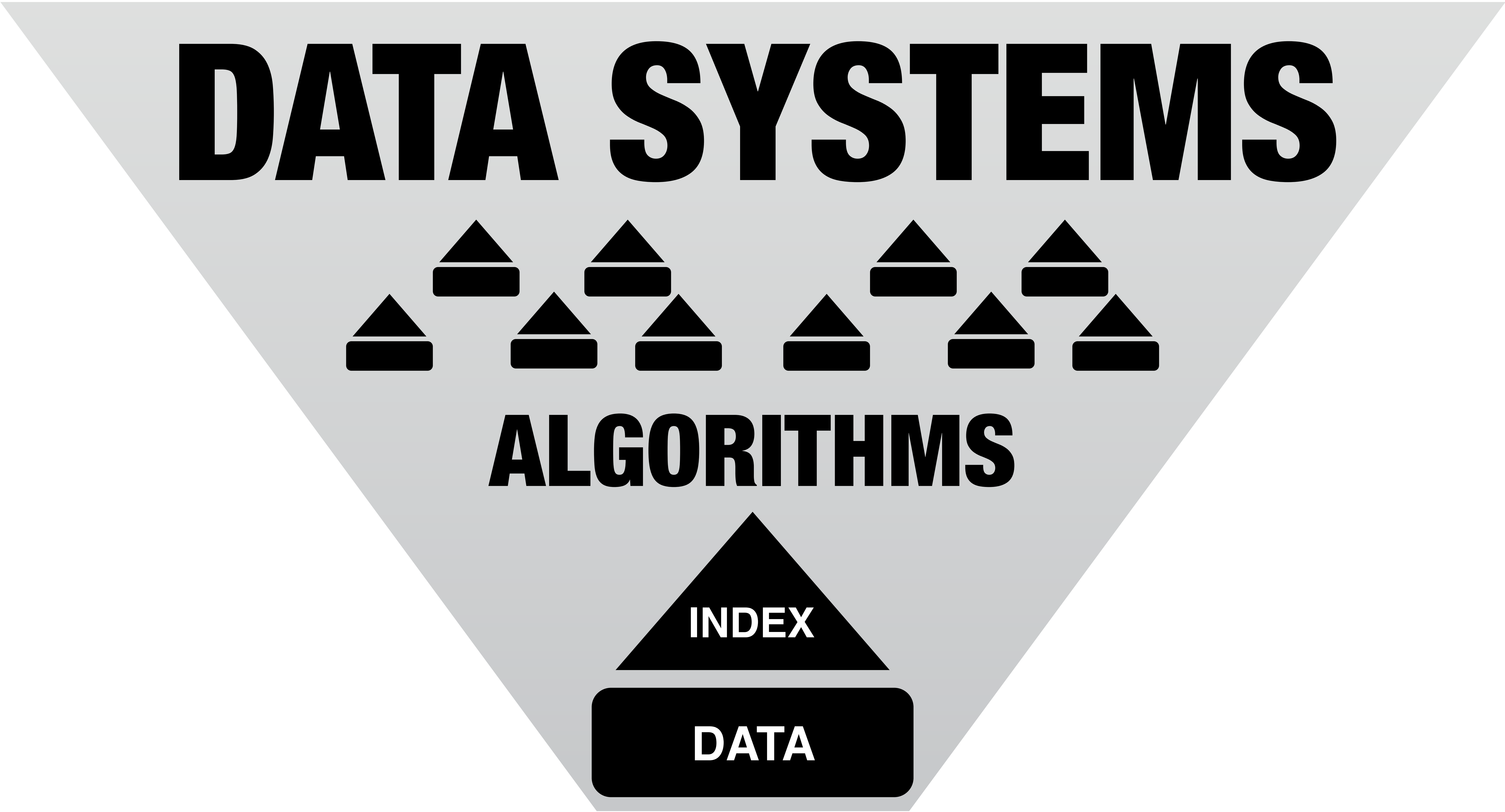
# Advanced Data Management (CSCI 640/490)

## Review

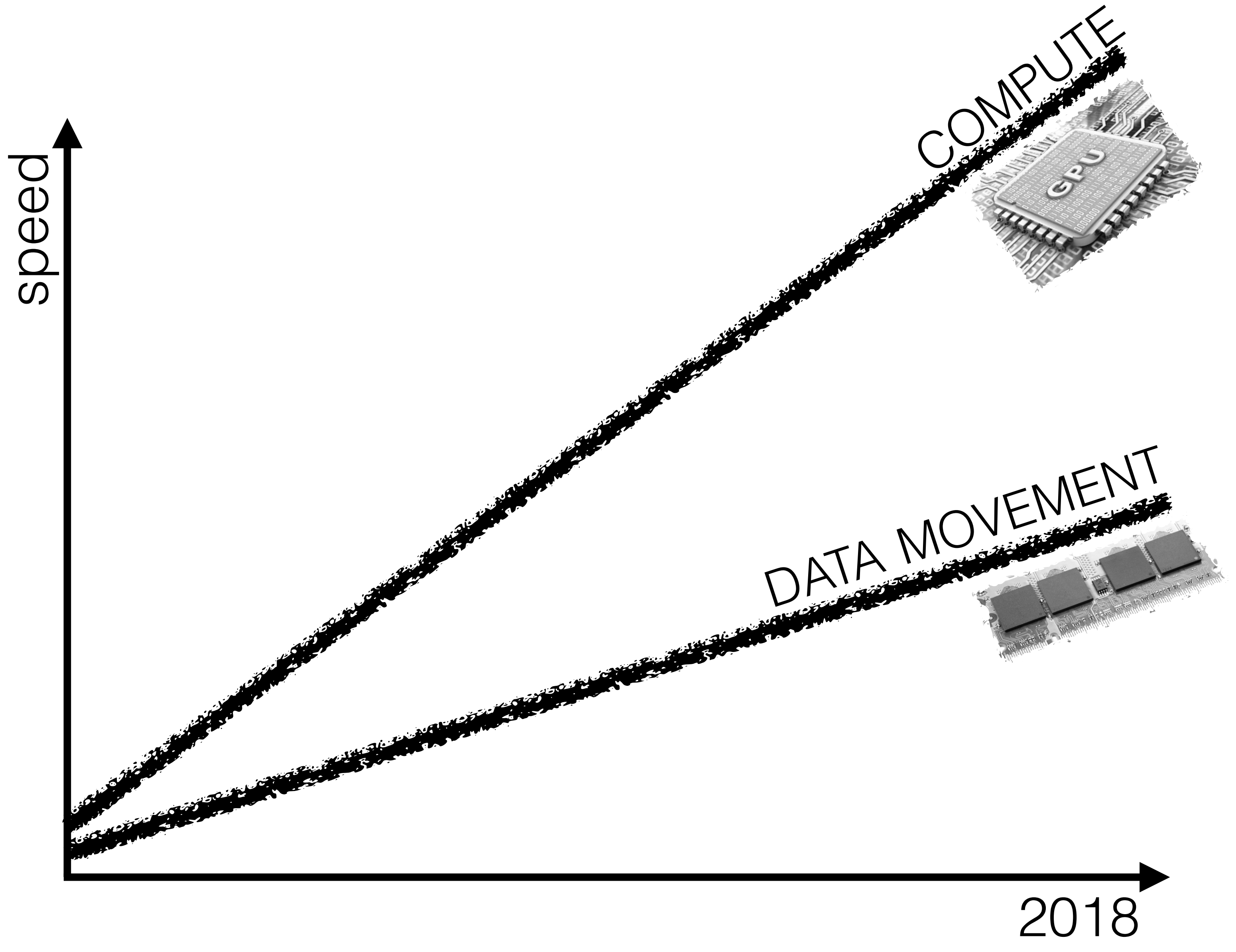
Dr. David Koop

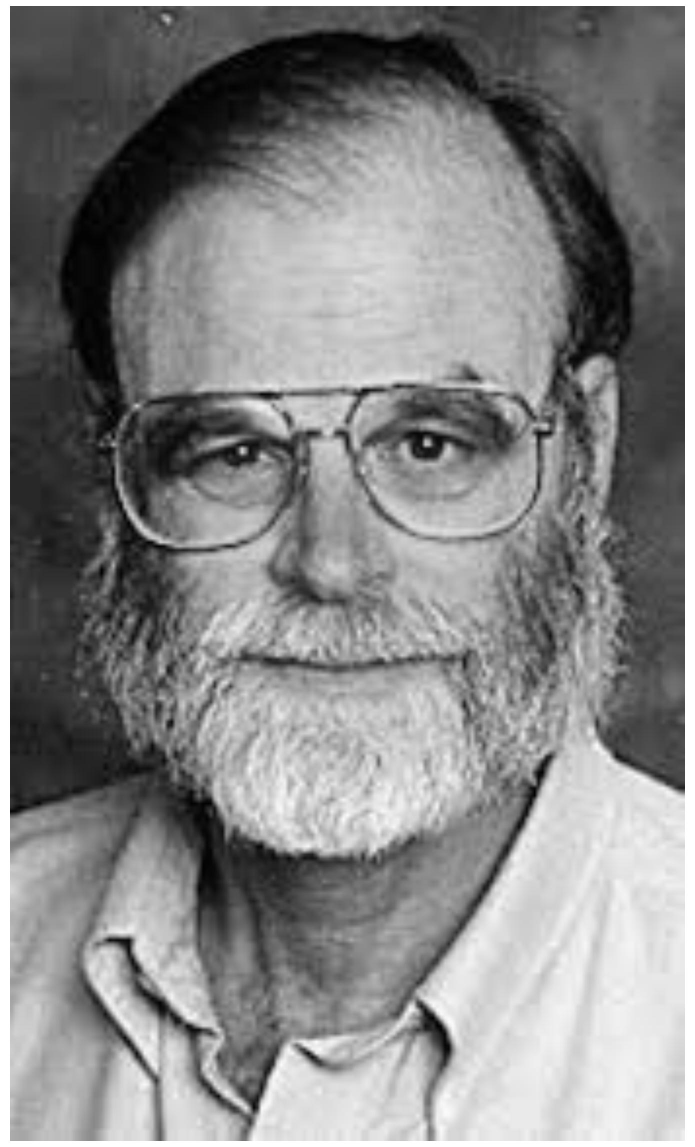
# Data systems rely on algorithms




[S. Idreos, 2019]

# Data structures define performance



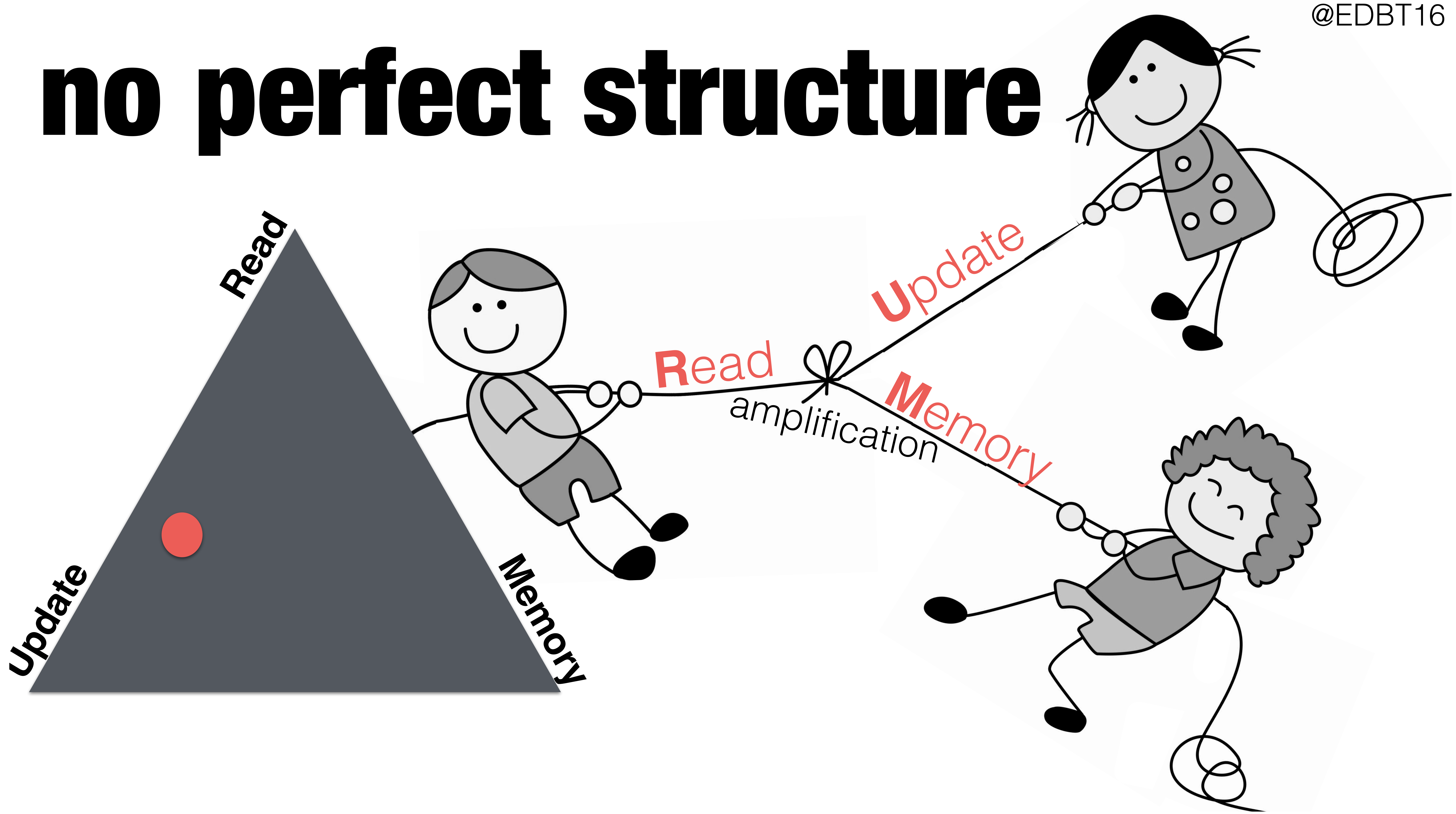



register = this room
caches = this city
memory = nearby city
**disk = Pluto**

Jim Gray, Turing Award 1998

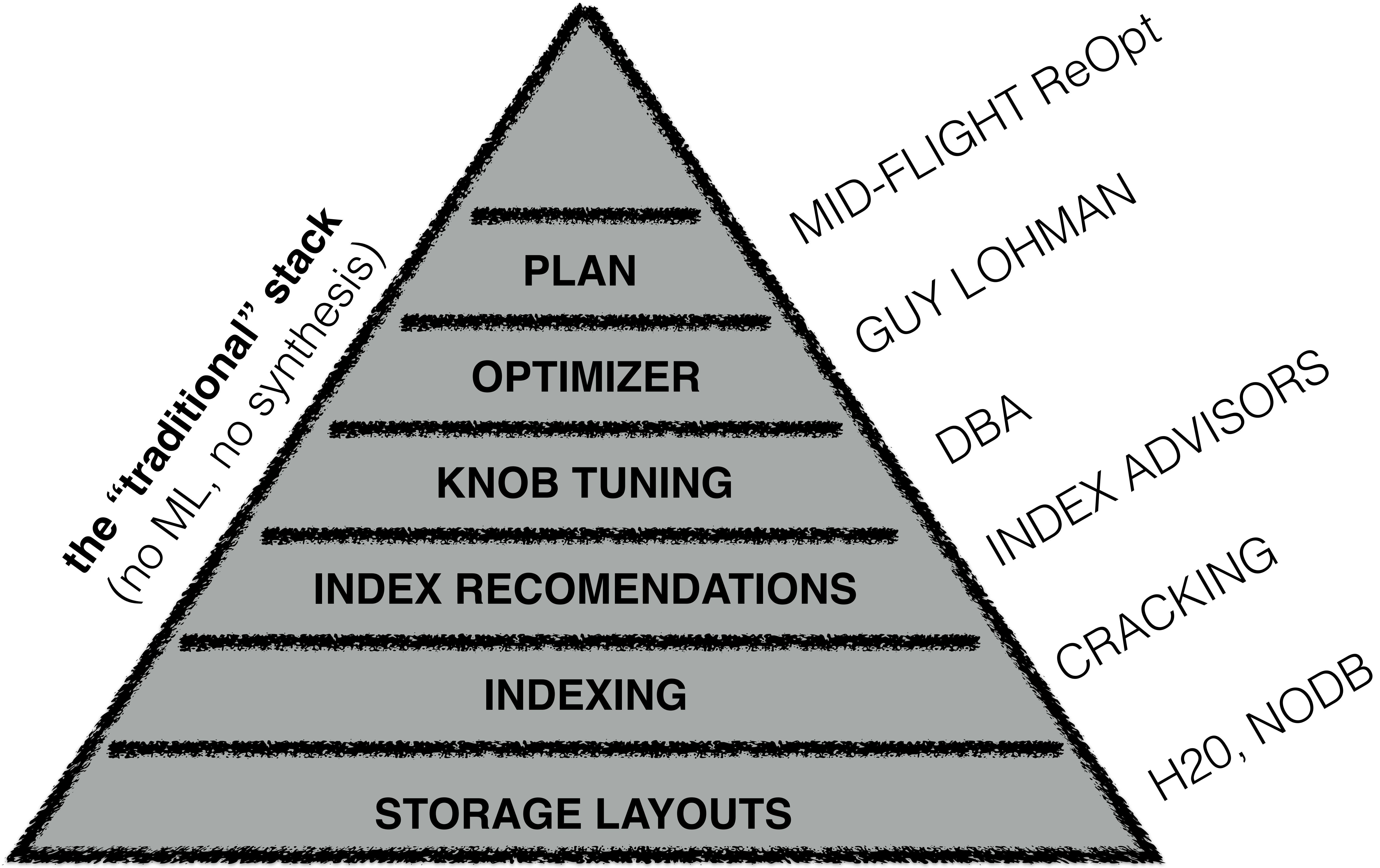
[S. Idreos, 2019]

# Tradeoffs in each structure



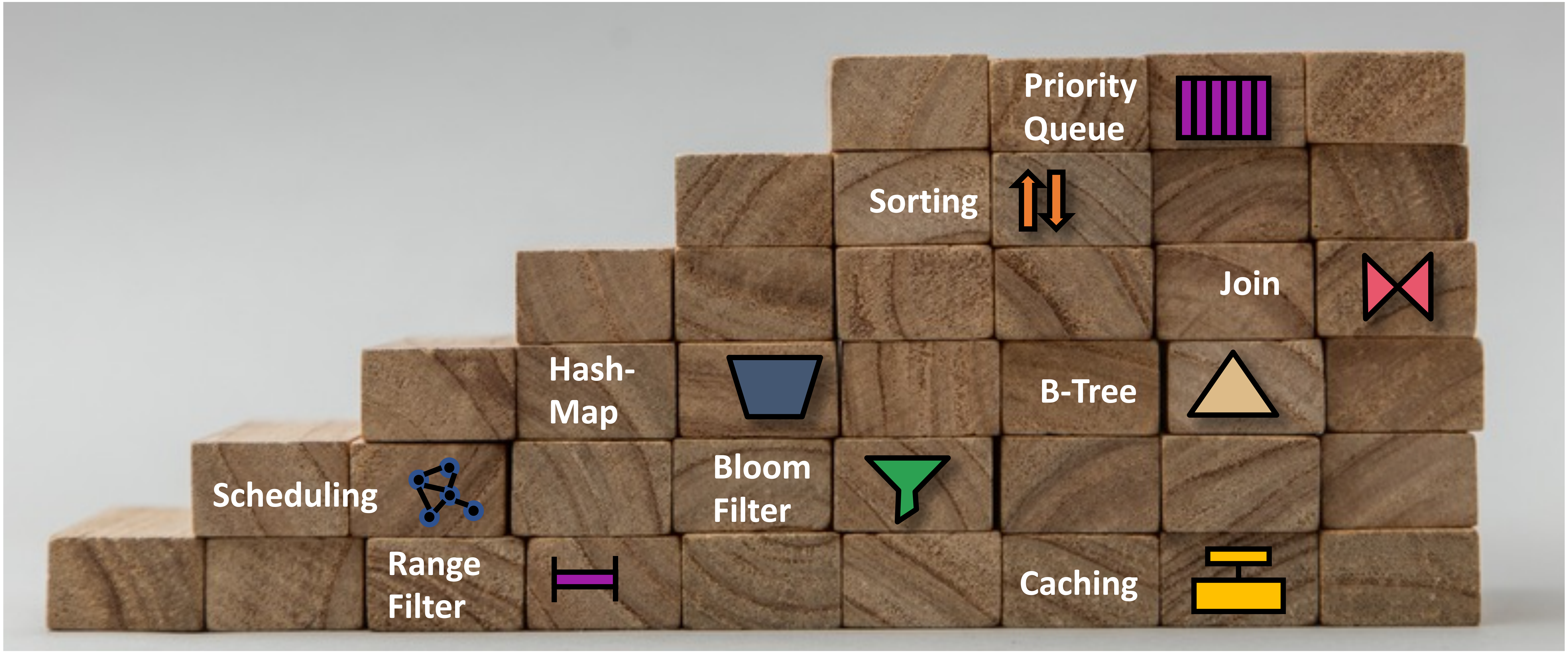

[S. Idreos, 2019]

# "Traditional" Database Research

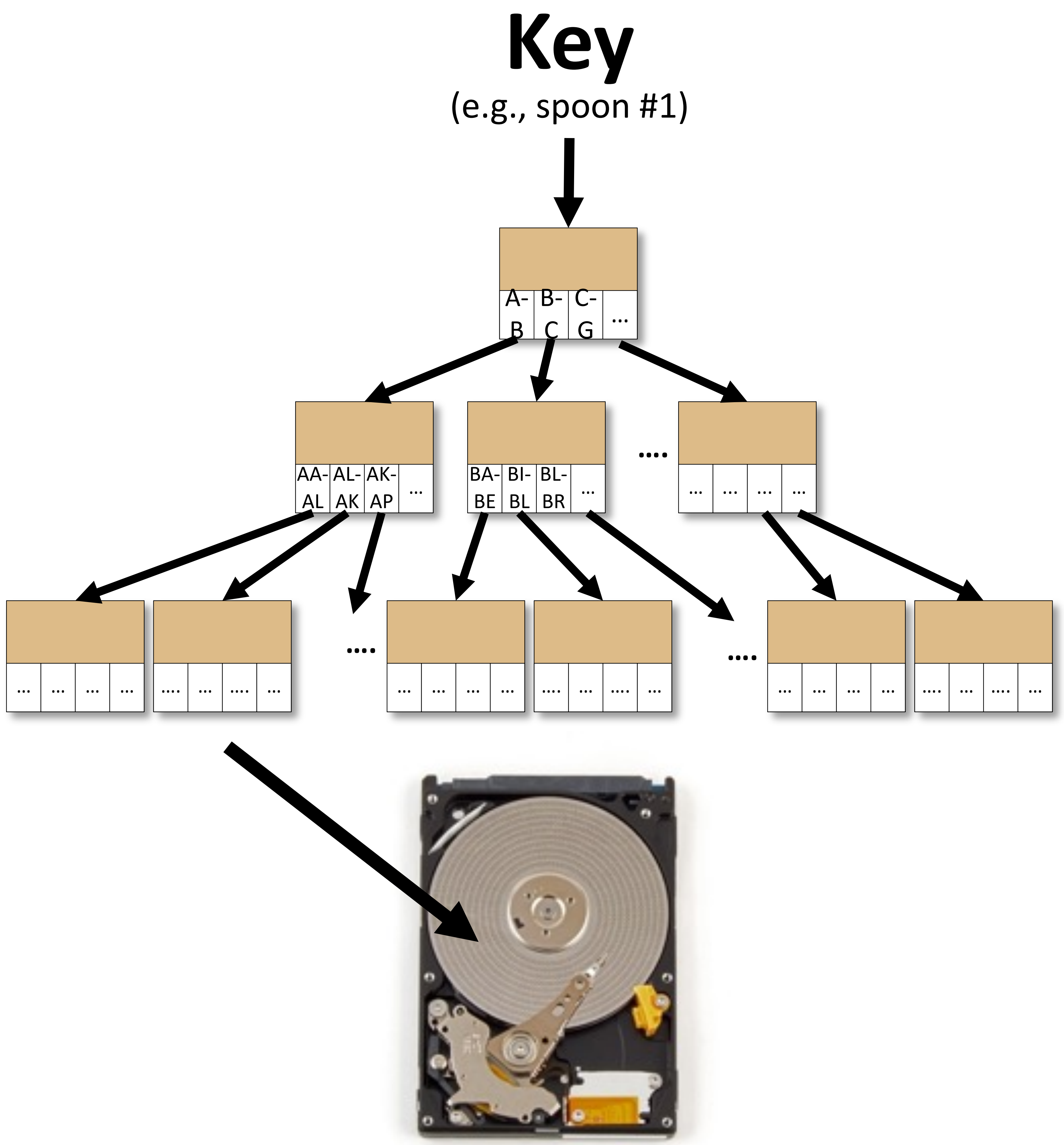


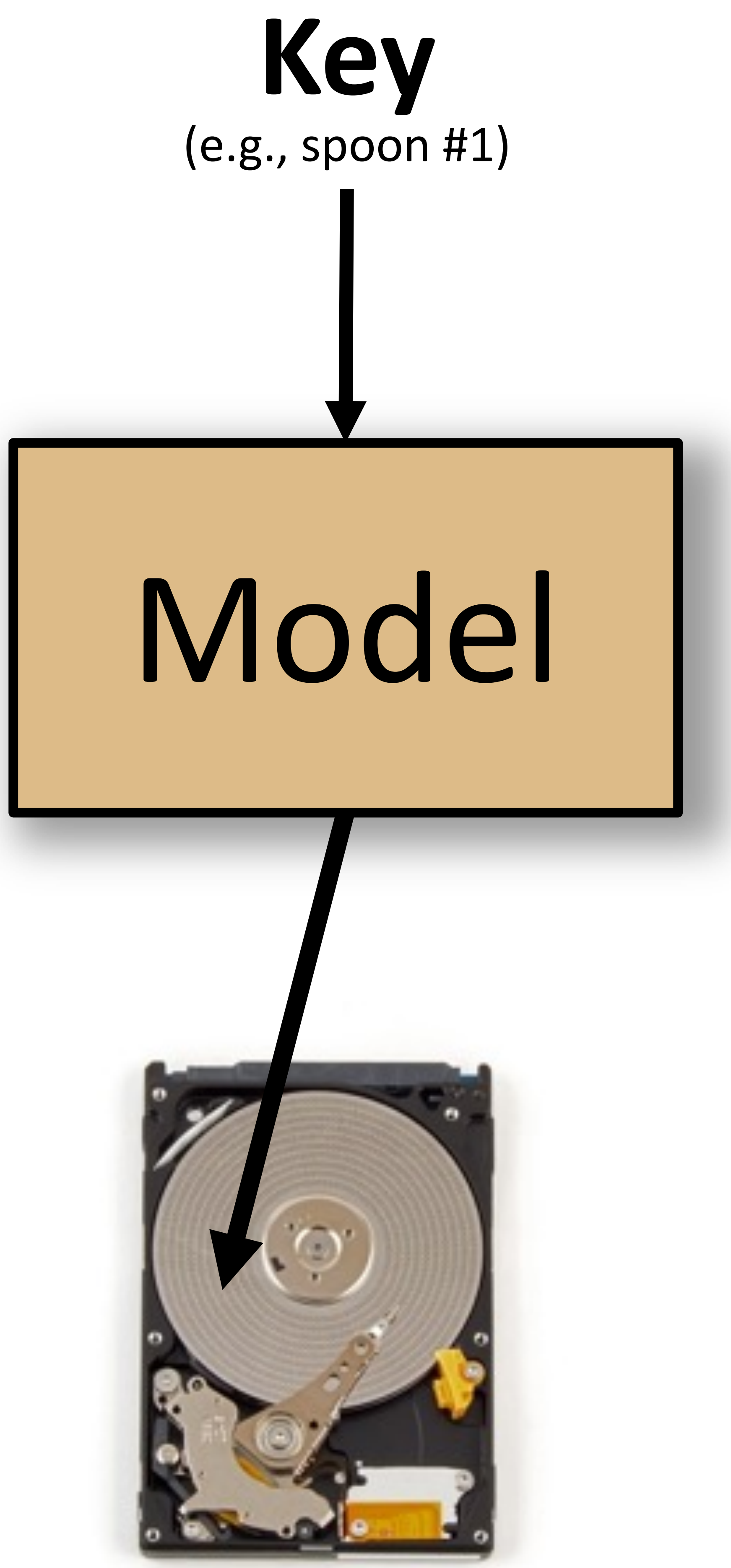

[S. Idreos, 2019]

# Learned Data Structures and Algorithms



# B-Tree



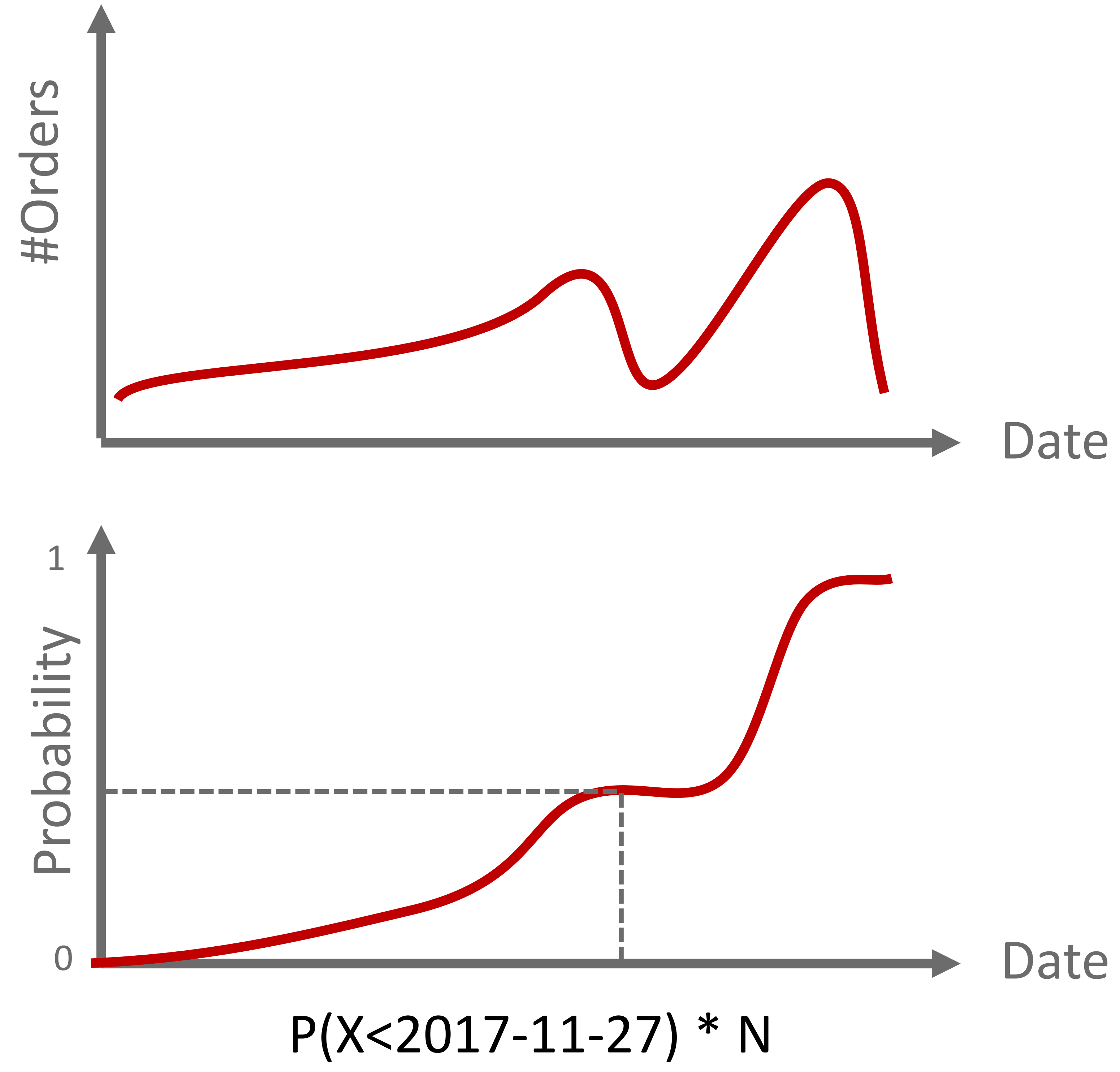



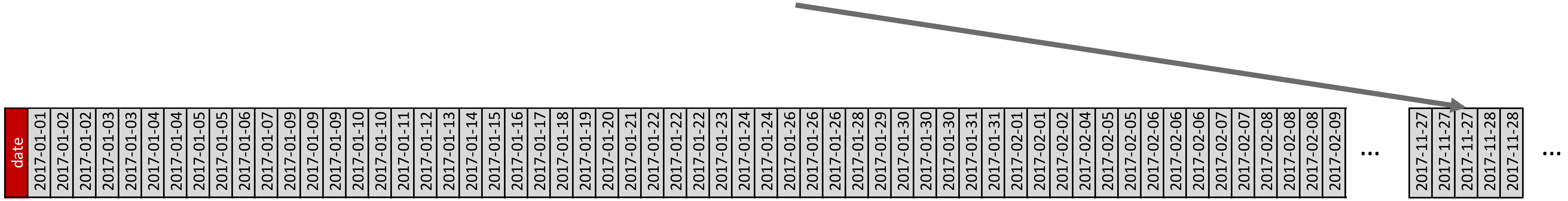

[T. Kraska, 2019]

# Model to Predict Data's Location on Disk

Frequency Distribution

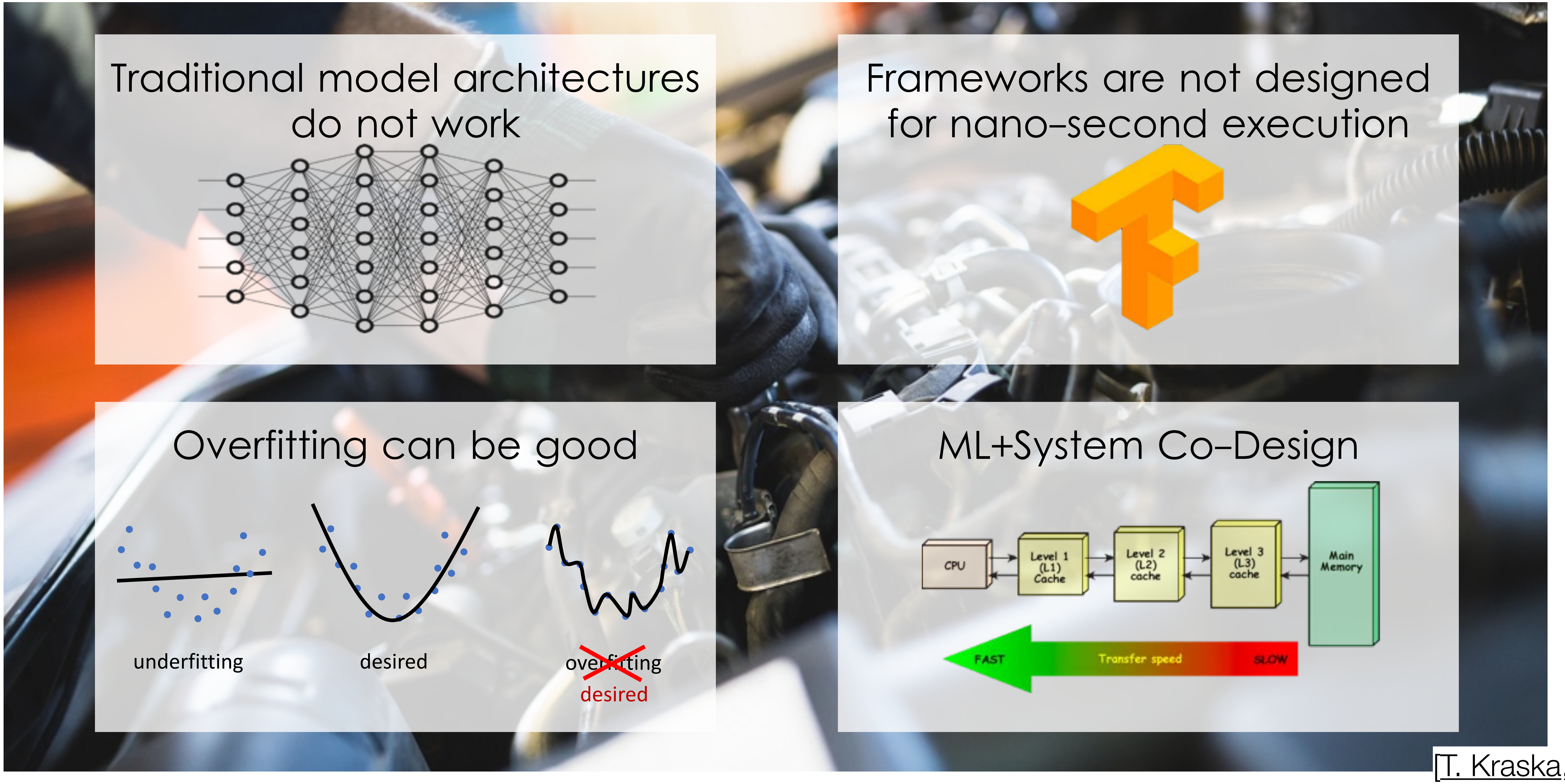
Cumulative Distribution Function (CDF)



