baz	one	A	5
		B	6
	two	A	7
		B	8

MultiIndex

stacked.unstack()

		A	B
first	second		
bar	one	1	2
	two	3	4
baz	one	5	6
	two	7	8

MultiIndex

http://jalammar.github.io/visualizing-pandas-pivoting-and-reshaping/

Grouping Functions

Unstack(1)

stacked

first	second		
bar	one	A	1
		B	2
	two	A	3
		B	4
baz	one	A	5
		B	6
	two	A	7
		B	8

MultiIndex

stacked.unstack(1)
or
stacked.unstack('second')

	second	one	two
first			
bar	A	1	3
	B	2	4
baz	A	5	7
	B	6	8

MultiIndex

http://jalammar.github.io/visualizing-pandas-pivoting-and-reshaping/

```
Series.dropna()
Series.fillna(value="<something>")
```

Another Approach: Drill

Another Approach: Drill

- Drill is an open source query engine which allows you to query many kinds of self-describing data using ANSI SQL.
- Drill is fast, scalable and extremely versatile.

Another Approach: Drill

Out of the box, Drill can query:

- Delimited Data (csv, tsv, psv)
- Apache log files
- Avro
- Parquet
- JSON
- PCAP
- Syslog
- And more...

There are extensions available on GitHub that allow you to query log files and other data.

Another Approach: Drill

Out of the box, Drill can connect to:

- MySQL (or any JDBC compliant database)
- Hadoop
- Kafka
- Druid
- Splunk
- REST APIs
- S3/Azure/Google Cloud
- HBase
- Hive
- MongoDB
- And others...

Another Approach: Drill

```
from pydrill.client import PyDrill

drill = PyDrill(host='localhost', port=8047)

if not drill.is_active():
    raise ImproperlyConfigured('Please run Drill first')

query = drill.query('''<Your query here>''')

df = query.to_dataframe()
```

Another Approach: Drill

```
SELECT src_port, dst_port, COUNT(*) AS packet_count
FROM dfs.test.`dns.pcap`
GROUP BY src_port, dst_port
ORDER BY packet_count DESC
```

In-Class Exercise
Back at xx:xx

Please complete Worksheet 2.2: Exploratory Data Analysis

Scaling Pandas

- Pandas is limited by the amount of memory on your machine. You will need 5-10x as much RAM as the size of your datasets.
- Operations on DataFrames creates copies of the data in memory.
- Pandas 2.0 has a big improvement in memory management.

Scaling Pandas

Several drop-in or near drop-in replacements for Pandas exist that run on GPUs or parallelize operations.

- **Dask**: A partial Pandas replacement geared towards running code on compute clusters.
- **cuDF**: A drop in partial replacement for Pandas for use on GPUs. Developed by NVIDIA
- **Ray:** A unified low level framework for scaling AI and Python applications.
- **RAPIDS:** A set of libraries and APIs that runs on NVIDIA CUDA GPUs. It offers GPU-enabled substitutes for popular Python libraries, such as cuDF for Pandas, cuML for scikit-learn, and cuGraph for NetworkX.
- **Polars:** A fast dataframe library implemented in Rust. (Runs in Python).
- **PySpark:** The Python API for Spark that lets you harness the simplicity of Python and the power of Apache Spark.

Apache Arrow

- Apache Arrow is a standardized framework for developing data analytics applications that use columnar data.
- Arrow can be used in python (PyArrow), Spark and many other languages.
- Arrow is designed as a compliment to parquet format.
- Main advantages are interoperability, speed and efficiency.

Pandas 2.0

- Pandas 2.0 was released in early 2023 and now has an integration with Apache Arrow
- The Arrow integration can help overcome the limitations of the earlier versions of Pandas.
- The Arrow backend is up to 35x faster.
- Pandas 2.0 has better support for analytic datatypes via Arrow.

```
pd.read_csv("data.csv", engine='pyarrow', dtype_backend='pyarrow')
```

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Pandas 2.0: Copy on Write Optimization

- One of the big challenges of Pandas is that it creates multiple copies of your data frame when you chain methods together.
- Pandas 2.0 introduces a new copy on write option which, when set to True, returns views rather than copies, minimizing data duplication.
- When enabled, chained assignments will not work.

```
pd.options.mode.copy_on_write = True
```

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Questions?