TI2736-B

Big Data Processing

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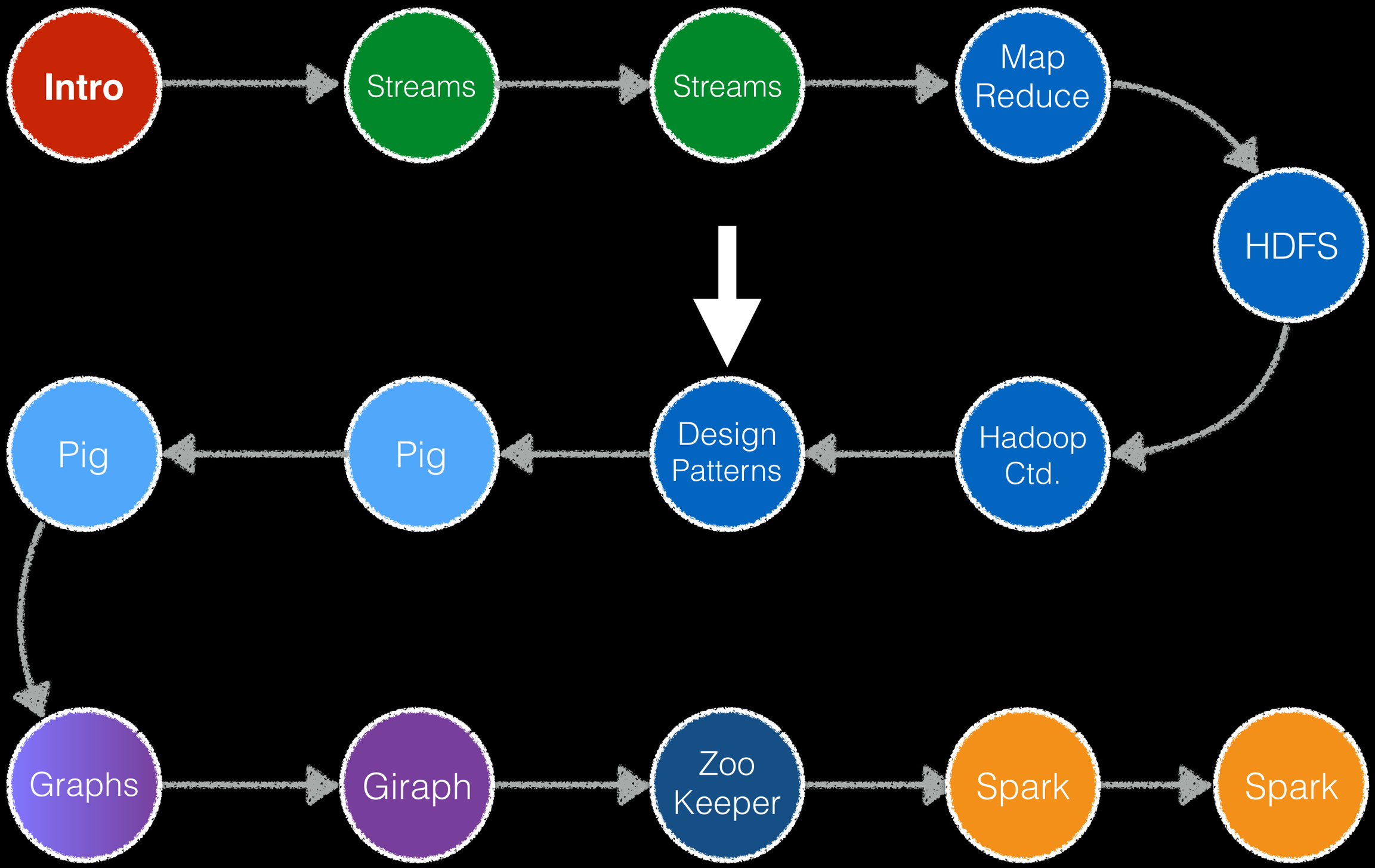
TU Delft


Intro
Streams
Streams
Map Reduce
HDFS
Hadoop Ctd.
Design Patterns
Pig
Pig
Graphs
Giraph
Zoo Keeper
Spark
Spark

Learning objectives

- **Implement** the four introduced design patterns and **choose** the correct one according to the usage scenario
- **Express** common **database operations** as MapReduce jobs and argue about the pros & cons of the implementations
  - Relational joins
  - Union, Selection, Projection, Intersection

MapReduce design patterns

- local aggregation
- order inversion
- pairs & stripes
- secondary sorting

Design patterns

"Arrangement of components and specific techniques designed to **handle frequently encountered situations** across a variety of problem domains."

- Programmer's tasks (Hadoop does the rest):
  - Prepare data
  - **Write mapper code**
  - **Write reducer code**
  - Write combiner code
  - Write partitioner code

But: every task needs to be converted into the Mapper/ Reducer schema

Design patterns

- In parallel/distributed systems, synchronisation of intermediate results is difficult

- MapReduce paradigm offers **one opportunity** for cluster-wide synchronisation: shuffle & sort phase

- Programmers have little control over:
  - **Where** a Mapper/Reducer runs
  - **When** a Mapper/Reducer starts & ends
  - **Which** key/value pairs are processed by which Mapper or Reducer

Controlling the data flow

- **Complex data structures** as keys and values (e.g. `PairOfIntString`)

- Execution of user-specific **initialisation & termination** code at each Mapper/Reducer

- **State preservation** in Mapper/Reducer across multiple input or intermediate keys (Java objects)

- User-controlled **partitioning of the key space** and thus the set of keys that a particular Reducer encounters

```java
public class PairOfIntString implements WritableComparable<PairOfIntString> {
  private int leftElement;
  private String rightElement;

  /**
   * Creates a pair.
   */
  public PairOfIntString() {
  }

  /**
   * Creates a pair.
   *
   * @param left the left element
   * @param right the right element
   */
  public PairOfIntString(int left, String right) {
    set(left, right);
  }
```

