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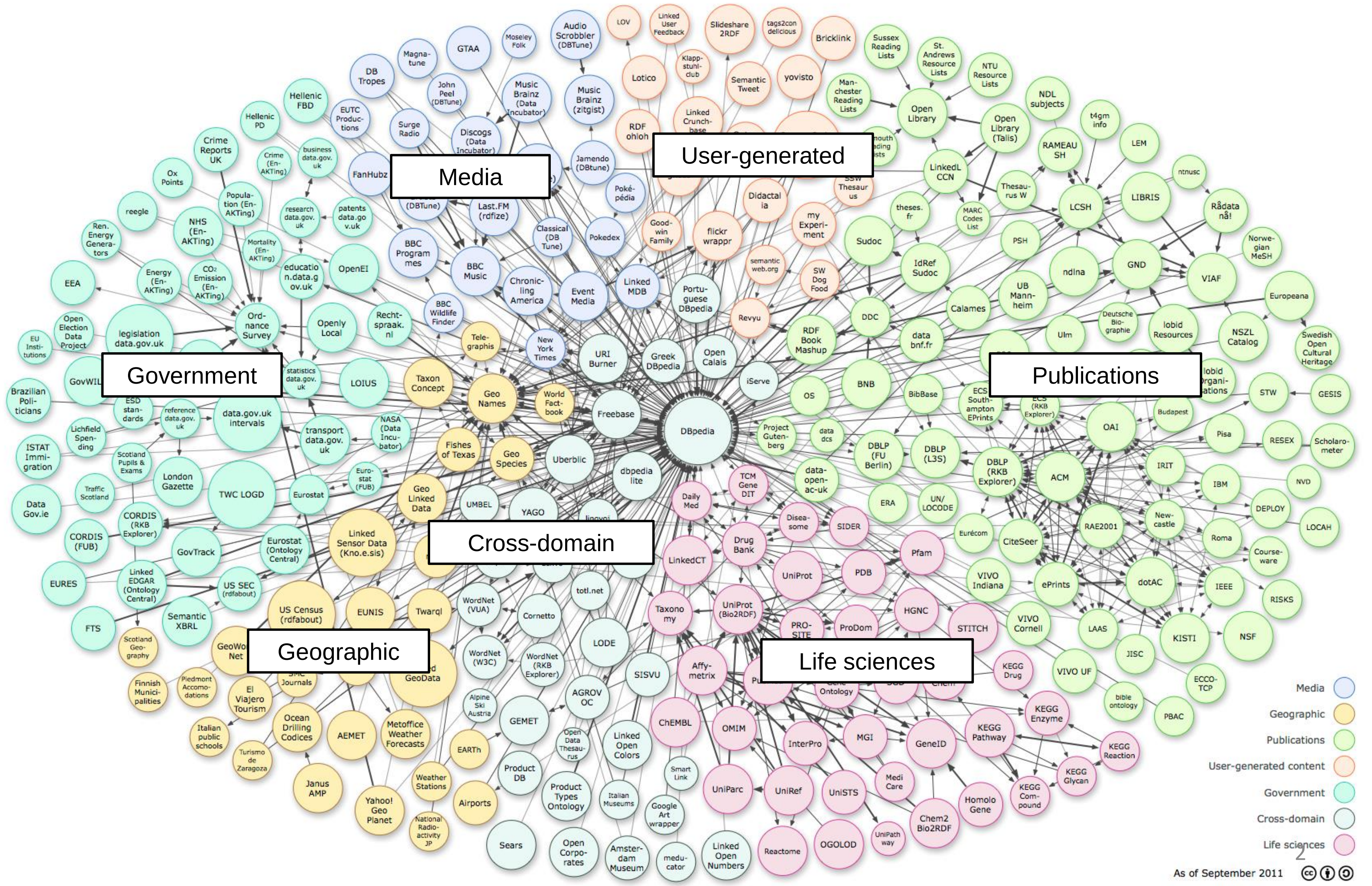
# Entity Resolution in the Web of Data

Kostas Stefanidis[1], Vasilis Efthymiou[1,2],
Melanie Herschel[3,4], Vassilis Christophides[5]

kstef@ics.forth.gr, vefthym@ics.forth.gr, melanie.herschel@lri.fr
vassilis.christophides@technicolor.com

[1]FORTH, [2]University of Crete, [3]Université Paris Sud, [4]Inria Saclay,
[5]Paris R&I Center, Technicolor

# LOD Cloud and the Web of Data



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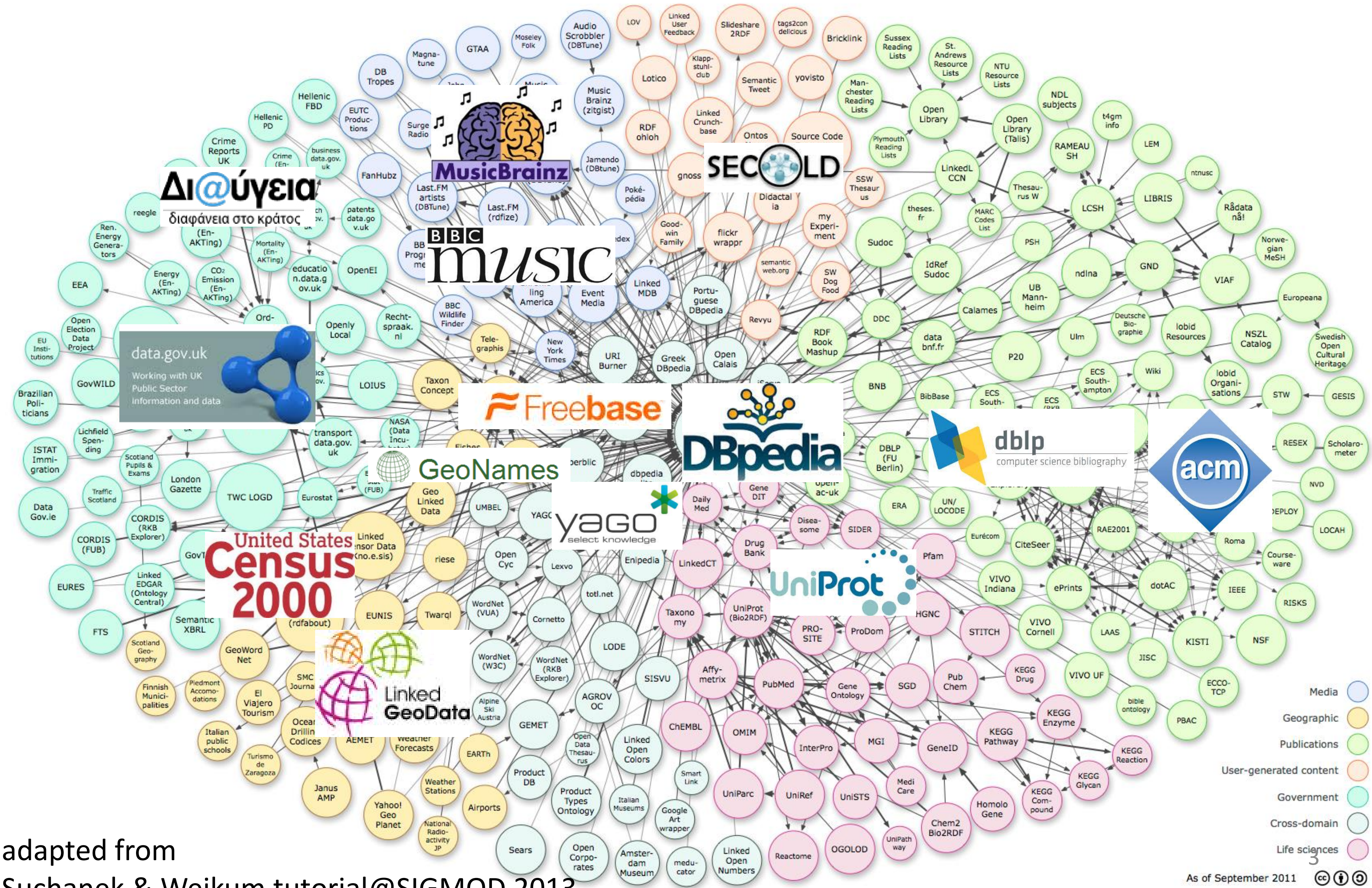
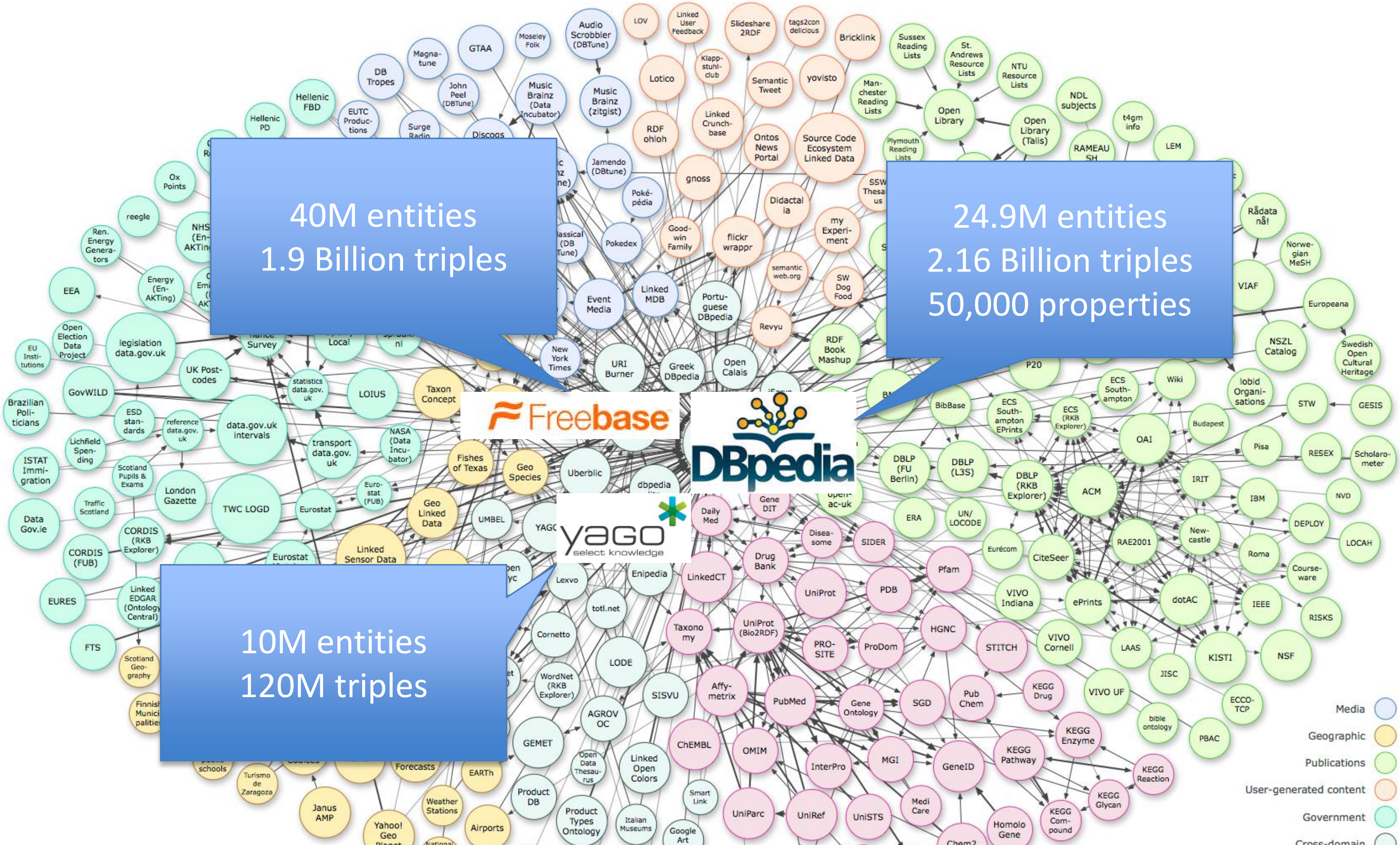



