Data Wrangling (I): Munging, Tidy Data, and Working with Multiple Data Tables

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CMPS3660 – Introduction to Data Science – Fall 2019

https://rebrand.ly/TUDataScience

Many Thanks
Slides based off Introduction to Data Science from John P. Dickerson -
https://cmsc320.github.io/

Announcements

- Project1 and Milestone1 Updates
  - Reading really important here!
- Survey Results!
- Lab 4 + Lab 5
- Weekly Questions 4
- On to DATA!

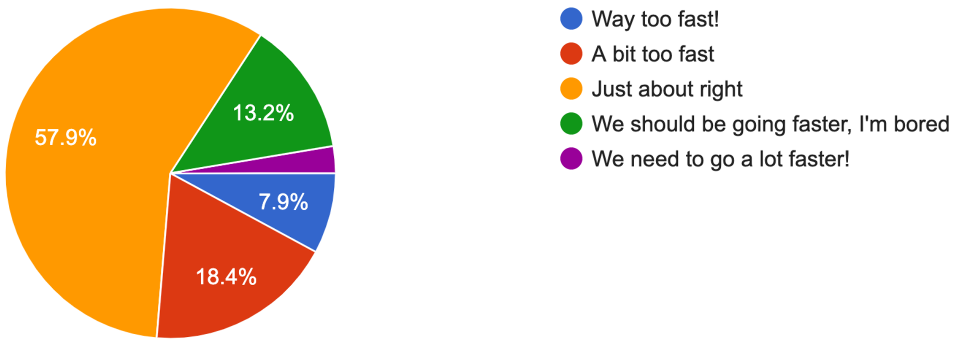
Survey Take Home Messages

- 28+ of you like or really like notebooks!
  - 2 of you really hate them!
- Some of you say I'm talking too fast!
- 6-7 of you Hate Docker!

- What we want (that I'll deliver):
  - More Depth, More Theory (5)
  - PPT/Lectures (5-7)?
    - Too much, Not enough; interesting, boring; clear, too muddled
  - More Feedback!
- What we want (I can't fix).
  - Class too early.
  - Too much programming.

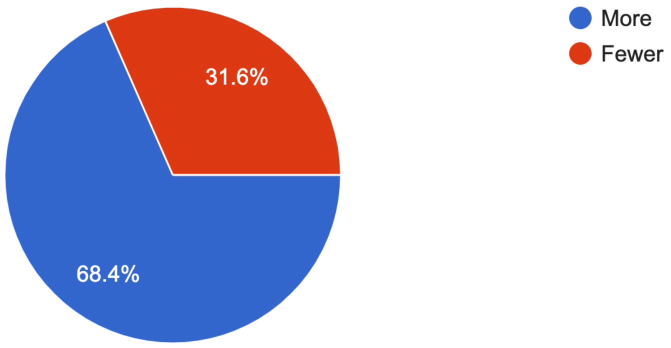
The course is moving...

