Advanced Data Management (CSCI 490/680)

Data Wrangling

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pandas

- Contains high-level data structures and manipulation tools designed to make data analysis fast and easy in Python
- Built on top of NumPy
- Requirements:
  - Data structures with labeled axes (aligning data)
  - Time series data
  - Arithmetic operations that include metadata (labels)
  - Handle missing data
  - Merge and relational operations

Series

- A one-dimensional array (with a type) with an **index**
- Index defaults to numbers but can also be text (like a dictionary)
- Allows easier reference to specific items
- `obj = pd.Series([7,14,-2,1])`
- Basically two arrays: `obj.values` and `obj.index`
- Can specify the index explicitly and use strings
- ```
  obj2 = pd.Series([4, 7, -5, 3],
                   index=['d', 'b', 'a', 'c'])
  ```
- Kind of like fixed-length, ordered dictionary + can create from a dictionary
- ```
  obj3 = pd.Series({'Ohio': 35000, 'Texas': 71000,
                    'Oregon': 16000, 'Utah': 5000})
  ```

Data Frame

- A dictionary of Series (labels for each series)
- A spreadsheet with column headers
- Has an index shared with each series
- Allows easy reference to any cell
- ```
  df = DataFrame({'state': ['Ohio', 'Ohio', 'Ohio', 'Nevada'],
                  'year': [2000, 2001, 2002, 2001],
                  'pop': [1.5, 1.7, 3.6, 2.4]})
  ```
- Index is automatically assigned just as with a series but can be passed in as well via index kwarg
- Can reassign column names by passing columns kwarg
  ```

Indexing

- Same as with NumPy arrays but can use Series's index labels
- Slicing with labels: NumPy is **exclusive**, Pandas is **inclusive**!
  - ```
    s = Series(np.arange(4))
    s[0:2] # gives two values like numpy
    ```
  - ```
    s = Series(np.arange(4), index=['a', 'b', 'c', 'd'])
    s['a':'c'] # gives three values, not two!
    ```
- Obtaining data subsets
  - `[]`: get columns by label
  - `loc`: get rows/cols by label
  - `iloc`: get rows/cols by position (integer index)

- For single cells (scalars), also have `at` and `iat`

Indexing Data Frames

- Brackets can be ambiguous:
  - `df['Address']`
  - `df[0:4]`
- `.loc` and `.iloc` require more code (always row and column), but are clearer
  - `df.loc[:,'Address']`
  - `df.iloc[0:4,:]`
- Putting them together:
  - `df.iloc[0:4,:].loc[:,'Address']`
  - `df.loc[df.index[0:4],'Address']`

Sorting by Value (sort_values)

- `sort_values` method on series
  - `obj.sort_values()`
- Missing values (`NaN`) are at the end by default (`na_position` controls, can be first)
- `sort_values` on DataFrame:
  - `df.sort_values(<list-of-columns>)`
  - `df.sort_values(by=['a', 'b'])`
  - Can also use `axis=1` to sort by index labels

Unique Values and Value Counts

- `unique` returns an array with only the unique values (no index)
  - ```
    s = Series(['c','a','d','a','a','b','b','c','c'])
    s.unique() # array(['c', 'a', 'd', 'b'])
    ```
- Data Frames use `drop_duplicates`
- `value_counts` returns a Series with index frequencies:
  - ```
    s.value_counts() # Series({'c': 3,'a': 3,'b': 2,'d': 1})
    ```

Statistics

- `sum`: column sums (`axis=1` gives sums over rows)
- missing values are excluded unless the whole slice is `NaN`
- `idxmax, idxmin` are like argmax, argmin (return index)
- `describe`: shortcut for easy stats!

```
In [204]: df.describe()
Out[204]:
            one       two
count  3.000000  2.000000
mean   3.083333 -2.900000
std    3.493685  2.262742
min    0.750000 -4.500000
25%    1.075000 -3.700000
50%    1.400000 -2.900000
75%    4.250000 -2.100000
max    7.100000 -1.300000
```

```
In [205]: obj = Series(['a', 'a', 'b', 'c'] * 4)

In [206]: obj.describe()
Out[206]:
count     16
unique     3
top        a
freq       8
dtype: object
```

Assignment 2

- Similar to Assignment 1, now with pandas
- Part 5:
  - CS 680 → Required
  - CS 490 → Extra Credit
- Due Friday, Feb. 7

month	1	2	3	4	5	6	7	8	9	10	11	12	All
year													
1851	0	0	0	0	0	1	2	1	1	1	0	0	6
1852	0	0	0	0	0	0	0	1	3	1	0	0	5
1853	0	0	0	0	0	0	0	3	4	1	0	0	8
1854	0	0	0	0	0	1	0	1	2	1	0	0	5
1855	0	0	0	0	0	0	0	4	1	0	0	0	5
...	...	...	...	...	...	...	...	...	...	...	...	...	...
2015	0	0	0	0	1	1	1	3	5	0	1	0	12
2016	1	0	0	0	1	2	0	5	5	1	1	0	16
2017	0	0	0	1	0	2	3	4	4	3	1	0	18
2018	0	0	0	0	1	0	2	3	7	3	0	0	16
All	4	1	1	6	38	125	171	448	623	353	89	14	1873

169 rows × 13 columns

Data Formats

Comma-separated values (CSV) Format

- Comma is a field separator, newlines denote records
  - ```
    a,b,c,d,message
    1,2,3,4,hello
    5,6,7,8,world
    9,10,11,12,foo
    ```
- May have a header (`a,b,c,d,message`), but not required
- No type information: we do not know what the columns are (numbers, strings, floating point, etc.)
  - Default: just keep everything as a string
  - Type inference: Figure out the type to make each column based on values
- What about commas in a value? → double quotes
    ```