adapted from
Suchanek & Weikum tutorial@SIGMOD 2013

# LOD Cloud and the Web of Data

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# Entities: An Invaluable Asset

Monuments

“Entities” is what a large part of our knowledge is about

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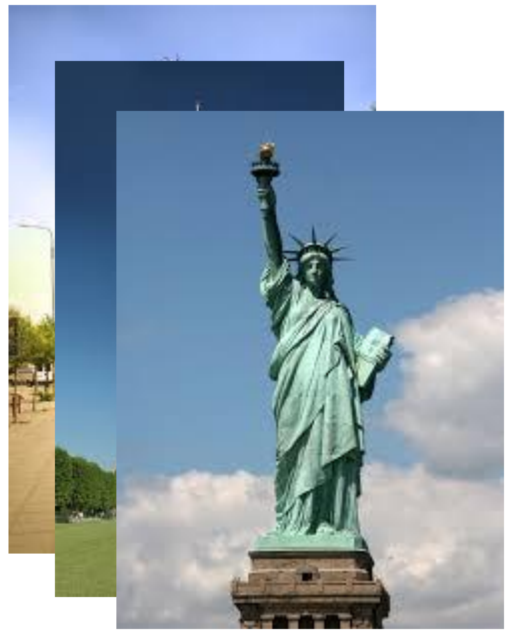
Locations



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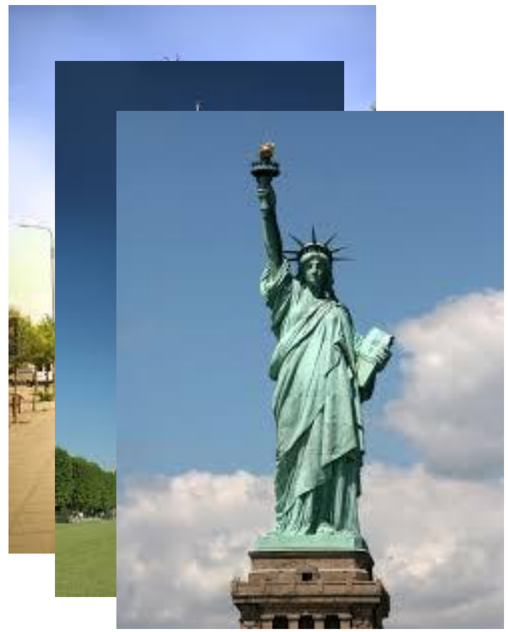
"Entities" is what a large part of our knowledge is about

# Entities: An Invaluable Asset


Locations



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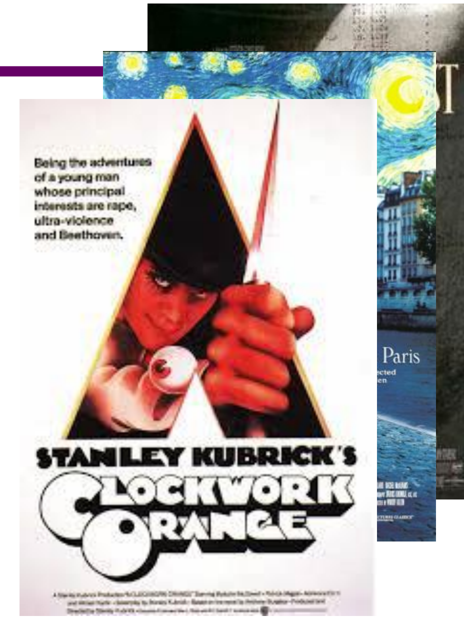
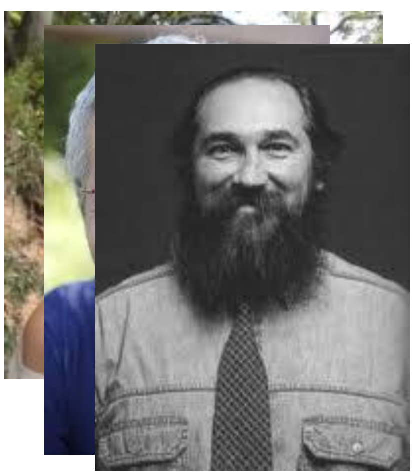
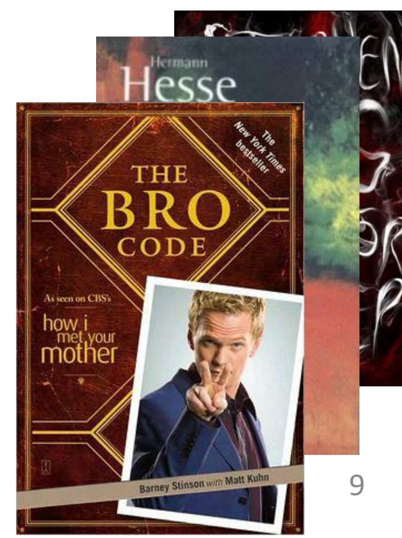



