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# Entity Resolution in the Web of Data

# Part II

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# Iterative Approaches

# Iterative Entity Resolution

Basic algorithm for entity resolution in one source $E$ (dirty)

- Compare each entity description $e_i \in S$ with all other entity descriptions in $E$, i.e., with all $e_j \in E \setminus \{e_i\}$
- For comparison, use a match function to classify each pair $(e_i, e_j)$ as a match/non-match
  - Based on similarity measures
  - Based on domain-specific rules
  - Based on a combination of both
- Complexity: $O(N^2)$, with $N$ being the number of entity descriptions in $E$

Algorithm easily extends to entity resolution among two sources (clean-clean or dirty-dirty)

# Iterative Entity Resolution

Partial results of the entity resolution process can be propagated to generate new results

Iterative approaches can be grouped into:

– Matching-based: Exploit relationships between entity descriptions
  - *If descriptions related to $e_i$ are similar to descriptions related to $e_j$, this is an evidence that $e_i$ and $e_j$ are also similar*
– Merging-based: Exploit the partial results of merging descriptions

# Iterative Entity Resolution on Complex Data

- Tabular data
  - Homogeneous structure
  - Similarity measures focus on variations in the values, not the structure
- Tree data
  - Structure of entity descriptions (of same and different types) varies
  - Similarity measures consider values, structure, and parent-child relationships
- Graph data
  - Structure of entity descriptions varies
  - Similarity functions consider values, structure, and neighbor relationships

# Iterative Entity Resolution – Tabular Data

Table example

| Name | Year | Architects | Location |
|---|---|---|---|
| Eiffel Tower | 1889 | Sauvestre | Paris |
| typo | | missing value | conflicting values |
| Eifel Tower | 1889 | NULL | France |

- Input:
  - A relation with $N$ tuples
  - A similarity measure
- Output:
  - Classes (clusters) of equivalent tuples (= matches)
- Problem: a large number of tuples
  - Comparing each pair is too costly

**=> Effectiveness strongly depends on good choice**

**=> Avoid comparisons that (most likely) yield no match**

# Swoosh [Benjelloun et al. 2009]

A generic approach for entity resolution in tabular data

Black-boxes:

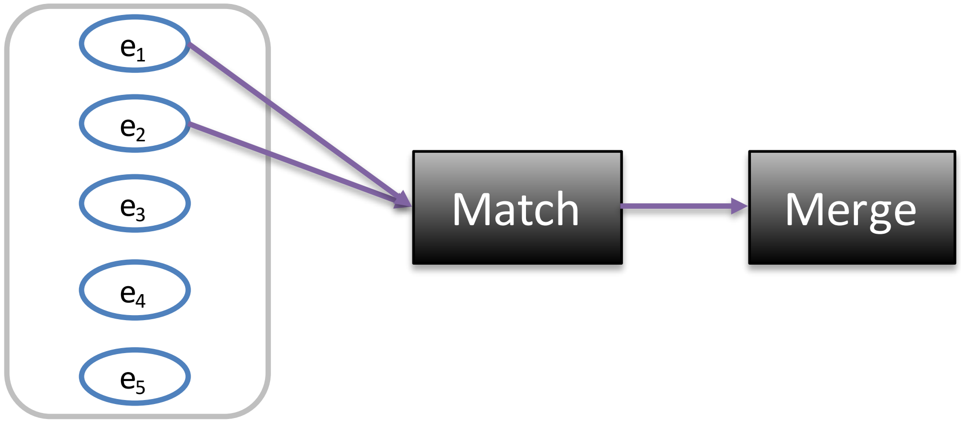
- A match function M
- A merge function μ

The goal:

*Minimize the number of invocations to the these expensive black-boxes*

Merged entity descriptions are considered as new entity descriptions

– Possible match candidates to other, already examined descriptions



# Swoosh

A generic approach for entity resolution in tabular data

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- A <u>match</u> function M
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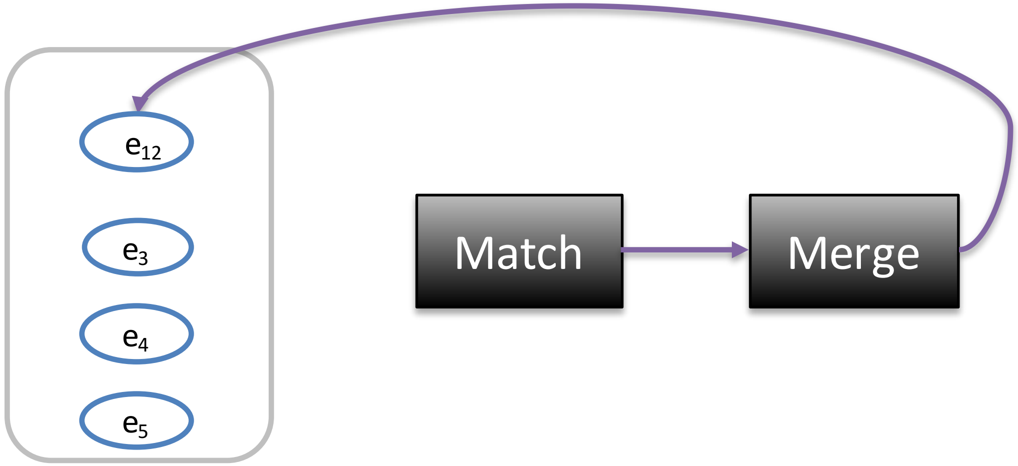


# Swoosh

Properties that can be exploited to enhance efficiency

- Idempotence:

$M(e_1, e_1) = true$ and $\mu(e_1, e_1) = e_1$

- Commutativity:

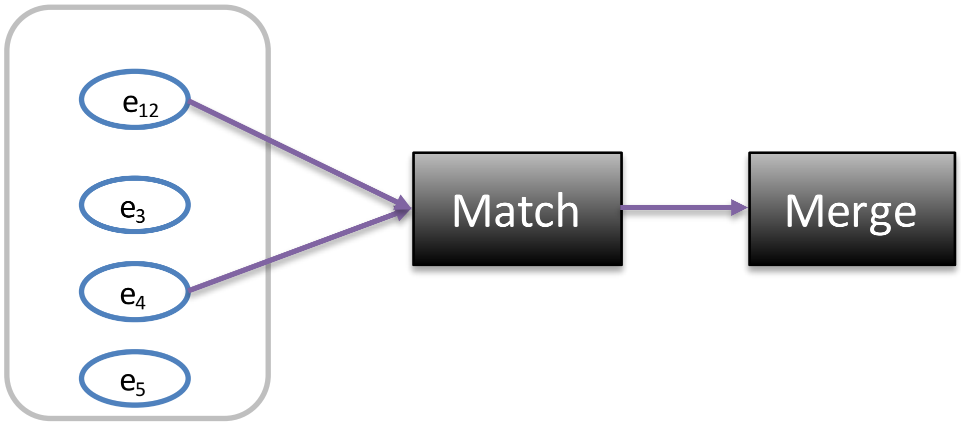
$M(e_1, e_2) = M(e_2, e_1)$ and $\mu(e_1, e_2) = \mu(e_2, e_1)$

- Associativity:

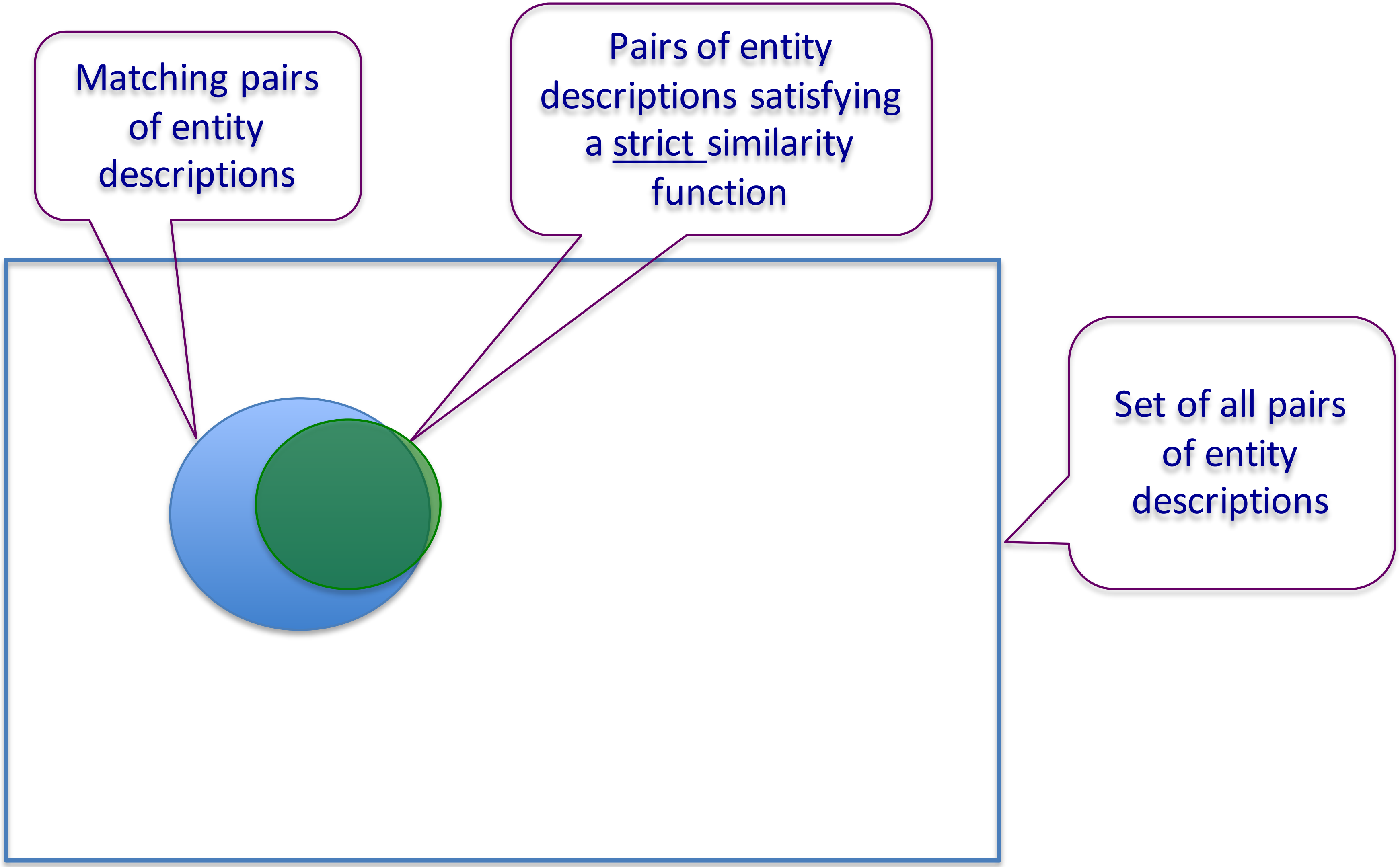
$\mu(e_1, \mu(e_2, e_3)) = \mu(\mu(e_1, e_2), e_3)$

- Representativity:

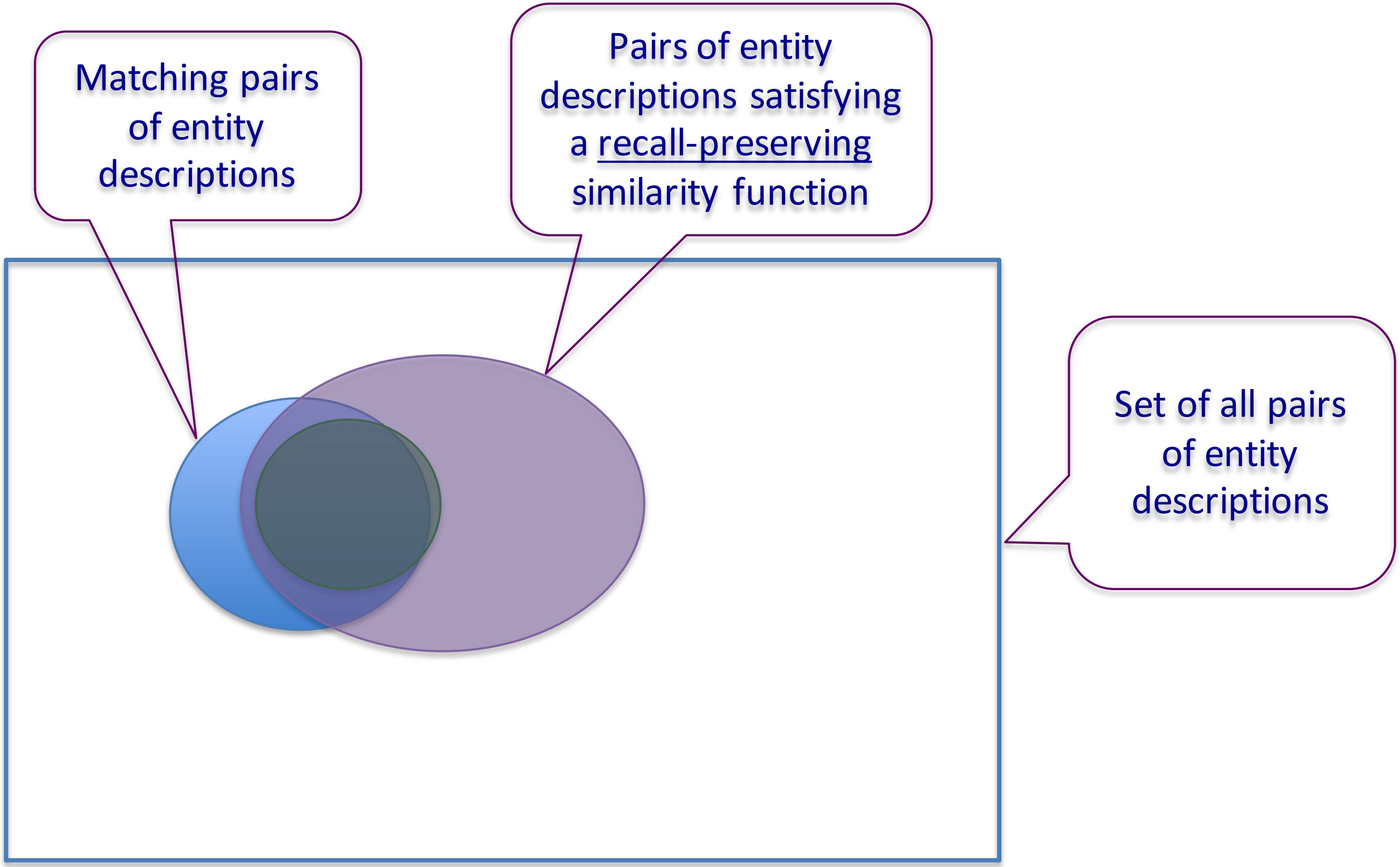
if $\mu(e_1, e_2) = e_3$ and $M(e_1, e_4) = true$, then $M(e_3, e_4) = true$



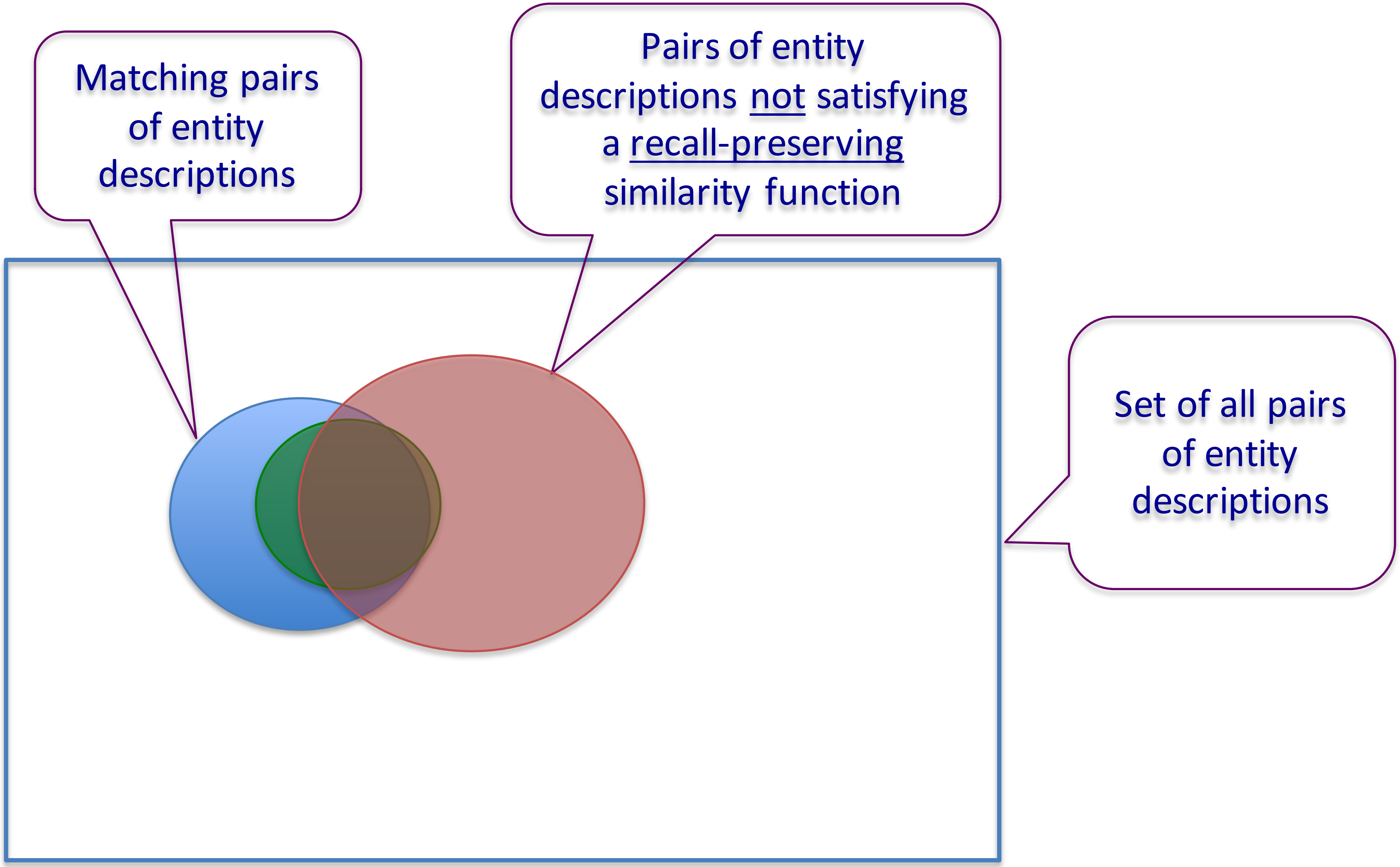
# Recall-Maintaining Similarity Functions



# Recall-Maintaining Similarity Functions



# Recall-Maintaining Similarity Functions



# Iterative Entity Resolution – Tree Data

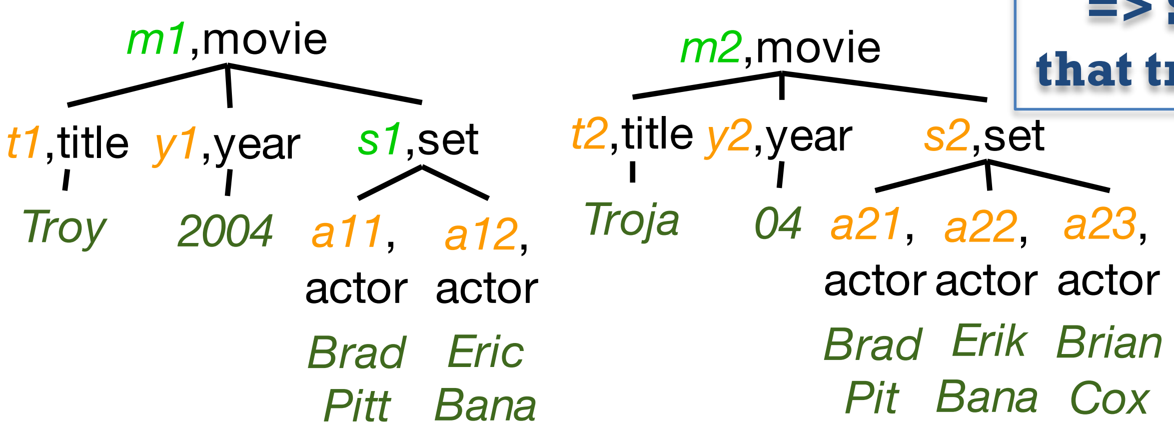
- Examples of hierarchically organized data
  - Relational star / snowflake schema [Ananthakrishna et al. 2002]

| ID | Actor | Film |
| --- | --- | --- |
| S1 | Al Pacino | F1 |
| S2 | Al Pacino | F2 |
| S3 | Marlon Brando | F2 |

| ID | Name | Year | Rating |
| --- | --- | --- | --- |
| F1 | The Godfather | 1972 | 9.2 |
| F2 | Gottvatter, The | 72 | |

**=> Specialized similarity measures**

  - Hierarchical XML data [CHL10]




**=> Specialized algorithms that traverse the tree structure**

# DELPHI Containment Metric [ACG02]

- Hybrid similarity measure [Ananthakrishna et al. 2002] considering
  - Similarity of attribute values (*tcm*)
  - Similarity of children sets reached by following foreign keys (*fkcm*)
- Similarity of attribute values
  - Divide tuples into tokens → token sets *TS*
  - Compute the edit distance between token sets
  - Determine weight of each token using IDF [Baeza-Yates & Ribeiro-Neto 1999]
  - The token similarity metric *tcm* measures which fraction of one tuple *T* is covered by the other tuple *T'*

$$tcm(T,T') = \frac{\sum idf(TS(T) \cap TS(T'))}{\sum idf(TS(T))}$$

# DELPHI Containment Metric [ACG02]

- Similarity of children sets
  - The children set of a tuple $T$ includes all tuples referencing $T$ from other relations by means of a foreign key
    → Children sets $CS$
  - Foreign-key containment metric ($fkcm$) measures at what extent the children set of a tuple $T$ is covered by the children set of a tuple $T'$

$$fkcm(T,T') = \frac{|CS(T) \cap CS(T')|}{|CS(T)|}$$

# Containment Metric

- Combining *tcm* and *fkcm*:
  - Both *tcm* and *fkcm* are assigned an IDF weight
  - Use of a classification function:
    *pos(x) = 1 if x > 0,*
    *-1 otherwise*
  - Threshold for *tcm*: *s1*
  - *Threshold for fkcm: s2*
  - Classification of pairwise comparison between *T* and *T'* using

$$pos(IDF(TS) * pos(tcm(T,T') - s1) + IDF(CS) * pos(fkcm(T,T') - s2))$$

  - If final result equals 1, then match, otherwise non-match

# Containment Metric - Example

| ID | Actor | Film |
|---|---|---|
| S1 | Al Pacino | F1 |
| S2 | Al Pacino | F2 |
| S3 | Marlon Brando | F2 |

| ID | Name | Year | Rating |
|---|---|---|---|
| F1 | The Godfather | 1972 | 9.2 |
| F2 | Gottvatter, The | 72 | |

**1. Token sets:**
*TS(F1)* = {The, Godfather, 1972, 9.2}
*TS(F2)* = {Gottvatter, The, 72}

**2. Attribute similarities**
The = The, Godfather = Gottvatter, 1972 = 72.

**3. Weights**
For simplification, we assume all tokens have equal weight.

**4. Token containment metric**
tcm(F1,F2) = ¾, tcm(F2,F1) = 1

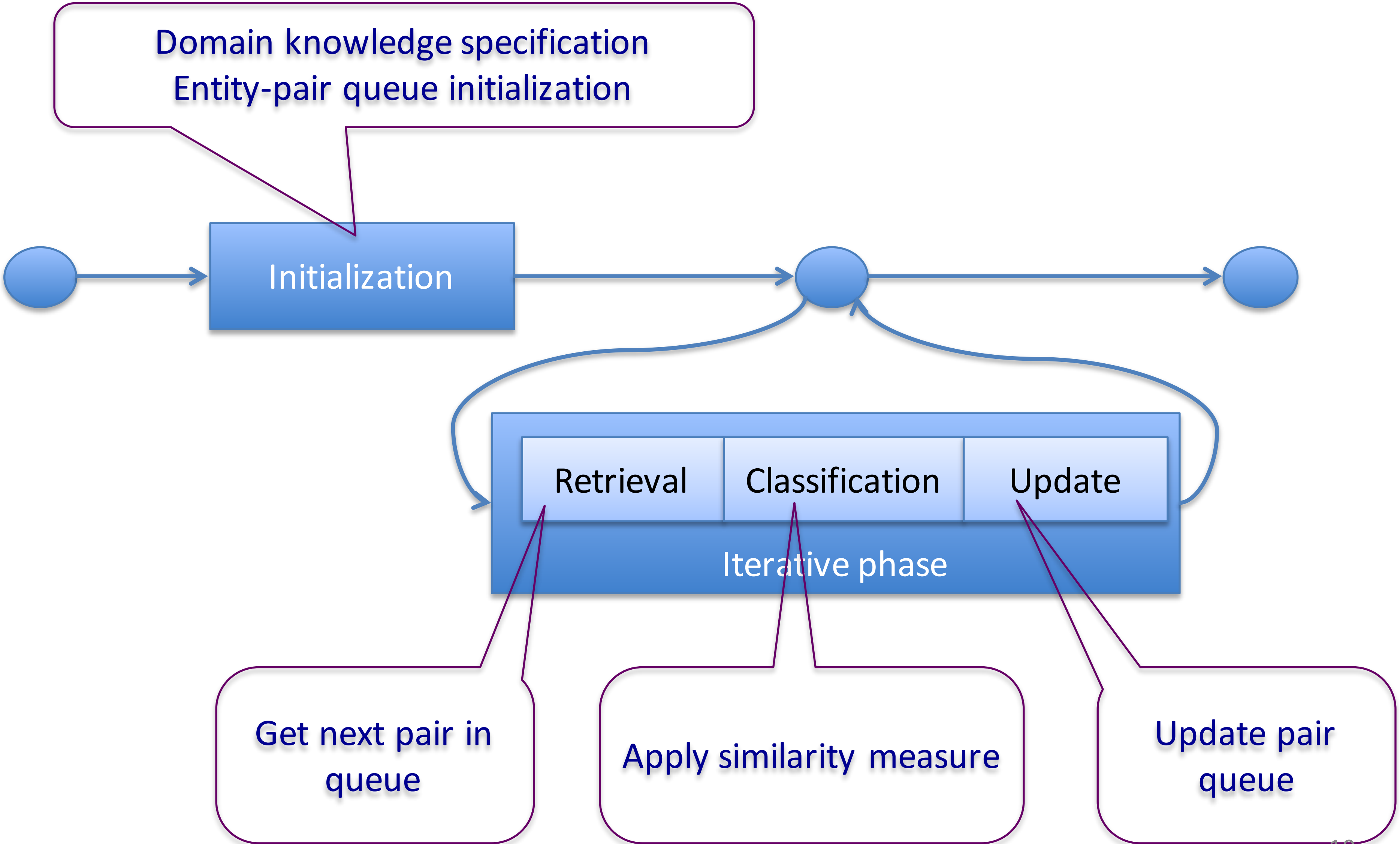
**5. Children co-occurrence**
*fkcm(F1,F2)* = 1, *fkcm(F2,F1)* = ½

6. **Combination of both metrics**
($s1 = s2 = 0.5$, weights = 1)
*pos( pos(3/4 - 0.5) + pos(1 - 0.5) = 1*
→ F1 and F2 match