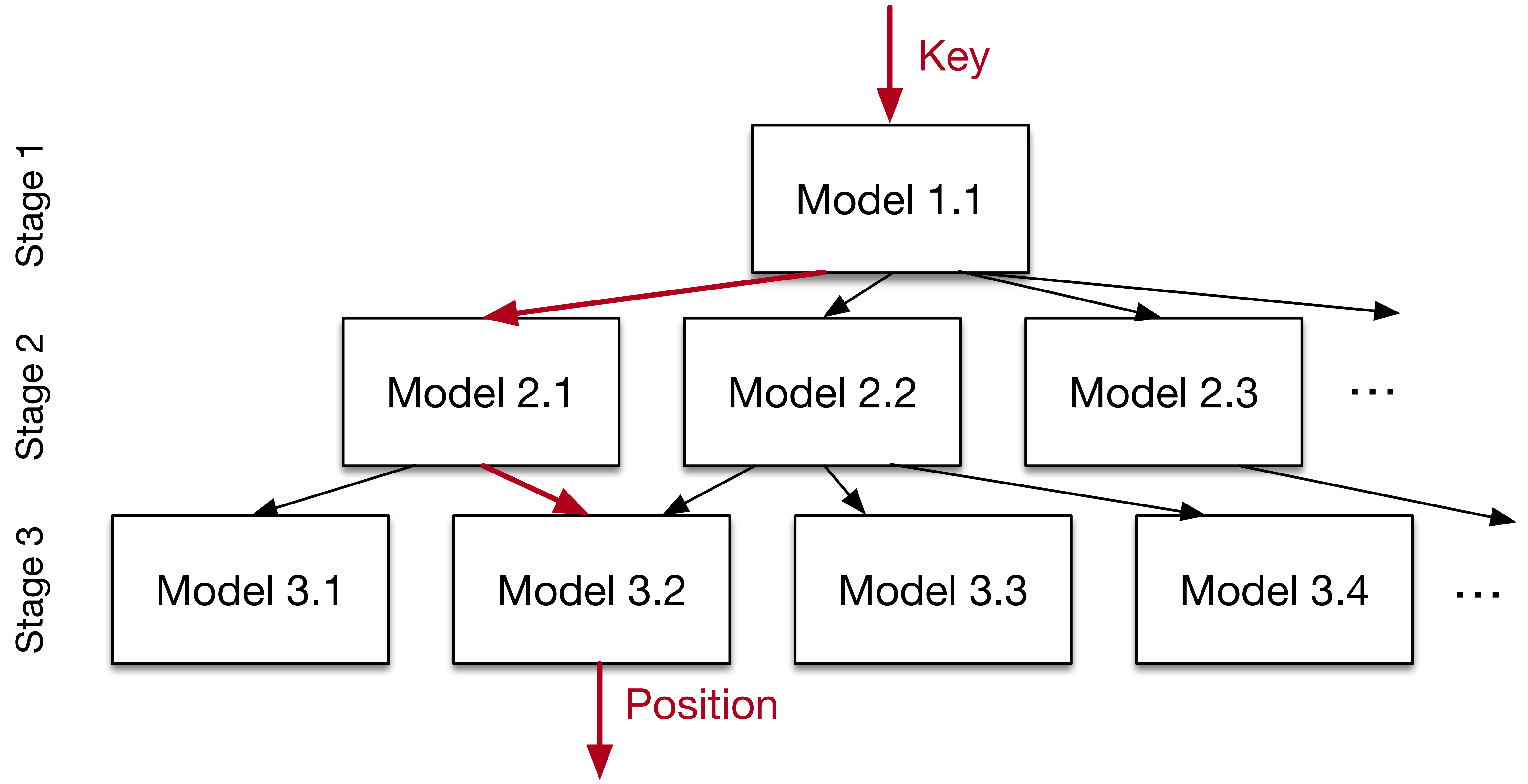

[T. Kraska, 2019]

# Challenges




[T. Kraska, 2019]

# Recursive Model Index (RMI)




## 2-Stage RMI with Linear Model

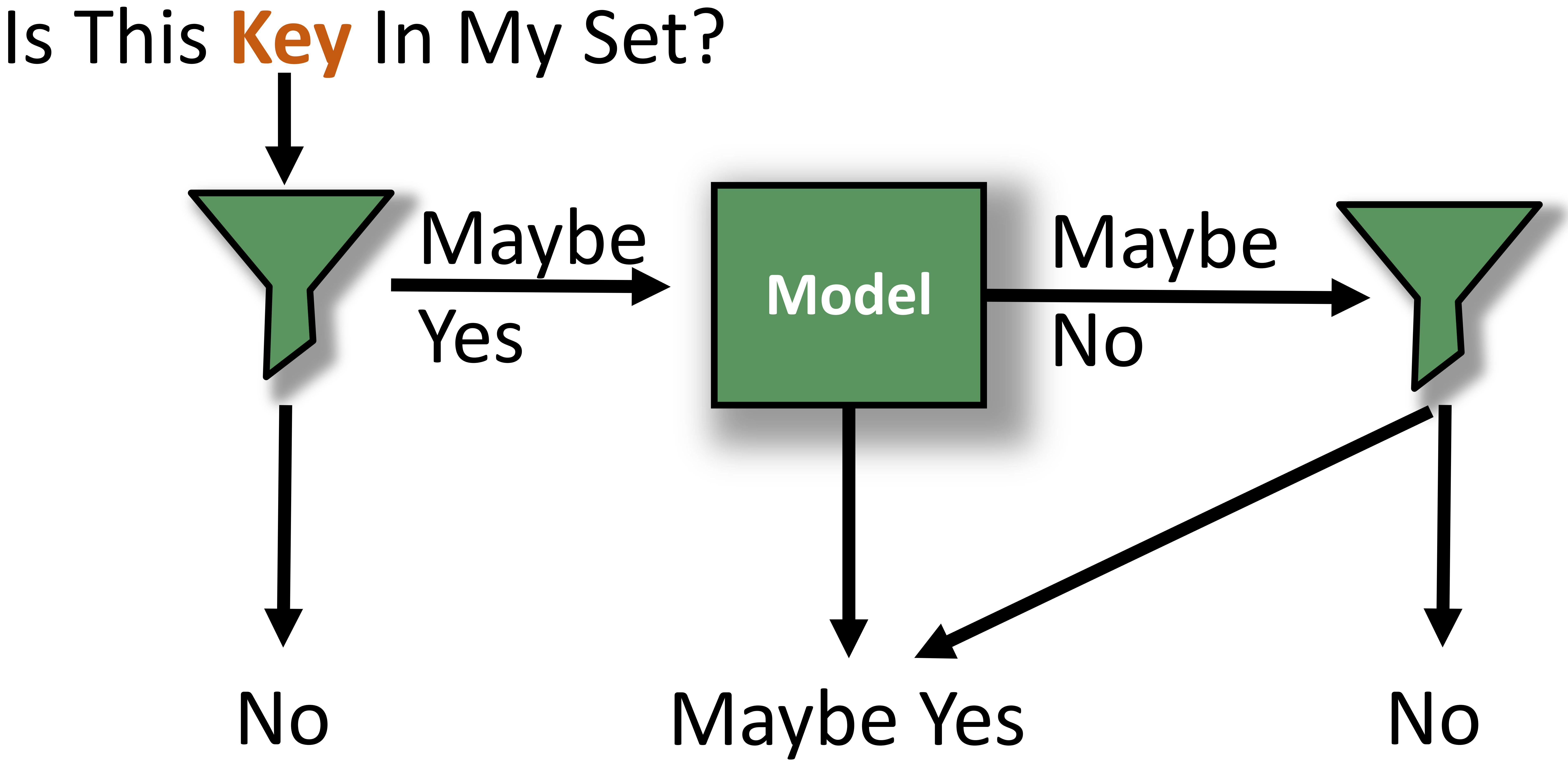
$$pos_0 = a_0 + b_0 * key$$

$$pos_1 = m_1[pos_0].a + m_1[pos_0].b * key$$

`record = local-search(key, pos1)`

[T. Kraska, 2019]

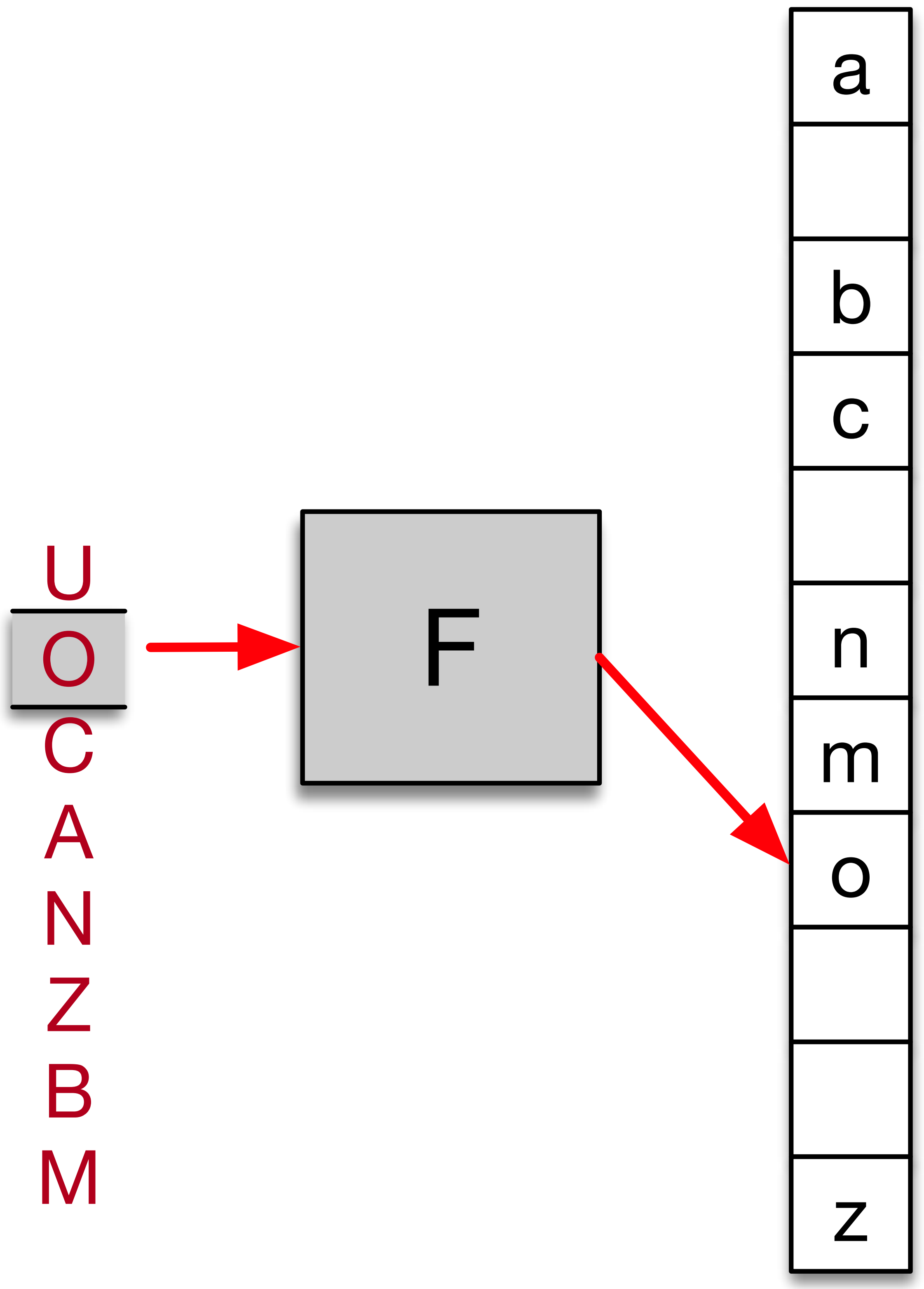
# Sandwiched Bloom Filter



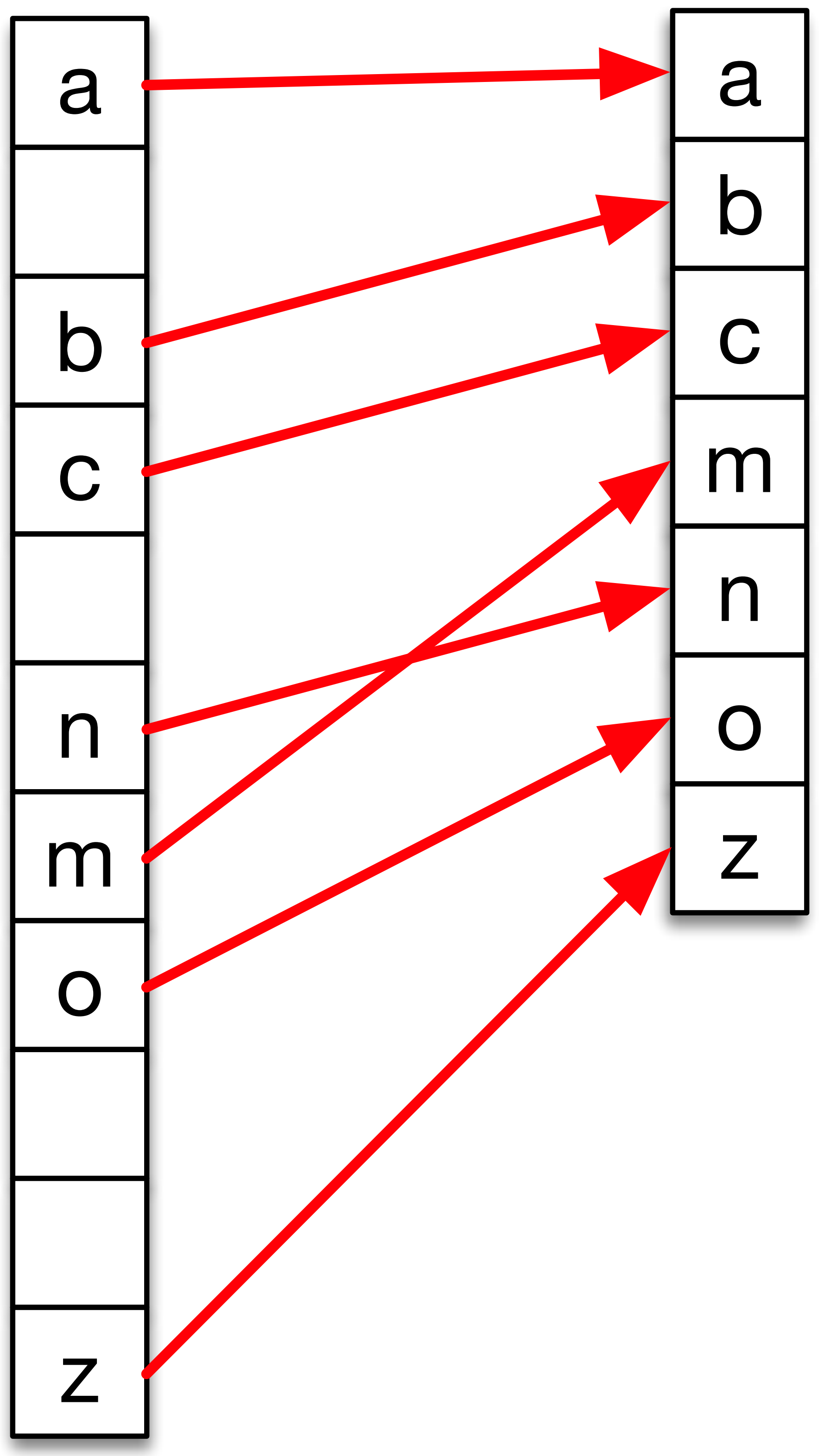

[M. Mitzenmacher, 2018 via T. Kraska, 2019]

# Sorting

(a) CDF Model Pre-Sorts



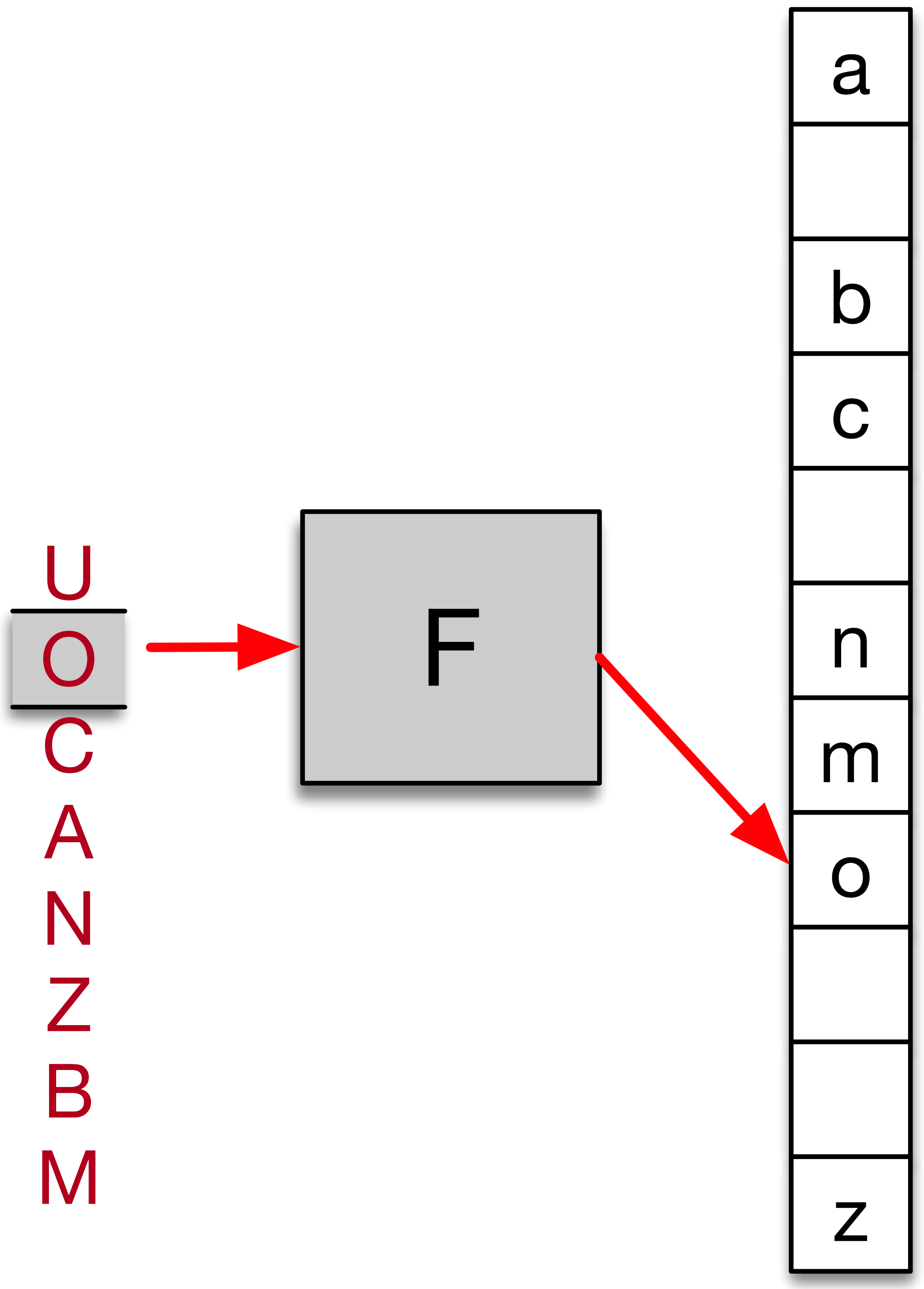

(b) Compact & local sort

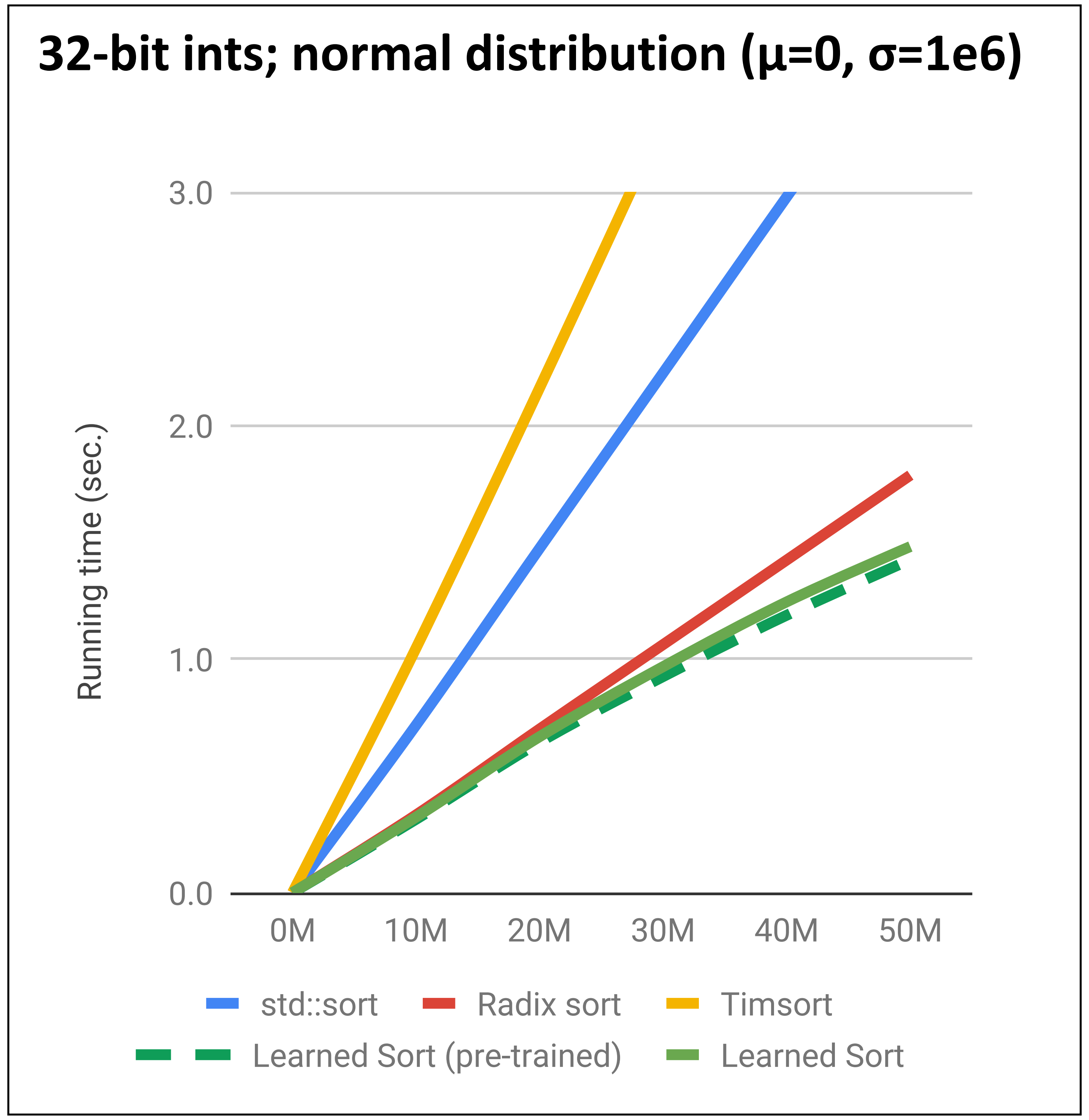



[T. Kraska, 2019]

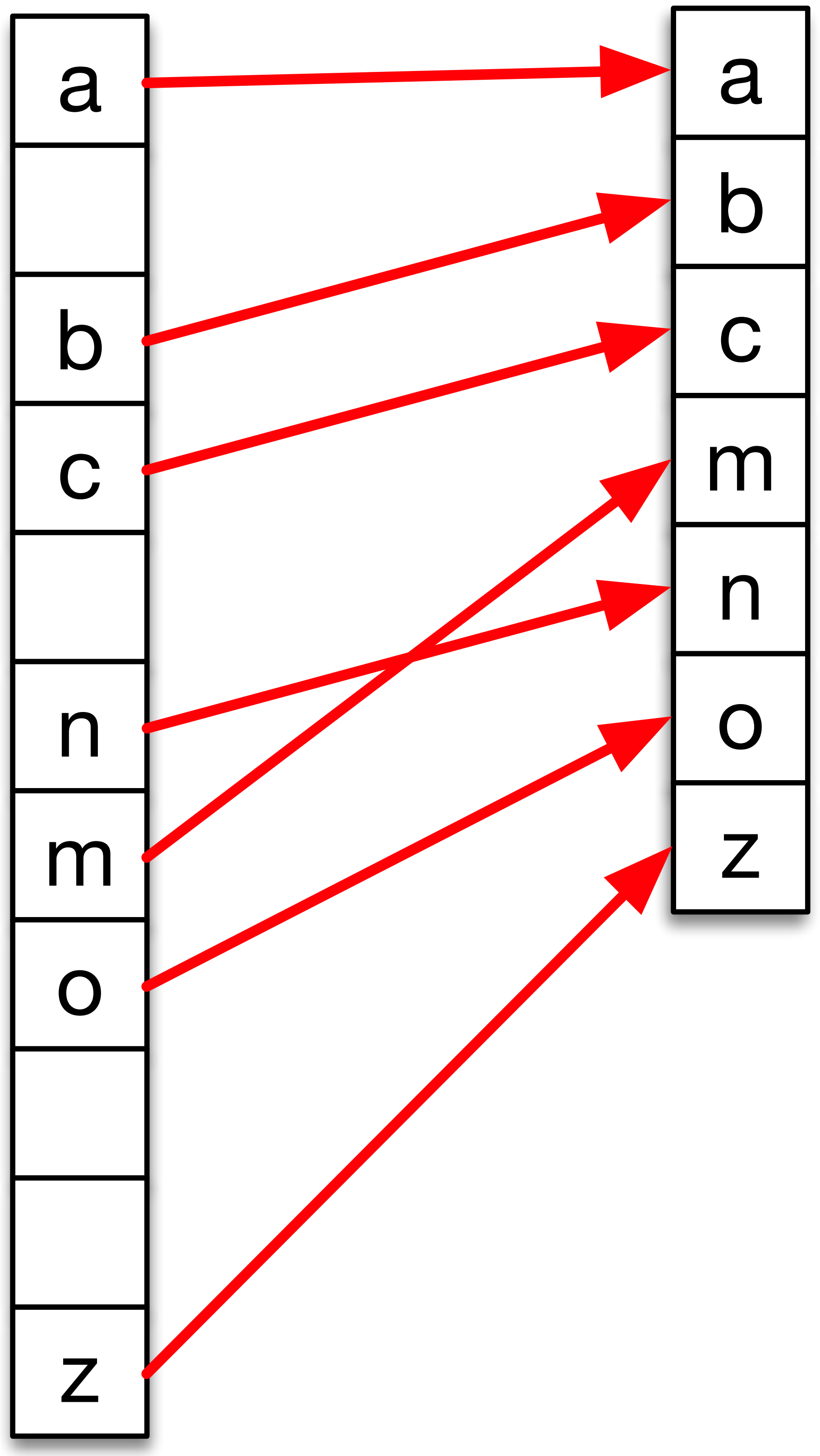
# Sorting

(a) CDF Model Pre-Sorts



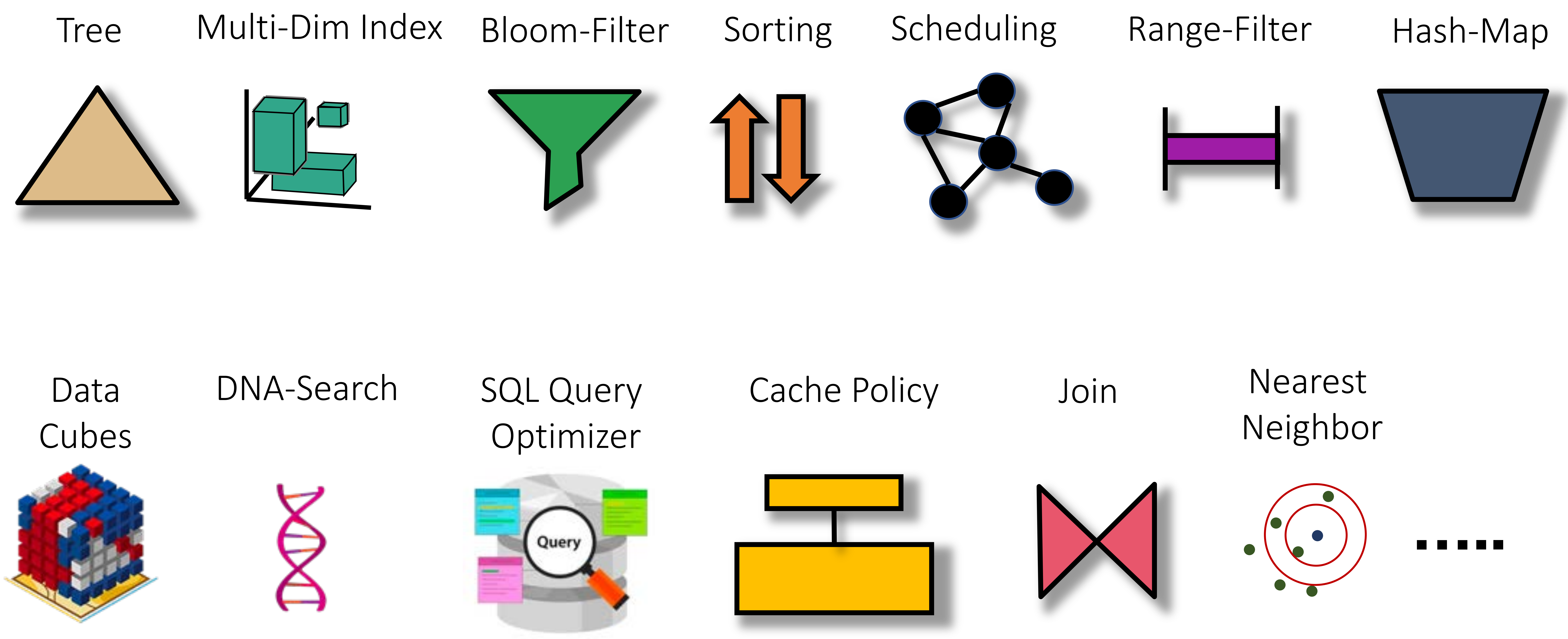




(b) Compact & local sort



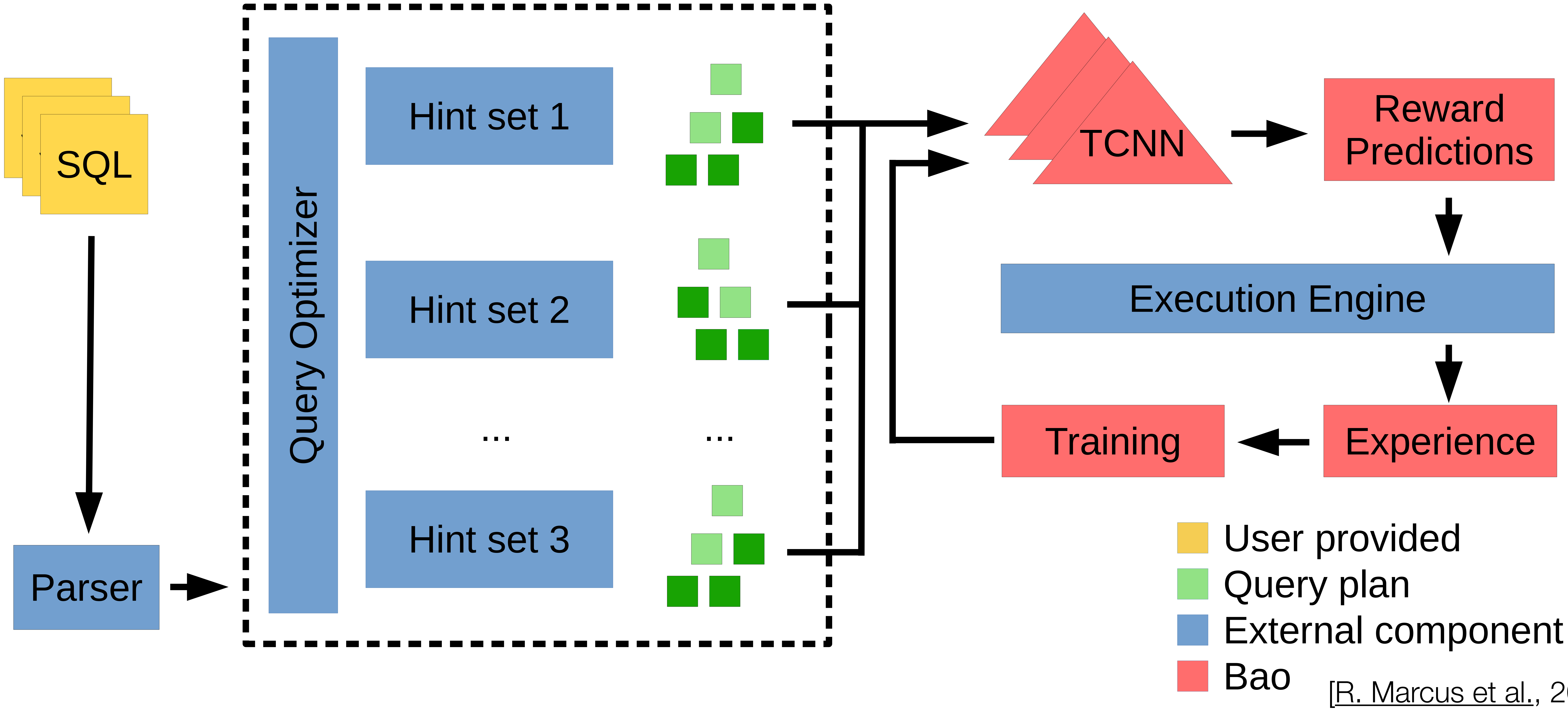

[T. Kraska, 2019]

# More…




[T. Kraska, 2019]

# Query Optimization




[R. Marcus et al., 2021]

# Final Exam

- Wednesday, May 10, **8:00**-9:50am, PM 253
- Similar format
- More comprehensive (questions from topics covered in Test 1 & 2)
- Will also have questions from graph/spatial/temporal data, provenance, reproducibility, machine learning

# Questions?

# Review

Re

What did we do this semester?

# What's involved in dealing with data?

### Data Acquisition

- Structured data
- Unstructured data
- Event processing
- Sensor networks
- Protocols
- Real-time
- Data streams
- Multimodality

### Data Analysis

- Stream mining
- Semantic analysis
- Machine learning
- Information extraction
- Linked Data
- Data discovery
- 'Whole world' semantics
- Ecosystems
- Community data analysis
- Cross-sectorial data analysis

### Data Curation

- Data Quality
- Trust / Provenance
- Annotation
- Data validation
- Human-Data Interaction
- Top-down/Bottom-up
- Community / Crowd
- Human Computation
- Curation at scale
- Incentivisation
- Automation
- Interoperability

### Data Storage

- In-Memory DBs
- NoSQL DBs
- NewSQL DBs
- Cloud storage
- Query Interfaces
- Scalability and Performance
- Data Models
- Consistency, Availability, Partition-tolerance
- Security and Privacy
- Standardization

### Data Usage

- Decision support
- Prediction
- In-use analytics
- Simulation
- Exploration
- Visualisation
- Modeling
- Control
- Domain-specific usage

[Big Data Value Chain, Curry et al., 2014]

# Python!

- Just assign expressions to variables, no typing

```
a = 12
a = "abc"
b = a + "de"
```

- Functions defined using def, called using parenthesis:

```
def hello(name1="Joe", name2="Jane"):
    print(f"Hello {name1} and {name2}")
hello(name2="Mary")
```

- Always indent blocks (if-else-elif, while, for, etc.):

```
z = 20
if x > 0:
    if y > 0:
        z = 100
else:
    z = 10
```

# Python Containers

- List: `[1,"abc",12.34]`
- Tuple: `(1, "abc", 12.34)`
- Indexing/Slicing:
  - `x[0], x[:-1], x[1:2], x[::2]`
- Set: `{1, "abc", 12.34}`
- Dictionary: `{'x': 1, 'y': "abc", 'z': 12.34}`
- Mutable vs. Immutable
- Stored by reference
- Iterators: objects that traverse containers, just know how to get next element
- You cannot index/slice an iterator (`d.values()[-1]` doesn't work)

# Comprehensions

- List Comprehensions:
  - `squares = [i**2 for i in range(10)]`
- Dictionary Comprehensions:
  - `squares = {i: i**2 for i in range(10)}`
- Set Comprehensions:
  - `squares = {i**2 for i in range(10)}`
- Comprehensions allow filters:
  - `squares = [i**2 for i in range(10) if i % 2 == 0]`

# JupyterLab

- An interactive, configurable programming environment
- Supports many activities including notebooks
- Runs in your web browser
- Notebooks:
  - Originally designed for Python
  - Supports other languages, too
  - Displays results (even interactive maps) inline
  - You decide how to divide code into executable cells
  - Shift+Enter to execute a cell

# Relational Algebra

- Definition: A procedural language consisting of a set of operations that take one or two relations as input and produce a new relation as their result.
- Six basic operators
  - select: σ
  - project: ∏
  - union: ∪
  - set difference: –
  - Cartesian product: x
  - rename: ρ

[A. Silberschatz et al.]

