Advanced Data Management (CSCI 490/680)

Data and Pandas

Dr. David Koop

Arrays

What is the difference between an array and a list (or a tuple)?

Arrays

- Usually a fixed size—lists are meant to change size
- Are mutable—tuples are not
- Store only one type of data—lists and tuples can store anything
- Are faster to access and manipulate than lists or tuples
- Can be multidimensional:
  - Can have list of lists or tuple of tuples but no guarantee on shape
  - Multidimensional arrays are rectangles, cubes, etc.

Why NumPy?

- Fast **vectorized** array operations for data munging and cleaning, subsetting and filtering, transformation, and any other kinds of computations
- Common array algorithms like sorting, unique, and set operations
- Efficient descriptive statistics and aggregating/summarizing data
- Data alignment and relational data manipulations for merging and joining together heterogeneous data sets
- Expressing conditional logic as array expressions instead of loops with `if-elif-else` branches
- Group-wise data manipulations (aggregation, transformation, function application).

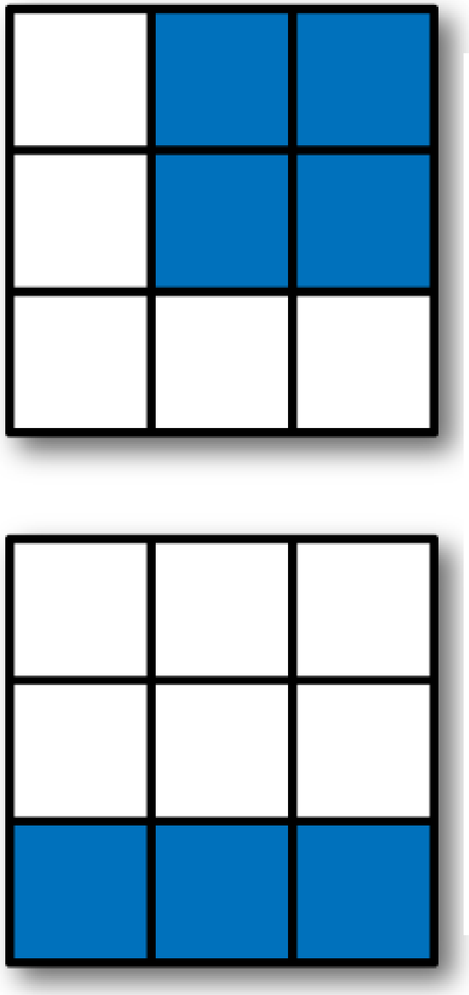
[W. McKinney, Python for Data Analysis]

NumPy Arrays

- `data1 = [6, 7.5, 8, 0, 1]`
  `arr1 = np.array(data1)`
- Zeros: `np.zeros(10)`, Ones: `np.ones((4,5))`,
  Empty: `np.empty((2,2))`
- # of dimensions: `arr2.ndim`, Shape: `arr2.shape`, Type: `arr2.dtype`
- Types: Each array has a fixed type unlike other variables in python

2D Array Slicing

How to obtain the blue slice from array `arr`?



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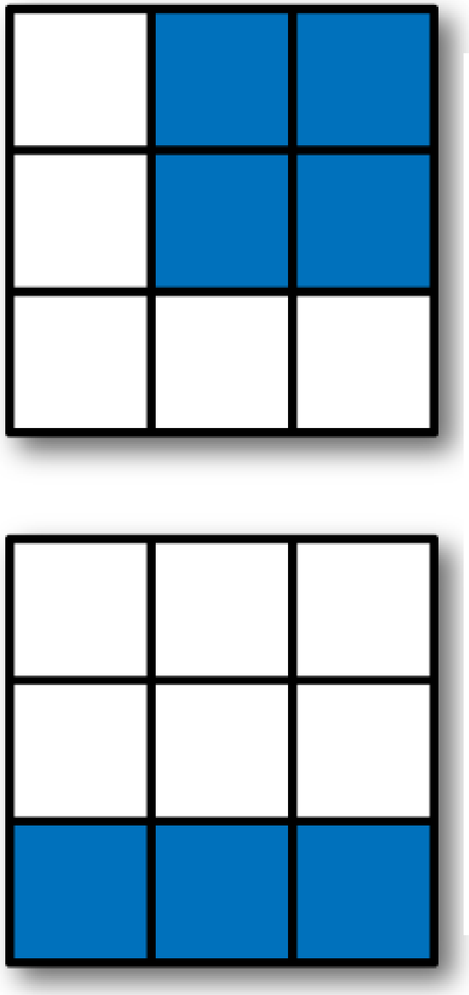

