REVIEW OF LAST LECTURE(S)

1. **NumPy: Python Library for Manipulating nD Arrays**

   Multidimensional Arrays, and a variety of operations including Linear Algebra

2. **Pandas: Python Library for Manipulating Tabular Data, & Tidy Data**

   Series, Tables (also called **DataFrames**)
   Many operations to manipulate and combine tables/series

3. **Relational Databases**

   Tables/Relations, and SQL (similar to Pandas operations)

4. **Apache Spark**

   Sets of objects or key-value pairs
   MapReduce and SQL-like operations

DATA MANIPULATION AND COMPUTATION

Data Science == manipulating and computing on data

Large to very large, but somewhat "structured" data

We will see several tools for doing that this semester

Thousands more out there that we won't cover

Need to learn to shift thinking from:

Imperative code to manipulate data structures

to:

Sequences/pipelines of operations on data

Should still know how to implement the operations themselves, especially for debugging performance (covered in classes like 420, 424), but we won't cover that much

THE NUMPY STACK

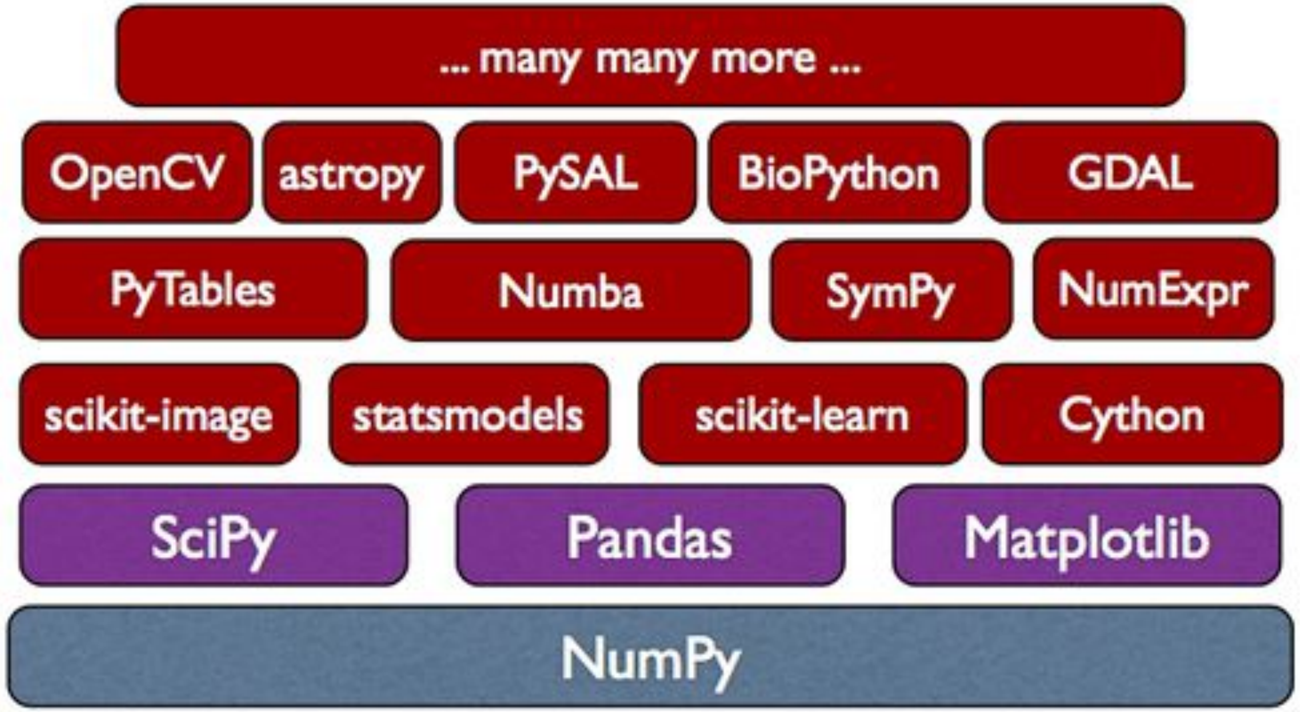

Image from Continuum Analytics

NEXT FEW CLASSES

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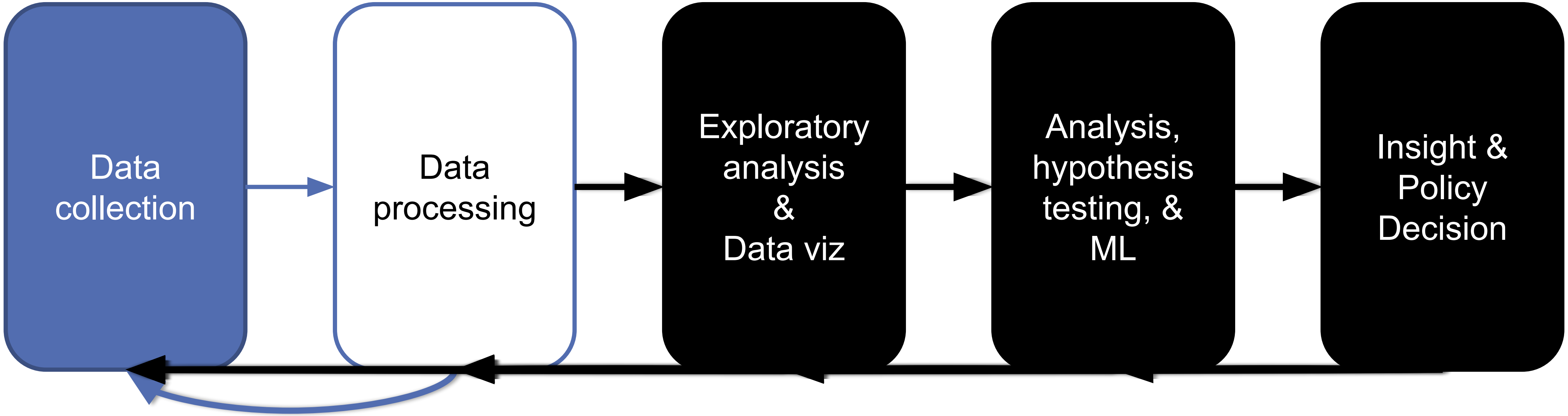
THE DATA LIFECYCLE



TODAY/NEXT CLASS

- **Tables**
  - Abstraction
  - Operations
- **Pandas**
- **Tidy Data**
- **SQL**

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

TABLES

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

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

199.72.81.55 - - [01/Jul/1995:00:00:01 -0400] "GET /history/apollo/ HTTP/1.0" 200 6245
unicomp6.unicomp.net - - [01/Jul/1995:00:00:06 -0400] "GET /shuttle/countdown/ HTTP/1.0" 200 3985
199.120.110.21 - - [01/Jul/1995:00:00:09 -0400] "GET /shuttle/missions/sts-73/mission-sts-73.html HTTP/1.0" 200 4085

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

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

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")

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

Compute one 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 = 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

B = 1

Sum (C)
1.2

B = 2

Sum (C)
7.2

B = 3

Sum (C)
22.6

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

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

∪

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

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

What about IDs not present in both tables?

Often need to keep them around

Can “pad” with NaN

7. MERGE OR 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
4	foo	3	NaN
5	NaN	NaN	8.0

SUMMARY

- **Tables: A simple, common abstraction**
  - Subsumes a set of “strings” – a common input
- **Operations**
  - Select, Map, Aggregate, Reduce, Join/Merge, Union/Concat, Group By
- **In a given system/language, the operations may be named differently**
  - E.g., SQL uses “join”, whereas Pandas uses “merge”
- **Subtle variations in the definitions, especially for more complex operations**

ID	A	B	C
1	foo	3	6.6
2	baz	2	4.7
3	foo	4	3.1
4	baz	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 'A'

A. 1

$\boxed{\textbf{B.}\ 3}$

C. 5

D. 8

HOW MANY GROUPS IN THE ANSWER?

foo -> ...
baz -> …
bar -> …

ID	A	B	C
1	foo	3	6.6
2	baz	2	4.7
3	foo	4	3.1
4	baz	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 ‘A’, ‘B’ →

A. 1
B. 3
C. 4
$\boxed{\textbf{D.}\ 6}$

HOW MANY GROUPS IN THE ANSWER?

(foo, 3) -> ...
(baz, 2) -> ...
(foo, 4) -> ...
(baz, 3) -> ...
(bar, 1) -> ...
(bar, 2) -> ...

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

$\bowtie$

ID	C
2	1.2
4	2.5
6	2.3
7	8.0

A. 1

$\boxed{\textbf{B.}\ 2}$

C. 4

D. 6

HOW MANY TUPLES IN THE ANSWER?

Inner join:
1 – XX
2 – 2 !!
4 – 4 !!
5 – XX
XX – 6
XX – 7

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

$⟗$

ID	C
2	1.2
4	2.5
6	2.3
7	8.0

FULL OUTER JOIN

All IDs will be present in the answer
With NaNs

A. 1

B. 4

C. 6

D. 8

Inner join:

1 – X !!
2 – 2 !!
4 – 4 !!
5 – X !!
X – 6 !!
X – 7 !!

HOW MANY TUPLES IN THE ANSWER?

CONTINUING TO PANDAS …

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PANDAS: HISTORY

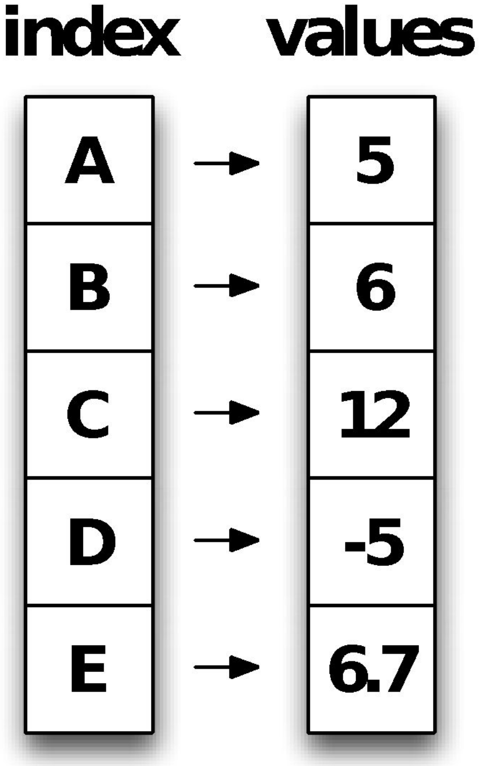
- **Written by: Wes McKinney**
  - Started in 2008 to get a high-performance, flexible tool to perform quantitative analysis on financial data

- **Highly optimized for performance, with critical code paths written in Cython or C**

- **Key constructs:**
  - Series (like a NumPy Array)
  - DataFrame (like a Table or Relation, or R data.frame)

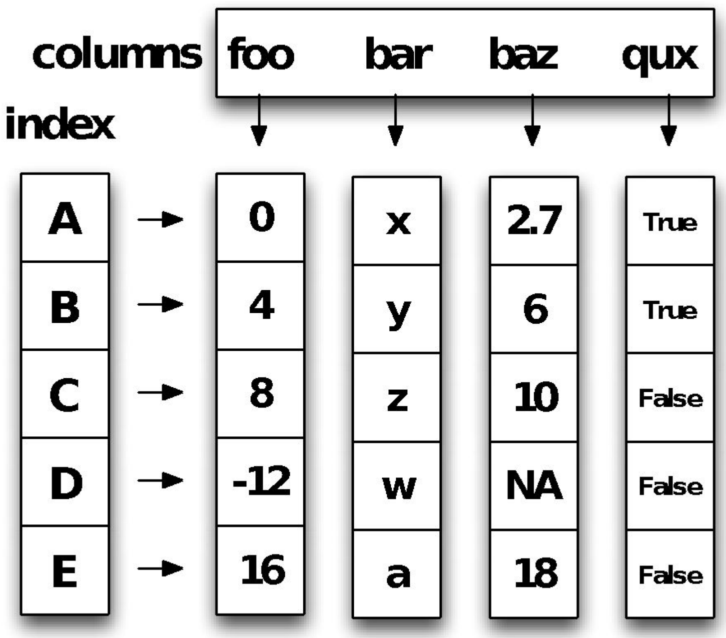
- **Foundation for Data Wrangling and Analysis in Python**

PANDAS: SERIES



- Subclass of `numpy.ndarray`
- Data: any type
- Index labels need not be ordered
- Duplicates possible but result in reduced functionality

PANDAS: DATAFRAME



- Each column can have a different type
- Row and Column index
- Mutable size: insert and delete columns

- **Note the use of word “index” for what we called “key”**
  - Relational databases use “index” to mean something else

- **Non-unique index values allowed**
  - May raise an exception for some operations