Delimiter-separated Values

- Comma is a **delimiter**, specifies boundary between fields
- Could be a tab, pipe (|), or perhaps spaces instead
- All of these follow similar styles to CSV

Fixed-width Format

- Old school
- Each field gets a certain number of spots in the file
- Example:
  - ```
    id8141    360.242940   149.910199   11950.7
    id1594    444.953632   166.985655   11788.4
    id1849    364.136849   183.628767   11806.2
    id1230    413.836124   184.375703   11916.8
    id1948    502.953953   173.237159   12468.3
    ```
- Specify exact character ranges for each field, e.g. 0-6 is the id
    ```

Reading & Writing Data in Pandas

Format	Data Description	Reader	Writer
text	CSV	read_csv	to_csv
text	Fixed-Width Text File	read_fwf	
text	JSON	read_json	to_json
text	HTML	read_html	to_html
text	Local clipboard	read_clipboard	to_clipboard
	MS Excel	read_excel	to_excel
binary	OpenDocument	read_excel	
binary	HDF5 Format	read_hdf	to_hdf
binary	Feather Format	read_feather	to_feather
binary	Parquet Format	read_parquet	to_parquet
binary	ORC Format	read_orc	
binary	Msgpack	read_msgpack	to_msgpack
binary	Stata	read_stata	to_stata
binary	SAS	read_sas	
binary	SPSS	read_spss	
binary	Python Pickle Format	read_pickle	to_pickle
SQL	SQL	read_sql	to_sql
SQL	Google BigQuery	read_gbq	to_gbq

[https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html]

Types of arguments for readers

- Indexing: choose a column to index the data, get column names from file or user
- Type inference and data conversion: automatic or user-defined
- Datetime parsing: can combine information from multiple columns
- Iterating: deal with very large files
- Unclean Data: skip rows (e.g. comments) or deal with formatted numbers (e.g. 1,000,345)

read_csv

- Convenient method to read csv files
- Lots of different options to help get data into the desired format
- Basic: `df = pd.read_csv(fname)`
- Parameters:
  - `path`: where to read the data from
  - `sep` (or `delimiter`): the delimiter (`','`, `' '`, `'\t'`, `'\s+'`)
  - `header`: if `None`, no header
  - `index_col`: which column to use as the row index
  - `names`: list of header names (e.g. if the file has no header)
  - `skiprows`: number of list of lines to skip

More read_csv/read_tables arguments

Argument	Description
`skiprows`	Number of rows at beginning of file to ignore or list of row numbers (starting from 0) to skip.
`na_values`	Sequence of values to replace with NA.
`comment`	Character(s) to split comments off the end of lines.
`parse_dates`	Attempt to parse data to `datetime`; `False` by default. If `True`, will attempt to parse all columns. Otherwise can specify a list of column numbers or name to parse. If element of list is tuple or list, will combine multiple columns together and parse to date (e.g., if date/time split across two columns).
`keep_date_col`	If joining columns to parse date, keep the joined columns; `False` by default.
`converters`	Dict containing column number of name mapping to functions (e.g., `{'foo': f}` would apply the function `f` to all values in the `'foo'` column).
`dayfirst`	When parsing potentially ambiguous dates, treat as international format (e.g., 7/6/2012 -> June 7, 2012); `False` by default.
`date_parser`	Function to use to parse dates.
`nrows`	Number of rows to read from beginning of file.
`iterator`	Return a `TextParser` object for reading file piecemeal.
`chunksize`	For iteration, size of file chunks.

[W. McKinney, Python for Data Analysis]

Chunked Reads

- With very large files, we may not want to read the entire file
- Why?
  - Time
  - Want to understand part of data before processing all of it
- Reading only a few rows:
  - `df = pd.read_csv('example.csv', nrows=5)`
- Reading chunks:
  - Get an iterator that returns the next chunk of the file
  - `chunker = pd.read_csv('example.csv', chunksize=1000)`
  - ```
    for piece in chunker:
        process_data(piece)
    ```
    ```

Python csv module

- Also, can read csv files outside of pandas using csv module
  - ```
    import csv
    with open('persons_of_concern.csv', 'r') as f:
        for i in range(3):
            next(f)
        reader = csv.reader(f)
        records = [r for r in reader] # r is a list
    ```
- or
  - ```
    import csv
    with open('persons_of_concern.csv', 'r') as f:
        for i in range(3):
            next(f)
        reader = csv.DictReader(f)
        records = [r for r in reader] # r is a dict
    ```

Writing CSV data with pandas

- Basic: `df.to_csv(<fname>)`
- Change delimiter with sep kwarg:
  - `df.to_csv('example.dsv', sep='|')`
- Change missing value representation
  - `df.to_csv('example.dsv', na_rep='NULL')`
- Don't write row or column labels:
  - `df.to_csv('example.csv', index=False, header=False)`
- Series may also be written to csv

eXtensible Markup Language (XML)