Expression	Shape
`arr[:2, 1:]`	`(2, 2)`

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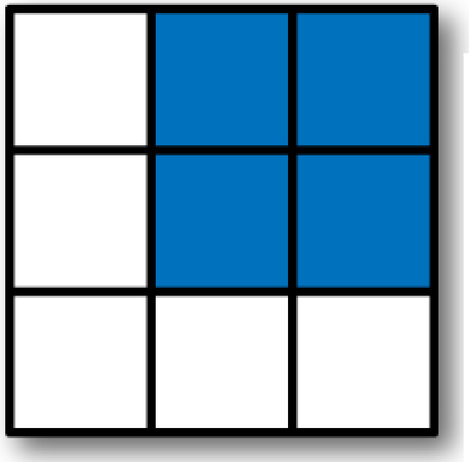

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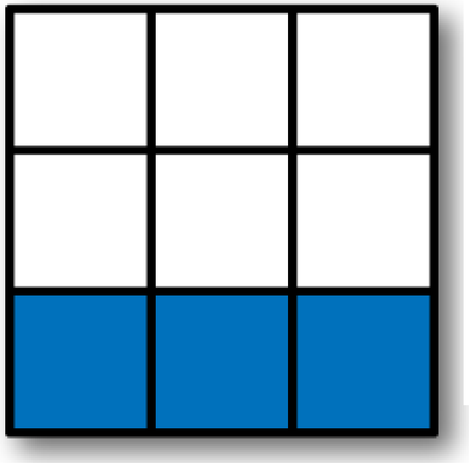


Expression	Shape
`arr[2]`	`(3,)`
`arr[2, :]`	`(3,)`
`arr[2:, :]`	`(1, 3)`

[W. McKinney, Python for Data Analysis]

Boolean Indexing

- `names == 'Bob'` gives back booleans that represent the element-wise comparison with the array `names`
- Boolean arrays can be used to index into another array:
  - `data[names == 'Bob']`
- Can even mix and match with integer slicing
- Can do boolean operations (`&`, `|`) between arrays (just like addition, subtraction)
  - `data[(names == 'Bob') | (names == 'Will')]`
- Note: `or` and `and` do not work with arrays
- We can set values too! `data[data < 0] = 0`