HIERARCHICAL INDEXES

Sometimes more intuitive organization of the data

Makes it easier to understand and analyze higher-dimensional data

e.g., instead of 3-D array, may only need a 2-D array

```
day             Fri    Sat    Sun    Thur
sex    smoker
Female No       3.125  2.725  3.329  2.460
       Yes      2.683  2.869  3.500  2.990
Male   No       2.500  3.257  3.115  2.942
       Yes      2.741  2.879  3.521  3.058
```

```
first  second
bar    one       0.469112
       two      -0.282863
baz    one      -1.509059
       two      -1.135632
foo    one       1.212112
       two      -0.173215
qux    one       0.119209
       two      -1.044236
dtype: float64
```

ESSENTIAL FUNCTIONALITY

Reindexing to change the index associated with a DataFrame

- Common usage to interpolate, fill in missing values

```
In [84]: obj3 = Series(['blue', 'purple', 'yellow'], index=[0, 2, 4])

In [85]: obj3.reindex(range(6), method='ffill')
Out[85]:
0      blue
1      blue
2    purple
3    purple
4    yellow
5    yellow
```


From: Python for Data Analysis; Wes McKinney

ESSENTIAL FUNCTIONALITY

“drop” to delete entire rows or columns

Indexing, Selection, Filtering: very similar to NumPy

Arithmetic Operations

- Result index union of the two input indexes
- Options to do “fill” while doing these operations

```
In [128]: s1
Out[128]:
a     7.3
c    -2.5
d     3.4
e     1.5
```

```
In [129]: s2
Out[129]:
a    -2.1
c     3.6
e    -1.5
f     4.0
g     3.1
```

```
In [130]: s1 + s2
Out[130]:
a     5.2
c     1.1
d     NaN
e     0.0
f     NaN
g     NaN
```

FUNCTION APPLICATION AND MAPPING

```
In [158]: frame = DataFrame(np.random.randn(4, 3), columns=list('bde'),
   .....:                   index=['Utah', 'Ohio', 'Texas', 'Oregon'])
```

```
In [159]: frame
Out[159]:
               b         d         e
Utah   -0.204708  0.478943 -0.519439
Ohio   -0.555730  1.965781  1.393406
Texas   0.092908  0.281746  0.769023
Oregon  1.246435  1.007189 -1.296221
```

```
In [160]: np.abs(frame)
Out[160]:
               b         d         e
Utah    0.204708  0.478943  0.519439
Ohio    0.555730  1.965781  1.393406
Texas   0.092908  0.281746  0.769023
Oregon  1.246435  1.007189  1.296221
```

```
In [161]: f = lambda x: x.max() - x.min()
```

```
In [162]: frame.apply(f)
Out[162]:
b    1.802165
d    1.684034
e    2.689627
```

```
In [163]: frame.apply(f, axis=1)
Out[163]:
Utah      0.998382
Ohio      2.521511
Texas     0.676115
Oregon    2.542656
```

From: *Python for Data Analysis; Wes McKinney*

SORTING AND RANKING

```
In [169]: obj = Series(range(4), index=['d', 'a', 'b', 'c'])

In [170]: obj.sort_index()
Out[170]:
a    1
b    2
c    3
d    0
```

```
In [187]: frame = DataFrame({'b': [4.3, 7, -3, 2], 'a': [0, 1, 0, 1],
   .....:                    'c': [-2, 5, 8, -2.5]})
```

```
In [188]: frame
Out[188]:
   a    b    c
0  0  4.3 -2.0
1  1  7.0  5.0
2  0 -3.0  8.0
3  1  2.0 -2.5
```

```
In [189]: frame.rank(axis=1)
Out[189]:
   a  b  c
0  2  3  1
1  1  3  2
2  2  1  3
3  2  3  1
```

From: Python for Data Analysis; Wes McKinney

DESCRIPTIVE AND SUMMARY STATISTICS

Table 5-10. Descriptive and summary statistics

Method	Description
`count`	Number of non-NA values
`describe`	Compute set of summary statistics for Series or each DataFrame column
`min, max`	Compute minimum and maximum values
`argmin, argmax`	Compute index locations (integers) at which minimum or maximum value obtained, respectively
`idxmin, idxmax`	Compute index values at which minimum or maximum value obtained, respectively
`quantile`	Compute sample quantile ranging from 0 to 1
`sum`	Sum of values
`mean`	Mean of values
`median`	Arithmetic median (50% quantile) of values
`mad`	Mean absolute deviation from mean value
`var`	Sample variance of values
`std`	Sample standard deviation of values
`skew`	Sample skewness (3rd moment) of values
`kurt`	Sample kurtosis (4th moment) of values
`cumsum`	Cumulative sum of values
`cummin, cummax`	Cumulative minimum or maximum of values, respectively
`cumprod`	Cumulative product of values
`diff`	Compute 1st arithmetic difference (useful for time series)
`pct_change`	Compute percent changes

From: Python for Data Analysis; Wes McKinney

CREATING DATAFRAMES

Directly from Dict or Series

From a Comma-Separated File – CSV file

- pandas.read_csv()
- Can infer headers/column names if present, otherwise may want to reindex

From an Excel File

- pandas.read_excel()

From a Database using SQL (see the reading for an example)

From Clipboard, URL, Google Analytics, …

…

From: Python for Data Analysis; Wes McKinney

MORE…

Unique values, Value counts

Correlation and Covariance

Functions for handling missing data – in a few classes

- dropna(), fillna()

Broadcasting

Pivoting

We will see some of these as we discuss data wrangling, cleaning, etc.

CONTINUING TO TIDY DATA …

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   Sets of objects or key-value pairs
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Variables
(also called Attributes, or
Columns, or Labels)

Index

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Rows, or
Tuples

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2	11.0	40.8	143.8
3	15.6	65.3	165.3
4	35.1	84.2	185.8

But also:

- **Names of files/DataFrames = description of one dataset**
- **Enforce one data type per dataset (ish)**

EXAMPLE

Identifier Variable: measure or attribute:

- age, weight, height, sex

Value: measurement of attribute:

- 12.2, 42.3kg, 145.1cm, M/F

Observation: all measurements for an object

- A specific person is [12.2, 42.3, 145.1, F]

TIDYING DATA I

Name	Treatment A	Treatment B
John Smith	-	2
Jane Doe	16	11
Mary Johnson	3	1

?????????????

Name	Treatment A	Treatment B	Treatment C	Treatment D
John Smith	-	2	-	-
Jane Doe	16	11	4	1
Mary Johnson	3	1	-	2

?????????????

Thanks to http://jeannicholashould.com/tidy-data-in-python.html

TIDYING DATA II

In a few lectures …

Name	Treatment	Result
John Smith	A	-
John Smith	B	2
John Smith	C	-
John Smith	D	-
Jane Doe	A	16
Jane Doe	B	11
Jane Doe	C	4
Jane Doe	D	1
Mary Johnson	A	3
Mary Johnson	B	1
Mary Johnson	C	-
Mary Johnson	D	2

MELTING DATA

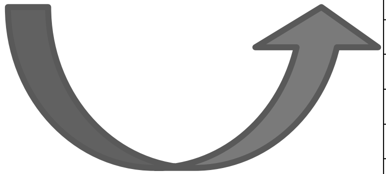
What we just did was “unpivot” the dataframe from wide to long format.

Pandas: Melt (https://pandas.pydata.org/docs/reference/api/pandas.melt.html)

This function is useful to massage a DataFrame into a format where:

- One or more columns are identifier variables (*id_vars*),
- All other columns, considered measured variables (*value_vars*), are “unpivoted” to the row axis, leaving just two non-identifier columns, ‘variable’ and ‘value’.

Name	Treatment A	Treatment B	Treatment C	Treatment D
John Smith	-	2	-	-
Jane Doe	16	11	4	1
Mary Johnson	3	1	-	2



Name	Treatment	Result
John Smith	A	-
John Smith	B	2
John Smith	C	-
John Smith	D	-
Jane Doe	A	16
Jane Doe	B	11
Jane Doe	C	4
Jane Doe	D	1
Mary Johnson	A	3
Mary Johnson	B	1
Mary Johnson	C	-
Mary Johnson	D	2

[NM]

MELTING DATA I

religion	<$10k	$10-20k	$20-30k	$30-40k	$40-50k	$50-75k
Agnostic	27	34	60	81	76	137
Atheist	12	27	37	52	35	70
Buddhist	27	21	30	34	33	58
Catholic	418	617	732	670	638	1116
Dont know/refused	15	14	15	11	10	35
Evangelical Prot	575	869	1064	982	881	1486
Hindu	1	9	7	9	11	34
Historically Black Prot	228	244	236	238	197	223
Jehovahs Witness	20	27	24	24	21	30
Jewish	19	19	25	25	30	95

?????????????

MELTING DATA II

```
f_df = pd.melt(df,
               ["religion"],
               var_name="income",
               value_name="freq")
f_df = f_df.sort_values(by=["religion"])
f_df.head(10)
```

religion	income	freq
Agnostic	<$10k	27
Agnostic	$30-40k	81
Agnostic	$40-50k	76
Agnostic	$50-75k	137
Agnostic	$10-20k	34
Agnostic	$20-30k	60
Atheist	$40-50k	35
Atheist	$20-30k	37
Atheist	$10-20k	27
Atheist	$30-40k	52

MORE COMPLICATED EXAMPLE

Billboard Top 100 data for songs, covering their position on the Top 100 for 75 weeks, with two "messy" bits:

- Column headers for each of the 75 weeks
- If a song didn't last 75 weeks, those columns have are null

year	artist.inverted	track	time	genre	date.entered	date.peaked	x1st.week	x2nd.week	...
2000	Destiny's Child	Independent Women Part I	3:38	Rock	2000-09-23	2000-11-18	78	63.0	...
2000	Santana	Maria, Maria	4:18	Rock	2000-02-12	2000-04-08	15	8.0	...
2000	Savage Garden	I Knew I Loved You	4:07	Rock	1999-10-23	2000-01-29	71	48.0	...
2000	Madonna	Music	3:45	Rock	2000-08-12	2000-09-16	41	23.0	...
2000	Aguilera, Christina	Come On Over Baby	3:38	Rock	2000-08-05	2000-10-14	57	47.0	...
2000	Janet	Doesn't Really Matter	4:17	Rock	2000-06-17	2000-08-26	59	52.0	...

Messy columns!

Thanks to http://jeannicholashould.com/tidy-data-in-python.html

MORE COMPLICATED EXAMPLE

```
# Keep identifier variables
id_vars = ["year",
           "artist.inverted",
           "track",
           "time",
           "genre",
           "date.entered",
           "date.peaked"]

# Melt the rest into week and rank columns
df = pd.melt(frame=df,
             id_vars=id_vars,
             var_name="week",
             value_name="rank")
```

Creates one row per week, per record, with its rank

MORE COMPLICATED EXAMPLE

```
# Formatting
df["week"] = df['week'].str.extract('(\d+)’,
                                    expand=False).astype(int)
df["rank"] = df["rank"].astype(int)
```

```
[…, “x2nd.week”, 63.0]  […, 2, 63]
```

```
# Cleaning out unnecessary rows
df = df.dropna()

# Create "date" columns
df['date'] = pd.to_datetime(
               df['date.entered']) +
               pd.to_timedelta(df['week'], unit='w') -
               pd.DateOffset(weeks=1)
```

MORE COMPLICATED EXAMPLE

```
# Ignore now-redundant, messy columns
df = df[["year",
         "artist.inverted",
         "track",
         "time",
         "genre",
         "week",
         "rank",
         "date"]]

df = df.sort_values(ascending=True,
 by=["year","artist.inverted","track","week","rank"])

# Keep tidy dataset for future usage
billboard = df

df.head(10)
```

MORE COMPLICATED EXAMPLE

year	artist.inverted	track	time	genre	week	rank	date
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	1	87	2000-02-26
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	2	82	2000-03-04
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	3	72	2000-03-11
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	4	77	2000-03-18
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	5	87	2000-03-25
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	6	94	2000-04-01
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	7	99	2000-04-08
2000	2Ge+her	The Hardest Part Of Breaking Up (Is Getting Ba...	3:15	R&B	1	91	2000-09-02
2000	2Ge+her	The Hardest Part Of Breaking Up (Is Getting Ba...	3:15	R&B	2	87	2000-09-09
2000	2Ge+her	The Hardest Part Of Breaking Up (Is Getting Ba...	3:15	R&B	3	92	2000-09-16

????????????

MORE TO DO?

Column headers are values, not variable names?

- Good to go!

Multiple variables are stored in one column?

- Maybe (depends on if genre text in raw data was multiple)

Variables are stored in both rows and columns?

- Good to go!

Multiple types of observational units in the same table?