- Older, self-describing format with nesting; each field has tags
- Example:

```
- <INDICATOR>
    <INDICATOR_SEQ>373889</INDICATOR_SEQ>
    <PARENT_SEQ></PARENT_SEQ>
    <AGENCY_NAME>Metro-North Railroad</AGENCY_NAME>
    <INDICATOR_NAME>Escalator Avail.</INDICATOR_NAME>
    <PERIOD_YEAR>2011</PERIOD_YEAR>
    <PERIOD_MONTH>12</PERIOD_MONTH>
    <CATEGORY>Service Indicators</CATEGORY>
    <FREQUENCY>M</FREQUENCY>
    <YTD_TARGET>97.00</YTD_TARGET>
  </INDICATOR>
```

- Top element is the **root**

XML

- No built-in method
- Use lxml library (also can use ElementTree)
- ```
  from lxml import objectify
  path = 'datasets/mta_perf/Performance_MNR.xml'
  parsed = objectify.parse(open(path))
  root = parsed.getroot()
  data = []
  skip_fields = ['PARENT_SEQ', 'INDICATOR_SEQ',
                 'DESIRED_CHANGE','DECIMAL_PLACES']
  for elt in root.INDICATOR:
      el_data = {}
      for child in elt.getchildren():
          if child.tag in skip_fields:
              continue
          el_data[child.tag] = child.pyval
      data.append(el_data)
  perf = pd.DataFrame(data)
  ```

[W. McKinney, Python for Data Analysis]
  ```

JavaScript Object Notation (JSON)

- A format for web data
- Looks very similar to python dictionaries and lists
- Example:
  - ```
    {"name": "Wes",
     "places_lived": ["United States", "Spain", "Germany"],
     "pet": null,
     "siblings": [{"name": "Scott", "age": 25, "pet": "Zuko"},
                  {"name": "Katie", "age": 33, "pet": "Cisco"}] }
    ```
- Only contains literals (no variables) but allows null
- Values: strings, arrays, dictionaries, numbers, booleans, or null
  - Dictionary keys must be strings
  - Quotation marks help differentiate string or numeric values
    ```

What is the problem with reading this data?

- ```
  [{"name": "Wes",
    "places_lived": ["United States", "Spain", "Germany"],
    "pet": null,
    "siblings": [
       {"name": "Scott", "age": 25, "pet": "Zuko"},
       {"name": "Katie", "age": 33, "pet": "Cisco"}]
   },
   {"name": "Nia",
    "address": {"street": "143 Main",
                "city": "New York",
                "state": "New York"},
    "pet": "Fido",
    "siblings": [
       {"name": "Jacques", "age": 15, "pet": "Fido"}]
   },
  …
  ]
  ```
  ```

Reading JSON data

- Python has a built-in `json` module
  - ```
    with open('example.json') as f:
        data = json.load(f)
    ```
  - Can also load/dump to strings:
    - `json.loads, json.dumps`
- Pandas has `read_json, to_json` methods
    ```