# Components of SQL

- **Data Definition Language (DDL)**: the specification of information about relations, including schema, types, integrity constraints, indices, storage
- **Data Manipulation Language (DML)**: provides the ability to query information from the database and to insert tuples into, delete tuples from, and modify tuples in the database.
- An SQL relation is defined using the create table command:

  `create table r` $(A_1\ D_1,\ A_2\ D_2,\ \ldots,\ A_n\ D_n,\ (C_1),\ \ldots,\ (C_k))$

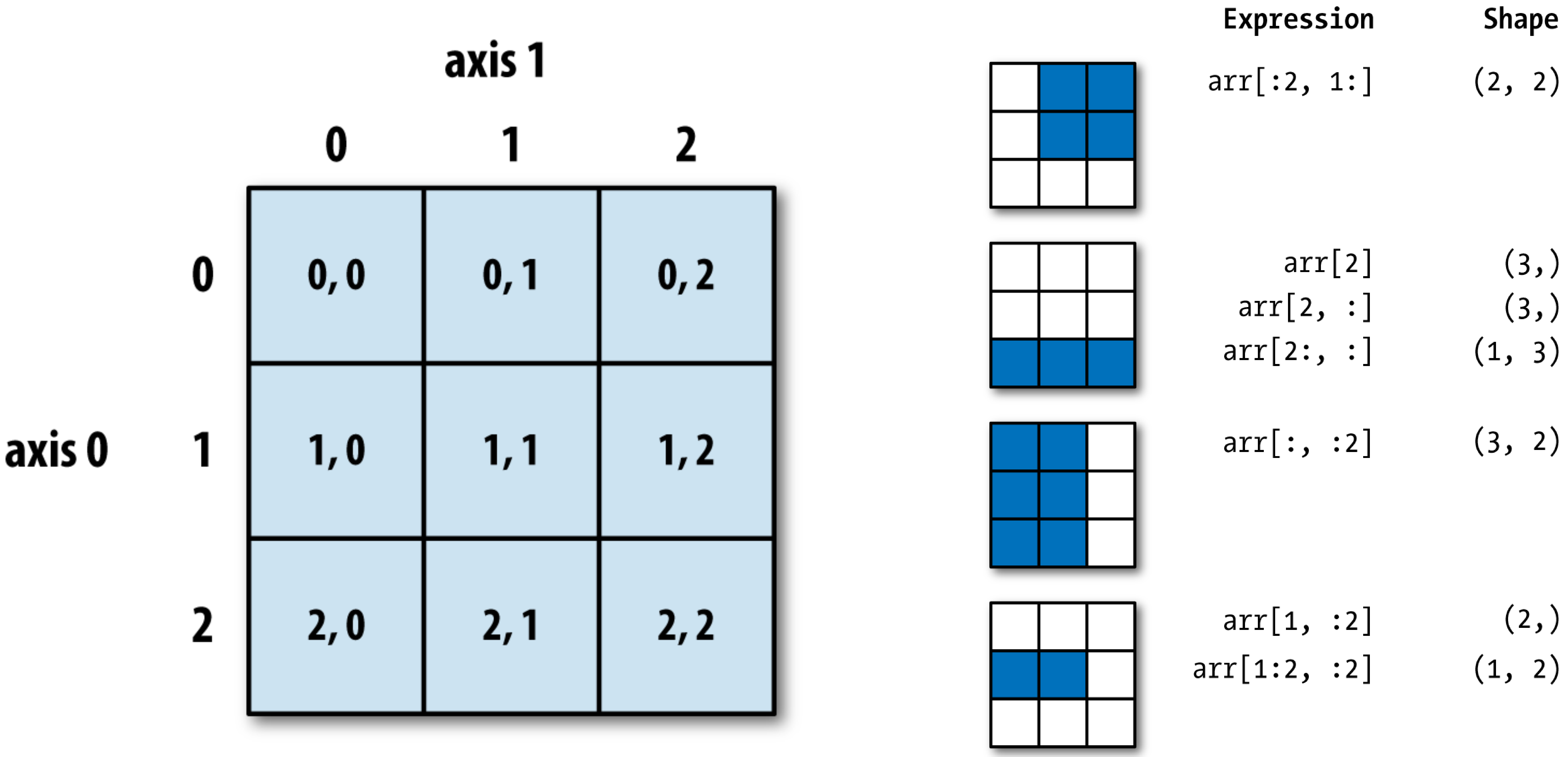
  - $A_i$ is an **attribute**
  - $D_i$ is the **data type**
  - $r_i$ represents a **relation**
  - $P$ is a **predicate**

- A typical SQL query has the form:

  **`select`** $A_1, A_2, \ldots, A_n$
  **`from`** $r_1, r_2, \ldots, r_m$
  **`where`** $P$

[A. Silberschatz et al.]

# NumPy arrays and slicing

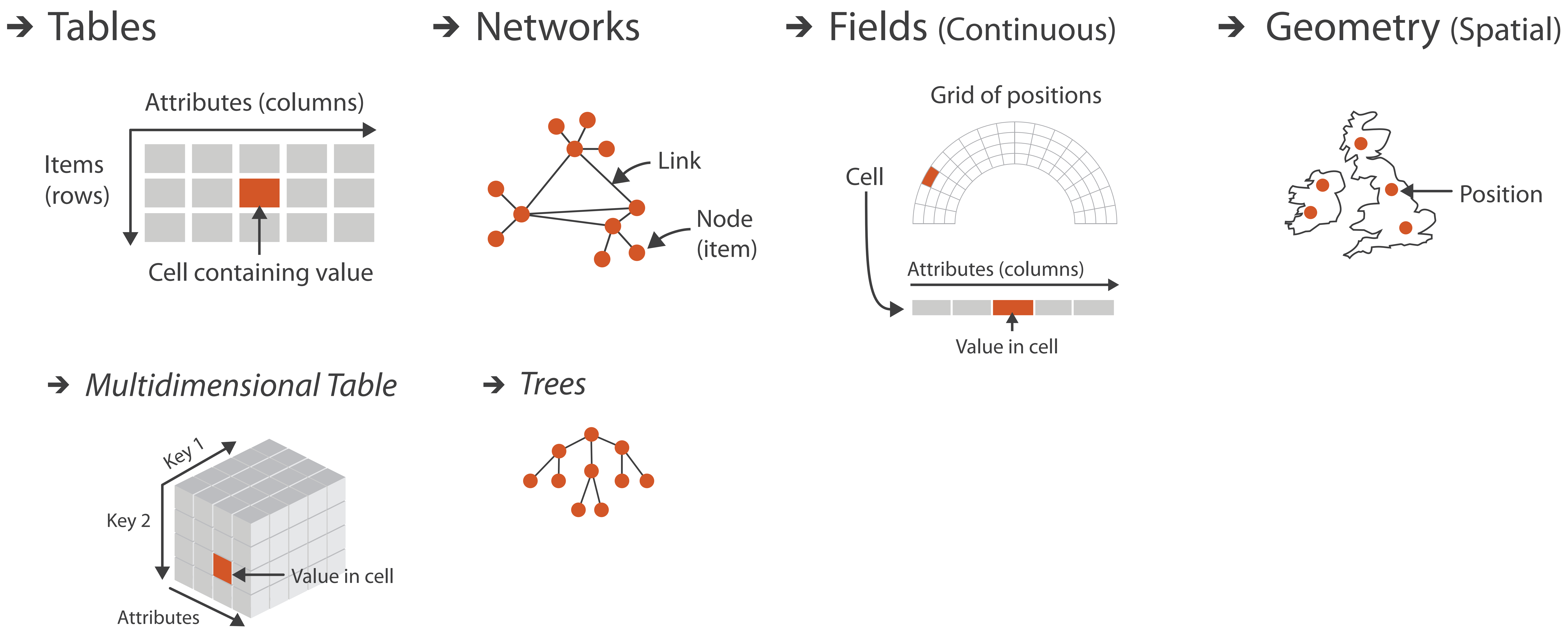



[W. McKinney, Python for Data Analysis]

# 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`

# What is Data?




[Munzner (ill. Maguire), 2014]

# Categorial, Ordinal, and Quantitative

| 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 | 0.72 | 7/17/07 |
| 32 | 7/16/07 | 2-High | Medium Box | 0.6 | 7/18/07 |
| 32 | 7/16/07 | 2-High | Medium Box | 0.65 | 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 | 6/4/05 | 4-Not Specified | Small Pack | 0.44 | 6/6/05 |
| 69 | 6/4/05 | 4-Not Spec[illegible] | [illegible] | 0.6 | 6/6/05 |
| 70 | 12/18/06 | 5-Low | [illegible] | 0.59 | 12/23/06 |
| 70 | 12/18/06 | 5-Low | [illegible] | 0.82 | 12/23/06 |
| 96 | 4/17/05 | 2-High | [illegible] | 0.55 | 4/19/05 |
| 97 | 1/29/06 | 3-Medium | [illegible] | 0.38 | 1/30/06 |
| 129 | 11/19/08 | 5-Low | [illegible] | 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 |

**quantitative**
**ordinal**
**categorical**

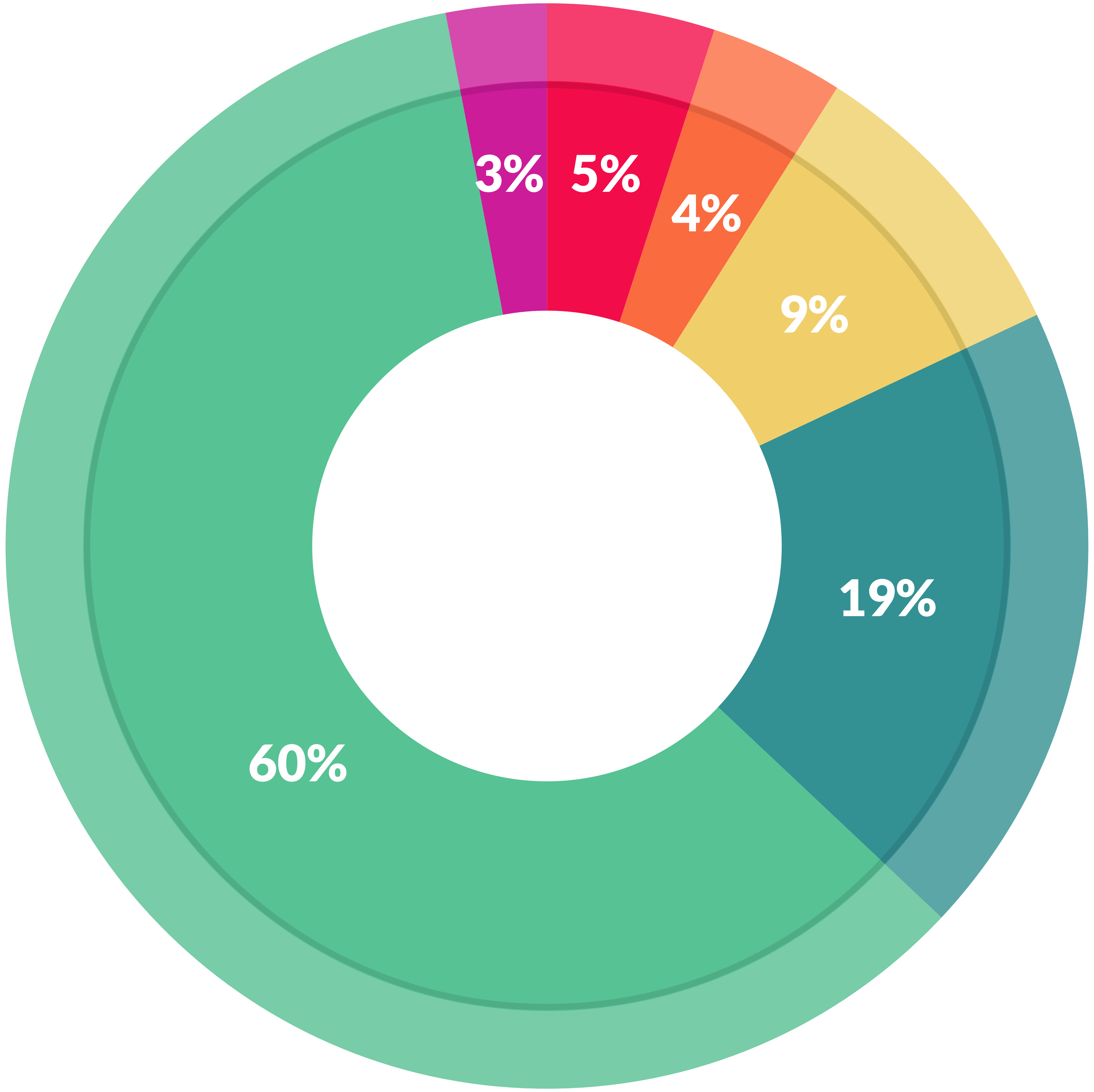
# Pandas and Data Frames

| | Inspection ID | DBA Name | AKA Name | License # | Facility Type | Risk | Address | City | State | Zip | Inspection Date | Inspection Type | Results |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2356580 | UNCOOKED LLC | UNCOOKED LLC | 2709319.0 | NaN | All | 210 N CARPENTER ST | CHICAGO | IL | 60607.0 | 01/13/2020 | License | Not Ready |
| **1** | 2356551 | MOJO 33 NORTH LASALLE LLC | MOJO 33 NORTH LASALLE LLC | 2689550.0 | Restaurant | Risk 1 (High) | 33 N LA SALLE ST | CHICAGO | IL | 60602.0 | 01/13/2020 | License Re-Inspection | Pass |
| **2** | 2356492 | LA BIZNAGA #2 | LA BIZNAGA #2 | 2708992.0 | NaN | Risk 1 (High) | 2949 W BELMONT AVE | CHICAGO | IL | 60618.0 | 01/10/2020 | License | Not Ready |
| **3** | 2356432 | LAS TABLAS | LAS TABLAS | 1617900.0 | Restaurant | Risk 1 (High) | 4920 W IRVING PARK RD | CHICAGO | IL | 60641.0 | 01/09/2020 | Canvass | Pass |
| **4** | 2356423 | GIORDANO'S OF BEVERLY | GIORDANO'S OF BEVERLY | 2074456.0 | Restaurant | Risk 1 (High) | 9613 S WESTERN AVE | CHICAGO | IL | 60643.0 | 01/09/2020 | Canvass | Pass |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **199687** | 112321 | PANDA EXPRESS #236 | PANDA EXPRESS #236 | 1801495.0 | Restaurant | Risk 1 (High) | 77 W JACKSON BLVD | CHICAGO | IL | 60604.0 | 02/18/2010 | Suspected Food Poisoning | Pass |
| **199688** | 74300 | KENNYS RIBS & CHICKEN | UNCLE JOE'S | 81030.0 | Restaurant | Risk 1 (High) | 1453 E HYDE PARK BLVD | CHICAGO | IL | 60615.0 | 02/08/2010 | Complaint | Pass |
| **199689** | 70314 | Cafe Marbella | Cafe Marbella | 2016764.0 | Restaurant | Risk 1 (High) | 5527-5531 N Milwaukee AVE | CHICAGO | IL | 60630.0 | 01/28/2010 | License Re-Inspection | Pass |
| **199690** | 78309 | WALGREENS # 07876 | WALGREENS # 07876 | 2004292.0 | Grocery Store | Risk 3 (Low) | 7544 S STONY ISLAND AVE | CHICAGO | IL | 60649.0 | 02/18/2010 | TASK FORCE LIQUOR 1474 | Pass |
| **199691** | 150209 | YSABEL'S FILIPINO CUISINE | YSABEL'S GRILL ASIAN CUISINE | 2013419.0 | Restaurant | Risk 1 (High) | 4908 W Irving Park RD | CHICAGO | IL | 60641.0 | 01/12/2010 | License Re-Inspection | Pass |

199692 rows × 17 columns

- Data Frames are tables with many database-like operations
- Index shared across all columns
- Can select, project, merge (join), and more
- Read and write many file formats

# How do data scientists spend their time?



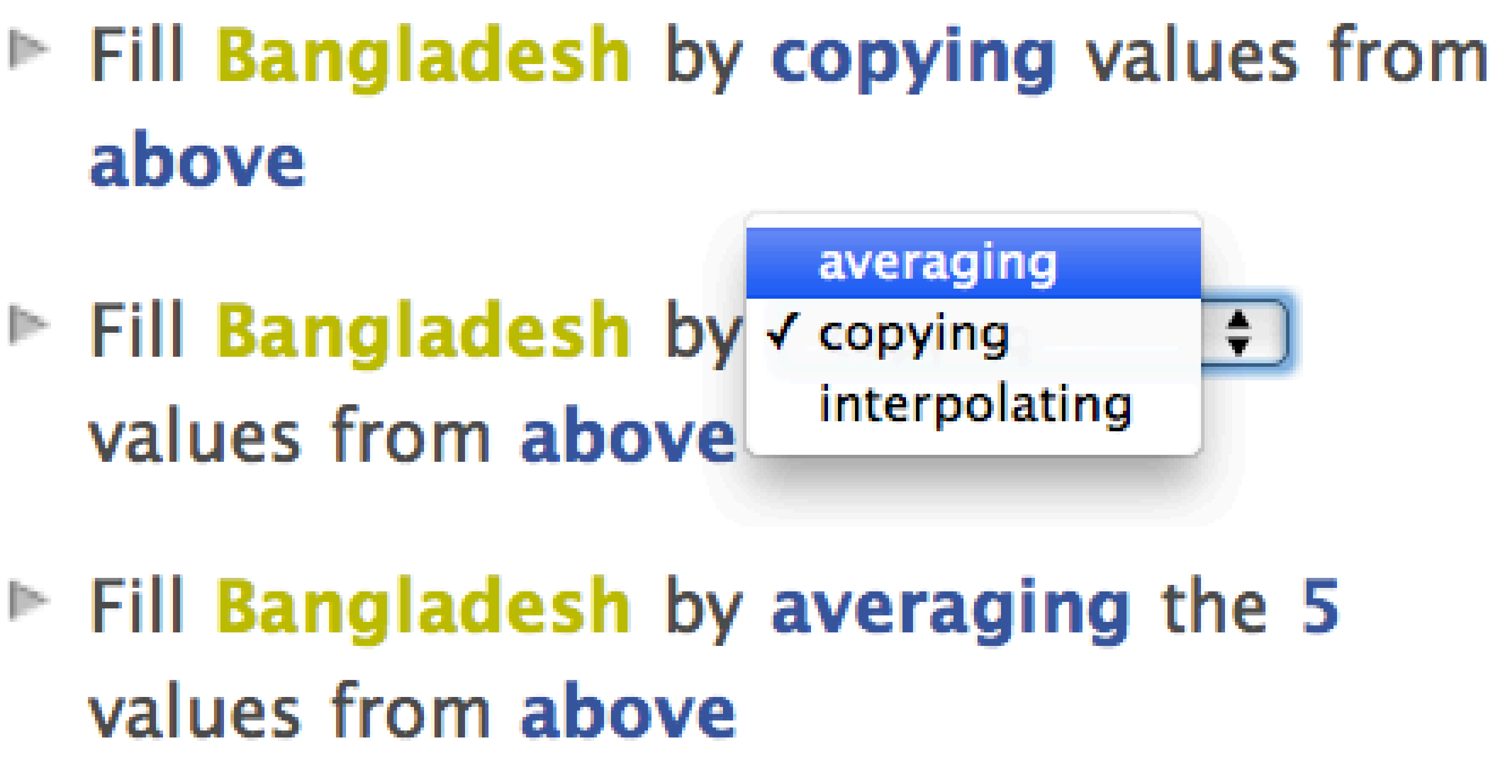

### What data scientists spend the most time doing

- *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]

# Data Wrangling

- Automated Transformation Suggestions
- Editable Natural Language Explanations




| split | split1 | split2 | split3 | split4 |
|---|---|---|---|---|
| | 2004 | 2004 | 2004 | 2003 |
| STATE | Participation Rate 2004 | Mean SAT I Verbal | Mean SAT I Math | Participation Rate |
| New York | 87 | 497 | 510 | 82 |
| Connecticut | 85 | 515 | 515 | 84 |
| Massachusetts | 85 | 518 | 523 | 82 |
| New Jersey | 83 | 501 | 514 | 85 |
| New Hampshire | 80 | 522 | 521 | 75 |
| D.C. | 77 | 489 | 476 | 77 |
| Maine | 76 | 505 | 501 | 70 |
| Pennsylvania | 74 | 501 | 502 | 73 |
| Delaware | 73 | 500 | 499 | 73 |
| Georgia | 73 | 494 | 493 | 66 |

| split | fold | fold1 | value |
|---|---|---|---|
| New York | 2004 | Participation Rate 2004 | 87 |
| New York | 2004 | Mean SAT I Verbal | 497 |
| New York | 2004 | Mean SAT I Math | 510 |
| New York | 2003 | Participation Rate 2003 | 82 |
| New York | 2003 | Mean SAT I Verbal | 496 |
| New York | 2003 | Mean SAT I Math | 510 |
| Connecticut | 2004 | Participation Rate 2004 | 85 |
| Connecticut | 2004 | Mean SAT I Verbal | 515 |
| Connecticut | 2004 | Mean SAT I Math | 515 |
| Connecticut | 2003 | Participation Rate 2003 | 84 |
| Connecticut | 2003 | Mean SAT I Verbal | 512 |

- Visual Transformation Previews
- Transformation History

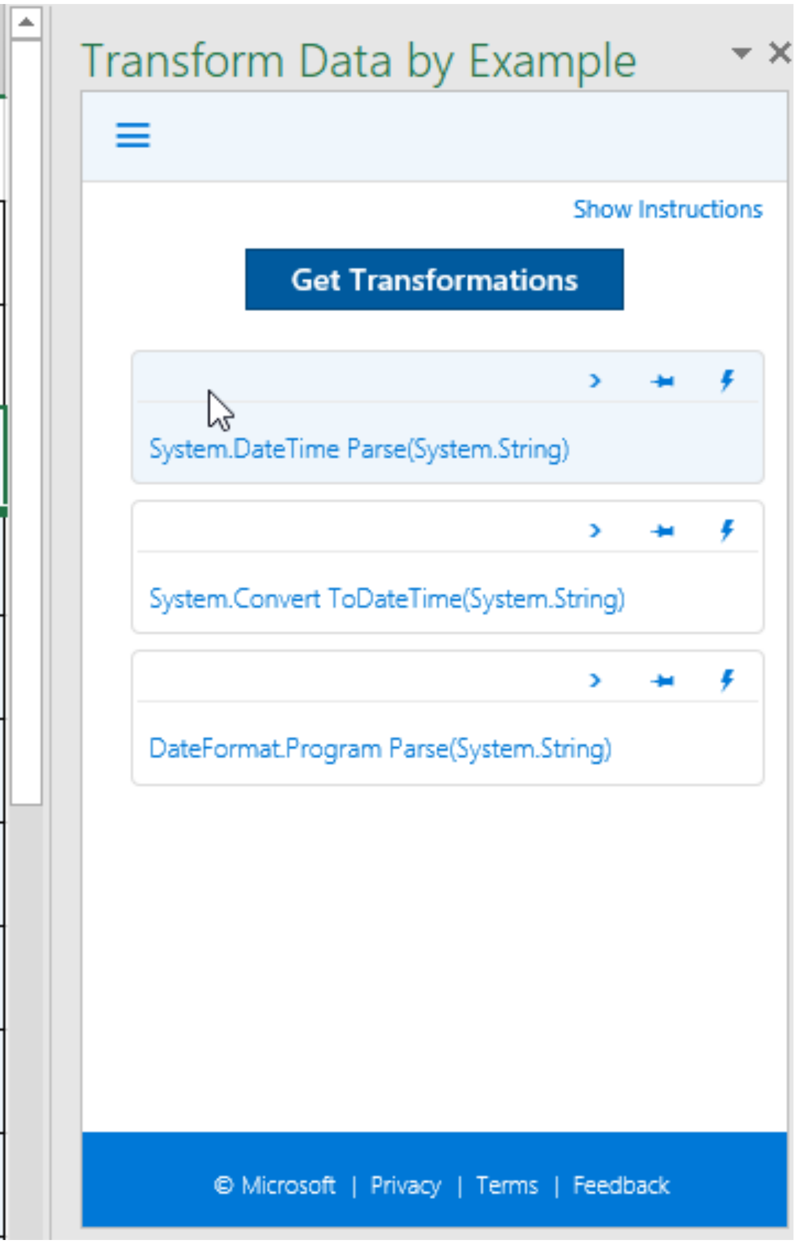
[S. Kandel et al., 2011]

# TDE: Transform Data by Example

| C | D |
|---|---|
| **Transaction Date** | **output** |
| Wed, 12 Jan 2011 | 2011-01-12-Wednesday |
| Thu, 15 Sep 2011 | 2011-09-15-Thursday |
| Mon, 17 Sep 2012 | |
| 2010-Nov-30 11:10:41 | |
| 2011-Jan-11 02:27:21 | |
| 2011-Jan-12 | |
| 2010-Dec-24 | |
| 9/22/2011 | |
| 7/11/2012 | |
| 2/12/2012 | |

→

| C | D |
|---|---|
| **Transaction Date** | **output** |
| Wed, 12 Jan 2011 | 2011-01-12-Wednesday |
| Thu, 15 Sep 2011 | 2011-09-15-Thursday |
| Mon, 17 Sep 2012 | 2012-09-17-Monday |
| 2010-Nov-30 11:10:41 | 2010-11-30-Tuesday |
| 2011-Jan-11 02:27:21 | 2011-01-11-Tuesday |
| 2011-Jan-12 | 2011-01-12-Wednesday |
| 2010-Dec-24 | 2010-12-24-Friday |
| 9/22/2011 | 2011-09-22-Thursday |
| 7/11/2012 | 2012-07-11-Wednesday |
| 2/12/2012 | 2012-02-12-Sunday |




[Y. He et al., 2018]

# Transform by Pattern: Automating Unify/Repair

- Auto-Unify

| S-timestamp | S-phone | S-coordinates |
|---|---|---|
| 2019-12-23 | (425) 882-8080 | (38°57'N, 95°15'W) |
| 2019-12-24 | (425) 882-8080 | (38°61'N, 95°21'W) |
| 2019-12-23 | (206) 876-1800 | (39°19'N, 95°18'W) |
| 2019-12-24 | (206) 876-1800 | (39°26'N, 95°23'W) |
| 2019-12-23 | (206) 903-8010 | (39°42'N, 96°38'W) |

| R-timestamp | R-phone | R-coordinates |
|---|---|---|
| Nov. 16 2019 | 650-853-1300 | N37°31′ W122°14′ |
| Nov. 17 2019 | 650-853-1300 | N37°18′ W122°19′ |
| Nov. 16 2019 | 425-421-1225 | N37°48′ W122°17′ |
| Nov. 17 2019 | 425-421-1225 | N37°60′ W123°08′ |
| Nov. 16 2019 | 650-253-0827 | N37°01′ W123°72′ |

- Auto-Repair

| Date | Opponents |
|---|---|
| January 12, 1997 | Venezuela |
| February 12, 1997 | Peru |
| April 2, 1997 | Colombia |
| 1997-06-04 | United States |
| 1997-06-11 | Chile |
| 1997-06-14 | Ecuador |

(a) EN-Wiki: Dates

| Year | Artist | Issue Price (BU) |
|---|---|---|
| 1989 | John Mardon | $16.25 |
| 1990 | D.J. Craig | $16.75 |
| 1991 | D.J. Craig | $16.75 |
| 1992 | Karsten Smith | 17.50 |
| 1993 | Stewart Sherwood | $17.50 |
| 1994 | Ian D. Sparkes | $17.95 |

(b) EN-Wiki: Currency values

| Women's winner | Time |
|---|---|
| Anikó Kálovics | 2:31:24 |
| Lenah Cheruiyot | 2:27:02 |
| Lenah Cheruiyot | 2:33.44 |
| Emily Kimuria | 2:28.42 |
| Jane Ekimat | 2:32.08 |

(c) EN-wiki:time

| # | Original air date[1] |
|---|---|
| 12 | March 23, 2008 |
| 13 | March 30, 2008 |
| 14 | April 6, 2008 |
| 15 | 13 April 2008 |
| 16 | 20 April 2008 |

(d) EN-Wiki: Date

# TBP: Learning from Tables


$T_1$

| Name | # | Born | Died |
|---|---|---|---|
| Washington, George | USA President (1) | 02/22/1732 | 12/14/1799 |
| Adams, John | USA President (2), VP (1) | 10/30/1735 | 07/04/1826 |
| Jefferson, Thomas | USA President (3), VP (2) | 04/13/1743 | 07/04/1826 |
| Madison, James | USA President (4) | 03/16/1751 | 06/28/1836 |
| Monroe, James | USA President (5) | 04/28/1758 | 07/04/1851 |

$T_2$

| Date of birth | President | Birthplace | State† of birth |
|---|---|---|---|
| February 22, 1732 | George Washington | Westmoreland County | Virginia† |
| October 30, 1735 | John Adams | Braintree | Massachusetts† |

$T_3$

| | | | | | |
|---|---|---|---|---|---|
| 30. | **George Washington** | – | 57y, 10d | 22.02.1732 | 14.12.1799 |
| 31. | **John Quincy Adams** | Nat-Rep | 57y, 7m, 20d | 11.07.1767 | 23.02.1848 |
| 32. | **Thomas Jefferson** | Dem-Rep | 57y, 10m, 18d | 13.04.1743 | 04.07.1826 |
| 33. | **James Madison** | Dem-Rep | 57y, 11m, 15d | 16.03.1751 | 28.06.1836 |
| 34. | **James Monroe** | Dem-Rep | 58y, 10m, 3d | 28.04.1758 | 04.07.1831 |

$T_4$

| | | | | |
|---|---|---|---|---|
| 1. | George Washington | Virginia | Feb. 22, 1732 | Dec. 14, 1797 |
| 3. | Thomas Jefferson | Virginia | Apr. 13, 1743 | July 4, 1826 |
| 4. | James Madison | Virginia | Mar. 16, 1751 | June 28, 1836 |
| 6. | John Quincy Adams | Massachusetts | July 11, 1767 | Feb. 23, 1848 |

$T_5$

| | Name and (party)[1] | Term | State of birth | Born | Died | Religion[2] | Age at inaug. | Age at death |
|---|---|---|---|---|---|---|---|---|
| 1. | Washington (F)[3] | 1789–1797 | Va. | 2/22/1732 | 12/14/1799 | Episcopalian | 57 | 67 |
| 2. | J. Adams (F) | 1797–1801 | Mass. | 10/30/1735 | 7/4/1826 | Unitarian | 61 | 90 |

$T_6$

| PRESIDENT | BIRTH DATE | BIRTH PLACE | DEATH DATE | LOCATION OF DEATH |
|---|---|---|---|---|
| George Washington | Feb 22, 1732 | Westmoreland Co., Va. | Dec 14, 1799 | Mount Vernon, Va. |
| John Adams | Oct 30, 1735 | Quincy, Mass. | July 4, 1826 | Quincy, Mass. |

# Tidy Data

| | treatmenta | treatmentb |
|---|---|---|
| John Smith | — | 2 |
| Jane Doe | 16 | 11 |
| Mary Johnson | 3 | 1 |

Initial Data

| | John Smith | Jane Doe | Mary Johnson |
|---|---|---|---|
| treatmenta | — | 16 | 3 |
| treatmentb | 2 | 11 | 1 |

Transpose

| name | trt | result |
|---|---|---|
| John Smith | a | — |
| Jane Doe | a | 16 |
| Mary Johnson | a | 3 |
| John Smith | b | 2 |
| Jane Doe | b | 11 |
| Mary Johnson | b | 1 |

Tidy Data

[H. Wickham, 2014]

# AutoSuggest

- Automate "Complex" Data Preparation steps
- Focus on frame transformations (not per-cell transformations)
- Learn from Jupyter Notebooks
- Two Types of Predictions:
  - Single-Operator Prediction
  - Next-Operator Prediction

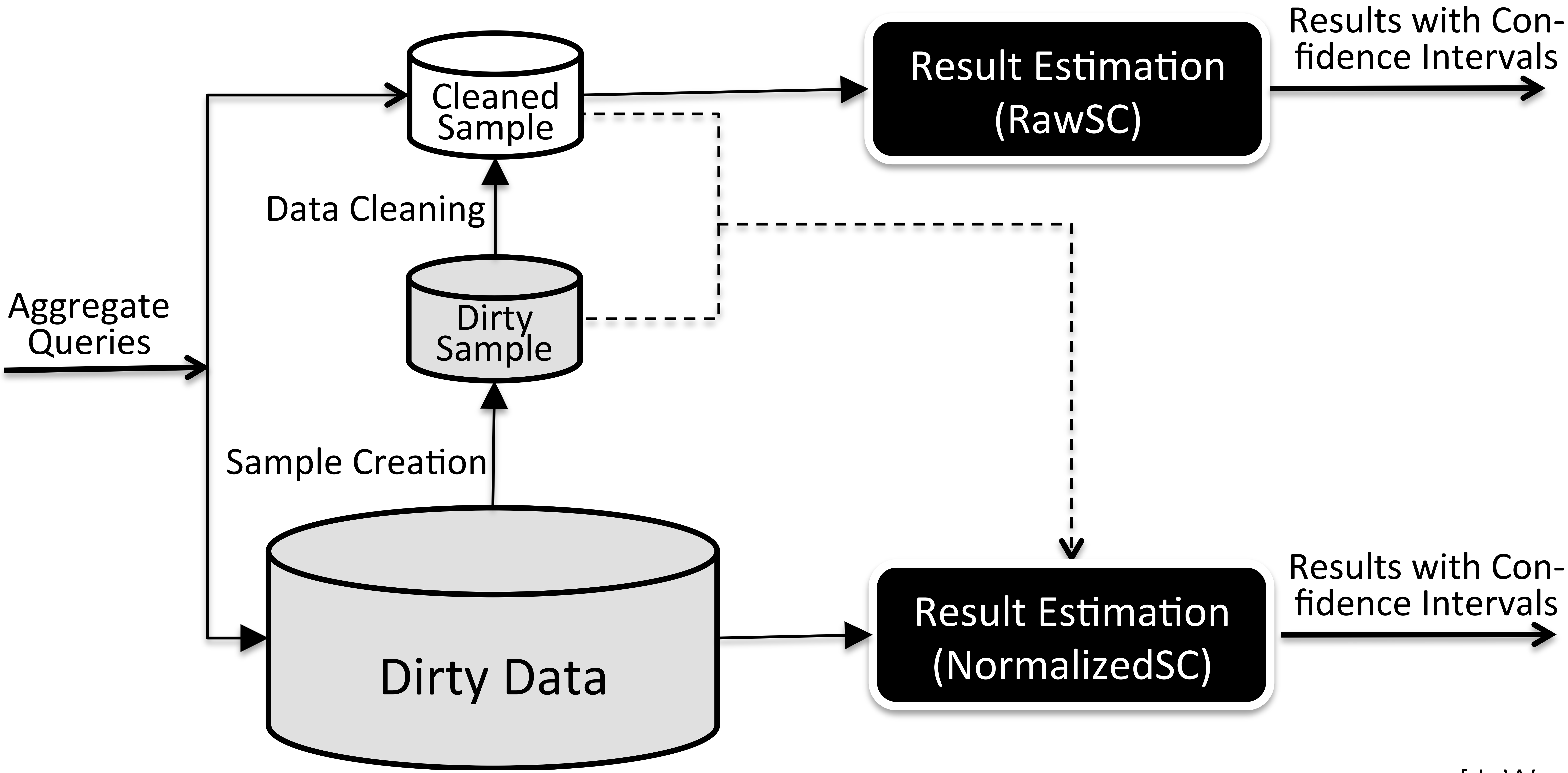
| Sector | Ticker | Company | Year | Quarter | Market Cap | Revenue |
|---|---|---|---|---|---|---|
| Aerospace | AJRD | AEROJET ROCKETD | 2006 | Q1 | 1442.67 | 472.07 |
| Aerospace | AJRD | AEROJET ROCKETD | 2006 | Q2 | 1514.80 | 489.22 |
| ... | ... | ... | ... | ... | ... | ... |
| Aerospace | BA | BOEING CO | 2006 | Q1 | 343.41 | 210.66 |
| ... | ... | ... | ... | ... | ... | ... |
| Utilities | YORW | YORK WATER CO | 2008 | Q4 | 600.19 | 271.73 |

| Sector | Ticker | Company | 2006 | 2007 | 2008 |
|---|---|---|---|---|---|
| Aerospace | AJRD | AEROJET ROCKETD | 6218.09 | 6342.45 | 7088.62 |
| | ATRO | ASTRONICS CORP | 1050.97 | 1071.99 | 1198.11 |
| Business Services | HHS | HARTE-HANKS INC | 2473.75 | 2523.22 | 2820.07 |
| | NCMI | NATL CINEMEDIA | 856.92 | 874.06 | 976.89 |
| Consumer Staples | YTEN | TIELD10 BIOSCI | 533.13 | 543.79 | 607.77 |
| | ... | ... | ... | ... | ... |
| Utilities | YORW | YORK WATER CO | 1902.37 | 1940.42 | 2168.70 |

| Ticker | Company | Year | Aerospace | Business Services | ... | Utilities |
|---|---|---|---|---|---|---|
| AJRD | AEROJET ROCKETD | 2006 | 6218.09 | NULL | ... | NULL |
| AJRD | AEROJET ROCKETD | 2007 | 6342.45 | NULL | ... | NULL |
| AJRD | AEROJET ROCKETD | 2008 | 7088.62 | NULL | ... | NULL |
| ATRO | ASTRONICS CORP | 2006 | 1050.97 | NULL | ... | NULL |
| ... | ... | ... | ... | ... | ... | ... |
| HHS | HARTE-HANKS INC | 2006 | NULL | 2473.75 | ... | NULL |
| ... | ... | ... | ... | ... | ... | ... |
| YORW | YORK WATER CO | 2008 | NULL | NULL | ... | 2168.7 |

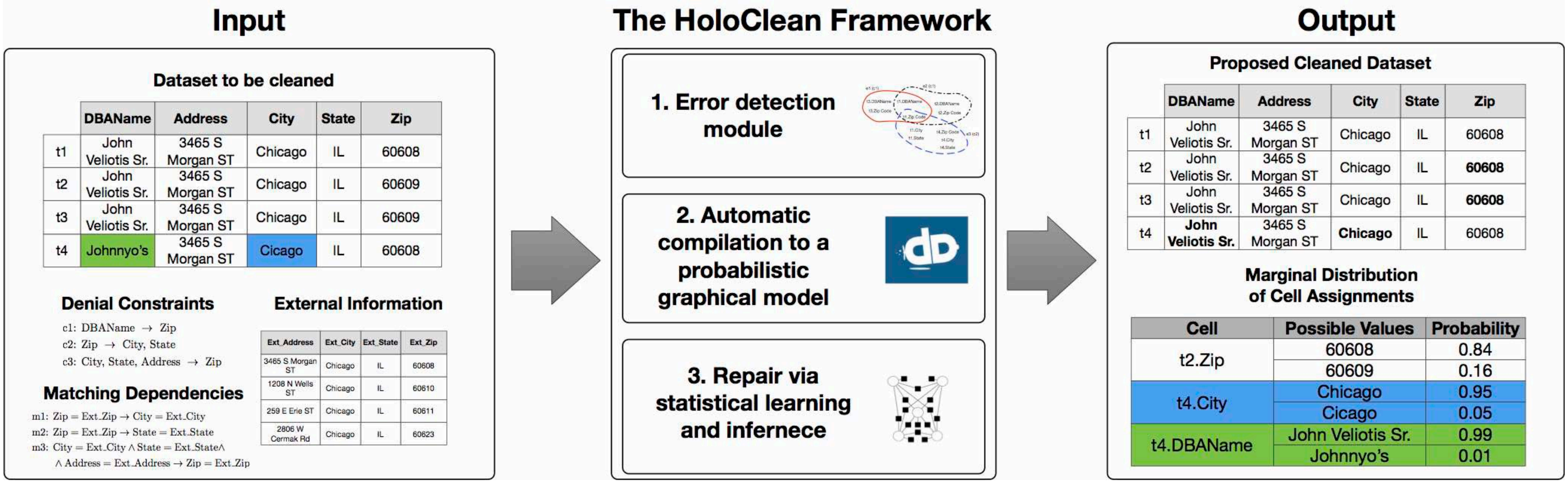
[C. Yan & Y. He]