- Good to go! One row per song's week on the Top 100.

A single observational unit is stored in multiple tables?

- Don't do this!

Repetition of data?

- Lots! Artist and song title's text names. Which leads us to …

ON WE GO! TO RELATIONAL DATABASES & SQL!

1. **NumPy: Python Library for Manipulating nD Arrays**

   Multidimensional Arrays, and a variety of operations including Linear Algebra

2. **Pandas: Python Library for Manipulating Tabular Data, & Tidy Data**

   Series, Tables (also called **DataFrames**)
   Many operations to manipulate and combine tables/series

3. **Relational Databases**

   Tables/Relations, and SQL (similar to Pandas operations)

4. **Apache Spark**

   Sets of objects or key-value pairs
   MapReduce and SQL-like operations

TODAY'S LECTURE

Relational data:

- What is a relation, and how do they interact?

Querying databases:

- SQL
- SQLite
- How does this relate to `pandas`?

Joins

Thanks to Zico Kolter for some structure for this lecture!

RELATION

Simplest relation: a table aka tabular data full of unique tuples

Variables
(called attributes)

Labels

Observations
(called 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

WHERE DOES THIS BREAK DOWN?

What's wrong with our last example???

- Lots of duplicated data

What happens if we add years?

- Need to be able to have different units of observation or different views!

What do we need?

- Different tables to store different kinds of observations!

year	artist.inverted	track	time	genre	week	rank	date
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	1	87	2000-02-26
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	2	82	2000-03-04
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	3	72	2000-03-11
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	4	77	2000-03-18
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	5	87	2000-03-25
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	6	94	2000-04-01
2000	2 Pac	Baby Don't Cry (Keep Ya Head Up II)	4:22	Rap	7	99	2000-04-08
2000	2Ge+her	The Hardest Part Of Breaking Up (Is Getting Ba...	3:15	R&B	1	91	2000-09-02
2000	2Ge+her	The Hardest Part Of Breaking Up (Is Getting Ba...	3:15	R&B	2	87	2000-09-09
2000	2Ge+her	The Hardest Part Of Breaking Up (Is Getting Ba...	3:15	R&B	3	92	2000-09-16

PRIMARY KEYS

ID	age	wgt_kg	hgt_cm	nat_id
1	12.2	42.3	145.1	1
2	11.0	40.8	143.8	1
3	15.6	65.3	165.3	2
4	35.1	84.2	185.8	1
5	18.1	62.2	176.2	3
6	19.6	82.1	180.1	1

ID	Nationality
1	USA
2	Canada
3	Mexico

The primary key is a unique identifier for every tuple in a relation

- **Each tuple has exactly one primary key**

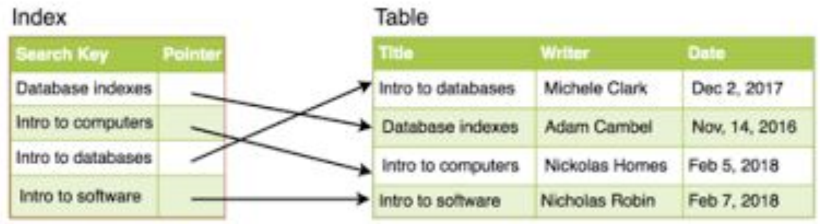
AREN'T THESE CALLED "INDEXES"?

Yes, in Pandas; but not in the database world

For most databases, an "index" is a data structure used to speed up retrieval of specific tuples

For example, to find all tuples with nat_id = 2:

- We can either scan the table – O(N)
- Or use an "index" (e.g., binary tree) – O(log N)



FOREIGN KEYS

ID	age	wgt_kg	hgt_cm	nat_id
1	12.2	42.3	145.1	1
2	11.0	40.8	143.8	1
3	15.6	65.3	165.3	2
4	35.1	84.2	185.8	1
5	18.1	62.2	176.2	3
6	19.6	82.1	180.1	1

ID	Nationality
1	USA
2	Canada
3	Mexico

Foreign keys are attributes (columns) that point to a different table's primary key

- **A table can have multiple foreign keys**

RELATION SCHEMA

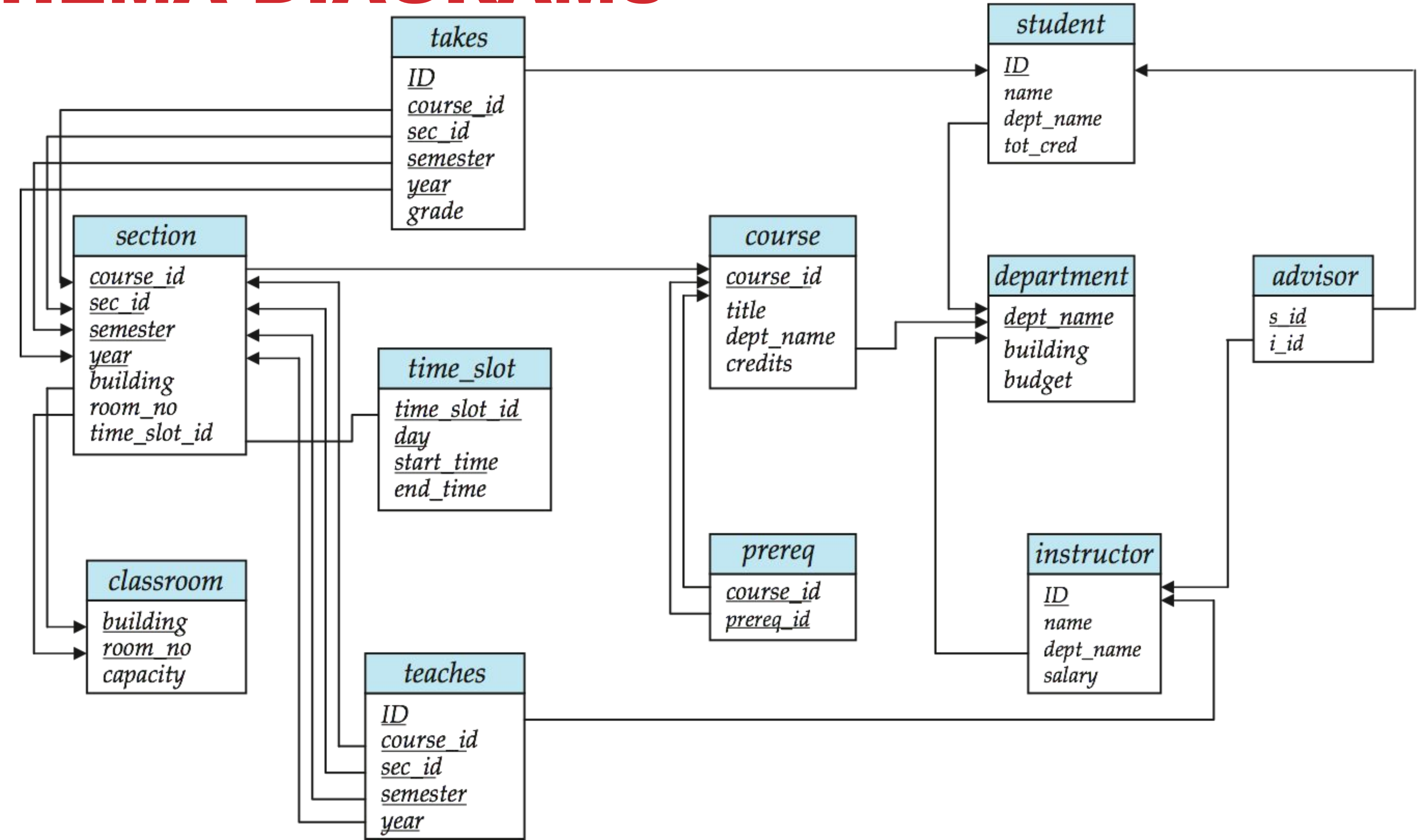
A list of all the attribute names, and their *domains*

```
create table department
    (dept_name varchar(20),
     building varchar(15),
     budget numeric(12,2) check (budget > 0),
     primary key (dept_name)
    );
```

SQL Statements
To create Tables

```
create table instructor (
    ID        char(5),
    name      varchar(20) not null,
    dept_name varchar(20),
    salary    numeric(8,2),
    primary key (ID),
    foreign key (dept_name) references department
)
```

SCHEMA DIAGRAMS



SEARCHING FOR ELEMENTS

Find all people with nationality Canada (nat_id = 2):

???????????????

ID	age	wgt_kg	hgt_cm	nat_id
1	12.2	42.3	145.1	1
2	11.0	40.8	143.8	1
3	15.6	65.3	165.3	2
4	35.1	84.2	185.8	1
5	18.1	62.2	176.2	3
6	19.6	82.1	180.1	1

O(n) 

INDEXES

Like a hidden sorted map of references to a specific attribute (column) in a table; allows O(log n) lookup instead of O(n)

loc	ID	age	wgt_kg	hgt_cm	nat_id
0	1	12.2	42.3	145.1	1
128	2	11.0	40.8	143.8	2
256	3	15.6	65.3	165.3	2
384	4	35.1	84.2	185.8	1
512	5	18.1	62.2	176.2	3
640	6	19.6	82.1	180.1	1

nat_id	locs
1	0, 384, 640
2	128, 256
3	512

INDEXES

Actually implemented with data structures like B-trees

- (Take courses like CMSC424 or CMSC420)

But: indexes are not free

- Takes memory to store
- Takes time to build
- Takes time to update (add/delete a row, update the column)

But, but: one index is (mostly) free

- Index will be built automatically on the primary key

Think before you build/maintain an index on other attributes!

RELATIONSHIPS

Primary keys and foreign keys define interactions between different tables aka entities. Four types:

- One-to-one
- One-to-one-or-none
- One-to-many and many-to-one
- Many-to-many

Connects (one, many) of the rows in one table to (one, many) of the rows in another table

ONE-TO-MANY & MANY-TO-ONE

One person can have one nationality in this example, but one nationality can include many people.

Person

Nationality

ID	age	wgt_kg	hgt_cm	nat_id
1	12.2	42.3	145.1	1
2	11.0	40.8	143.8	1
3	15.6	65.3	165.3	2
4	35.1	84.2	185.8	1
5	18.1	62.2	176.2	3
6	19.6	82.1	180.1	1

ID	Nationality
1	USA
2	Canada
3	Mexico

ONE-TO-ONE

Two tables have a one-to-one relationship if every tuple in the first tables corresponds to exactly one entry in the other

In general, you won't be using these (why not just merge the rows into one table?) unless:

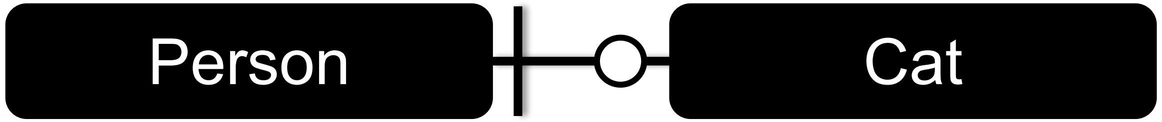
- Split a big row between SSD and HDD or distributed
- Restrict access to part of a row (some DBMSs allow column-level access control, but not all)
- Caching, partitioning, & serious stuff: take CMSC424

ONE-TO-ONE-OR-NONE

Say we want to keep track of people's cats:

Person ID	Cat1	Cat2
1	Chairman Meow	Fuzz Aldrin
4	Anderson Pooper	Meowly Cyrus
5	Gigabyte	Megabyte

People with IDs 2 and 3 do not own cats*, and are not in the table. Each person has at most one entry in the table.



Is this data tidy?

*nor do they have hearts, apparently.

MANY-TO-MANY

Say we want to keep track of people's cats' colorings:

ID	Name
1	Megabyte
2	Meowly Cyrus
3	Fuzz Aldrin
4	Chairman Meow
5	Anderson Pooper
6	Gigabyte

Cat ID	Color ID	Amount
1	1	50
1	2	50
2	2	20
2	4	40
2	5	40
3	1	100

One column per color, too many columns, too many nulls

Each cat can have many colors, and each color many cats

Cat — Color

ASSOCIATIVE TABLES

Cats

ID	Name
1	Megabyte
2	Meowly Cyrus
3	Fuzz Aldrin
4	Chairman Meow
5	Anderson Pooper
6	Gigabyte

Cat ID	Color ID	Amount
1	1	50
1	2	50
2	2	20
2	4	40
2	5	40
3	1	100

Colors

ID	Name
1	Black
2	Brown
3	White
4	Orange
5	Neon Green
6	Invisible

Used to model pure relationships (as opposed to discrete entities)

Primary key ???????????

- [Cat ID, Color ID] (+ [Color ID, Cat ID], case-dependent)

Foreign key(s) ???????????