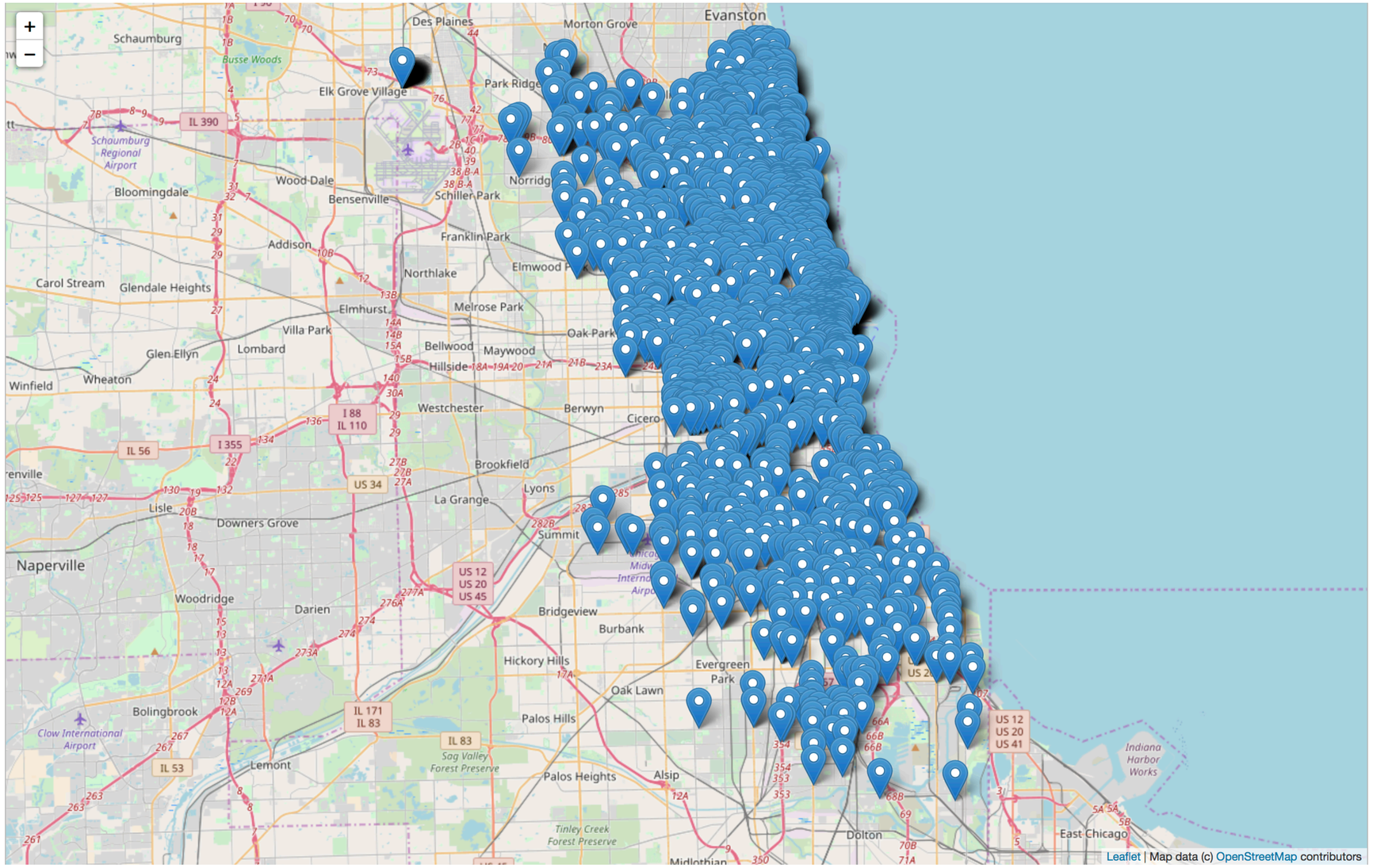
Assignment 1

- Using Python for data analysis
- Analyze hurricane data (through 2018)
- Provided `a1.ipynb` file (right-click and download)
- Use basic python (+ collections module) for now to demonstrate language knowledge
- Use Anaconda or hosted Python environment (Colab, Azure Notebooks, etc.)
- Due Wednesday
- Turn .ipynb file in via Blackboard

Chicago Food Inspections Exploration

- Based on David Beazley's PyData Chicago talk
- YouTube video: https://www.youtube.com/watch?v=j6VSAsKAj98
- Our in-class exploration:
  - Python can give answers fairly quickly
  - Data analysis questions:
    - What is information is available
    - **Questions** are interesting about this dataset
    - How to decide on good follow-up questions
    - What the computations mean

Chicago Food Inspections Exploration



Data

- What is data?
  - Types
  - Semantics
- How is data structured?
  - Tables (Data Frames)
  - Databases
  - Data Cubes
- What formats is data stored in?
- Raw versus derived data

Data

- What is this data?

R011	42ND STREET & 8TH AVENUE	00228985	00008471	00000441	00001455	00000134	00033341	00071255
R170	14TH STREET-UNION SQUARE	00224603	00011051	00000827	00003026	00000660	00089367	00199841
R046	42ND STREET & GRAND CENTRAL	00207758	00007908	00000323	00001183	00003001	00040759	00096613

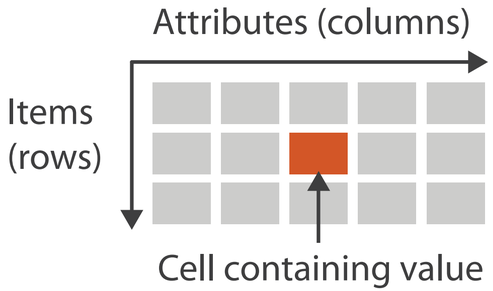
- Semantics: real-world meaning of the data
- Type: structural or mathematical interpretation
- Both often require metadata
  - Sometimes we can infer some of this information
  - Line between data and metadata isn't always clear

Data

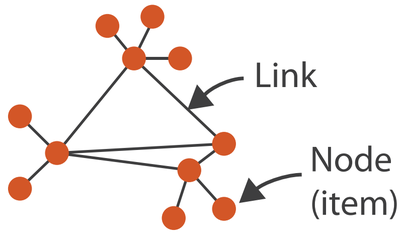
	REMOTE	STATION	FF	SEN/DIS	7-D AFAS UNL	D AFAS/RMF U	JOINT RR TKT	7-D UNL	30-D UNL
1	R011	42ND STREET & 8TH AVENUE	00228985	00008471	00000441	00001455	00000134	00033341	00071255
2	R170	14TH STREET-UNION SQUARE	00224603	00011051	00000827	00003026	00000660	00089367	00199841
3	R046	42ND STREET & GRAND CENTRAL	00207758	00007908	00000323	00001183	00003001	00040759	00096613
4	R012	34TH STREET & 8TH AVENUE	00188311	00006490	00000498	00001279	00003622	00035527	00067483
5	R293	34TH STREET - PENN STATION	00168768	00006155	00000523	00001065	00005031	00030645	00054376
6	R033	42ND STREET/TIMES SQUARE	00159382	00005945	00000378	00001205	00000690	00058931	00078644
7	R022	34TH STREET & 6TH AVENUE	00156008	00006276	00000487	00001543	00000712	00058910	00110466
8	R084	59TH STREET/COLUMBUS CIRCLE	00155262	00009484	00000589	00002071	00000542	00053397	00113966
9	R020	47-50 STREETS/ROCKEFELLER	00143500	00006402	00000384	00001159	00000723	00037978	00090745
10	R179	86TH STREET-LEXINGTON AVE	00142169	00010367	00000470	00001839	00000271	00050328	00125250
11	R023	34TH STREET & 6TH AVENUE	00134052	00005005	00000348	00001112	00000649	00031531	00075040
12	R029	PARK PLACE	00121614	00004311	00000287	00000931	00000792	00025404	00065362
13	R047	42ND STREET & GRAND CENTRAL	00100742	00004273	00000185	00000704	00001241	00022808	00068216
14	R031	34TH STREET & 7TH AVENUE	00095076	00003990	00000232	00000727	00001459	00024284	00038671
15	R017	LEXINGTON AVENUE	00094655	00004688	00000190	00000833	00000754	00020018	00055066
16	R175	8TH AVENUE-14TH STREET	00094313	00003907	00000286	00001144	00000256	00038272	00074661
17	R057	BARCLAYS CENTER	00093804	00004204	00000454	00001386	00001491	00039113	00068119
18	R138	WEST 4TH ST-WASHINGTON SQ	00093562	00004677	00000251	00000965	00000127	00031628	00074458