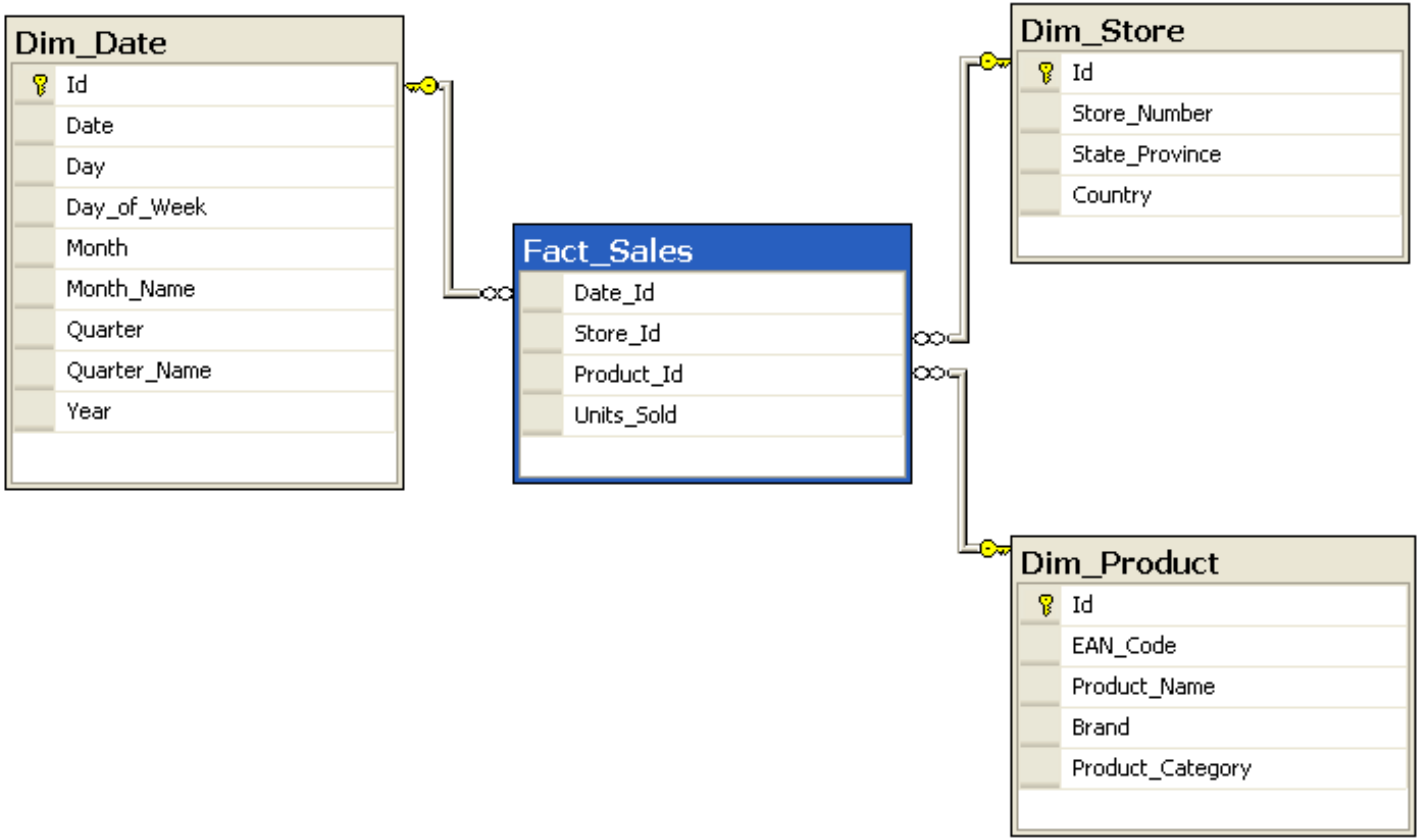
JSON Orientation

- Indication of expected JSON string format. Compatible JSON strings can be produced by `to_json()` with a corresponding orient value. The set of possible orients is:
  - `split`: dict like `{index -> [index],`
    `columns -> [columns],`
    `data -> [values]}`
  - `records`: list like `[{column -> value}, ... , {column -> value}]`
  - `index`: dict like `{index -> {column -> value}}`
  - `columns`: dict like `{column -> {index -> value}}`
  - `values`: just the values array

Binary Formats

- CSV, JSON, and XML are all text formats
- What is a binary format?
- Pickle: Python's built-in serialization
- HDF5: Library for storing large scientific data
  - Hierarchical Data Format
  - Interfaces in C, Java, MATLAB, etc.
  - Supports **compression**
  - Use `pd.HDFStore` to access
  - Shortcuts: `read_hdf/to_hdf`, need to specify object
- Excel: need to specify sheet when a spreadsheet has multiple sheets

Databases



[Wikipedia]

Databases

- Relational databases are similar to multiple data frames but have many more features
  - links between tables via foreign keys
  - SQL to create, store, and query data
- sqlite3 is a simple database with built-in support in python
- Python has a database API which lets you access most database systems through a common API.

Python DBAPI Example

```
import sqlite3
query = """CREATE TABLE test(a VARCHAR(20), b VARCHAR(20),
                             c REAL, d INTEGER);"""
con = sqlite3.connect('mydata.sqlite')
con.execute(query)
con.commit()
# Insert some data
data = [('Atlanta', 'Georgia', 1.25, 6),
        ('Tallahassee', 'Florida', 2.6, 3),
        ('Sacramento', 'California', 1.7, 5)]
stmt = "INSERT INTO test VALUES(?, ?, ?, ?)"
con.executemany(stmt, data)
con.commit()
```

[W. McKinney, Python for Data Analysis]