# Data Cleaning: SampleClean




[J. Wang et al., 2014]

# Data Cleaning: HoloClean




[T. Rekatsinas et al., 2017]

# Merges (aka Joins)

- Need to merge data from one DataFrame with data from another DataFrame
- Example: Football game data merged with temperature data

**Game**

| Id | Location | Date | Home | Away |
|---|---|---|---|---|
| 0 | Boston | 9/2 | 1 | 15 |
| 1 | Boston | 9/9 | 1 | 7 |
| 2 | Cleveland | 9/16 | 12 | 1 |
| 3 | San Diego | 9/23 | 21 | 1 |

**Weather**

| wId | City | Date | Temp |
|---|---|---|---|
| 0 | Boston | 9/2 | 72 |
| 1 | Boston | 9/3 | 68 |
| … | … | … | … |
| 7 | Boston | 9/9 | 75 |
| … | … | … | … |
| 21 | Boston | 9/23 | 54 |
| … | … | … | … |
| 36 | Cleveland | 9/16 | 81 |

No data for San Diego

# Inner Strategy

**Merged**

| Id | Location | Date | Home | Away | Temp | wId |
|---|---|---|---|---|---|---|
| 0 | Boston | 9/2 | 1 | 15 | 72 | 0 |
| 1 | Boston | 9/9 | 1 | 7 | 75 | 7 |
| 2 | Cleveland | 9/16 | 12 | 1 | 81 | 36 |

**No San Diego entry**

# Outer Strategy

**Merged**

| Id | Location | Date | Home | Away | Temp | wId |
|---|---|---|---|---|---|---|
| 0 | Boston | 9/2 | 1 | 15 | 72 | 0 |
| NaN | Boston | 9/3 | NaN | NaN | 68 | 1 |
| … | … | … | … | … | … | … |
| 1 | Boston | 9/9 | 1 | 7 | 75 | 7 |
| NaN | Boston | 9/10 | NaN | NaN | 76 | 8 |
| … | … | … | … | … | … | … |
| NaN | Cleveland | 9/2 | NaN | NaN | 61 | 22 |
| … | … | … | … | … | … | … |
| 2 | Cleveland | 9/16 | 12 | 1 | 81 | 36 |
| … | … | … | … | … | … | … |
| 3 | San Diego | 9/23 | 21 | 1 | NaN | NaN |

# Data Integration

```
select title, startTime
from Movie, Plays
where Movie.title=Plays.movie AND
          location="New York"  AND
          director="Woody Allen"
```

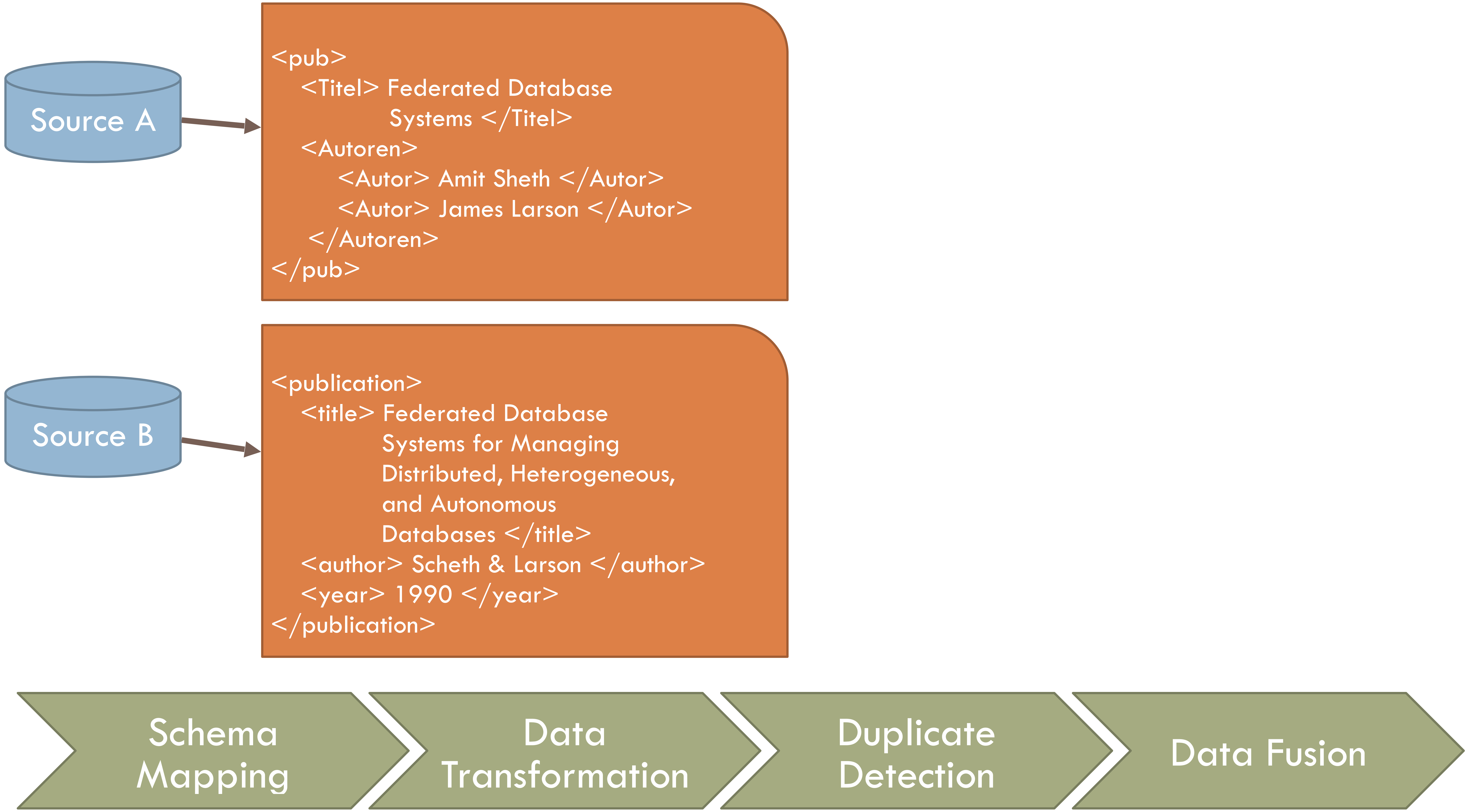
**Movie**: Title, director, year, genre
**Actors**: title, actor
**Plays**: movie, location, startTime
**Reviews**: title, rating, description

Sources S1 and S3 are relevant, sources S4 and S5 are irrelevant, and source S2 is relevant but possibly redundant.

| S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|
| Movies: name, actors, director, genre | Cinemas: place, movie, start | Cinemas in NYC: cinema, title, startTime | Cinemas in SF: location, movie, startingTime | Reviews: title, date grade, review |

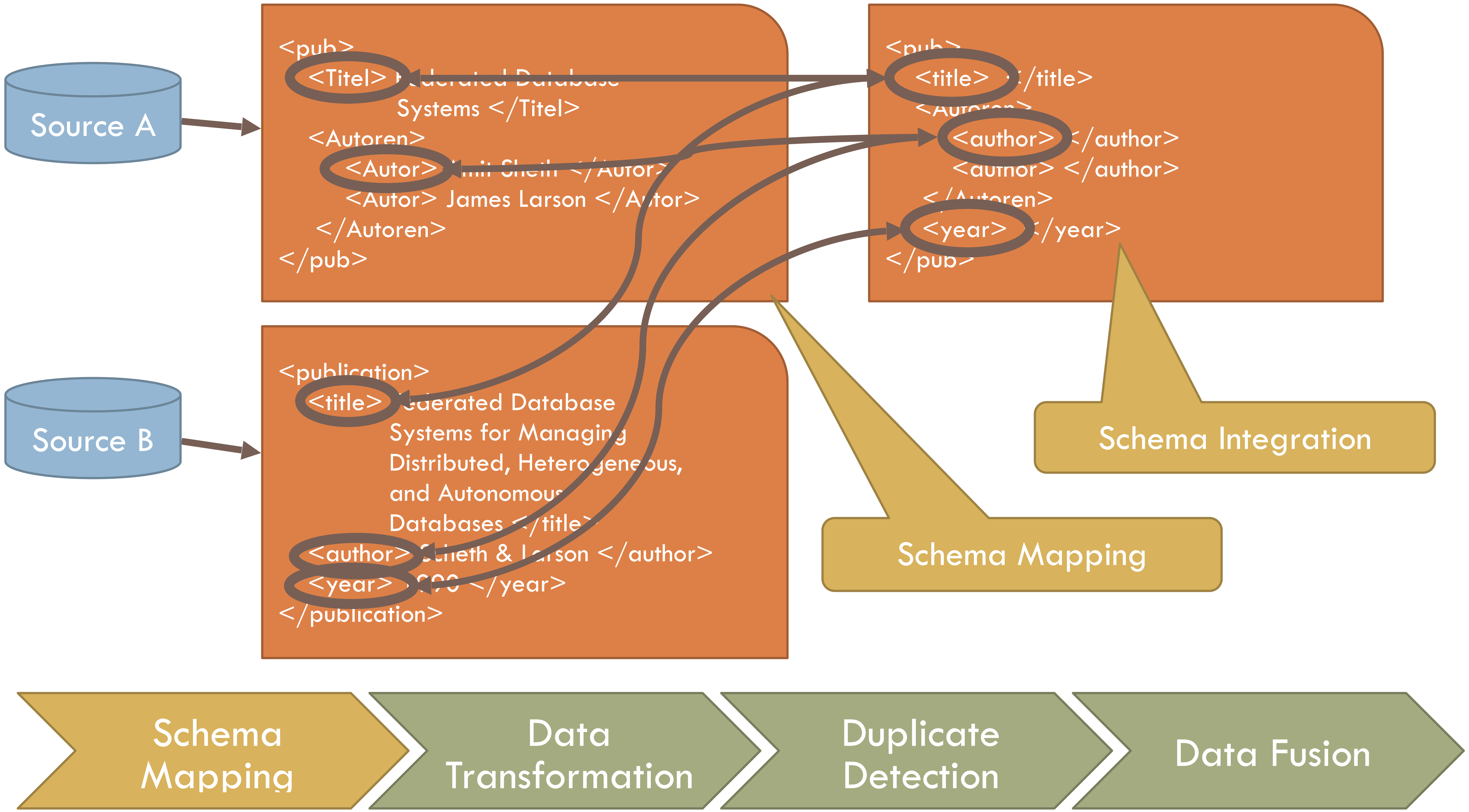
[AH Doan et al., 2012]

# Information Integration



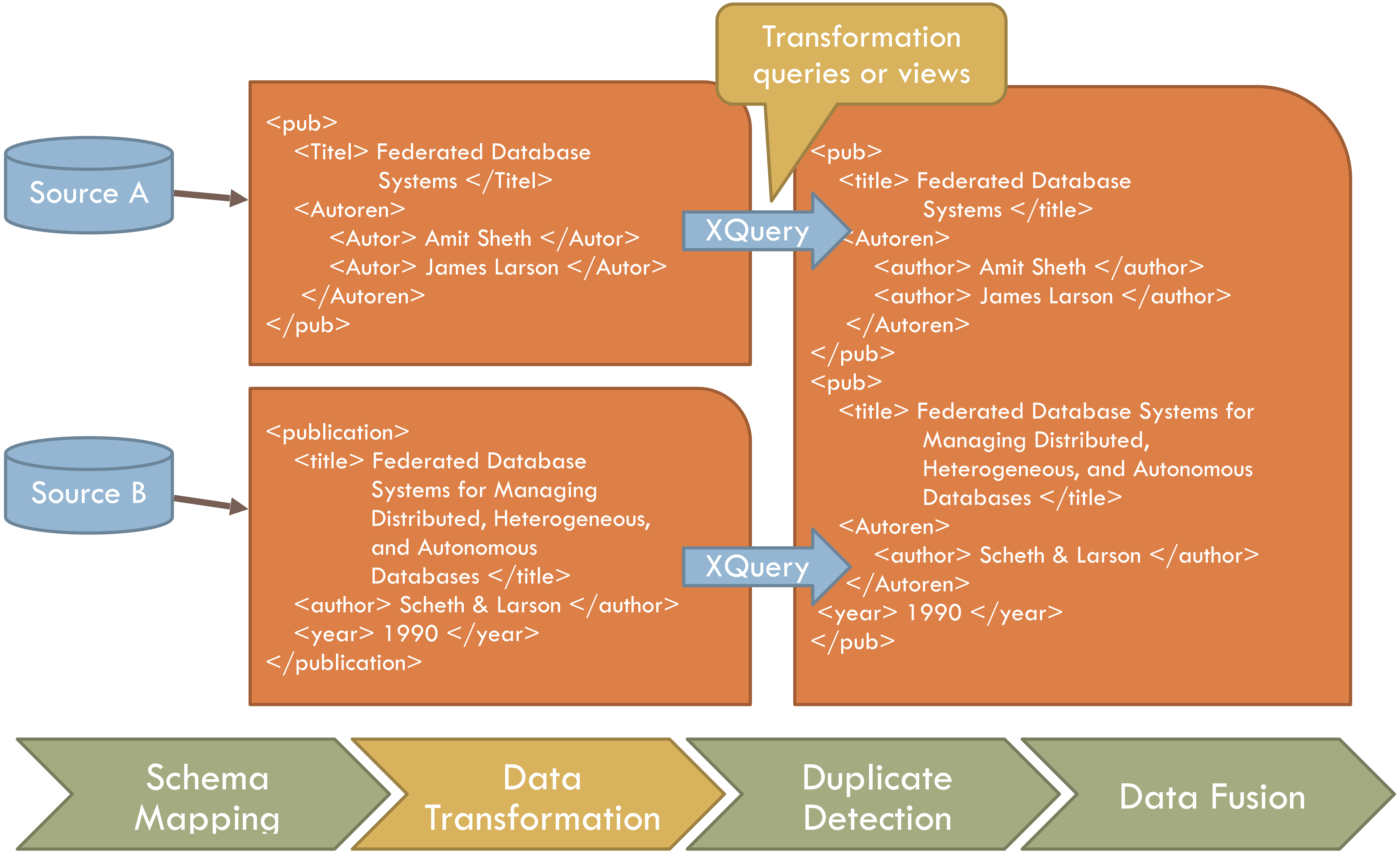

[L. Dong and F. Naumann, 2009]

# Information Integration



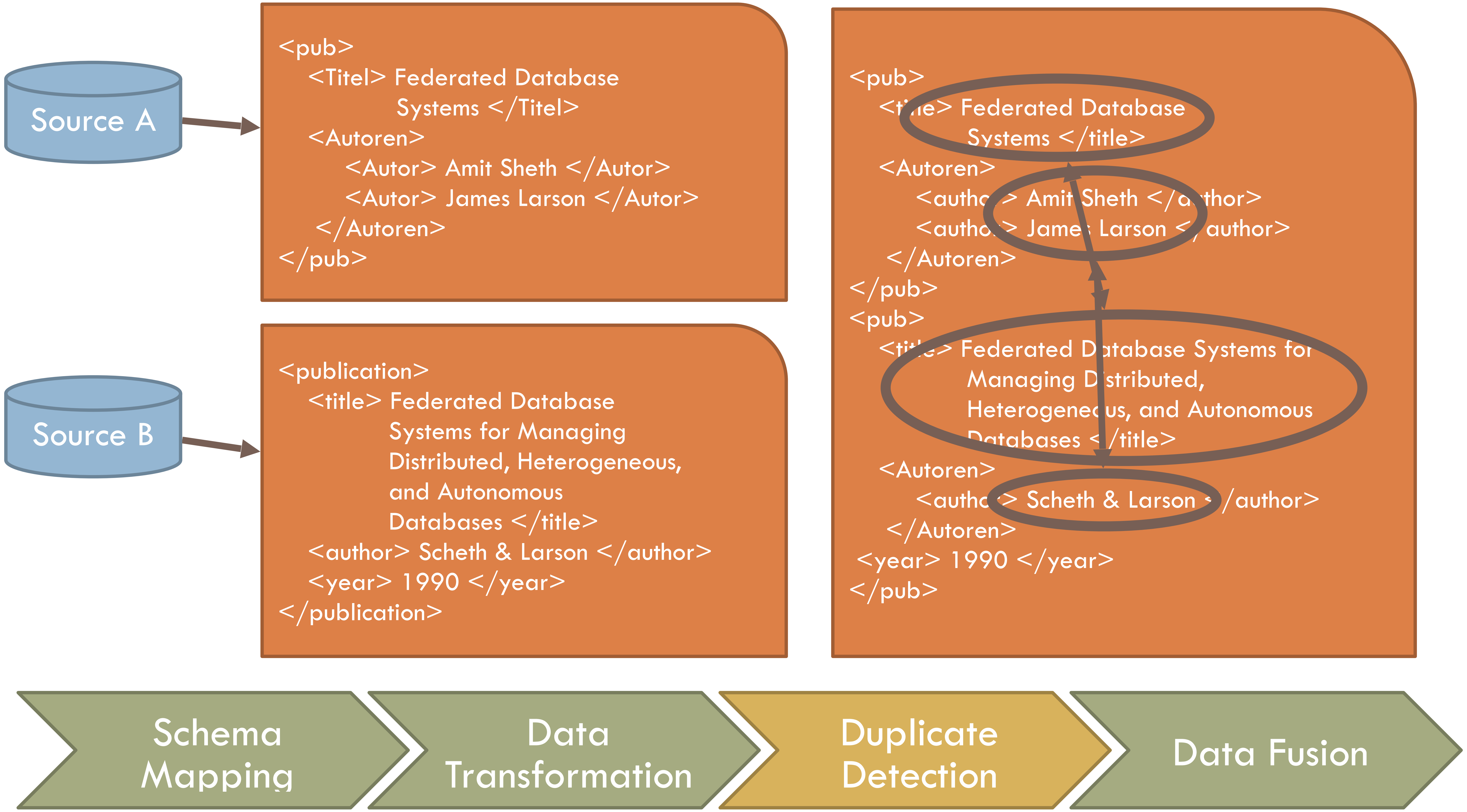

[L. Dong and F. Naumann, 2009]

# Information Integration



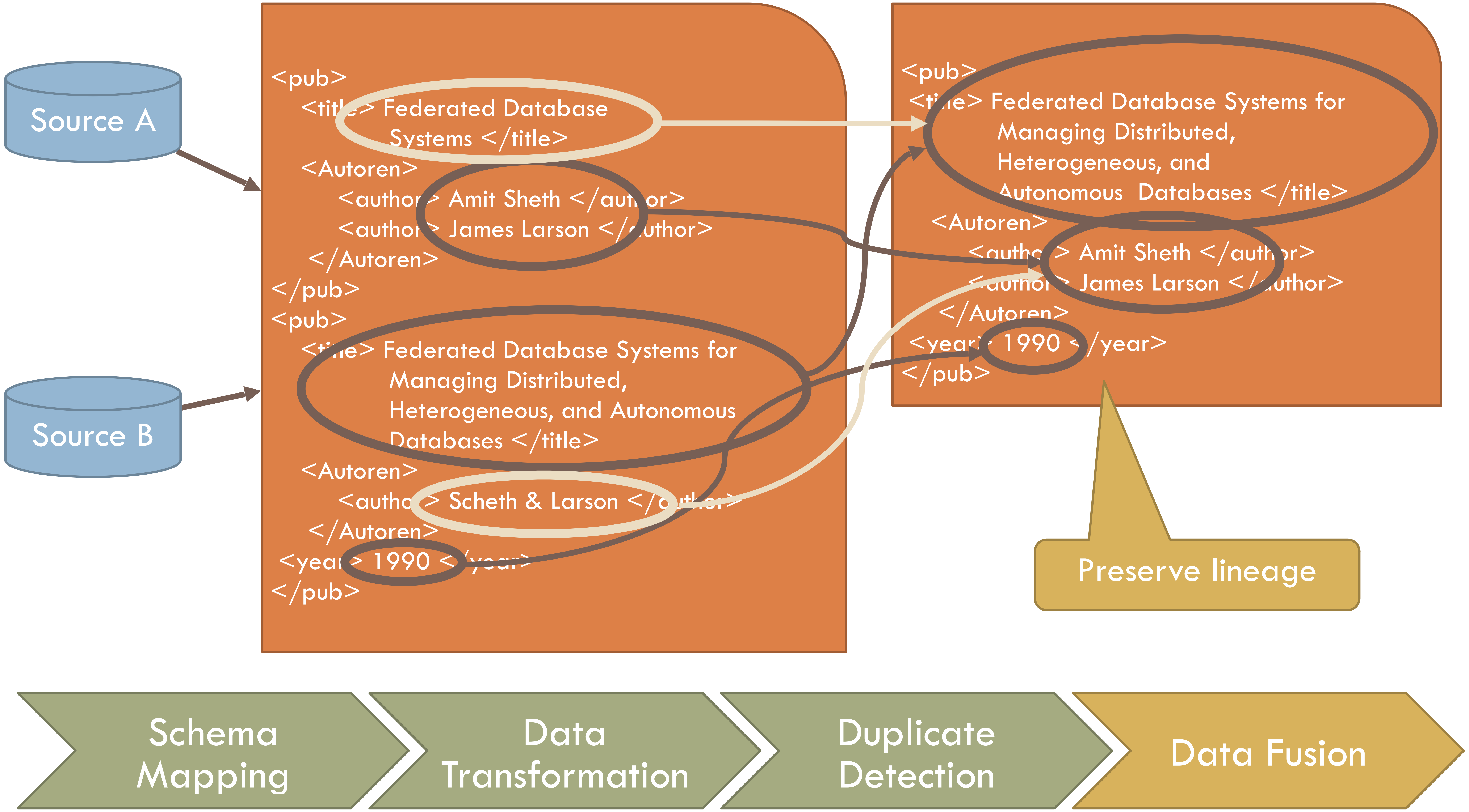

[L. Dong and F. Naumann, 2009]

# Information Integration




[L. Dong and F. Naumann, 2009]

# Information Integration




[L. Dong and F. Naumann, 2009]

# Challenges in Data Fusion when Sources Copy

| | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|
| Stonebraker | MIT | Berkeley | MIT | MIT | MS |
| Dewitt | MSR | MSR | UWisc | UWisc | UWisc |
| Bernstein | MSR | MSR | MSR | MSR | MSR |
| Carey | UCI | AT&T | BEA | BEA | BEA |
| Halevy | Google | Google | UW | UW | UW |

[X L Dong et al., 2009]

# Challenges in Data Fusion when Sources Copy

| | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|
| Stonebraker | MIT | Berkeley | MIT | MIT | MS |
| Dewitt | MSR | MSR | UWisc | UWisc | UWisc |
| Bernstein | MSR | MSR | MSR | MSR | MSR |
| Carey | UCI | AT&T | BEA | BEA | BEA |
| Halevy | Google | Google | UW | UW | UW |

[X L Dong et al., 2009]

# Challenges in Data Fusion when Sources Copy

2. With only a snapshot it is hard to decide which source is a copier.

| | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|
| Stonebraker | MIT | Berkeley | MIT | MIT | MS |
| Dewitt | MSR | MSR | UWisc | UWisc | UWisc |
| Bernstein | MSR | MSR | MSR | MSR | MSR |
| Carey | UCI | AT&T | BEA | BEA | BEA |
| Halevy | Google | Google | UW | UW | UW |

[X L Dong et al., 2009]

# Challenges in Data Fusion when Sources Copy

1. Sharing common data does not in itself imply copying.

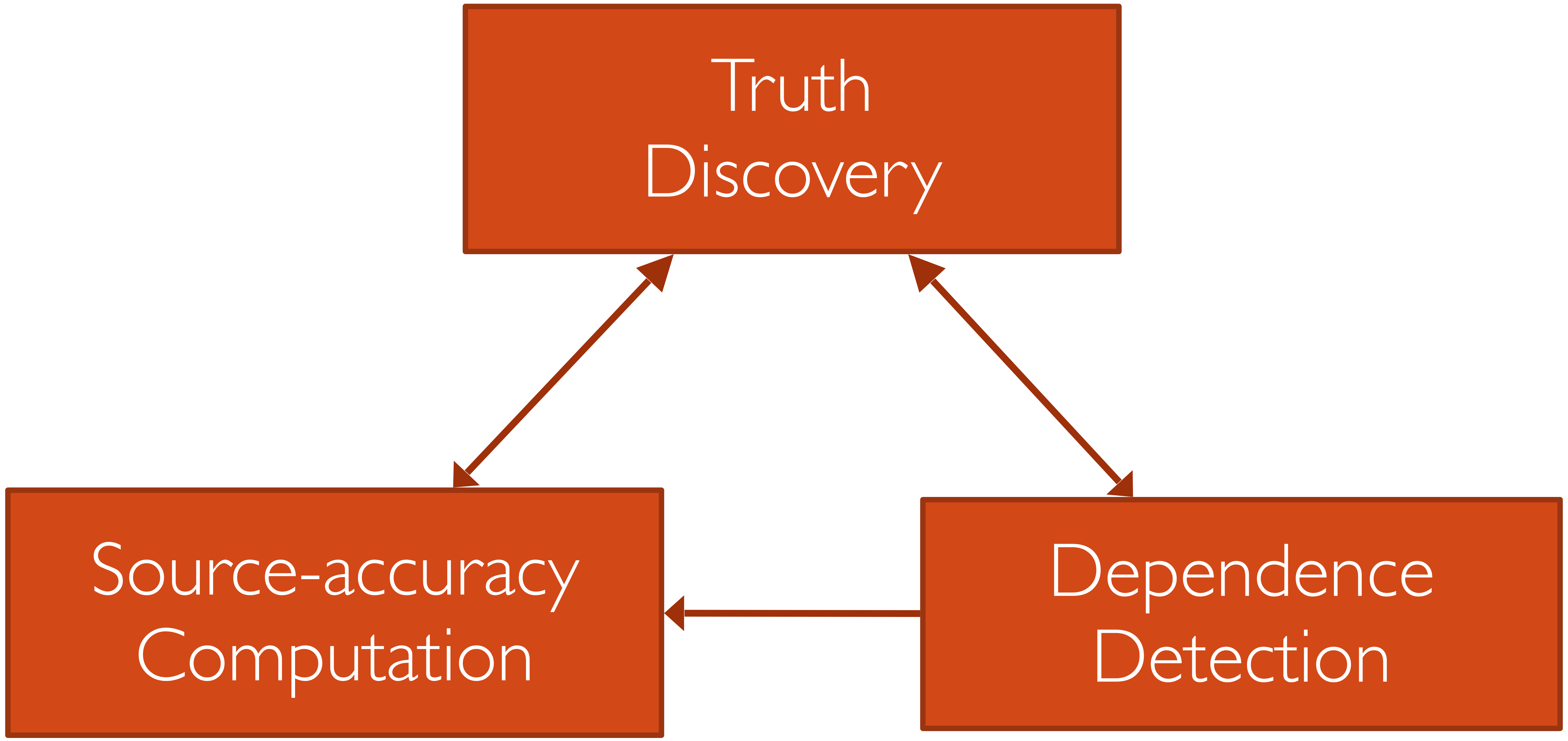
2. With only a snapshot it is hard to decide which source is a copier.

| | S1 | S2 | S3 | S4 | S5 |
|---|---|---|---|---|---|
| Stonebraker | MIT | Berkeley | MIT | MIT | MS |
| Dewitt | MSR | MSR | UWisc | UWisc | UWisc |
| Bernstein | MSR | MSR | MSR | MSR | MSR |
| Carey | UCI | AT&T | BEA | BEA | BEA |
| Halevy | Google | Google | UW | UW | UW |

3. A copier can also provide or verify some data by itself, so it is inappropriate to ignore all of its data.

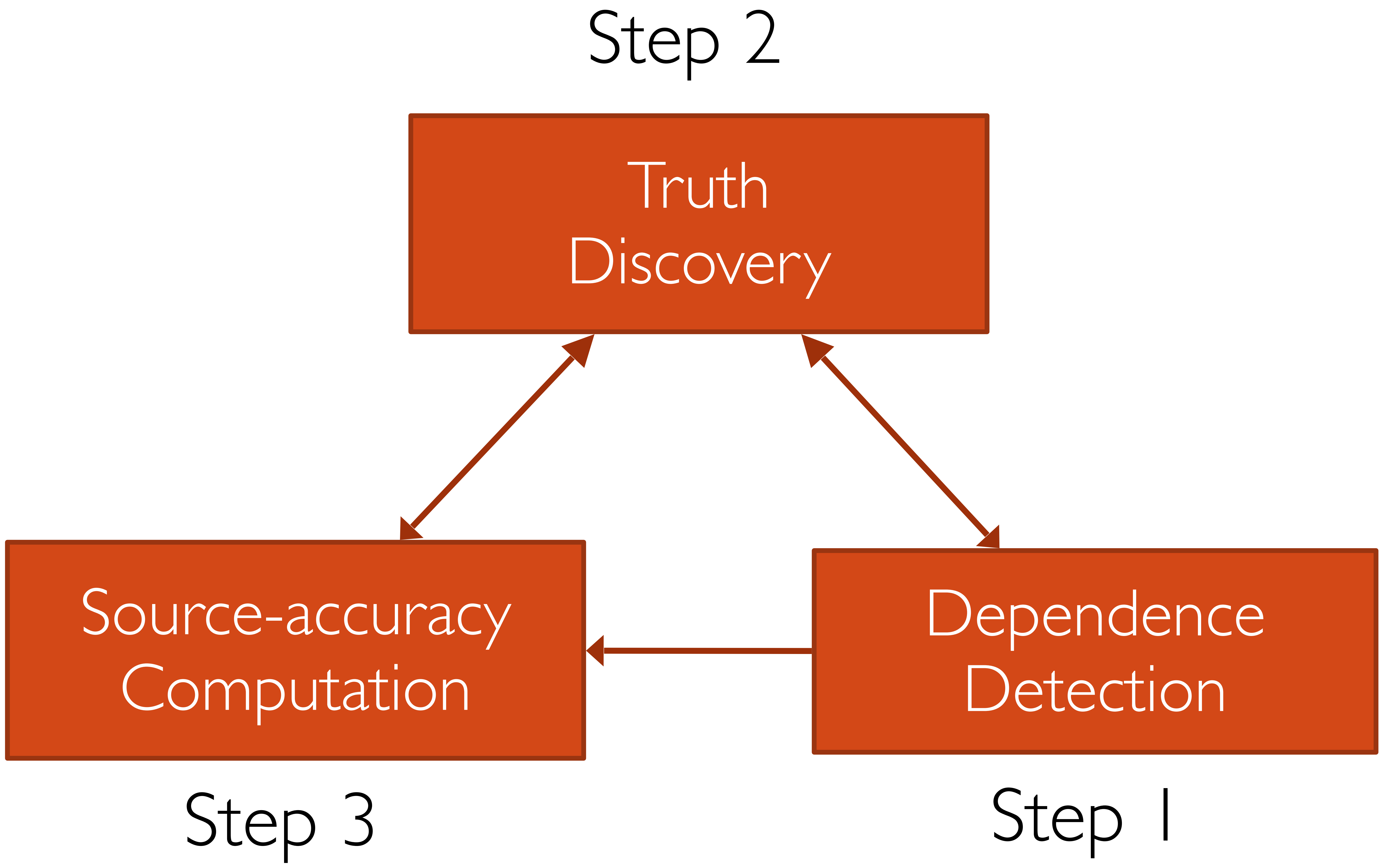
[X L Dong et al., 2009]

# Source Dependence: Iteration on Truth and Sources




[X L Dong et al., 2009]

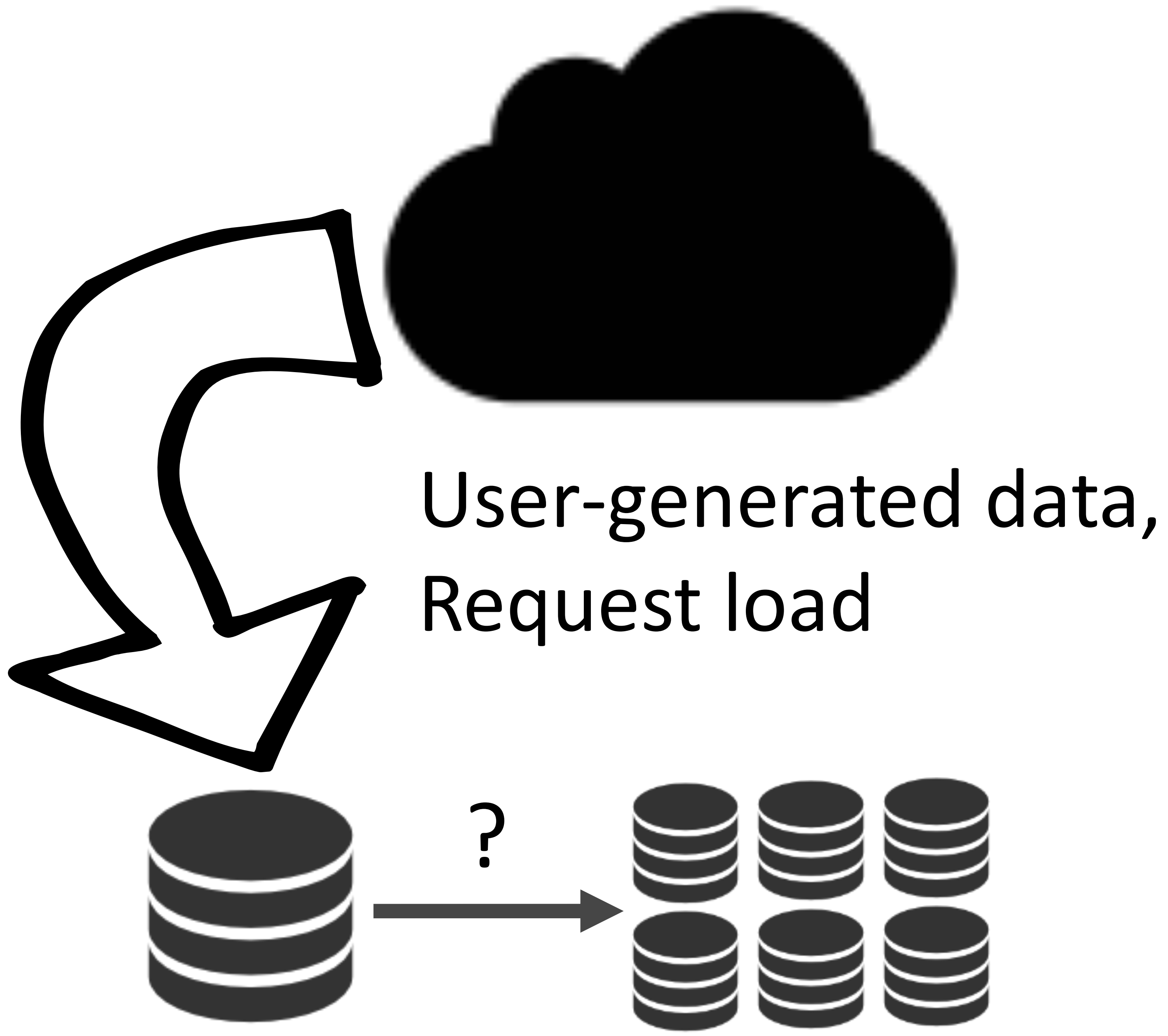
# Source Dependence: Iteration on Truth and Sources



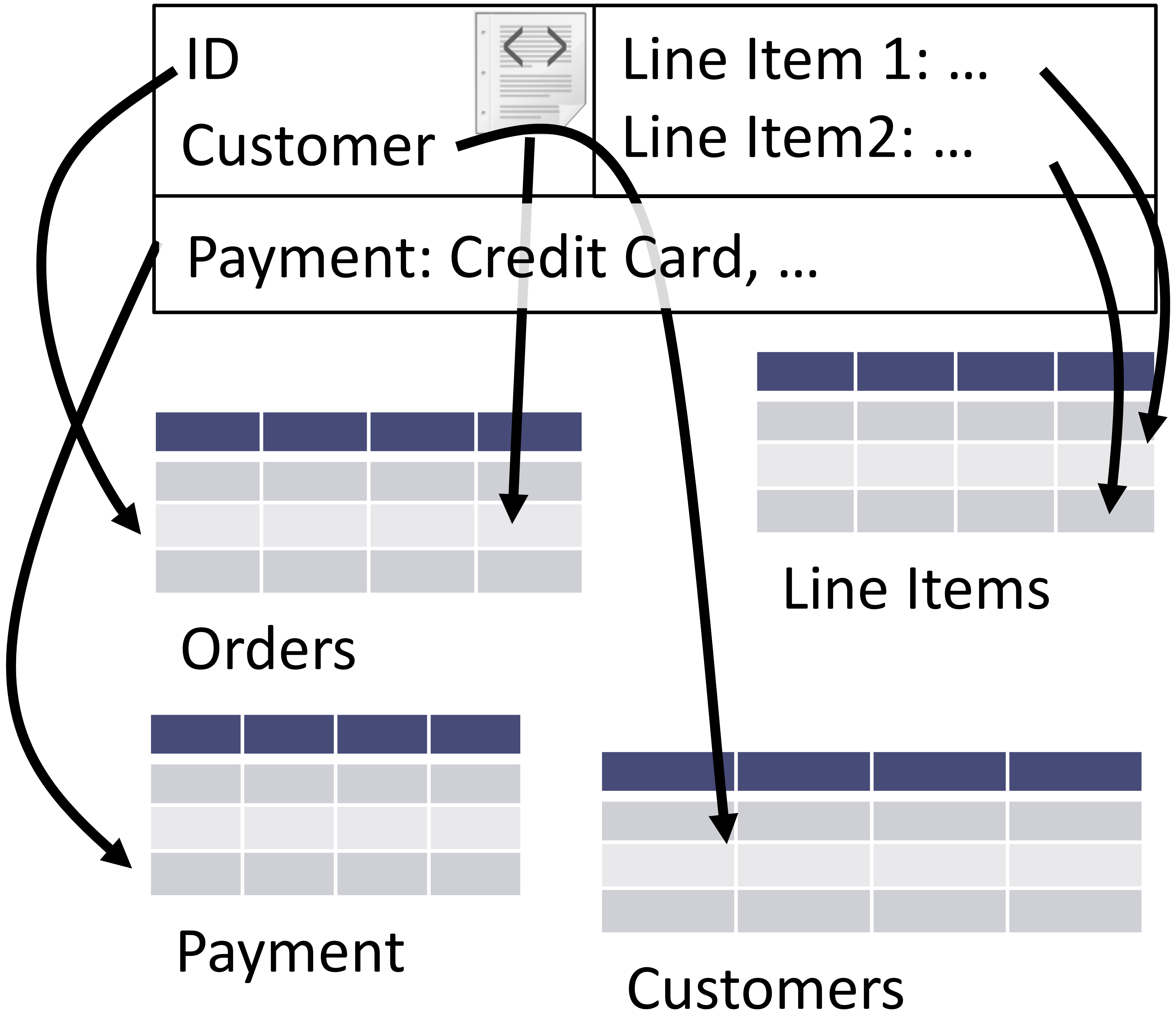

[X L Dong et al., 2009]