38 responses



I'd like to do [ANSWER] Lab Days

38 responses



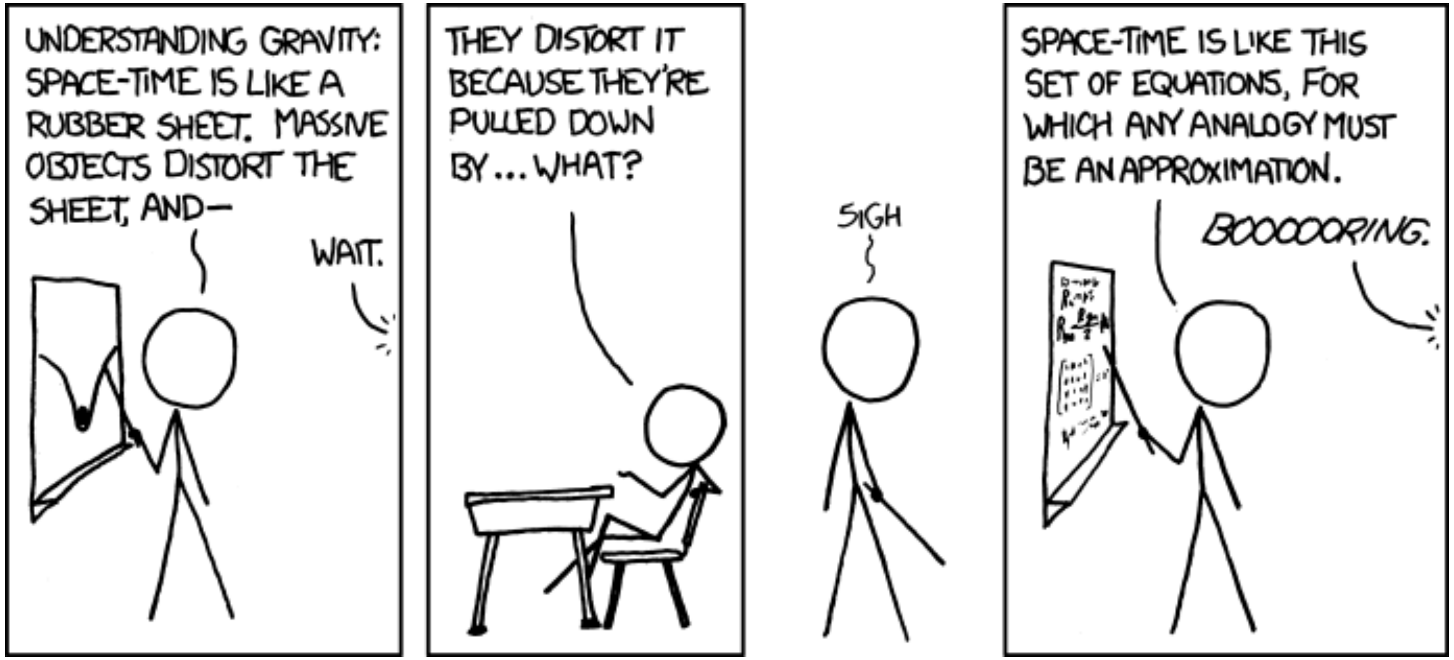
Next Couple of Lectures (Till Midterm)