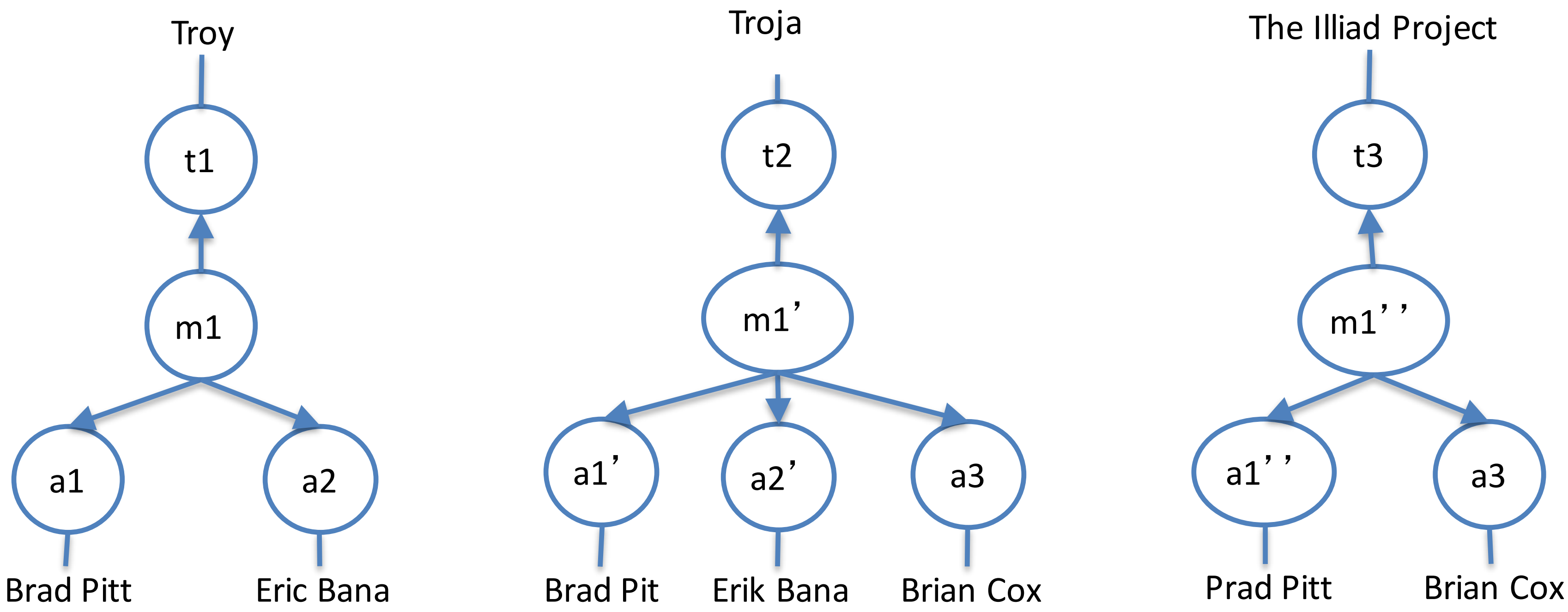
# Iterative Entity Resolution - Graph Data

- In the most general case, data not only form a tree, but a graph
  - LOD graph
  - General relational schema
  - Domain-knowledge about entity relationships
  - …
- In graph data, there is no clear order of comparisons (top down, bottom-up?)
- Several algorithms for entity resolution in graph data have been proposed [Dong et al. 2005, Weis & Naumann 2006, Bhattacharya & Getoor 2007, …]
  - Based on an entity graph
    (1 node = 1 entity, 1 edge = relationship between 2 entities)
  - Based on reference graph
    (1 node = 2 entities, 1 edge = relationship to another entity pair)
- Many of them conform to a general framework [Herschel et al. 2012]

# Iterative Entity Resolution – Graph Framework

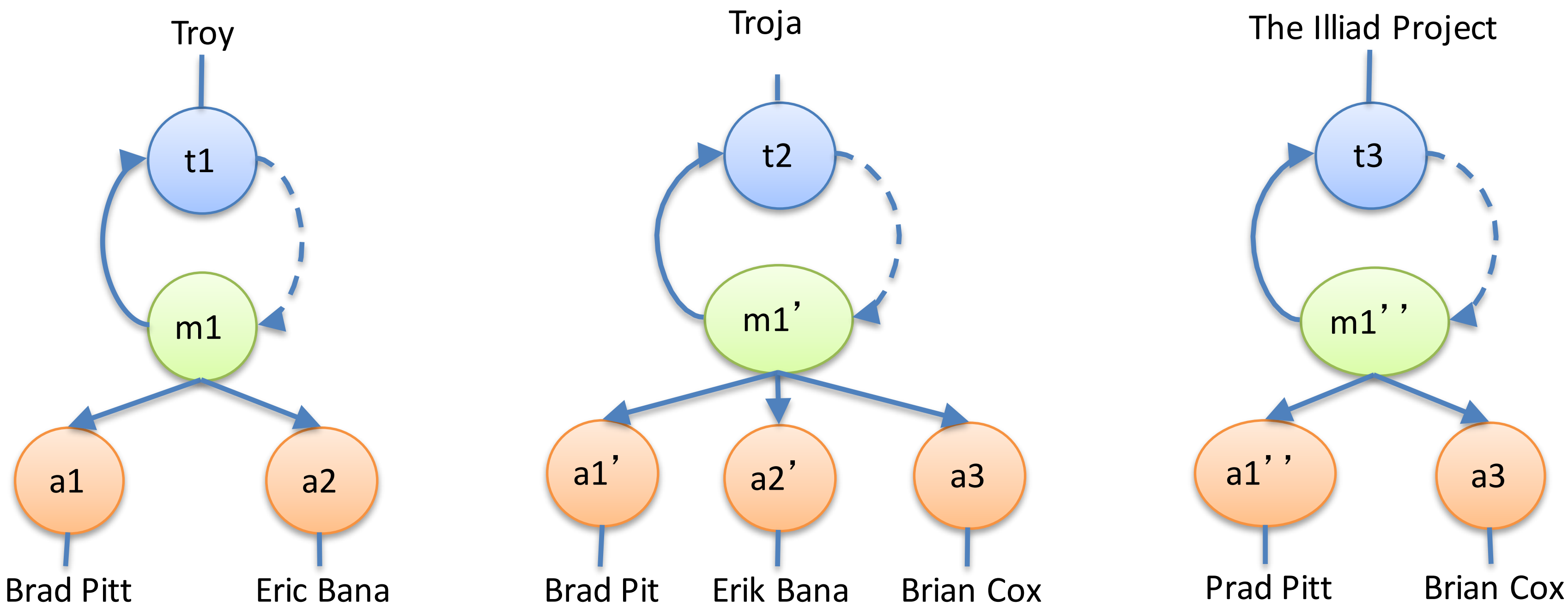


# Domain Expert Knowledge Specification




- Domain expert specifies
  - Duplicate candidate entities (e.g., movie, actor, title)
  - (Additional) relationships between candidates (e.g., title → movie)

# Domain Expert Knowledge Specification

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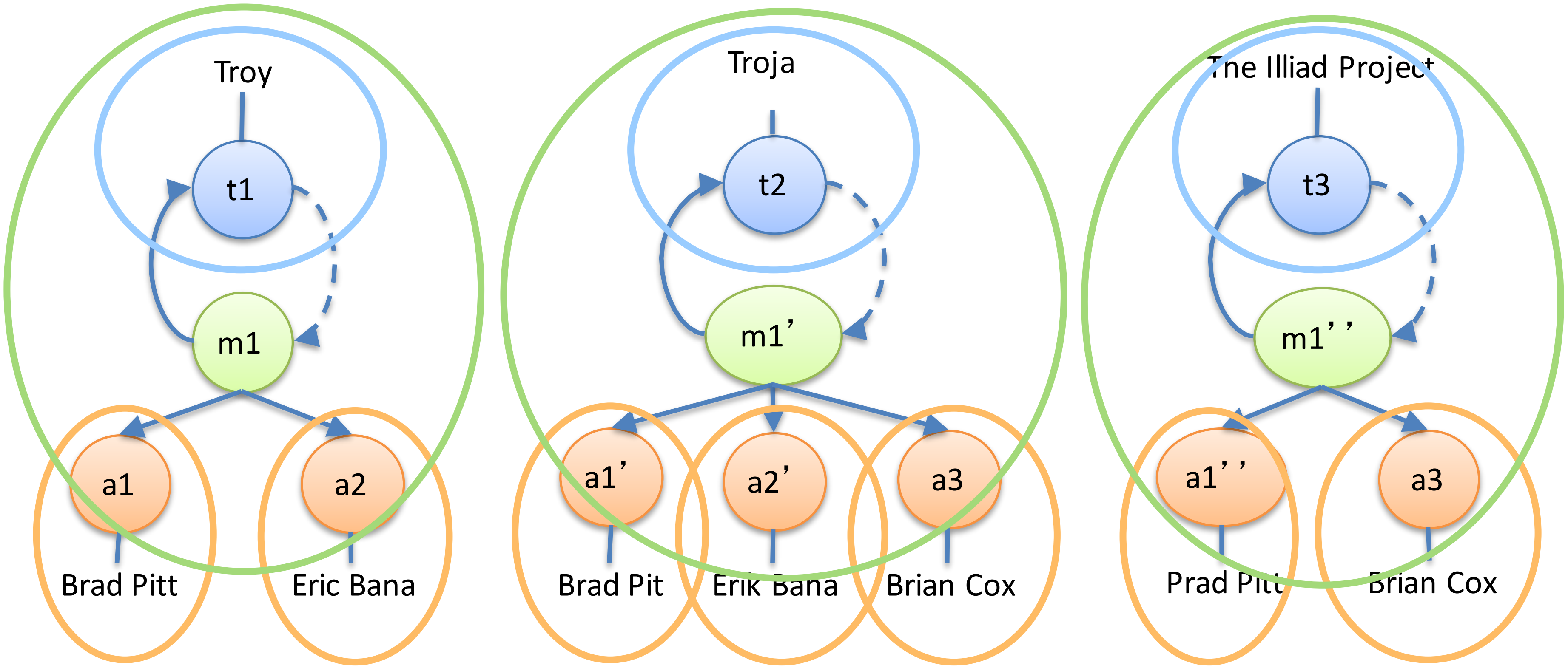
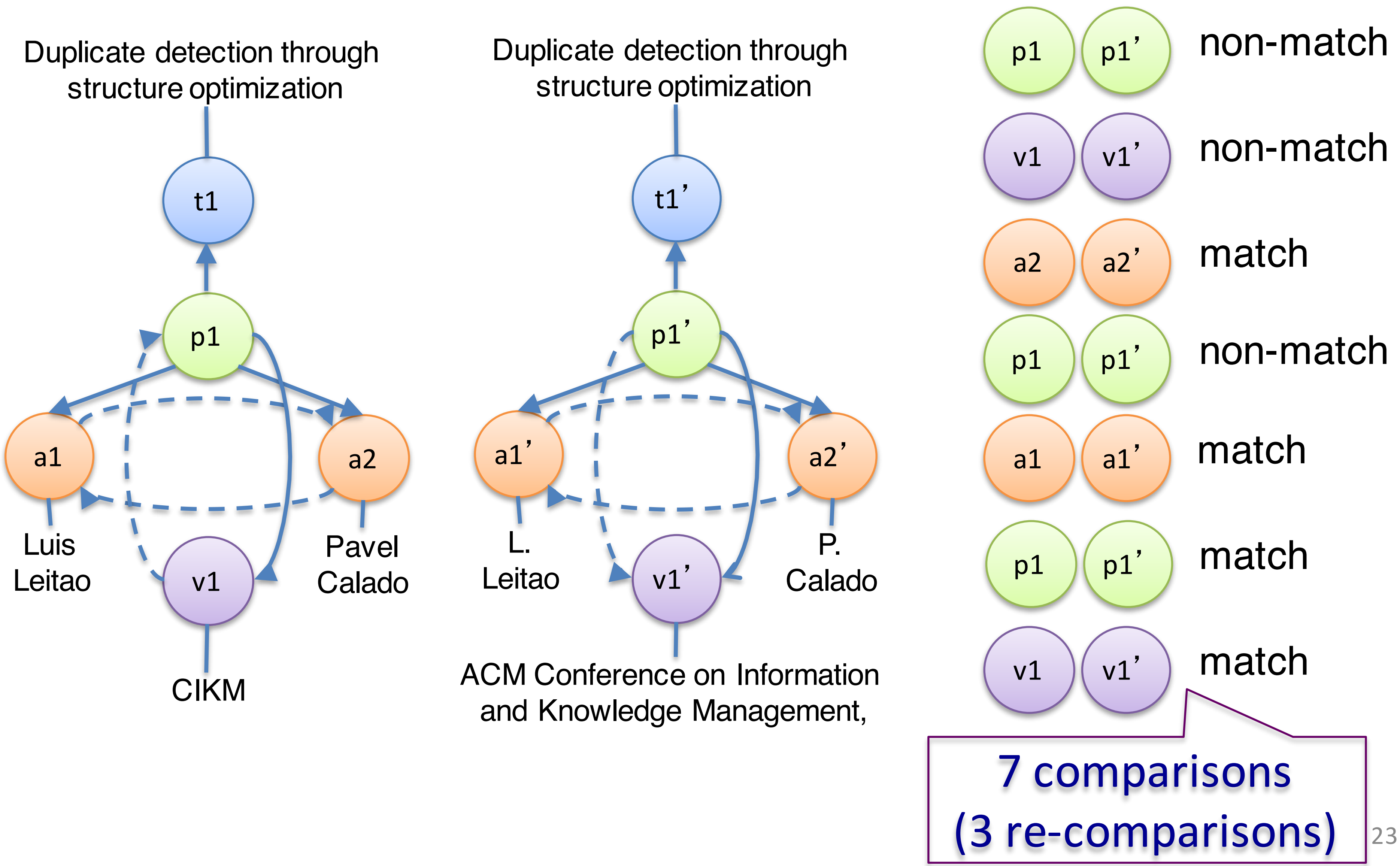
# Domain Expert Knowledge Specification

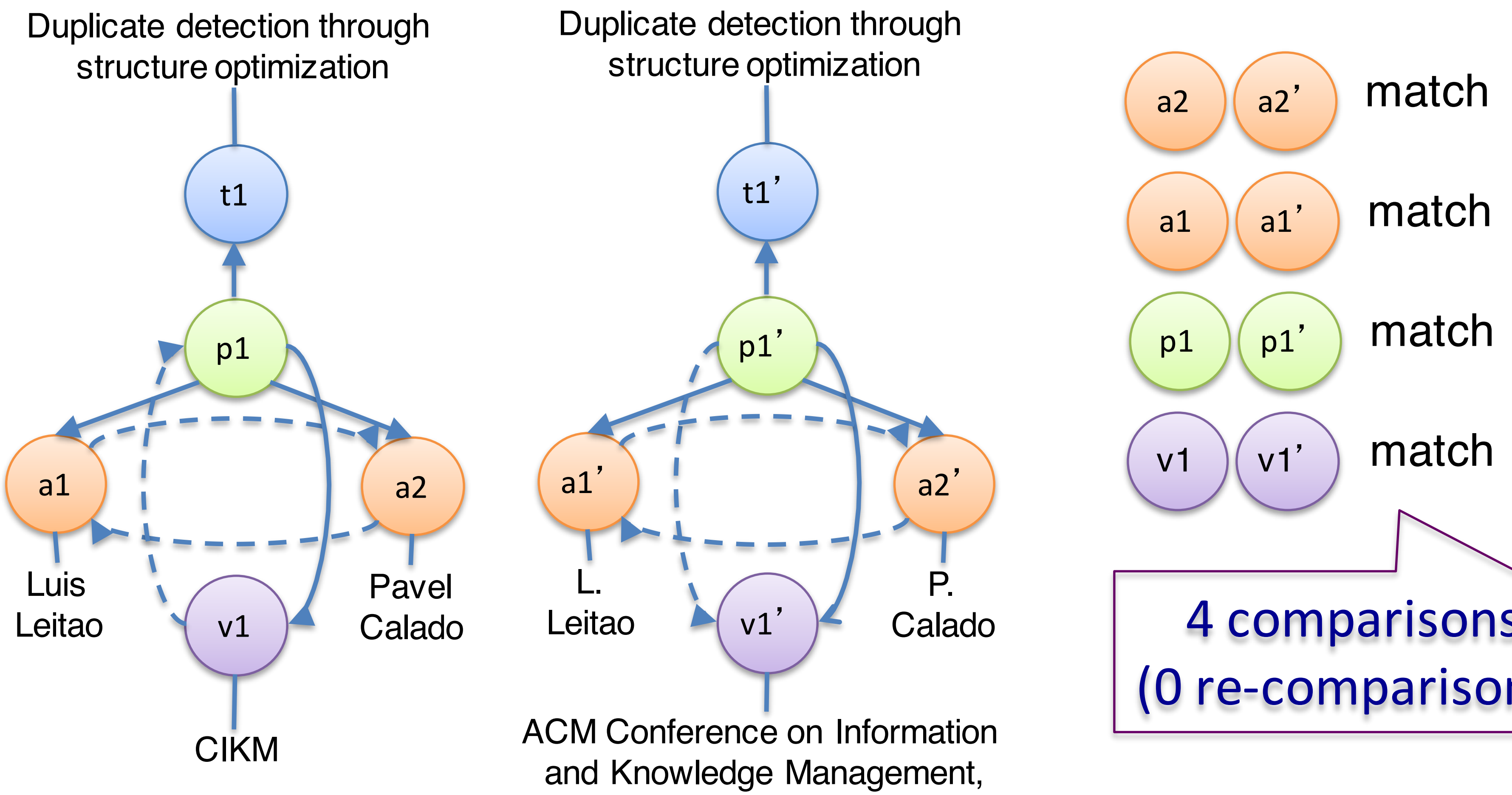



- For pairwise similarity computation, domain expert also selects what information is relevant for comparisons
  - Entity description (attribute values)
  - Influencing neighbor candidates

# Entity Pair Queue



# Entity Pair Queue




4 comparisons
(0 re-comparisons)

# Entity Pair Queue

- Queue maintenance necessary whenever a match is found
  - Manage order in which pairs are compared to reduce re-comparisons
  - Merge matches:
    - Let $m = merge\ (e1,e2)$
    - Replace all occurrences of e1 and e2 in pair queue by *m*
    - *A*dd additional pairs to queue that compare *m* with entities already compared to either *e1* or *e2*

- In general, goal of maintaining the priority queue is to reduce the number of re-comparisons while maximizing effectiveness

# Iterative blocking

*Entity resolution interleaved with blocking*

# Iterative Blocking [Whang et al. 2009]

*Blocking is not just a simple preprocessing step of entity resolution*

Perform entity resolution on each block, and propagate results to other blocks

*Entity resolution results of a processed block, may help identifying more matches in another block*

- Newly created entity descriptions, i.e. merges of descriptions found matching, are distributed to other blocks, replacing the found matches

Blocks are processed multiple times, until no new matches are found

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
| $e_1$ | Eiffel Tower | 1889 | Sauvestre | Paris |
| $e_2$ | Statue of Liberty | 1886 | Bartholdi, Eiffel | NY |
| $e_3$ | Lady Liberty | 1885 | Eiffel | Liberty Island, NY |
| $e_4$ | Eiffel Tower | 1889 | | Paris |
| $e_5$ | Miss Liberty | 1886 | Gustave Eiffel | Liberty Island |

Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$ | $e_2$, $e_5$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_1$, $e_4$ | $e_2$ | $e_3$, $e_5$ |

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
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| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$ | $e_2$, $e_5$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_1$, $e_4$ | $e_2$ | $e_3$, $e_5$ |

$e_1$, $e_4$ match! they are merged as $e_{14}$

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
| $e_1$ | Eiffel Tower | 1889 | Sauvestre | Paris |
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Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$, $e_5$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$ | $e_3$, $e_5$ |

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
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Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$, $e_5$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$ | $e_3$, $e_5$ |

$e_2$, $e_5$ match! they are merged as $e_{25}$

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
| $e_1$ | Eiffel Tower | 1889 | Sauvestre | Paris |
| $e_2$ | Statue of Liberty | 1886 | Bartholdi, Eiffel | NY |
| $e_3$ | Lady Liberty | 1885 | Eiffel | Liberty Island, NY |
| $e_4$ | Eiffel Tower | 1889 | | Paris |
| $e_5$ | Miss Liberty | 1886 | Gustave Eiffel | Liberty Island |

Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$, $e_5$, $e_{25}$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$, $e_{25}$ | $e_3$, $e_5$, $e_{25}$ |

$e_2$, $e_5$ match! they are merged as $e_{25}$

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
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| $e_2$ | Statue of Liberty | 1886 | Bartholdi, Eiffel | NY |
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| $e_5$ | Miss Liberty | 1886 | Gustave Eiffel | Liberty Island |

Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1, e_4, e_{14}$ | $e_2, e_5, e_{25}$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_1, e_4, e_{14}$ | $e_2, e_{25}$ | $e_3, e_5, e_{25}$ |

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
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Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$, $e_5$, $e_{25}$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_{14}$ | $e_2$, $e_{25}$ | $e_3$, $e_5$, $e_{25}$ |

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
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Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$, $e_5$, $e_{25}$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_{14}$ | $e_{25}$ | $e_3$, $e_5$, $e_{25}$ |

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
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Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$, $e_5$, $e_{25}$ | $e_3$ |

| P | N | L |
|---|---|---|
| $e_{14}$ | $e_{25}$ | $e_3$, $e_{25}$ |

$e_3$, $e_{25}$ match! they are merged as $e_{235}$

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
| $e_1$ | Eiffel Tower | 1889 | Sauvestre | Paris |
| $e_2$ | Statue of Liberty | 1886 | Bartholdi, Eiffel | NY |
| $e_3$ | Lady Liberty | 1885 | Eiffel | Liberty Island, NY |
| $e_4$ | Eiffel Tower | 1889 | | Paris |
| $e_5$ | Miss Liberty | 1886 | Gustave Eiffel | Liberty Island |

Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_1$, $e_4$, $e_{14}$ | $e_2$, $e_5$, $e_{25}$, $e_{235}$ | $e_3$, $e_{235}$ |

| P | N | L |
|---|---|---|
| $e_{14}$ | $e_{25}$, $e_{235}$ | $e_3$, $e_{25}$, $e_{235}$ |

$e_3$, $e_{25}$ match! they are merged as $e_{235}$

# Iterative Blocking - Example

| | Name | Year | Architects | Location |
|---|---|---|---|---|
| $e_1$ | Eiffel Tower | 1889 | Sauvestre | Paris |
| $e_2$ | Statue of Liberty | 1886 | Bartholdi, Eiffel | NY |
| $e_3$ | Lady Liberty | 1885 | Eiffel | Liberty Island, NY |
| $e_4$ | Eiffel Tower | 1889 | | Paris |
| $e_5$ | Miss Liberty | 1886 | Gustave Eiffel | Liberty Island |

Blocks generated if blocking keys are the year and the 1st letter of the location:

| 1889 | 1886 | 1885 |
|---|---|---|
| $e_{14}$ | $e_2$, $e_5$, $e_{25}$, $e_{235}$ | $e_3$, $e_{235}$ |

| P | N | L |
|---|---|---|
| $e_{14}$ | $e_{25}$, $e_{235}$ | $e_3$, $e_{25}$, $e_{235}$ |

process continues iteratively, until no new matches are found

## Extend iterative blocking by using MinHash

# MinHash

Assume an entity description is a set of tokens:

e1 = {the, statue, of, liberty}

e2 = {lady, liberty, statue}

e3 = {the, eiffel, tower}

| token\description | e1 | e2 | e3 |
|---|---|---|---|
| the | 1 | 0 | 1 |
| statue | 1 | 1 | 0 |
| of | 1 | 0 | 0 |
| liberty | 1 | 1 | 0 |
| lady | 0 | 1 | 0 |
| eiffel | 0 | 0 | 1 |
| tower | 0 | 0 | 1 |

MinHash:

- Pick a permutation of the tokens
- minHash(ei): the first token of ei in the permuted order of tokens

minHash(e1) = 'of'

minHash(e2) = 'lady'

minhash(e3) = 'tower'

| token\description | e1 | e2 | e3 |
|---|---|---|---|
| lady | 0 | 1 | 0 |
| tower | 0 | 0 | 1 |
| of | 1 | 0 | 0 |
| eiffel | 0 | 0 | 1 |
| the | 1 | 0 | 1 |
| statue | 1 | 1 | 0 |
| liberty | 1 | 1 | 0 |

# MinHash as a Jaccard Approximation

P[minHash(ei) = minHash(ej)] = Jaccard(ei, ej)

- Type A rows: both descriptions have 1
- Type B rows: one has 1 and the other has 0
- Type C rows: both have 0

P[minHash(ei) = minHash(ej)] =
= #A / (#A + #B) =
= Jaccard(ei, ej)

| token\description | e1 | e2 | e3 |
|---|---|---|---|
| lady | 0 | 1 | 0 |
| tower | 0 | 0 | 1 |
| of | 1 | 0 | 0 |
| eiffel | 0 | 0 | 1 |
| the | 1 | 0 | 1 |
| statue | 1 | 1 | 0 |
| liberty | 1 | 1 | 0 |

Type C row

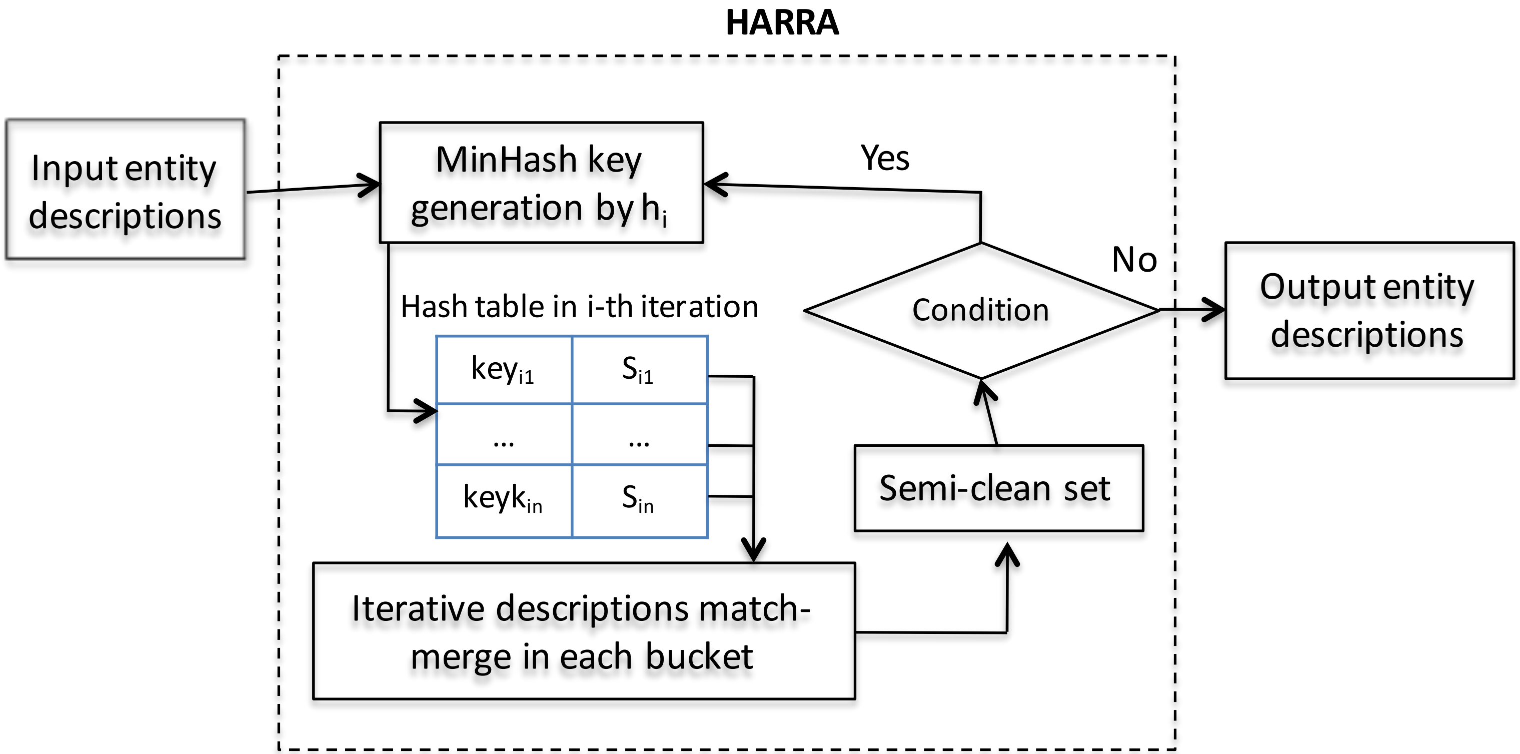
Type B row

Type A row

- Create several random permutations (h1, …, hn) of the tokens, n << #tokens
  - Permutations are expensive; hash functions can simulate this functionality
- For each permutation, find the minHash of each description
  - These, concatenated, constitute the minHash signature of each description
- Compare the minHash signatures of the descriptions
  - Using Locality-Sensitive Hashing (LSH)