Movies

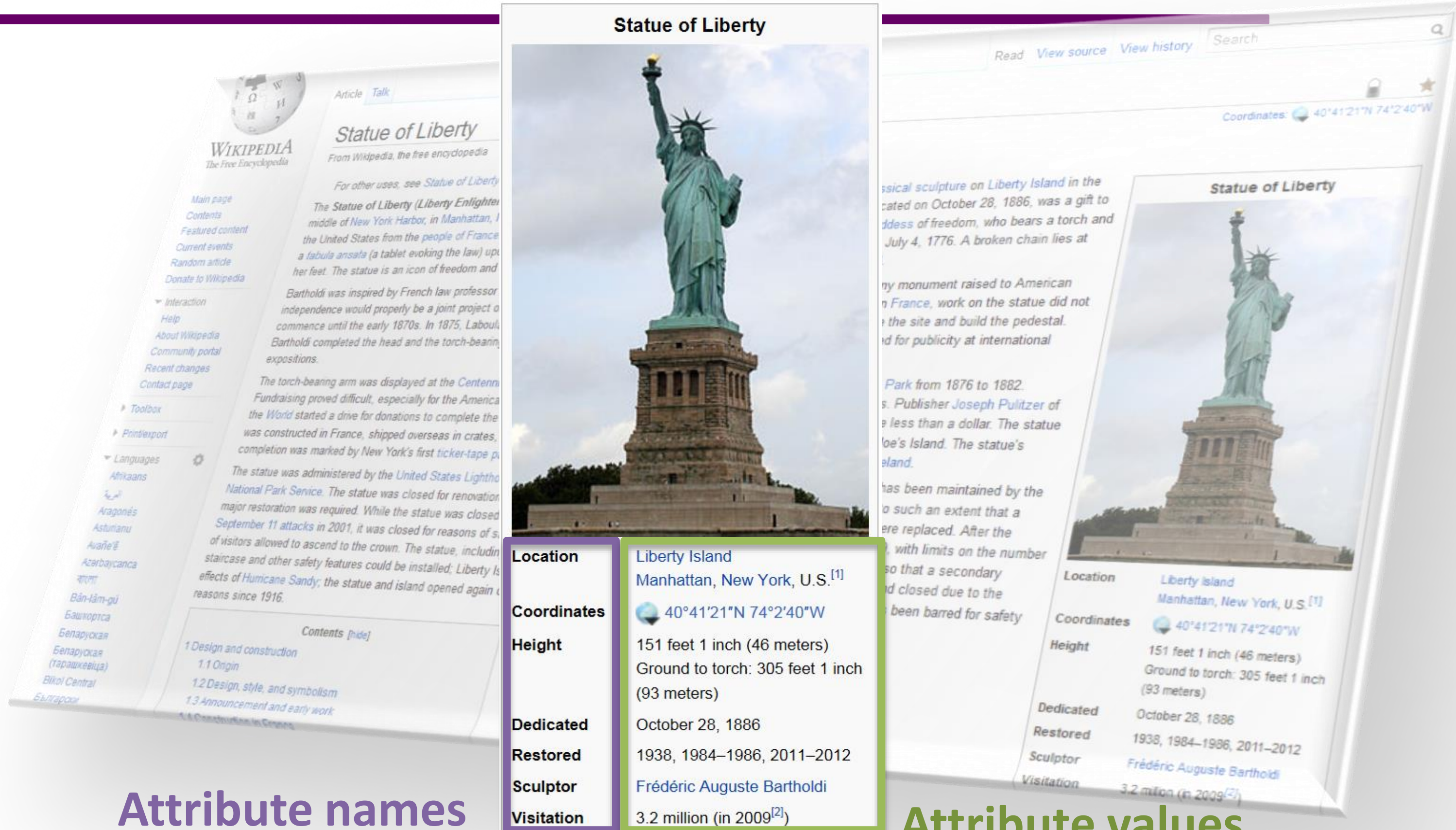


Persons

Books



# Example: General Knowledge Bases




Attribute names

Attribute values

yago select knowledge

DBpedia

Freebase

# Different Descriptions of the same Entity

| 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 |

| Freebase | fb:m.072p8 |
|---|---|
| fb:art_form | fb:m.06msq (Sculpture) |
| fb:media | fb:m.025rsfk (Copper) |
| fb:architect | fb:m.0jph6 (F. Bartholdi), fb:m.036qb (G. Eiffel), fb:m.02wj4z (R. Hunt) |
| fb:height_meters | 93 |
| fb:opened | 1886-10-28 |

| yago select knowledge | yago:Statue_of_Liberty |
|---|---|
| skos:prefLabel | Statue of Liberty |
| rdf:type | yago:History_museums_in_NY, yago:GeoEntity |
| yago:hasHeight | 46.0248 |
| yago:wasCreatedOnDate | 1886-##-## |
| yago:isLocatedIn | yago:Manhattan, yago:Liberty_Island, |
| yago:hasWikipediaUrl | http://en.wikipedia.org/wiki/Statue_of_Liberty |

# Linked Datasets Depend on Vocabularies

| DBpedia | dbpedia:Statue_of_Liberty |
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# Linked Datasets Have Varying Quality

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# The Problem Entity Resolution

*We need to identify that all descriptions refer to the same real-world object*

Entity resolution is the problem of identifying descriptions of the same entity within one or across multiple data sources

A prerequisite to several applications:

- Enable semantic search in terms of entities & relations (*on top of the web of text*)
- Interlink entity descriptions in autonomous sources (*strengthen the web of data*)
- Support deep reasoning using related ontologies (*create the web of knowledge*)

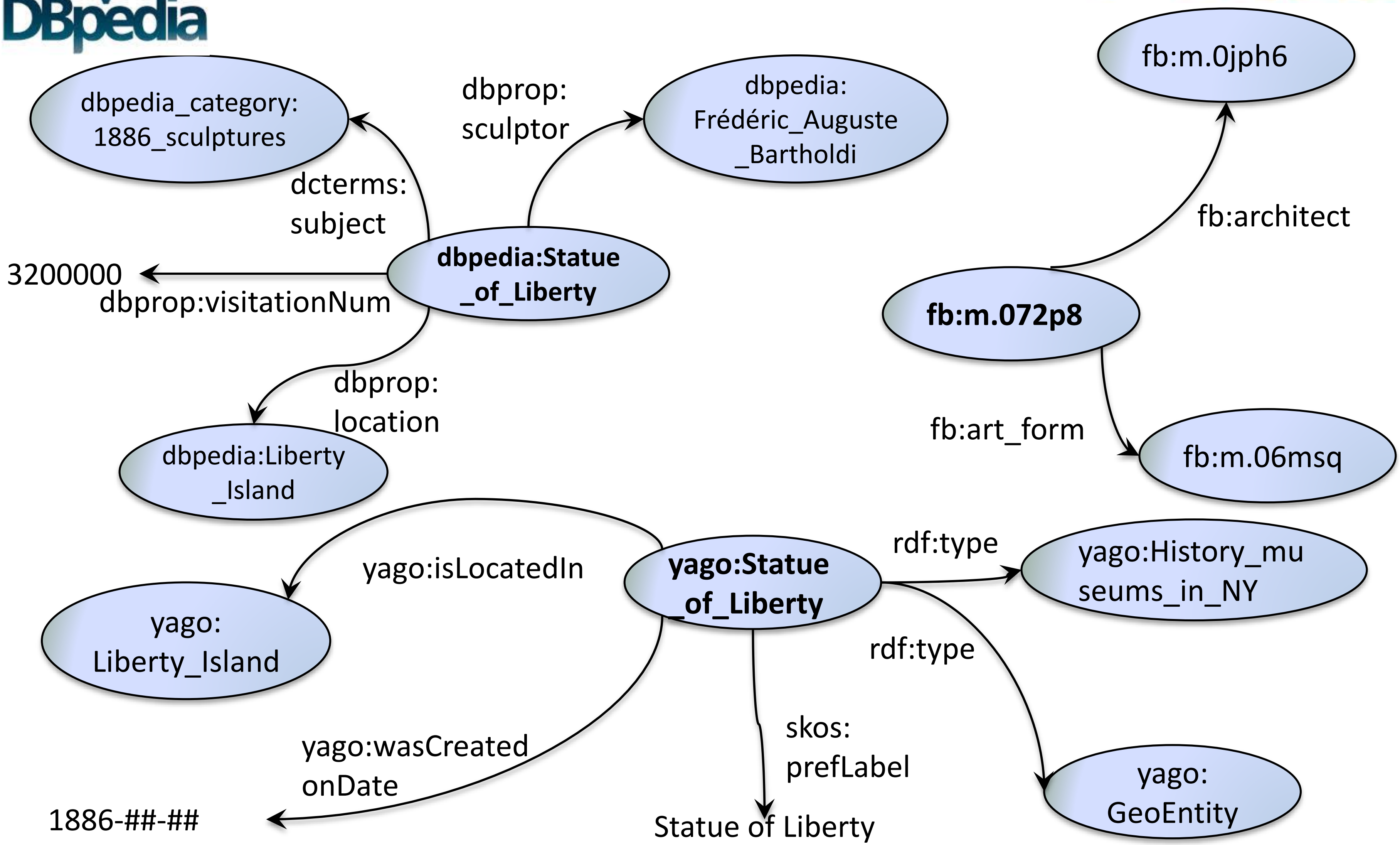
# Entity Collections and Entity Resolution Types

Two kinds of entity collections as input:

- Clean: duplicate-free
- Dirty: contains duplicate entity descriptions

An entity resolution task can be:

- Clean-Clean Entity Resolution: Given two clean, but overlapping entity collections, identify the common entity descriptions
  - a.k.a. *record linkage* in databases
- Dirty-Clean Entity Resolution
- Dirty Entity Resolution: Identify unique entity descriptions contained in one dirty entity collection
  - a.k.a. *deduplication* in databases


dbpedia_category:
1886_sculptures
dbprop:
sculptor
dbpedia:
Frédéric_Auguste
_Bartholdi
dcterms:
subject
dbpedia:Statue
_of_Liberty
3200000
dbprop:visitationNum
dbprop:
location
dbpedia:Liberty
_Island
fb:m.0jph6
fb:architect
fb:m.072p8
fb:art_form
fb:m.06msq
yago:isLocatedIn
yago:Statue
_of_Liberty
rdf:type
yago:History_mu
seums_in_NY
yago:
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rdf:type
skos:
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yago:wasCreated
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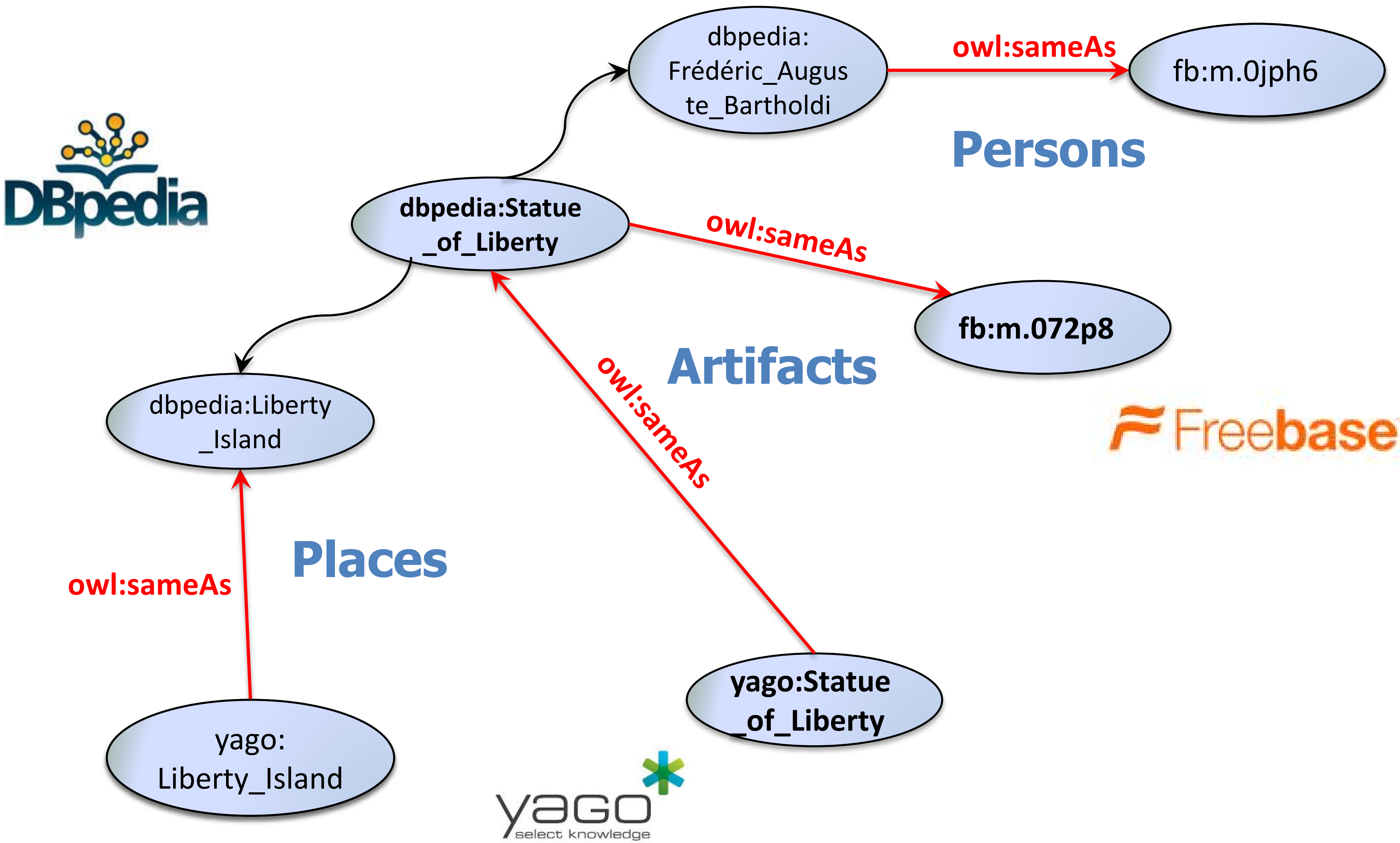
1886-##-##
Statue of Liberty
yago:
GeoEntity




⇒Need to infer also other kind of relationships than “equivalence”

# What Makes Entity Resolution Difficult for the Web of Data

Linked Data are inherently semi-structured

- Several semantic types could be employed (see rdf:type properties in Yago), resulting to quite different structures even for entity descriptions of the same type (persons, places, …)

**=> Deal with loosely structured entities**

Linked Data heavily rely on various vocabularies

- 366 distinct vocabulary spaces in the LOD cloud (http://lov.okfn.org/dataset/lov/)
- DBPedia 3.4: 50,000 attribute names

**=> Need for cross-domain techniques**

Linked Data are Big (semi-structured) Data

- LOD cloud: 60 billion RDF triples
- DBPedia 3.9: 2.46 billion triples, 24.9 million entity descriptions
- Freebase: 1.9 billion triples, 40 million entity descriptions
- Yago: >10 million entities, >120 million triples

**=> Call for efficient parallel techniques**

# Problem Statement

# Entity Description

Each description is expressed as a set of attribute-value pairs

An entity description $e_i \in E$ is defined as: $e_i = \{(a_{ij}, v_{ij}) \mid a_{ij} \in N, v_{ij} \in V\}$

N: a set of attribute names

V: a set of values

E: a set of entity descriptions

We use a generic definition for entity descriptions to cover different data models

*Structural type of $e_i$*: the set of attributes along with their domains in $e_i$

- In the Web of data, the descriptions even of the same entities do not always conform to the same structural type

# Entity Description Examples

| | |
|---|---|
| name | **Eiffel Tower** |
| architect | Sauvestre |
| year | 1889 |
| location | Paris |

**e1**

| | |
|---|---|
| name | **Statue of Liberty** |
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e2**

| | |
|---|---|
| about | **Lady liberty** |
| architect | Eiffel |
| location | NY |

**e3**

| | |
|---|---|
| about | **Eiffel Tower** |
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e4**

| | |
|---|---|
| name | **White Tower** |
| location | Thessaloniki |
| year-constructed | 1450 |

**e5**

# Entity Resolution – Formal Definition

**Entity resolution**: The problem of identifying descriptions of the same entity within one or across multiple data sources wrt. a match function

Formally:

$E = \{e_1, \ldots, e_m\}$ is a set of entity descriptions

$M : E \times E \rightarrow \{true, false\}$ is a match function

An entity resolution of E is a partition $P = \{p_1, \ldots, p_n\}$ of E, such that:

1. $\forall e_i, e_j \in E : M(e_i, e_j) = true, \exists p_k \in P : e_i, e_j \in p_k$
2. $\forall p_k \in P, \forall e_i, e_j \in p_k, M(e_i, e_j) = true$

each partition contains only matching descriptions

all the matching descriptions are in the same partition

# Entity Resolution - Example

| | |
|---|---|
| name | **Eiffel Tower** |
| architect | Sauvestre |
| year | 1889 |
| location | Paris **e1** |

| | |
|---|---|
| name | **Statue of Liberty** |
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY **e2** |

| | |
|---|---|
| about | **Eiffel Tower** |
| architect | Sauvestre |
| year | 1889 |
| located | Paris **e4** |

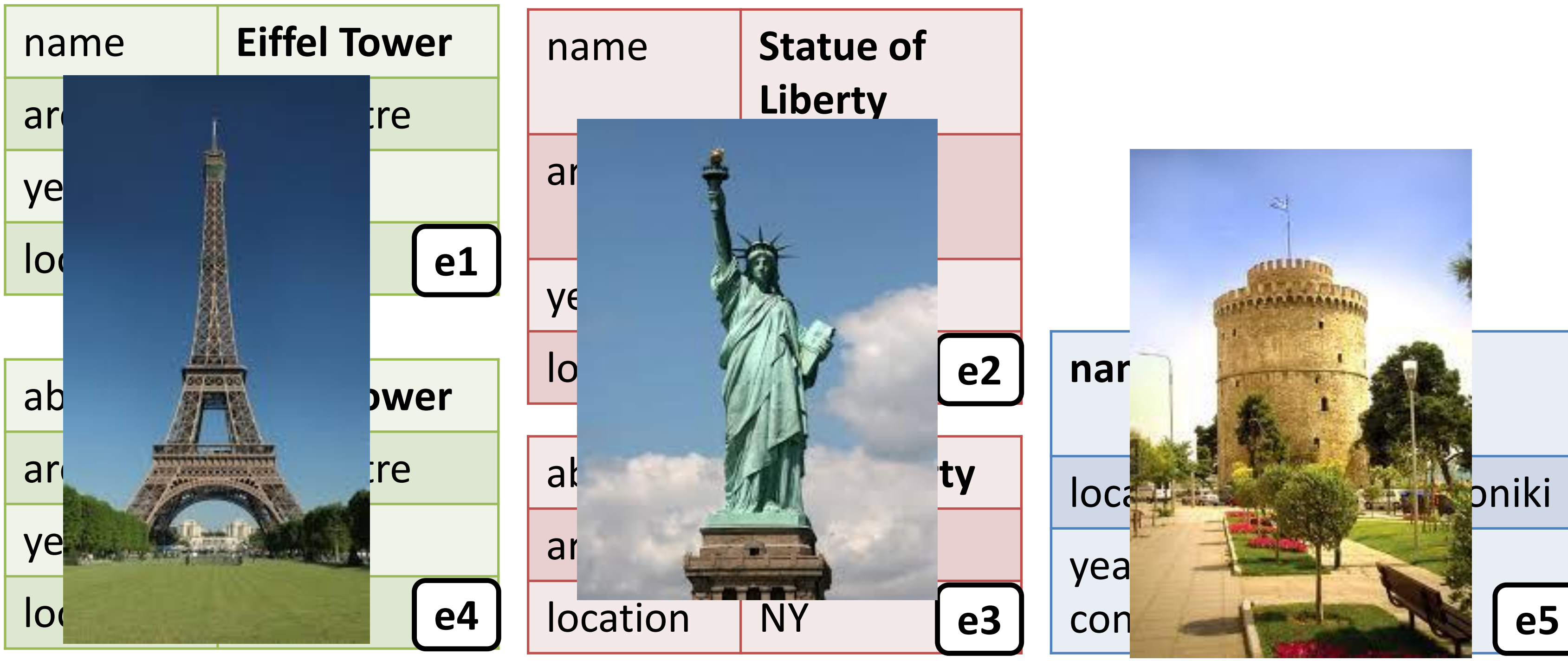
| | |
|---|---|
| about | **Lady liberty** |
| architect | Eiffel |
| location | NY **e3** |