Design pattern I:

Local aggregation

Local aggregation

- Moving data from Mappers to Reducers
  - **Data transfer** over the network
  - **Local disk** writes

- Local aggregation: **reduces** amount of **intermediate data** & increases algorithm efficiency

- Exploited concepts:
  - Combiners
  - State preservation

Most popular: in-mapper combining

Our WordCount example (once more)

```
map(docid a, doc d):
    foreach term t in doc:
        EmitIntermediate(t, count 1);
```

```
reduce(term t, counts[c1, c2, …])
    sum = 0;
    foreach count c in counts:
        sum += c;
    Emit(term t, count sum)
```

Local aggregation on two levels

```
map(docid a, doc d):
    H = associative_array;
    foreach term t in doc:
       H{t}=H{t}+1;
foreach term t in H:
    EmitIntermediate(t,count H{t});
```

Local aggregation on two levels

```
setup():
    H = associative_array;

map(docid a, doc d):
    foreach term t in doc:
        H{t}=H{t}+1;

cleanup():
    foreach term t in H:
        EmitIntermediate(t,count H{t});
```

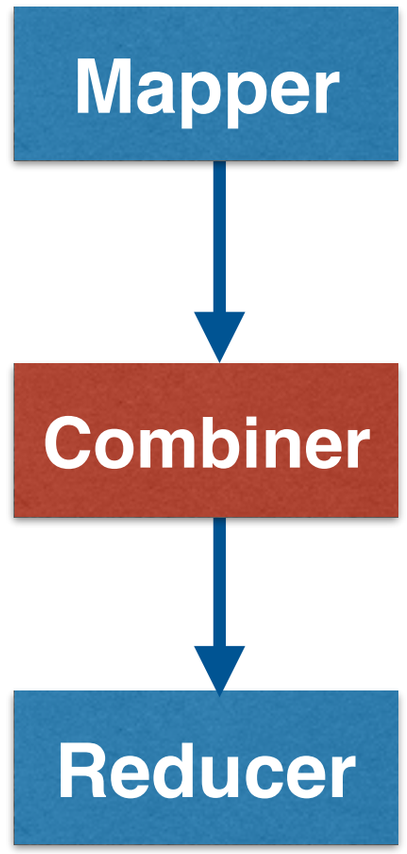
Correctness of local aggregation: the mean

```
map(string t, int r):
      EmitIntermediate(string t, int r)

combine(string t, ints [r1, r2, ..])
      sum = 0; count = 0;
      foreach int r in ints:
            sum += r;
            count += 1;
      EmitIntermediate(string t, pair(sum,count))

reduce(string t, pairs [(s1,c1), (s2,c2),..])
      sum = 0; count = 0;
      foreach pair (s,c) in pairs:
            sum += s;
            count += c;
      avg=sum/count;
      Emit(string t, int avg);
```