- Cat ID and Color ID

ASIDE: PANDAS

So, this kinda feels like pandas …

- And pandas kinda feels like a relational data system …

Pandas is not strictly a relational data system:

- No notion of primary / foreign keys

It does have indexes (and multi-column indexes):

- pandas.Index: ordered, sliceable set storing axis labels
- pandas.MultiIndex: hierarchical index

Rule of thumb: do heavy, rough lifting at the relational DB level, then fine-grained slicing and dicing and viz with pandas

SQLITE

On-disk relational database management system (RDMS)

- Applications connect directly to a file

Most RDMSs have applications connect to a server:

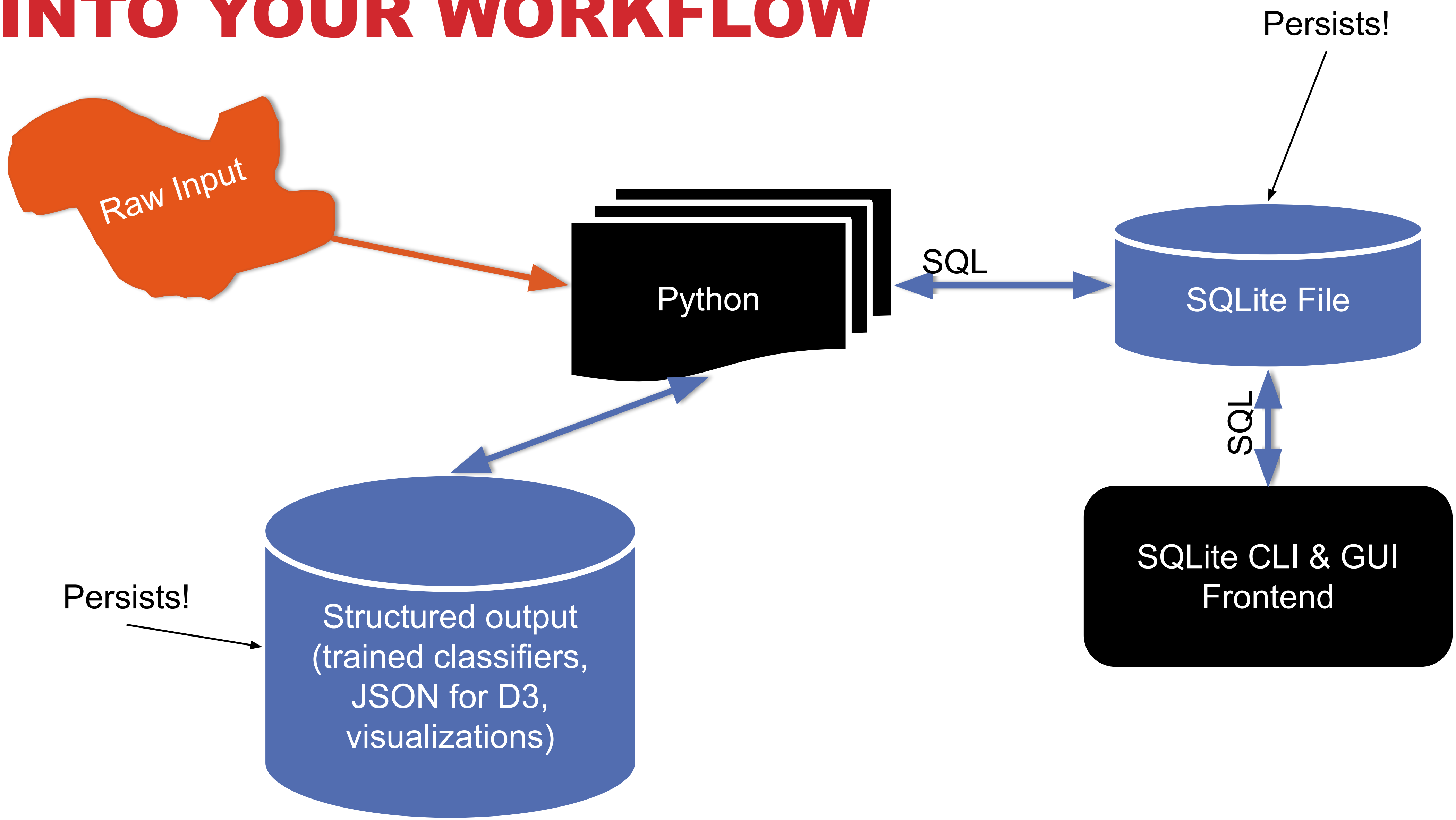
- Advantages include greater concurrency, less restrictive locking
- Disadvantages include, for this class, setup time ☺

Installation:

- `conda install -c anaconda sqlite`
- (Included in Docker container & Jupyter install; need install for raw Python)

All interactions use Structured Query Language (SQL)

HOW A RELATIONAL DB FITS INTO YOUR WORKFLOW



CRASH COURSE IN SQL (IN PYTHON)

```
import sqlite3

# Create a database and connect to it
conn = sqlite3.connect("cmsc320.db")
cursor = conn.cursor()

# do cool stuff
conn.close()
```

Cursor: temporary work area in system memory for manipulating SQL statements and return values

If you do not close the connection (`conn.close()`), any outstanding transaction is rolled back

- (More on this in a bit.)

CRASH COURSE IN SQL (IN PYTHON)

```
# Make a table
cursor.execute("""
CREATE TABLE cats (
    id INTEGER PRIMARY KEY,
    name TEXT
)""")
```

?????????

id	name

cats

Capitalization doesn't matter for SQL reserved words

- **SELECT = select = SeLeCt**

Rule of thumb: capitalize keywords for readability

CRASH COURSE IN SQL (IN PYTHON)

```
# Insert into the table
cursor.execute(“INSERT INTO cats VALUE (1, ’Megabyte’)”)
cursor.execute(“INSERT INTO cats VALUE (2, ‘Meowly Cyrus’)”)
cursor.execute(“INSERT INTO cats VALUE (3, ‘Fuzz Aldrin’)”)
conn.commit()
```

id	name
1	Megabyte
2	Meowly Cyrus
3	Fuzz Aldrin

```
# Delete row(s) from the table
cursor.execute(“DELETE FROM cats WHERE id == 2”);
conn.commit()
```

id	name
1	Megabyte
3	Fuzz Aldrin

CRASH COURSE IN SQL (IN PYTHON)

```
# Read all rows from a table
for row in cursor.execute("SELECT * FROM cats"):
    print(row)
```

```
# Read all rows into pandas DataFrame
pd.read_sql_query("SELECT * FROM cats", conn, index_col="id")
```

id	name
1	Megabyte
3	Fuzz Aldrin

index_col="id": treat column with label "id" as an index

index_col=1: treat column #1 (i.e., "name") as an index

(Can also do multi-indexing.)

JOINING DATA

A join operation merges two or more tables into a single relation. Different ways of doing this:

- Inner
- Left
- Right
- Full Outer

Join operations are done on columns that explicitly link the tables together

GOOGLE IMAGE SEARCH ONE SLIDE SQL JOIN VISUAL

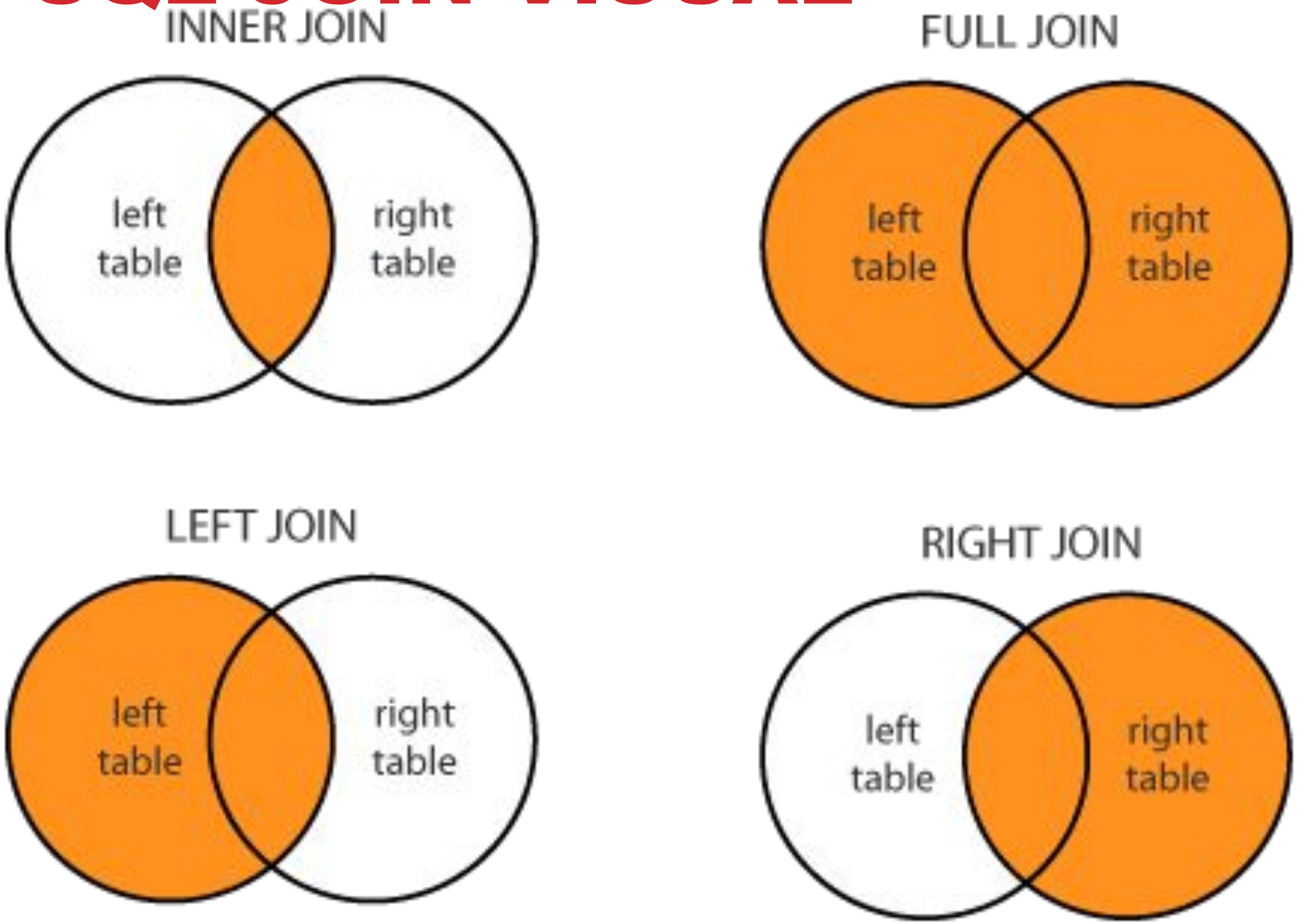


Image credit: http://www.dofactory.com/sql/join

INNER JOINS

id	name
1	Megabyte
2	Meowly Cyrus
3	Fuzz Aldrin
4	Chairman Meow
5	Anderson Pooper
6	Gigabyte

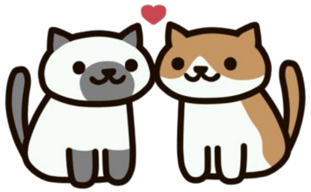
`cats`

cat_id	last_visit
1	02-16-2017
2	02-14-2017
5	02-03-2017

`visits`

Inner join returns merged rows that share the same value in the column they are being joined on (`id` and `cat_id`).

id	name	last_visit
1	Megabyte	02-16-2017
2	Meowly Cyrus	02-14-2017
5	Anderson Pooper	02-03-2017



INNER JOINS

```
# Inner join in pandas
df_cats = pd.read_sql_query("SELECT * from cats", conn)
df_visits = pd.read_sql_query("SELECT * from visits", conn)
df_cats.merge(df_visits, how = "inner",
              left_on = "id", right_on = "cat_id")
```

```
# Inner join in SQL / SQLite via Python
cursor.execute("""
               SELECT
                   *
               FROM
                   cats, visits
               WHERE
                   cats.id == visits.cat_id
               """)
```

LEFT JOINS

Inner joins are the most common type of joins (get results that appear in both tables)

Left joins: all the results from the left table, only some matching results from the right table

Left join (`cats`, `visits`) on (`id`, `cat_id`) ???????????

id	name	last_visit
1	Megabyte	02-16-2017
2	Meowly Cyrus	02-14-2017
3	Fuzz Aldrin	NULL
4	Chairman Meow	NULL
5	Anderson Pooper	02-03-2017
6	Gigabyte	NULL

RIGHT JOINS

Take a guess!