Databases

- Similar syntax from other database systems (MySQL, Microsoft SQL Server, Oracle, etc.)
- SQLAlchemy: Python package that abstracts away differences between different database systems
- SQLAlchemy gives support for reading queries to data frame:
  - ```
    import sqlalchemy as sqla
    db = sqla.create_engine('sqlite:///mydata.sqlite')
    pd.read_sql('select * from test', db)
    ```
    ```

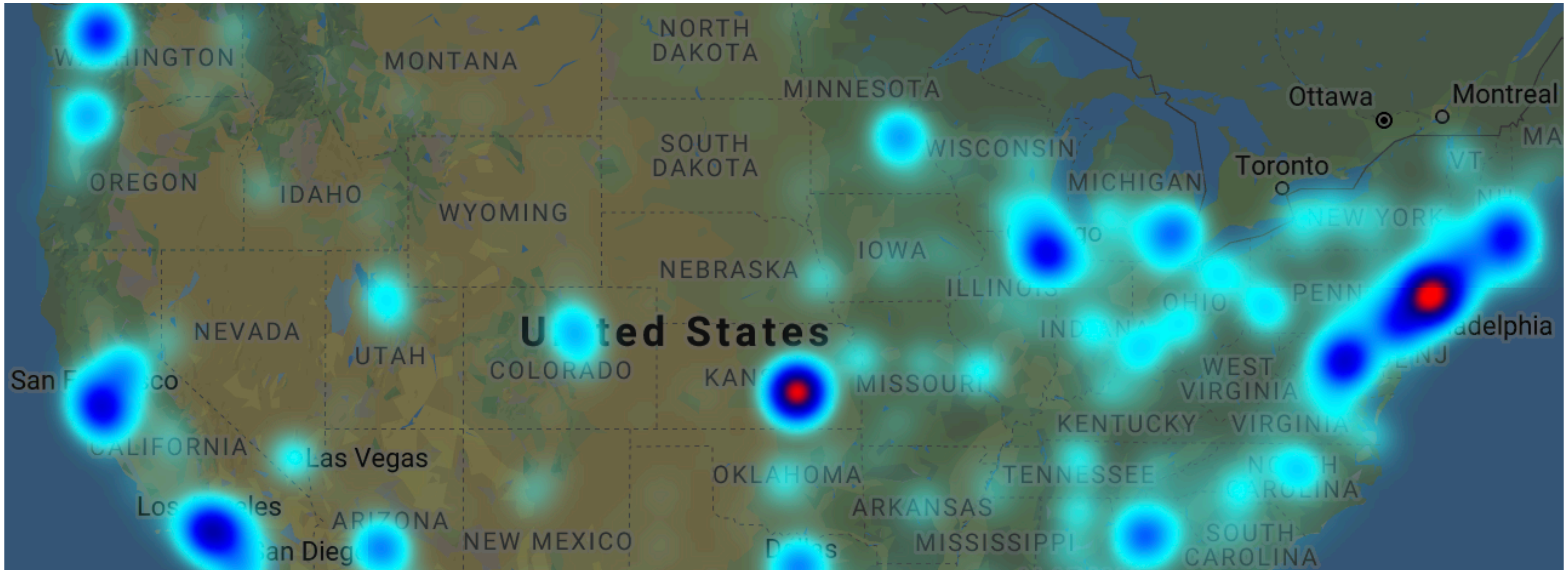
What if data isn't correct/trustworthy/in the right format?

Dirty Data

[Flickr]

Geolocation Errors

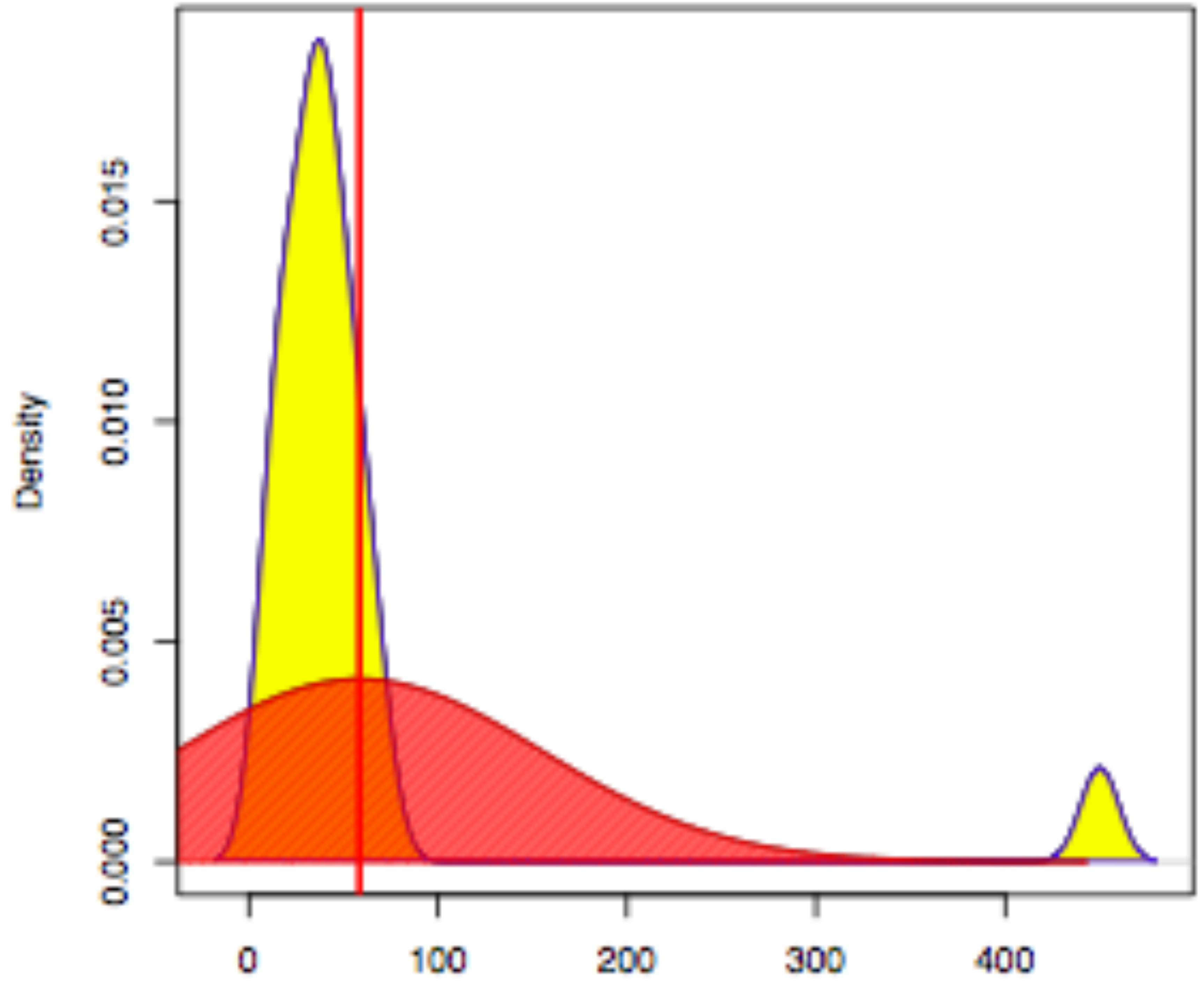
- Maxmind helps companies determine where users are located based on IP address
- "How a quiet Kansas home wound up with 600 million IP addresses and a world of trouble" [Washington Post, 2016]



Numeric Outliers

12	13	14	21	22	26	33	35	36	37	39	42	45	47	54	57	61	68	450

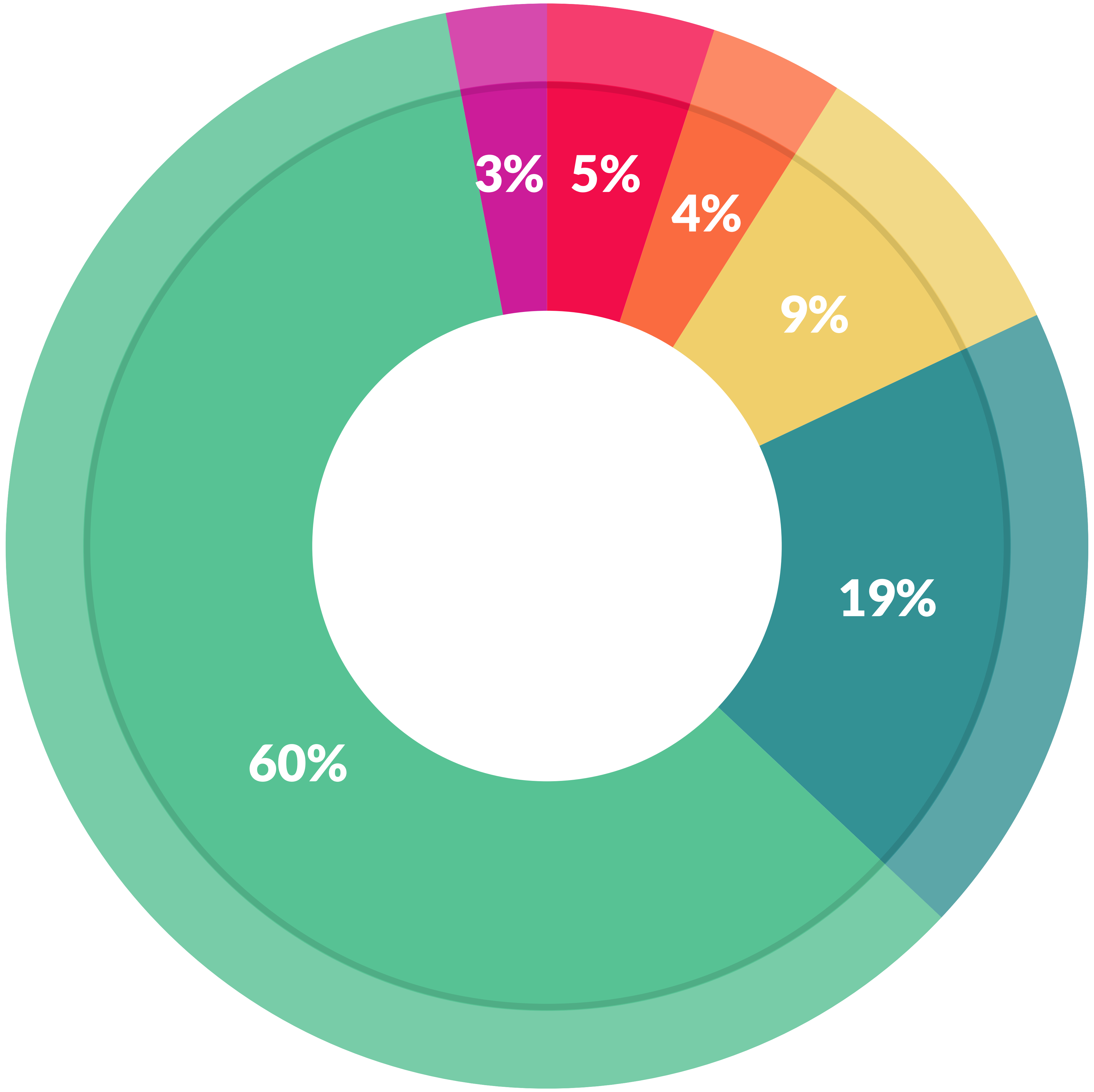
ages of employees (US)



- median 37
- mean 58.52632
- variance 9252.041

[J. Hellerstein via J. Canny et al.]

This takes a lot of time!

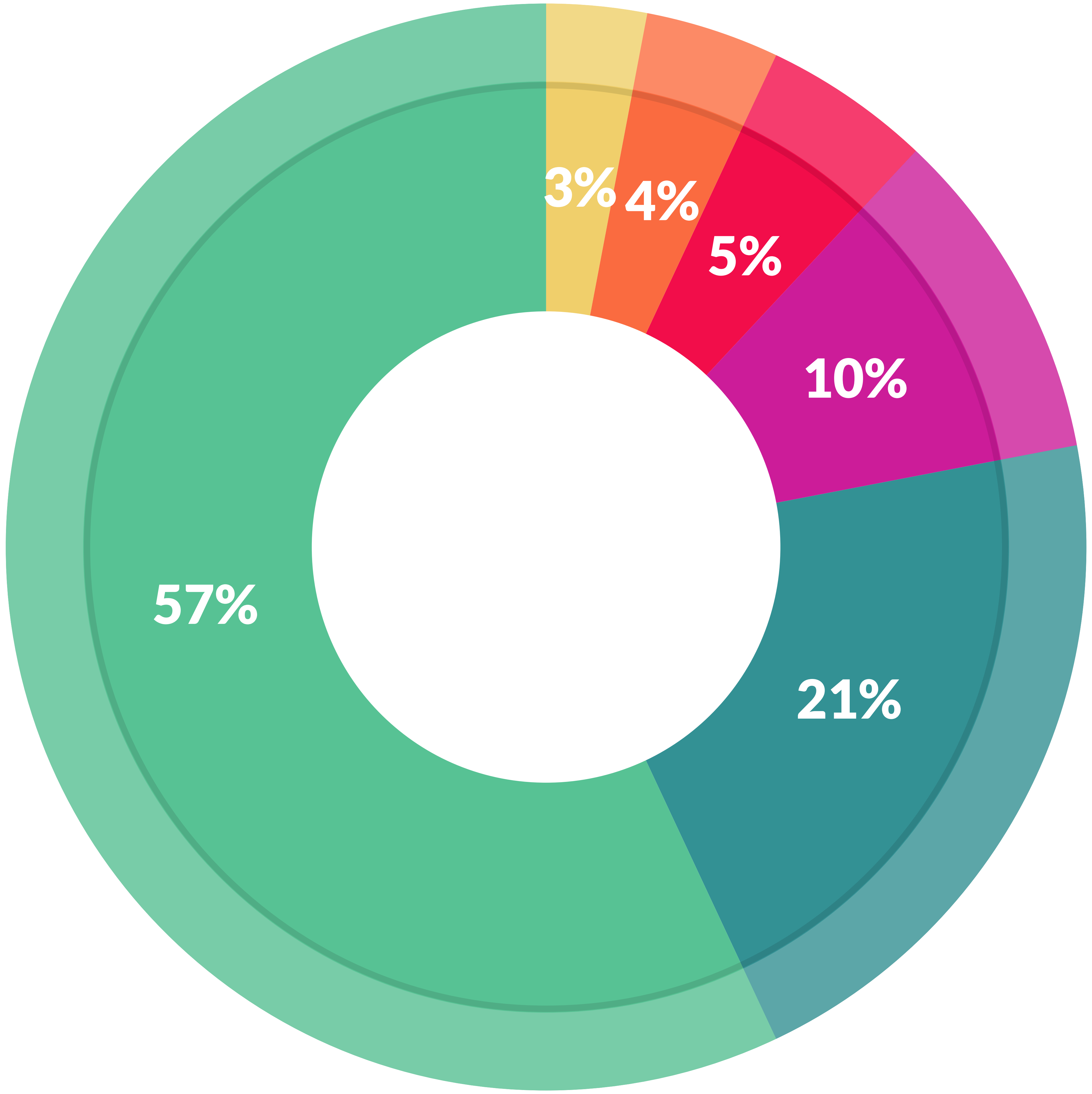


What data scientists spend the most time doing

- *Building training sets: 3%*
- *Cleaning and organizing data: 60%*