mapper output grouped by key



incorrect

Correctness of local aggregation: the mean

```
map(string t, int r):
      EmitIntermediate(string t, pair (r,1))

combine(string t, pairs [(s1,c1), (s2,c2),..])
      sum = 0; count = 0;
      foreach (s,c) in pairs:
            sum += s;
            count += c;
      EmitIntermediate(string t, pair(sum,count))

reduce(string t, pairs [(s1,c1), (s2,c2),..])
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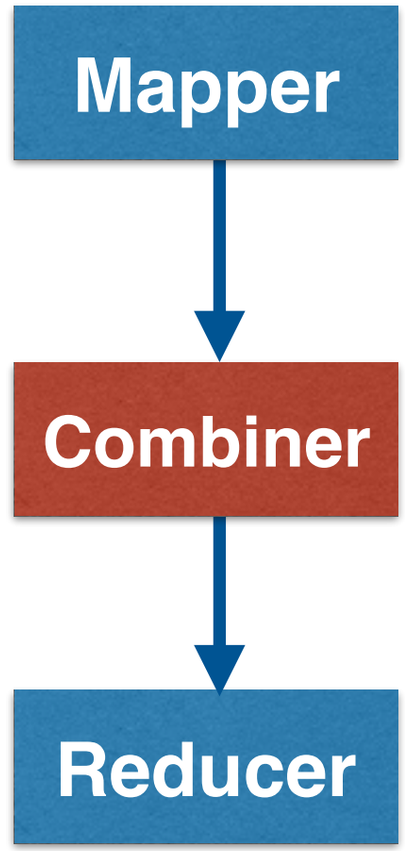


correct

Pros and cons: local aggregation vs. Combiners

- **Advantages:**
  - **Controllable** when & how aggregation occurs
  - **More efficient** (no disk spills, no object creation & destruction overhead)

- **Disadvantages:**
  - **Breaks functional programming paradigm** (state preservation between `map()` calls)
  - Algorithmic behaviour might depend on the **order** of `map()` input key/values (hard to debug)
  - **Scalability bottleneck** (programming effort to avoid it)

Local aggregation: always useful?

- Efficiency improvements **dependent** on
  - **Size of intermediate key space**
  - **Distribution** of keys
  - Number of key/value pairs emitted by individual map tasks

- WordCount
  - Scalability limited by vocabulary size

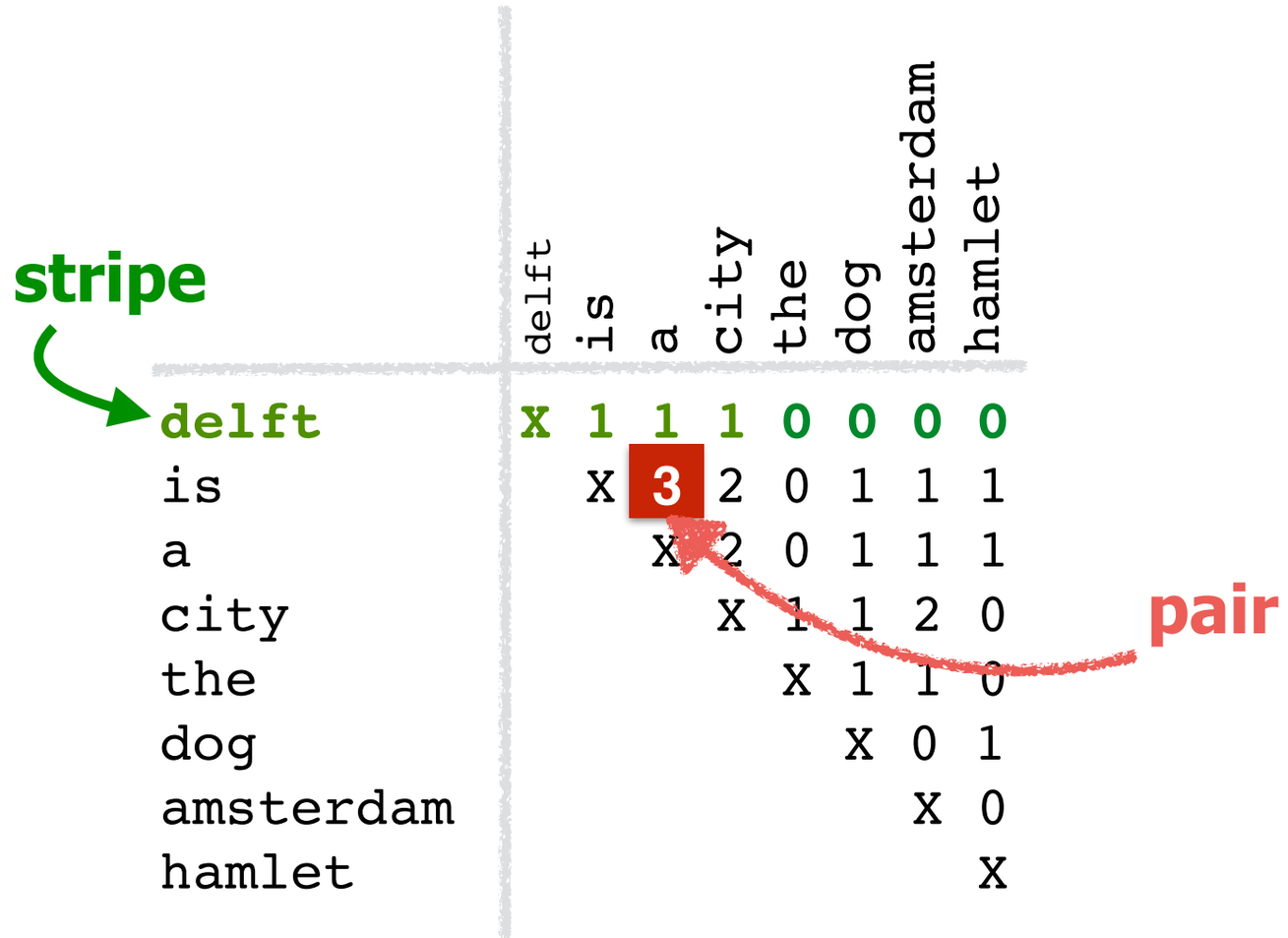
Design pattern II: Pairs & Stripes

To motivate the next design pattern .. co-occurrence matrices

Corpus: 3 documents
Delft is a city.
Amsterdam **is a** city.
Hamlet **is a** dog.

Co-occurrence matrix
(on the document level)

Applications:
clustering, retrieval,
stemming, text mining,
…



- Square matrix of size $n \times n$ (n: vocabulary size)
- Unit can be document, sentence, paragraph, …

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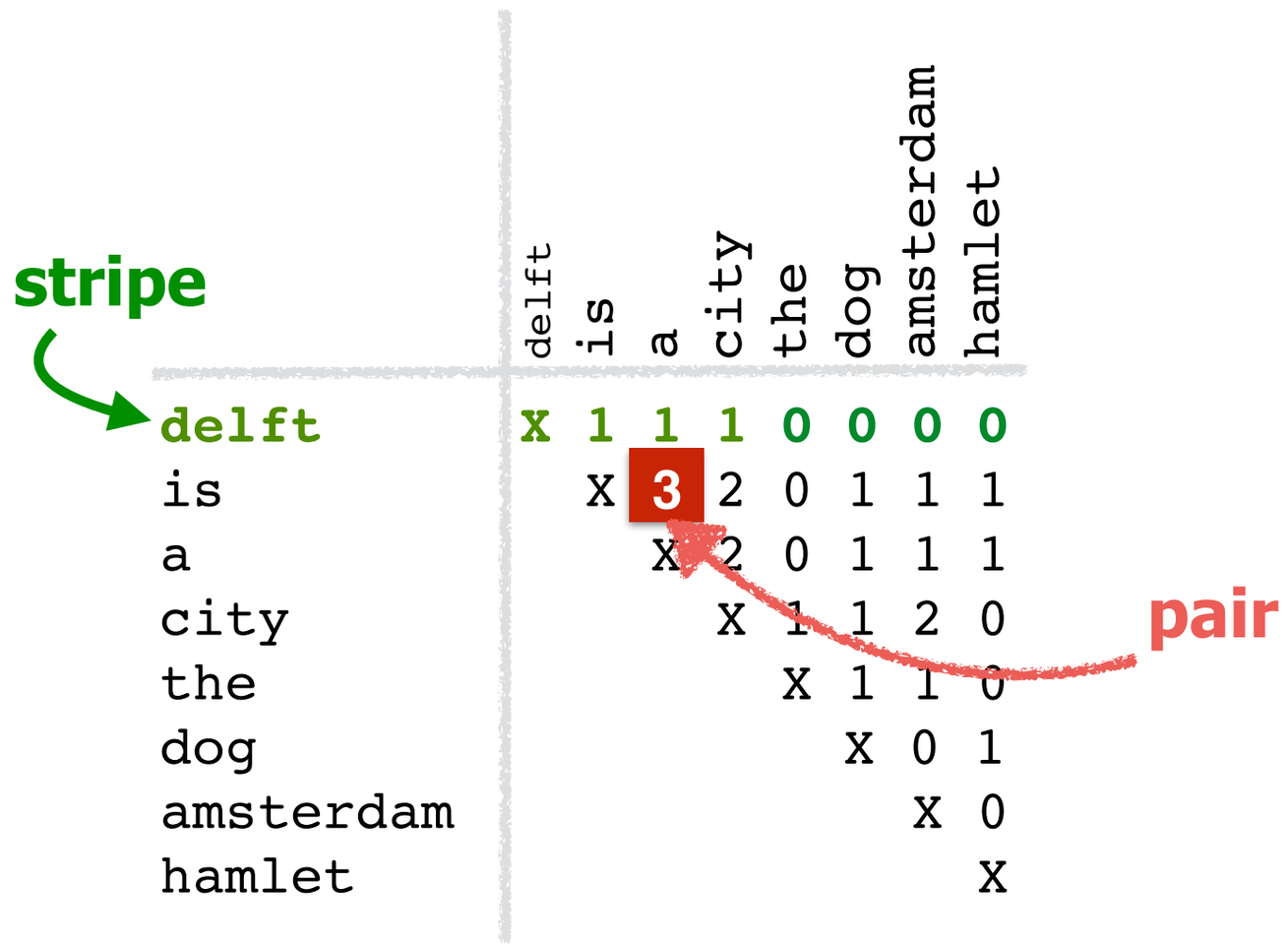


More general: **estimating distributions of discrete joint events** from a large number of observations.
Not just NLP/IR: think sales analyses (*people who buy X also buy Y)*

each pair is a **cell** in the **matrix** (**complex key**)

Pairs