Right join
(`cats, visits`)
on
(`id, cat_id`)
???????????

id	name
1	Megabyte
2	Meowly Cyrus
3	Fuzz Aldrin
4	Chairman Meow
5	Anderson Pooper
6	Gigabyte

`cats`

cat_id	last_visit
1	02-16-2017
2	02-14-2017
5	02-03-2017
7	02-19-2017
12	02-21-2017

`visits`

id	name	last_visit
1	Megabyte	02-16-2017
2	Meowly Cyrus	02-14-2017
5	Anderson Pooper	02-03-2017
7	NULL	02-19-2017
12	NULL	02-21-2017

LEFT/RIGHT JOINS

```
# Left join in pandas
df_cats.merge(df_visits, how = “left”,
              left_on = “id”, right_on = ”cat_id”)
```

```
# Left join in SQL / SQLite via Python
cursor.execute(“SELECT * FROM cats LEFT JOIN visits ON
                     cats.id == visits.cat_id”)
```

```
# Right join in pandas
df_cats.merge(df_visits, how = “right”,
              left_on = “id”, right_on = ”cat_id”)
```

```
# Right join in SQL / SQLite via Python
☹️
```

FULL OUTER JOIN

Combines the left and the right join ???????????

id	name	last_visit
1	Megabyte	02-16-2017
2	Meowly Cyrus	02-14-2017
3	Fuzz Aldrin	NULL
4	Chairman Meow	NULL
5	Anderson Pooper	02-03-2017
6	Gigabyte	NULL
7	NULL	02-19-2017
12	NULL	02-21-2017

```
# Outer join in pandas
df_cats.merge(df_visits, how = “outer”,
              left_on = “id”, right_on = ”cat_id”)
```

GROUP BY AGGREGATES

```
SELECT nat_id, AVG(age) as average_age
FROM persons GROUP BY nat_id
```

ID	age	wgt_kg	hgt_cm	nat_id
1	12.2	42.3	145.1	1
2	11.0	40.8	143.8	1
3	15.6	65.3	165.3	2
4	35.1	84.2	185.8	1
5	18.1	62.2	176.2	3
6	19.6	82.1	180.1	1

nat_id	average_age
1	19.48
2	15.6
3	18.1

RAW SQL IN PANDAS

If you “think in SQL” already, you’ll be fine with pandas:

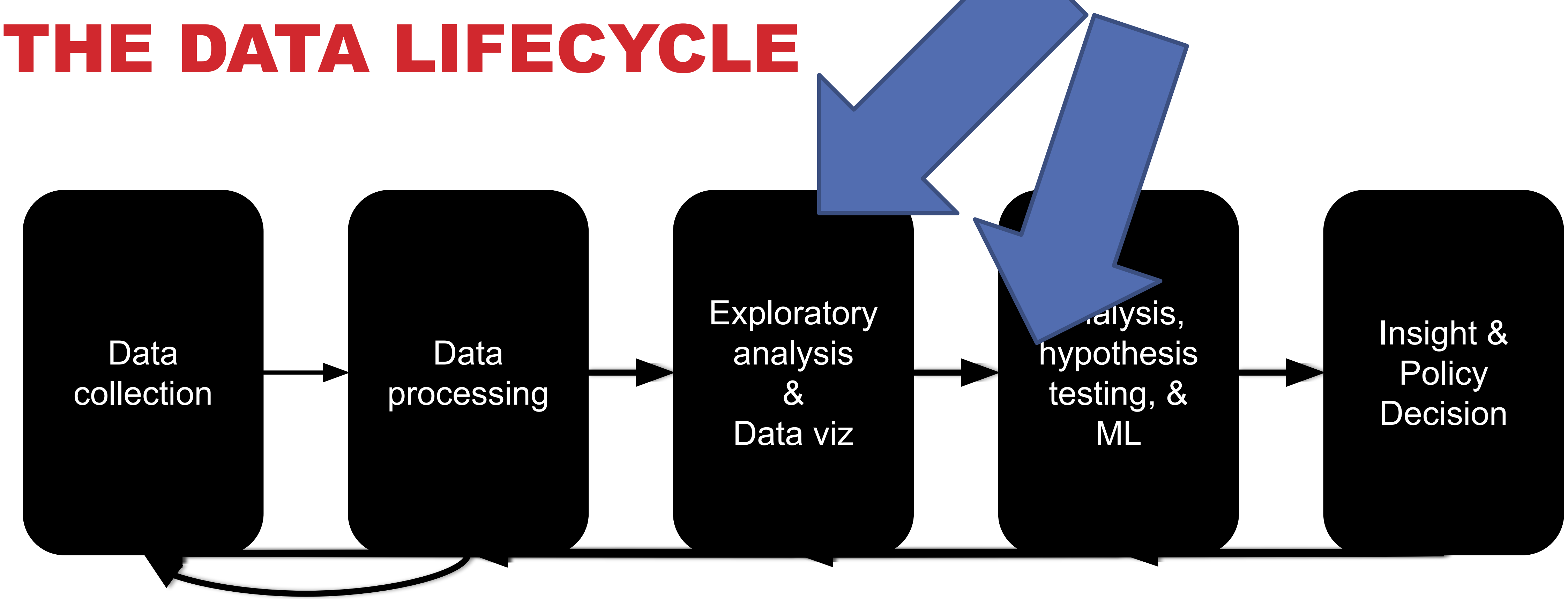
- `conda install -c anaconda pandasql`
- Info: http://pandas.pydata.org/pandas-docs/stable/comparison_with_sql.html

```
# Write the query text
q = """
    SELECT
        *
    FROM
        cats
    LIMIT 10;"""

# Store in a DataFrame
df = sqldf(q, locals())
```

THE DATA LIFECYCLE

Motivational teaser – *why* are we talking about this ”data” stuff?

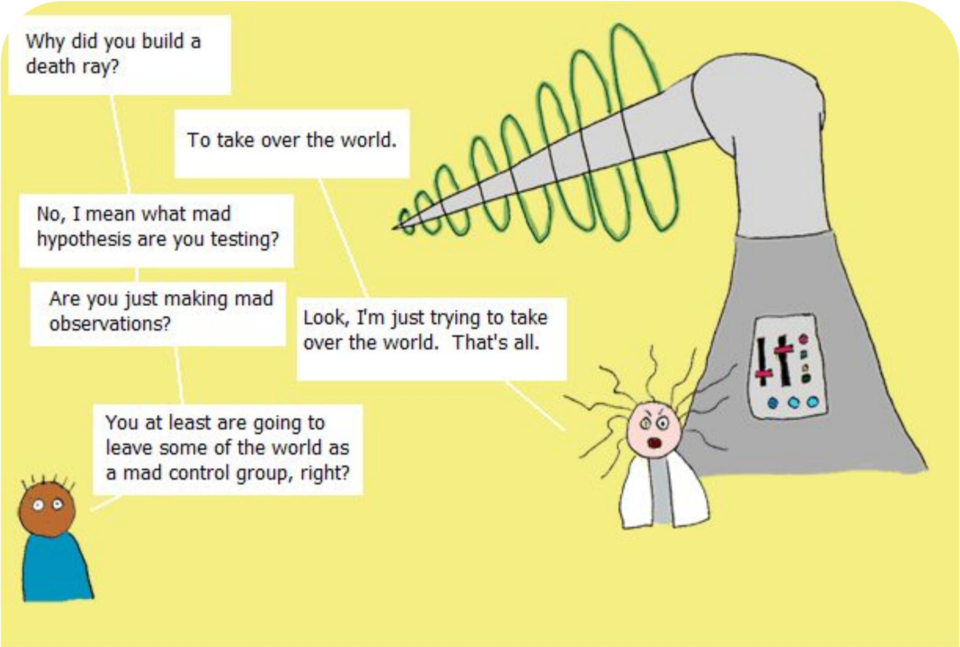


PUTTING THE SCIENCE BACK IN DATA SCIENCE

What's the "Science" part of data sciencce?

- Typically, "Science" is "determining some truth about the world…."

Suppose you work for a company that is considering a redesign of their website; does their new design (design B) offer any statistical advantage to their current design (design A)?



Sad truth: Most "mad scientists" are actually just mad engineers

In a linear regression, does a certain variable impact the response?

- Does energy consumption depend on whether or not a day is a weekday or weekend?

Both: concerned with making actual statements about the nature of the world.

[ZK, NM]

RECALL: WHAT IS DATA SCIENCE?

Drawing useful conclusions from data in a principled way.

Exploration

- Identifying patterns in information
- Uses visualizations, bringing data together

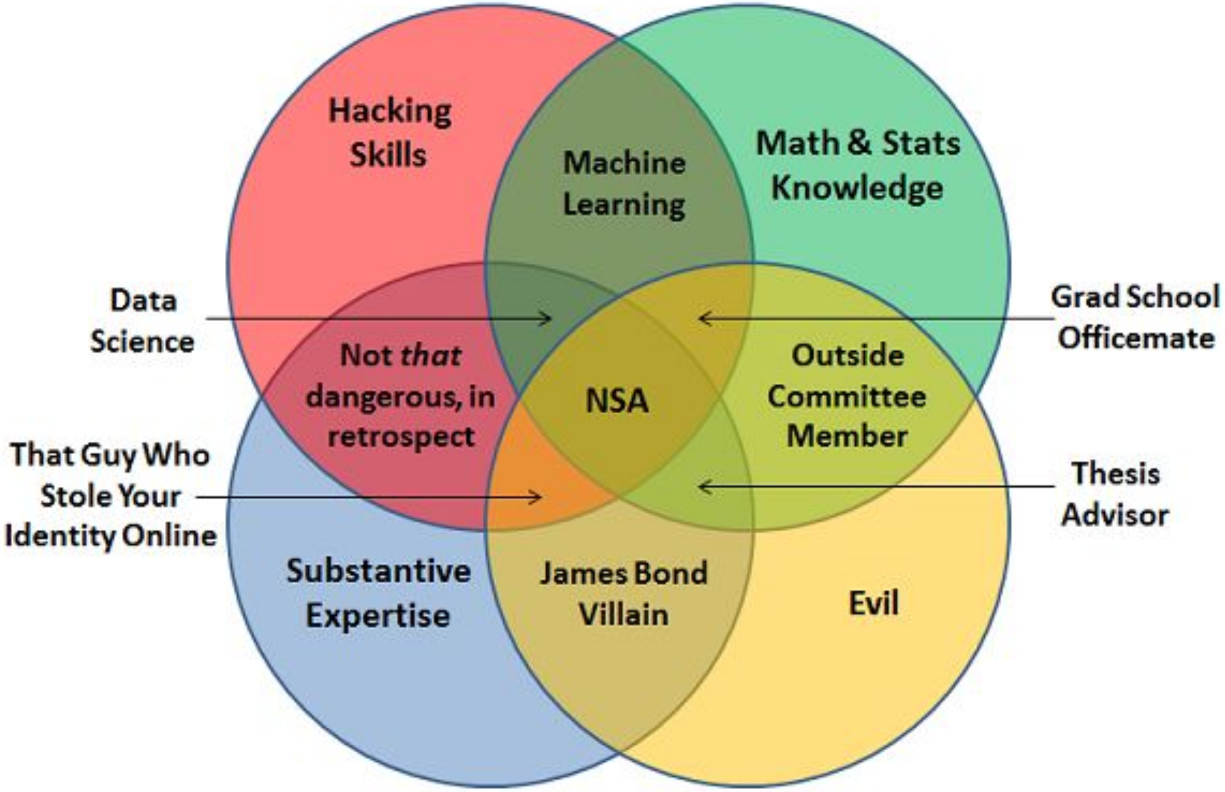
Prediction: **Given what I've seen, what is the most likely value I'll see in the future? Predictions forecast the most likely values of the data coming from the data generating process.**