Dataset Types

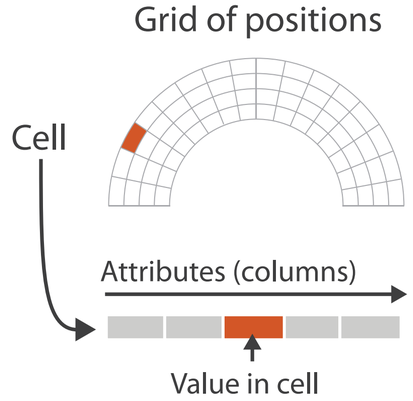
➔ Tables



➔ Networks

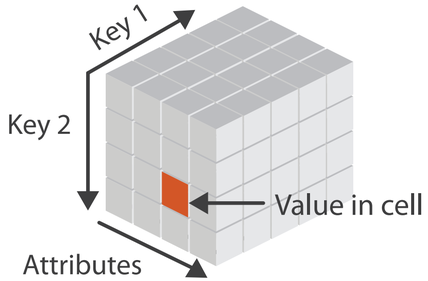


➔ Fields (Continuous)

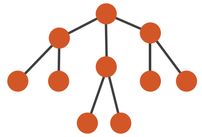


➔ Geometry (Spatial)

➔ *Multidimensional Table*



➔ *Trees*



[Munzner (ill. Maguire), 2014]

Data Terminology

- Items
  - An **item** is an individual discrete entity
  - e.g., a row in a table
- Attributes
  - An **attribute** is some specific property that can be measured, observed, or logged
  - a.k.a. variable, (data) dimension
  - e.g., a column in a table

Tables

A	B	C	S	T	U
Order ID	Order Date	Order Priority	Product Container	Product Base Margin	Ship Date
3	10/14/06	5-Low	Large Box	0.8	10/21/06
6	2/21/08	4-Not Specified	Small Pack	0.55	2/22/08
32	7/16/07	2-High	Small Pack	0.79	7/17/07
32	7/16/07	2-High	Jumbo Box		7/17/07
32	7/16/07	2-High	Medium Box		7/18/07
32	7/16/07	2-High	Medium Box		7/18/07
35	10/23/07	4-Not Specified	Wrap Bag	0.52	10/24/07
35	10/23/07	4-Not Specified	Small Box	0.58	10/25/07
36	11/3/07	1-Urgent	Small Box	0.55	11/3/07
65	3/18/07	1-Urgent	Small Pack	0.49	3/19/07
66	1/20/05	5-Low	Wrap Bag	0.56	1/20/05
69	6/6/05	4-Not Specified	Small Pack	0.44	6/6/05
69	6/6/05	4-Not Specified	Wrap Bag	0.6	6/6/05
70	12/18/06	5-Low	Small Box	0.59	12/23/06
70	12/18/06	5-Low	Wrap Bag	0.82	12/23/06
96	4/17/05	2-High	Small Box	0.55	4/19/05
97	1/29/06	3-Medium	Small Box	0.38	1/30/06
129	11/19/08	5-Low	Small Box	0.37	11/28/08
130	5/8/08	2-High	Small Box	0.37	5/9/08
130	5/8/08	2-High	Medium Box	0.38	5/10/08
130	5/8/08	2-High	Small Box	0.6	5/11/08
132	6/11/06	3-Medium	Medium Box	0.6	6/12/06
132	6/11/06	3-Medium	Jumbo Box	0.69	6/14/06
134	5/1/08	4-Not Specified	Large Box	0.82	5/3/08
135	10/21/07	4-Not Specified	Small Pack	0.64	10/23/07
166	9/12/07	2-High	Small Box	0.55	9/14/07
193	8/8/06	1-Urgent	Medium Box	0.57	8/10/06
194	4/5/08	3-Medium	Wrap Bag	0.42	4/7/08