# NoSQL Motivation

## Scalability




## Impedance Mismatch




[F. Gessert et al., 2017]

# Column Stores

row id = 1

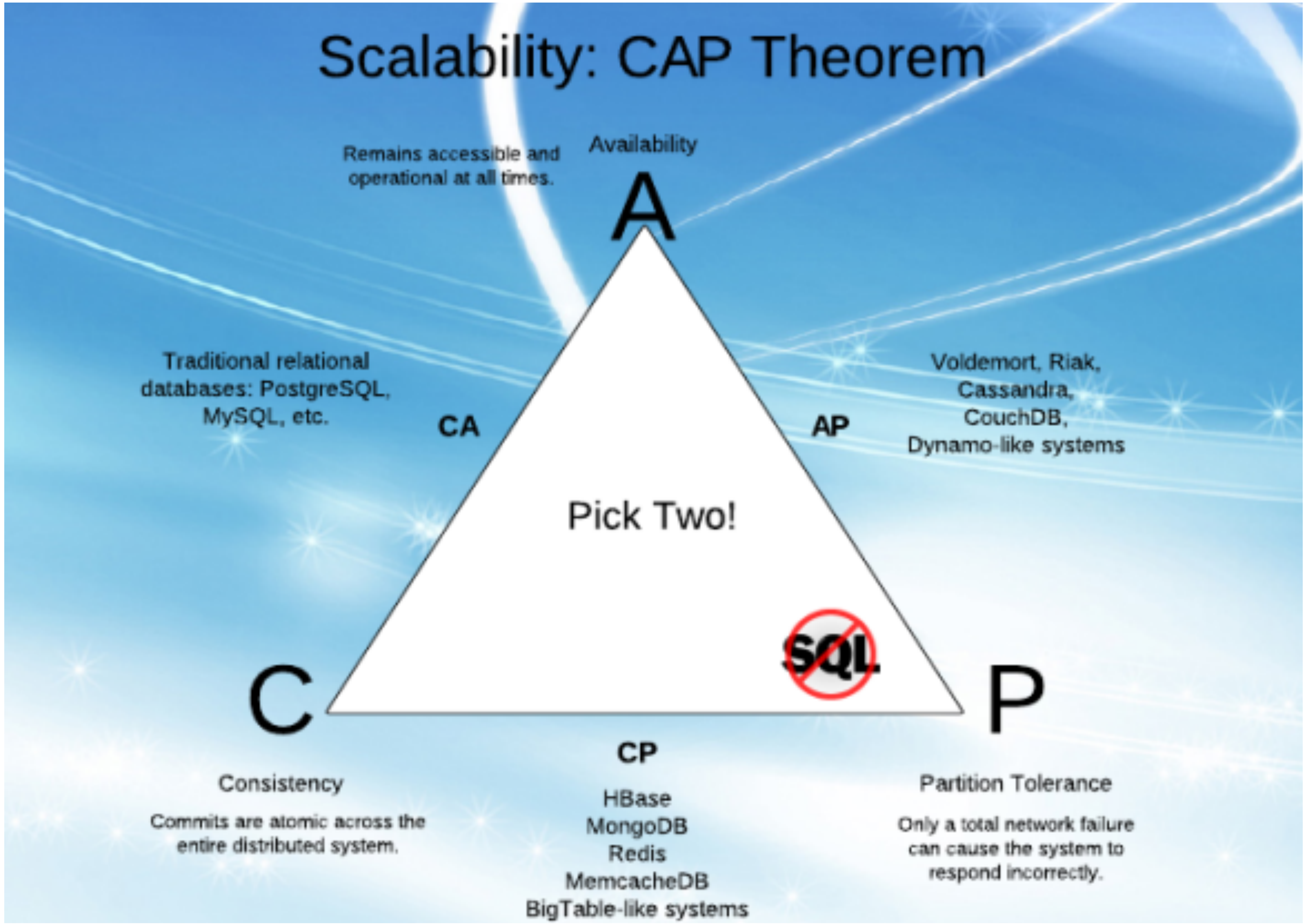
row id = 6

| id | Title | Person | Genre |
|---|---|---|---|
| 1 | Mrs. Doubtfire | Robin Williams | Comedy |
| 2 | Jaws | Roy Scheider | Horror |
| 3 | The Fly | Jeff Goldblum | Horror |
| 4 | Steel Magnolias | Dolly Parton | Drama |
| 5 | The Birdcage | Nathan Lane | Comedy |
| 6 | Erin Brokovitch | Julia Roberts | Drama |

Each column has a file or segment on disk

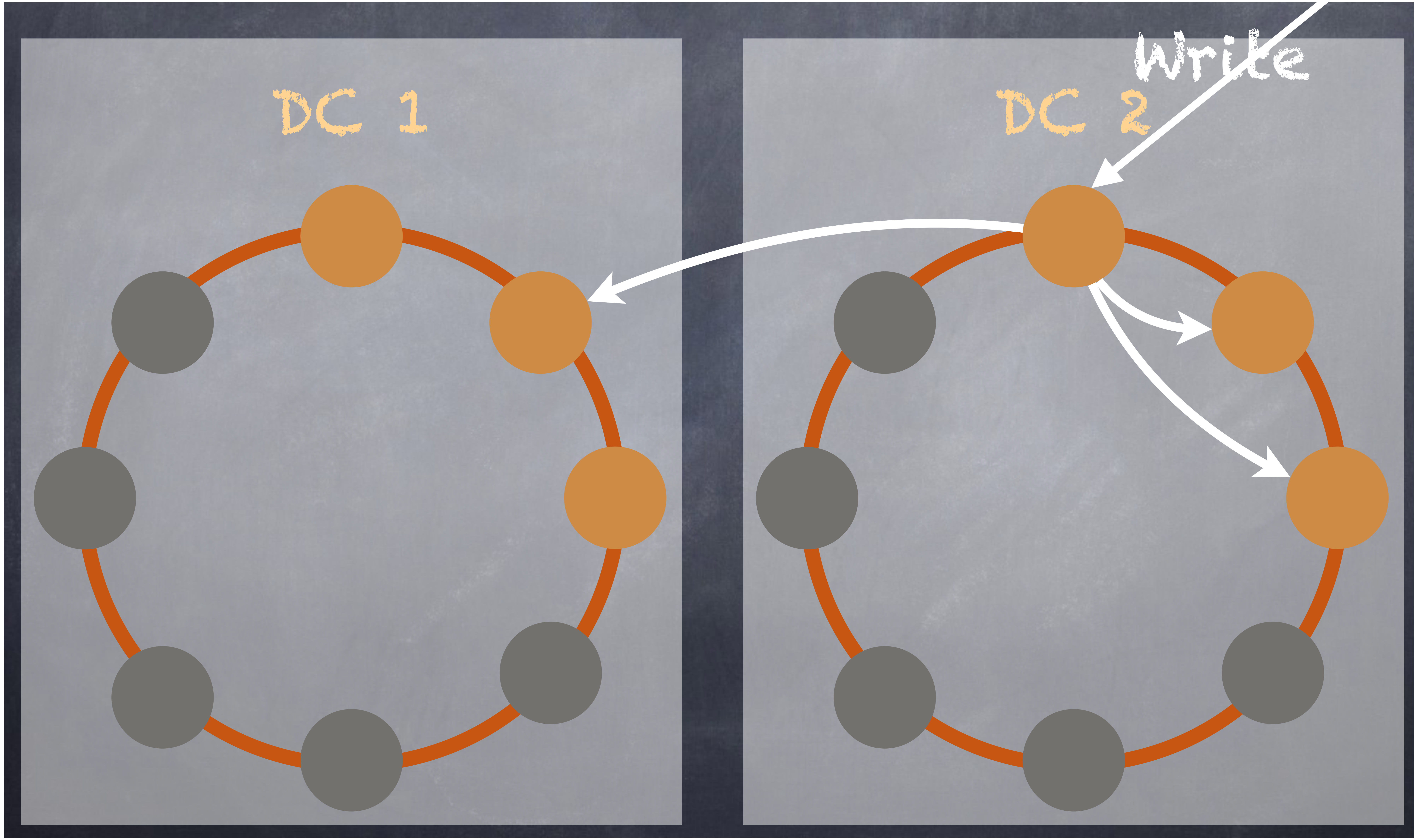
[J. Swanhart, Introduction to Column Stores]

# CAP Theorem




[E. Brewer]

# Cassandra: Replication and Consistency



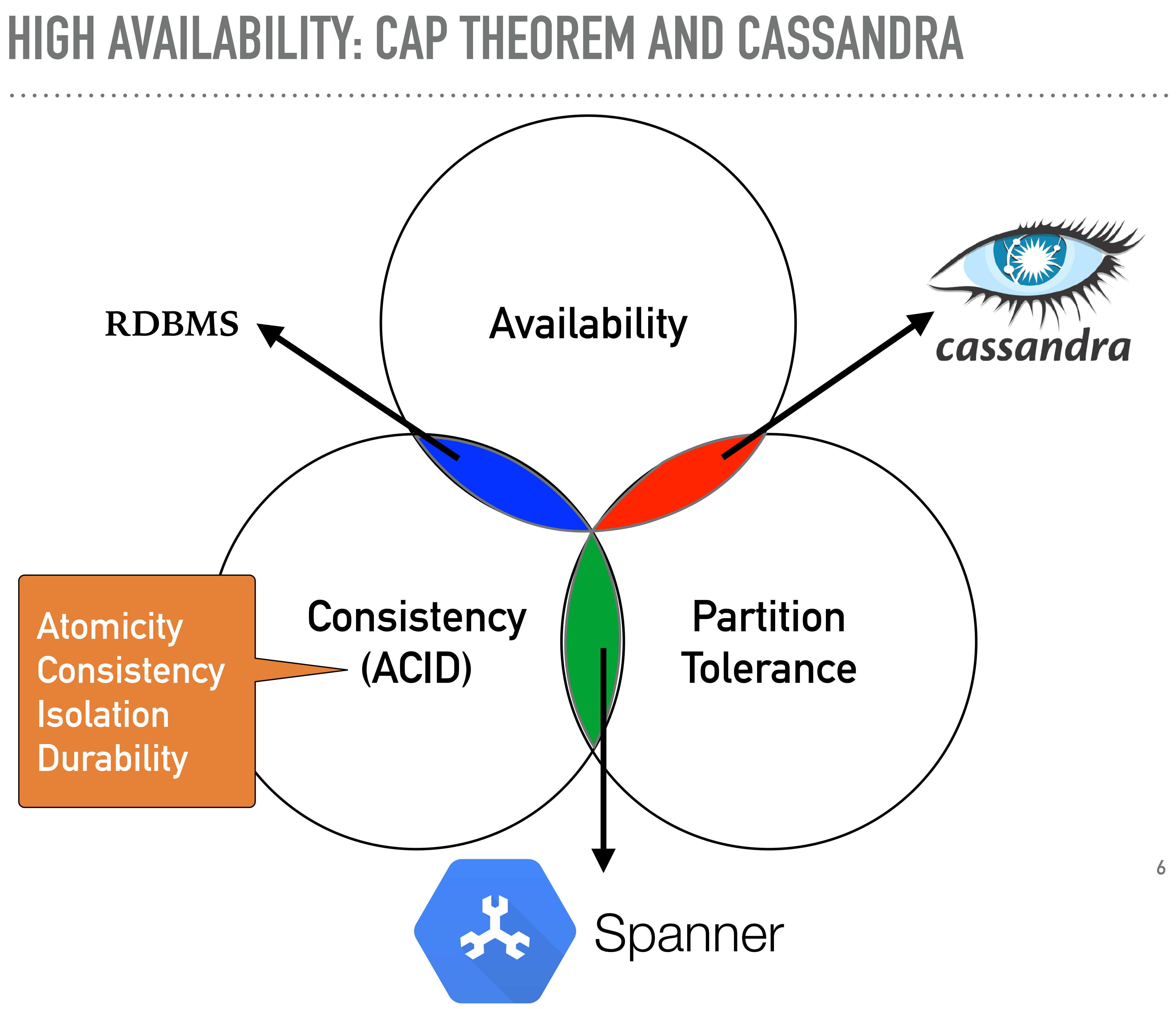

[R. Stupp]

# Three Types of NewSQL Systems

- New Architectures
  - New codebase without architectural baggage of legacy systems
  - Examples: VoltDB, Spanner, Clustrix
- Transparent Sharding Middleware:
  - Transparent data sharding & query redirecting over cluster of single-node DBMSs
  - Examples: citusdata, ScaleArc (usually support MySQL/postgres wire)
- Database-as-a-Service:
  - Distributed architecture designed specifically for cloud-native deployment
  - Examples: xeround, GenieDB, FathomDB (usually based on MySQL)

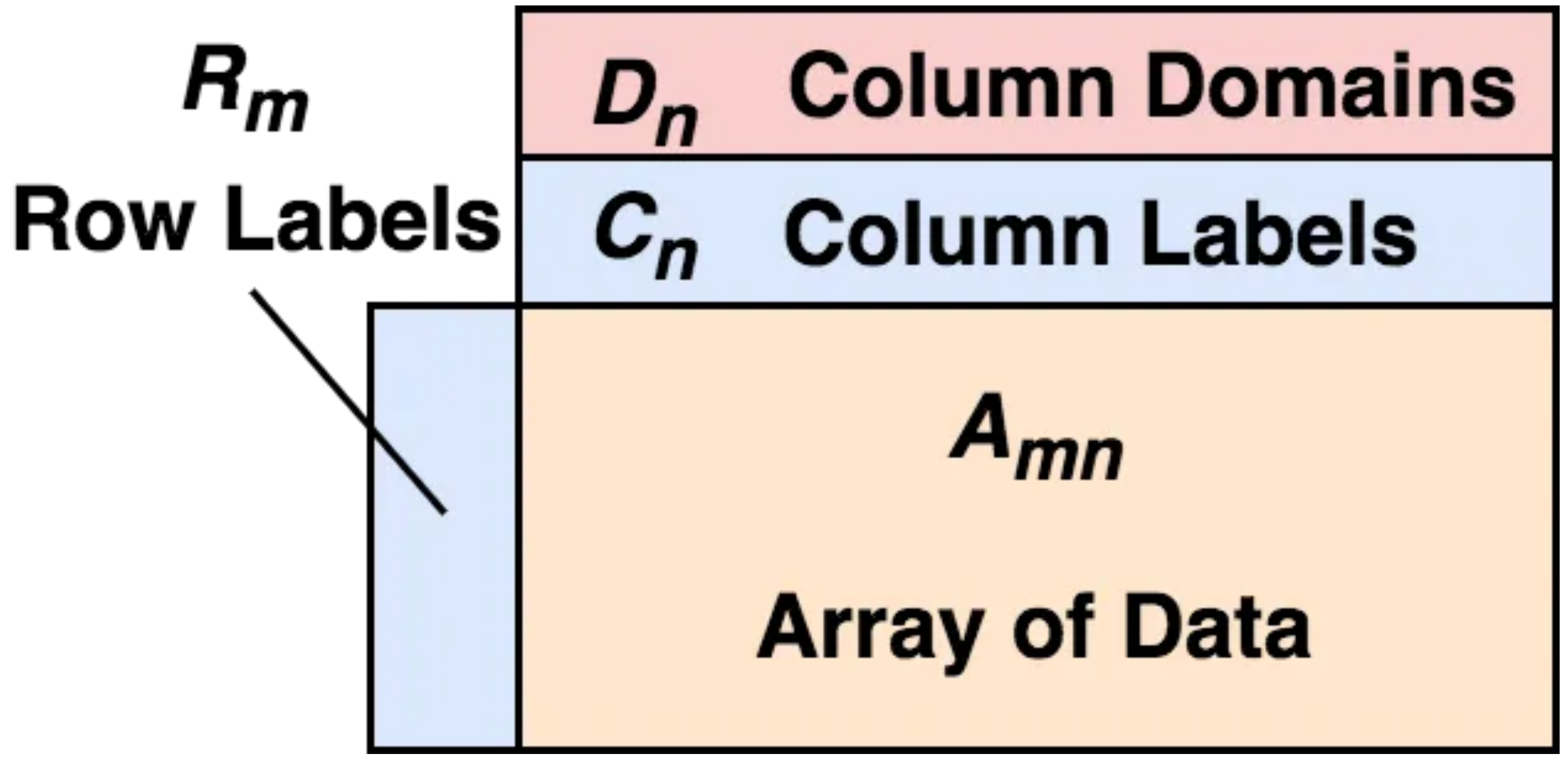
[A. Pavlo]

# Spanner: Google's NewSQL Cloud Database




- Which type of system is Spanner?
  - C: consistency, which implies a single value for shared data
  - A: 100% availability, for both reads and updates
  - P: tolerance to network partitions
- Which two?
  - CA: close, but not totally available
  - So actually **CP**

# Dataframe Data Model




- Combines parts of matrices, databases, and spreadsheets
- Ordered, but not necessarily sorted
  - Rows and columns
- No predefined schema necessary
  - Types can be induced at runtime
- Typed Row/column labels
  - Labels can become data
- Indexing by label or row/column number
  - "Named notation" or "Positional notation"

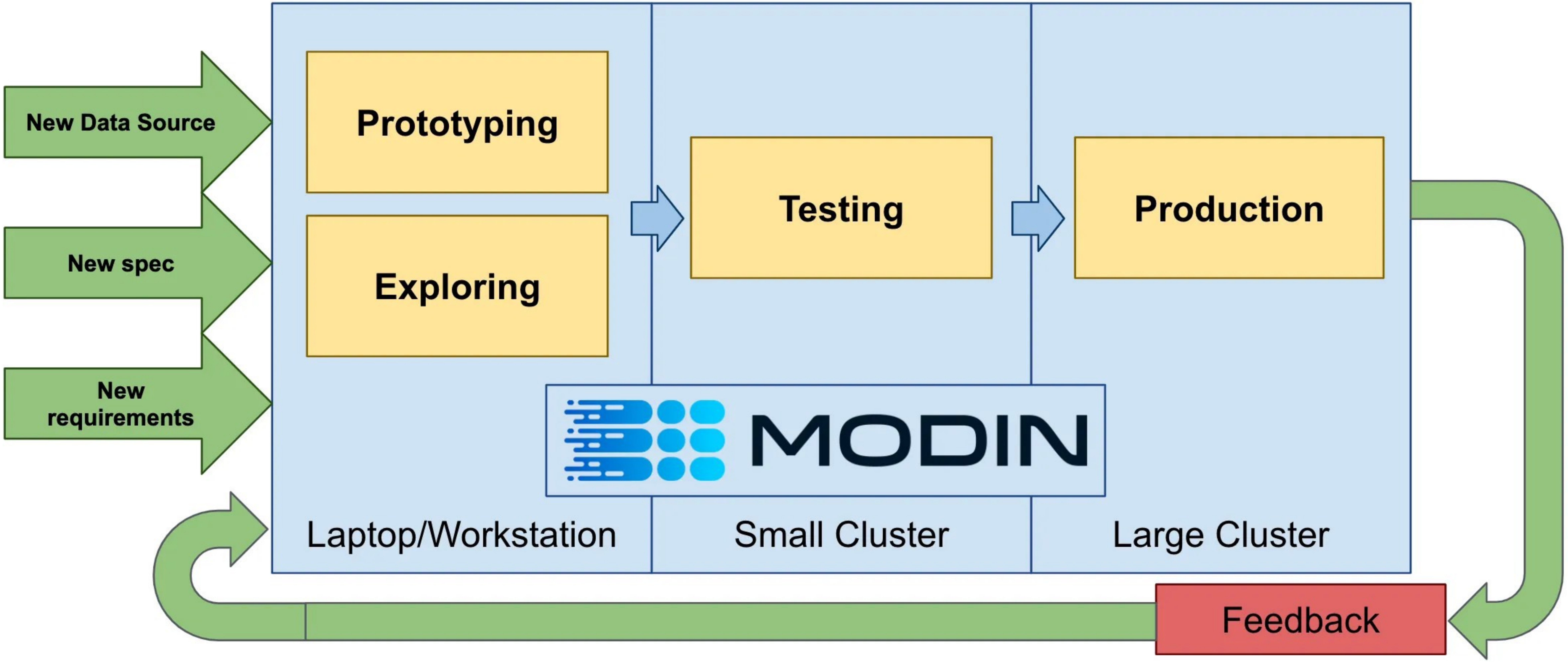
[D. Petersohn]

# Differences between Databases & Dataframes


| | | |
|---|---|---|
| **Convenience** | Entire query at once | Incremental + inspection |
| **Flexible** | Strict schema | Mixed types, R/C and data/metadata equiv. |
| **Versatility** | SFW or bust | 600+ functions |

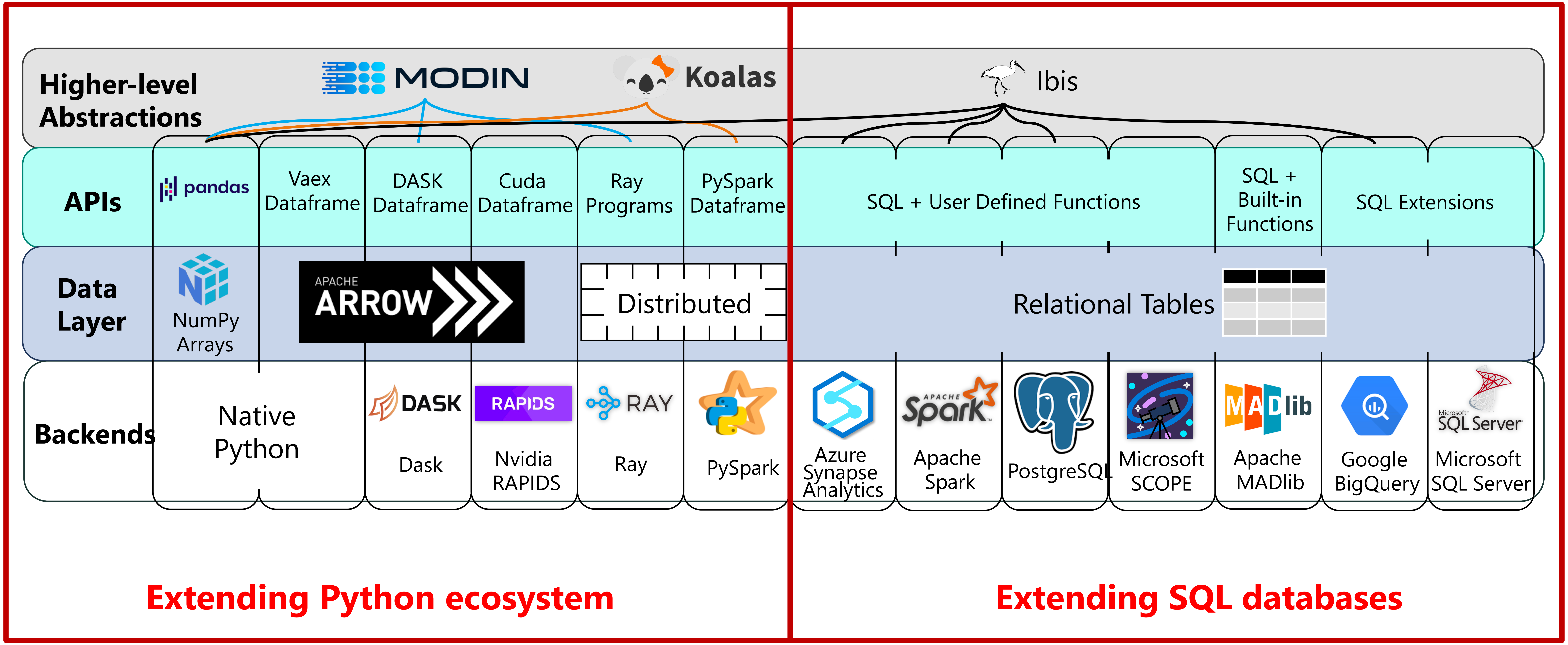
[D. Petersohn, 2022]

# Modin as a Way to Scale Dataframes



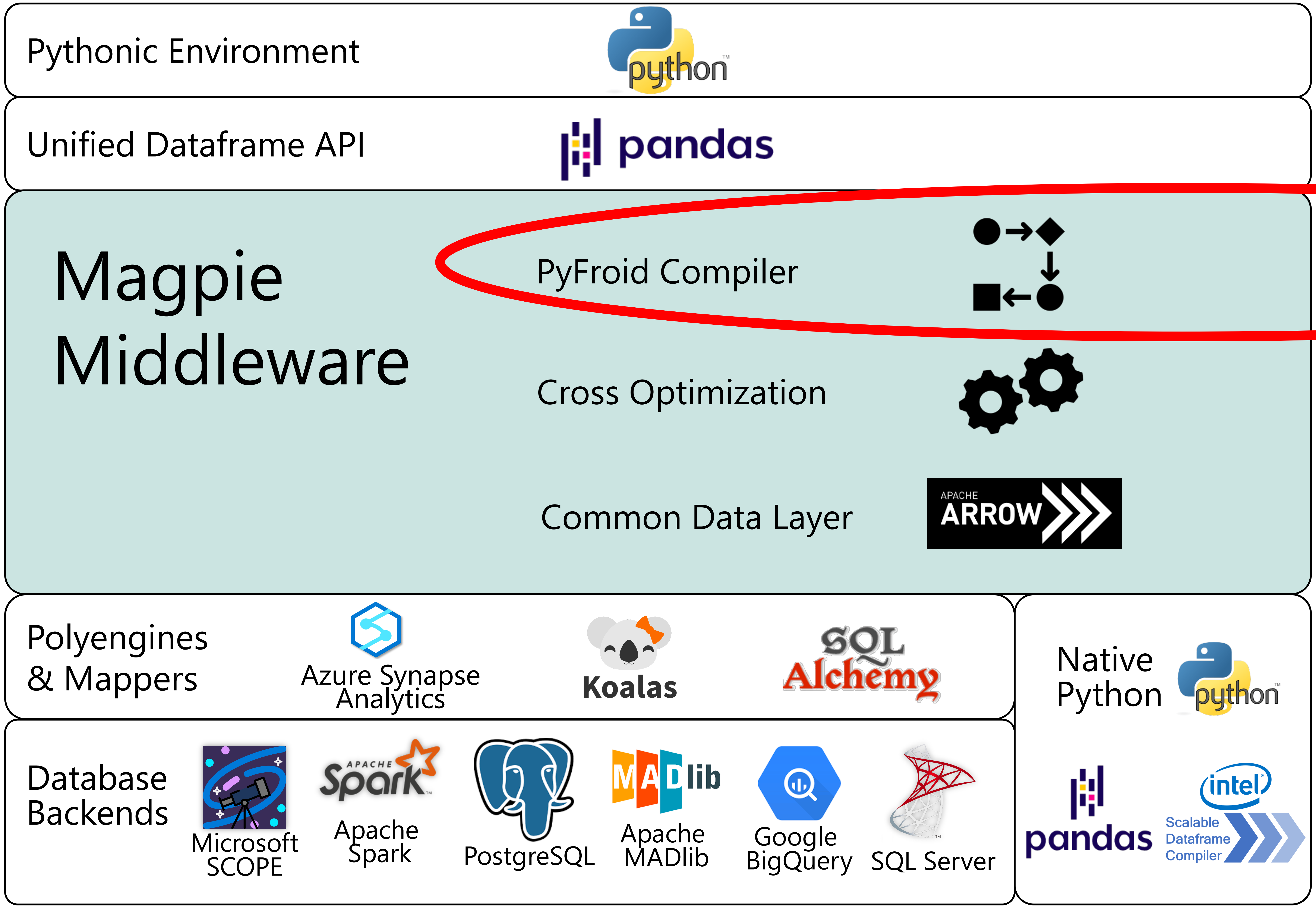

[D. Petersohn]

# Data Science Jungle



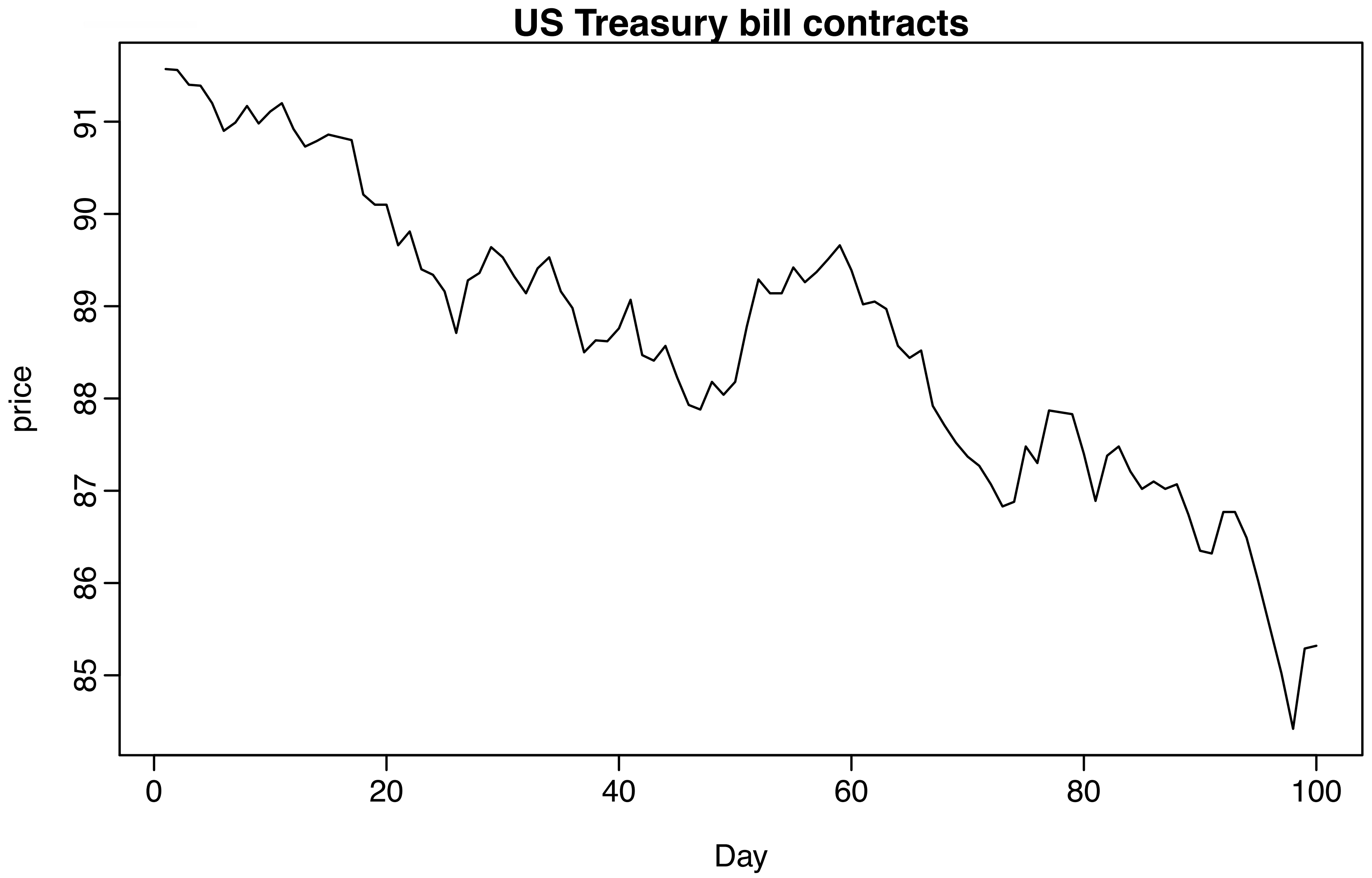

[A. Jindal et al., 2021]