- Making informed guesses
- Uses machine learning and optimization

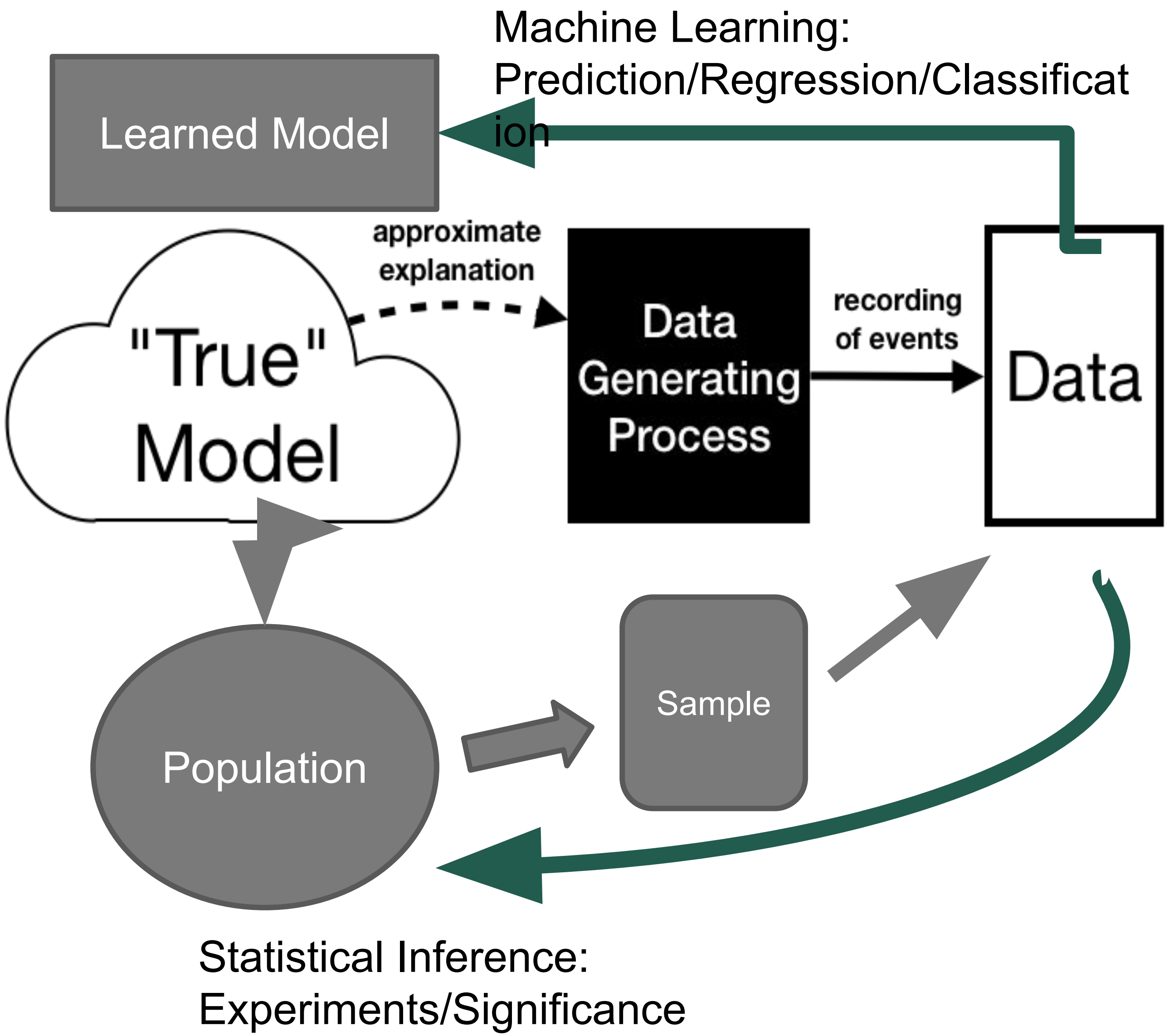
Inference: **How likely is what I observed representative of the broader picture? Statistical Inference draws conclusions (with confidence) about the structure of the data generating process (population).**

- Quantifying whether those patterns are reliable
- Uses randomization

Inference vs Prediction (TBD expanded!): **inference = learn about the data generation process, prediction = predict what's coming next**



HOW DATA AND MODELS INTERACT: EXAMPLE 1



True Model / Population: phenomenon under investigation

Data Generating Process / Sample: mechanisms that create the data that will be recorded (e.g. probabilistic, noisy)

Example: Understand customer satisfaction. Sends a text message to all previous customers to rate on a scale of 1-5.

True Model: the true opinion of all customers

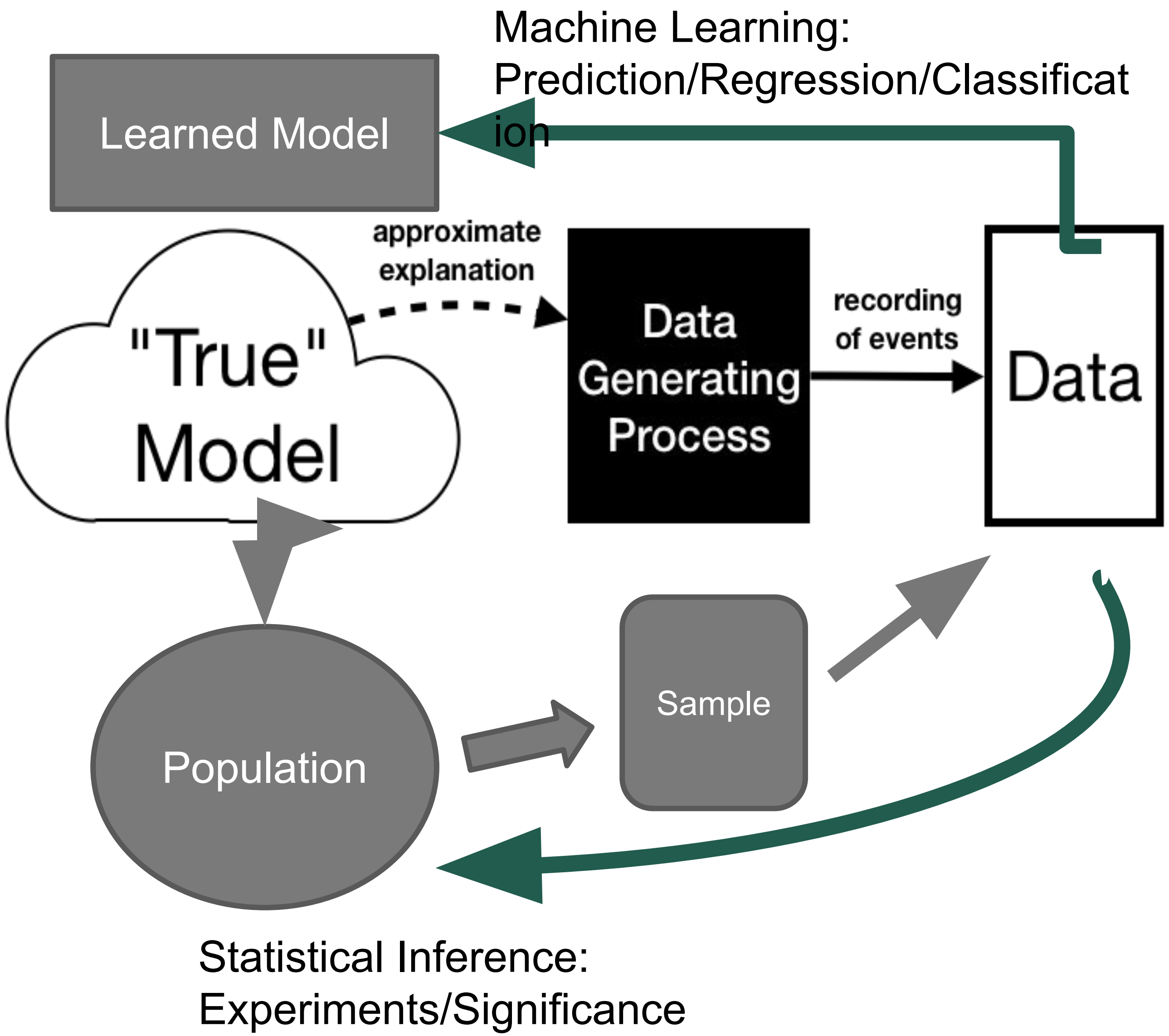
Data Generating Process: how and which customers responded (satisfaction, mood, too busy, don't care, ignored, etc.)

Data: all replies received and recorded.

Tasks:

- Predict Reviews from unseen customers
- Understand product comparison

HOW DATA AND MODELS INTERACT: EXAMPLE 2



A Model: theory or explanation of the data generating process (relationships).

Fit Model: an instance of a model that is likely to explain a fixed dataset.

Example: What is the relationship between the number of parking tickets and the weather?

Data Generating Process: data recorded of parking ticket and weather; noisy observations!

Model: more parking tickets are issued when the weather is temperate (neither hot nor cold).

Fit Model: quantitative relationship for a dataset:

- E.g, On data of tickets and weather in San Diego, a car is 5x more likely to get a ticket when the weather is temperate.
- Model fit on data from Minneapolis might specify a different quantity (e.g. 3x) but same structure.

[NM]

WHAT MAKES A MODEL GOOD?

A fit model finds the most likely parameters that explain the observed data under the given model.

These parameters are found by minimizing a loss function – typically some notion of 'error' or 'cost'.

A model is good if it effectively explains the phenomenon under investigation. Two questions:

1. Is the model choice reasonable? Does the structure of the model capture the general understanding of how the Data Generating Process behaves?
2. Does the fit model describe the data well? How small is the error?

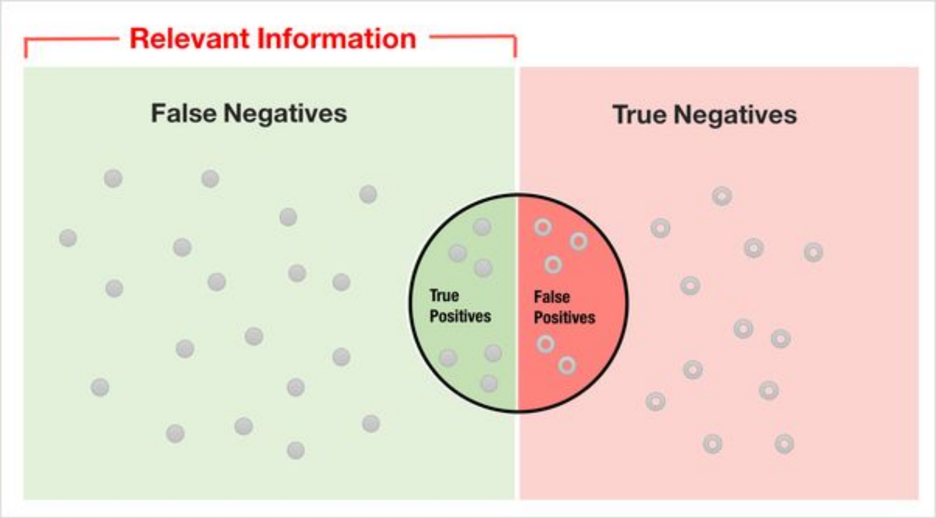
(1) is about the applicability of the model to new observations (bias).

(2) is about the ability of a model to explain the observed data (variance).

- More later on this semester!

Predicted Class

		Positive	Negative	
Actual Class	Positive	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	Negative Predictive Value $\frac{TN}{(TN+FN)}$	Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$



STATISTICAL MODEL: INFERENCE

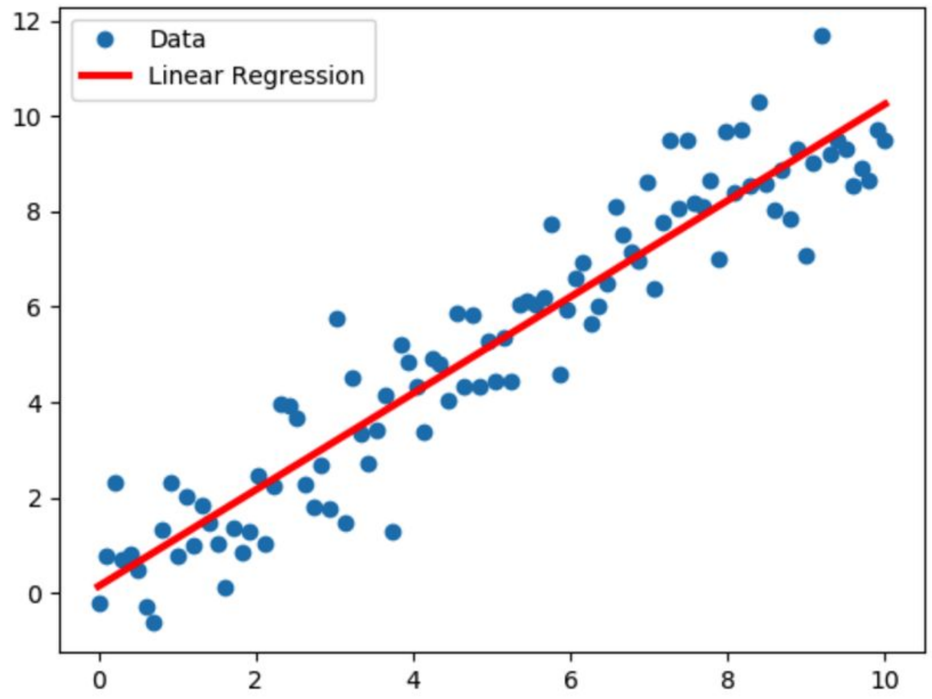
A statistical model is a quantitative relationship between properties in observed data.

A statistical model is a function S : X → R^n that measures properties of X.

Example: Is there a linear relationship between the heights of children and the height of their biological mother?