| | |
|---|---|
| **name** | **White Tower** |
| location | Thessaloniki |
| year-constructed | 1450 **e5** |

Assume as input of entity resolution, the set $E = \{e_1, e_2, e_3, e_4, e_5\}$

- A possible output $P = \{\{e_1, e_4\}, \{e_2, e_3\}, \{e_5\}\}$ indicates that:

# Entity Resolution - Example




Assume as input of entity resolution, the set E = {$e_1$, $e_2$, $e_3$, $e_4$, $e_5$}

- A possible output P = {{$e_1$, $e_4$}, {$e_2$, $e_3$}, {$e_5$}} indicates that:
  - $e_1$, $e_4$ refer to the same real-world object, the Eiffel Tower
  - $e_2$, $e_3$ represent a different object, the Statue of Liberty
  - $e_5$ represents a third object, the White Tower

# Entity Resolution - Match

Matches: Sets of entity descriptions that refer to the same real-world entity

Intuitively:

- Matching entity descriptions are placed in the same subset of P
- All the descriptions of the same subset of P match

A match function maps each pair of entity descriptions ($e_i$, $e_j$) to {true, false}

- $M(e_i, e_j)$ = true => $e_i$, $e_j$ are matching descriptions
- $M(e_i, e_j)$ = false => $e_i$, $e_j$ are non-matches

# Entity Resolution - Similarity

*Typically, the match function is expressed wrt. a similarity measure sim*

– *sim* counts how close two entity descriptions are to each other

Given a similarity threshold t:

– $M(e_i, e_j)$ = true, if $sim(e_i, e_j) \geq t$
– $M(e_i, e_j)$ = false, if $sim(e_i, e_j) < t$

# Similarity of Entity Descriptions

How can we identify that two entity descriptions refer to the same entity?

# Similarity of Entity Descriptions

How can we identify that two entity descriptions refer to the same entity?

- If they are identical, then we assume they match (exact match function)

E.g.

| | | |
|---|---|---|
| name | Eiffel Tower | |
| architect | Sauvestre | |
| year | 1889 | |
| location | Paris | **e1** |

| | | |
|---|---|---|
| name | Eiffel Tower | |
| architect | Sauvestre | |
| year | 1889 | |
| location | Paris | **e2** |

# Similarity of Entity Descriptions

How can we identify that two entity descriptions refer to the same entity?

- If they are identical, then we assume they match (exact match function)
  - Even this assumption could be false!

E.g.

| | | |
|---|---|---|
| first | John | |
| last | Doe | |
| born | 1980 | |
| location | UK | **e1** |

| | | |
|---|---|---|
| first | John | |
| last | Doe | |
| born | 1980 | |
| location | UK | **e2** |

*… could describe namesakes, born in the same country and year*

# Similarity of Entity Descriptions

How can we identify that two entity descriptions refer to the same entity?

- What if they are not identical, but it looks like they match?
  - e.g.

| | | |
|---|---|---|
| about | Gustave Eiffel | e1 |

| | | |
|---|---|---|
| name | G. Eiffel | e2 |

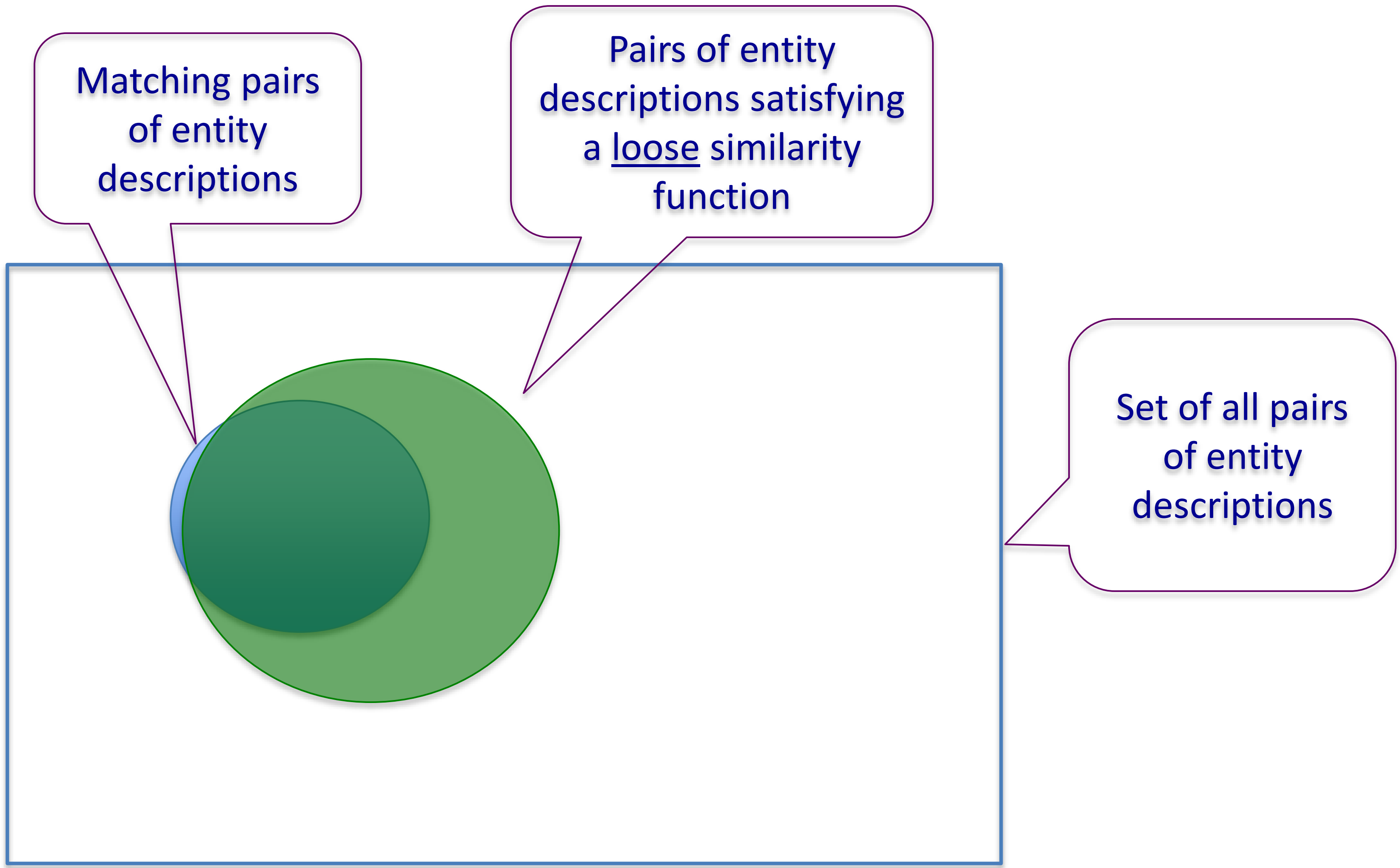
Exact match is rather impractical for entity resolution in the Web of data