# HARRA [Kim & Lee 2010]

Extends iterative blocking by employing MinHash (for Jaccard approximation)

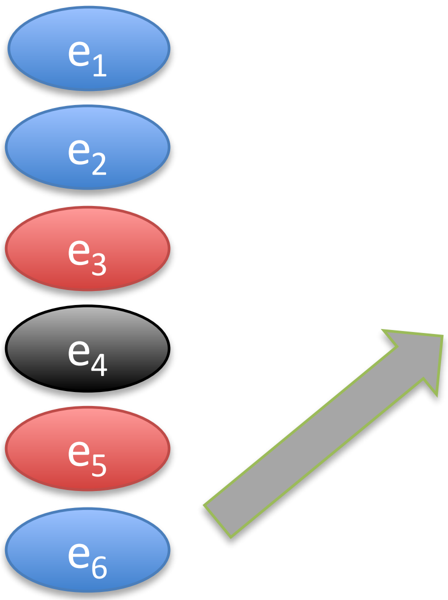



Scalability: A single hash table is used

- Before placing a description in a block, the description is compared to the contents of the block

# HARRA - Example

$e_6$ should be placed in the blue bucket




Hash Table:

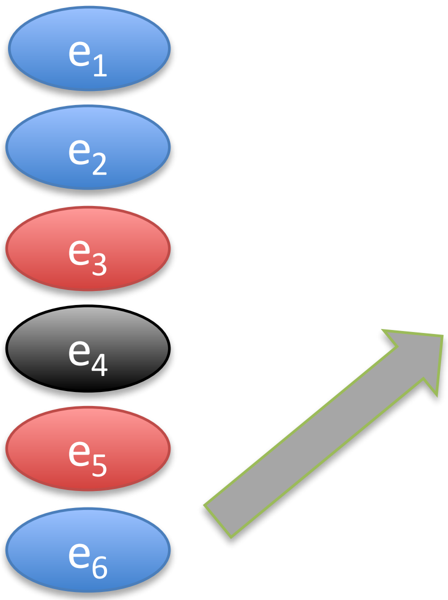
| Keys | Values |
|---|---|
| Blue | $e_1$ $e_2$ |
| Red | $e_3$ $e_5$ |
| Black | $e_4$ |

# HARRA - Example

Before placing it there, we check if it matches $e_1$ or $e_2$

$e_6$ = $e_1$ ? NO

$e_6$ = $e_2$ ? YES




Hash Table:

| Keys | Values |
|---|---|
| Blue | $e_1$ $e_2$ |
| Red | $e_3$ $e_5$ |
| Black | $e_4$ |

# HARRA - Example

Before placing it there, we check if it matches $e_1$ or $e_2$

$e_6$ = $e_1$ ? NO

$e_6$ = $e_2$ ? YES

$e_{26}$ is the result of merging $e_6$ and $e_2$

$e_{26}$ = $e_1$ ? NO

$e_1$

$e_2$

$e_3$

$e_4$

$e_5$

$e_6$

Hash Table:

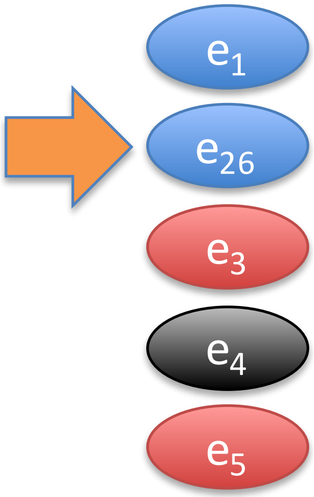
| Keys | Values |
|---|---|
| Blue | $e_1$ $e_{26}$ |
| Red | $e_3$ $e_5$ |
| Black | $e_4$ |

# HARRA - Example

Continue until:

- no merge occurs, OR
- saved comparisons > threshold, OR
- # iterations > constant

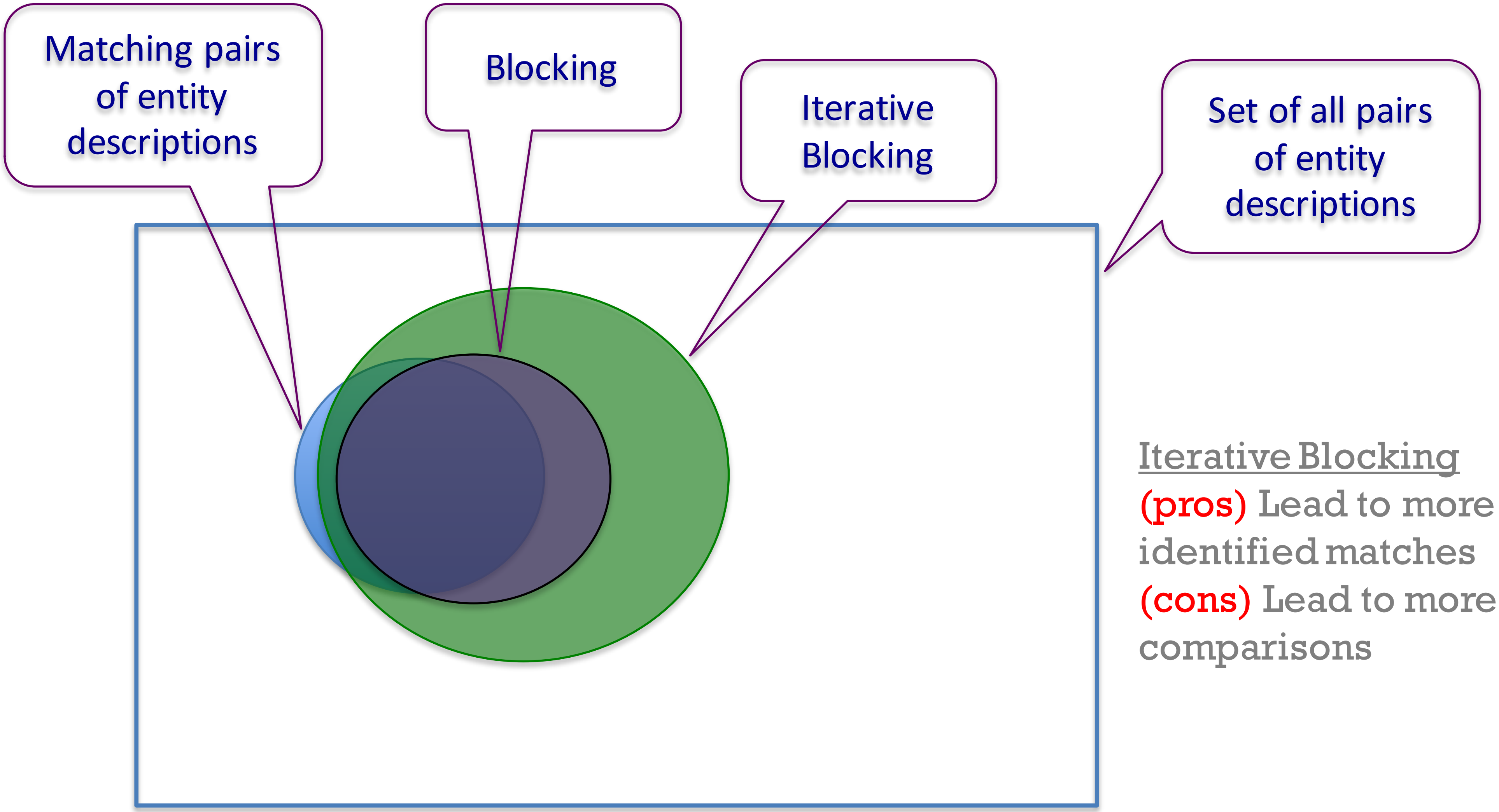
Re-initialize the input:




Hash Table:

| Keys | Values |
|---|---|
| Blue | |
| Red | |
| Black | |

# Blocking vs Iterative Blocking




<u>Iterative Blocking</u>

(pros) Lead to more identified matches

(cons) Lead to more comparisons

# Discussion on Iterative Approaches

Each iteration is based on new knowledge

- Identified matches
- Merged descriptions of identified matches

Hybrid methods, i.e. *iterative blocking*, benefit from:

- The *efficiency* of blocking approaches
- The *effectiveness* of iterative approaches

Iterative approaches seem to fit well to similarity functions using relationships

- Relationships between descriptions are an important part of the available semantics

# A Classification of Iterative Approaches

| Approach | Matching-based | Merging-based |
|---|---|---|
| Bhattacharya & Getoor 2004, 2007 | • | |
| Rastogi et al. 2011 | • | |
| Dong et al. 2005 | • | |
| Herschel et al. 2012 | • | |
| Weis & Naumann 2006 | □ | |
| Weis & Naumann 2004 | □ | |
| Leitão et al. 2007, 2013 | □ | |
| Puhlmann et al. 2006 | □ | |
| Böhm et al. 2012 | + | |
| Benjelloun et al. 2009 | | • |
| Benjelloun et al. 2007 | | • |
| Whang et al. 2009 | | • |
| Kim & Lee 2010 | | • |

- • : tabular data
- □ : tree data
- \+ : graph data

# Scalability Limitations

Computations are sequential

- High time requirements
  - E.g., 66 hours, just to create the clusters of attributes for attribute clustering blocking for a dataset of 3M entities

Data reside in the memory of a single machine

- High memory and space requirements
  - I.e., "out of memory" errors, when datasets get bigger and in some cases "no space left on device" errors

*Parallel algorithms can be used to overcome these limitations*

*For handling huge volumes of data*

# MapReduce

# MapReduce

Input data are partitioned

Input data partitions are sent to different nodes (mappers) in the cluster

- Map phase: distribute the current partition to multiple nodes (reducers)
  - Emit (key, value) pairs
  - Pairs with the same key are processed by the same reducer

- Reduce phase: process the pairs having the same key
  - Emit (key, value) pairs – the output of the program

# MapReduce

For handling huge volumes of data:

*Proceed entity resolution in partitions!*

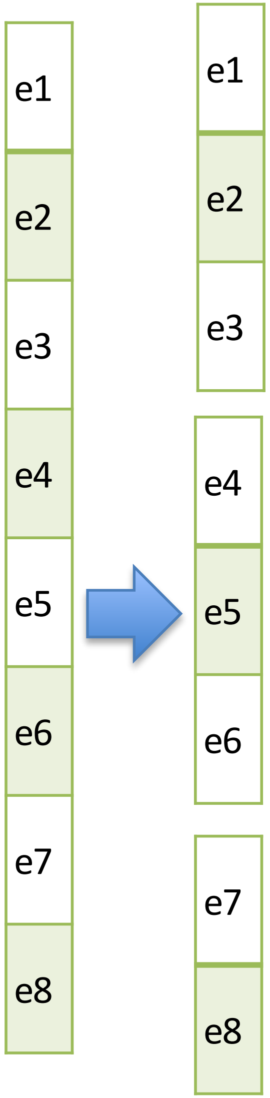
The map phase reflects blocking (re-distribute descriptions)

The reduce phase reflects entity resolution (check for matches)

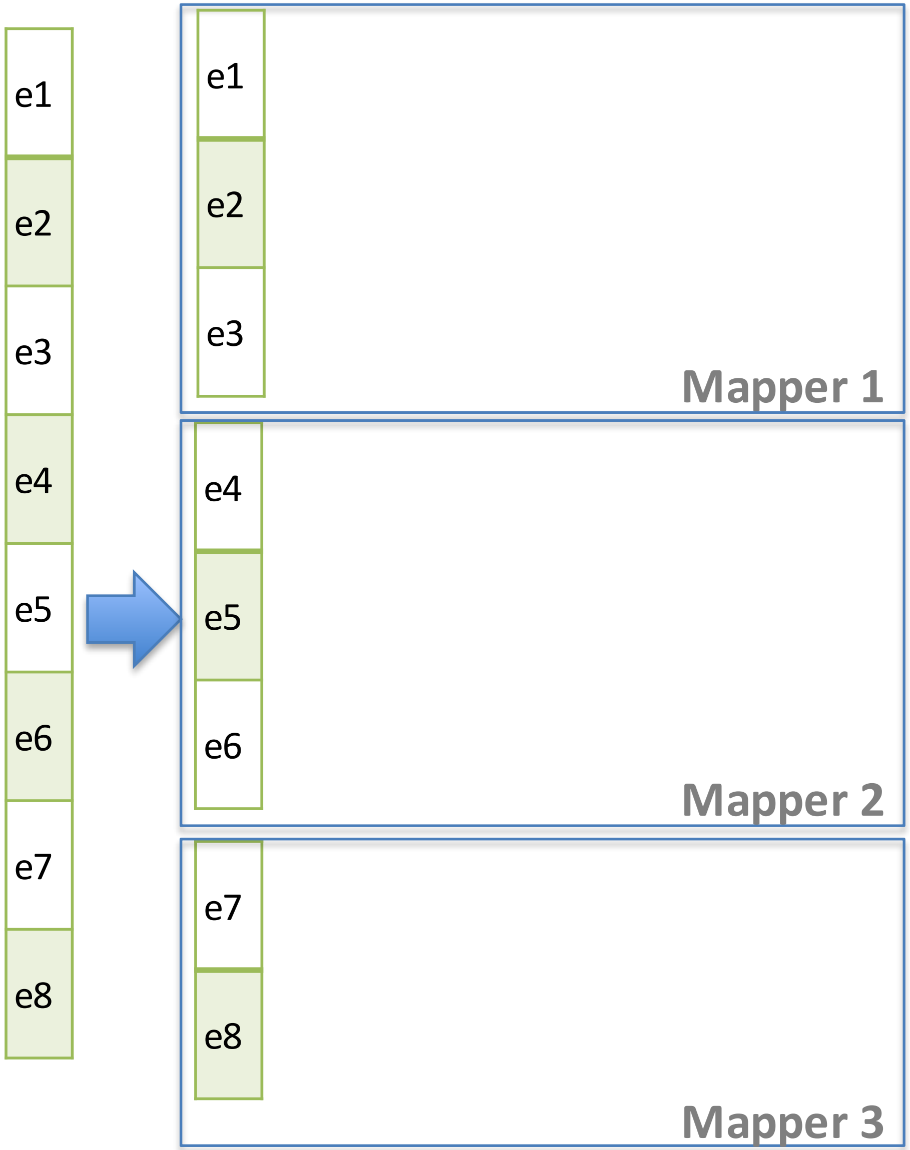
# MapReduce – Input Data

| |
|---|
| e1 |
| e2 |
| e3 |
| e4 |
| e5 |
| e6 |
| e7 |
| e8 |

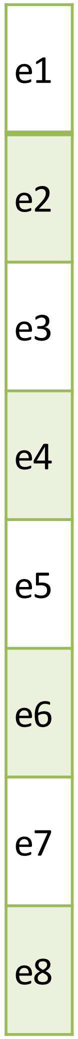
# MapReduce – Input Data Partitioning

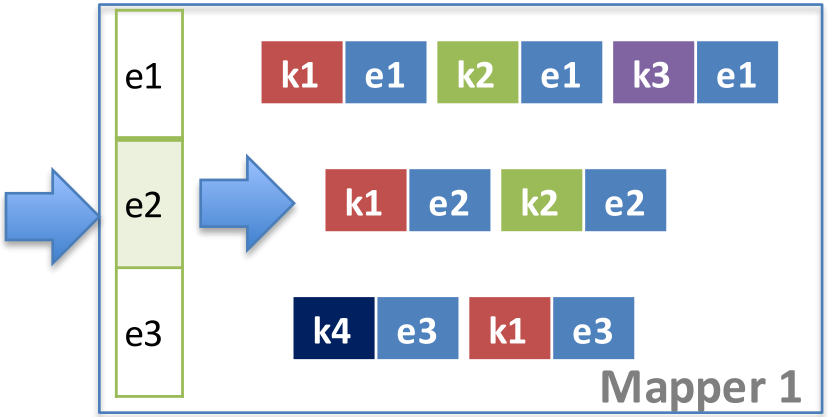


# MapReduce – Mapper Input



# MapReduce – Mapper Example



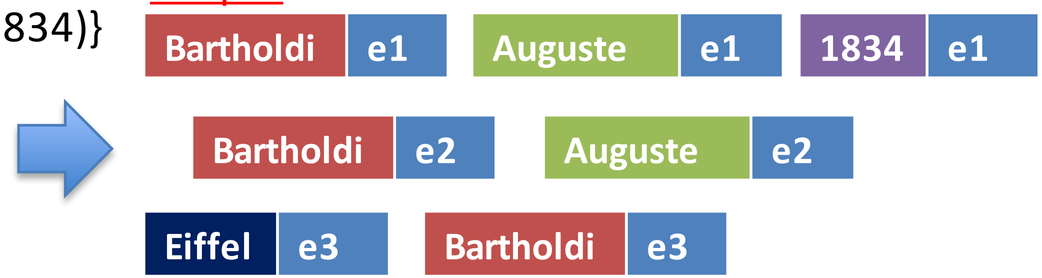




Input :
e1={(name, Auguste Bartholdi),(year,1834)}

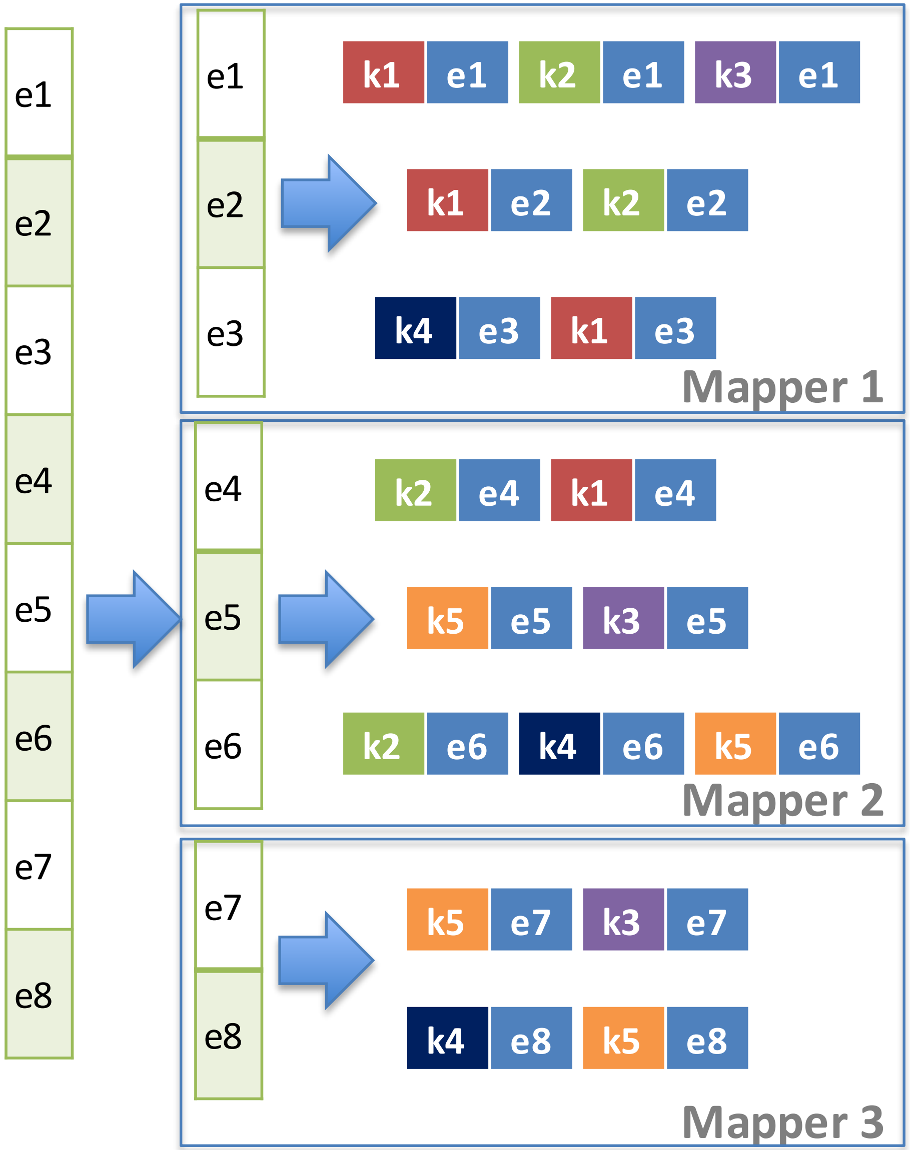
e2={(about, Auguste Bartholdi)}

e3={(architects, Bartholdi Eiffel)

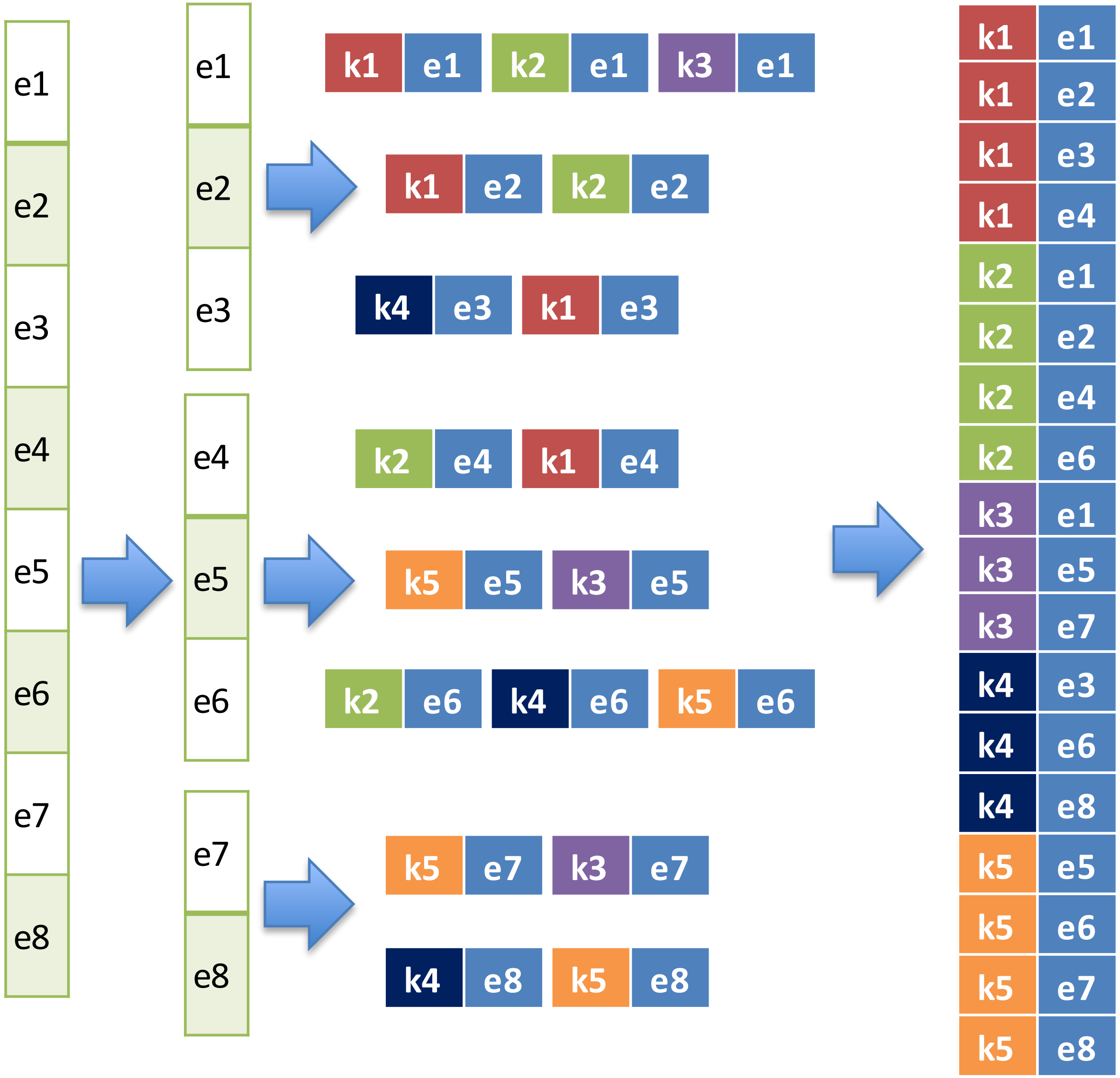
Output :