```
map(docid a, doc d):
        foreach term w in d:
            foreach term u in d:
                EmitIntermediate(pair(w,u),1)

reduce(pair p, counts [c1, c2, …]
    s = 0;
    foreach c in counts:
        s += c;
    Emit(pair p, count s);
```

emit co-occurrence count

a single cell in the co-occurrence matrix

each stripe is a **row** in the **matrix** (**complex value**)

Stripes

```
map(docid a, doc d):
        foreach term w in d:
            H = associative_array;
            foreach term u in d:
                H{u}=H{u}+1;
            EmitIntermediate(term w, Stripe H);

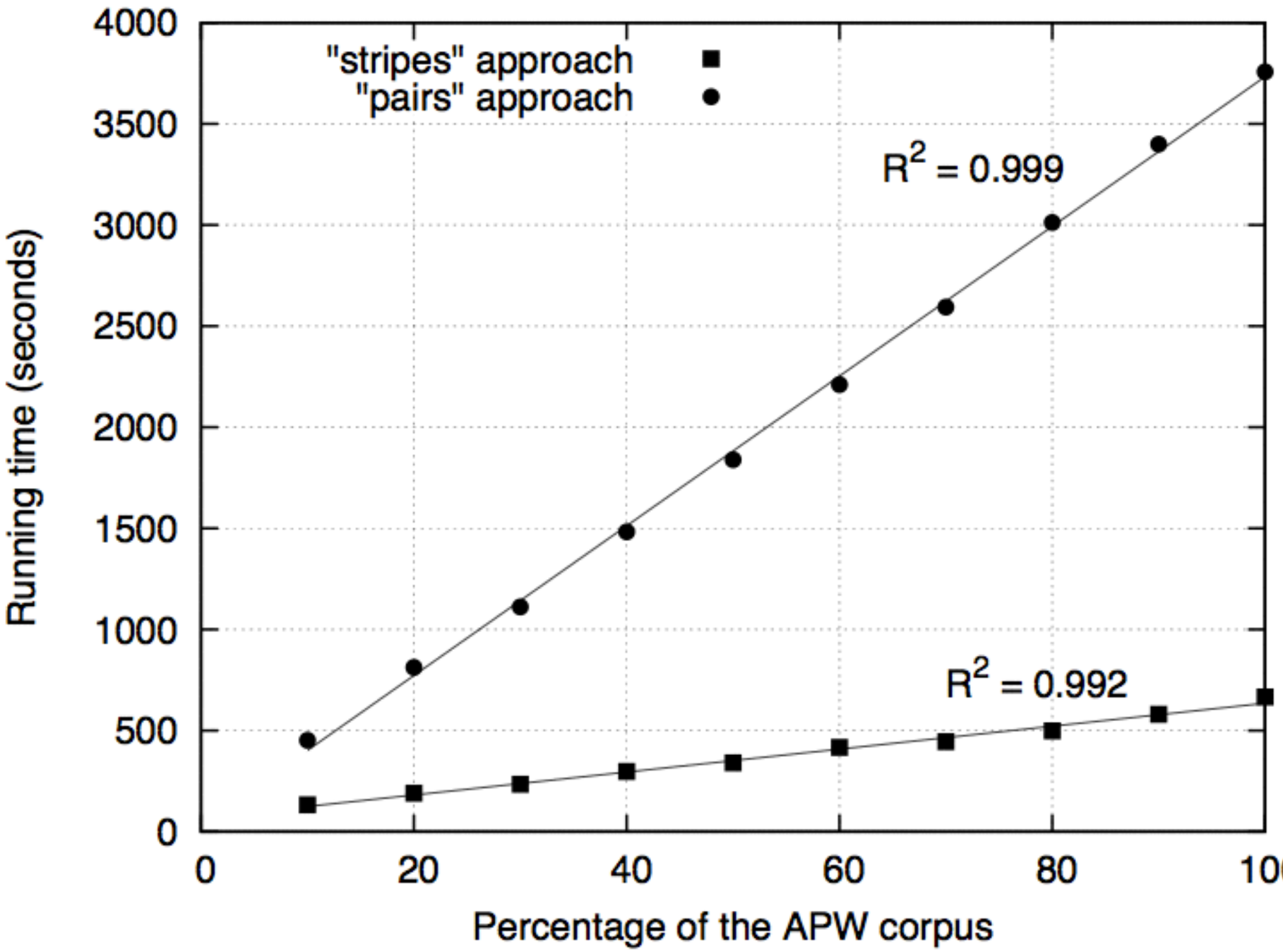
reduce(term w, stripes [H1,H2,..])
    F = associative_array;
    foreach H in stripes:
        sum(F,H);
    Emit(term w, stripe F)
```

emit terms co-occurring with term w

one row in the co-occurrence matrix

Pairs & Stripes

2.3M documents
Co-occurrence window: 2
19 nodes in the cluster



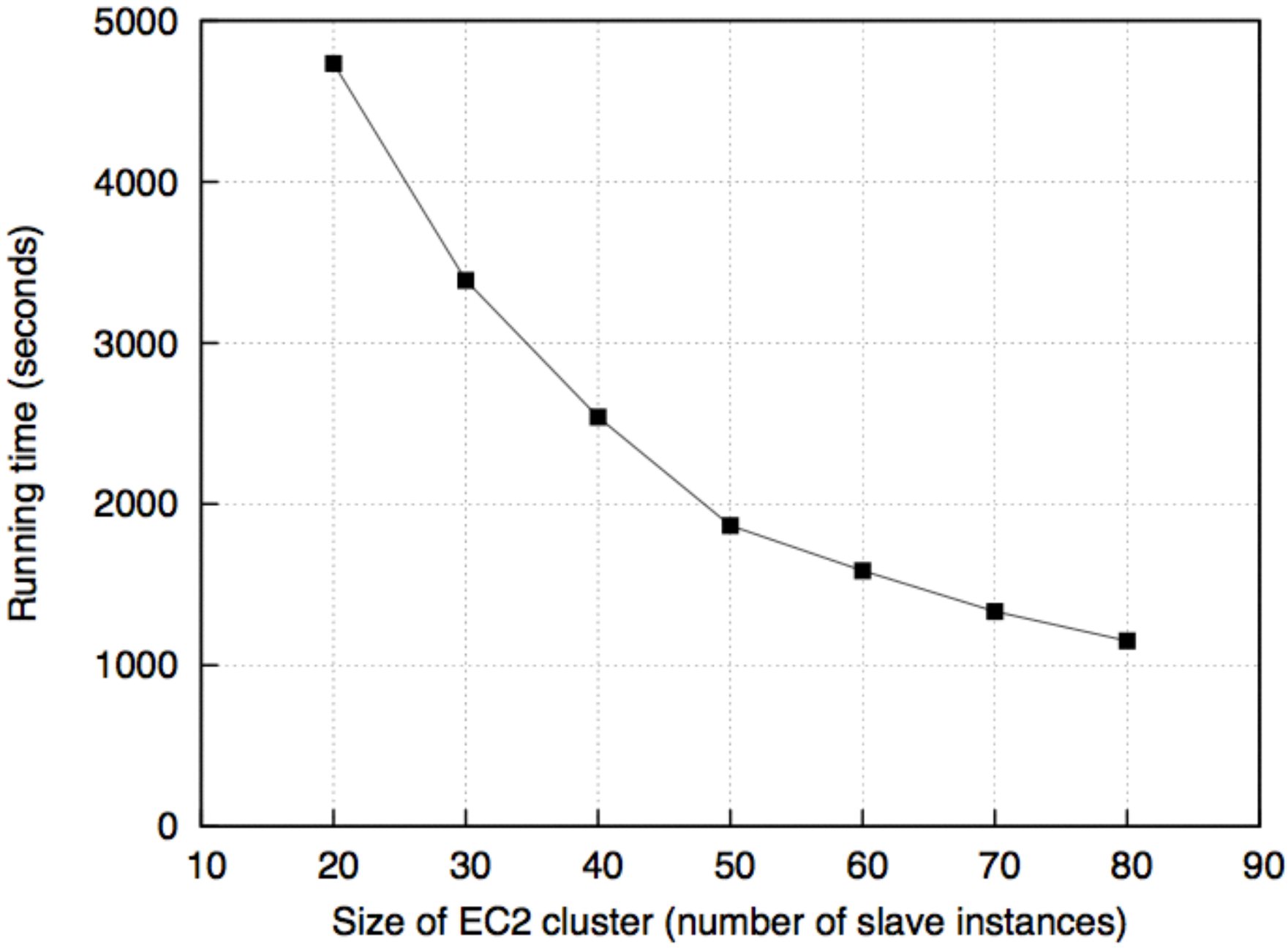
1 hour
2.6 billion intermediate key/value pairs;
after combiner run: **1.1B**
final key/value pairs: 142M

11 minutes
653M intermediate key/value pairs;
after combiner run: **29M**
final: 1.69M rows

Source: Jimmy Lin's MapReduce Design Patterns book

Stripes

2.3M documents
Co-occurrence window: 2
Scaling up (on EC2)



Source: Jimmy Lin's MapReduce Design Patterns book