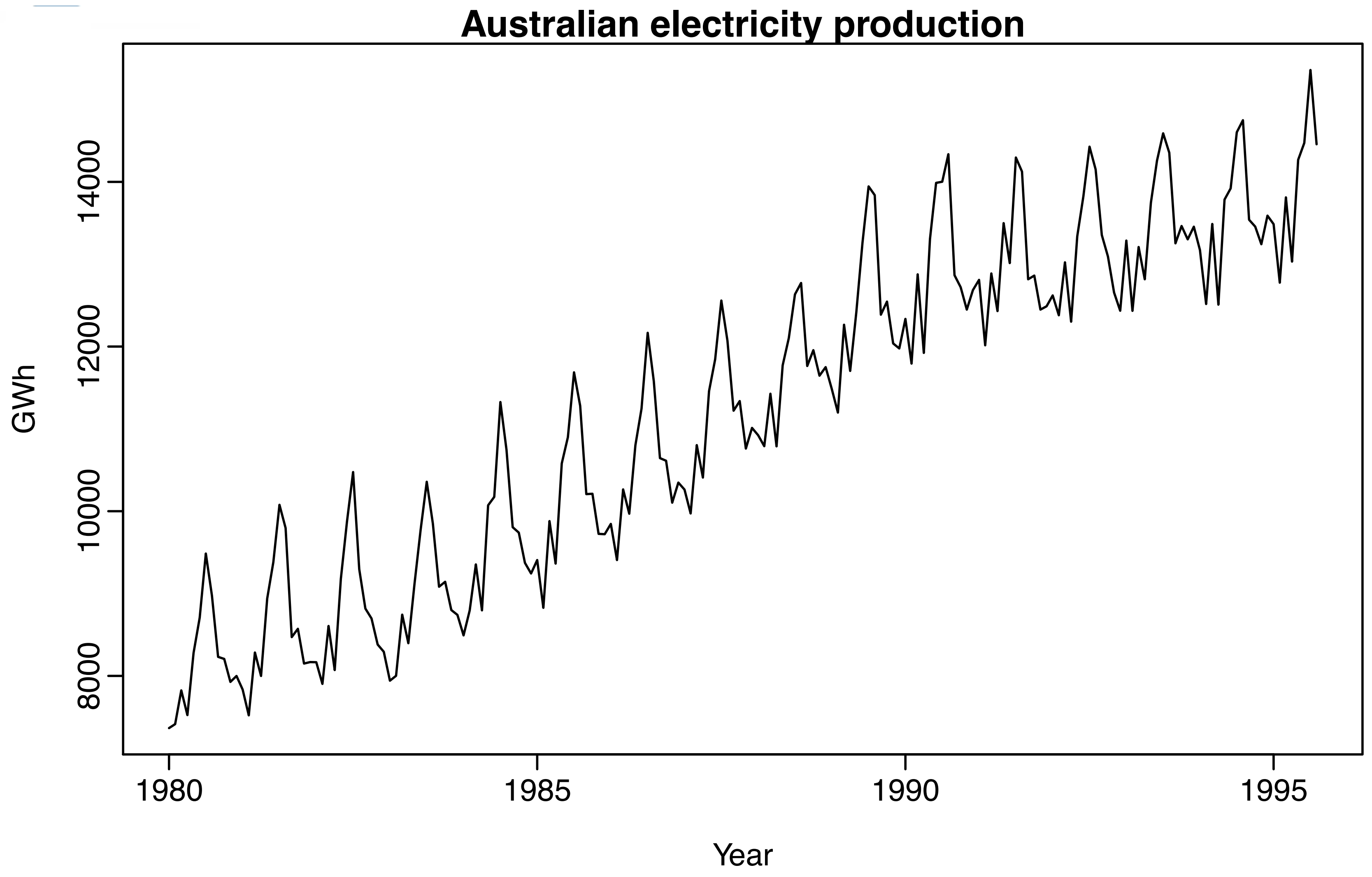
# Magpie Goals

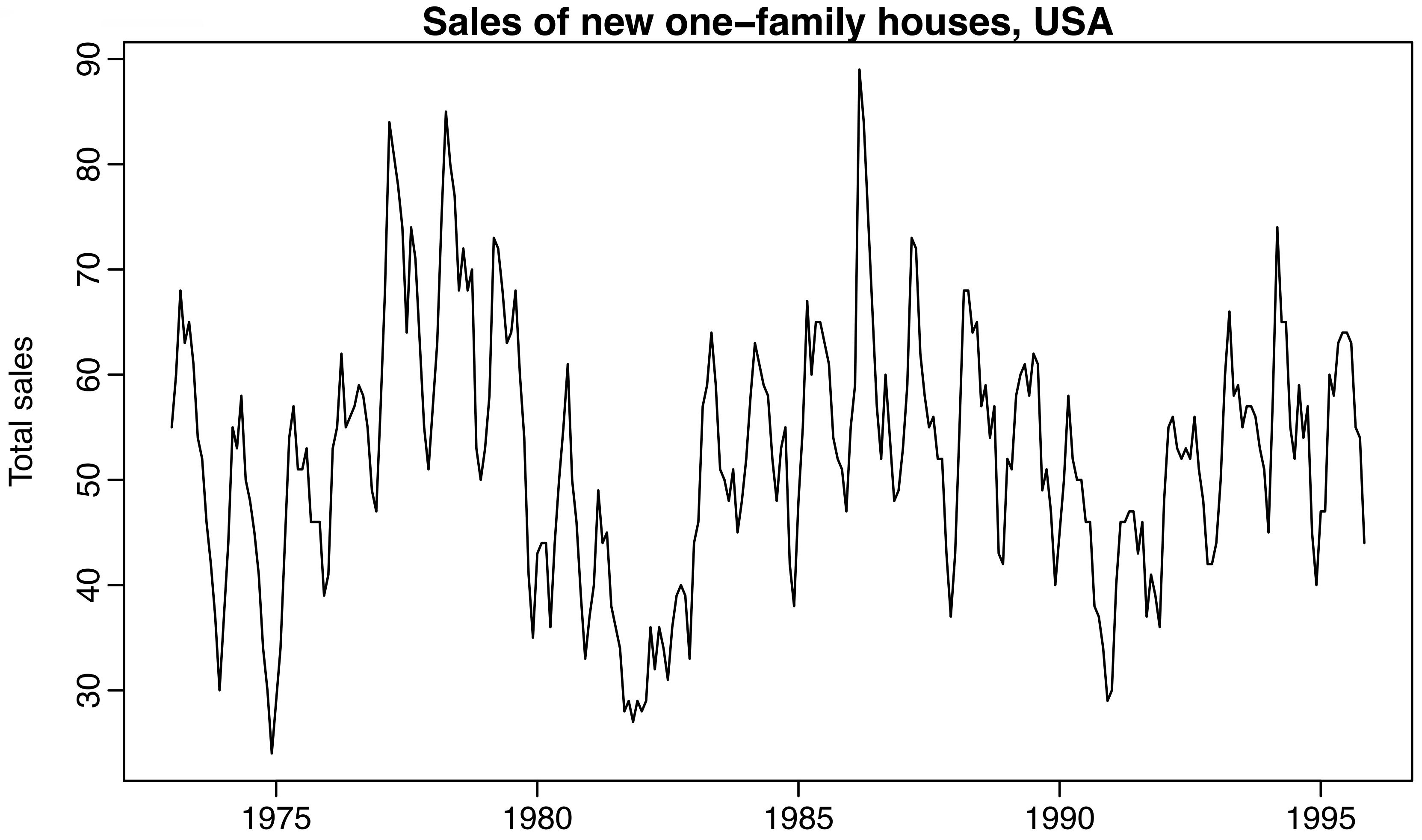


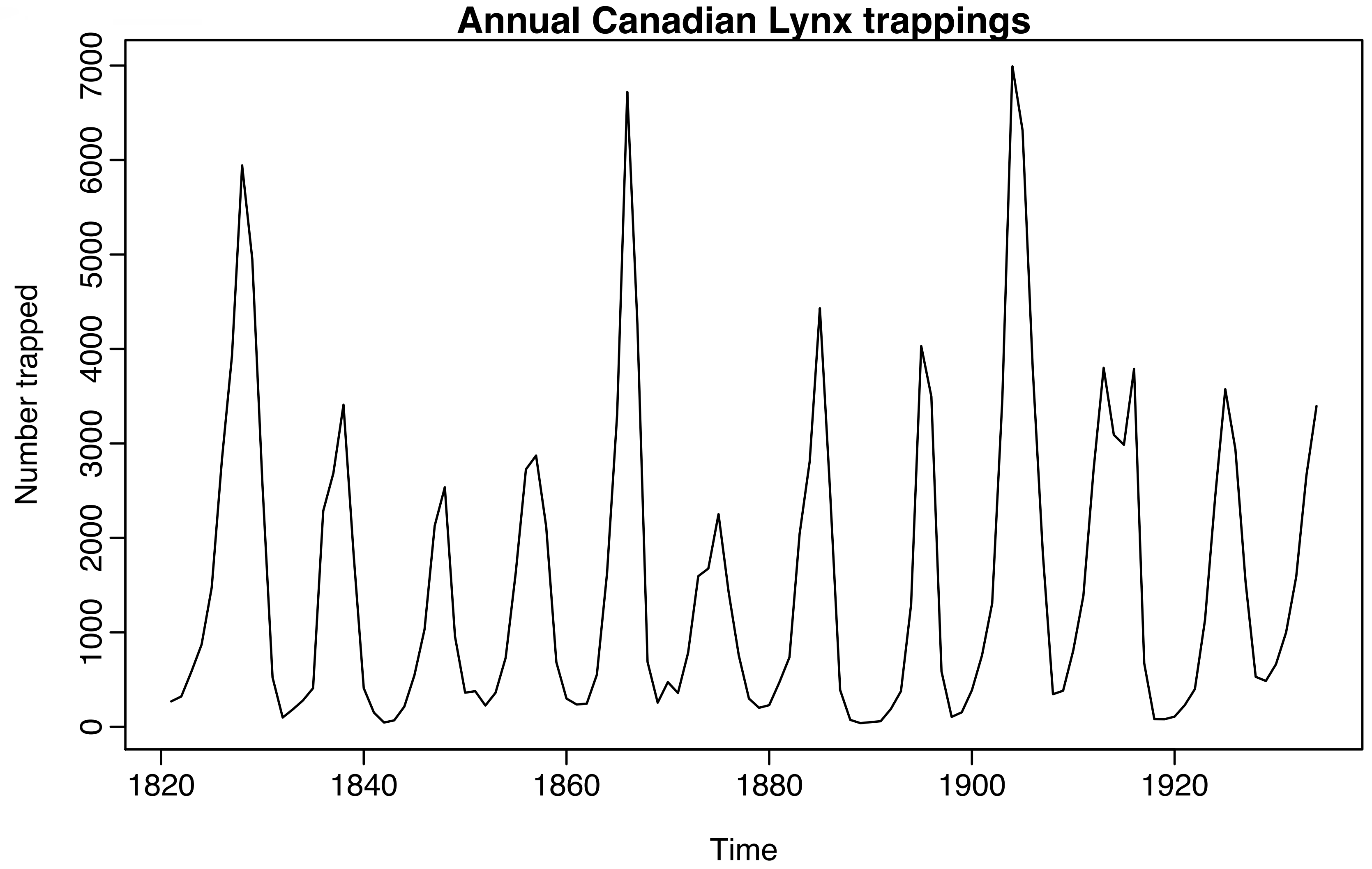

- Familiar Python surface
- Ongoing standardization
- Batching Pandas into large query expressions
- Backend selection using past workloads
- Cache commonly seen dataframes
- Multi-backend environments and libraries
- Cloud backends

# Time Series Data



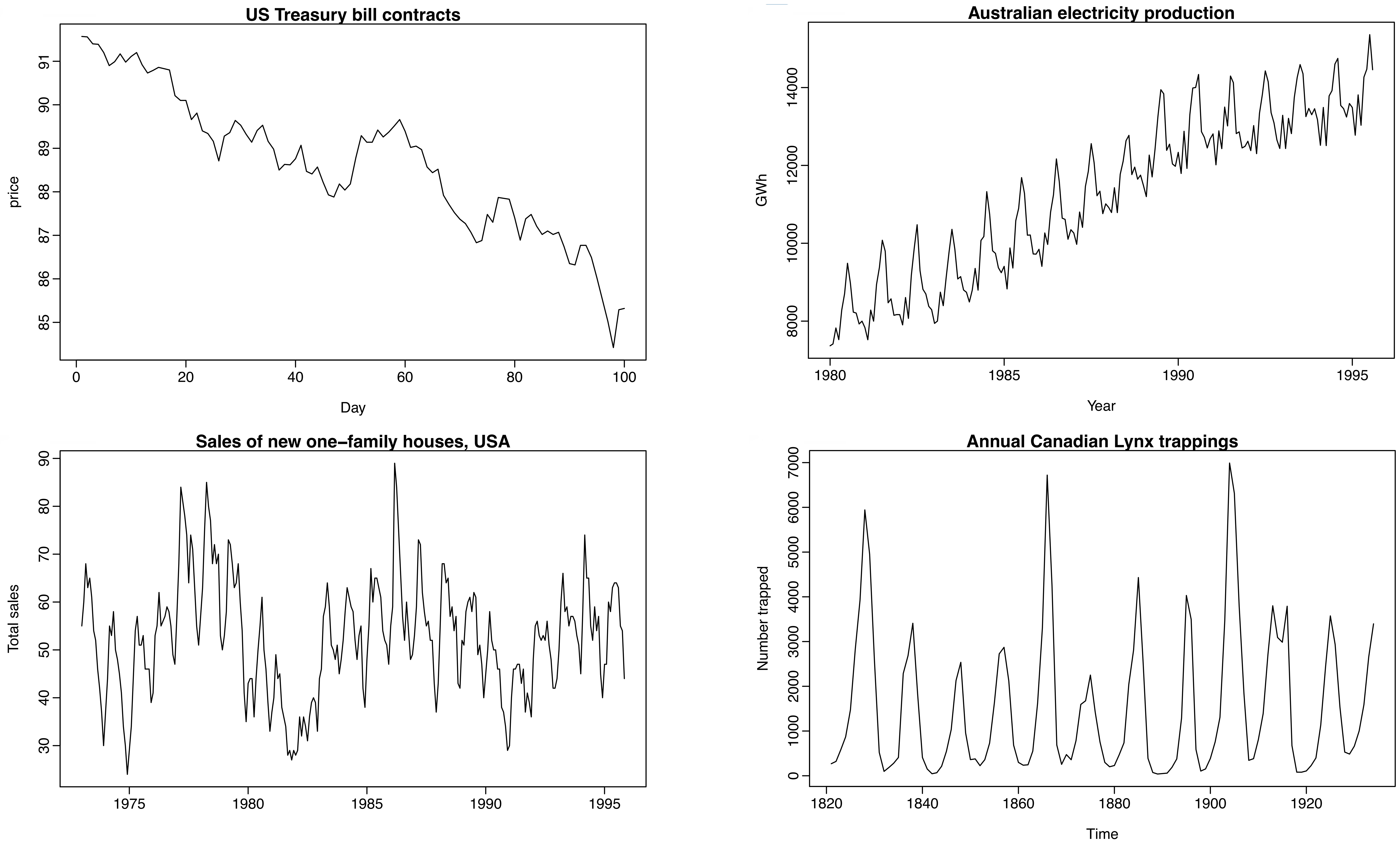




[R. J. Hyndman]

# Time Series Data

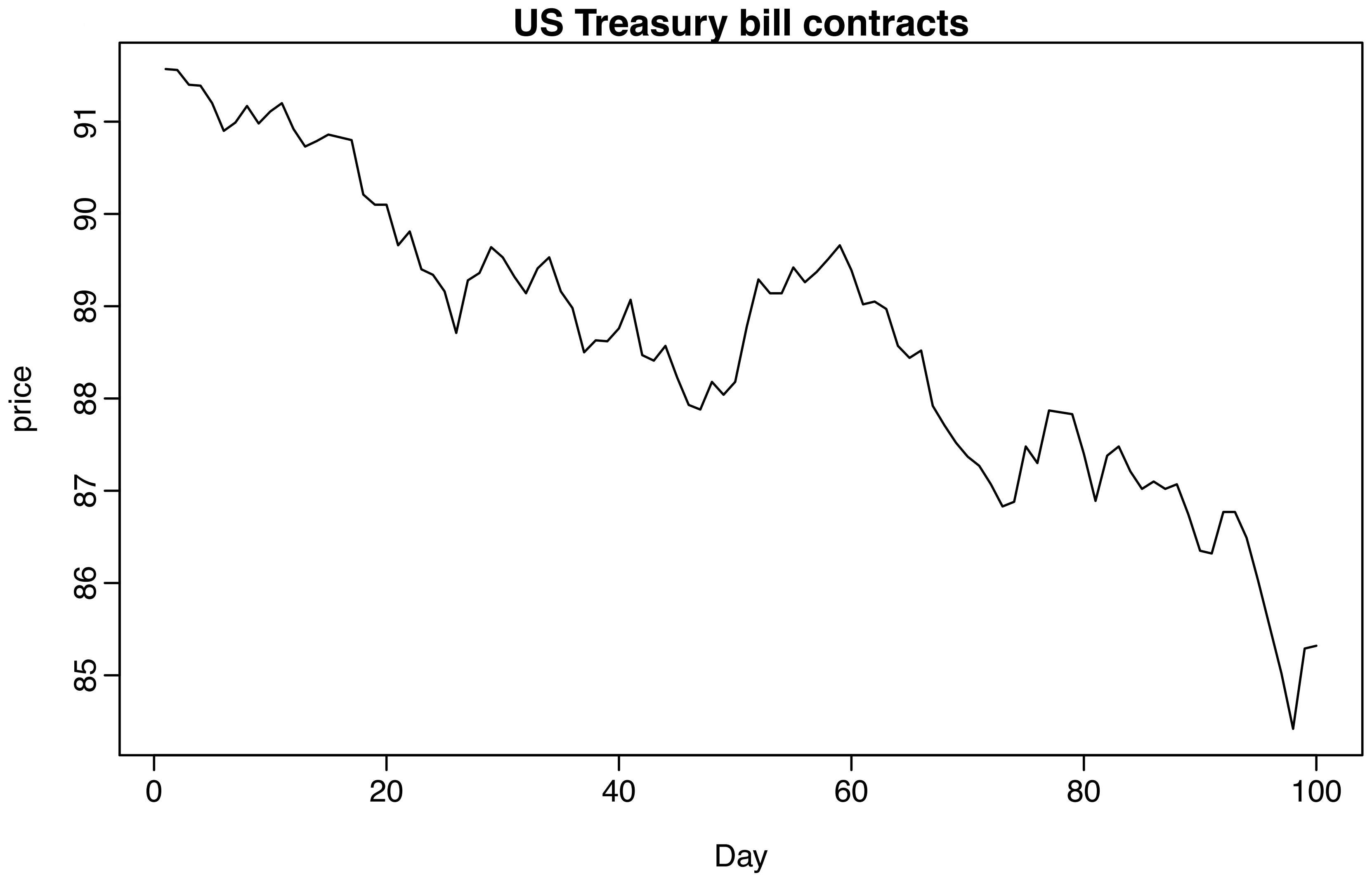
Trend

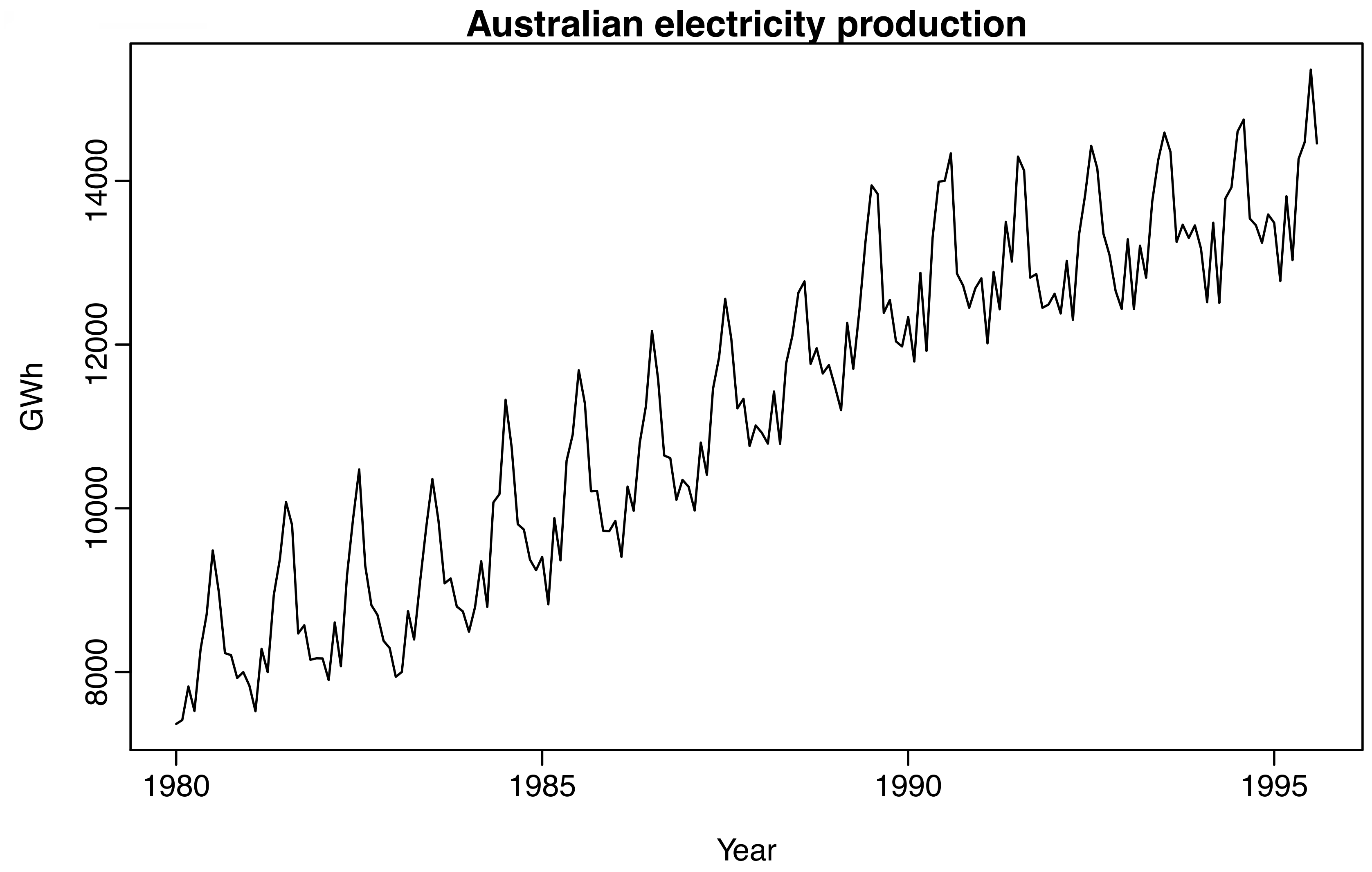



[R. J. Hyndman]

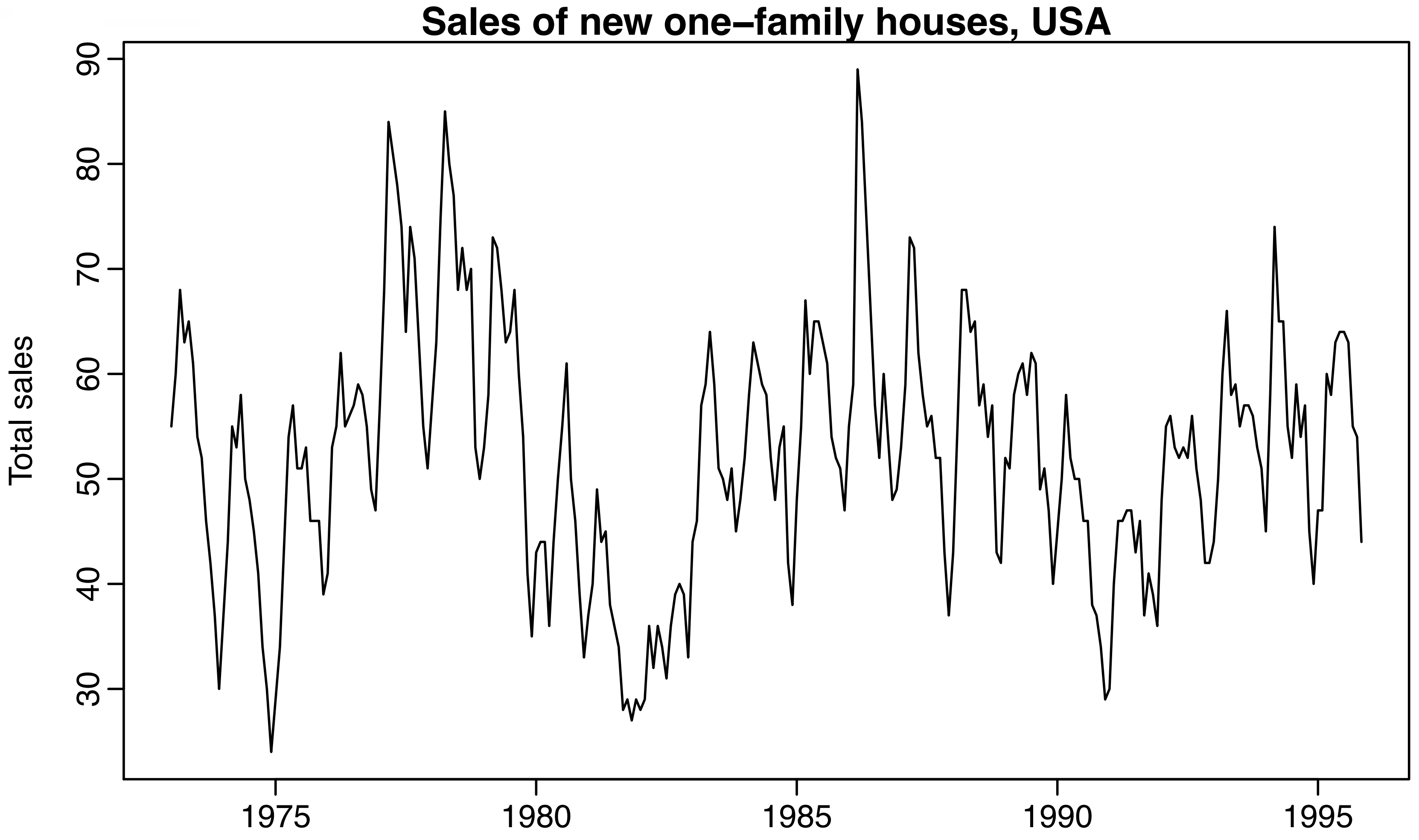
# Time Series Data

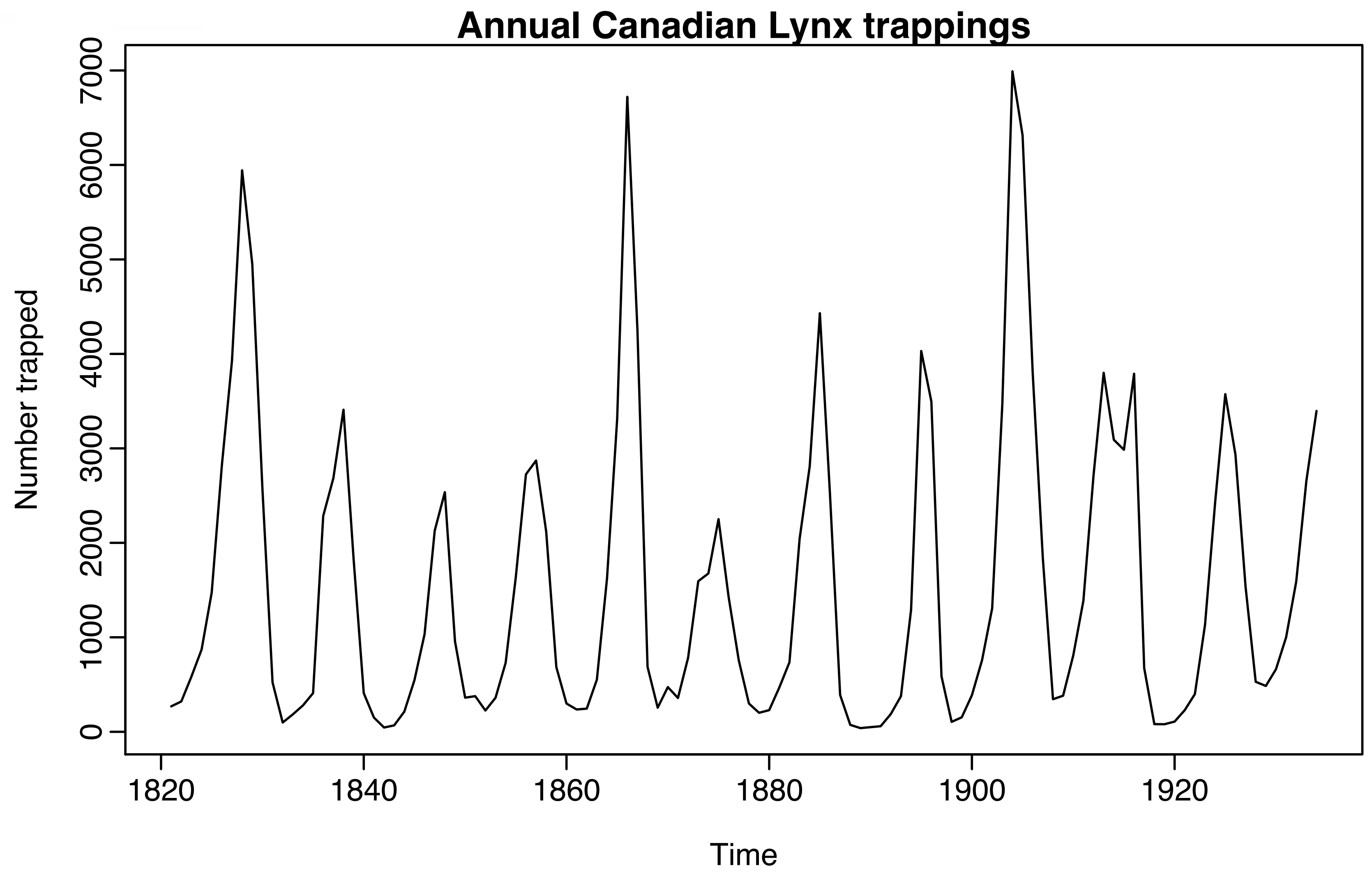
Trend




Trend + Seasonality

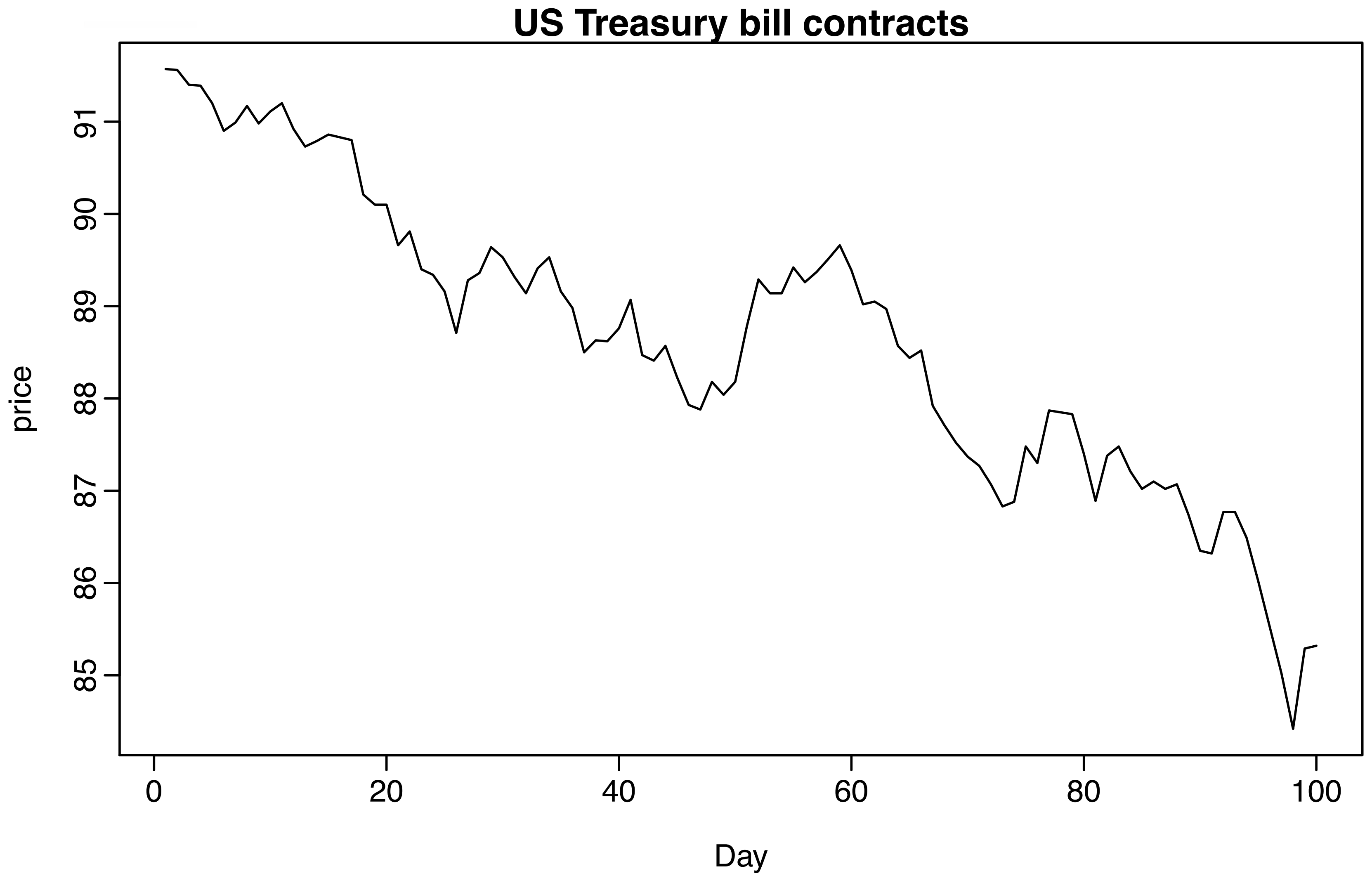


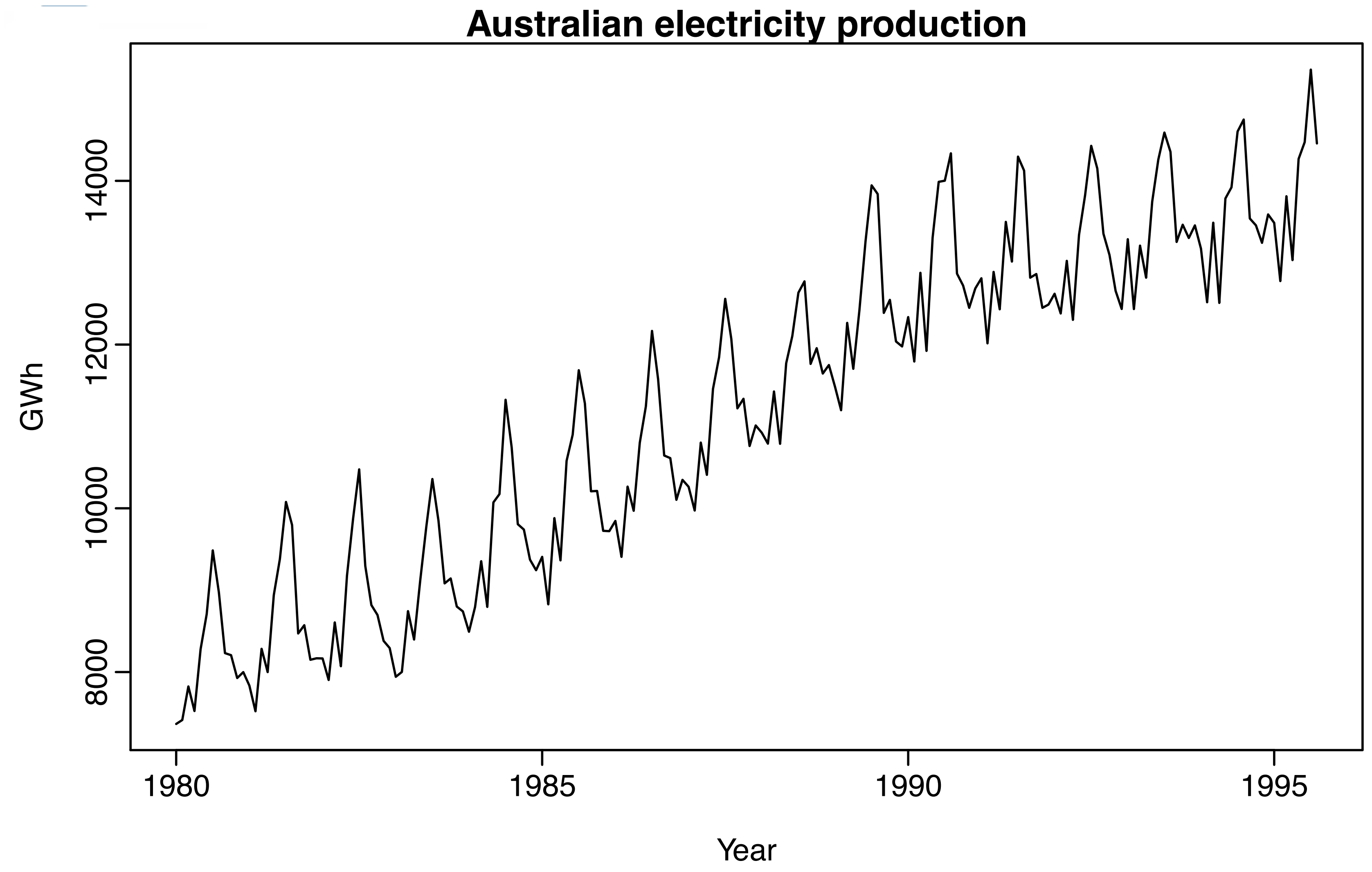




[R. J. Hyndman]