- Tables in the Abstract
  - How, Why
  - Operations

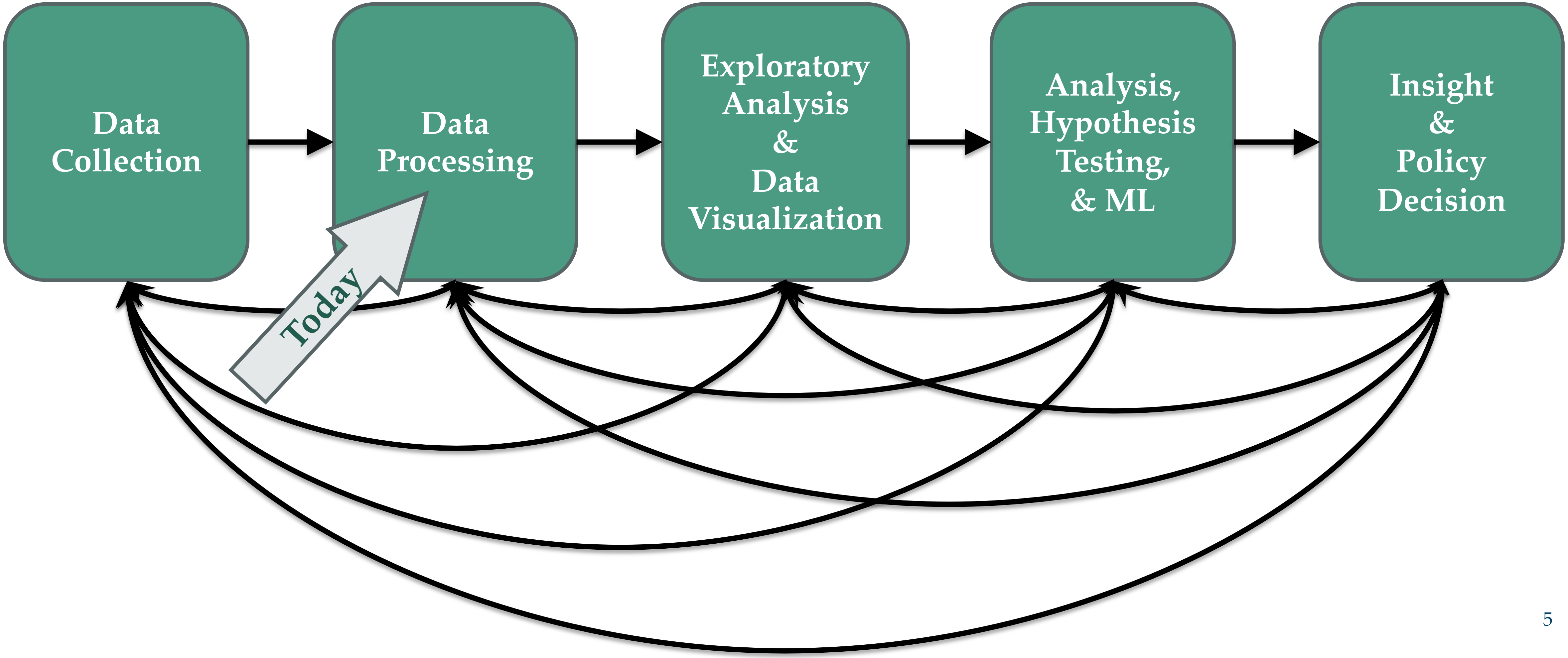
- Principles of Tidy Data

- Tables in Pandas
- Tables in SQL and RMDBS

- 2 More Labs.



The Data LifeCycle



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Tables

Special Column, called “Index”, or “ID”, or “Key”
Usually, no duplicates Allowed

Variables
(also called Attributes, or Columns, or Labels)

Observations, Rows, or Tuples

ID	age	wgt_kg	hgt_cm
1	12.2	42.3	145.1
2	11.0	40.8	143.8
3	15.6	65.3	165.3
4	35.1	84.2	185.8

Entries or values

1. Select/Slicing

- Select only some of the rows, or some of the columns, or a combination.

ID	age	wgt_kg	hgt_cm
1	12.2	42.3	145.1
2	11.0	40.8	143.8
3	15.6	65.3	165.3
4	35.1	84.2	185.8

Only columns
ID and Age

ID	age
1	12.2
2	11.0
3	15.6
4	35.1

Only rows
with wgt > 41

ID	age	wgt_kg	hgt_cm
1	12.2	42.3	145.1
3	15.6	65.3	165.3
4	35.1	84.2	185.8

Both

ID	age
1	12.2
3	15.6
4	35.1

2. Aggregate/Reduce

- Combine values across a column into a single value

ID	age	wgt_kg	hgt_cm
1	12.2	42.3	145.1
2	11.0	40.8	143.8
3	15.6	65.3	165.3
4	35.1	84.2	185.8

SUM

73.9	**232.6**	**640.0**

MAX

35.1	**84.2**	**185.8**

SUM(wgt_kg^2 - hgt_cm)

14167.66

What about ID/Index column?

Usually not meaningful to aggregate across it

May need to explicitly add an ID column

Practical Interlude: *np.nan*

- We use numpy.nan to signify a value is missing or not a number.
- If we don't use NaN's then Pandas doesn't know how to handle the data.
- Breaks in all sorts of awful ways.
- (Demo Notebook)

ID	age	wgt_kg	hgt_cm
1	12.2	42.3	145.1
2	11.0	40.8	143.8
3	15.6	65.3	165.3
4	--	84.2	185.8

SUM

ERROR!

ID	age	wgt_kg	hgt_cm
1	12.2	42.3	145.1
2	11.0	40.8	143.8
3	15.6	65.3	165.3
4	np.NaN	84.2	185.8

SUM

38.8

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3. Map

- Apply a function to every row, possibly creating more or fewer columns

ID	Address
1	College Park, MD, 20742
2	Washington, DC, 20001
3	Silver Spring, MD 20901

SPLIT(“,”)

ID	City	State	Zipcode
1	College Park	MD	20742
2	Washington	DC	20001
3	Silver Spring	MD	20901

Variations that allow one row to generate multiple rows in the output (sometimes called “flatmap” or “melt” as we’ll see later.)

4. Group By

- Group tuples together by column/dimension.

ID	A	B	C
1	foo	3	6.6
2	bar	2	4.7
3	foo	4	3.1
4	foo	3	8.0
5	bar	1	1.2
6	bar	2	2.5
7	foo	4	2.3
8	foo	3	8.0

By 'A' →

A = foo

ID	B	C
1	3	6.6
3	4	3.1
4	3	8.0
7	4	2.3
8	3	8.0

A = bar

ID	B	C
2	2	4.7
5	1	1.2
6	2	2.5

4. Group By

- Group tuples together by column/dimension.