- Too strict for a highly heterogeneous information space

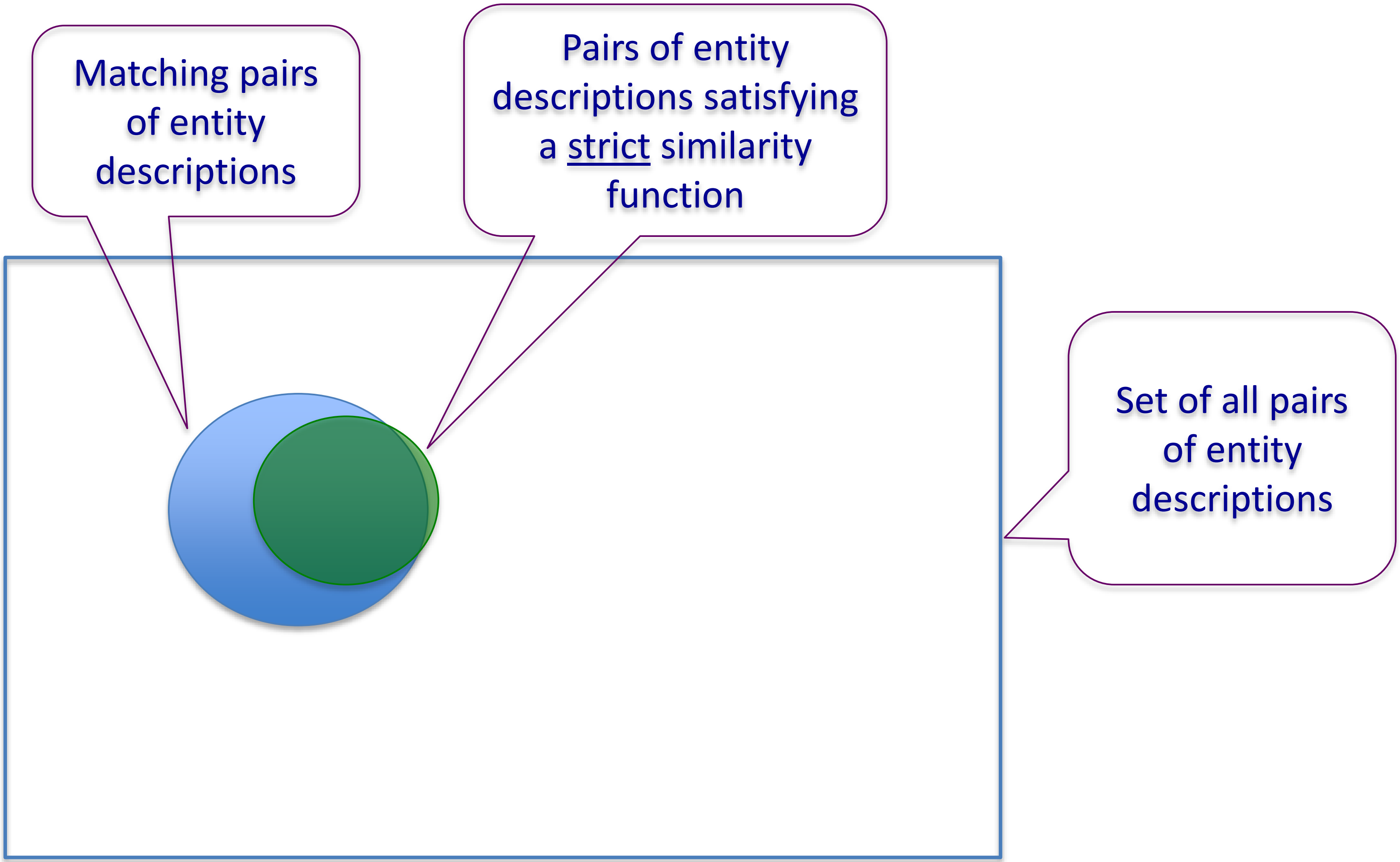
A more loose similarity measure could identify more matches, but…

- Which similarity measure is that?
- What should it compare? Values/Structure/Neighbors?
- It might be too loose and return many false matches too!

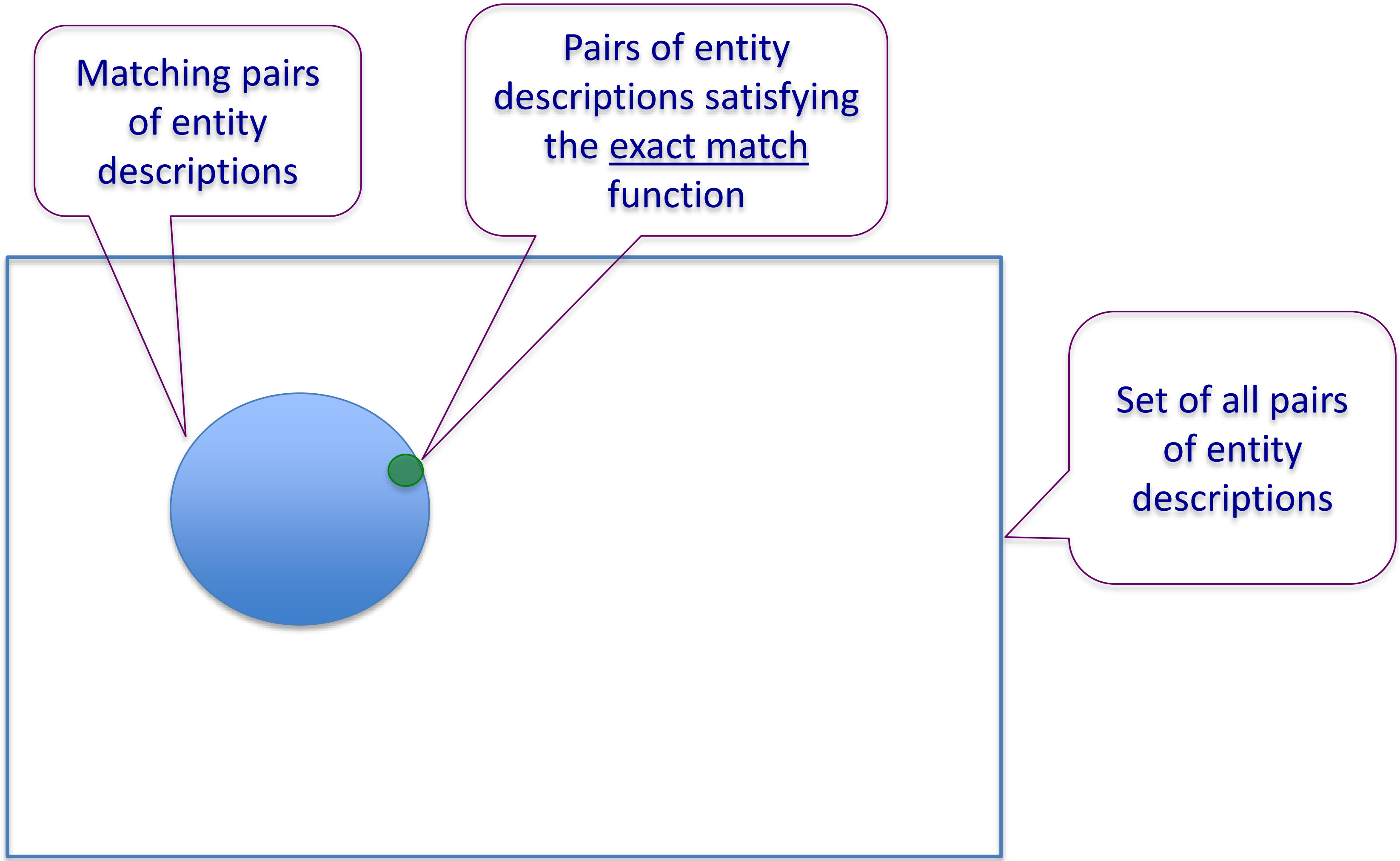
# The Role of Similarity Functions – Loose Function