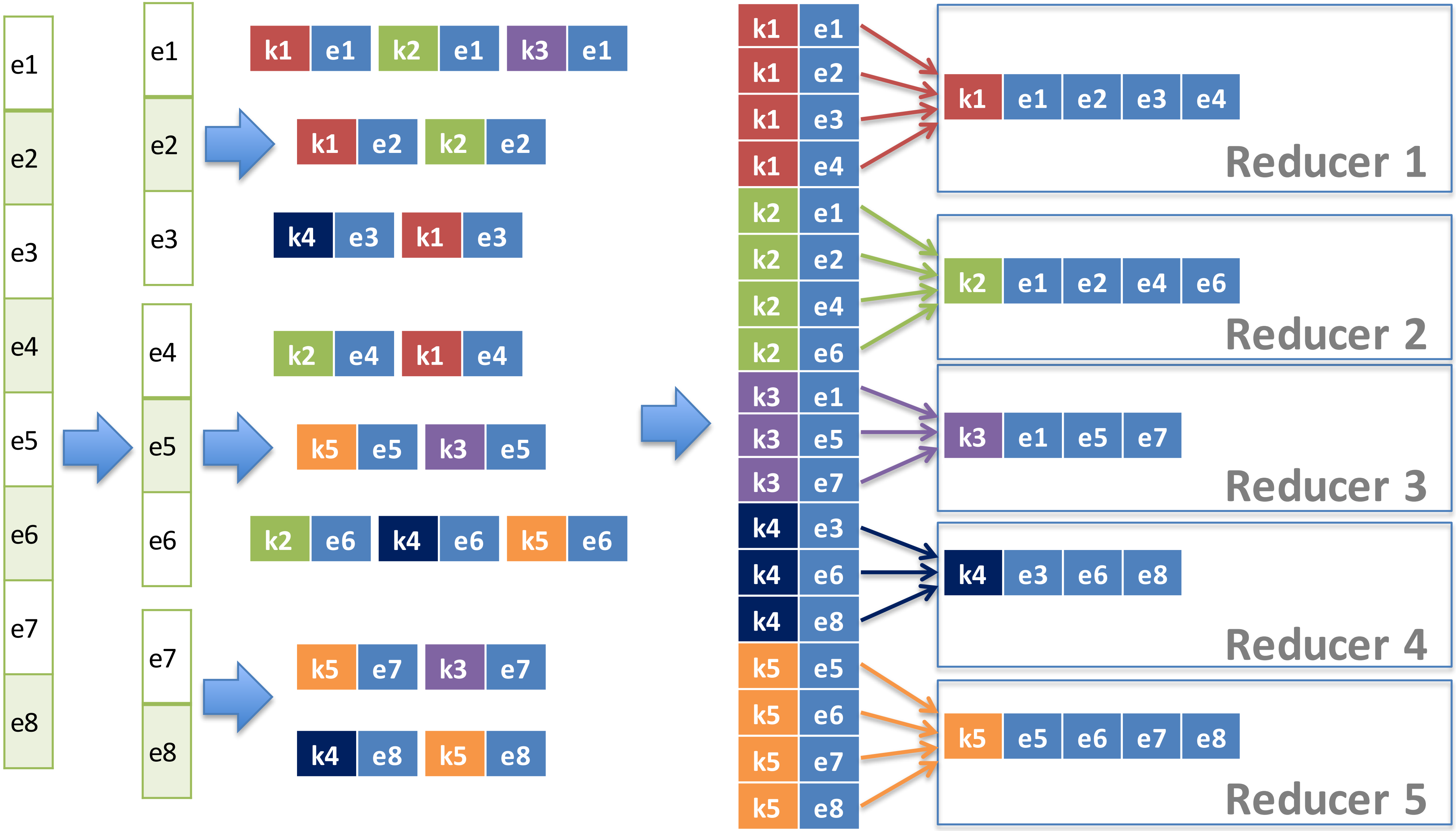
# MapReduce – Mapper Output



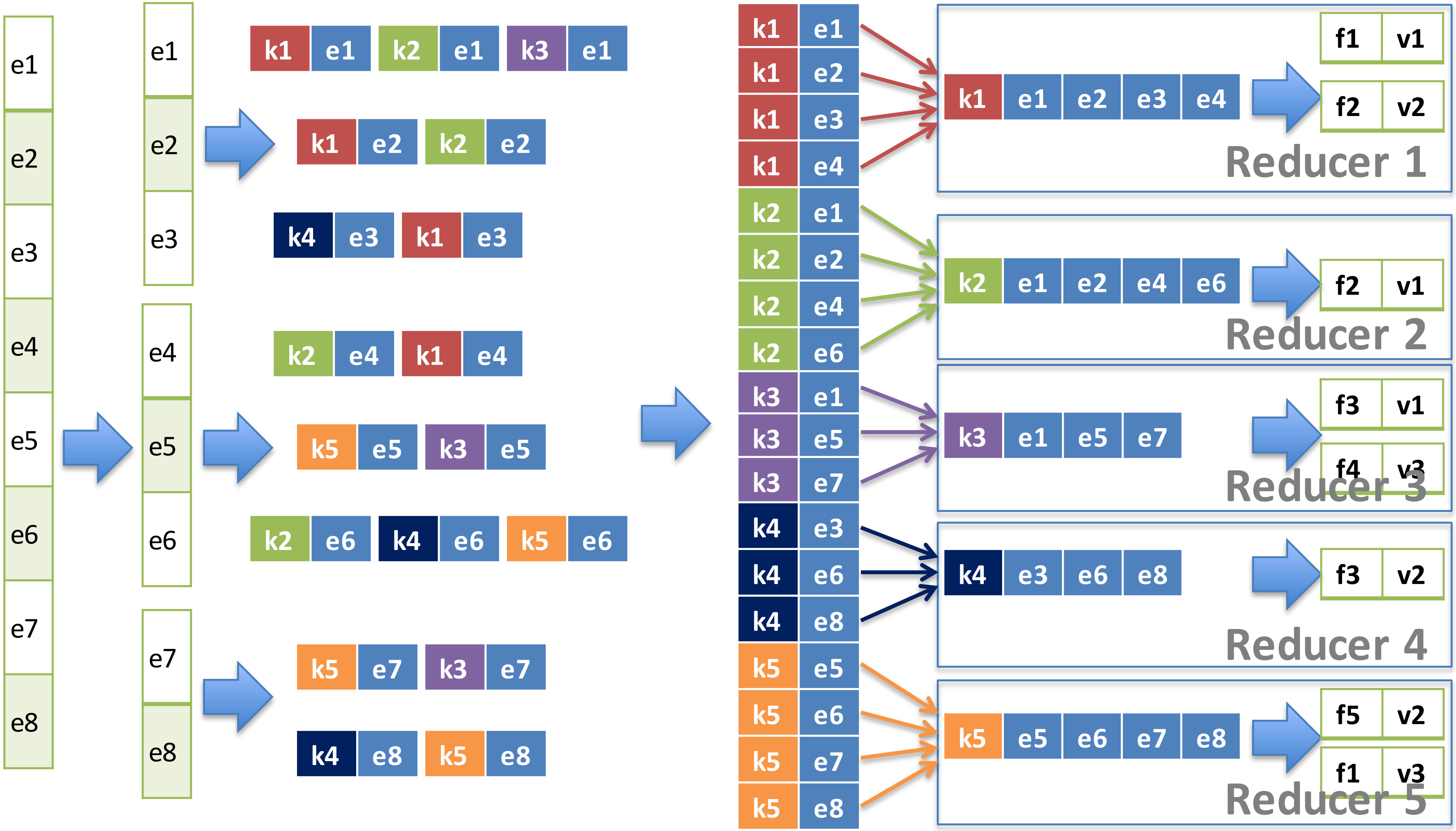
# MapReduce – Shuffling & Sorting



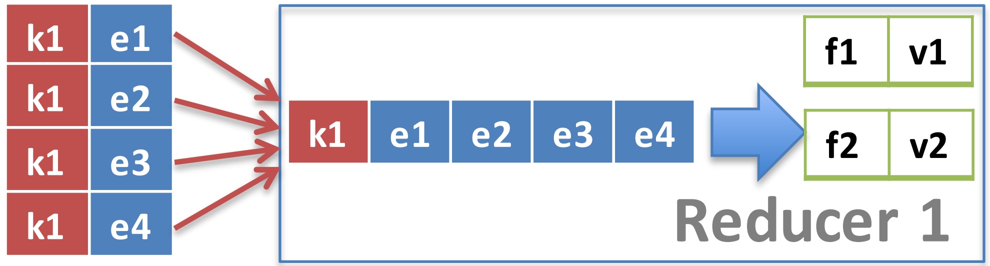
# MapReduce – Merging

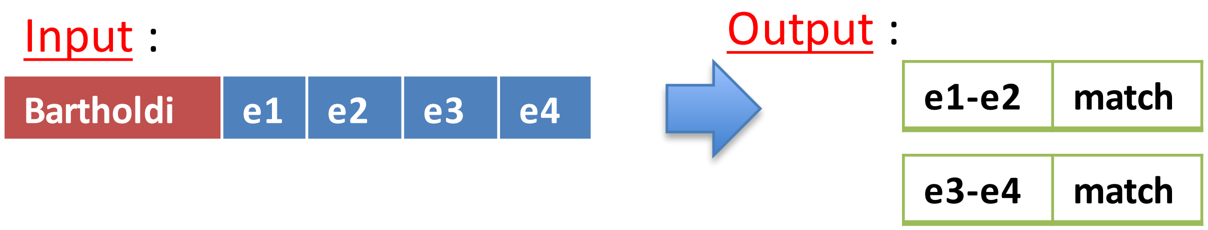


# MapReduce – Reducer



# MapReduce – Reducer Example



# Dedoop – Standard Blocking [Kolb et al. 2012]

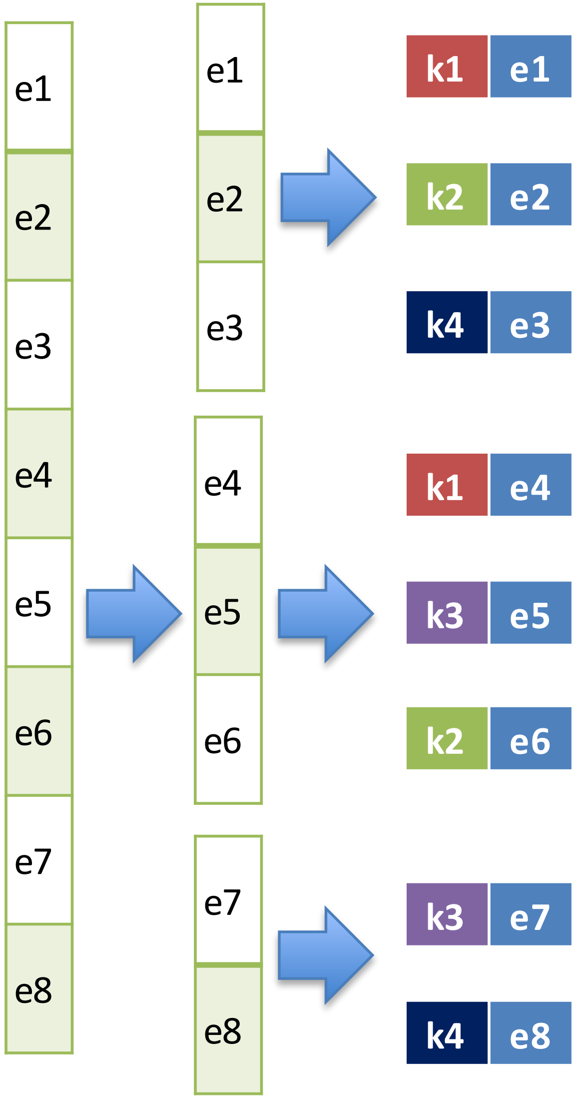
*Dedoop performs standard blocking using MapReduce*

Map function
- Input: an entity description
- Output: a (key, value) pair
  - key: the BKV of the description
  - value: the description having this BKV

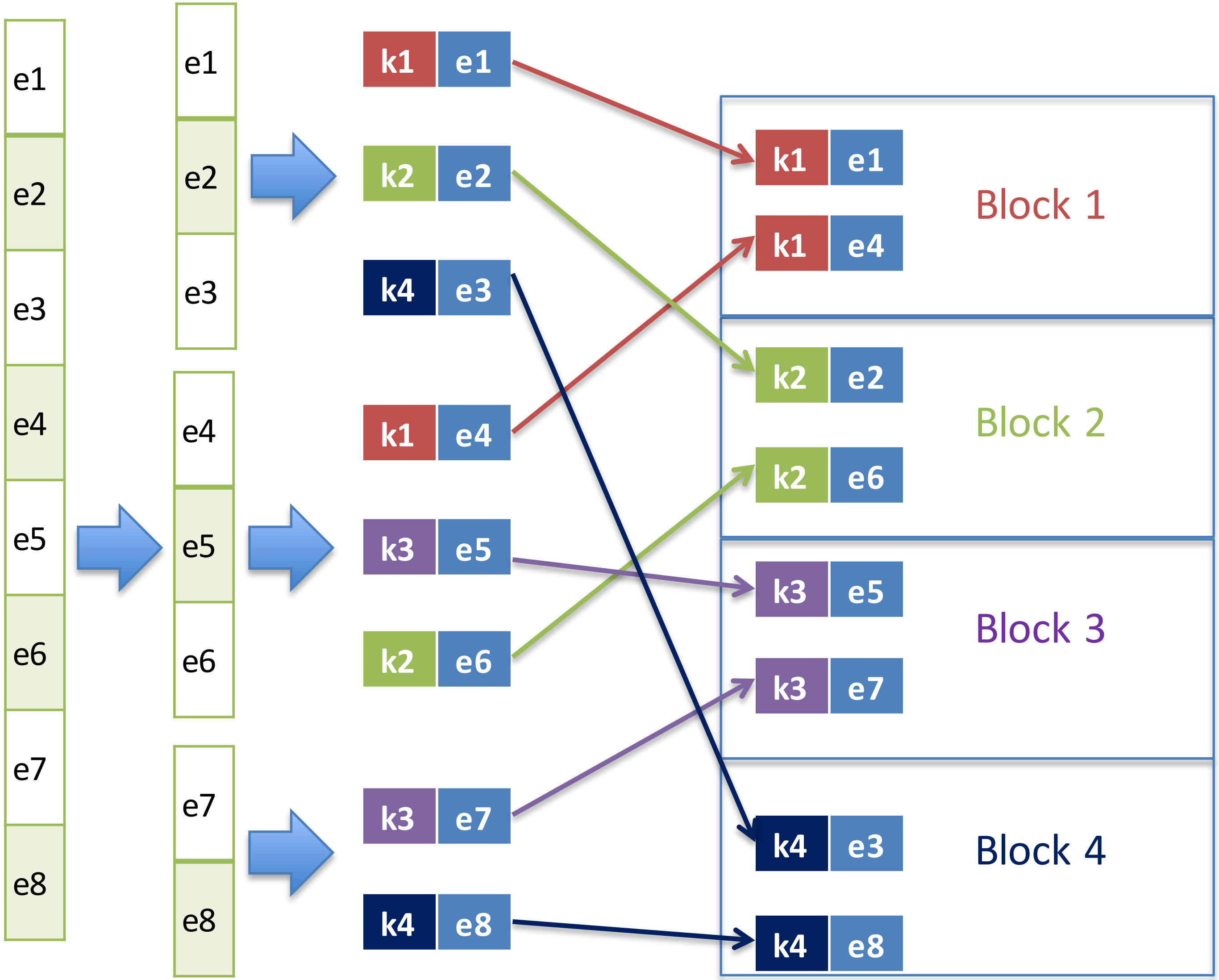
The partitioning operates on the BKVs and distributes (key, value) pairs among reduce tasks
- All entities sharing the same BKV are assigned to the same reduce task

Reduce function: Computes in each block the similarities between all description pairs within the block
- Input: A BKV along with descriptions with this BKV
- Output: (key, value) pairs
  - key: a pair of descriptions
  - value: match/non-match

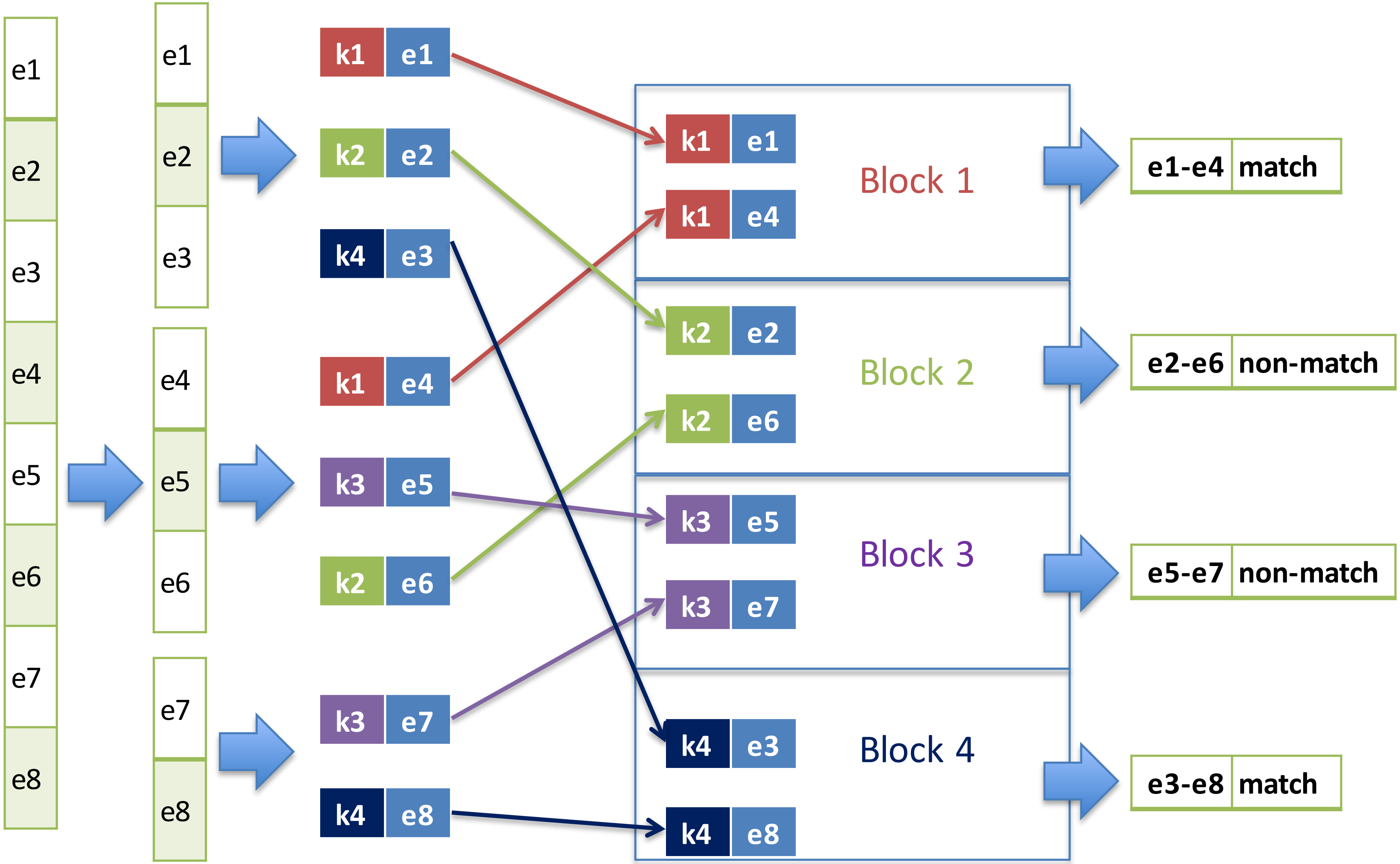
# Dedoop – Mapper: BKVs as intermediate keys



# Dedoop – Mappers: Build Blocks

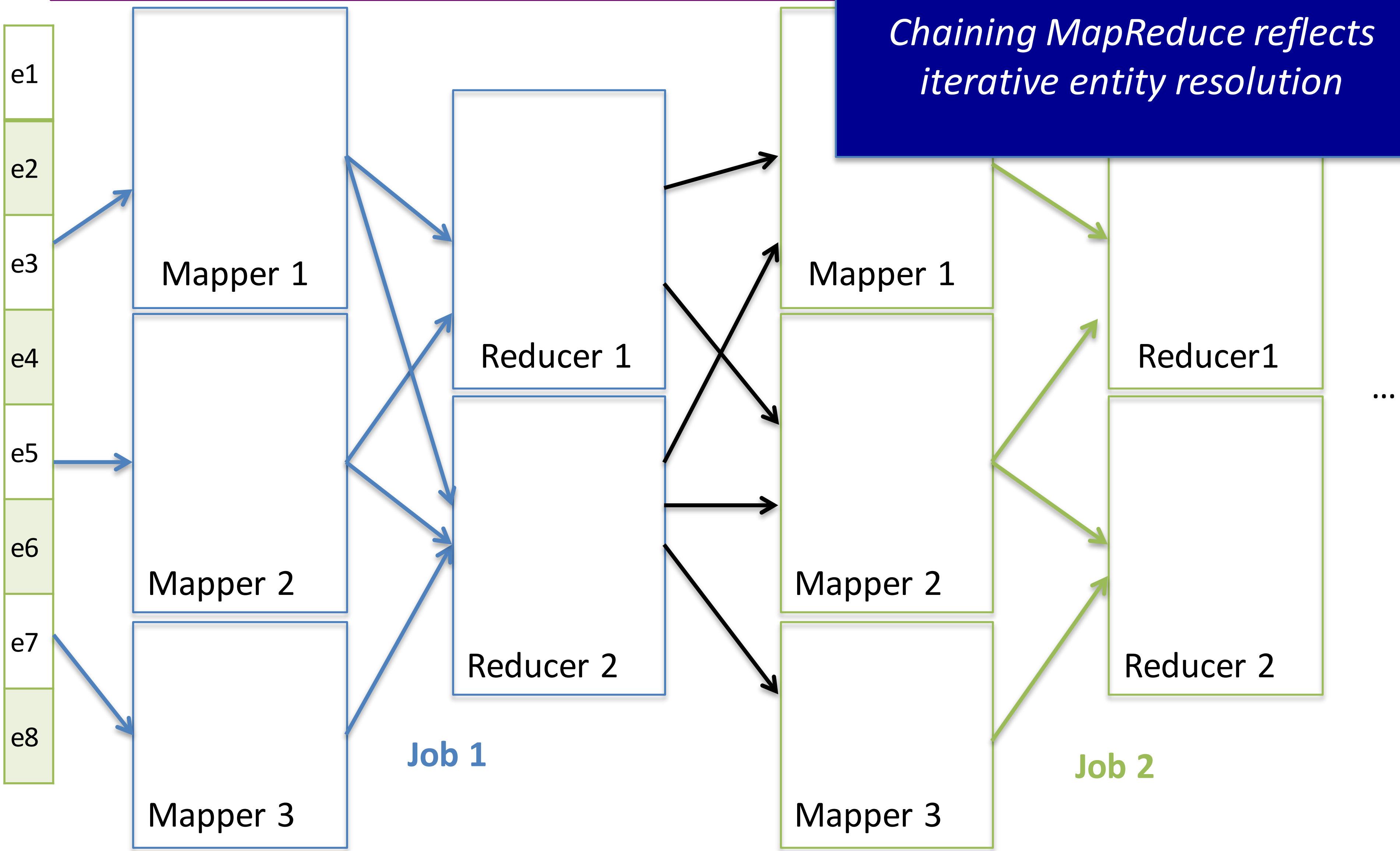


# Dedoop – Reducers: Compare Block Contents



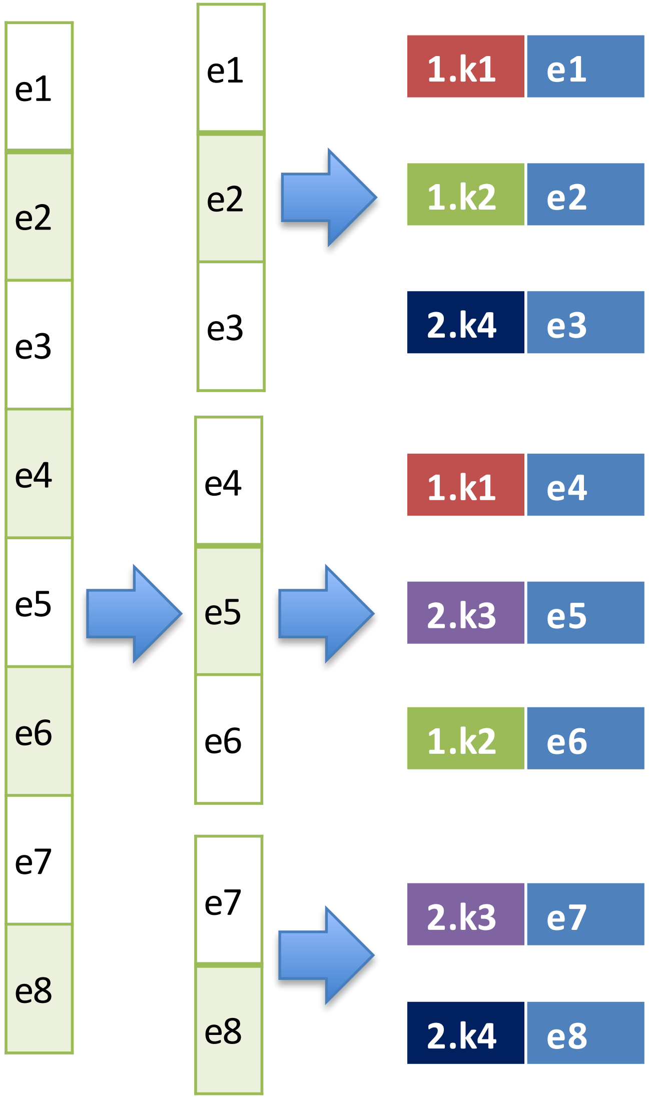
# Chaining MapReduce Jobs

*Chaining MapReduce reflects iterative entity resolution*




The output of a MapReduce Job can be the input of another

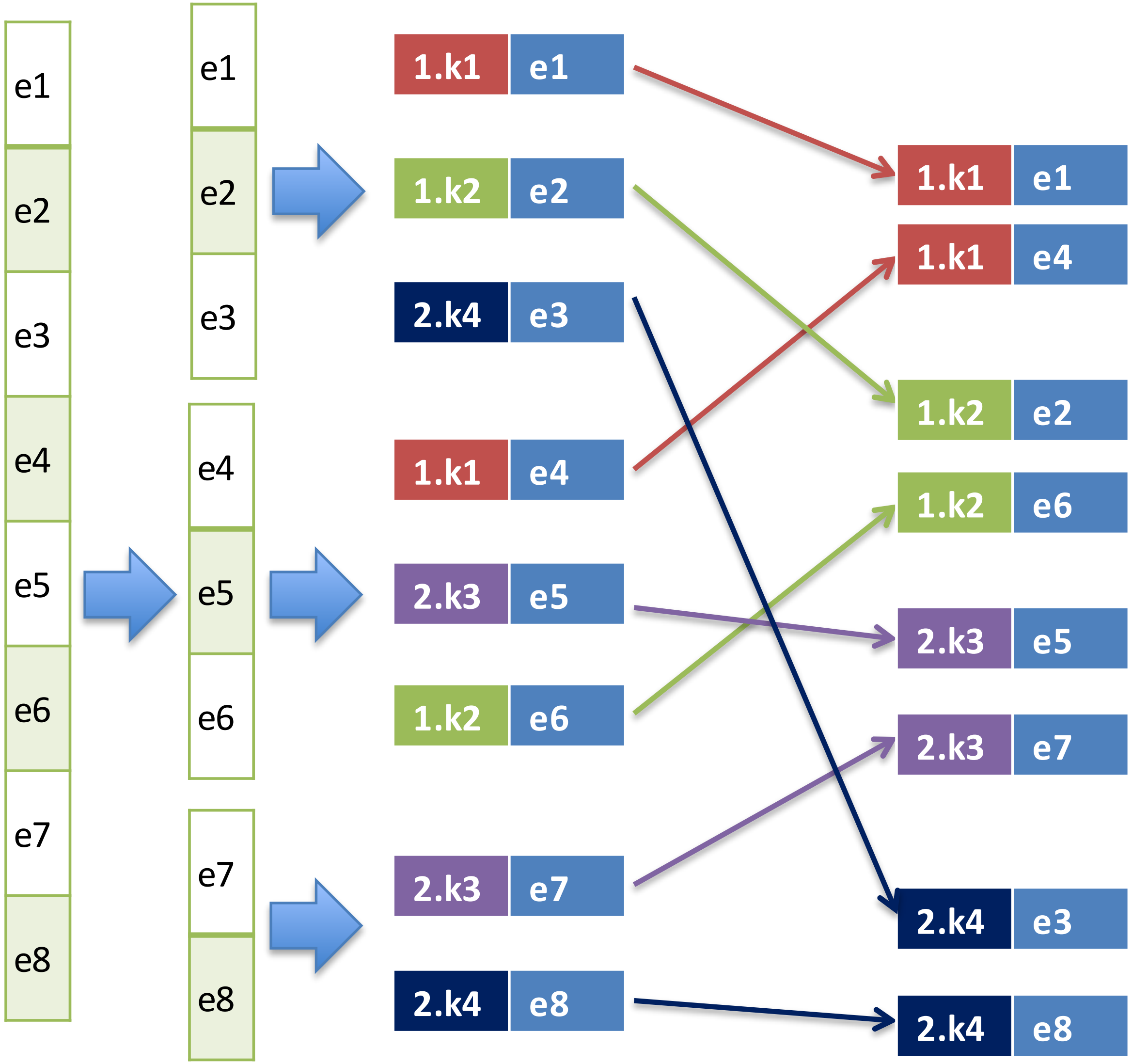
# Dedoop – Sorted Neighborhood [Kolb et al. 2011]