ID	A	B	C
1	foo	3	6.6
2	bar	2	4.7
3	foo	4	3.1
4	foo	3	8.0
5	bar	1	1.2
6	bar	2	2.5
7	foo	4	2.3
8	foo	3	8.0

By 'B' →

B = 1

ID	A	C
5	bar	1.2

B = 2

ID	A	C
2	bar	4.7
6	bar	2.5

B = 3

ID	A	C
1	foo	6.6
4	foo	8.0
8	foo	8.0

B = 4

ID	A	C
3	foo	3.1
7	foo	2.3

4. Group By

- Group tuples together by column/dimension.

ID	A	B	C
1	foo	3	6.6
2	bar	2	4.7
3	foo	4	3.1
4	foo	3	8.0
5	bar	1	1.2
6	bar	2	2.5
7	foo	4	2.3
8	foo	3	8.0

By ‘A’, ‘B’ →

A = bar, B = 1

ID	C
5	1.2

A = bar, B = 2

ID	C
2	4.7
6	2.5

A = foo, B = 3

ID	C
1	6.6
4	8.0
8	8.0

A = foo, B = 4

ID	C
3	3.1
7	2.3

5. Group By Aggregate

- Group the aggregate per group.

ID	A	B	C
1	foo	3	6.6
2	bar	2	4.7
3	foo	4	3.1
4	foo	3	8.0
5	bar	1	1.2
6	bar	2	2.5
7	foo	4	2.3
8	foo	3	8.0

Group by 'B'
Sum on C

B = 1

ID	A	C
5	bar	1.2

B = 1

Sum (C)
1.2

B = 2

ID	A	C
2	bar	4.7
6	bar	2.5

B = 2

Sum (C)
7.2

B = 3

ID	A	C
1	foo	6.6
4	foo	8.0
8	foo	8.0

B = 3

Sum (C)
22.6

B = 4

ID	A	C
3	foo	3.1
7	foo	2.3

B = 4

Sum (C)
5.4

5. Group By Aggregate

- Final result usually seen as a table.

ID	A	B	C
1	foo	3	6.6
2	bar	2	4.7
3	foo	4	3.1
4	foo	3	8.0
5	bar	1	1.2
6	bar	2	2.5
7	foo	4	2.3
8	foo	3	8.0

Group by 'B'
Sum on C

B = 1

Sum (C)
1.2

B = 2

Sum (C)
7.2

B = 3

Sum (C)
22.6

B = 4

Sum (C)
5.4

B	SUM(C)
1	1.2
2	7.2
3	22.6
4	5.4

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5.5 Pivot Tables (Data Cubes)

- Laying out the possible values of multiple axes and aggregating them.
  - Can have more than two dimensions, need hierarchal indexes (later).

ID	A	B	C
1	foo	3	6.6
2	bar	2	4.7
3	foo	4	3.1
4	foo	3	8.0
5	bar	1	1.2
6	bar	2	2.5
7	foo	4	2.3
8	foo	3	8.0

Index A, Columns B

Values C, Agg=Sum

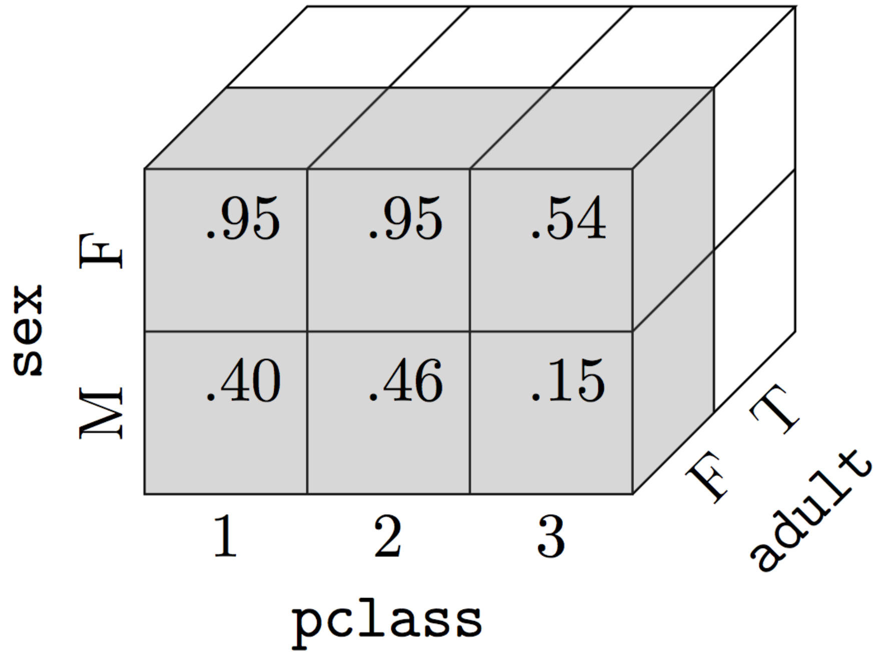
A B>	1	2	3	4
foo	0	0	22.6	5.4
bar	1.2	7.2	0	0