# Time Series Data

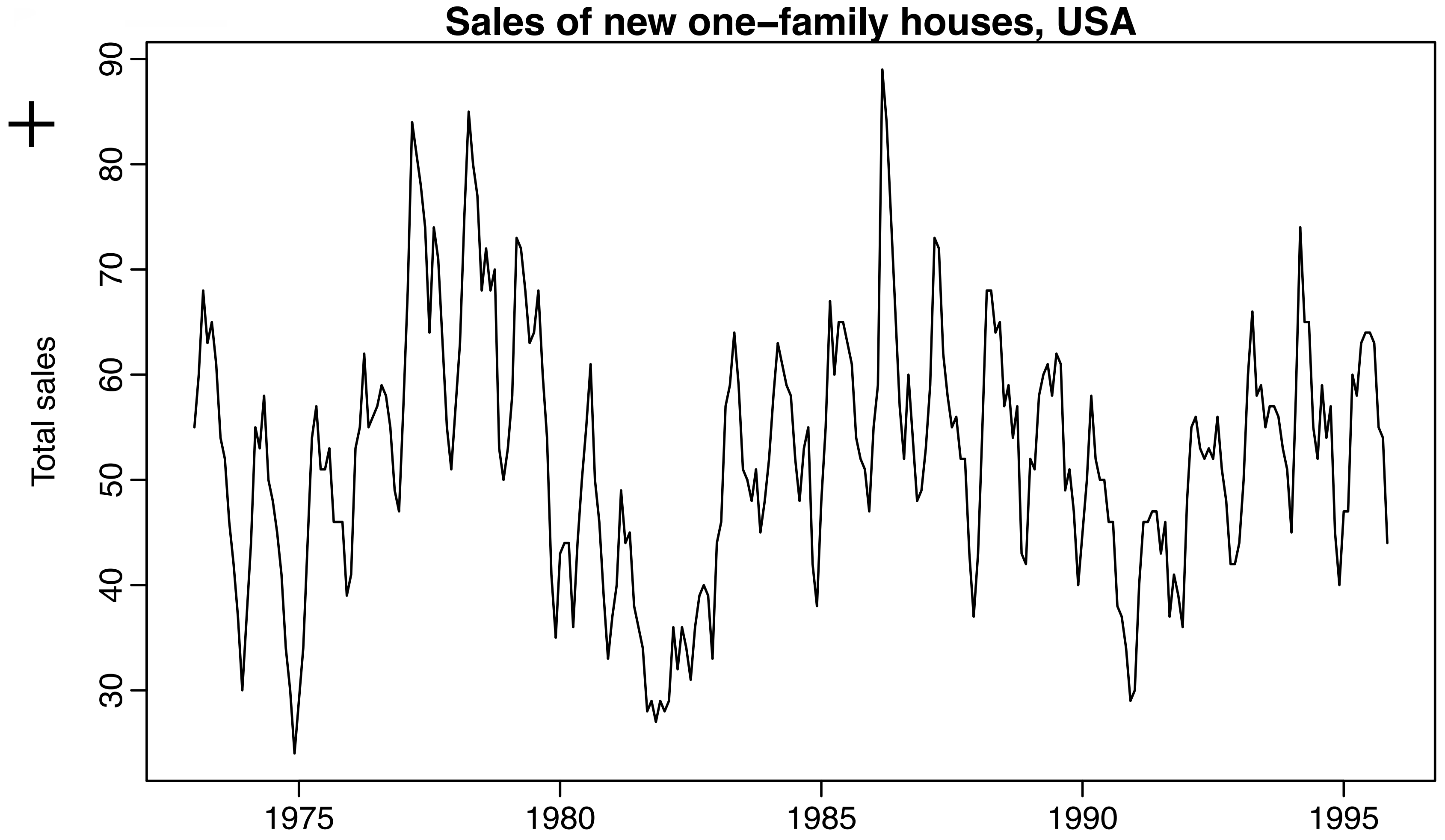
Trend

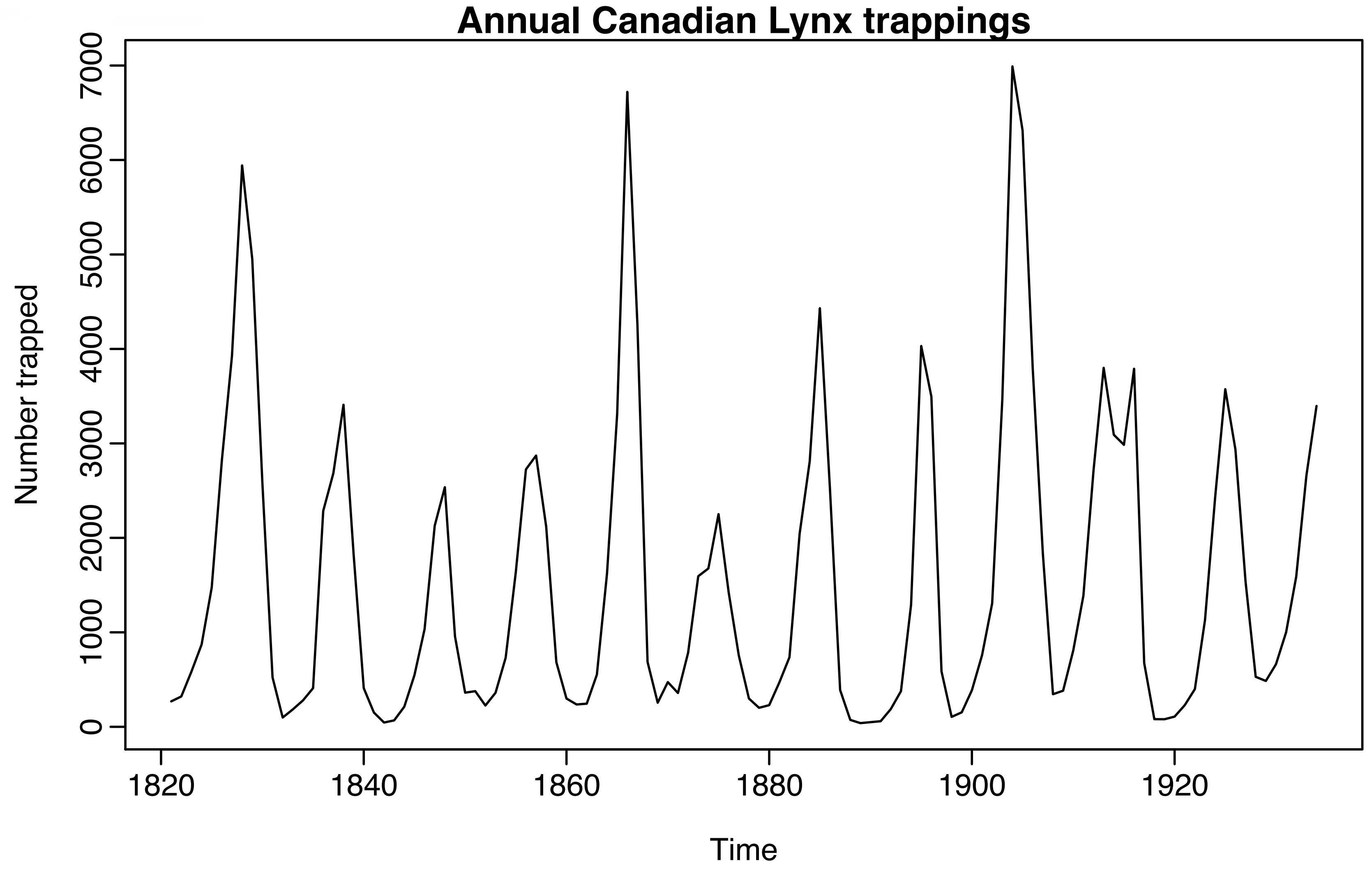



Trend + Seasonality

Seasonality + Cyclic

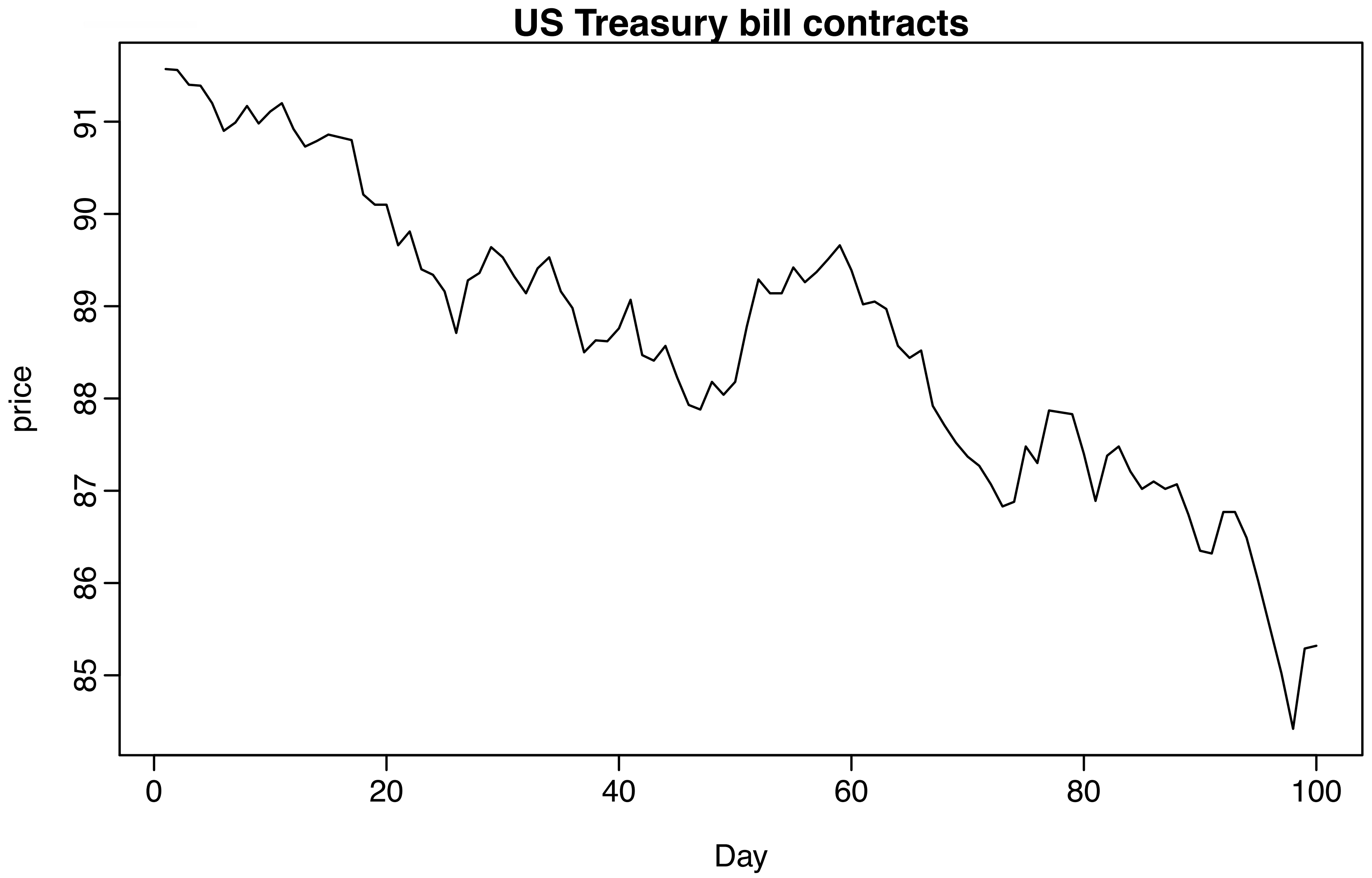


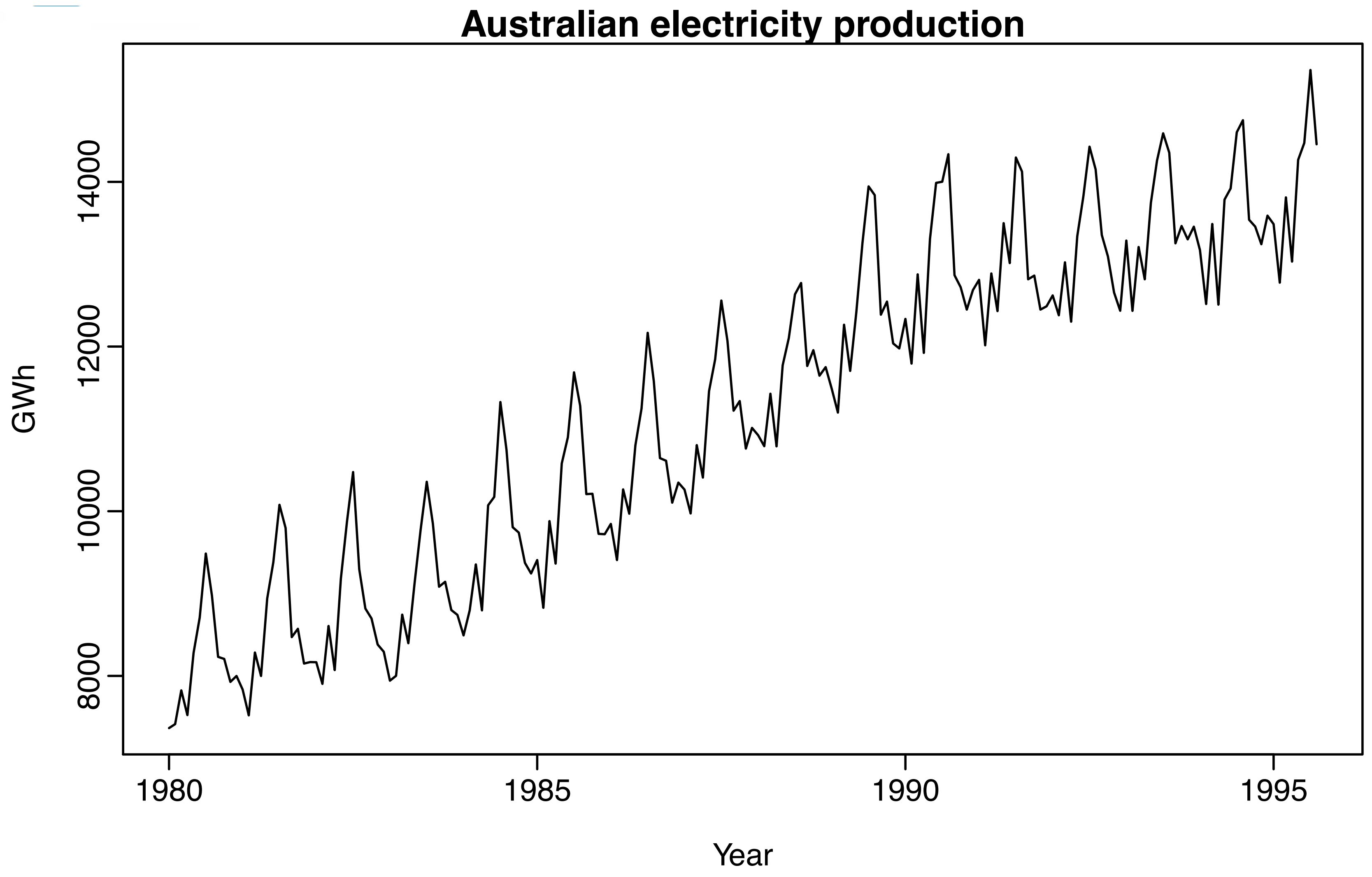




[R. J. Hyndman]

# Time Series Data

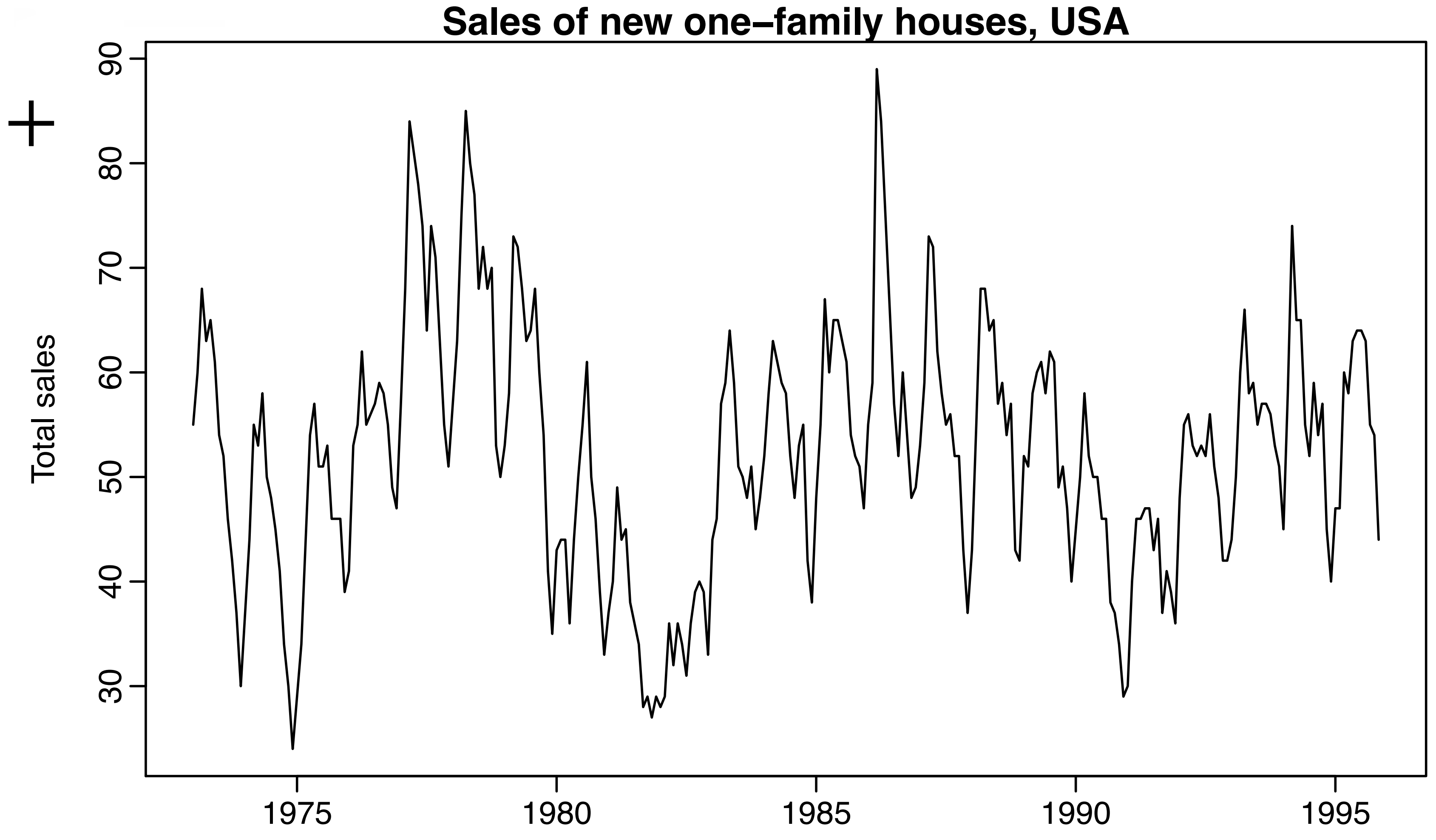
Trend

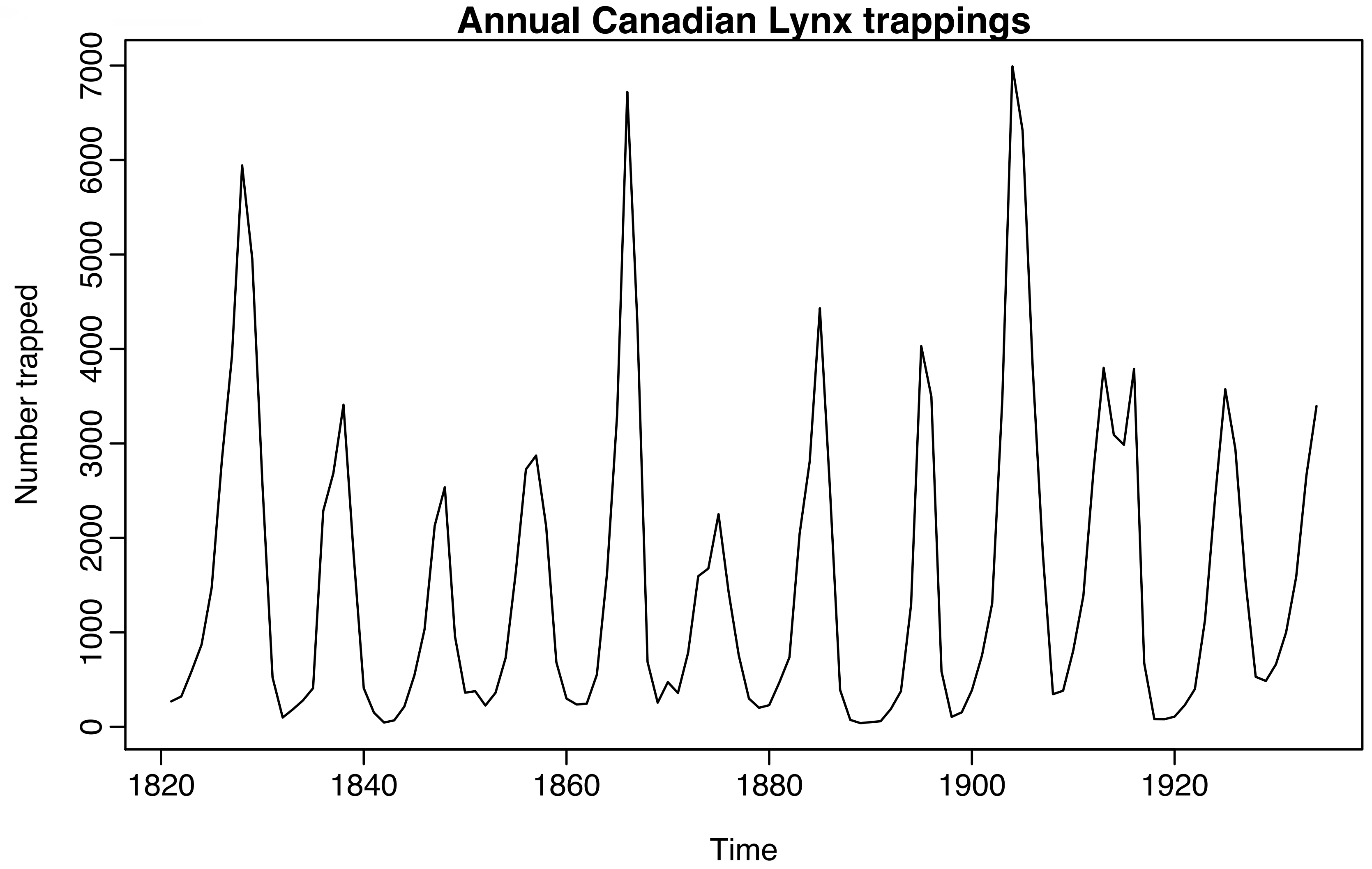



Trend + Seasonality

Seasonality + Cyclic

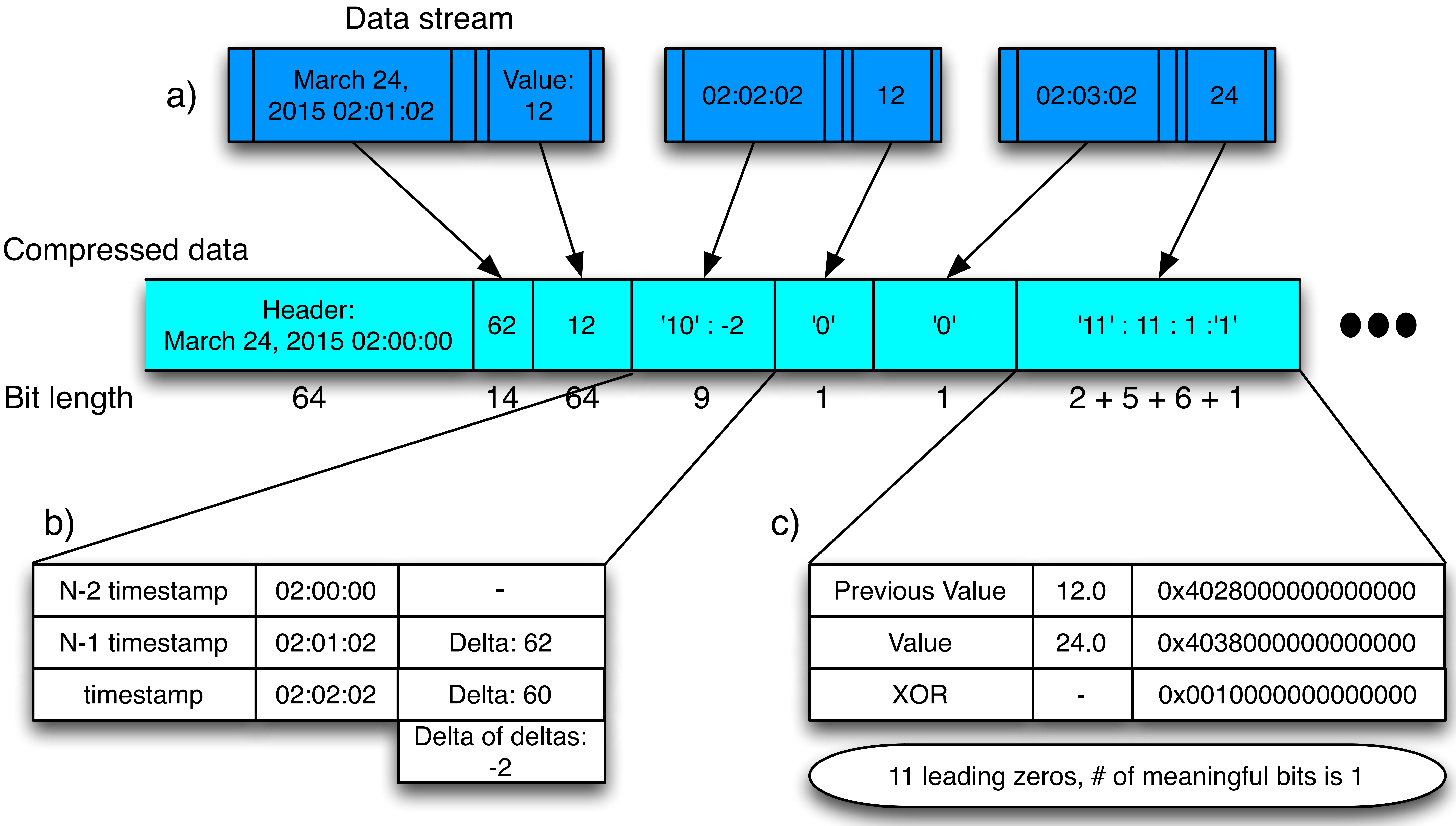



Stationary

[R. J. Hyndman]

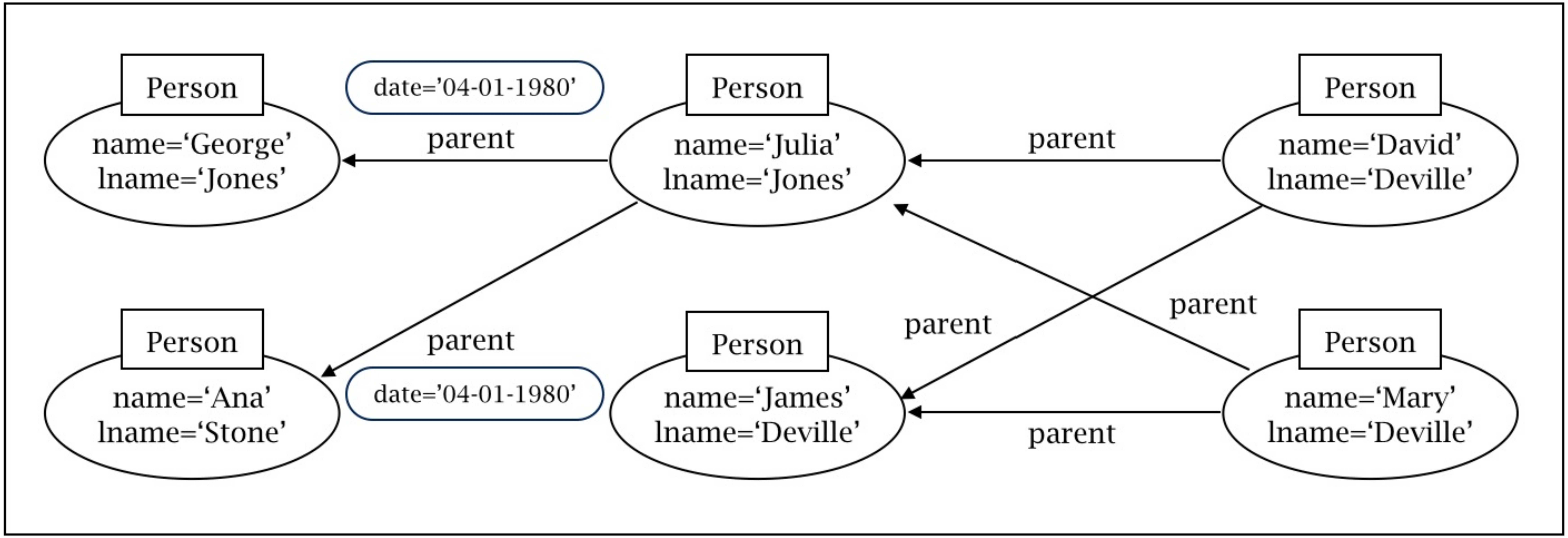
# Gorilla Time Series Data Compression




[Pelkonen et al., 2015]

# Graph Databases focus on relationships

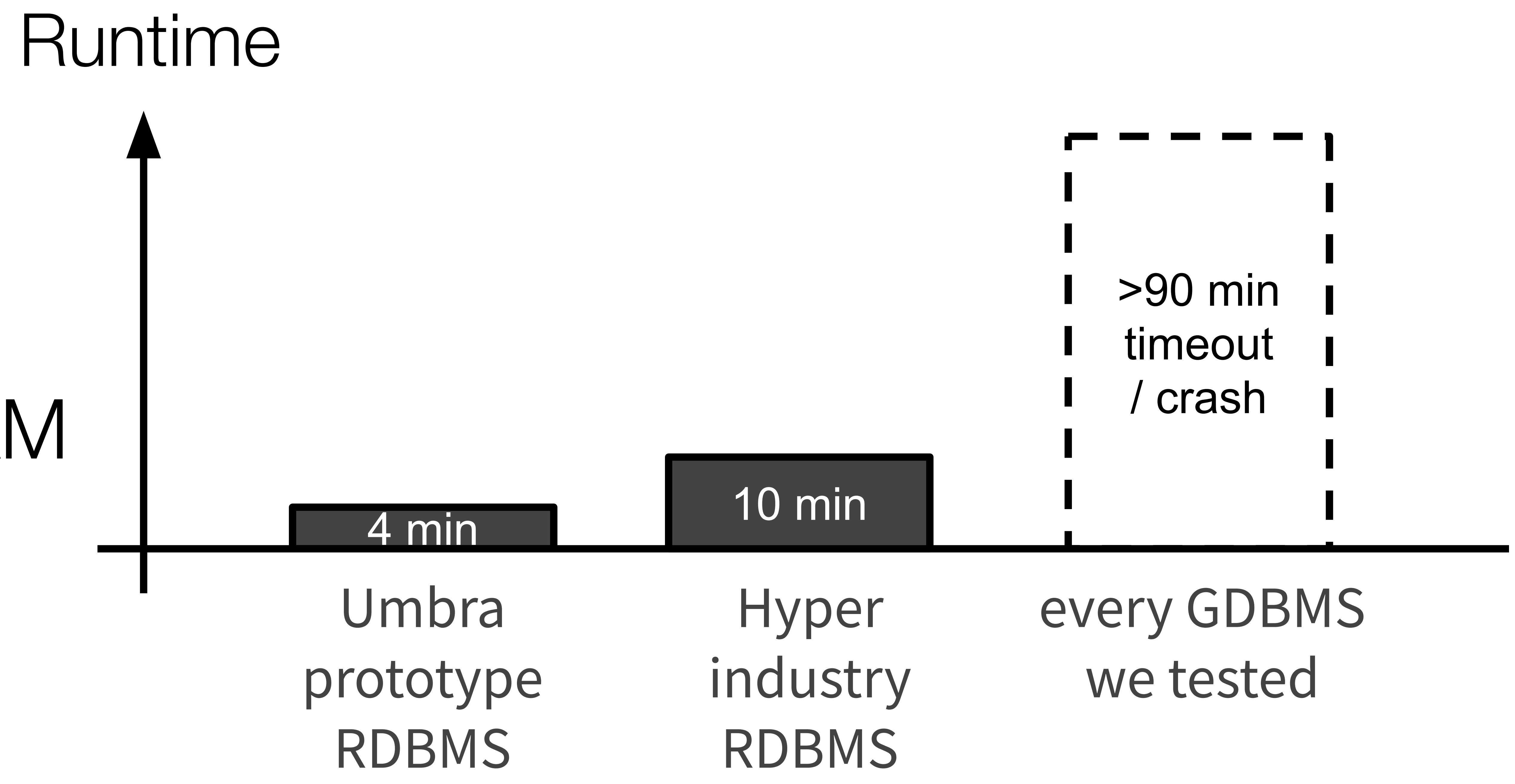
- Directed, labelled, attributed multigraph
- Properties are **key/value pairs** that represent metadata for nodes and edges




[R. Angles and C. Gutierrez, 2017]

# Graph DBMS Problems

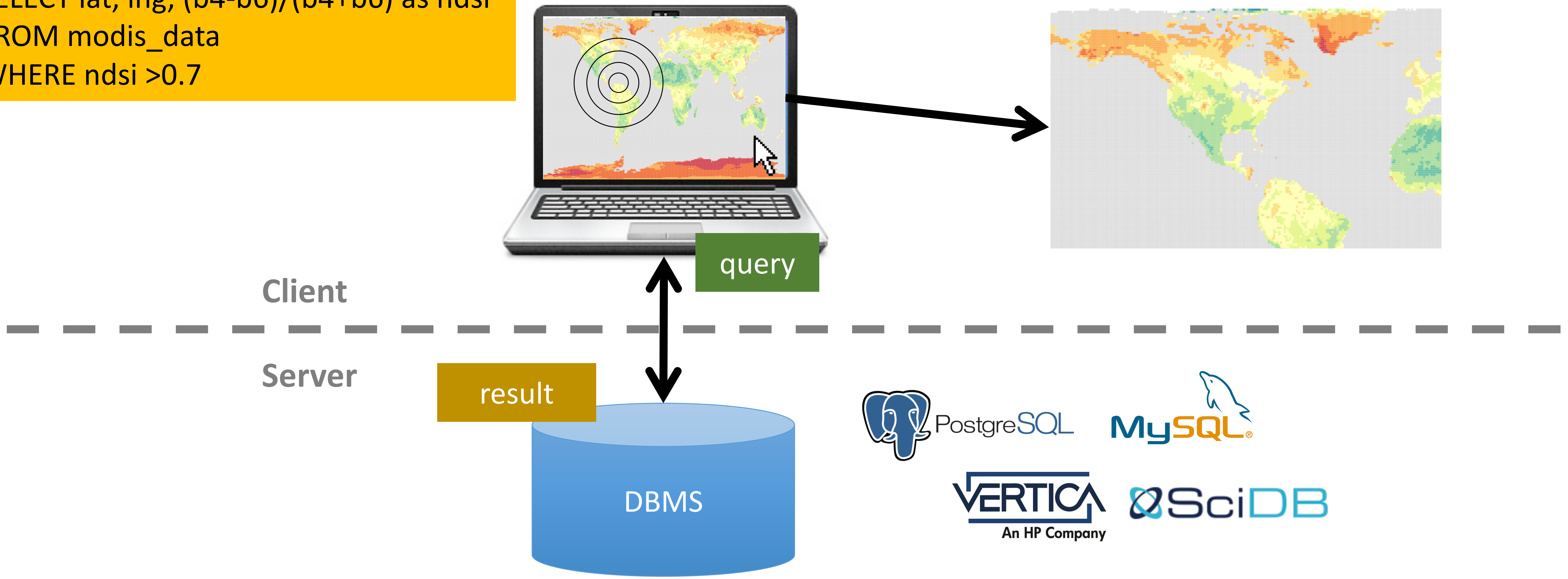
- performance
  - Slow loading speeds
  - Query speeds over magnitude slower than RDBMS
- scalability
  - Low datasize limit, typically << RAM
  - Little benefit from parallelism
- reliability
  - Loads never terminate
  - Query run out of memory or crash
  - Bugs




[P. Boncz, 2022]

# Interactive Exploration of Spatial Data

```
SELECT lat, lng, (b4-b6)/(b4+b6) as ndsi
FROM modis_data
WHERE ndsi >0.7
```




[L. Battle, 2017]