- X = mother_height ∈ R
- Y = child_height ∈ R
- S is the *correlation coefficient* (measure of strength of relationship between the relative movement of mother_height and child_height)

Inference results in interpreting properties (e.g., significance) of the data generating process from the parameters of the model (e.g. correlation).



PREDICTION MODEL: REGRESSION

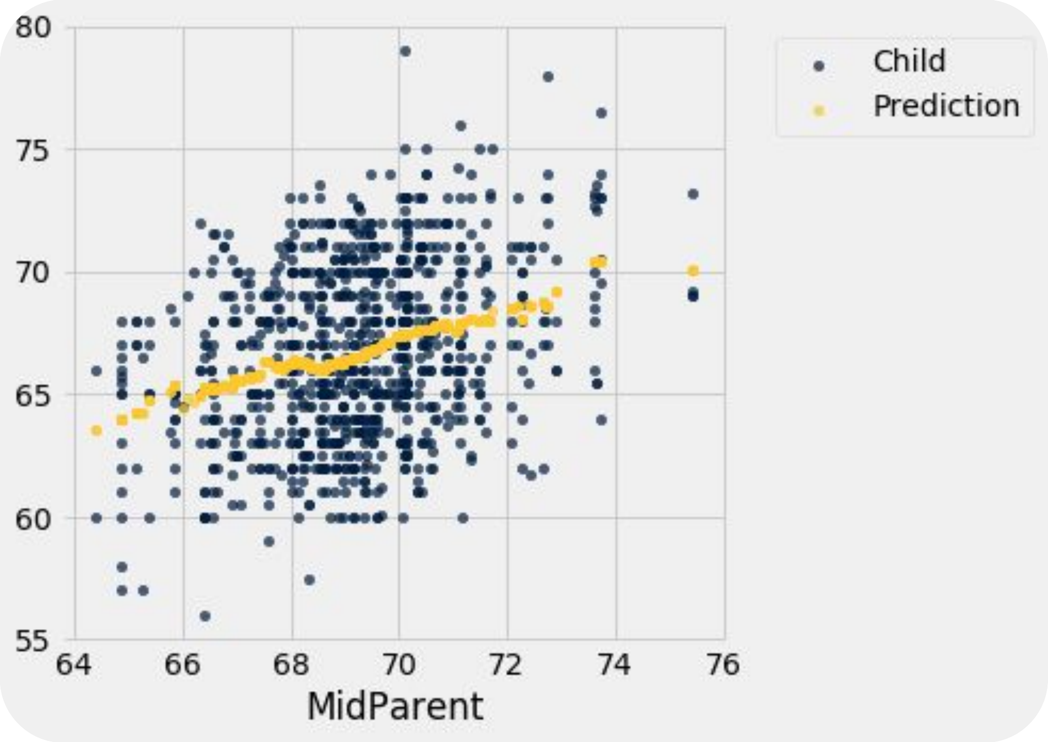
Regression models attempt to predict the most likely quantitative value associated to an observation (set of input features).

A regressor is a function F: X→R that predicts the value y∈R of an observation x∈X.

Example: Given the heights of a child's parents, what is the height of their child?

- X = (father_height, mother_height) ∈ R^2
- Y = child_height ∈ R
- F predicts child heights.

Regression results in having a model that we can use to predict a numerical value for data that we have not see yet.



PREDICTION MODEL: CLASSIFICATION

Classification models attempt to predict the most likely class associated to an observation (set of input features)

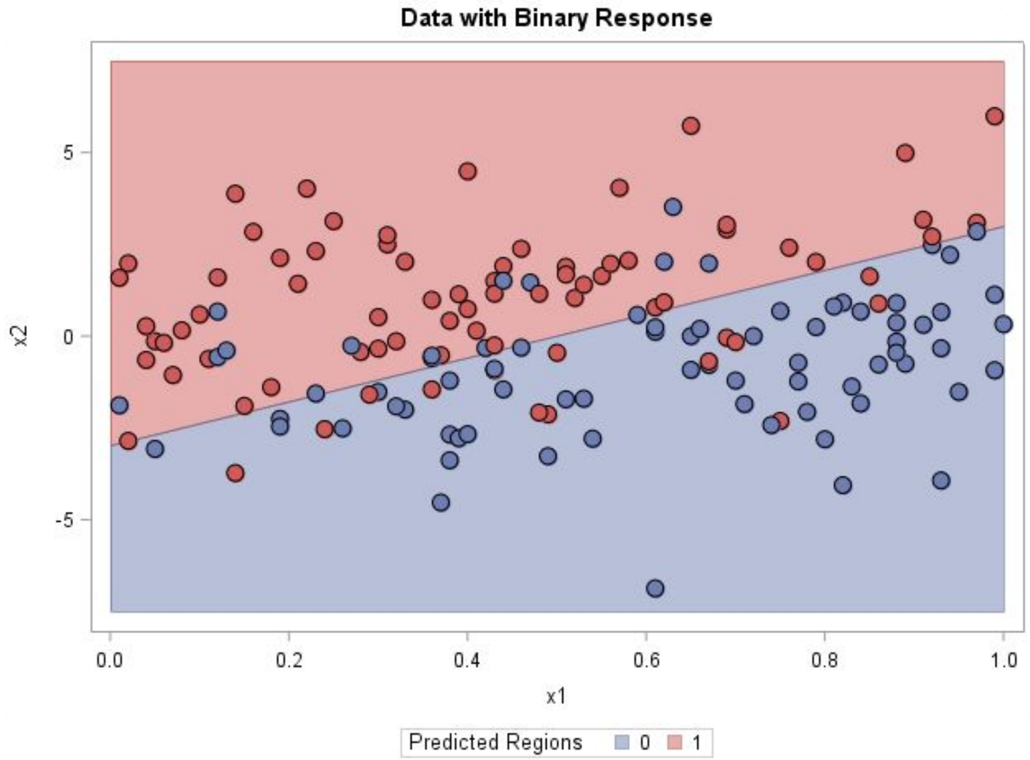
- Class is a nominal attribute (e.g., 1='YES' v 0='NO').

A classifier is a function F: X→Y that predicts whether an observation x∈X belongs to a class y∈Y.

Example: Given product purchase attributes (item, price, age, state), can one predict whether the person was satisfied with their purchase?

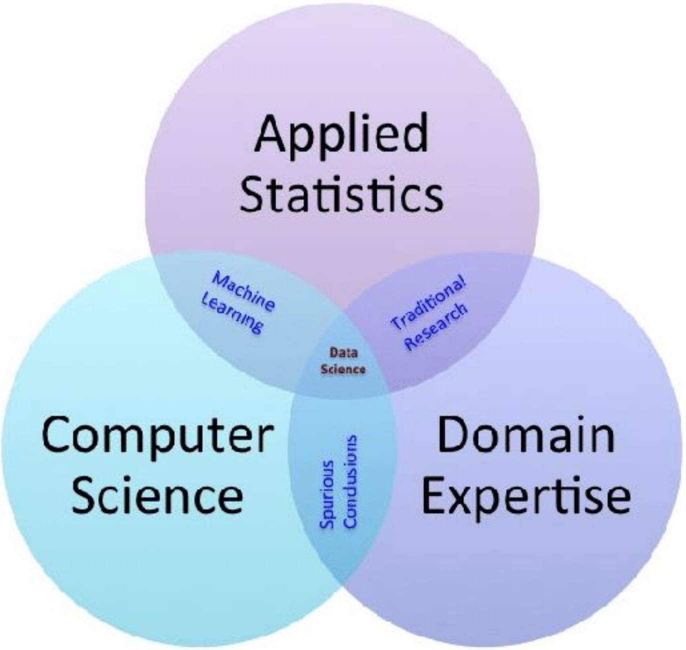
- X = (item, price, age, state) ∈ R^4
- Y = 'SATISFIED','NOT SATISFIED' ∈ {0,1}
- F predicts product satisfaction.

Classification results in a model that we can use to predict labels for data we have not seen.



A SIDE NOTE ON TERMS

For linear regression we want to know the relationship between an outcome, given some set/vector of predictors.



If you have a ML background:

- Get target, outcome given predictors/observations

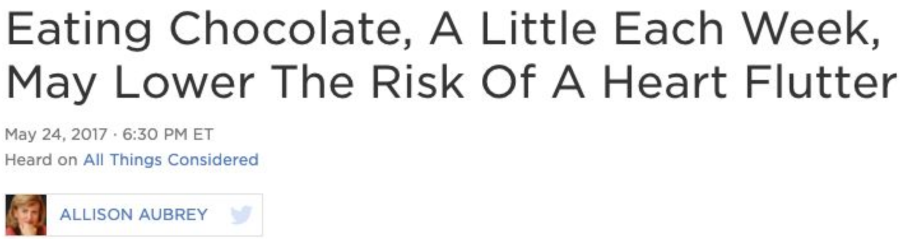
If you have a “stats” background:

- Get endogenous variables given exogenous variables

If you are more of a “math” person:

- Get dependent variable given one or more independent variables

TEASER I: PUTTING ON OUR STATS HAT


Eating Chocolate, A Little Each Week, May Lower The Risk Of A Heart Flutter

May 24, 2017 · 6:30 PM ET
Heard on All Things Considered

ALLISON AUBREY

Population (Individuals, study subjects, participants)

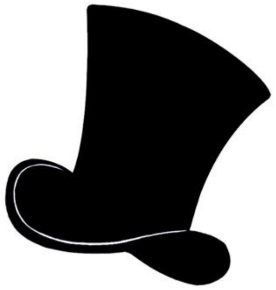
- European adults

Treatment: Something (drug, price, web headline) to which a subjects are exposed

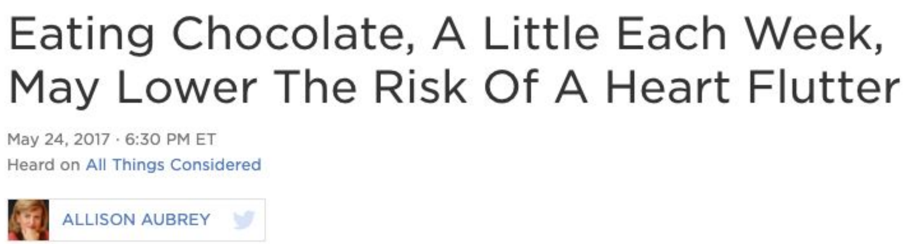
- Chocolate consumption

Outcome: dependent variable, response, target, output

- Heart disease



TEASER II: PUTTING ON OUR STATS HAT


Eating Chocolate, A Little Each Week, May Lower The Risk Of A Heart Flutter

May 24, 2017 · 6:30 PM ET
Heard on All Things Considered

ALLISON AUBREY

Question: Is there any relation between chocolate consumption and heart disease?

- Association: any relation
- Not necessarily causal! “The rooster does not make the sun rise.”

Data:

- “Among those in the top tier of chocolate consumption, 12 percent developed or died of cardiovascular disease during the study, compared to 17.4 percent of those who didn’t eat chocolate.”
- - Howard LeWine of Harvard Health Blog, reported by npr.org

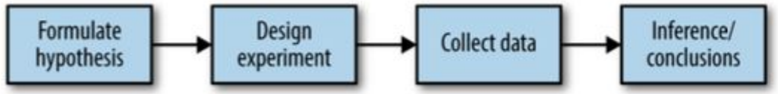


Figure 3-1. The classical statistical inference pipeline

NOW, TRAVEL BACK TO LONDON IN THE 1800S …

MIASMAS, MIASMATISM, MIASMATISTS

Bad smells given off by waste and rotting matter …

Believed to be the main source of disease (cholera)

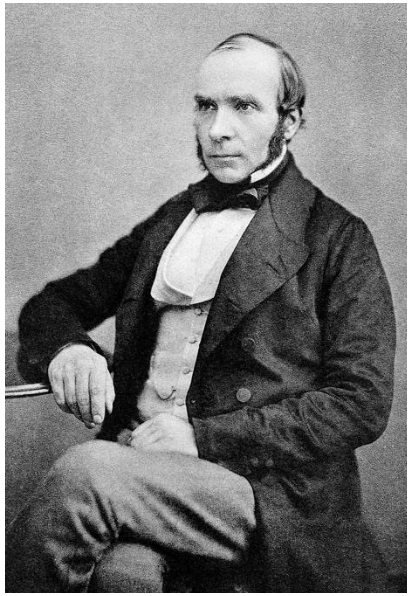
Suggested remedies:

- “fly to clene air”
- “a pocket full o’posies”
- “fire off barrels of gunpowder”

JO(H)N SNOW, 1813—58

Which one?