5.5 Pivot Tables (Data Cubes)

- Laying out the possible values of multiple axes and aggregating them.
  - Can have more than two dimensions, need hierarchal indexes (later).

```
survivors_cube = titanic_df.pivot_table(
    index="sex", columns=["adult", "pclass"],
    values="survived", aggfunc=np.mean)
survivors_cube
```

adult	False			True		
pclass	1	2	3	1	2	3
sex						
female	0.947368	0.952381	0.536364	0.968000	0.870588	0.443396
male	0.400000	0.464286	0.147059	0.326389	0.083916	0.155709



6. Union/Intersection/Difference

- Set operations – only if the two tables have identical attributes/columns

ID	A	B	C
1	foo	3	6.6
2	bar	2	4.7
3	foo	4	3.1
4	foo	3	8.0

U

ID	A	B	C
5	bar	1	1.2
6	bar	2	2.5
7	foo	4	2.3
8	foo	3	8.0

→

ID	A	B	C
1	foo	3	6.6
2	bar	2	4.7
3	foo	4	3.1
4	foo	3	8.0
5	bar	1	1.2
6	bar	2	2.5
7	foo	4	2.3
8	foo	3	8.0

Similarly Intersection and Set Difference manipulate tables as Sets

IDs may be treated in different ways, resulting in somewhat different behaviors

7. Merge or Join

- Combine rows/tuples across two tables *if they have the same key.*

- This example is called an *Inner Join*

ID	A	B
1	foo	3
2	bar	2
3	foo	4
4	foo	3

$\bowtie$

ID	C
1	1.2
2	2.5
3	2.3
5	8.0

→

ID	A	B	C
1	foo	3	1.2
2	bar	2	2.5
3	foo	4	2.3

What about IDs not present in both tables?

Often need to keep them around

Can “pad” with NaN (depends on software!)

7. Merge or Join (Outer or Full Join)

- Combine rows/tuples across two tables if they have the same key.
- Outer joins can be used to ”pad” IDs that don’t appear in both tables
  - Three variants: LEFT, RIGHT, FULL
  - SQL Terminology -- Pandas has these operations as well