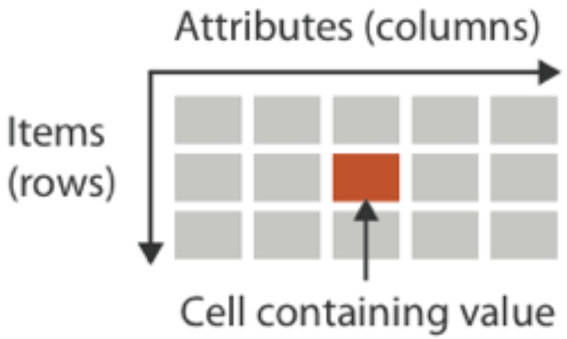
attribute

cell

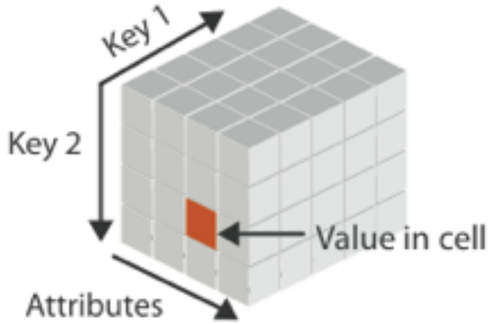
item

Tables

Flat



Multidimensional



- Data organized by rows & columns
  - row ~ item (usually)
  - column ~ attribute
  - label ~ attribute name
- Key: identifies each item (row)
  - Usually **unique**
  - Allows **join** of data from 2+ tables
  - Compound key: key split among multiple columns, e.g. (state, year) for population
- Multidimensional:
  - Split compound key

[Munzner (ill. Maguire), 2014]

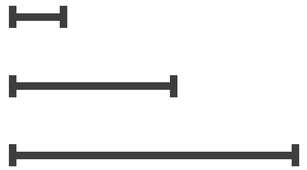
Attribute Types

➔ Categorical

➔ Ordered

➔ *Ordinal*

➔ *Quantitative*



[Munzner (ill. Maguire), 2014]

Categorial, Ordinal, and Quantitative

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32	7/16/07	2-High	Jumbo Box	0.72	7/17/07
32	7/16/07	2-High	Medium Box	0.6	7/18/07
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35	10/23/07	4-Not Specified	Wrap Bag	0.52	10/24/07
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quantitative
ordinal
categorical

Categorial, Ordinal, and Quantitative

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quantitative
ordinal
categorical

Attribute Types

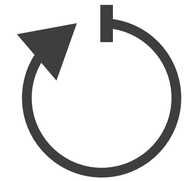
- May be further specified for computational storage/processing
  - **Categorical**: string, boolean, blood type
  - **Ordered**: enumeration, t-shirt size
  - **Quantitative**: integer, float, fixed decimal, datetime
- Sometimes, types can be **inferred** from the data
  - e.g. numbers and none have decimal points → integer
  - could be incorrect (data doesn't have floats, but could be)

Ordering Direction

➔ Sequential

➔ Diverging

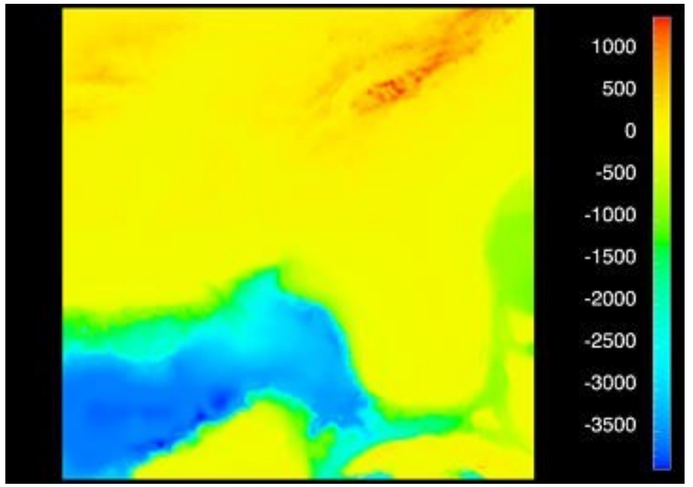
➔ Cyclic



[Munzner (ill. Maguire), 2014]

Sequential and Diverging Data

- Sequential: homogenous range from a minimum to a maximum
  - Examples: Land elevations, ocean depths
- Diverging: can be deconstructed into two sequences pointing in opposite directions
  - Has a **zero point** (not necessary 0)
  - Example: Map of both land elevation and ocean depth



[Rogowitz & Treinish, 1998]