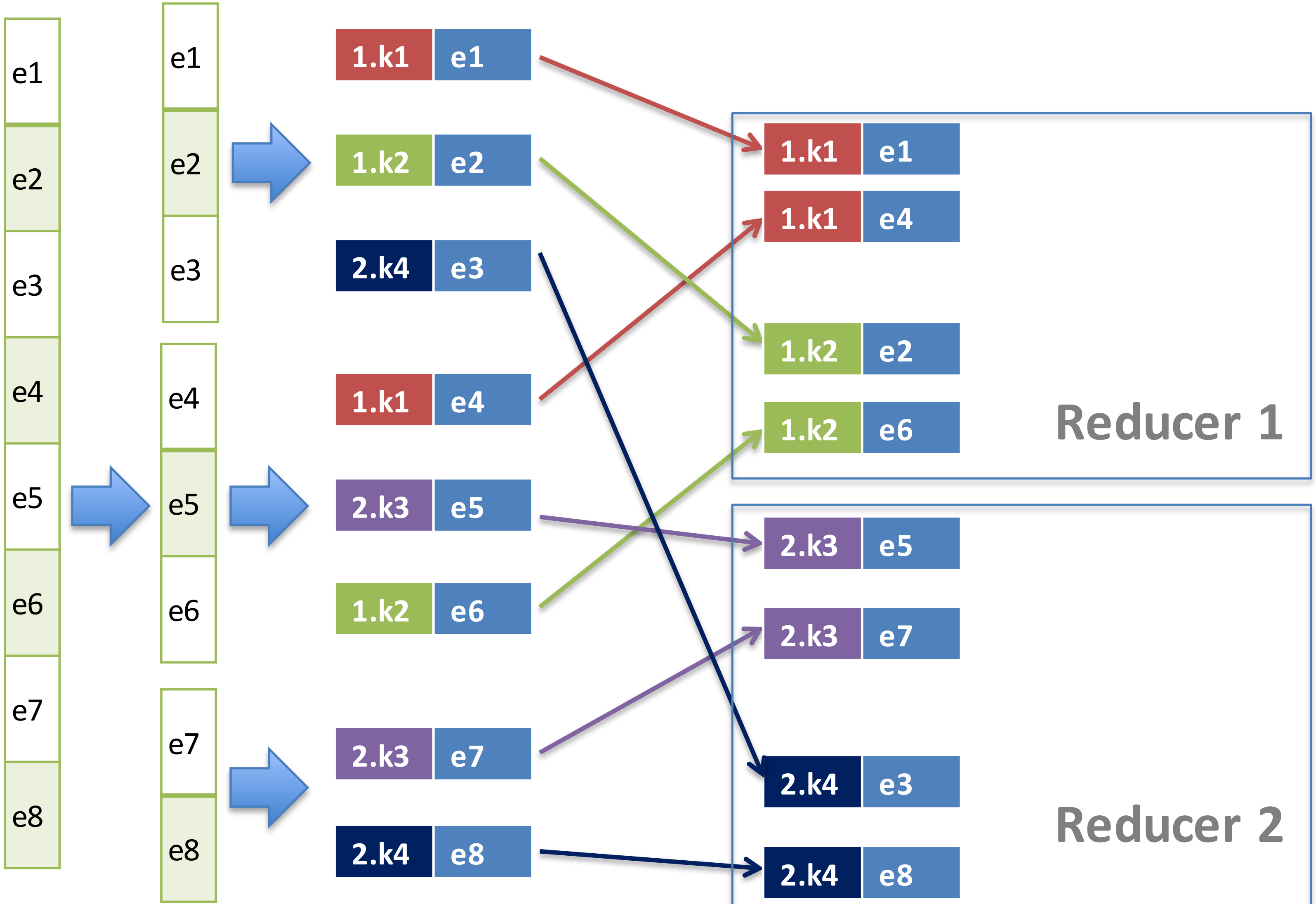

composite key = (partitionID, BKV)
partitionID(BKV) = 1, if BKV < "k3"
partitionID(BKV) = 2, else

(we know that we have two reducers available)

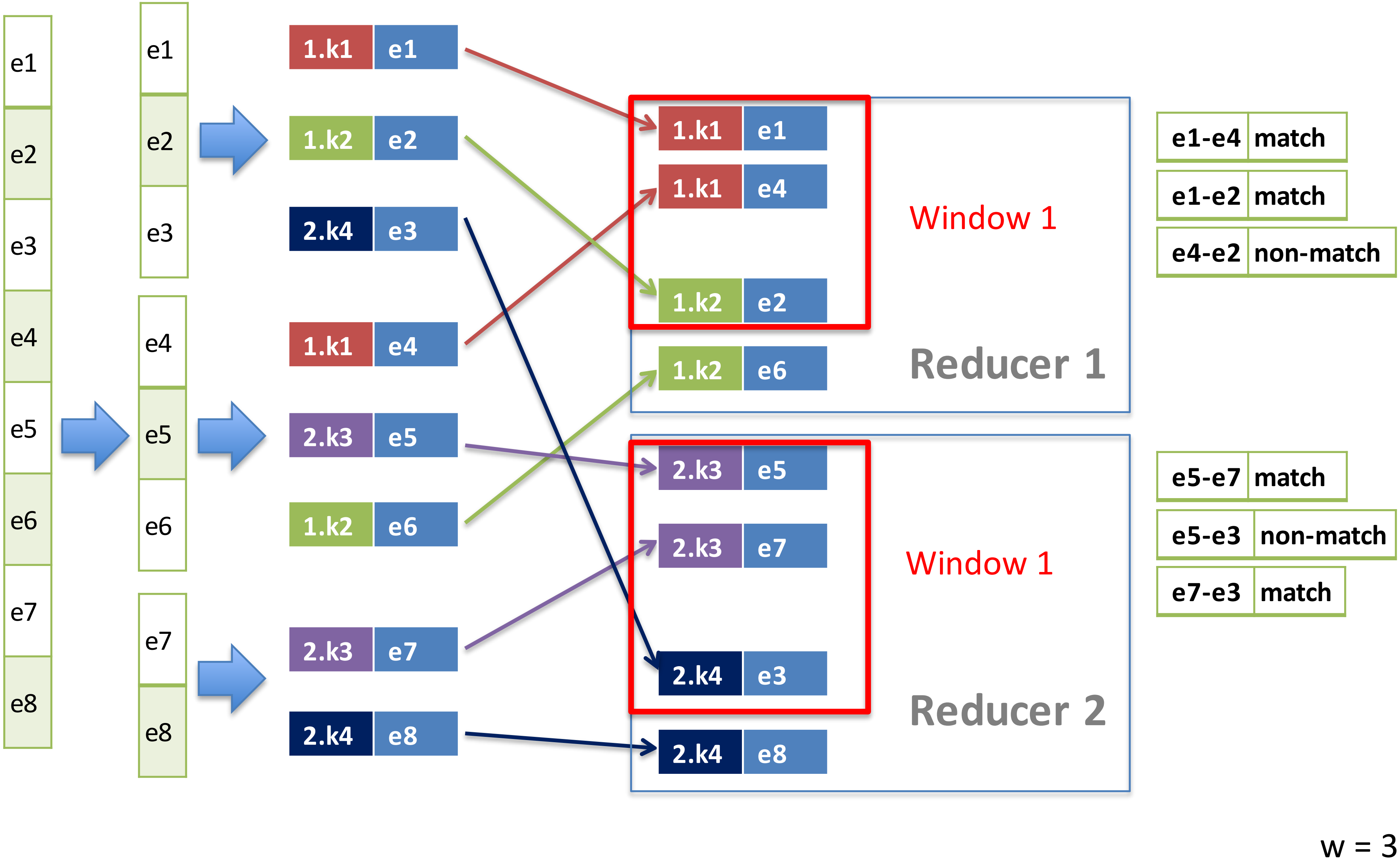
# Dedoop SN: Sorting the Keys



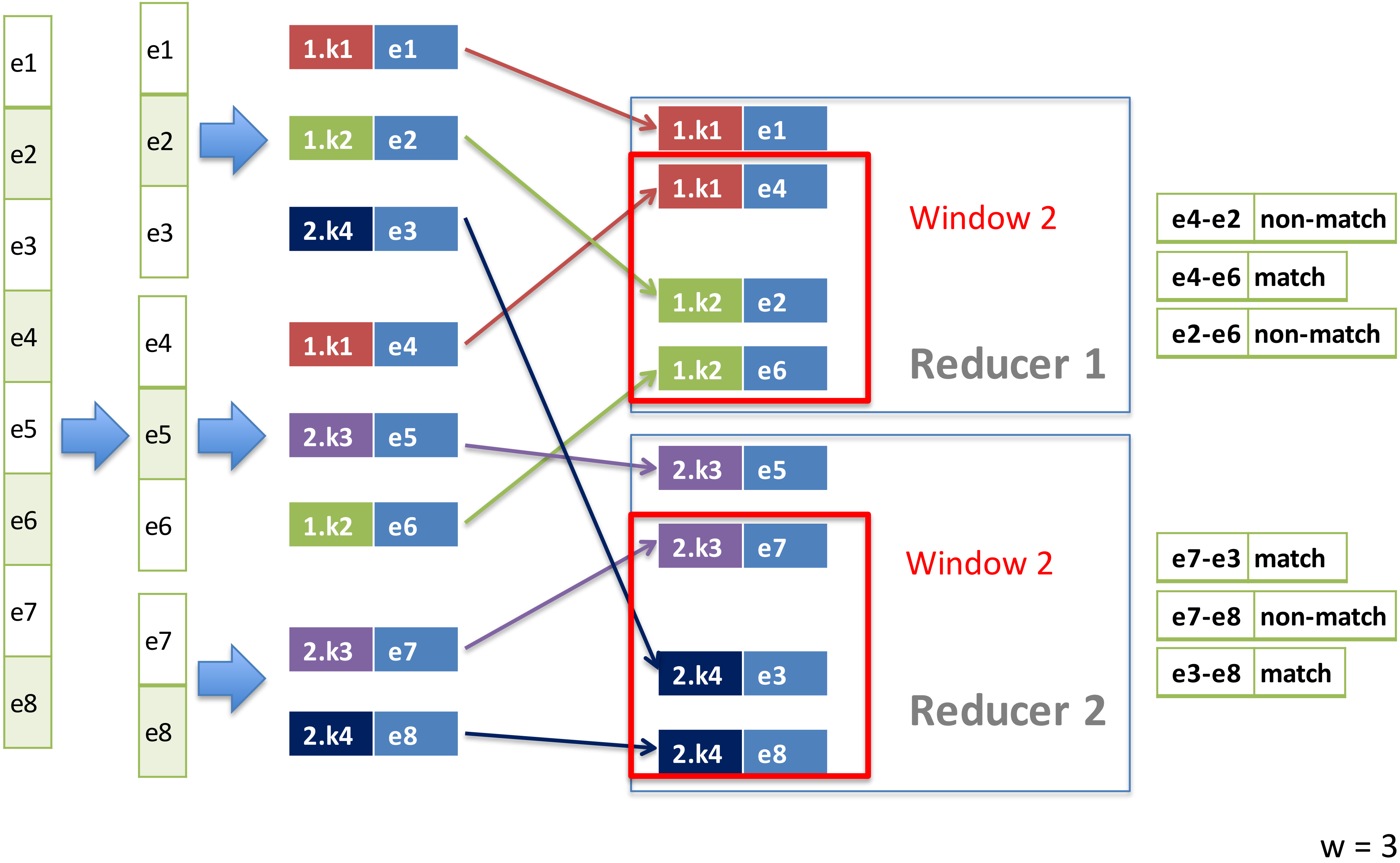
# Dedoop SN: Reducers Apply the Sliding Window



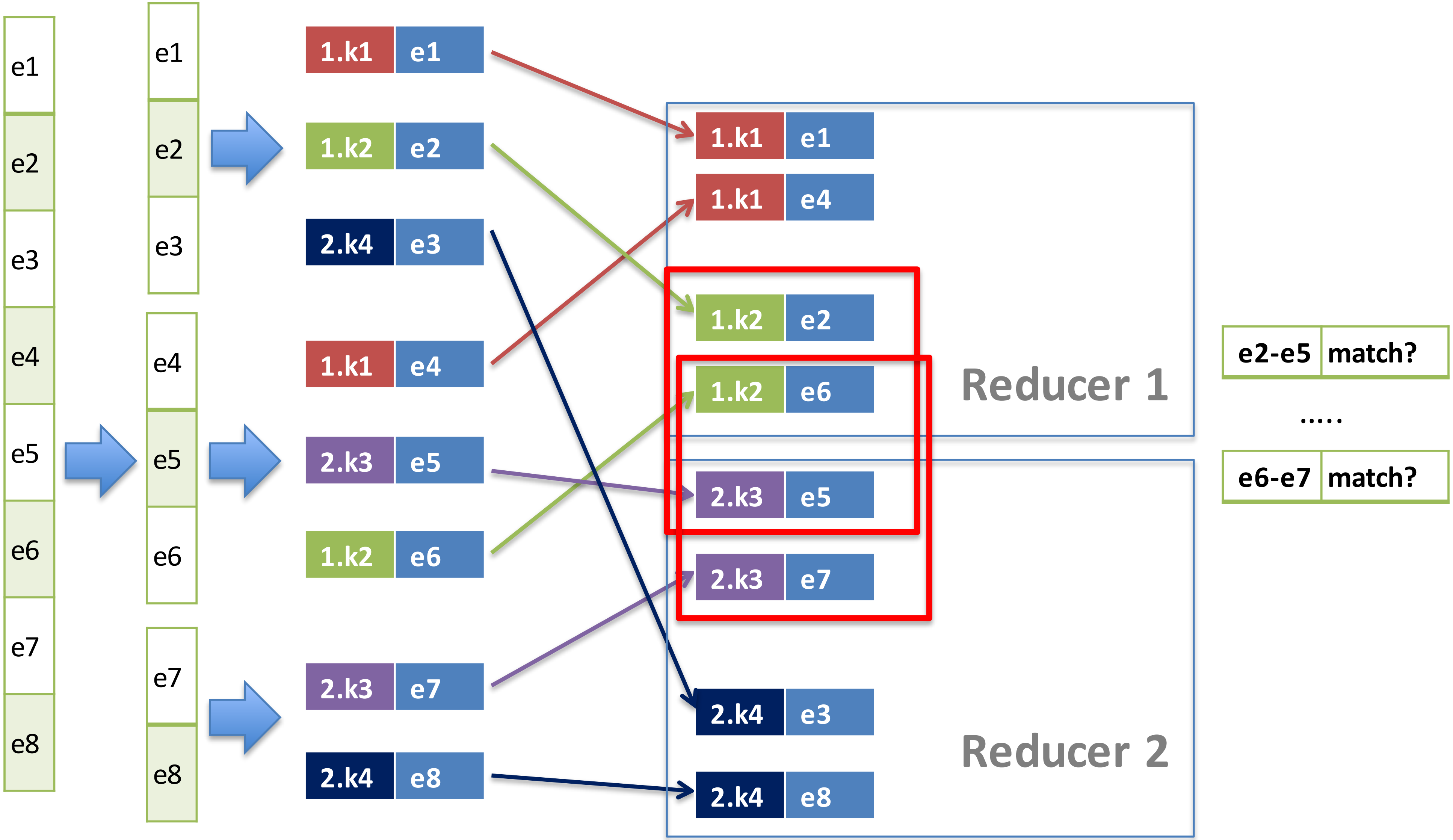
# Dedoop SN: Reducers Apply the Sliding Window



# Dedoop SN: Reducers Apply the Sliding Window



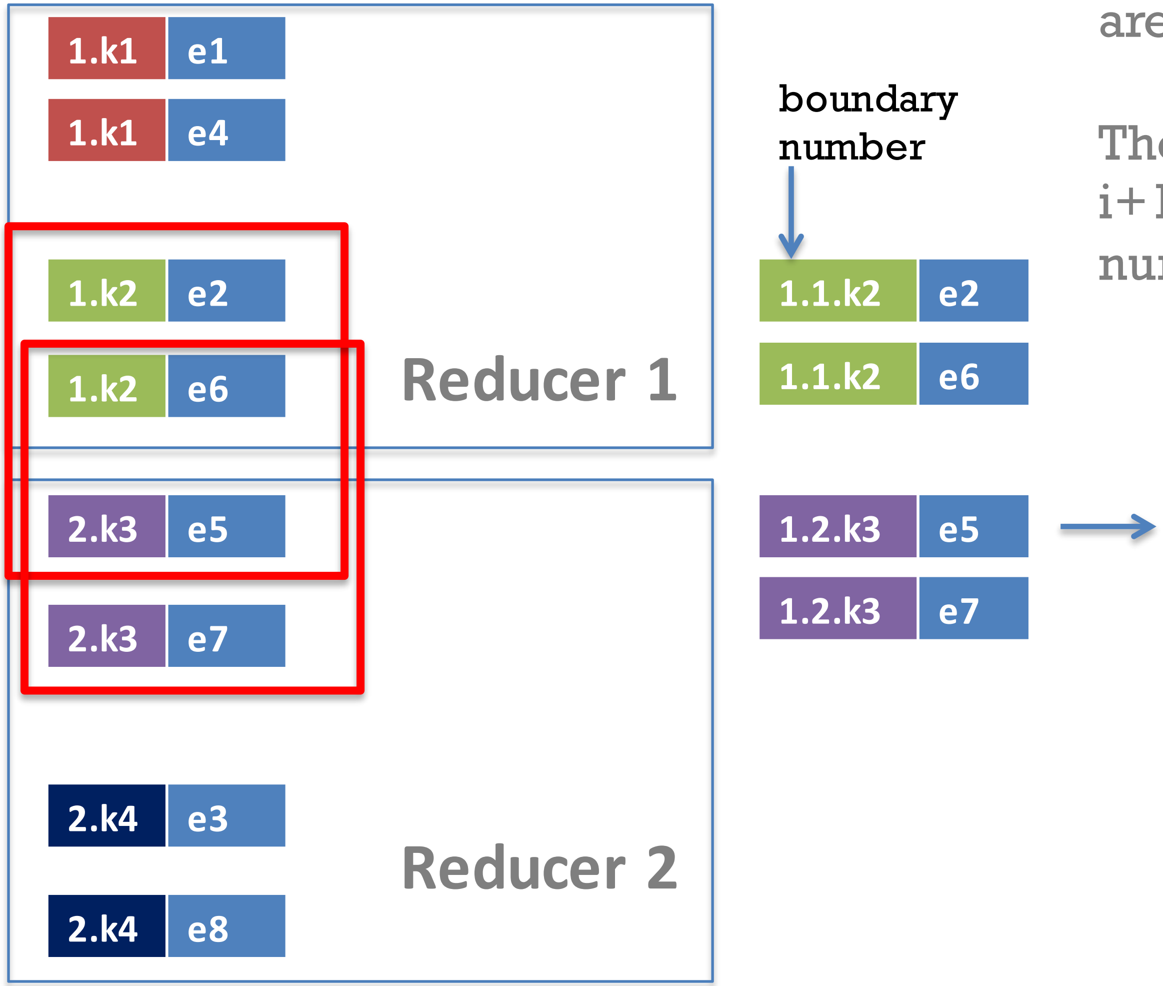
# Dedoop SN: We Also Need To Compare The Boundary Entities




w = 3

# Dedoop SN: Reducers Also Output the Boundary Descriptions

Add a boundary number prefix to the output composite keys




**Boundary number:**

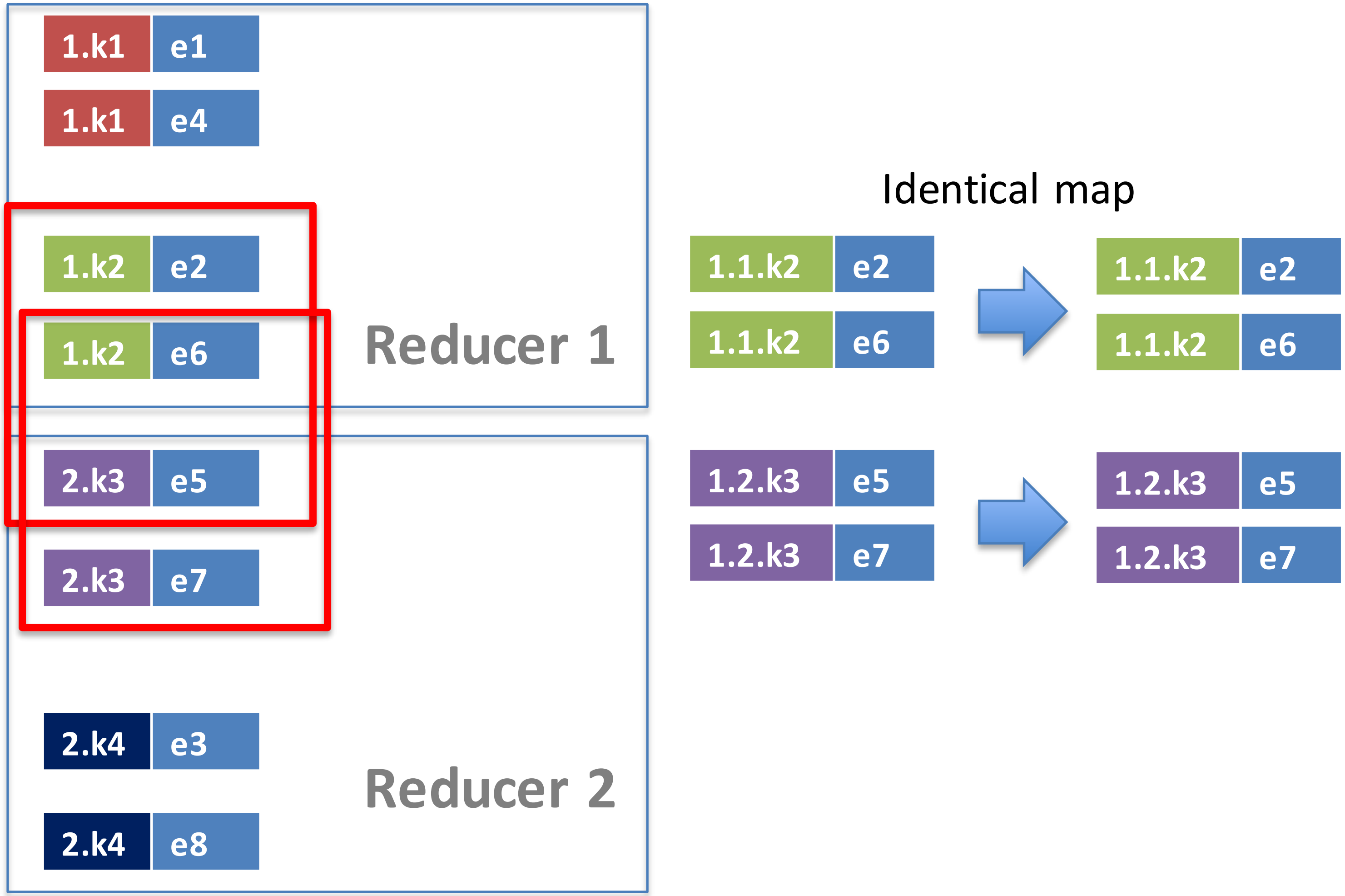
The last w-1 descriptions of reducer i are assigned the boundary number i

The first w-1 descriptions of reducer i+1 are also assigned the boundary number i

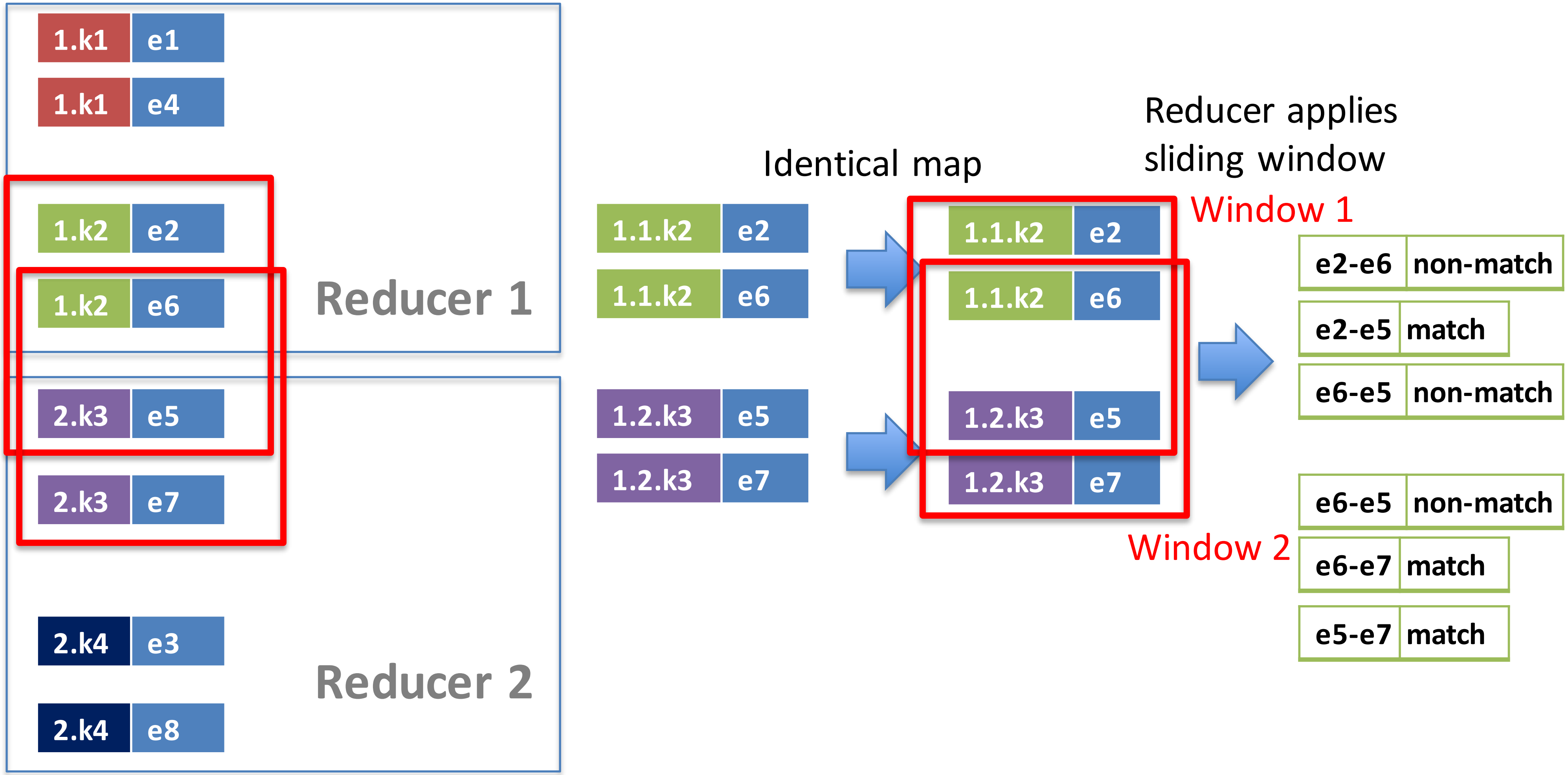
The actual blocking key of e5 is k3, it was assigned to reducer 2 and it is associated with boundary number 1

w = 3

# Dedoop SN: New MapReduce Job for the Boundary Pairs

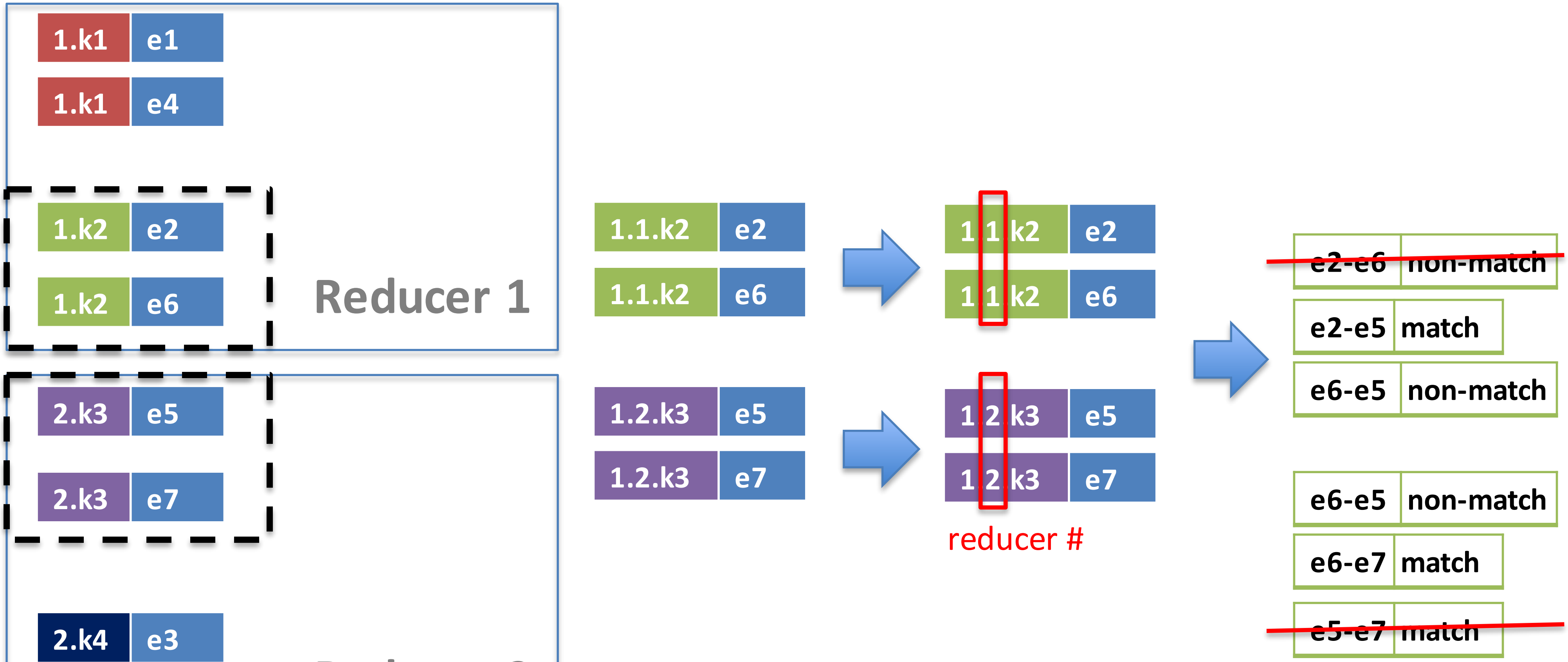


# Dedoop SN: Partition by Boundary Number



*Still, there are repeated comparisons*

# Dedoop SN: Skipping Repeated Comparisons




These comparisons are not performed again:
They have been performed in the previous
MapReduce job (they come from the same reducer)