Pairs & Stripes: two ends of a spectrum

Pairs ⟷ **Stripes**

each co-occurring event is recorded

all co-occurring events wrt. the conditioning event are recorded

Middle ground: divide key space into buckets and treat each as a "**sub-stripe**".
If one bucket in total: stripes, if #buckets==vocabulary: pairs.

Design pattern III:

Order inversion

From absolute counts to relative frequencies

number of times a co-occurring word pair is observed

$$f(w_j \mid w_i) = \frac{\overbrace{N(w_i, w_j)}}{\sum_{w'} N(w_i, w')}$$

Corpus: 3 documents

Delft is a city.
Amsterdam is a city.
Hamlet is a dog.

Co-occurrence matrix
(on the document level)

	delft	is	a	city	the	dog	amsterdam	hamlet
delft	x	1	1	1	0	0	0	0
is		x	3	2	0	1	1	1
a			x	2	0	1	1	1
city				x	1	1	2	0
the					x	1	1	0
dog						x	0	1
amsterdam							x	0
hamlet								x

The marginal

$$f(\text{a} \mid \text{is}) = \frac{3}{3+2+4\times 1} = \frac{1}{3}$$

$$f(\text{city} \mid \text{amsterdam}) = \frac{2}{2+3\times 1} = \frac{2}{5}$$

$$f(\text{city} \mid \text{is}) = \frac{2}{3+2+4\times 1} = \frac{2}{9}$$

From absolute counts to relative frequencies: Stripes

$$f(w_j \mid w_i) = \frac{N(w_i, w_j)}{\sum_{w'} N(w_i, w')}$$

Marginal can be computed easily in one job.
Second Hadoop job to compute the relative frequencies.