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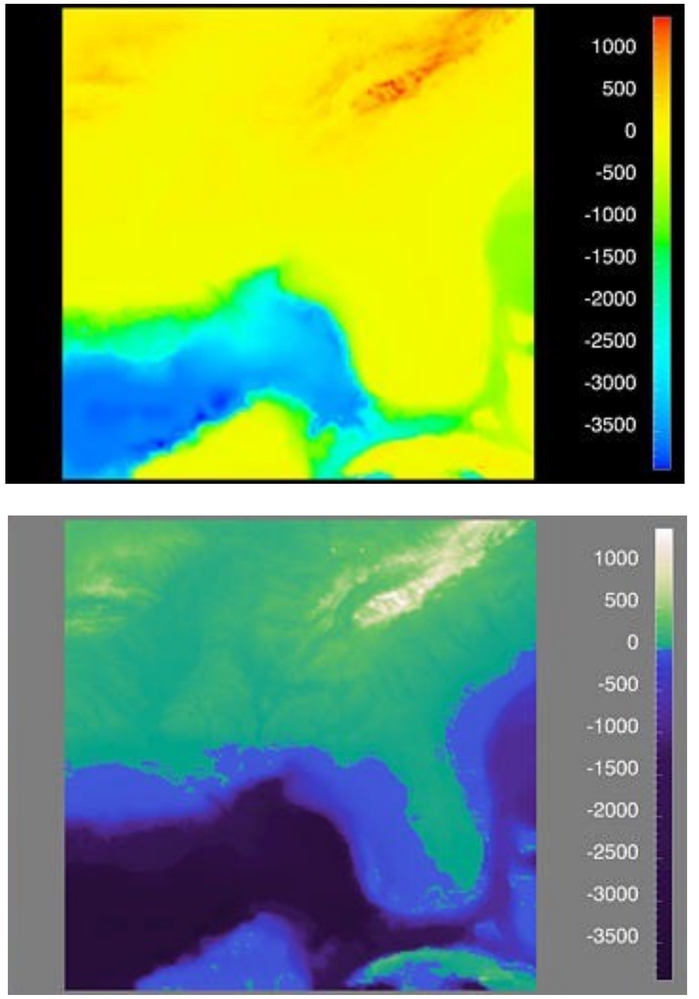