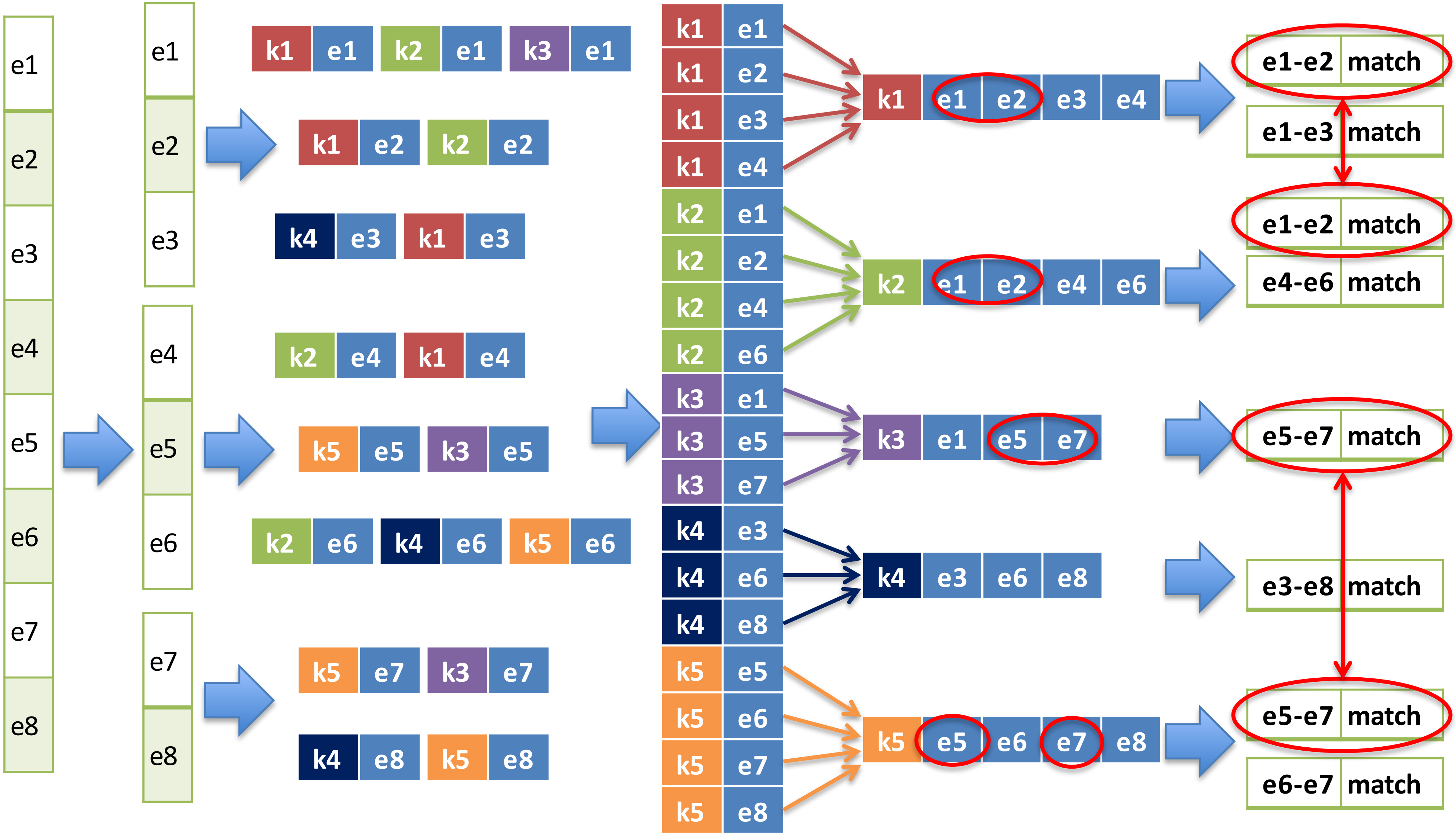
# Don’t match twice [Kolb et al. 2013]

Overlapping blocks lead to repeated comparisons

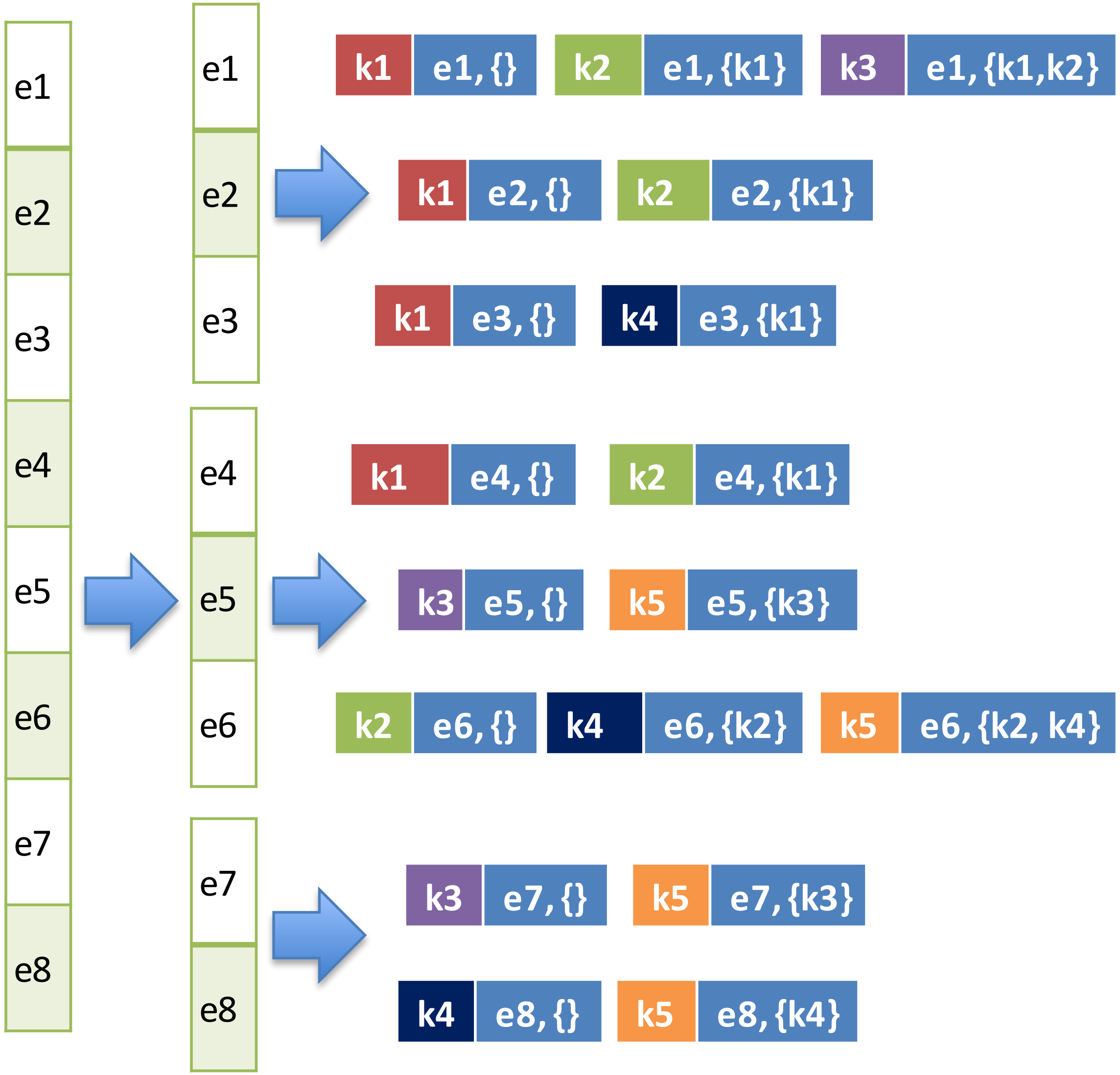
Adopt Comparison Propagation [Papadakis et al. 2012] to MapReduce:

- Descriptions need to be compared only within their least common block

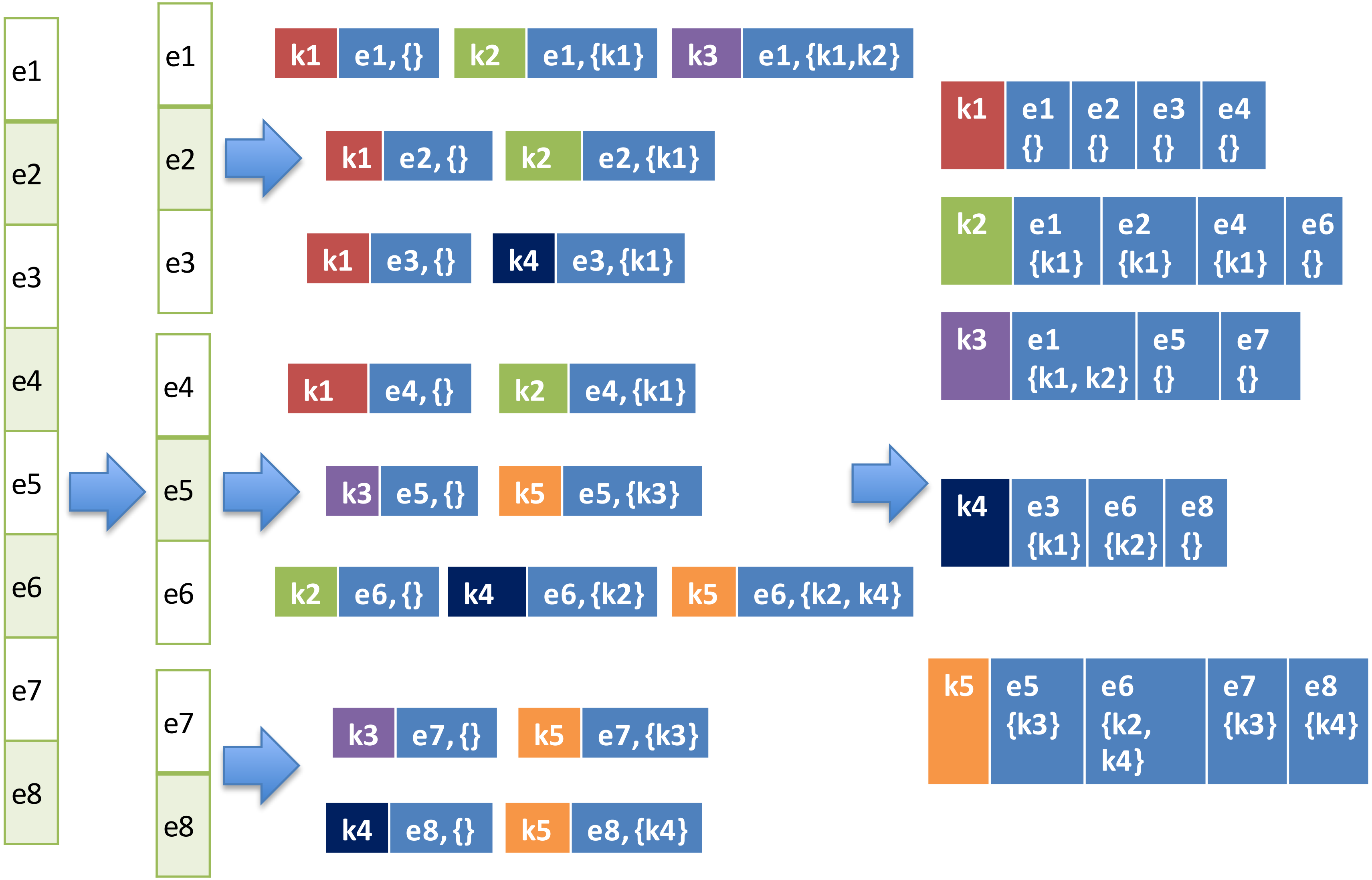
# Overlapping Blocks Lead to Repeated Comparisons



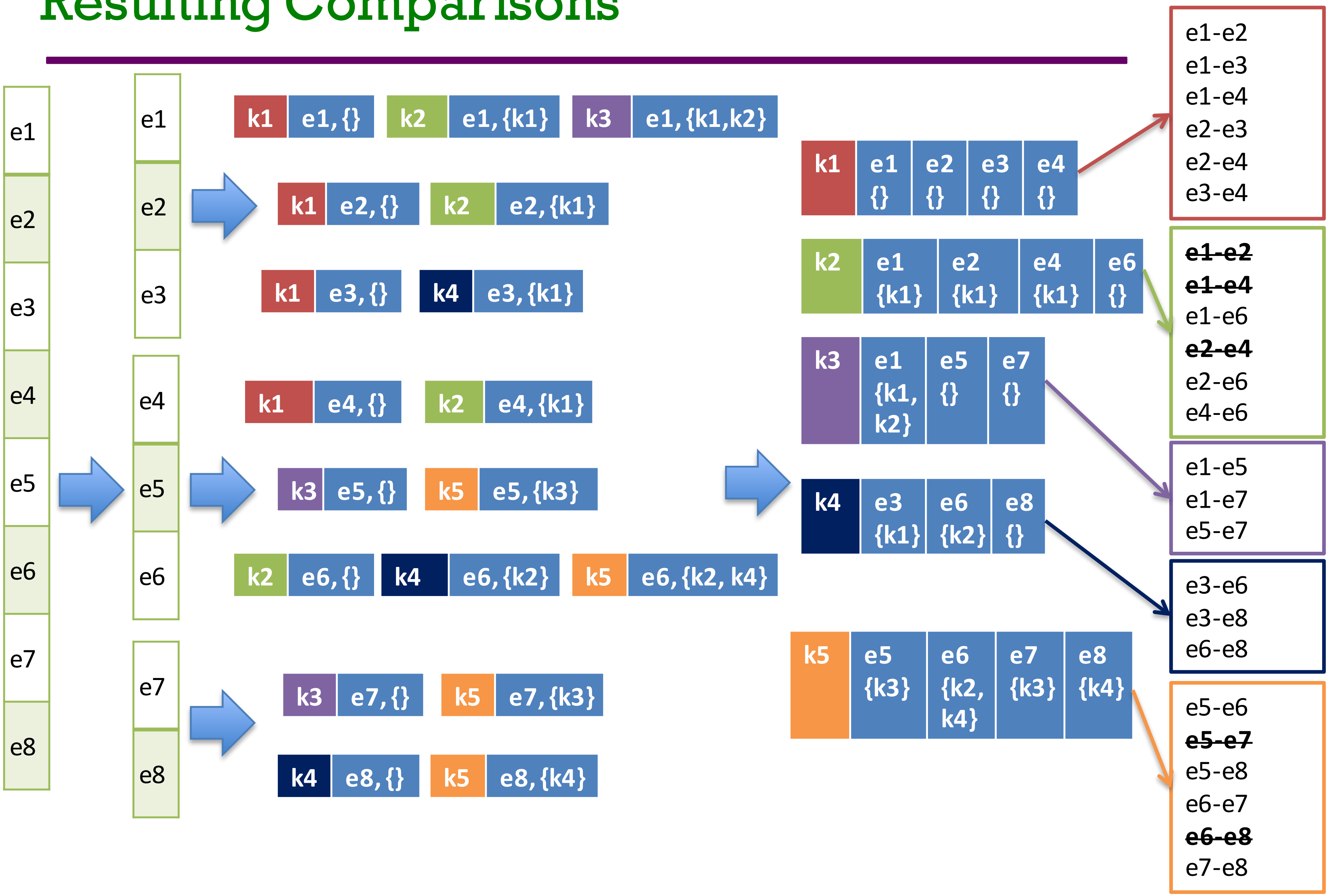
# Map: Append the Subset of Smaller Keys for the Same Description



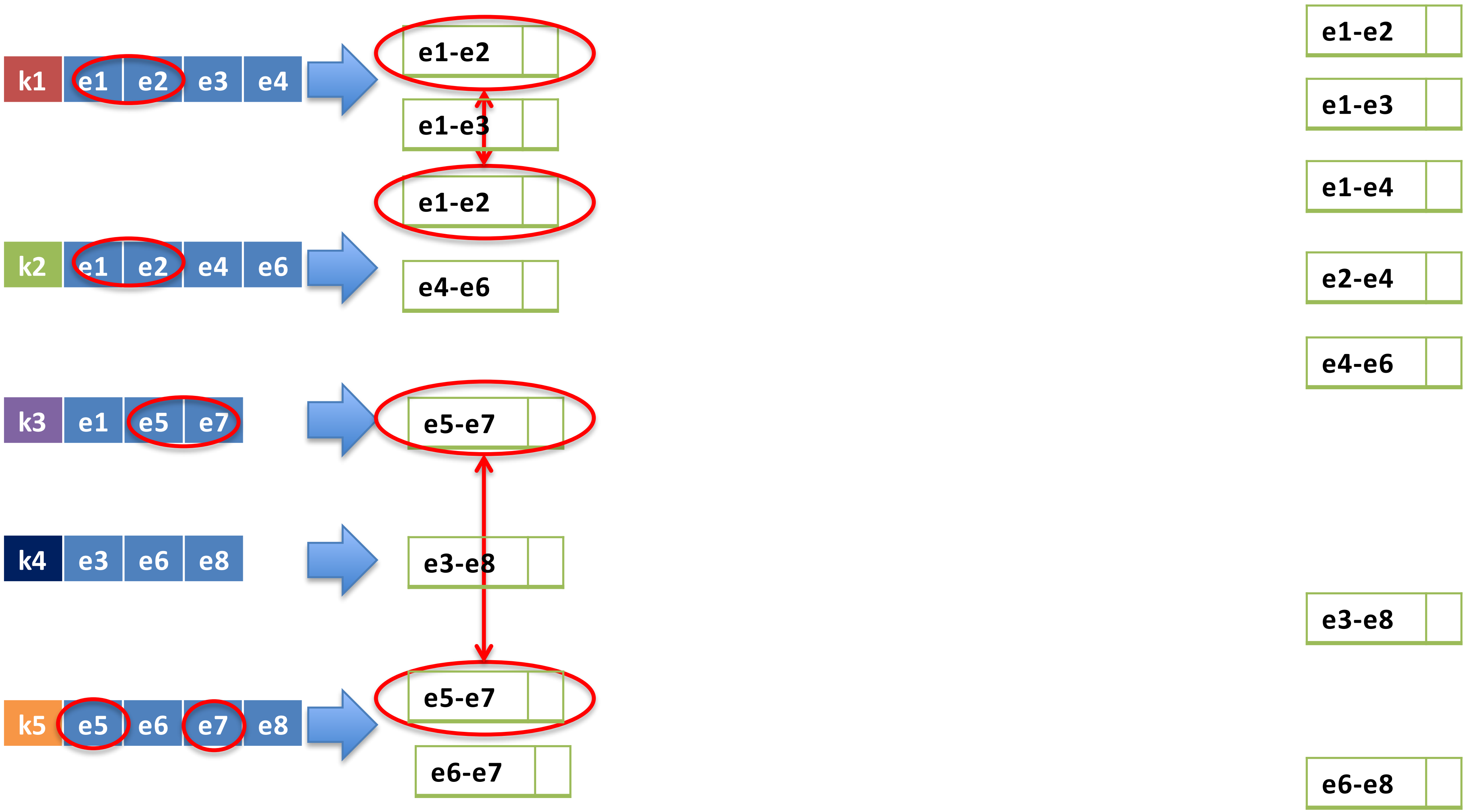
# Map: Append the Subset of Smaller Keys for the Same Description



# Resulting Comparisons

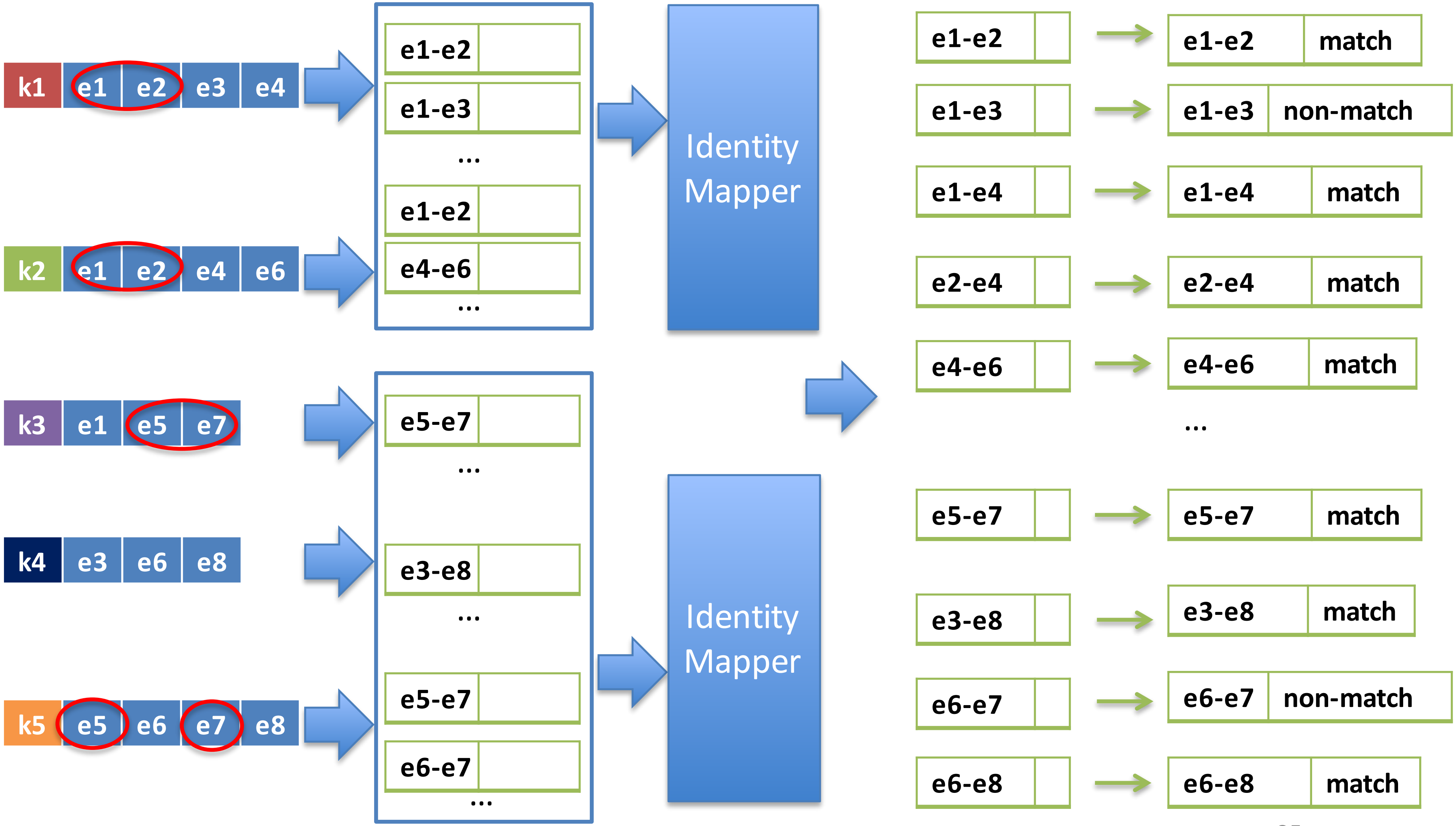


# A More Efficient Approach [Vernica et al. 2010]




Reducer's output...

# A More Efficient Approach [Vernica et al. 2010]



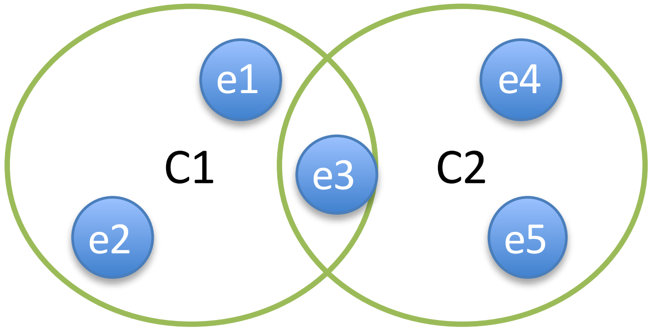

...becomes a new job's input

# Large-Scale Collective Entity Matching
[Rastogi et al. 2011]

Assume that there is a rule *R: Match(e1, e2) => Match(e4, e5)*

and that we have inferred: *Match(e1, e2)*

In C2, we cannot infer *Match(e4, e5)*




map: assign each Ci to a cluster node and run entity resolution on it

reduce: bring all the new evidence for each Ci together

We should somehow inform C2 that e1 matches e2

- Then we could infer that e4 matches e5, according to rule R

Solution: message passing

- After matching in C1 finishes, send a message "Match(e1, e2)"
- In the next MapReduce round, entity resolution runs with the new evidence and infers *Match(e4, e5)*

# Linda [Böhm et al. 2012]

- Works on an <u>entity graph</u> constructed from RDF triples having URIs as subject, predicate and object
  - Literals are stored for each entity e as L(e)

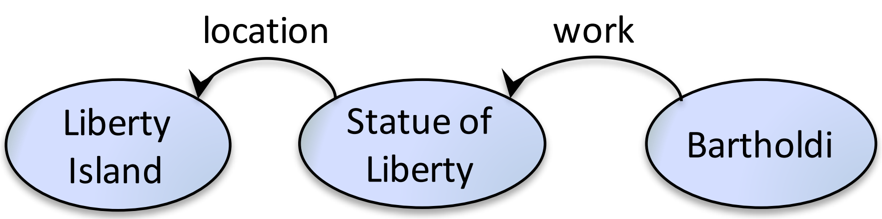
- Matches are identified using <u>two kinds of similarities</u>:
  - String similarity (token-based) of their literal values L(e)
    - Checked once
  - Contextual similarity (based on neighbors in the entity graph)
    - Checked iteratively

# Contextual Similarity

What is context?