- https://en.wikipedia.org/wiki/John_Snow

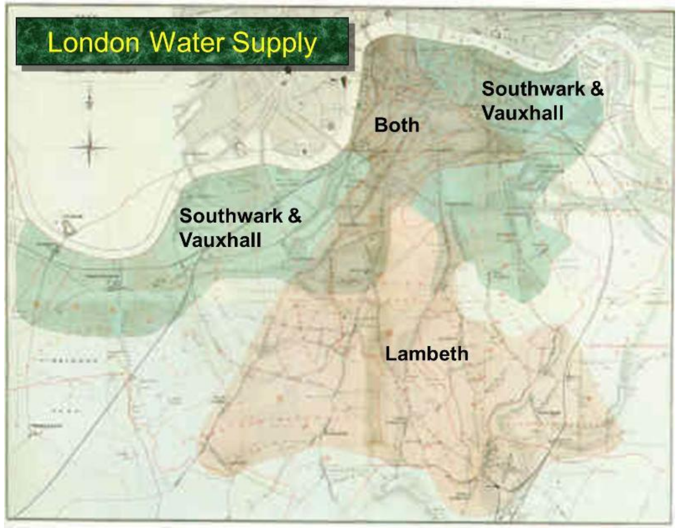


Big name in epidemiology, the study of determinants of population-level disease

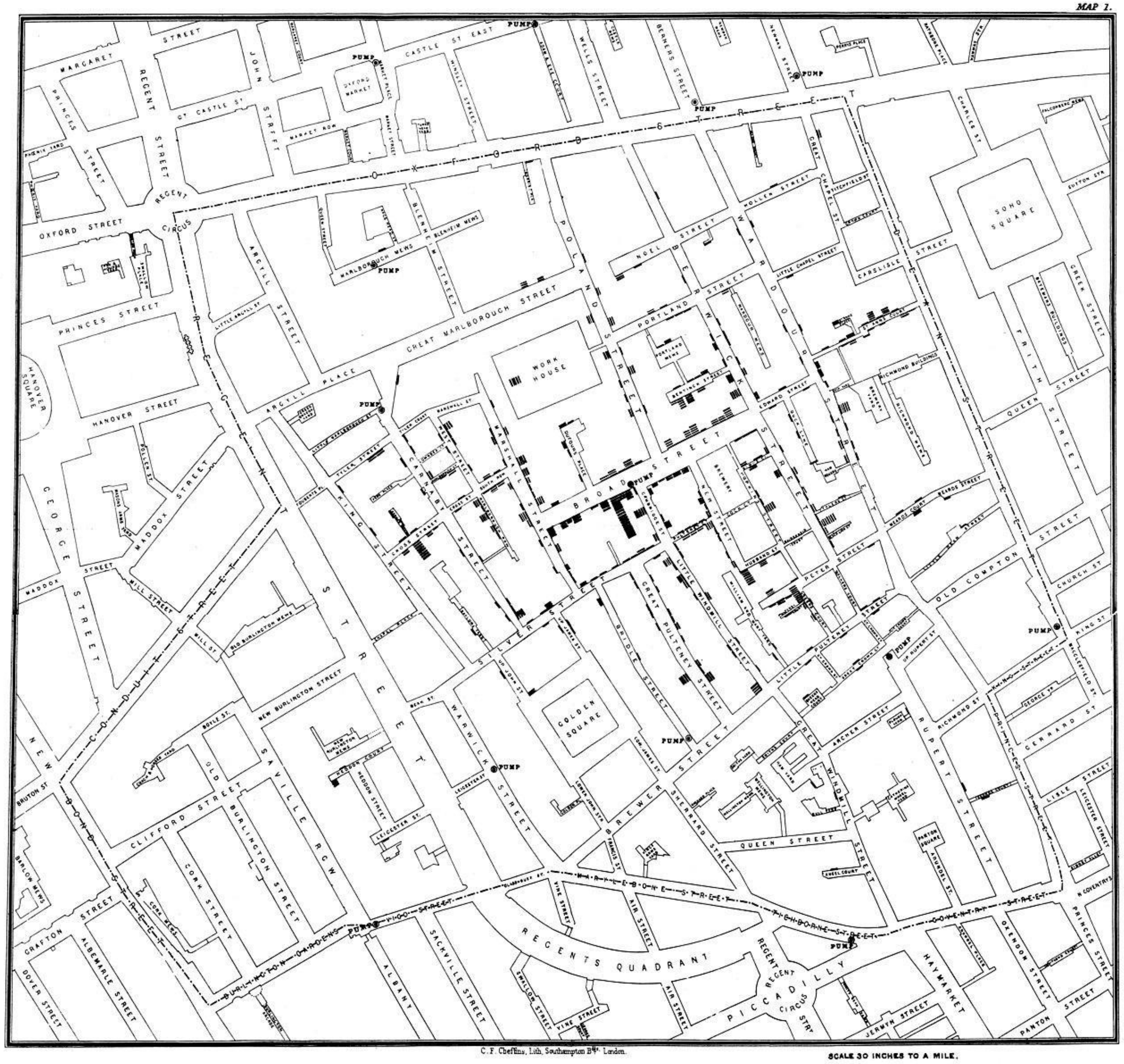
Big name (Jon, not John) in the North, let down by some writers

A public house built at the epicenter of a truly virulent cholera outbreak circa 1800s

JOHN SNOW'S MAP



Some houses served by S&V, which drew water from the Thames; otherws by Lambeth, which didn't



Snow's Map:

- Black bar represents one death.
- Multiple deaths at same address □ bars stacked on top of each other
- Black discs mark the locations of water pumps.
- Creates a "natural experiment"

TERMINOLOGY TEASER

Treatment: Something (drug, price, web headline) to which subjects are exposed

Treatment group

- A group of subjects exposed to a specific treatment

Control group

- A group of subjects exposed to no (or standard) treatment

Randomization

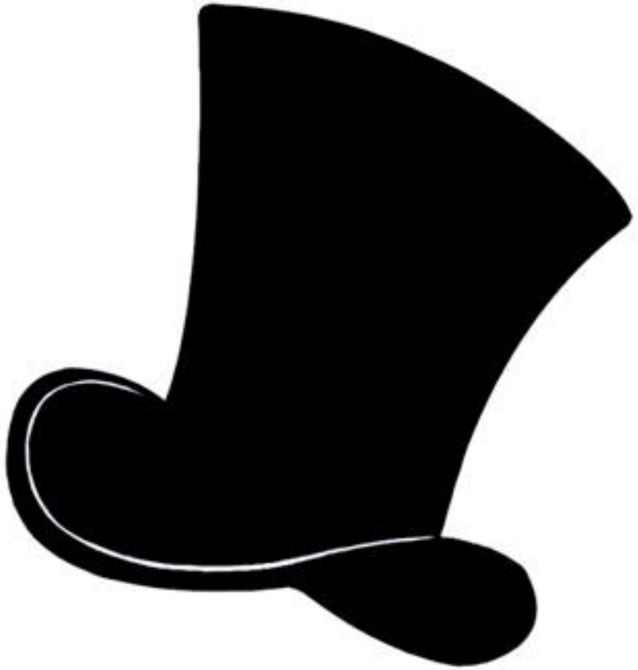
- The process of randomly assigning subjects to treatments

Subjects

- The items (web visitors, patients, etc.) that are exposed to treatments

Test statistic

- The metric used to measure the effect of the treatment



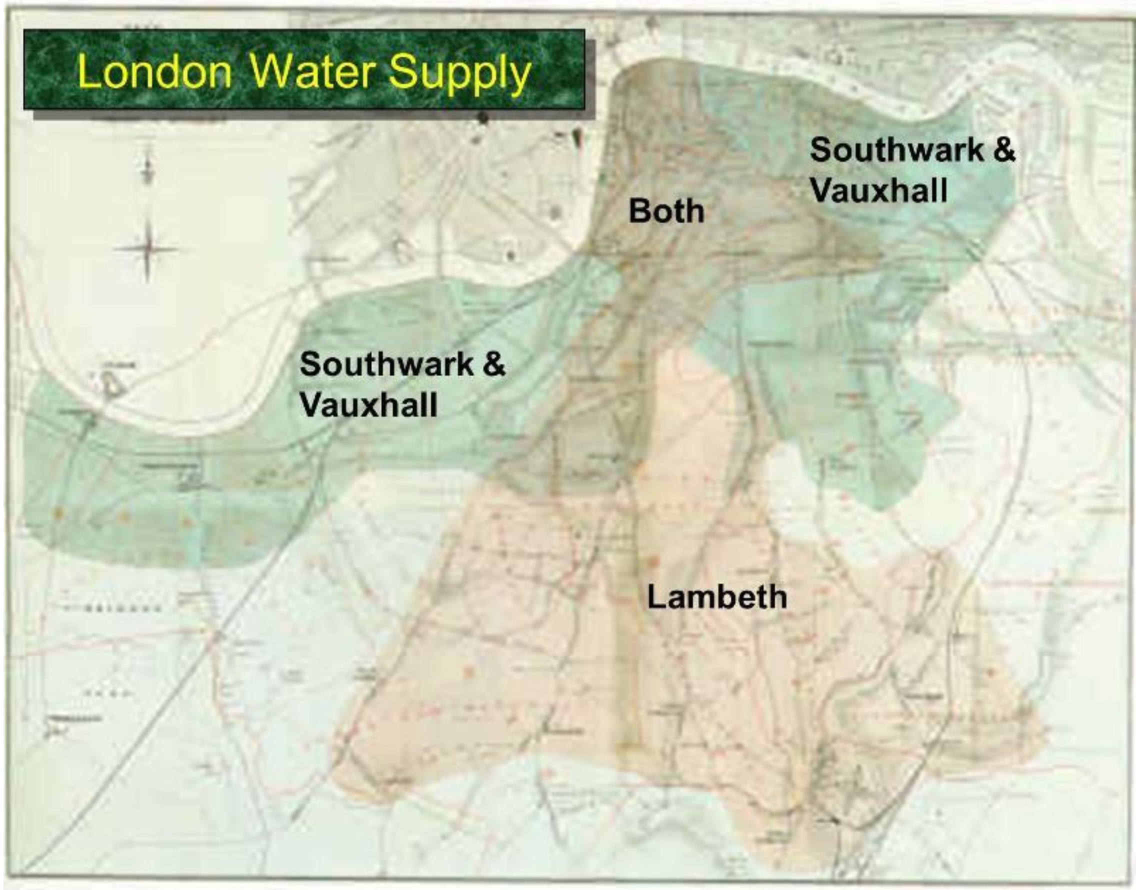
QUESTIONS

Treatment Group ?????????

Control Group ?????????

Which houses were part of the treatment group?

- All houses in the region of overlap.
- Houses served by S&V (dirty water) in the region of overlap.
- Houses served by Lambeth (clean water) in the region of overlap?



In the language of stats:

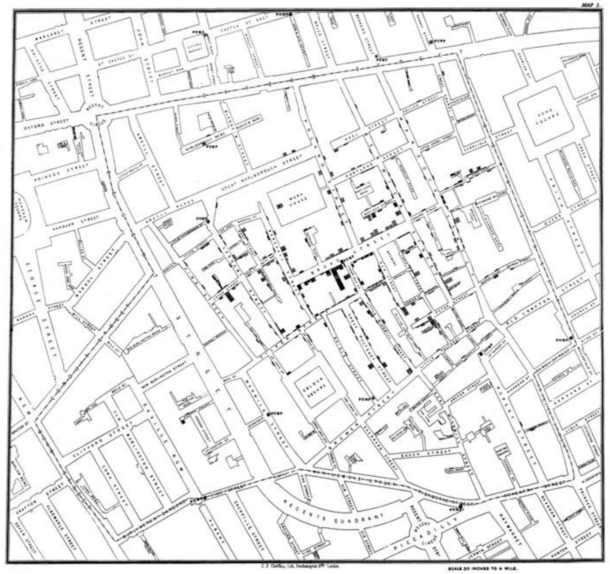
- S&V houses as the treatment group
- Lambeth houses at the control group.
- A crucial element in Snow's analysis was that the people in the two groups were comparable to each other, apart from the treatment.

JOHN SNOW'S EXPERIMENT

"… there is no difference whatever in the houses or the people receiving the supply of the two Water Companies, or in any of the physical conditions with which they are surrounded …"

The only difference was in the water supply, "one group being supplied with water containing the sewage of London, and amongst it, whatever might have come from the cholera patients, the other group having water quite free from impurity."

The map displays a striking revelation—the deaths are roughly clustered around the Broad Street pump.



Supply Area	Num. of Houses	Cholera Deaths	Deaths/10k Houses
S & V (Dirty Water)	40,046	1,263	315
Lambeth (Clean Water)	26,107	98	37
Rest of London	256,423	1,422	59

NEXT CLASS:

EXPLORATORY ANALYSIS