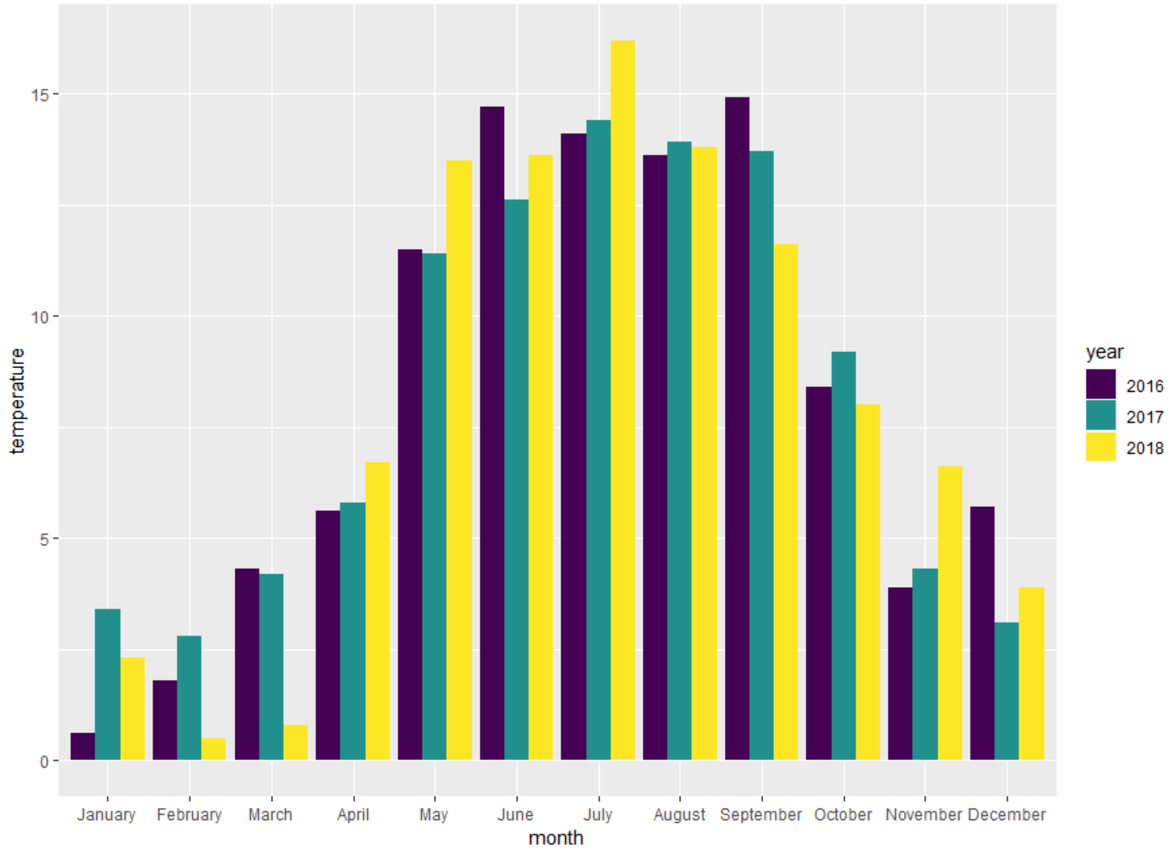
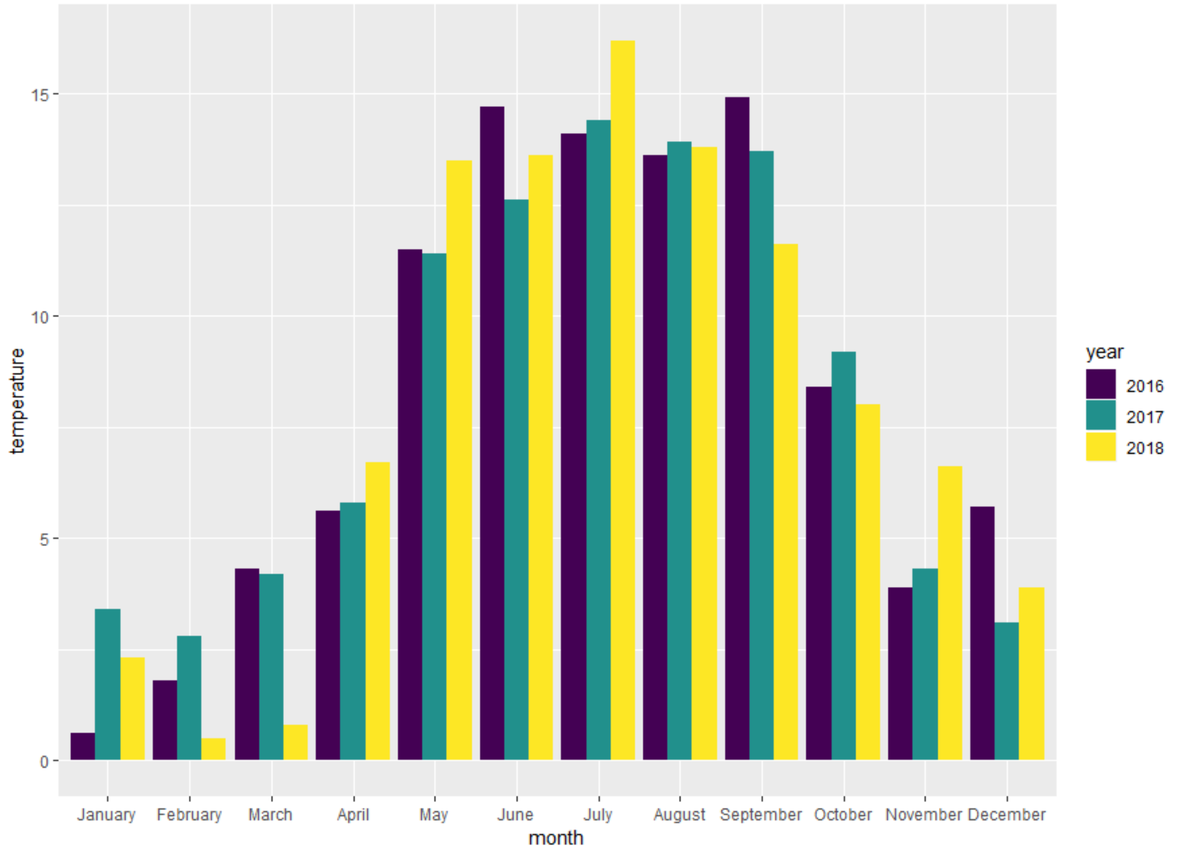