- Let node n in an entity graph correspond to an RDF subject or object, identified by a URI
- The context C(n) of n is a set of tuples $(p_i, z_i, w_i)$, where
  - $z_i$ is a neighboring node of n
  - $p_i$ is the predicate associated with an edge connecting n with $z_i$
  - $w_i$ is a numeric weight (how discriminative this information is)

That is, *the context of n includes objects $z_i$ of triples with n as subject and subjects $z_i$ of triples with n as object*




C(Statue of liberty) =
{(location, Liberty Island, w1),
(*is* work *of*, Bartholdi, w2)}

# Contextual Similarity

The contextual similarity of nodes n and m is:

context_sim(n,m) =

- $\sum_{(p_i, z_i, w_i) \in C(n)} \max_{(p_j, z_j, w_j) \in C(m)} w_i \cdot x_{z_i, z_j} \cdot sim(p_i, p_j), if\ |C(n)| \leq |C(m)|$
- $\sum_{(p_j, z_j, w_j) \in C(m)} \max_{(p_i, z_i, w_i) \in C(n)} w_j \cdot x_{z_i, z_j} \cdot sim(p_i, p_j), else$

where

$x_{n,m}$ is 1, if n, m are identified as matches, and 0, else

$sim(p_i, p_j)$ is the string similarity of the predicates of n, m

*Intuitively, the contextual similarity finds matching neighbors and sums up their similarity values*

# Contextual Similarity

Overall similarity: combine sim and context_sim

The similarity score for descriptions n and m is:

$$sim(n, m) + \beta \cdot context\_sim(C(n), C(m)) - \theta$$

β controls the contextual influence

θ is used for re-normalization to values around 0

- positive scores reflect likely mappings
- negative scores imply dissimilarities

*Experiments have shown β = 1 to perform well*

# LINDA Algorithm

Two square matrices (|E|x|E|) are used:

- X captures the identified matches (binary values)
- Y captures the pair-wise similarities (real values)
  - Initialization: common neighbors and string similarity of literals
  - Updates: Use the new identified matches of X

Until a priority queue of pairs (extracted from Y) becomes empty:

- Get the pair ($e_i$, $e_j$) with the highest similarity
  - ($e_i$, $e_j$) match by default!
    - Update X: matches of $e_i$ are also matches of $e_j$
- Update the queue wrt. the new matches

# LINDA – Distributed Entity Resolution Using MapReduce

Distribute across a cluster the input entity graph

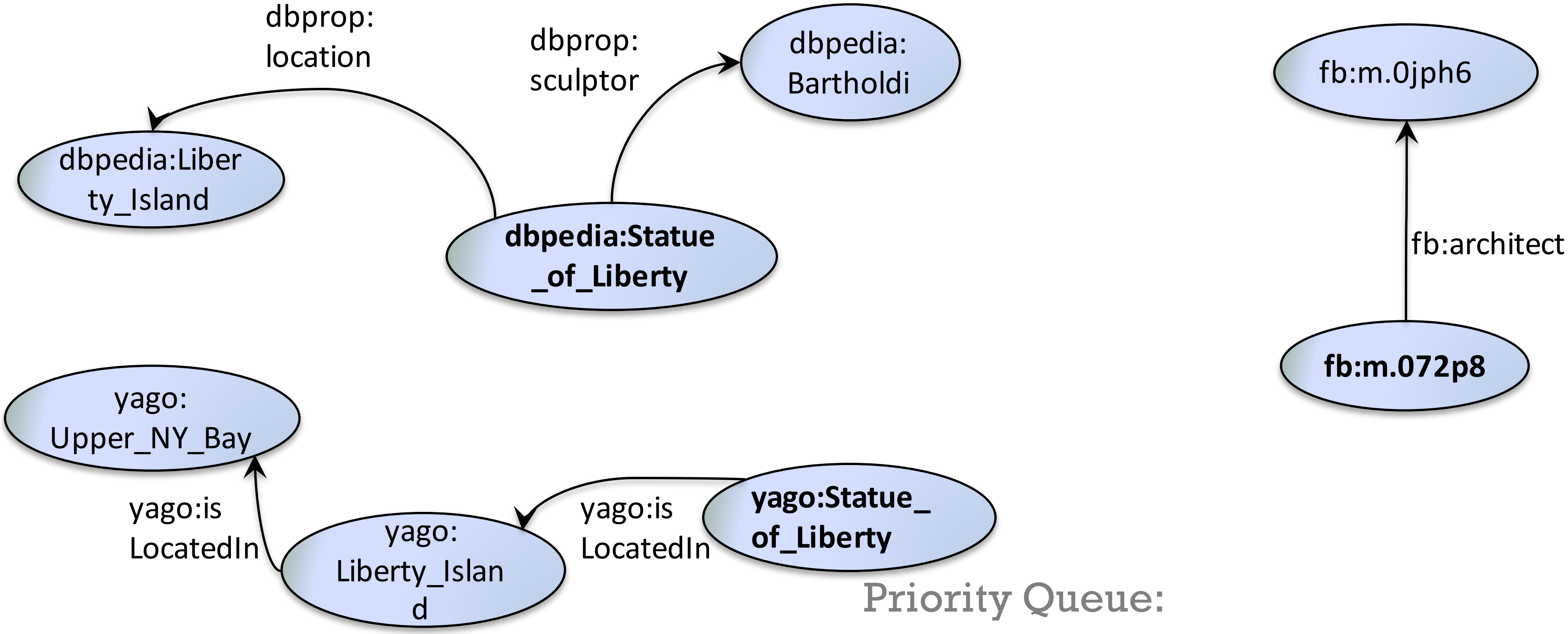
- A node i holds a portion $Q_i$ of the priority queue and the respective part $G_i$ of the graph

<u>Map phase</u>

- Mapper i reads $Q_i$ and forwards messages to reducers for similarities re-computations
  - Matrix X of identified matches is updated

<u>Reduce phase</u>

- Similarities re-computations (Matrix Y)
- Updates on priority queues




## Priority Queue:

| |
|---|
| (dbpedia:Statue_of_Liberty, yago:Statue_of_Liberty) |
| (dbpedia:Statue_of_Liberty, yago:Liberty_Island) |
| (dbpedia:Liberty_Island,yago:Upper_NY_Bay) |
| (dbpedia:Liberty_Island, yago:Liberty_Island) |
| (dbpedia:Liberty_Island, yago:Statue_of_Liberty) |
| (dbpedia:Bartholdi, fb:m.0jph6) |
| (dbpedia:Bartholdi, yago:Statue_of_Liberty) |
| (dbpedia:Bartholdi, fb:m.072p8) |

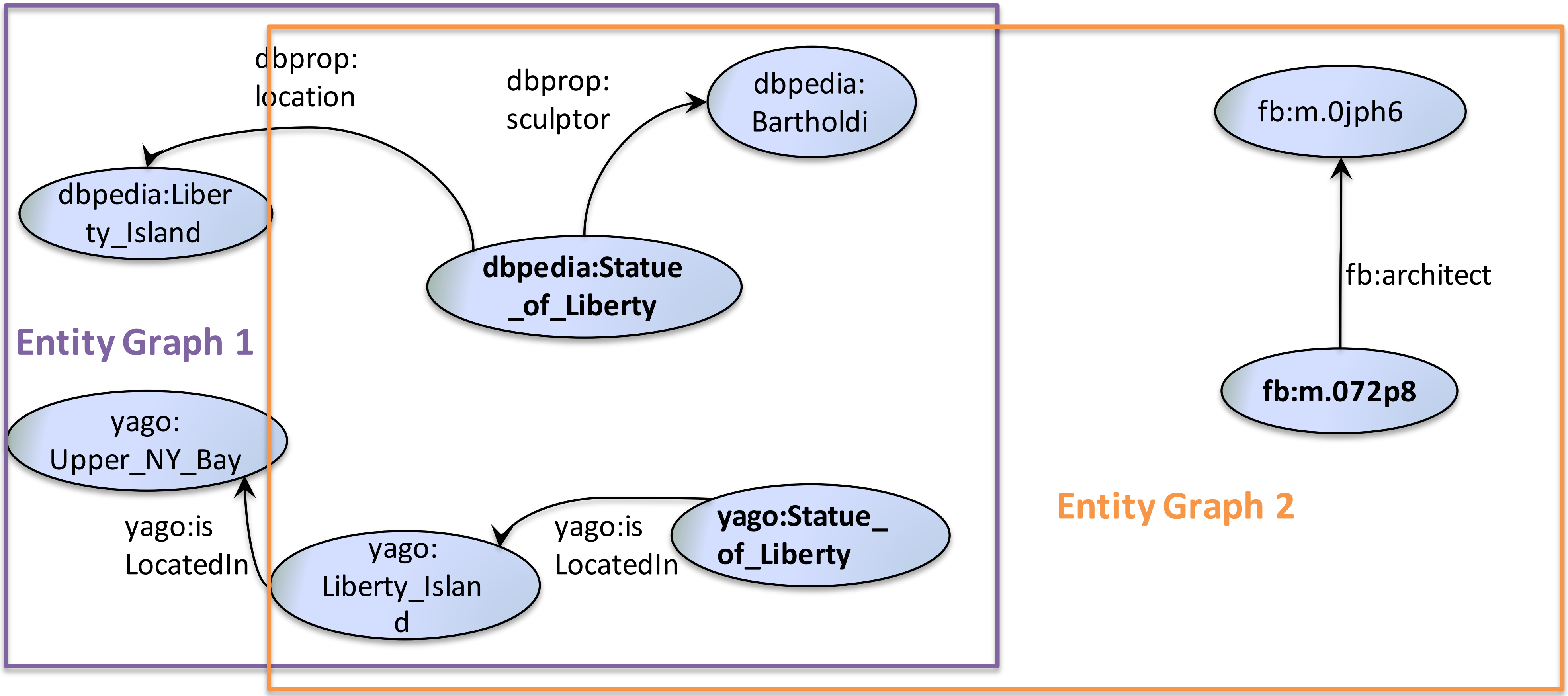
Priority Queue 1 (machine 1):

| |
|---|
| (dbpedia:Statue_of_Liberty, yago:Statue_of_Liberty) |
| (dbpedia:Statue_of_Liberty, yago:Liberty_Island) |
| (dbpedia:Liberty_Island,yago:Upper_NY_Bay) |
| (dbpedia:Liberty_Island, yago:Liberty_Island) |
| (dbpedia:Liberty_Island, yago:Statue_of_Liberty) |

Priority Queue 2 (machine 2):

| |
|---|
| (dbpedia:Bartholdi, fb:m.0jph6) |
| (dbpedia:Bartholdi, yago:Statue_of_Liberty) |
| (dbpedia:Bartholdi, fb:m.072p8) |

The priority queue is partitioned and partitions are sent to the MapReduce nodes



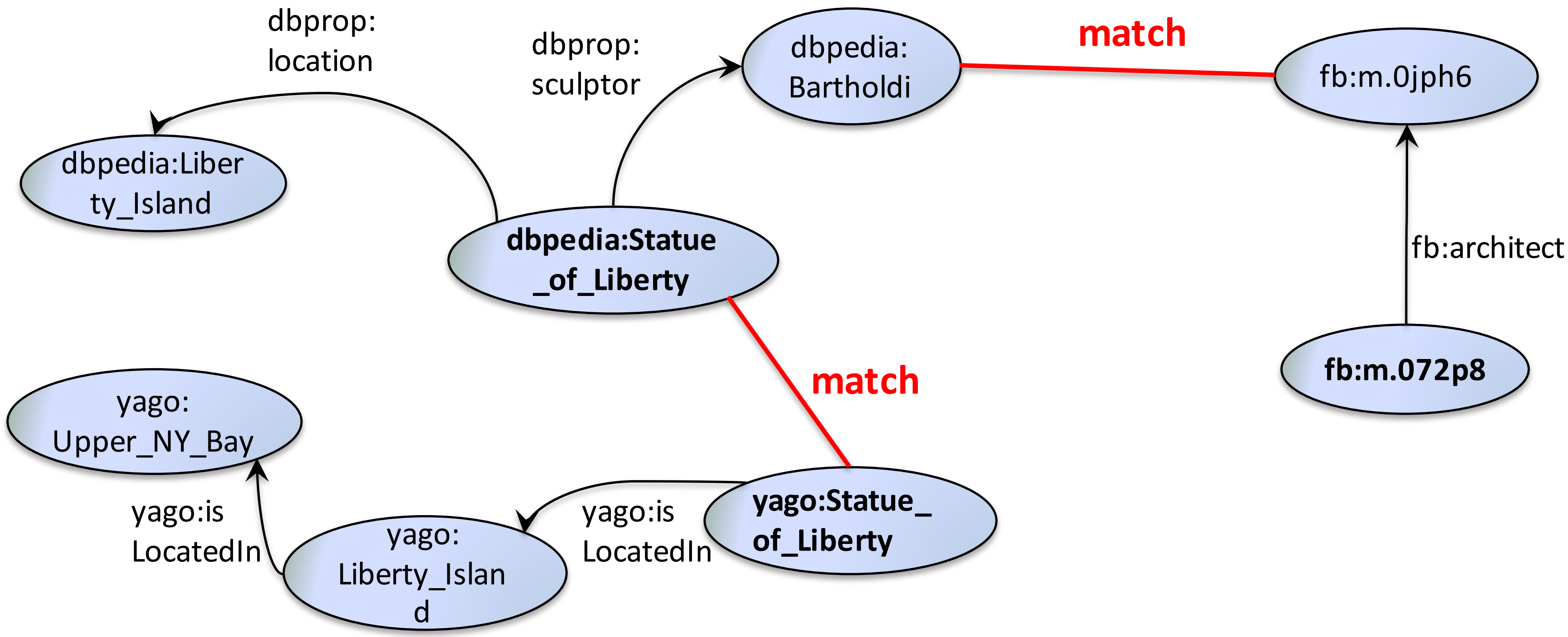

Priority Queue 1 (machine 1):

| |
|---|
| (dbpedia:Statue_of_Liberty, yago:Statue_of_Liberty) |
| (dbpedia:Statue_of_Liberty, yago:Liberty_Island) |
| (dbpedia:Liberty_Island,yago:Upper_NY_Bay) |
| (dbpedia:Liberty_Island, yago:Liberty_Island) |
| (dbpedia:Liberty_Island, yago:Statue_of_Liberty) |

Priority Queue 2 (machine 2):

| |
|---|
| (dbpedia:Bartholdi, fb:m.0jph6) |
| (dbpedia:Bartholdi, yago:Statue_of_Liberty) |
| (dbpedia:Bartholdi, fb:m.072p8) |

The priority queue is partitioned and partitions are sent to the MapReduce nodes




Priority Queue 1:

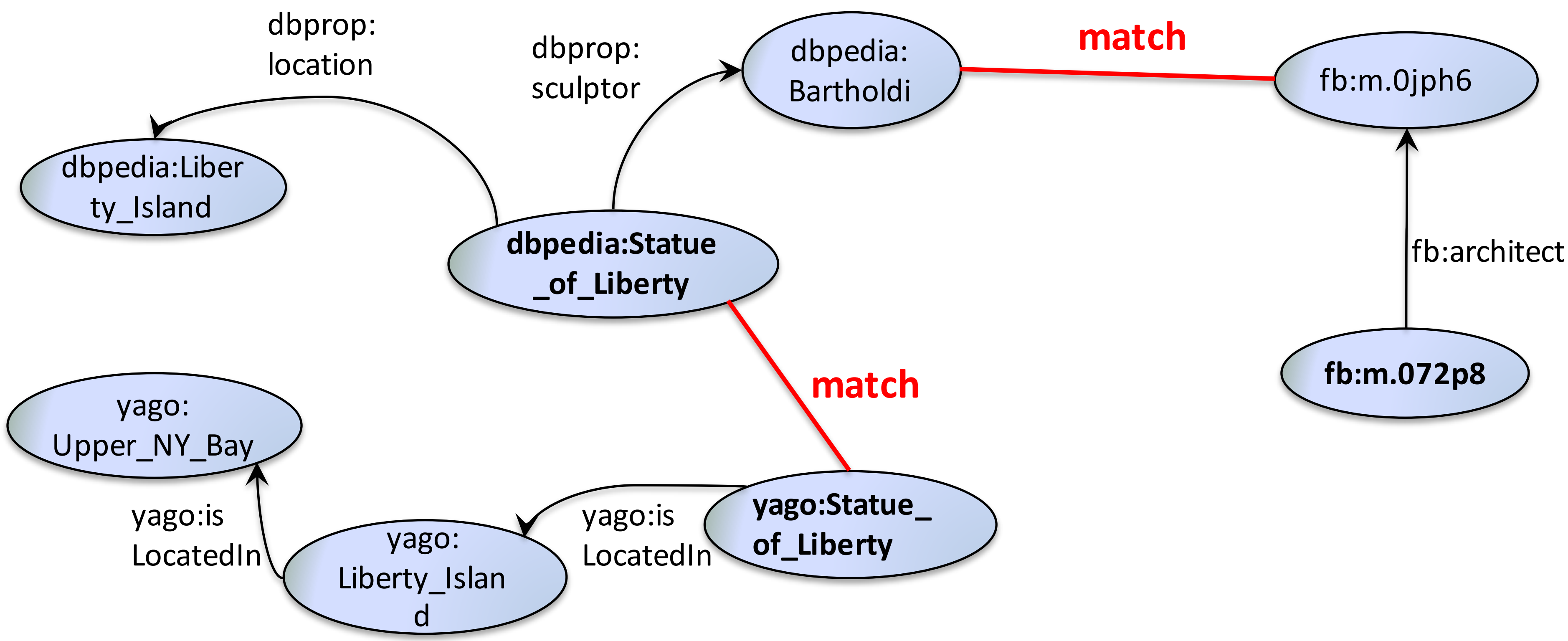
| |
|---|
| (dbpedia:Statue_of_Liberty, yago:Statue_of_Liberty) |
| (dbpedia:Statue_of_Liberty, yago:Liberty_Island) |
| (dbpedia:Liberty_Island,yago:Upper_NY_Bay) |
| (dbpedia:Liberty_Island, yago:Liberty_Island) |
| (dbpedia:Liberty_Island, yago:Statue_of_Liberty) |

Priority Queue 2:

| |
|---|
| (dbpedia:Bartholdi, fb:m.0jph6) |
| (dbpedia:Bartholdi, yago:Statue_of_Liberty) |
| (dbpedia:Bartholdi, fb:m.072p8) |

The head of each queue is a match by default

This triggers update messages



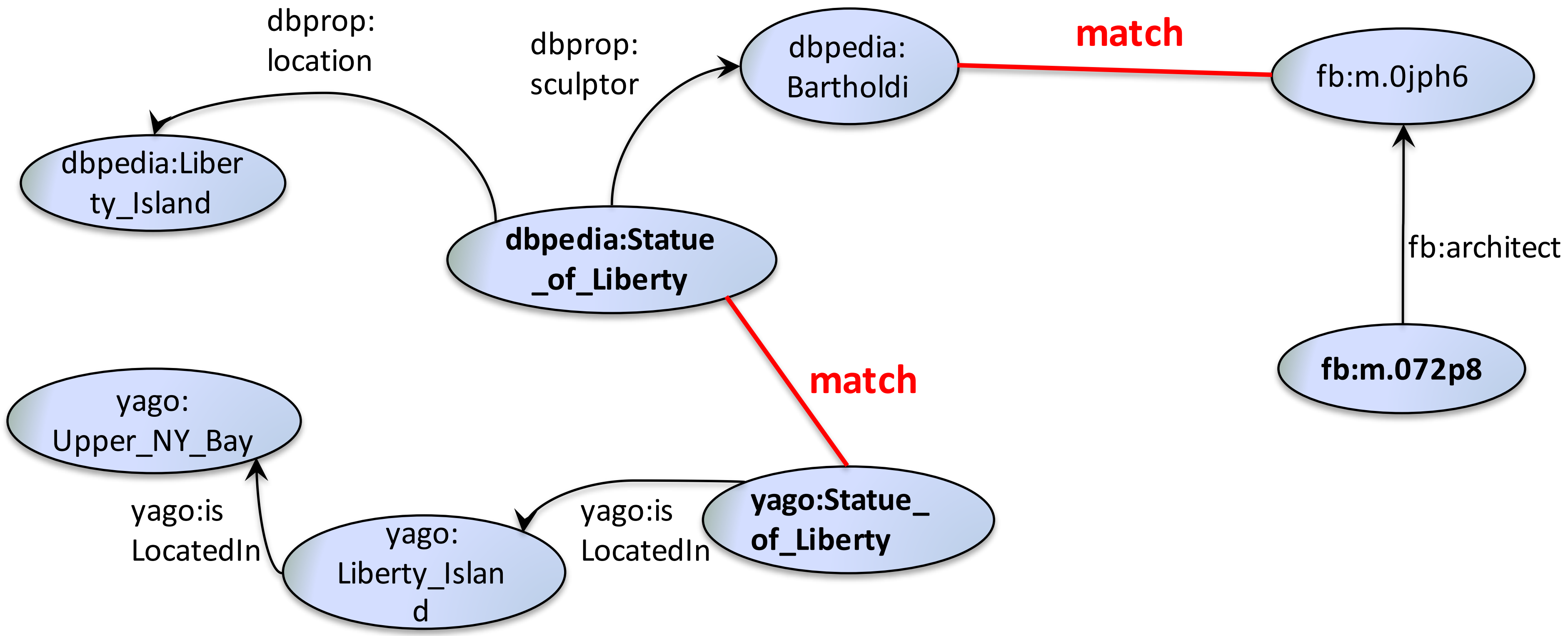

Priority Queue 1:

| |
|---|
| (dbpedia:Statue_of_Liberty, yago:Statue_of_Liberty) |
| ~~(dbpedia:Statue_of_Liberty, yago:Liberty_Island)~~ |
| (dbpedia:Liberty_Island,yago:Upper_NY_Bay) |
| (dbpedia:Liberty_Island, yago:Liberty_Island) |
| ~~(dbpedia:Liberty_Island, yago:Statue_of_Liberty)~~ |

Priority Queue 2:

| |
|---|
| (dbpedia:Bartholdi, fb:m.0jph6) |
| (dbpedia:Bartholdi, yago:Statue_of_Liberty) |
| ~~(dbpedia:Bartholdi, fb:m.072p8)~~ |

Dequeue these pairs, as each entity can be mapped to at most one entity per data source



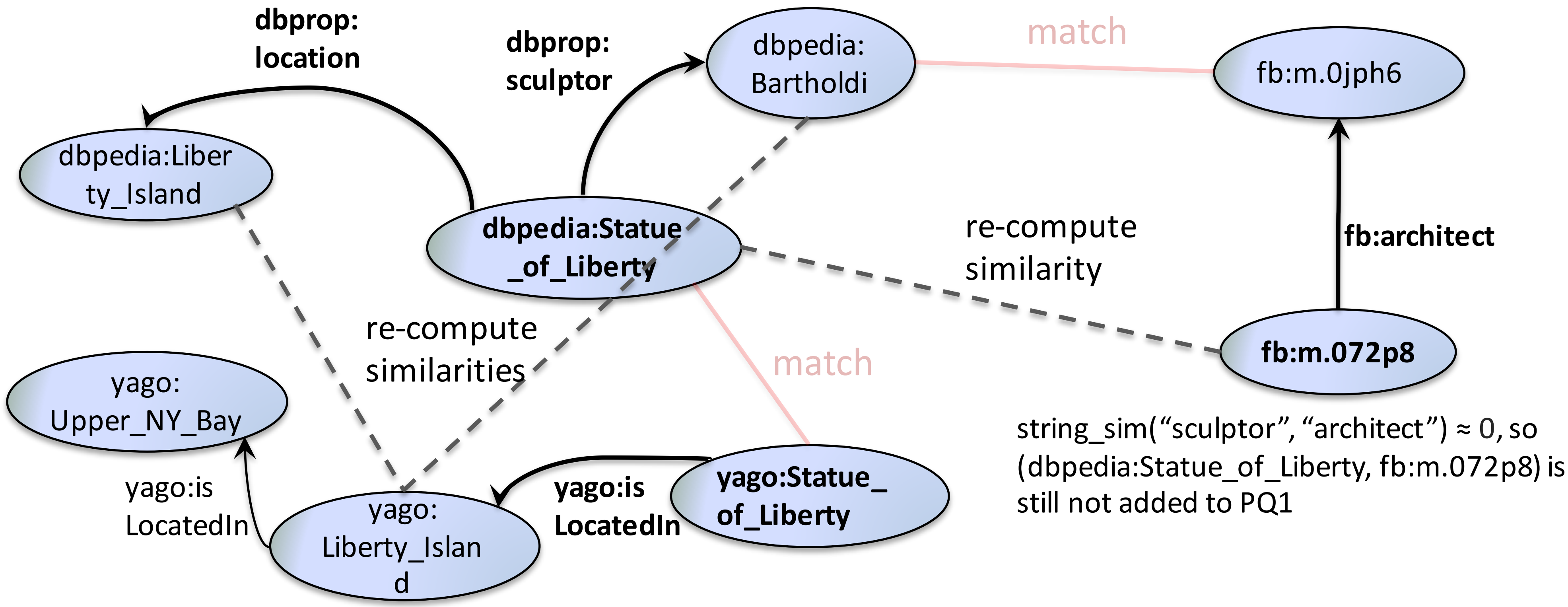

Priority Queue 1:

| |
|---|
| (dbpedia:Statue_of_Liberty, yago:Statue_of_Liberty) |
| ~~(dbpedia:Statue_of_Liberty, yago:Liberty_Island)~~ |
| (dbpedia:Liberty_Island,yago:Upper_NY_Bay) |
| (dbpedia:Liberty_Island, yago:Liberty_Island) |
| ~~(dbpedia:Liberty_Island, yago:Statue_of_Liberty)~~ |

Priority Queue 2:

| |
|---|
| (dbpedia:Bartholdi, fb:m.0jph6) |
| ~~(dbpedia:Bartholdi, yago:Statue_of_Liberty)~~ |
| ~~(dbpedia:Bartholdi, fb:m.072p8)~~ |

Send messages to the other nodes and check this constraint again




Priority Queue 1:

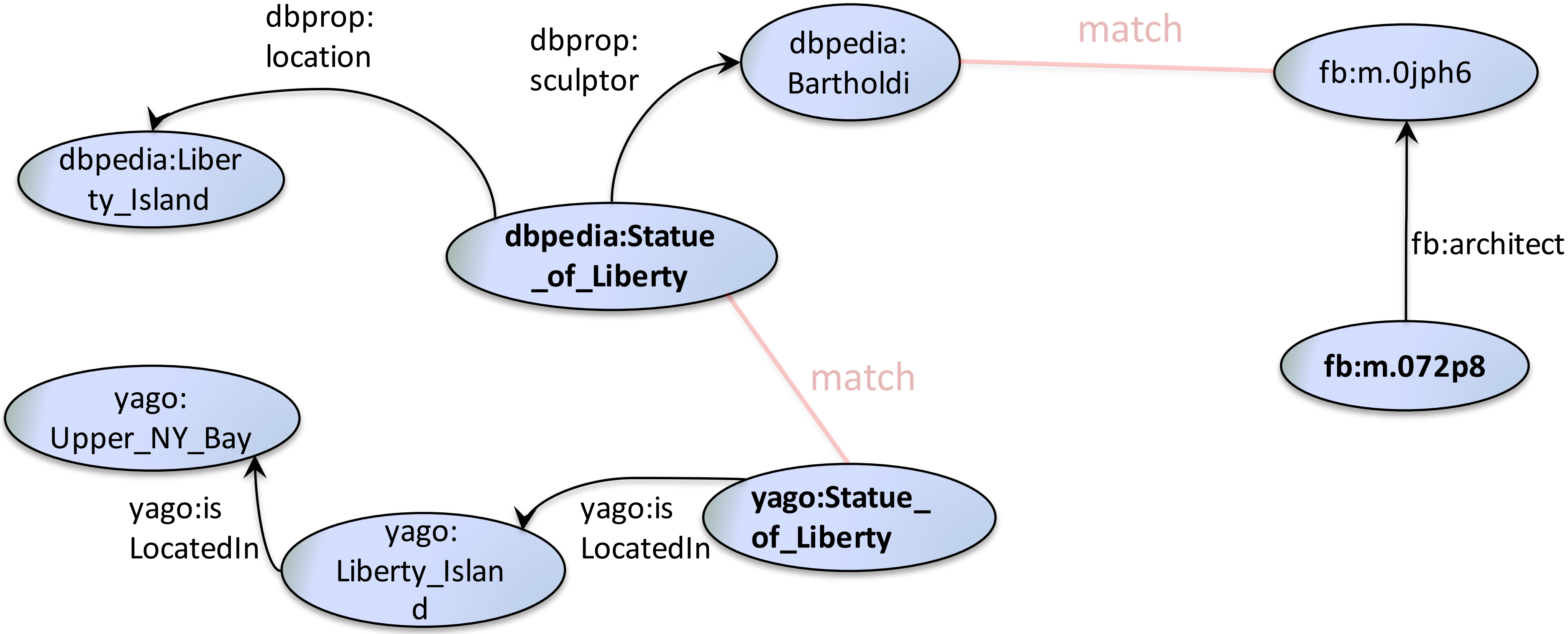
(dbpedia:Liberty_Island,yago:Upper_NY_Bay)