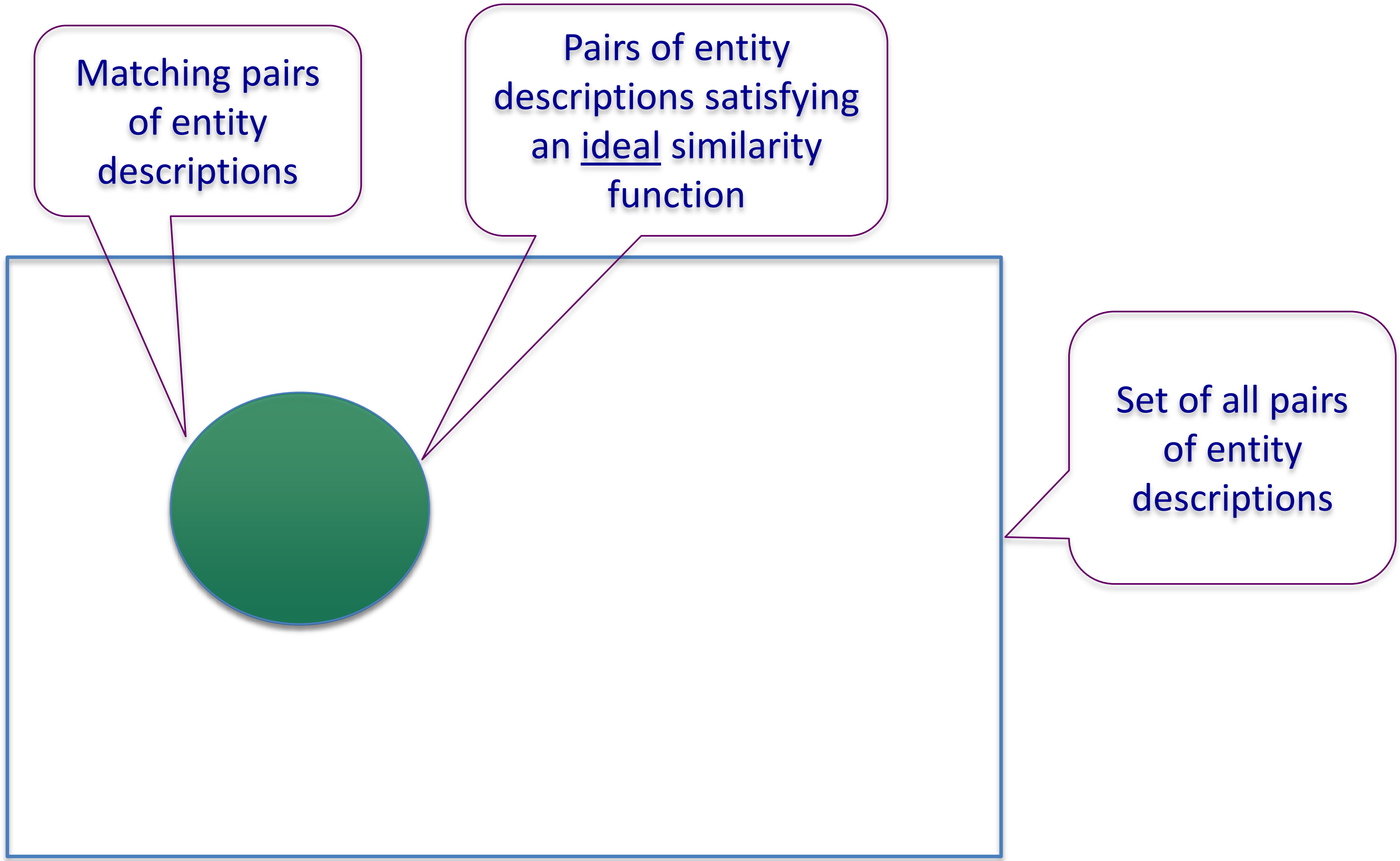
# The Role of Similarity Functions – Strict Function



# The Role of Similarity Functions – Exact Match



# The Role of Similarity Functions – Ideal Case

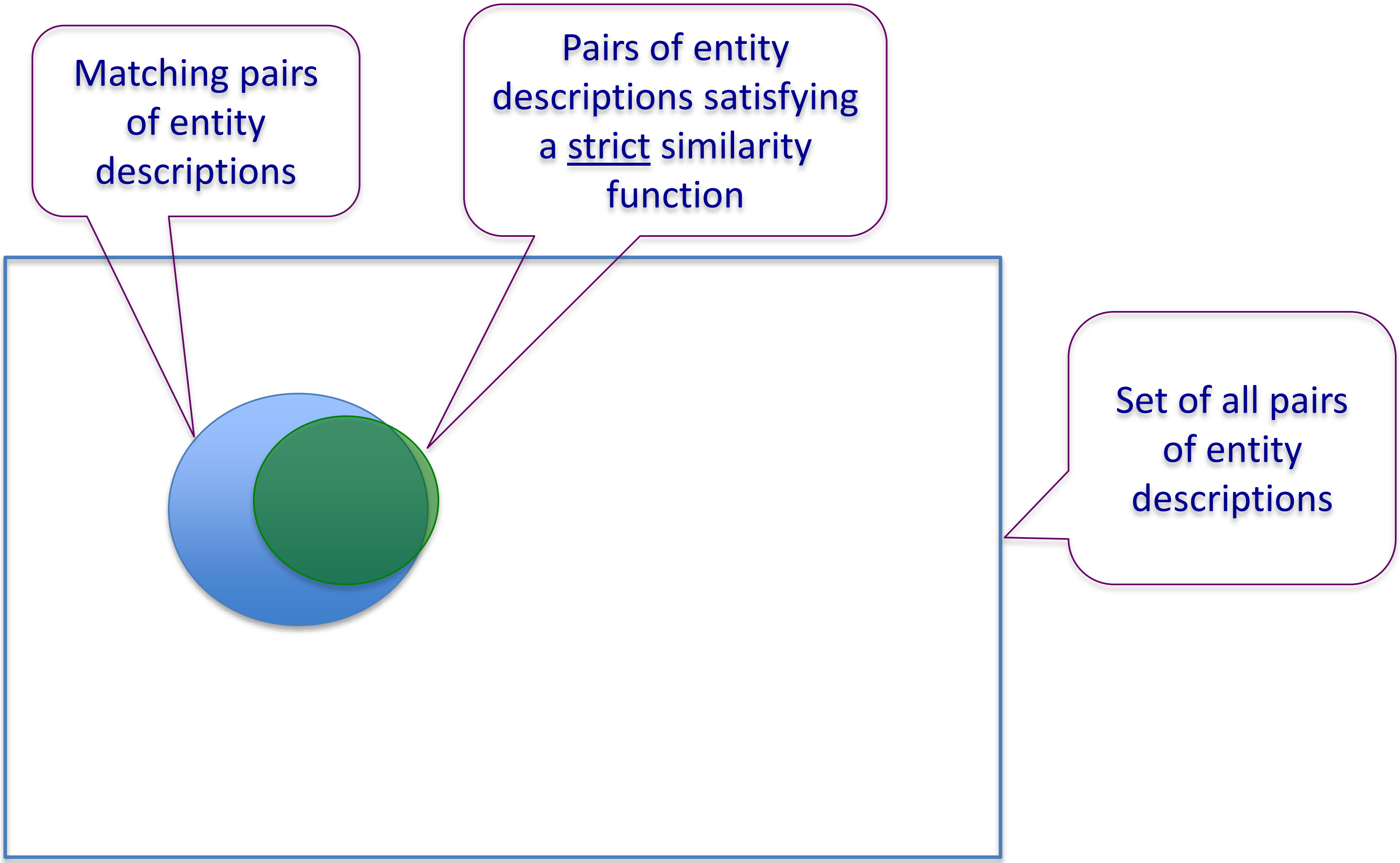


# Using Relationships

- Transitivity: If (A,B) are matches and (B, C) are matches, then (B,C) are also matches
- Duplicate dependency: If entities Author1 and Author2 are matches, then related entities Publication1 and Publication2 are more likely to be matches than before the matching of Author1 and Author2
- Merge dependency: Once a matching pair has been identified, the merged entity descriptions create a new description that should be compared to the remaining ones