- *Collecting data sets; 19%*
- *Mining data for patterns: 9%*
- *Refining algorithms: 4%*
- *Other: 5%*

[CrowdFlower Data Science Report, 2016]

…and it isn't the most fun thing to do



What's the least enjoyable part of data science?

- *Building training sets: 10%*
- *Cleaning and organizing data: 57%*
- *Collecting data sets: 21%*
- *Mining data for patterns: 3%*
- *Refining algorithms: 4%*
- *Other: 5%*

[CrowdFlower Data Science Report, 2016]

Dirty Data: Statistician's View

- Some process produces the data
- Want a model but have non-ideal samples:
  - Distortion: some samples corrupted by a process
  - Selection bias: likelihood of a sample depends on its value
  - Left and right censorship: users come and go from scrutiny
  - Dependence: samples are not independent (e.g. social networks)
- You can add/augment models for different problems, but cannot model everything
- Trade-off between accuracy and simplicity

[J. Canny et al.]

Dirty Data: Database Expert's View

- Got a dataset
- Some values are missing, corrupted, wrong, duplicated
- Results are absolute (relational model)
- Better answers come from improving the quality of values in the dataset

[J. Canny et al.]

Dirty Data: Domain Expert's View

- Data doesn't look right
- Answer doesn't look right
- What happened?
- Domain experts carry an implicit model of the data they test against
- You don't always need to be a domain expert to do this
  - Can a person run 50 miles an hour?
  - Can a mountain on Earth be 50,000 feet above sea level?
  - Use common sense

[J. Canny et al.]

Dirty Data: Data Scientist's View

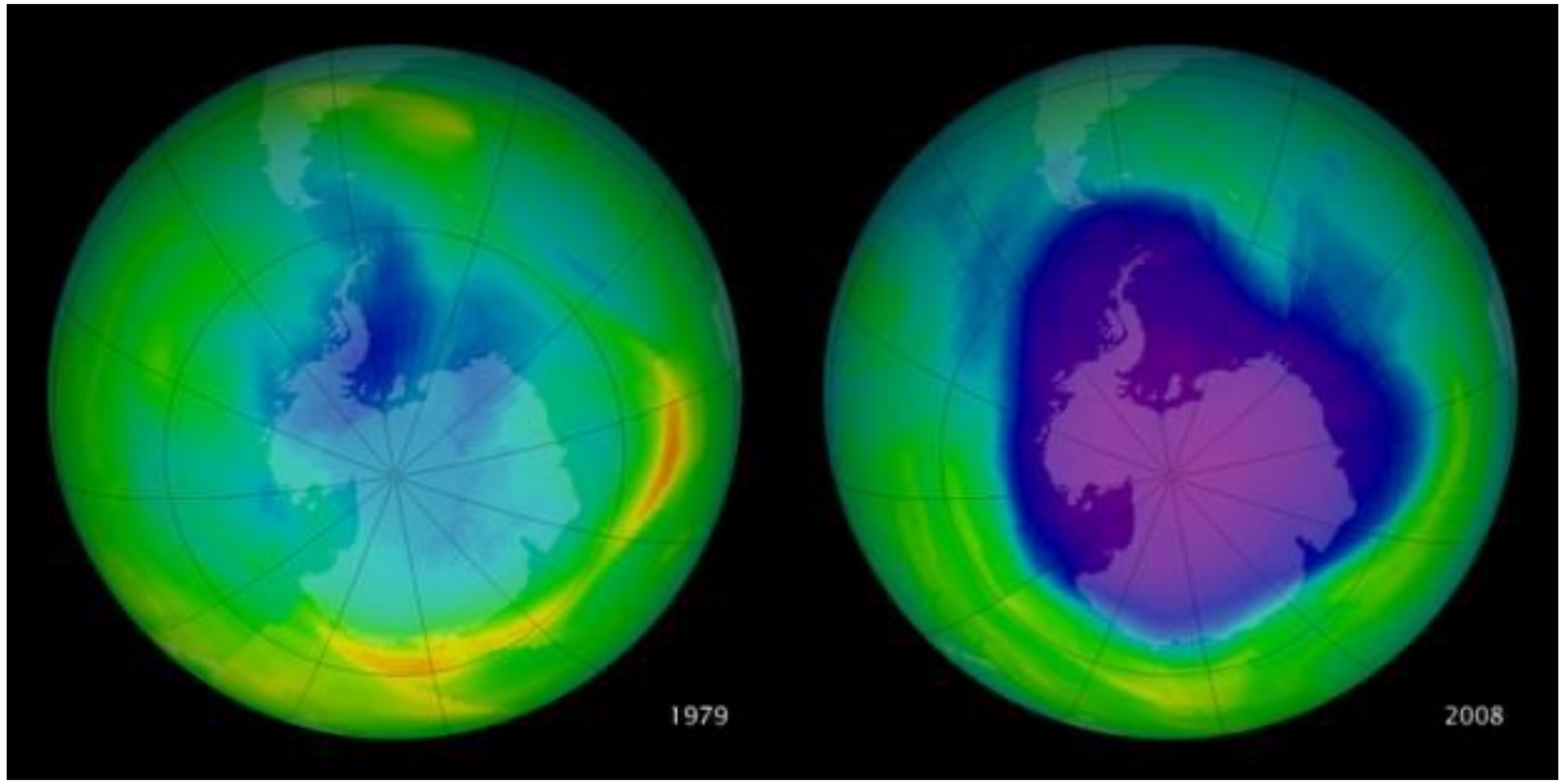
- Combination of the previous three views
- All of the views present problems with the data
- The goal may dictate the solutions:
  - Median value: don't worry too much about crazy outliers
  - Generally, aggregation is less susceptible by numeric errors
  - Be careful, the data may be correct…

[J. Canny et al.]

Be careful how you detect dirty data

- The appearance of a hole in the earth's ozone layer over Antarctica, first detected in 1976, was so unexpected that scientists didn't pay attention to what their instruments were telling them; they thought their instruments were malfunctioning.

  – National Center for Atmospheric Research



[Wikimedia]

Where does dirty data originate?

- Source data is bad, e.g. person entered it incorrectly