**(dbpedia:Liberty_Island, yago:Liberty_Island)**

Priority Queue 2:

Contextual similarity re-computations

Property names are also taken into account



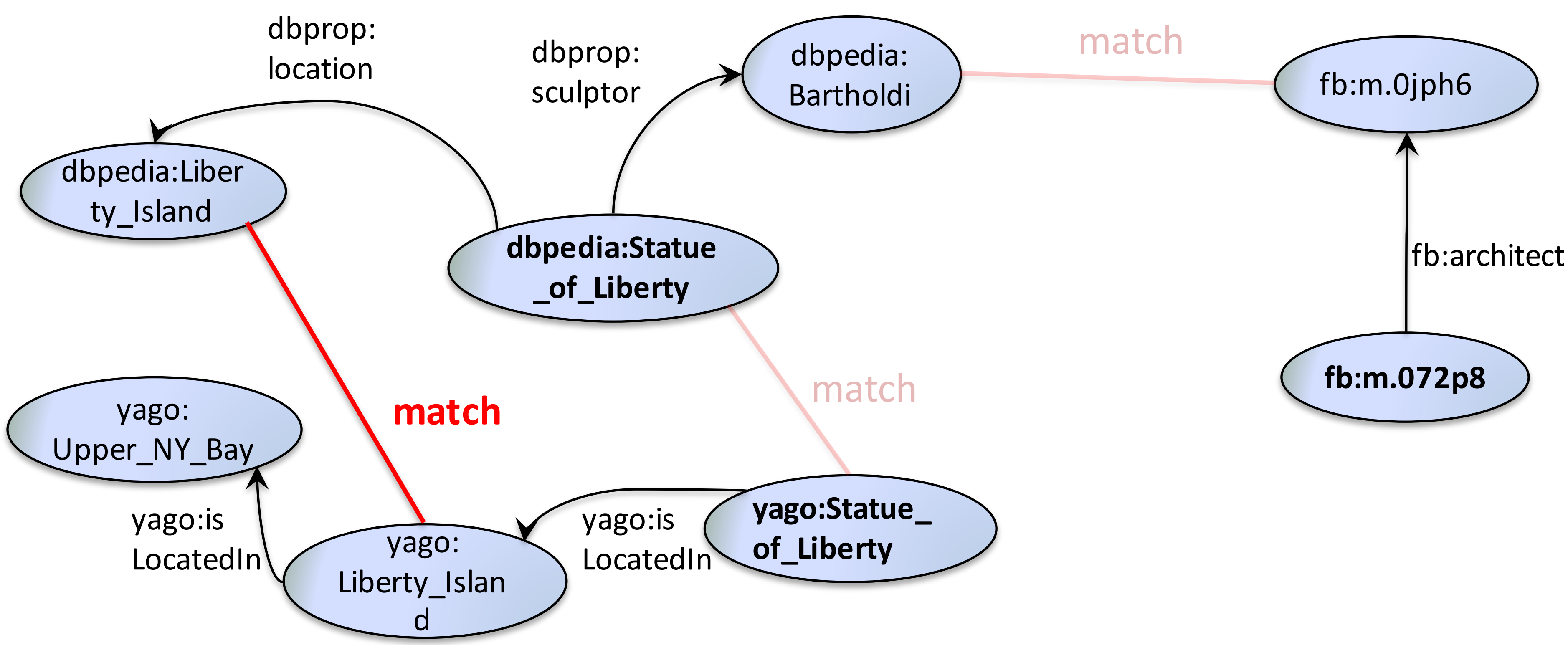

Priority Queue 1:

| |
|---|
| **(dbpedia:Liberty_Island, yago:Liberty_Island)** |
| (dbpedia:Liberty_Island,yago:Upper_NY_Bay) |

Priority Queue 2:

| |
|---|
| |

Priority queues are updated based on the new similarities




Priority Queue 1:

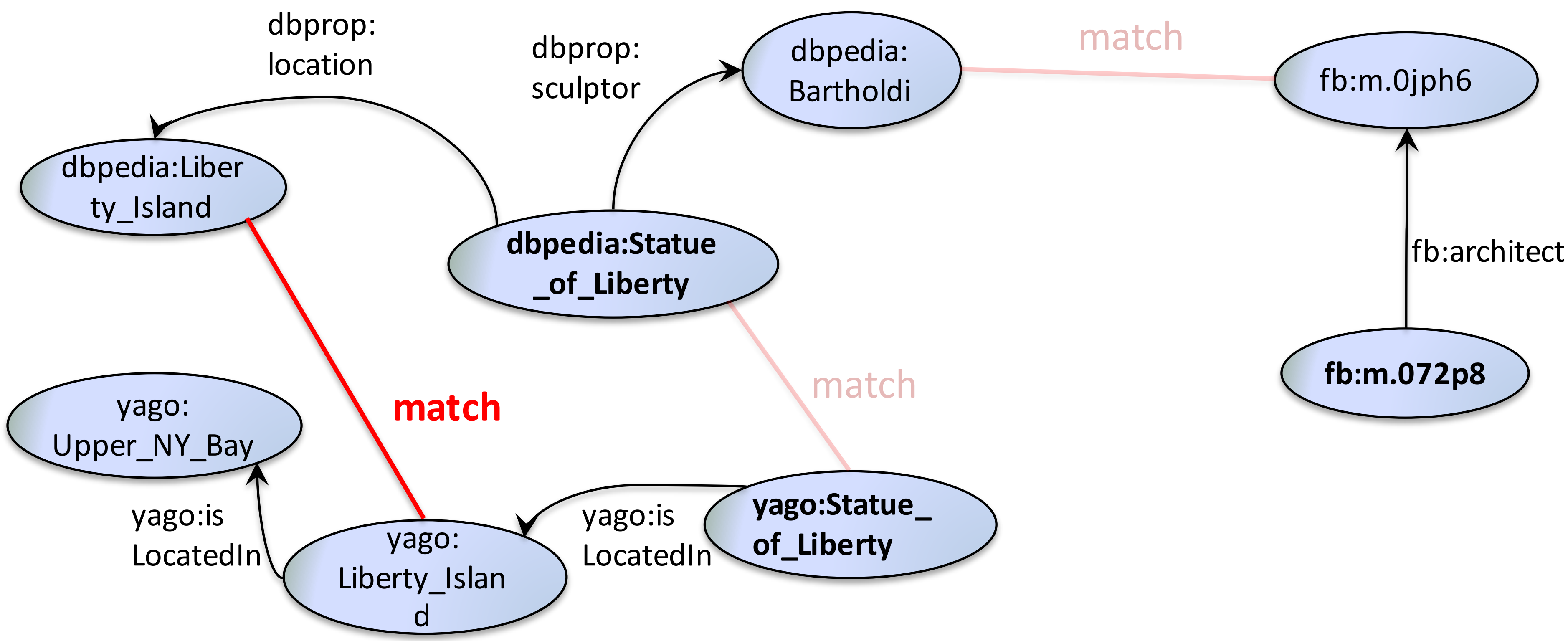
| |
|---|
| **(dbpedia:Liberty_Island, yago:Liberty_Island)** |
| (dbpedia:Liberty_Island,yago:Upper_NY_Bay) |

Priority Queue 2:

| |
|---|
| |

The head of each queue is a match by default

This triggers update messages



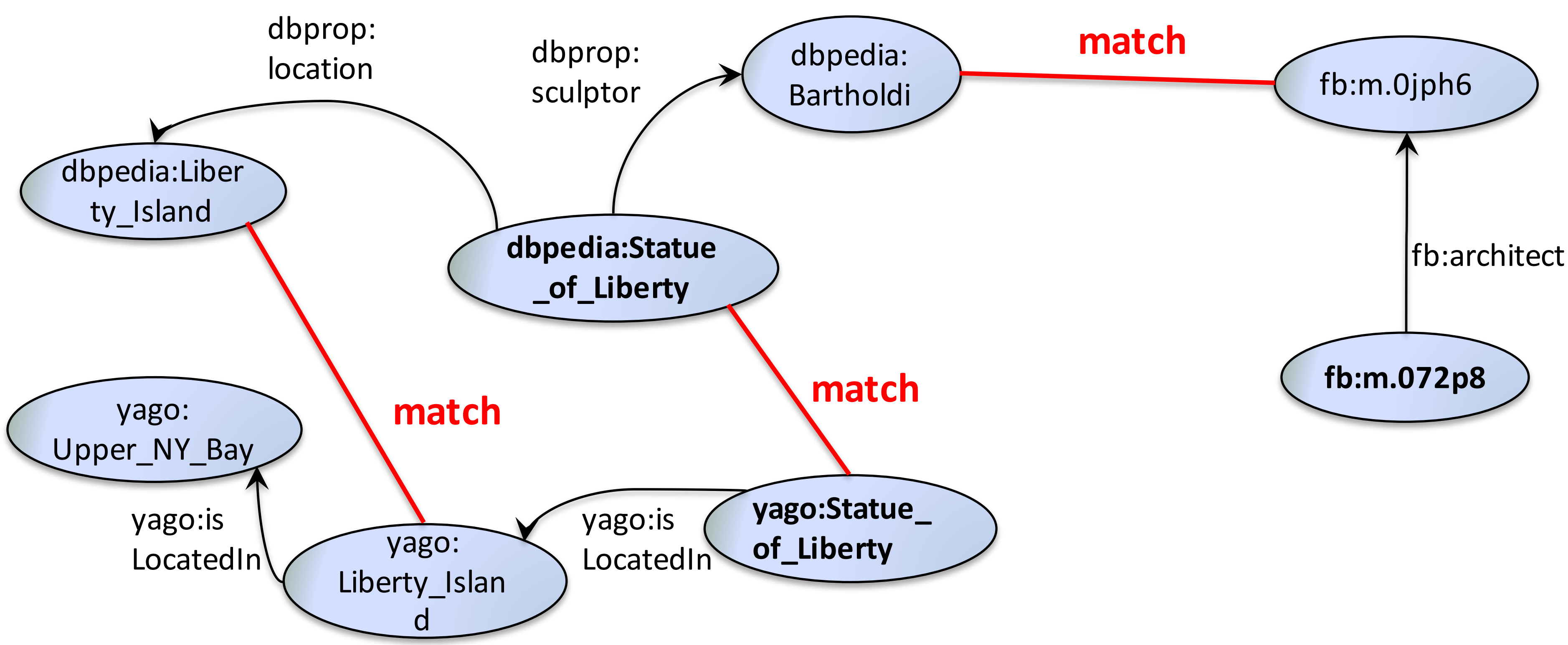

Priority Queue 1:

| |
|---|
| **(dbpedia:Liberty_Island, yago:Liberty_Island)** |
| ~~(dbpedia:Liberty_Island,yago:Upper_NY_Bay)~~ |

Priority Queue 2:

| |
|---|
| |

Dequeue this pair, as each entity can be mapped to at most one entity per data source

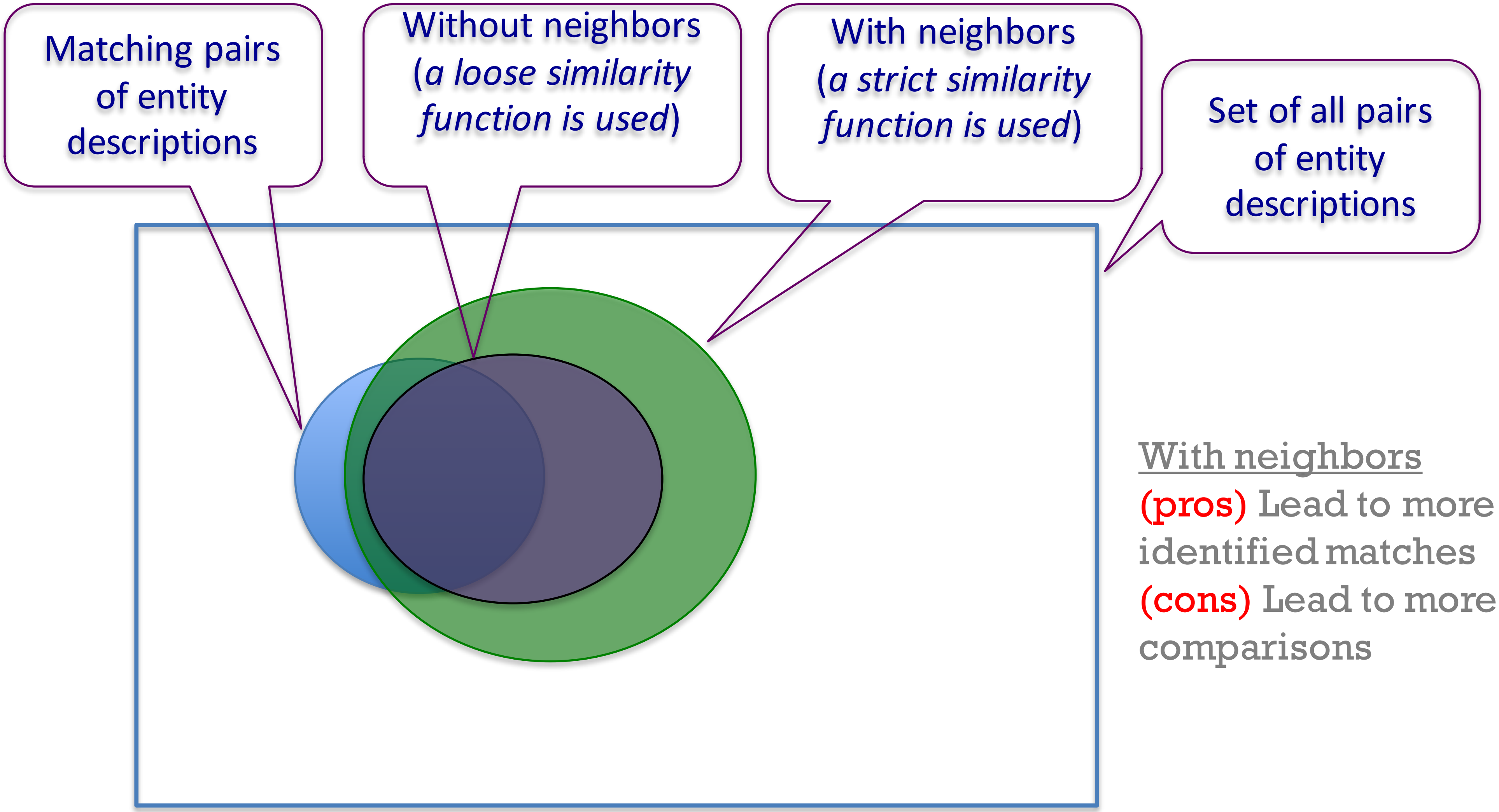



Priority Queue 1:

Priority Queue 2:

Output mappings

# Using Neighbors for Computing Similarities




<u>With neighbors</u>
(pros) Lead to more identified matches
(cons) Lead to more comparisons

# Entity Resolution in the Web of Data

*So far…*

Rely on the values of the descriptions

- *A good way to handle data heterogeneity and low structuredness*

**=> Deal with loosely structured entities**

**=> Deal with various vocabularies**
**(*side effect*)**

**=> Deal with large volumes of data**

Still, many redundant comparisons are per

- Can we also use the structural type of th

A brief overview of our ongoing work on blocking using MapReduce follows…

# Methods and Datasets

MapReduce implementations of:

- Token Blocking (ToB)
- Attribute Clustering Blocking (AtC)
- Prefix-Infix(-Suffix) Blocking (PIS)

Datasets: [Billion Triples Challenge 2012] (BTC12)

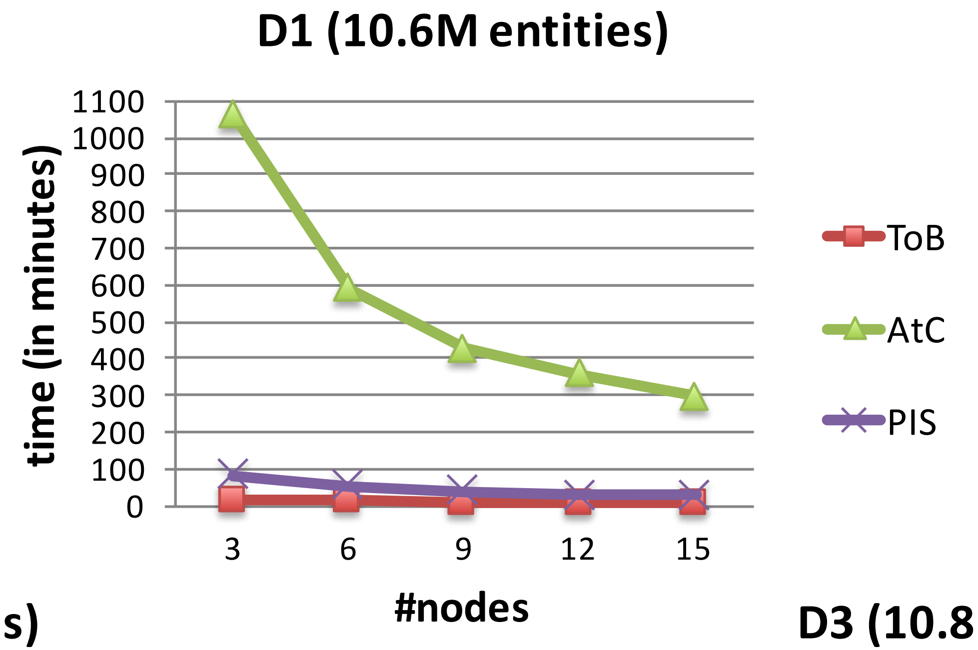
- D1: BTC12 DBpedia (~148M triples) and [DBpedia 3.5] (~32M triples)
- D2: BTC12 DBpedia and BTC12 Rest (~918K triples)
- D3: BTC12 DBpedia and BTC12 Freebase (~29M triples)

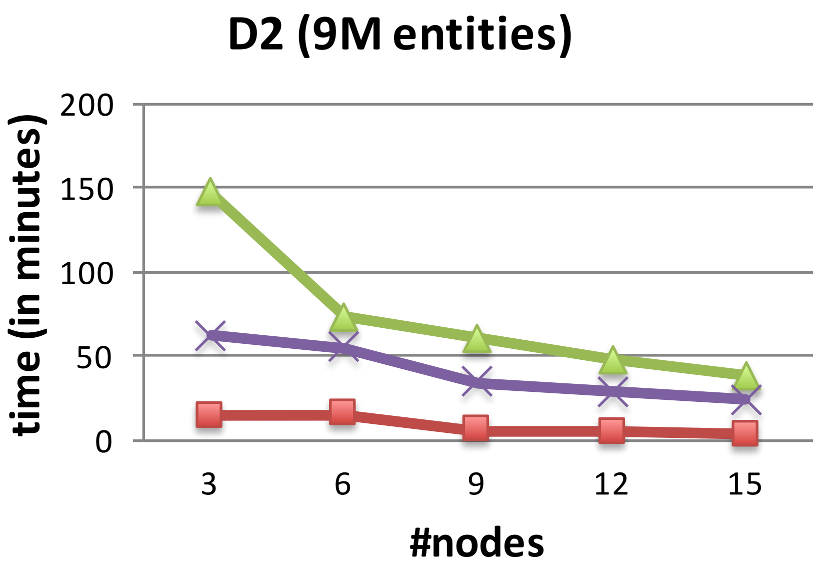
On a cluster of 15 nodes (each with 8 CPUs, 8GB RAM, and 60GB HDD)

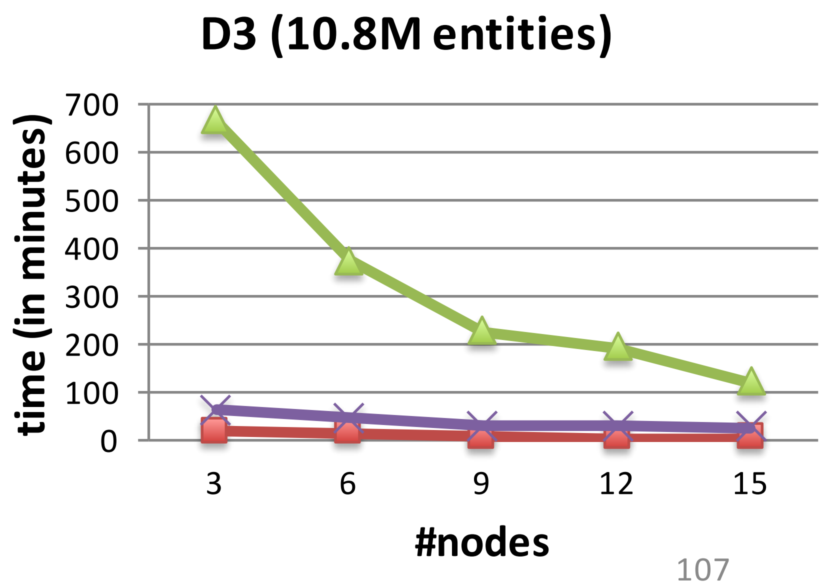
For ground-truth, we used the *owl:sameAs* links provided by DBpedia

For each dataset, we performed both dirty and clean-clean ER

# Scalability



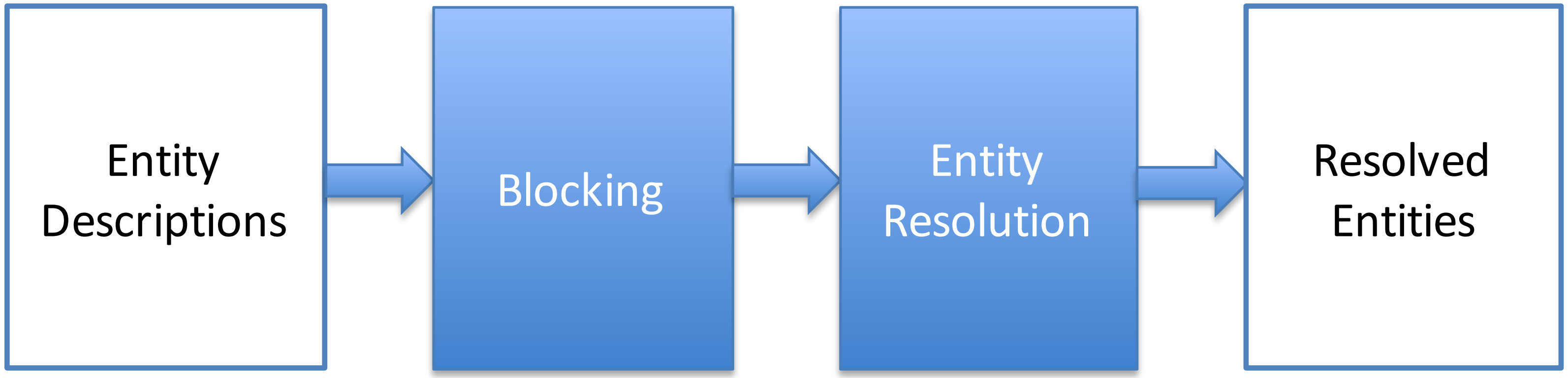
# Quality Results

| | | ToB (Dirty) | AtC (Clean-Clean) | PIS (Dirty) |
|---|---|---|---|---|
| Precision | D1 | $3.598 \cdot 10^{-7}$ | $8.064 \cdot 10^{-6}$ | $9.955 \cdot 10^{-7}$ |
| | D2 | $2.540 \cdot 10^{-8}$ | $6.103 \cdot 10^{-6}$ | $5.964 \cdot 10^{-8}$ |
| | D3 | $4.376 \cdot 10^{-7}$ | $9.759 \cdot 10^{-6}$ | $3.729 \cdot 10^{-6}$ |
| Recall | D1 | 90.5% | 88% | 91.7% |
| | D2 | 86.3% | 70.6% | 87.6% |
| | D3 | 86.5% | 84.3% | 84.4% |
| RR | D1 | 90.1% | 97.8% | 92.5% |
| | D2 | 90.9% | 98.6% | 91.7% |
| | D3 | 92.7% | 98.9% | 90.8% |
| #comparisons | D1 | 5,588 B | 322 B | 4,394 B |
| | D2 | 3,681 B | 4 B | 3,449 B |
| | D3 | 4,272 B | 184 B | 5,339 B |

# Room for Improvement

<u>Ideally</u>:

- Similar entity descriptions in the same block
- Dissimilar entity descriptions in different blocks?



# Current Trends

# Temporal Entity Resolution

Entity resolution should account for changes over time

- Entities evolve over time
- Entities have a lifetime

# Linked Datasets Evolve Over Time

**Current** version of DBpedia

| DBpedia | dbpedia:Statue_of_Liberty |
|---|---|
| rdfs:label | Statue of Liberty, Freiheitsstatue, … |
| dbpprop:location | New York City, New York, U.S., dbpedia:Liberty_Island |
| dbpprop:sculptor | dbpedia:Frédéric_Auguste_Bartholdi |
| dcterms:subject | dbpedia_category:1886_sculptures, … |
| foaf:isPrimaryTopicOf | http://en.wikipedia.org/wiki/Statue_of_Liberty |
| dbpprop:beginningDate | 1886-10-28 (xsd:date) |
| dbpprop:restored | 19381984 (xsd:integer) |
| dbpprop:visitationNum | 3200000 (xsd:integer) |
| dbpprop:visitationYear | 2009 (xsd:integer) |
| http://www.w3.org/ns/prov#wasDerivedFrom | http://en.wikipedia.org/wiki/Statue_of_Liberty?oldid=494328330 |

**Previous** version of DBpedia

| DBpedia | dbpedia:Statue_of_Liberty |
|---|---|
| rdfs:label | Statue of Liberty, Freiheitsstatue, … |
| dbpprop:location | New York City, New York, U.S., dbpedia:Liberty_Island |
| dbpprop:sculptor | dbpedia:Frédéric_Auguste_Bartholdi |
| dcterms:subject | dbpedia_category:1886_sculptures, … |
| foaf:isPrimaryTopicOf | http://en.wikipedia.org/wiki/Statue_of_Liberty |
| dbpprop:built | 1886-10-28 (xsd:date) |
| dbpprop:restored | 19381984 (xsd:integer) |
| dbpprop:hasHeight | 151 (xsd:integer) |
| http://www.w3.org/ns/prov#wasDerivedFrom | http://en.wikipedia.org/wiki/Statue_of_Liberty?oldid=494328330 |

# Entities Have a Lifetime

Example: Matching a description of Ronal Reagan, stating that he **was** the US President to a description of Barack Obama, stating that he **is** the US President

Yago2 [Hoffart et al. 2012]: A temporal knowledge base, built with data from Wikipedia, GeoNames and Wordnet

- Entities are assigned a time span to denote their existence in time
  - e.g. Ronal Reagan is associated with 1911-02-06 (birthdate) and 2004-06-05 (time of death)
- Facts are assigned a time point, or a time span
  - e.g. the fact "Ronald Reagan is US President" is associated with the time span from 1981-01-20 to 1989-01-20

# Privacy Protection

Example ([PleaseRobMe.com](http://PleaseRobMe.com)): Exploit Foursquare to detect the current location of Twitter users and identify houses easy to burgle, as the inhabitants are traveling at the time

*Measure one's ability to link two matching descriptions and then, try to minimize it*

Privacy breach can be measured in terms of how much of the complete information about a person is available to an adversary [Whang et al. 2011, 2013]

- Use *disinformation* to make entity resolution for an adversary difficult:
  - Link a description to irrelevant descriptions
  - Add "incorrect but believable" information to a description

# Crowdsourcing

Instead of machine-only approaches, use hybrid human-machine approaches

- Pass the critical (expensive/difficult) decisions to the users

Machines do a first, coarse pass over all the data (e.g. blocking)

- When algorithms fail to reach a match decision, ask humans [Demartini et al. 2013]
- Humans are used to verify only the most likely matches [Wang et al. 2012]

Humans can make mistakes too! (spam, low attention, etc.)

- Given a set of descriptions, find which questions between pairs of descriptions will reveal the most about the underlying entities [Verroios et al. 2014]

# Thank You!

Other points for future work?

Questions?

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