# Interactive Exploration of Spatial Data

```
SELECT lat, lng, (b4-b6)/(b4+b6) as ndsi
FROM modis_data
WHERE ndsi >0.7
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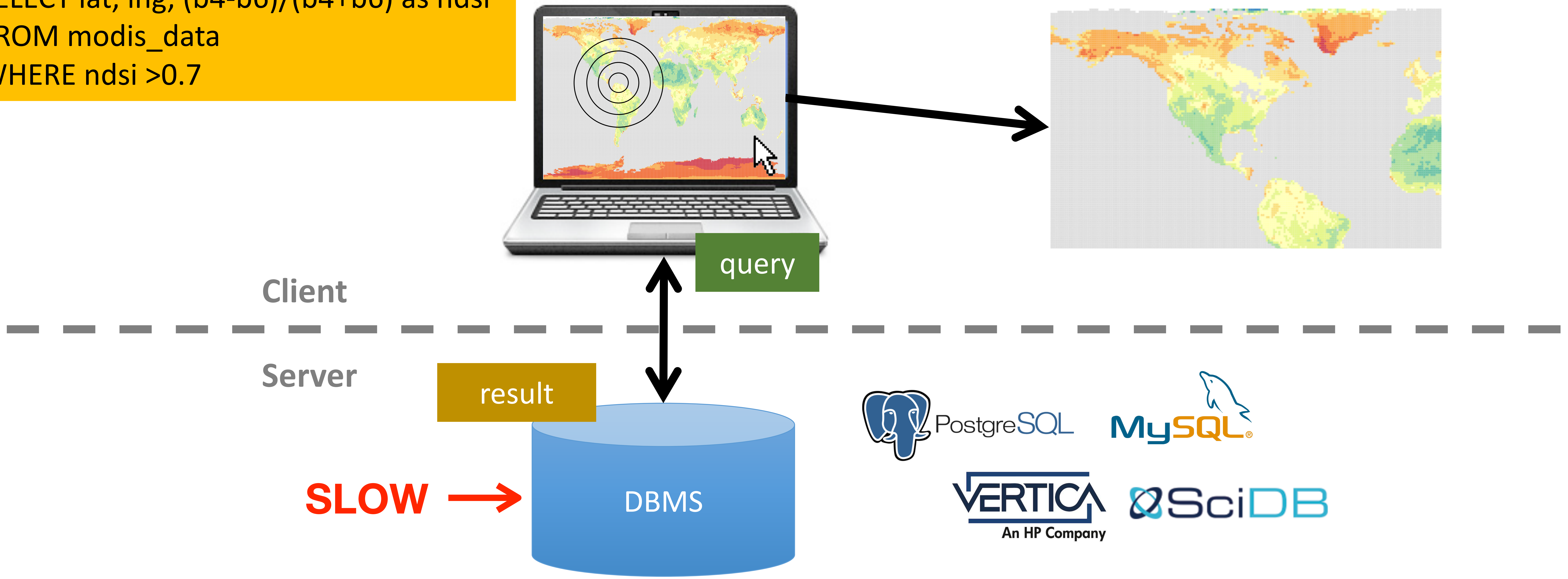
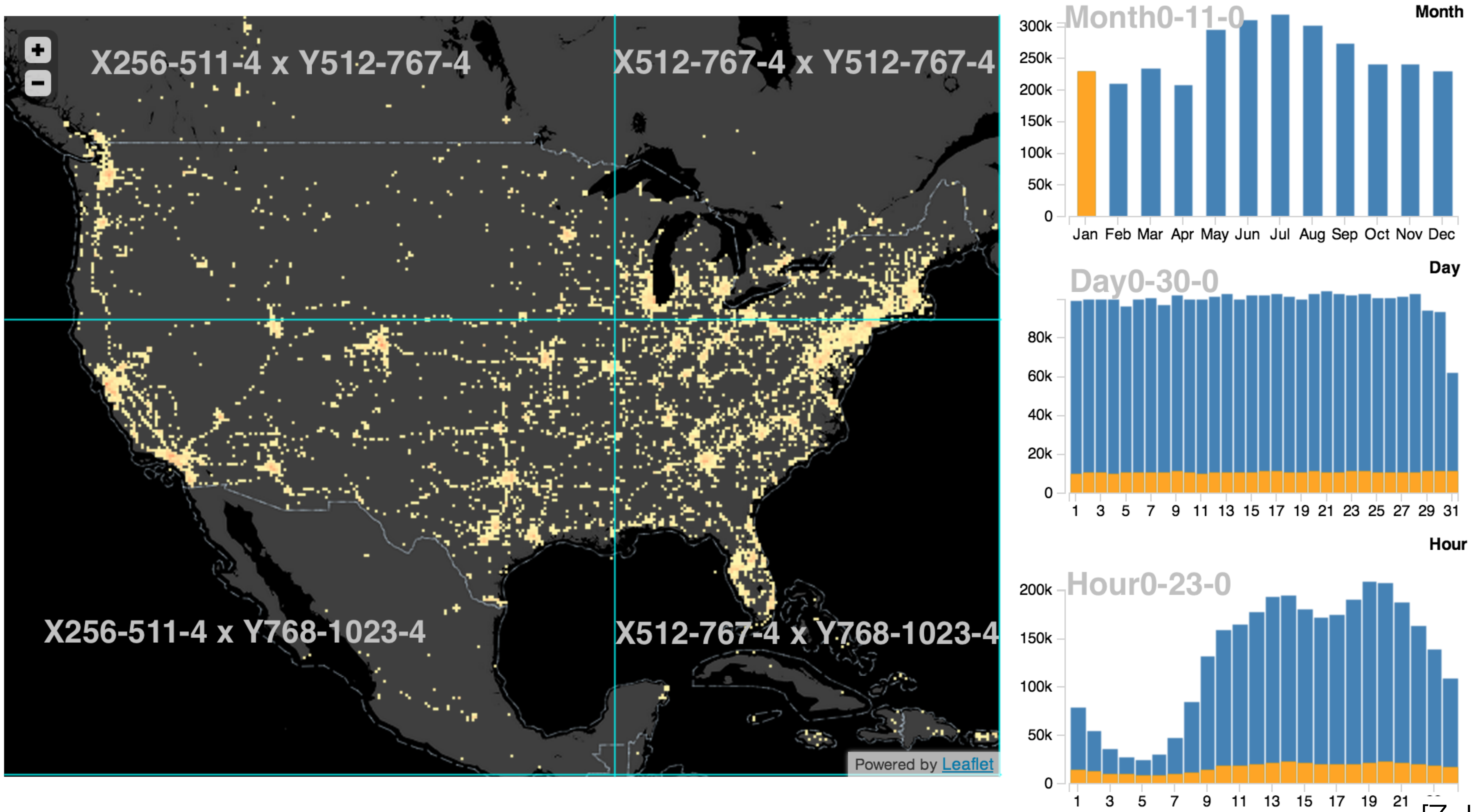


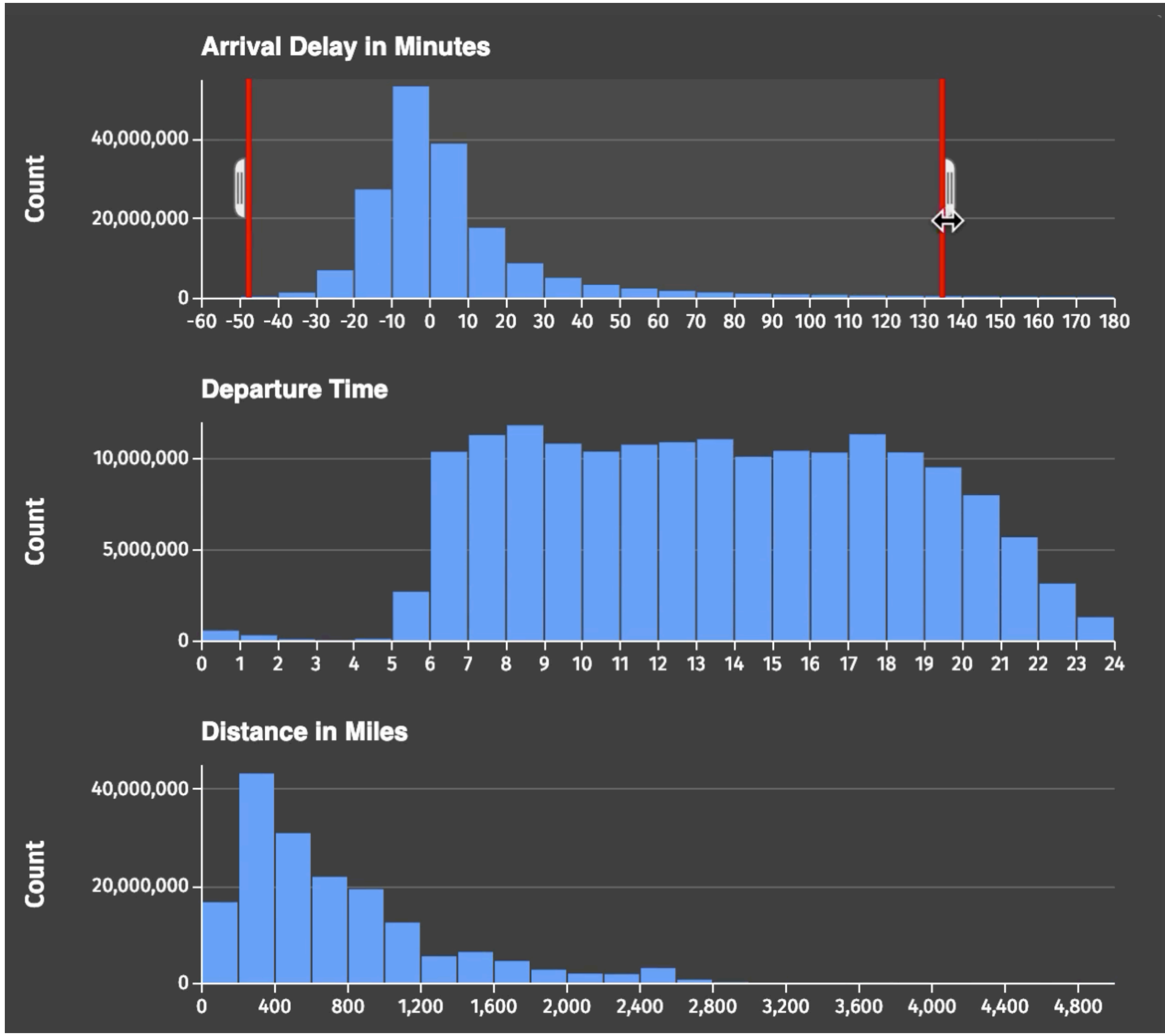

[L. Battle, 2017]

# Visualization: Minimize Latency




[Z. Liu et al., 2013]

# Visualization: Task-Prioritized Prefetching




*brushes in the precomputed view*

*serves requests from a data cube*

Data Cube. Gray et al. *1997.*

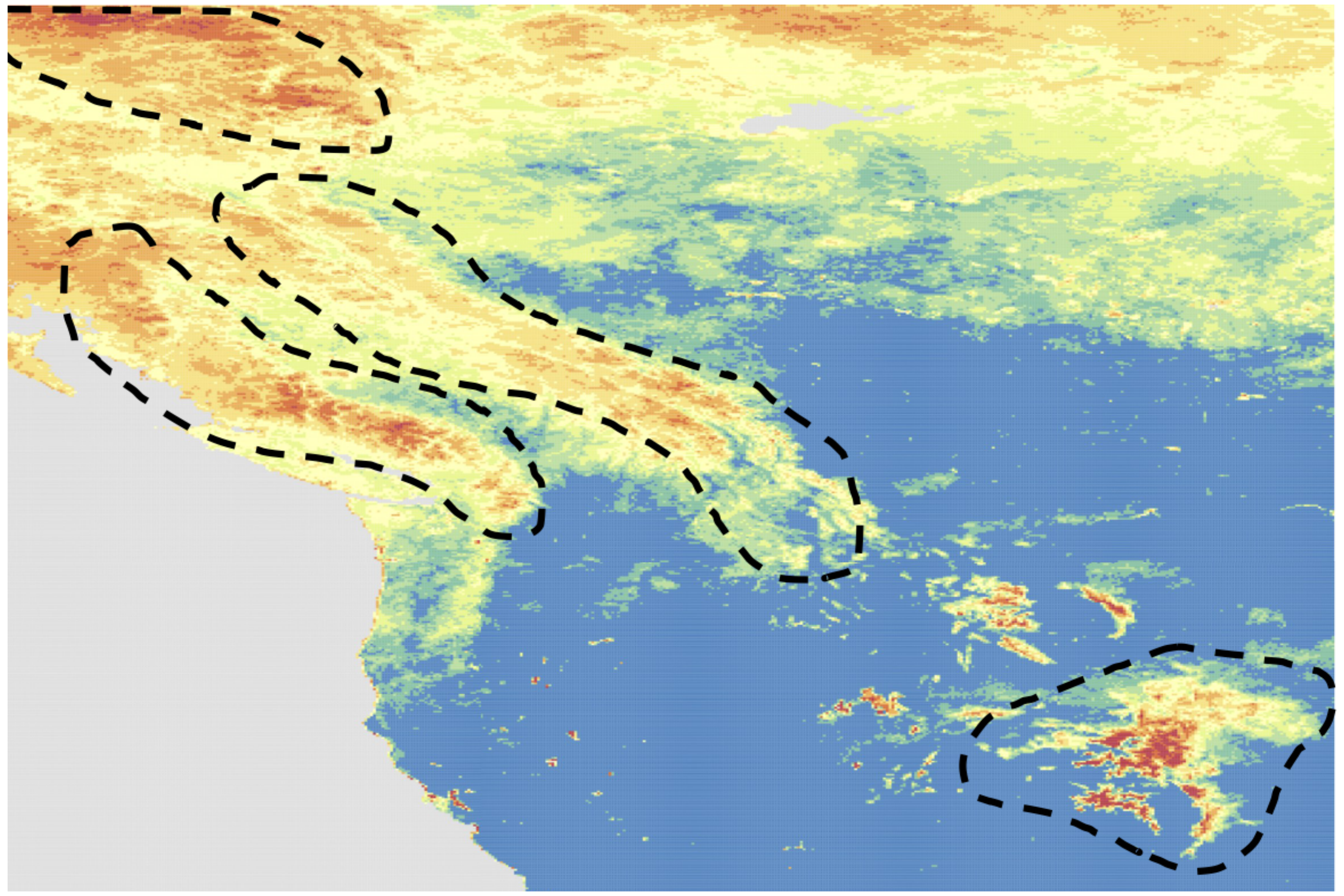
*interacts with a new view*

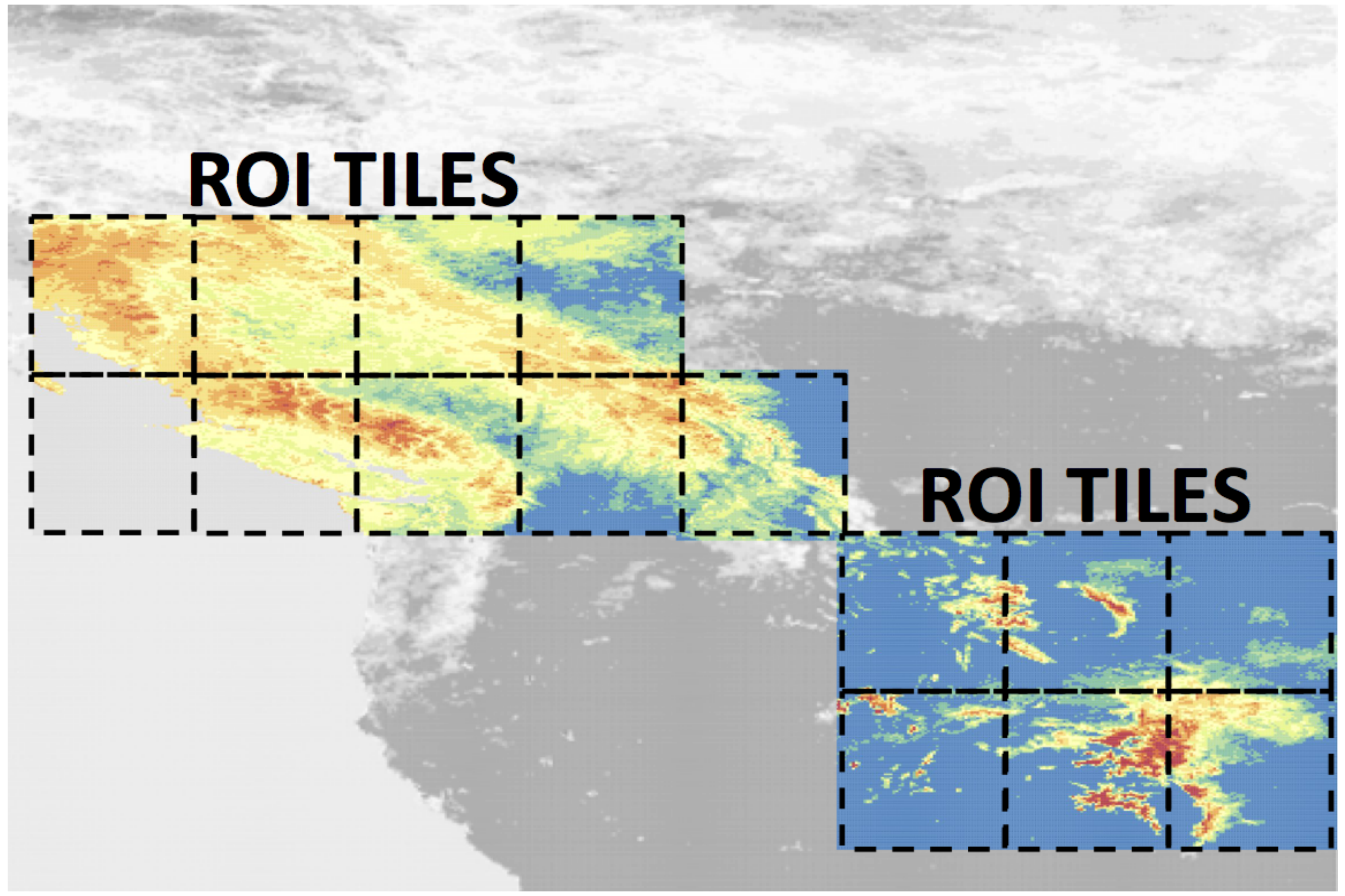
*query for new data cubes*

[D. Moritz et al. via J. Heer]

# Visualization: Prefetching

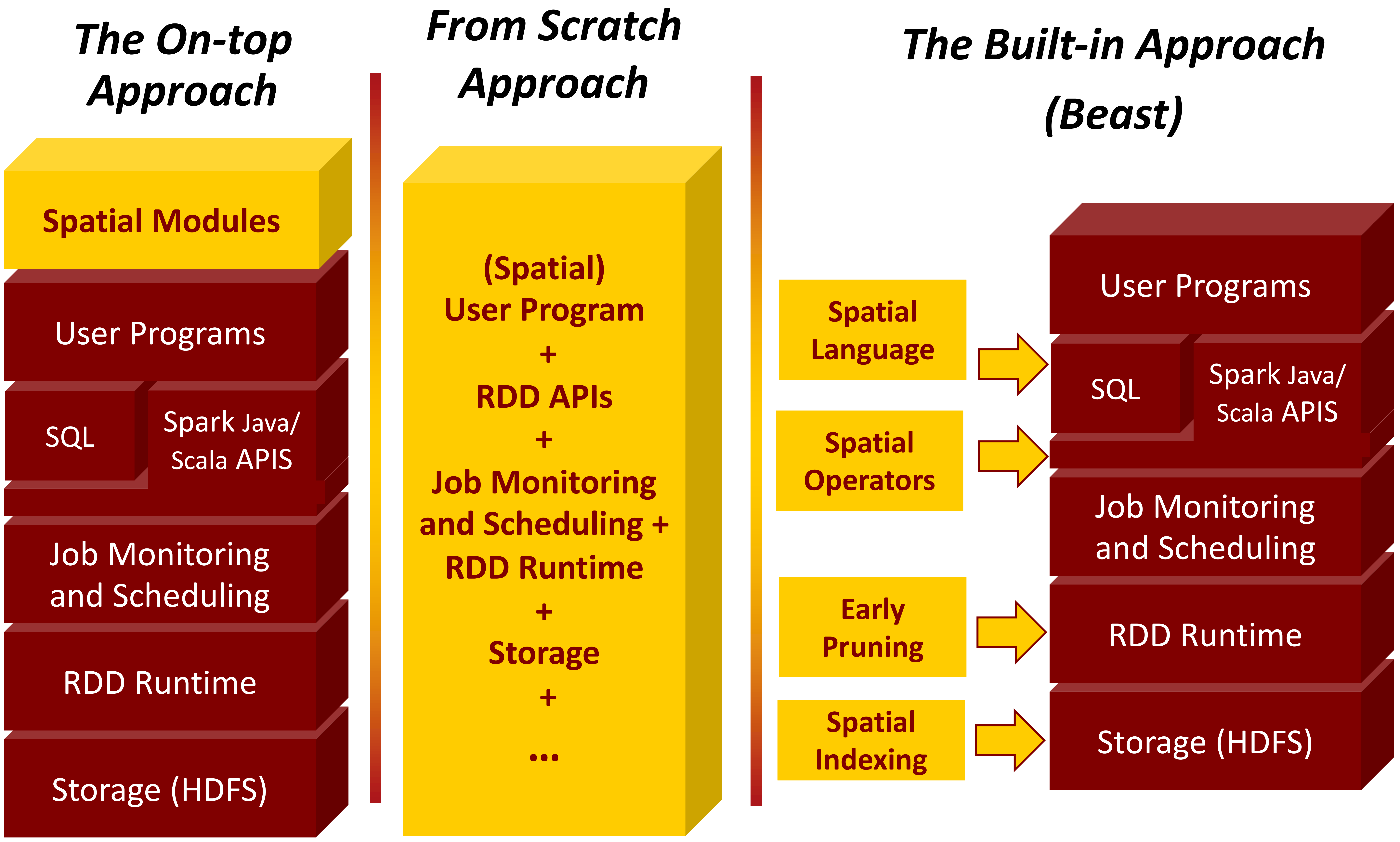
- Predict which tiles a user will need next and prefetch those
  - Use common patterns (zoom, pan)
  - Use regions of interest (ROIs)





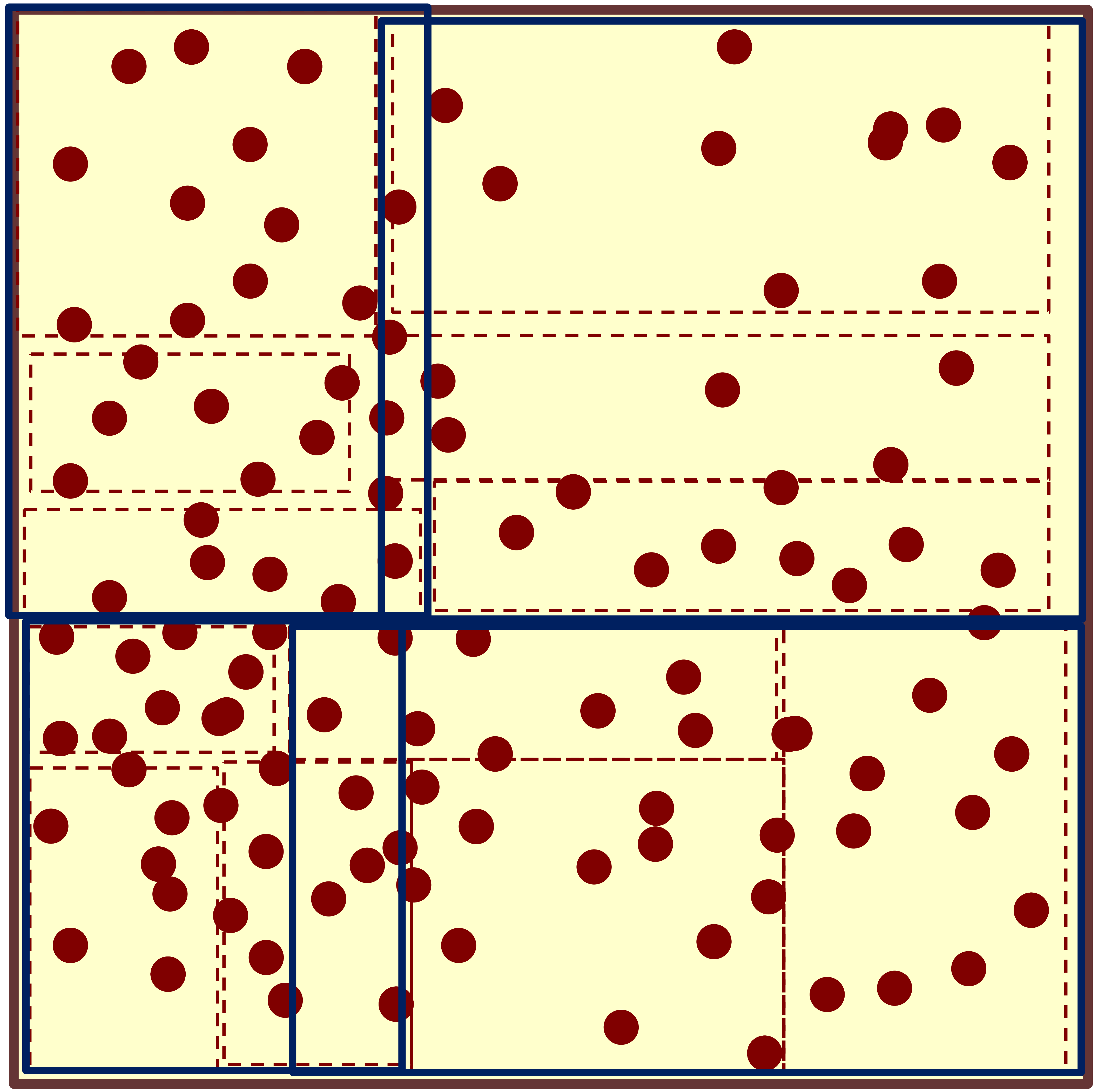

[Battle et al., 2016]

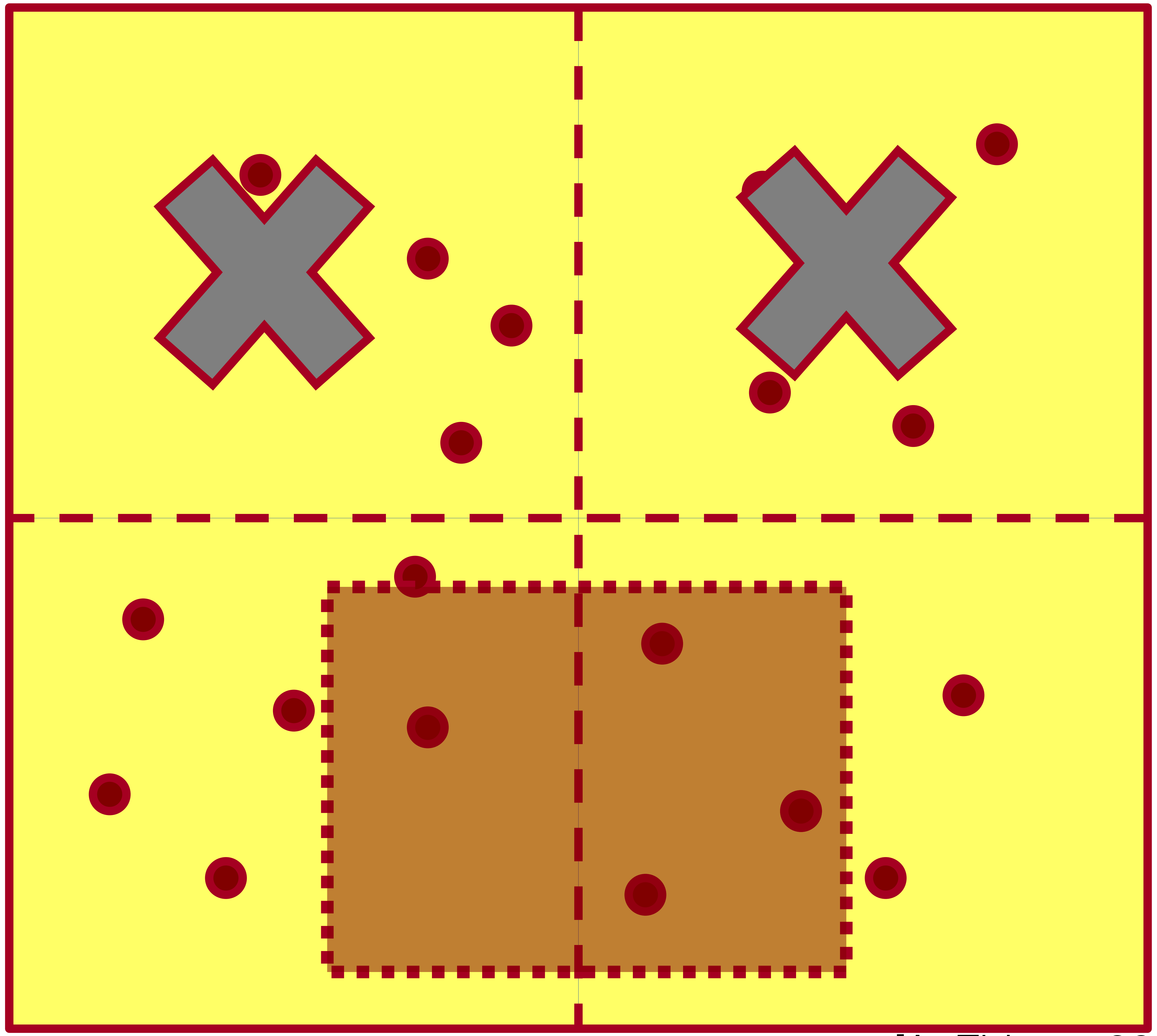
# Spatial Data: Beast Architecture




[A. Eldawy, 2021]

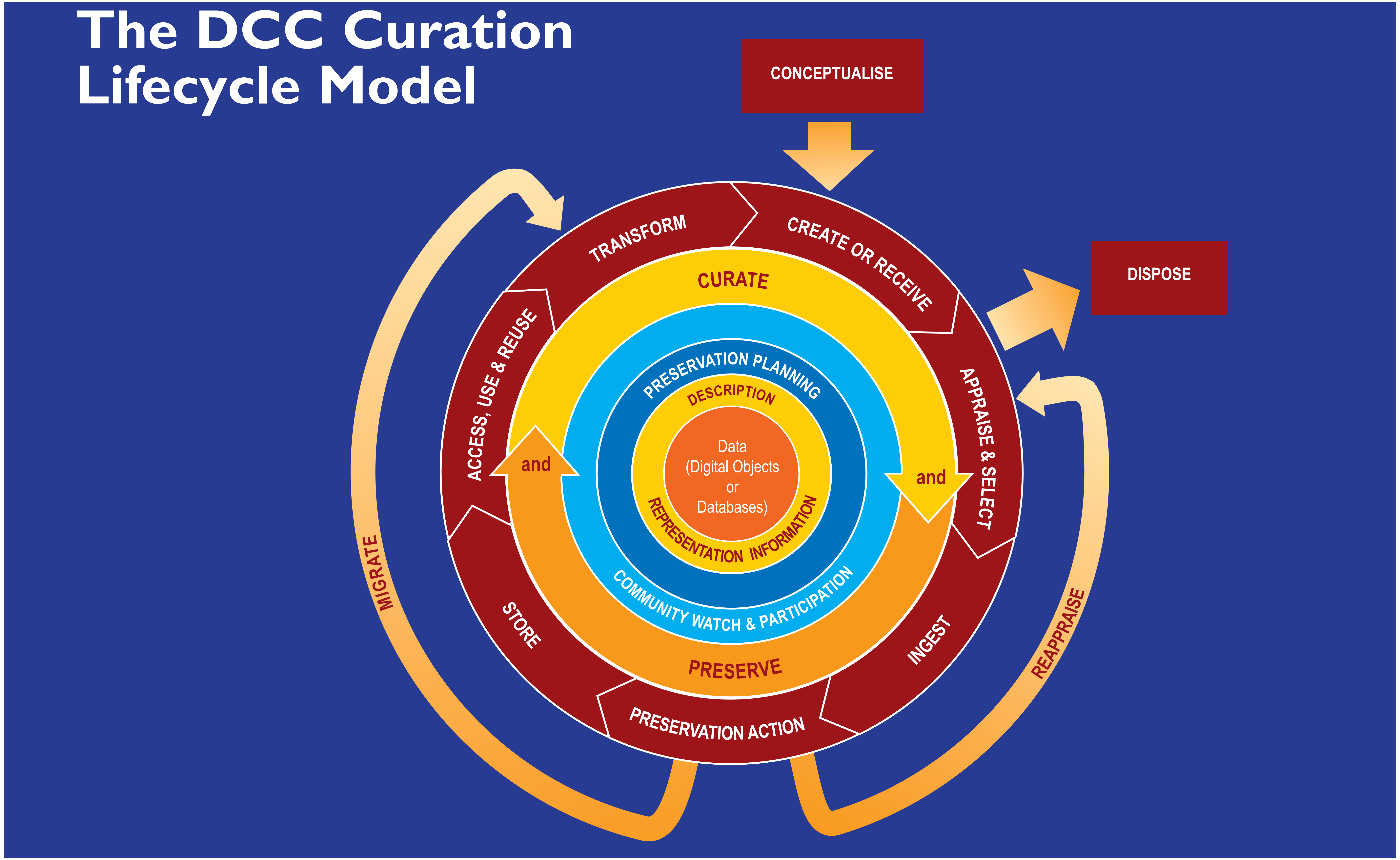
# Spatial Data: Partitioning/Indexing & Range Query





[A. Eldawy, 2021]

# Data Curation



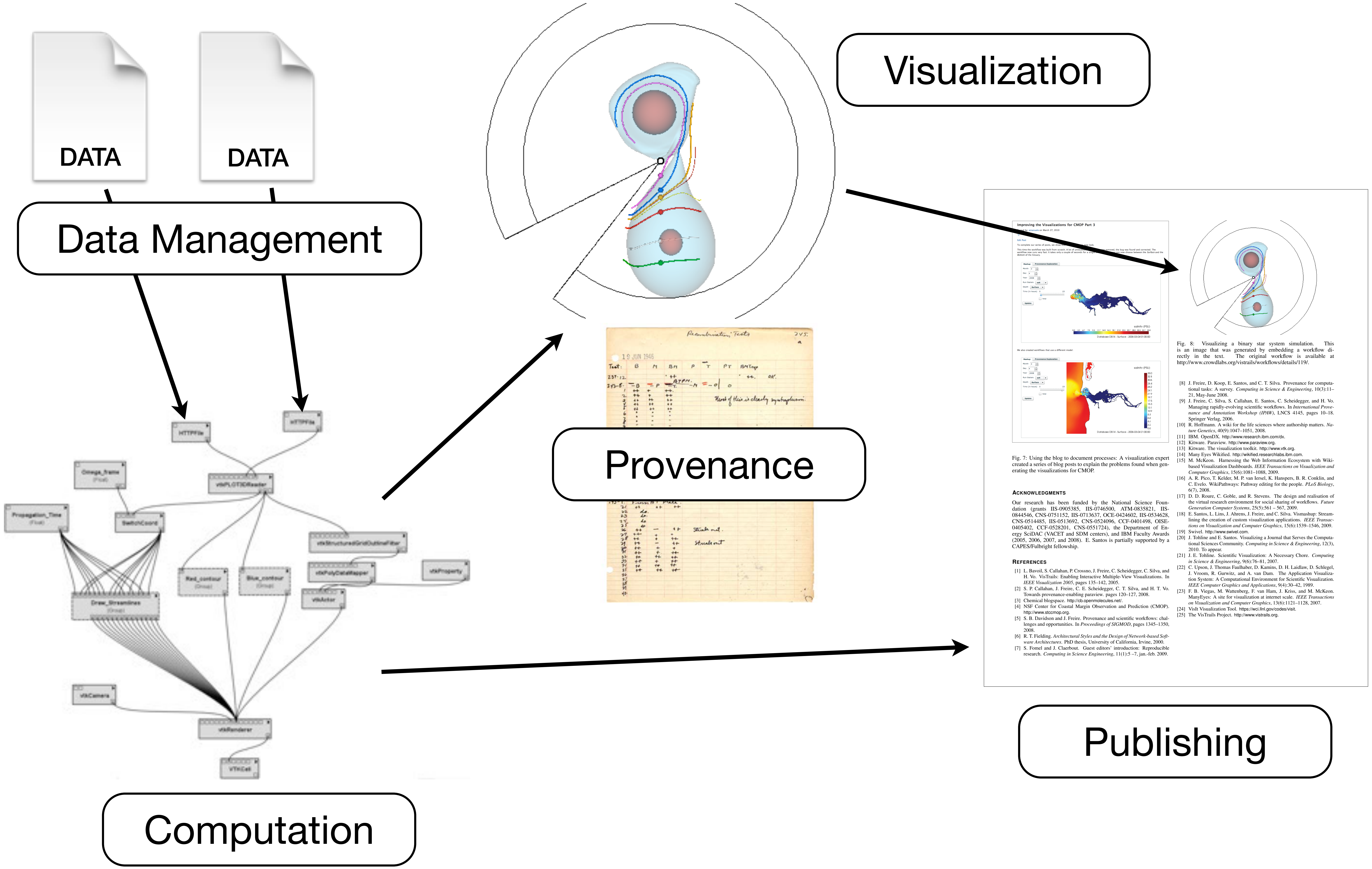

[DCC]

# Data Curation: FAIR Principles

- Findable: Metadata and data should be easy to find for both humans and computers
- Accessible: Users need to know how data can be accessed, possibly including authentication and authorization
- Interoperable: Can be integrated with other data, and can interoperate with applications or workflows for analysis, storage, and processing
- Reusable: Optimize the reuse of data. Metadata and data should be well-described so they can be replicated and/or combined in different settings

[GO FAIR]

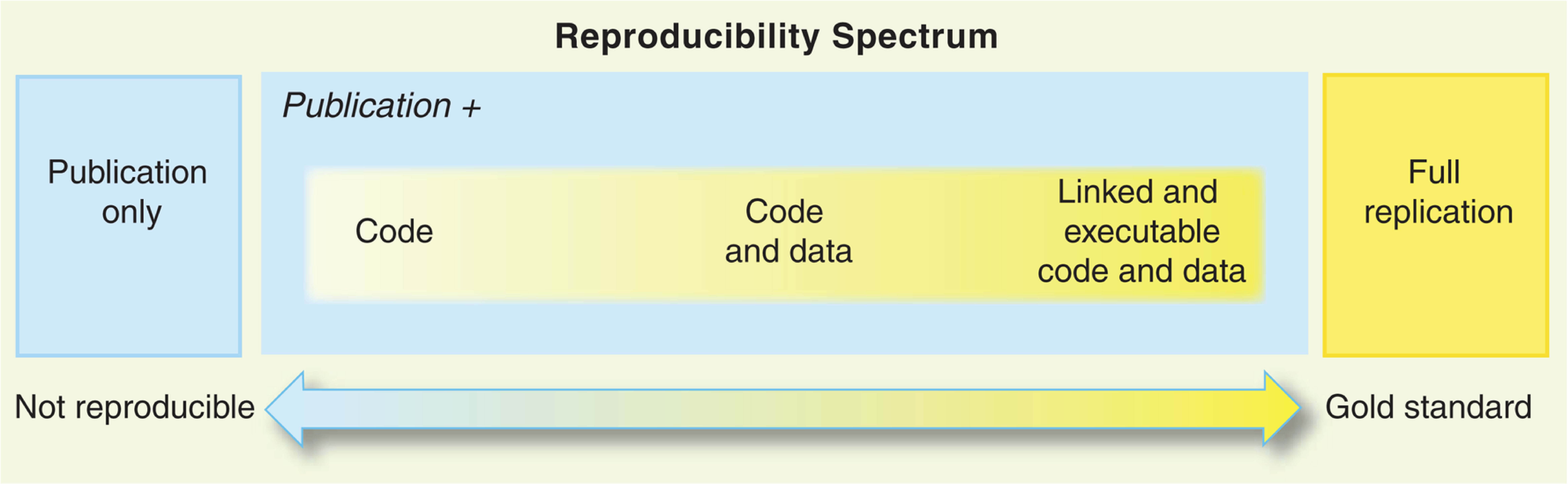
# Provenance


DATA
DATA
Data Management
Visualization
Provenance
Computation
Publishing

# Prospective and Retrospective Provenance

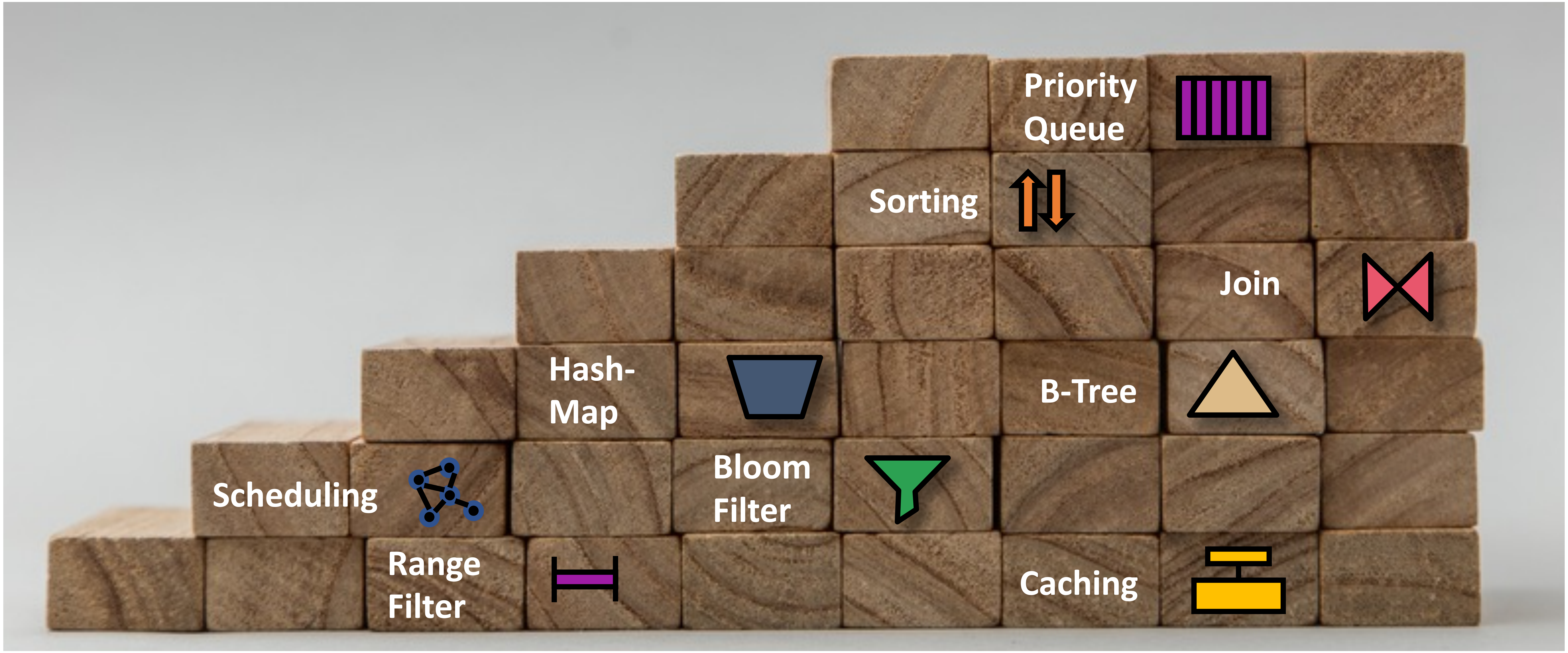
- Recipe for baking a cake versus the actual process & outcome
- Prospective provenance is what was specified/intended
  - a workflow, script, list of steps
- Retrospective provenance is what actually happened
  - actual data, actual parameters, errors that occurred, timestamps, machine information
- **Do not need** prospective provenance to have retrospective provenance!

# Reproducibility




[R. D. Peng]

# Machine Learning and Databases




[T. Kraska, 2019]

Questions?

# Final Exam

- Wednesday, May 10, **8:00**-9:50am, PM 253
- Similar format
- More comprehensive (questions from topics covered in Test 1 & 2)
- Will also have questions from graph/spatial/temporal data, provenance, reproducibility, machine learning