[Rogowitz & Treinish, 1998]

Cyclic Data


15
10
5
0
temperature
January
February
March
April
May
June
July
August
September
October
November
December
month
year
2016
2017
2018

Cyclic Data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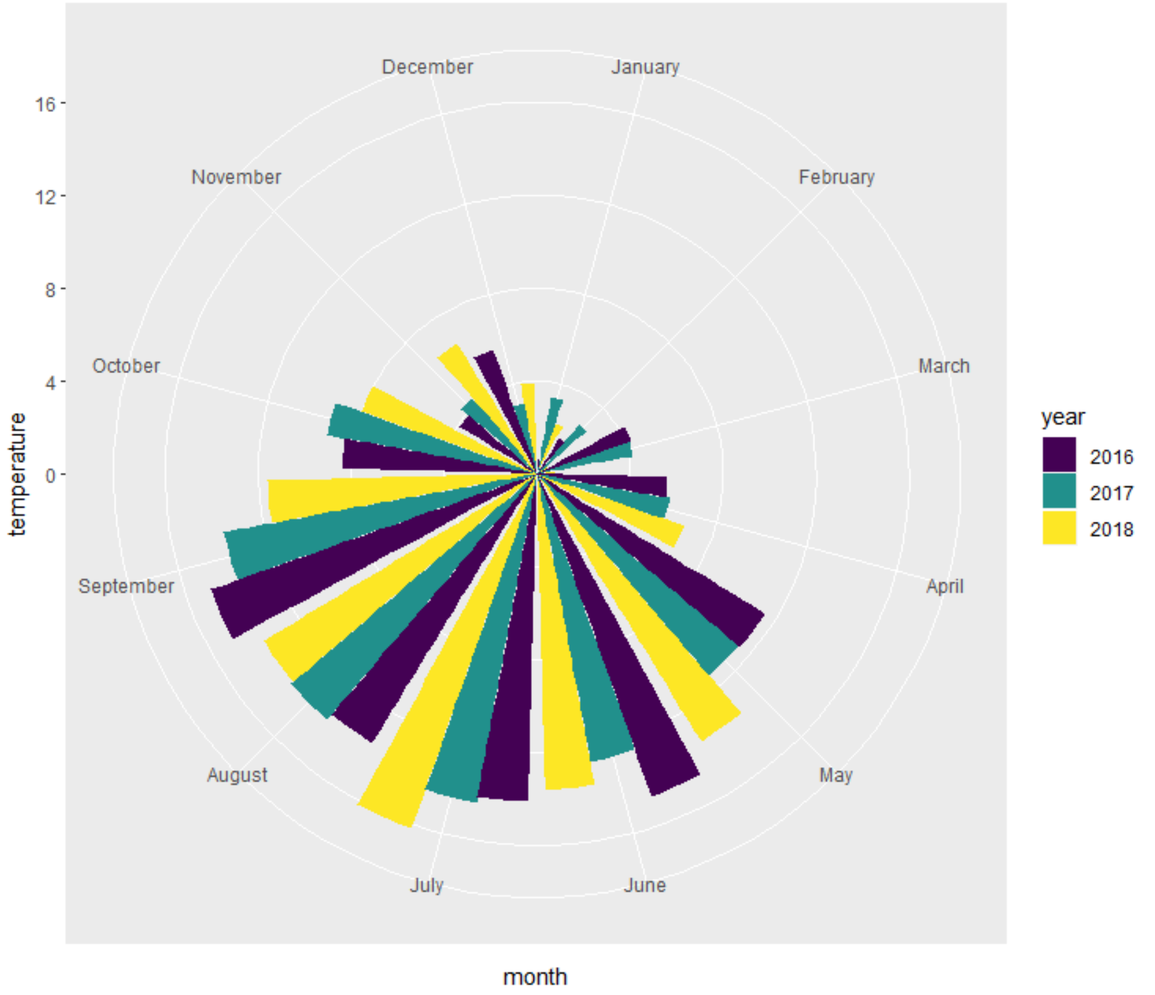
temperature
16
12
8
4
0
December
January
February
March
April
May
June
July
August
September
October
November
month
year
2016
2017
2018

Semantics

- The meaning of the data
- Example: 94023, 90210, 02747, 60115

Semantics

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- Example: 94023, 90210, 02747, 60115
  - Attendance at college football games?

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  - Salaries?

Semantics

- The meaning of the data
- Example: 94023, 90210, 02747, 60115
  - Attendance at college football games?
  - Salaries?
  - Zip codes?
- Cannot always infer based on what the data looks like
- Often require semantics to better understand data
- Column names help with semantics
- May also include rules about data: a zip code is part of an address that uniquely identifies a residence

Data Model vs. Conceptual Model

- Data Model: raw data that has a specific data type (e.g. floats):
  - Temperature Example: `[32.5, 54.0, -17.3]` (floats)
- Conceptual Model: how we think about the data
  - Includes semantics, reasoning
  - Temperature Example:
    - Quantitative: `[32.50, 54.00, -17.30]`

[via A. Lex, 2015]

Data Model vs. Conceptual Model

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  - Temperature Example: `[32.5, 54.0, -17.3]` (floats)
- Conceptual Model: how we think about the data
  - Includes semantics, reasoning
  - Temperature Example:
    - Quantitative: `[32.50, 54.00, -17.30]`
    - Ordered: `[warm, hot, cold]`

[via A. Lex, 2015]

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    - Categorical: `[not burned, burned, not burned]`

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- Example 3: `Points`
  - Want to have a column indicating how that point total ranks
  - `Rank = index in sorted list of all Point values`

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

Pandas Code Conventions

- Universal:
  - `import pandas as pd`
- Also used:
  - `from pandas import Series, DataFrame`

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})
  ```

Series

- Indexing: `s[1]` or `s['Oregon']`
- Can check for missing data: `pd.isnull(s)` or `pd.notnull(s)`
- Both index and values can have an associated name:
  - `s.name = 'population'; s.index.name = 'state'`
- Addition and NumPy ops work as expected and preserve the index-value link
- These operations **align**:

```
In [28]: obj3
Out[28]:
Ohio      35000
Oregon    16000
Texas     71000
Utah       5000
dtype: int64
```

```
In [29]: obj4
Out[29]:
California      NaN
Ohio          35000
Oregon        16000
Texas         71000
dtype: float64
```

```
In [30]: obj3 + obj4
Out[30]:
California       NaN
Ohio           70000
Oregon         32000
Texas         142000
Utah             NaN
dtype: float64
```

[W. McKinney, Python for Data Analysis]

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
  ```

Examples

- See ch05.ipynb