ID	A	B
1	foo	3
2	bar	2
3	foo	4
4	foo	3

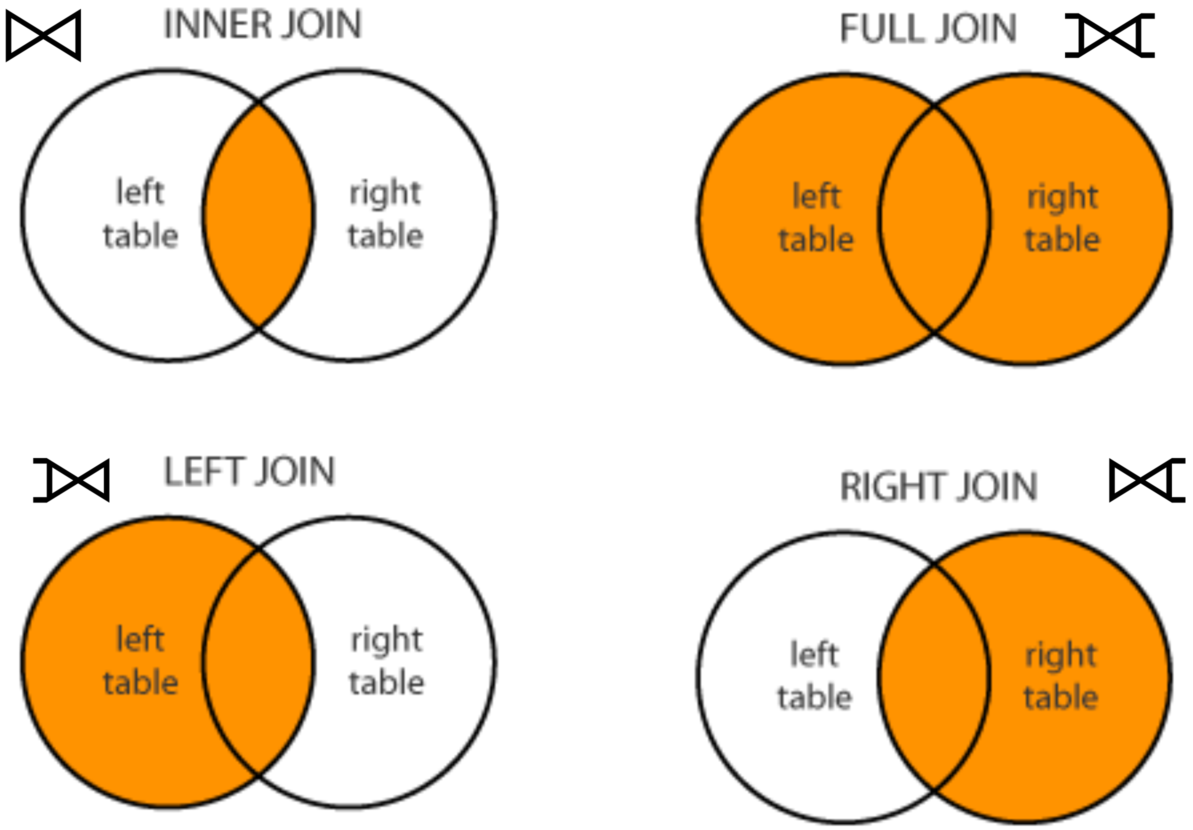
$\bowtie$

ID	C
1	1.2
2	2.5
3	2.3
5	8.0

→

ID	A	B	C
1	foo	3	1.2
2	bar	2	2.5
3	foo	4	2.3
4	foo	3	NaN
5	NaN	NaN	8.0

Types of Joins



In Pandas this is called a FULL OUTTER JOIN!

Image credit: http://www.dofactory.com/sql/join

7. Merge or Join (Left Join)

- Combine rows/tuples across two tables if they have the same key.
- Outer joins can be used to ”pad” IDs that don’t appear in both tables
  - Three variants: LEFT, RIGHT, FULL
  - SQL Terminology -- Pandas has these operations as well

ID	A	B
1	foo	3
2	bar	2
3	foo	4
4	foo	3

$\bowtie$

ID	C
1	1.2
2	2.5
3	2.3
5	8.0

$\rightarrow$

ID	A	B	C
1	foo	3	1.2
2	bar	2	2.5
3	foo	4	2.3
4	foo	3	NaN

7. Merge or Join (Right Join)

- Combine rows/tuples across two tables if they have the same key.
- Outer joins can be used to ”pad” IDs that don’t appear in both tables
  - Three variants: LEFT, RIGHT, FULL
  - SQL Terminology -- Pandas has these operations as well

ID	A	B
1	foo	3
2	bar	2
3	foo	4
4	foo	3

⟖

ID	C
1	1.2
2	2.5
3	2.3
5	8.0

ID	A	B	C
1	foo	3	1.2
2	bar	2	2.5
3	foo	4	2.3
5	NaN	NaN	8.0

Quick Review

- Tables: A simple, common abstraction
  - Subsumes a set of "strings" – a common input, or a list of lists, or a list of dicts with the same keys.

- Operations on tables:
  - Select, Map, Aggregate, Reduce, Join/Merge, Union/Concat, Group By

- ***These may have different names!*** In Pandas it's a *merge* while in SQL it's a *join.*
  - Actually, this isn't quite right -- Pandas has a *join* command that will only join based on the *index!* It also has a *merge* command that allows for more options – see Lab 7!
  - Pandas also uses *merge* as we'll see in lab while SQL uses Union

- There can be subtle variations in implementation on different data systems. Remember I'm giving you the high level but you need to *read the docs for your software* when you use this stuff!