```
map(docid a, doc d):
        foreach term w in d:
                H = associative_array;
                foreach term u in d:
                        H{u}=H{u}+1;
                EmitIntermediate(term w, Stripe H);

reduce(term w, stripes [H1,H2,..])
        F = associative_array;
        foreach H in stripes:
                sum(F,H);
        Emit(term w, stripe F)
```

From absolute counts to relative frequencies: Pairs

$$f(w_j \mid w_i) = \frac{N(w_i, w_j)}{\sum_{w'} N(w_i, w')}$$

2 options to make Pairs work:

- build in-memory associative array; but advantage of pairs approach (no memory bottleneck) is removed
- **properly sequence the data**: (1) compute marginal, (2) for each joint count, compute relative frequency

```
map(docid a, doc d):
        foreach term w in d:
                foreach term u in d:
                        EmitIntermediate(pair(w,u),1)

reduce(pair p, counts [c1, c2, ..])
        s = 0;
        foreach c in counts:
                s += c;
        Emi(pair p, count s);
```

From absolute counts to relative frequencies: Pairs

$$f(w_j \mid w_i) = \frac{N(w_i, w_j)}{\sum_{w'} N(w_i, w')}$$

```
map(docid a, doc d):
        foreach term w in d:
                foreach term u in d:
                        EmitIntermediate(pair(w,u),1)
                        EmitIntermediate(pair(w,*),1)

reduce(pair p, counts [c1, c2, ..])
        s = 0;
        foreach c in counts:
                s += c;
        if(p.right==*)
                marginal=s;//keep marginal across reduce calls
        else
                Emit(pair p, s/marginal);
```

extra key/value pair for marginal

assumes a specific key ordering (* before the rest)

From absolute counts to relative frequencies: Pairs

$$f(w_j \mid w_i) = \frac{N(w_i, w_j)}{\sum_{w'} N(w_i, w')}$$

```
map(docid a, doc d):
        foreach term w in d:
                foreach term u in d:
                        EmitIntermed
                        EmitIntermed