- Transformations corrupt the data, e.g. certain values processed incorrectly due to a software bug
- Integration of different datasets causes problems
- Error propagation: one error is magnified

[J. Canny et al.]

Types of Dirty Data Problems

- Separator Issues: e.g. CSV without respecting double quotes
  - `12, 13, "Doe, John", 45`
- Naming Conventions: `NYC` vs. `New York`
- Missing required fields, e.g. key
- Different representations: `2` vs. `two`
- Truncated data: `"Janice Keihanaikukauakahihuliheekahaunaele"` becomes `"Janice Keihanaikukauakahihuliheek"` on Hawaii license
- Redundant records: may be exactly the same or have some overlap
- Formatting issues: `2017-11-07` vs. `07/11/2017` vs. `11/07/2017`

[J. Canny et al.]

Data Wrangling

- Data wrangling: transform raw data to a more meaningful format that can be better analyzed
- Data cleaning: getting rid of inaccurate data
- Data transformations: changing the data from one representation to another
- Data reshaping: reorganizing the data
- Data merging: combining two datasets

Data Cleaning

Wrangler: Interactive Visual Specification of Data Transformation Scripts

S. Kandel, A. Paepcke, J. Hellerstein, J. Heer

Data Wrangler Demo

- http://vis.stanford.edu/wrangler/app/