reduce(pair p, counts [c1, c2, ..])
        s = 0;
        foreach c in counts:
                s += c;
        if(p.right==*)
                marginal=s;//keep ma
        else
                Emit(pair p, s/margi
```

Properly sequence the data:

- Custom **partitioner**: partition based on left part of pair
- Custom **key sorting**: * before anything else
- Combiner usage (or in-memory mapper) required for (w,*)
- Preserving state of marginal

extra key/value pair for marginal

assumes a specific key ordering (* before the rest)

Design pattern: order inversion

From absolute counts to relative frequencies: Pairs

$$f(w_j \mid w_i) = \frac{N(w_i, w_j)}{\sum_{w'} N(w_i, w')}$$

Example data flow for pairs approach:

key	values	
(dog, ∗)	[6327, 8514, . . .]	compute marginal: $\sum_{w'} N(\text{dog}, w') = 42908$
(dog, aardvark)	[2,1]	$f(\text{aardvark}\|\text{dog}) = 3/42908$
(dog, aardwolf)	[1]	$f(\text{aardwolf}\|\text{dog}) = 1/42908$
. . .		
(dog, zebra)	[2,1,1,1]	$f(\text{zebra}\|\text{dog}) = 5/42908$
(doge, ∗)	[682, . . .]	compute marginal: $\sum_{w'} N(\text{doge}, w') = 1267$
. . .		

Order inversion

- **Goal**: compute the result of a computation (marginal) in the reducer **before** the data that requires it is processed (relative frequencies)

- **Key insight**: convert **sequencing** of computation into a **sorting** problem

- Ordering of key/value pairs and key partitioning controlled by the programmer
  - Create a notion of "**before**" and "**after**"

- **Major benefit**: reduced memory footprint

Design pattern IV:

Secondary sorting

Secondary sorting

- **Order inversion pattern: sorting by key**

- What about **sorting by value** (a “secondary” sort)?
  - **Hadoop does not allow it**

(t_1, m_1, r_{80521})
(t_1, m_2, r_{14209})
(t_1, m_3, r_{76042})
…
(t_2, m_1, r_{21823})
(t_2, m_2, r_{66508})
(t_2, m_3, r_{98347})

time, sensor, reading

Goal: activity of each sensor over time
Idea: sensor id as intermediate key,
the rest as value $m_1 \rightarrow (t_1, r_{1234})$

Wanted: secondary sort by timestamp

Secondary sorting

- **Solution**: move part of the value into the intermediate key and **let Hadoop do the sorting**

$$m_1 \rightarrow (t_1, r_{1234})$$
$$(m_1, t_1) \rightarrow r_{1234}$$

- Also called "**value-to-key**" conversion

$$(m_1, t_1) \rightarrow [(r_{80521})]$$
$$(m_1, t_2) \rightarrow [(r_{21823})]$$
$$(m_1, t_3) \rightarrow [(r_{146925}]$$

Secondary sorting

- **Solution**: move part of the value into the intermediate key and **let Hadoop do the sorting**

$$m_1 \rightarrow (t_1, r_{1234})$$
$$(m_1, t_1) \rightarrow r_{1234}$$

- Also called "**value-to-key**" con

$$(m_1, t_1) \rightarrow [(r_{80521})]$$
$$(m_1, t_2) \rightarrow [(r_{21823})]$$
$$(m_1, t_3) \rightarrow [(r_{146925}]$$

Requires:

- **Custom key sorting**: first by left element (sensor id), and then by right element (timestamp)
- **Custom partitioner**: partition based on sensor id only
- **State across `reduce()` calls tracked** (complex key)

Database operations

Databases….

Relation *Hyperlinks*

attributes / tuples

FROM	TO
url1	url2
url2	url3
url3	url5

"link table" with **billions** of entries

- **Scenario**
  - Database tables can be written out to file, one tuple per line
  - MapReduce jobs can perform standard database operations
  - Useful for operations that pass over most (all) tuples

- **Example**
  - Find all paths of length 2 in the table Hyperlinks
  - Result should be tuples `(u,v,w)` where a link exists between `(u,v)` and between `(v,w)`

Databases….

Relation *Hyperlinks*

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- **Example**
  - Find all paths of length 2 in the table Hyperlinks
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join Hyperlinks with itself

$FROM_1$	TO_1
url1	url2
url2	url3
url3	url5

$FROM_2$	TO_2
url1	url2
url2	url3
url3	url5

(url1,url2,url3)
(url2,url3,url5)

Database operations: relational joins

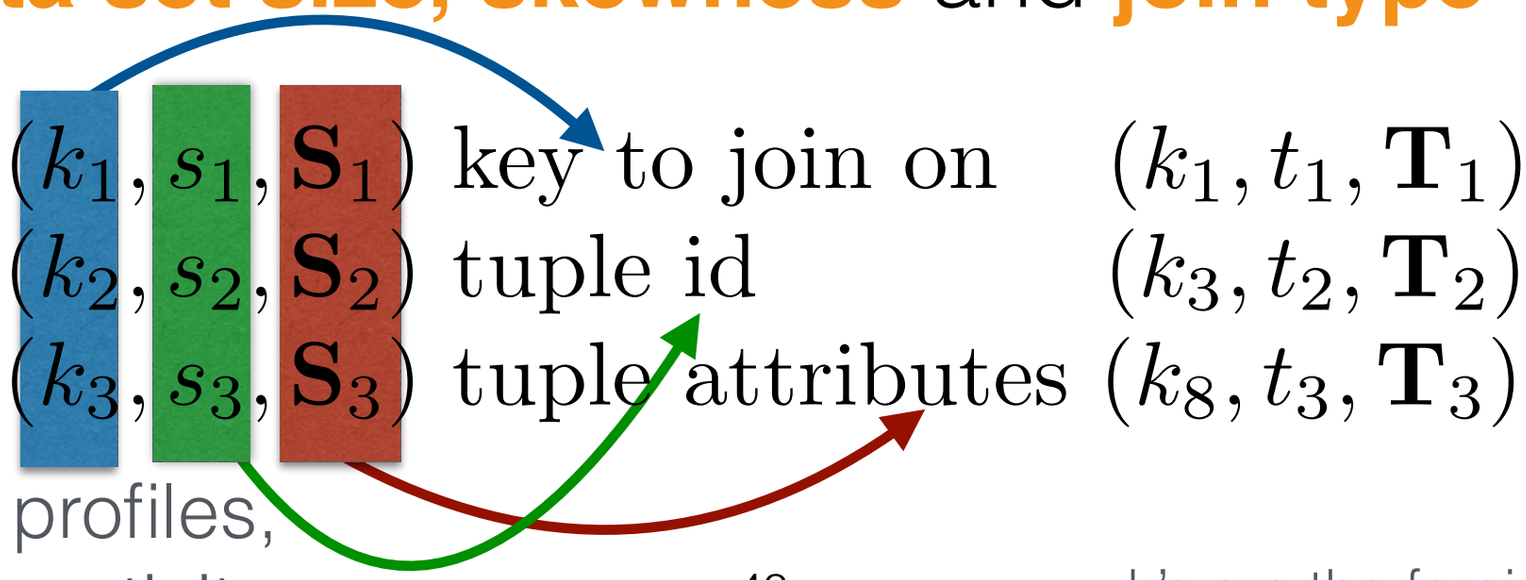
reduce side joins

- one-to-one
- one-to-many
- many-to-many

map side joins

Relational joins

- Popular application: data-warehousing
  - Often data is relational (sales transactions, product inventories,..)
  - **Different strategies** to perform relational joins on two datasets (tables in a DB) **S** and **T** depending on **data set size, skewness** and **join type**



S may be user profiles,
T logs of online activity

k's are the foreign keys

Relational joins: reduce side

database tables exported to file

- **Idea**: map over both **datasets** and emit the join key as intermediate key and the tuple as value

- **One-to-one join**: ***at most*** one tuple from **S** and **T** share the same join key

$$k_{23} \rightarrow [(s_{64}, S_{64}), (t_{84}, T_{84})]$$
$$k_{37} \rightarrow [(s_{68}, S_{68})]$$
$$k_{59} \rightarrow [(t_{97}, T_{97}), (s_{81}, S_{81})]$$
$$\ldots$$

Four possibilities for the values in `reduce()`:

- a tuple from S
- a tuple from T
- (1) a tuple from S, (2) a tuple from T
- (1) a tuple from T, (2) a tuple from S

reducer emits key/value if the value list contains 2 elements

Relational joins: reduce side

- **Idea**: map over both **datasets** and emit the join key as intermediate key and the tuple as value

- **One-to-many join**: the primary key in **S** can join to ***many keys*** in **T**

$k_{23} \rightarrow [(t_{55}, T_{55}), (t_{44}, T_{44}), (s_{64}, S_{64}), (t_{84}, T_{84})]$
$k_{37} \rightarrow [(s_{68}, S_{68})]$
...

Better (less memory intensive): value-to-key conversion to create a composite key (join key, tuple id)

$(k_{82}, s_{105}) \rightarrow [(S_{105})]$
$(k_{82}, t_{98}) \rightarrow [(T_{98})]$
...

Requires:
(1) Sort order by keys
(2) Custom partitioner

Relational joins: reduce side

- **Idea**: map over both **datasets** and emit the join key as intermediate key and the tuple as value

- **Many-to-many join**: many tuples in **S** can join to many tuples in **T**

Possible solution: **employ the one-to-many approach**.

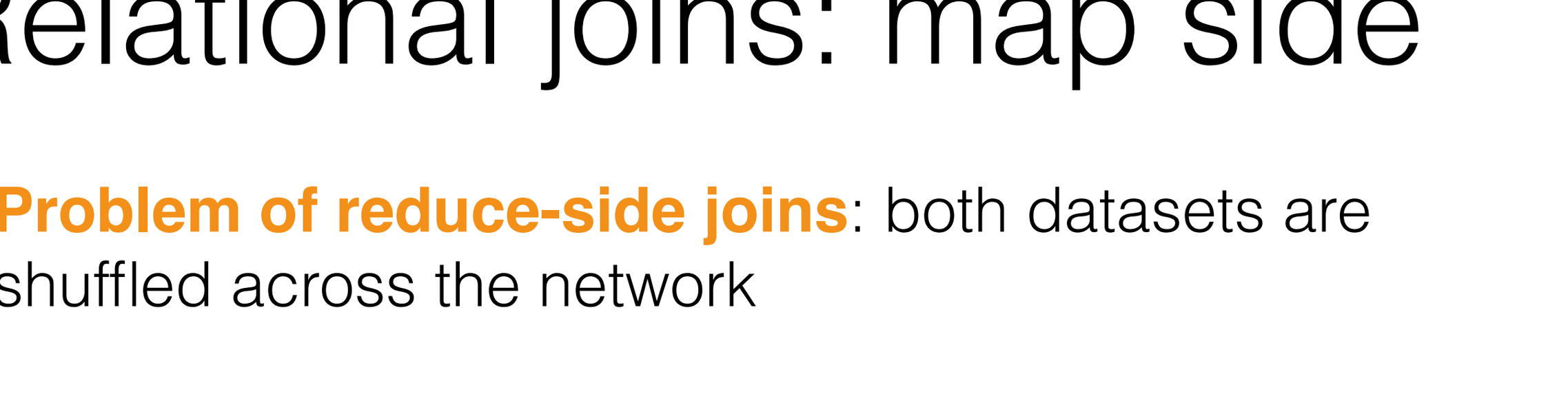
Works well if **S** has only a few tuples per join (requires data knowledge).

$$(k_{82}, s_{105}) \rightarrow [(S_{105})]$$
$$(k_{82}, s_{145}) \rightarrow [(S_{145})]$$
$$\ldots$$
$$(k_{82}, t_{98}) \rightarrow [(T_{98})]$$
$$(k_{82}, t_{101}) \rightarrow [(T_{101})]$$
$$(k_{82}, t_{137}) \rightarrow [(T_{137})]$$
$$\ldots$$

Relational joins: map side

- **Problem of reduce-side joins**: both datasets are shuffled across the network

- In **map side joins** we assume that both datasets **are sorted by join key**; they can be joined by "scanning" both datasets simultaneously



Relational joins: comparison

- Problem of **reduce-side joins**: both datasets are shuffled across the network
- **Map-side join**: no data is shuffled through the network, very efficient
- **Preprocessing** steps take up more time in map-side join (partitioning files, sorting by join key)
- **Usage scenarios**:
  - Reduce-side: adhoc queries
  - Map-side: queries as part of a longer workflow; preprocessing steps are part of the workflow (can also be Hadoop jobs)

Database operations: the rest

Selections

Web_pages

Url	Category	Last_crawl_date	Page_length	Lng
news.yahoo.de	news	03-12-2013 07:08:45	765443	GER
nu.nl	news	03-12-2013 11:45:00	64435	NL
chess.com	game	23-10-2013 19:34:01	1264	EN
www.bbc.com/ sport/0/football/	sports	03-12-2013 14:13:22	6324	EN

SELECT * **FROM** Web_pages **WHERE** Url **LIKE** 'nu.nl'
SELECT * **FROM** Web_pages **WHERE** Lng **LIKE** 'GER'

Projections

Web_pages

Url	Category	Last_crawl_date	Page_length	Lng
news.yahoo.de	news	03-12-2013 07:08:45	765443	GER
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www.bbc.com/ sport/0/football/	sports	03-12-2013 14:13:22	6324	EN

SELECT category **FROM** Web_pages

Union

Web_pages_crawler1

Url	Category	Page_length	Lng
news.yahoo.de	news	765443	GER
nu.nl	news	64435	
chess.com	game	1264	
www.bbc.com/ sport/0/football/	sports	6324	

Web_pages_crawler2

Url	Category	Page_length	Lng
news.yahoo.de	news	765443	GER
volkskrant.nl	news	234445	NL
chessbase.com	game	1264	EN
www.bbc.com/ sport/0/football/	sports	6324	EN

Intersection

Web_pages_crawler1

Url	Category	Page_length	Lng
news.yahoo.de	news	765443	GER
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chess.com	game	1264	
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Web_pages_crawler2

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Summary

- Design patterns for MapReduce
- Common database operations

Recommended reading

- **Mining of Massive Datasets** by Rajaraman & Ullman. Available online. Chapter 2.
  - The last part of this lecture (database operations) has been drawn from this chapter.
- **Data-Intensive Text Processing with MapReduce** by Lin et al. Available online. Chapter 3.
  - The lecture is mostly based on the content of this chapter.

THE END