*Using these relationships lead to identifying more matches*

# Impact of Using Relationships



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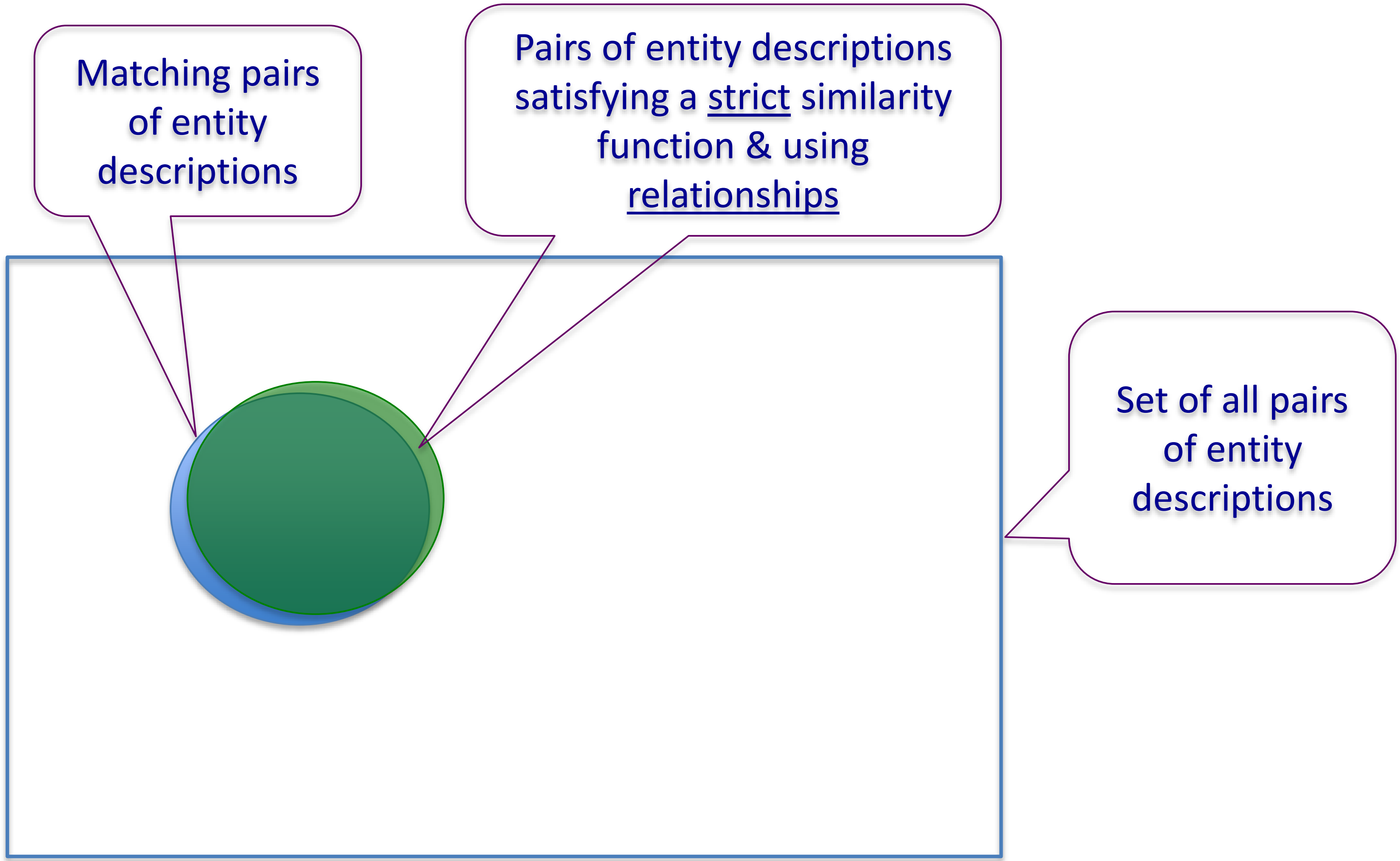
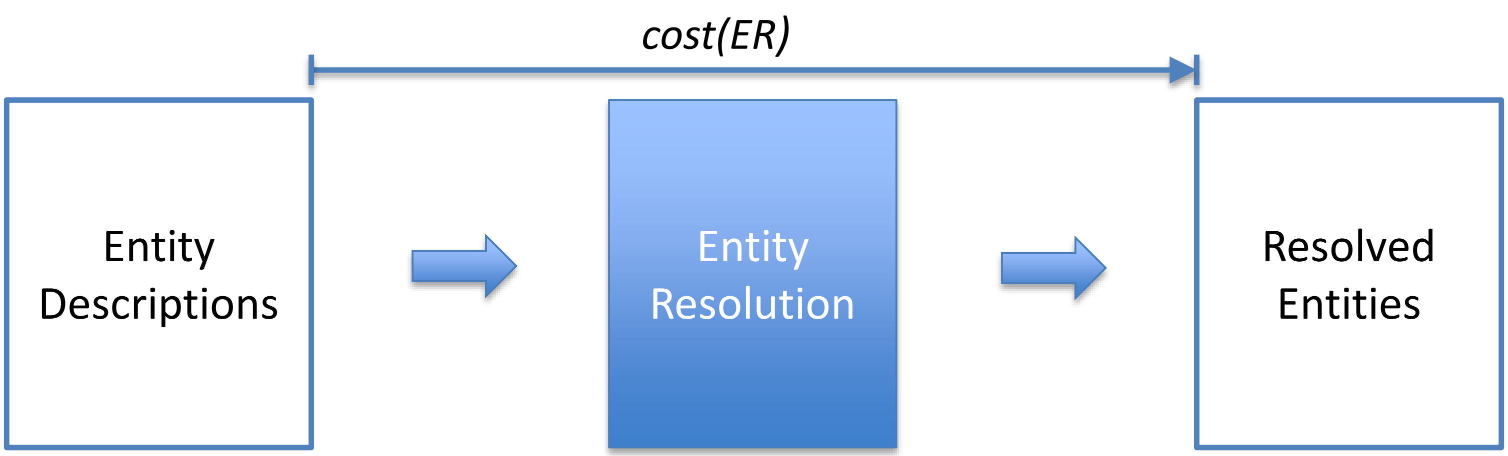


# Entity Resolution Workflow

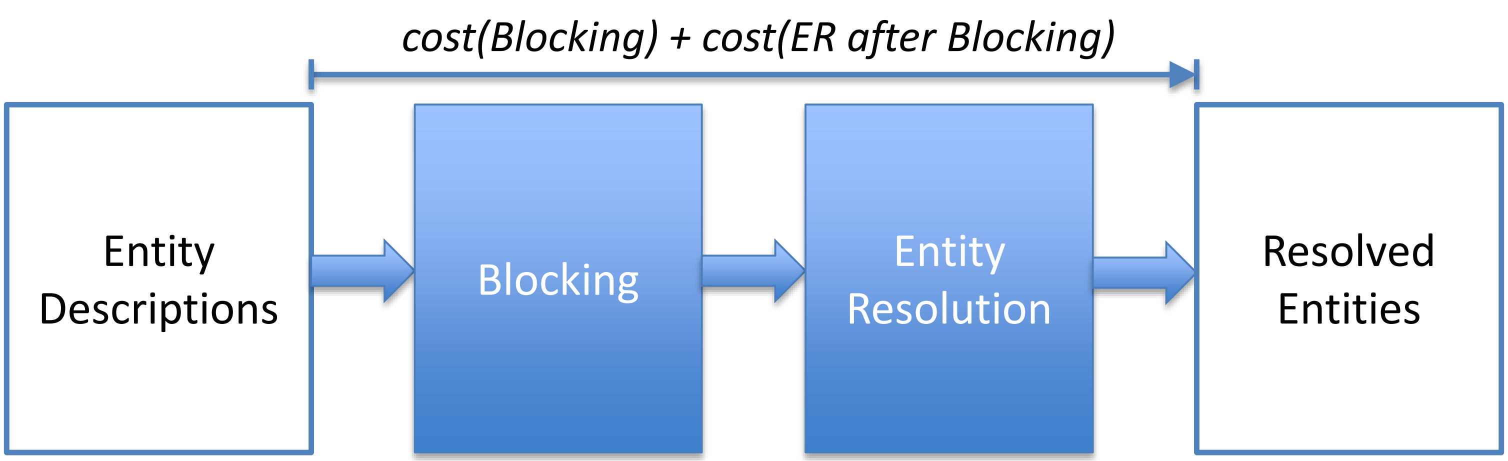


*<u>This is a global optimization problem!</u>*

Good balance between:

- Number of identified matching descriptions
- Number of generated comparisons

# Entity Resolution Workflow




A preprocessing step to group together descriptions close to each other - *Fewer comparisons*

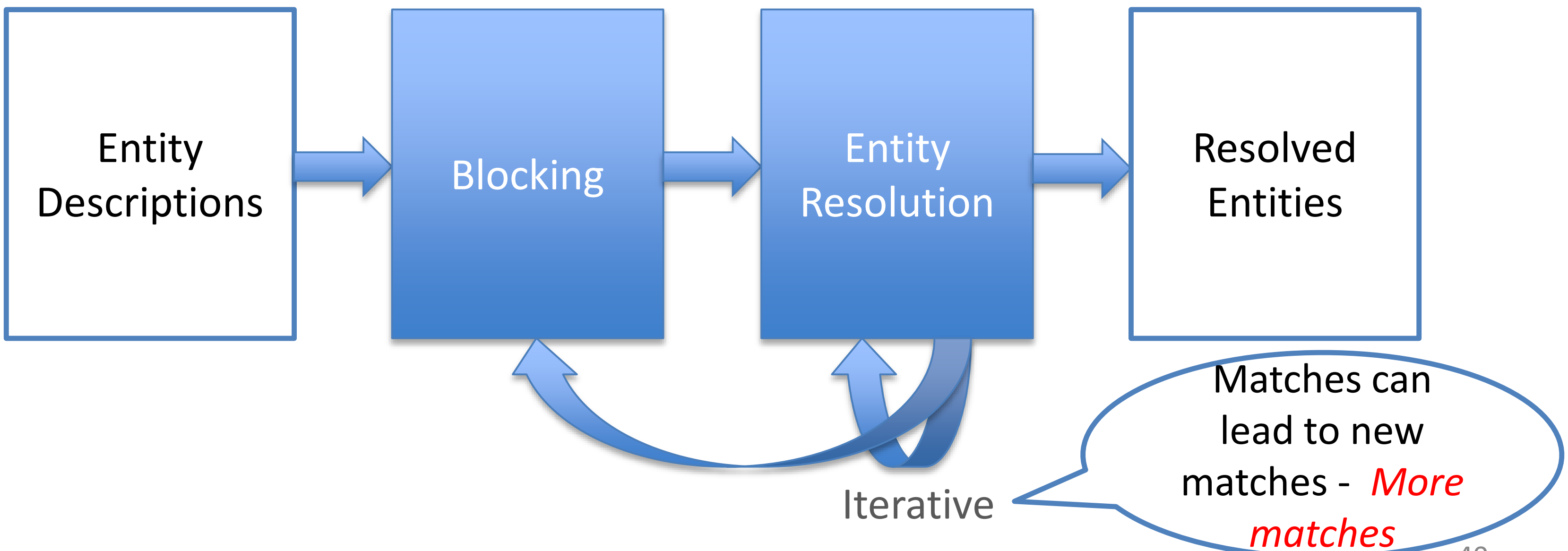
- *cost(ER after Blocking) < cost(ER)*

*benefit(Blocking) = cost(ER) – cost(ER after Blocking)*

- *cost(Blocking) + cost(ER after Blocking) < cost (ER)*

*cost(Blocking) < benefit(Blocking) ???*

# Entity Resolution Workflow



# Blocking Approaches

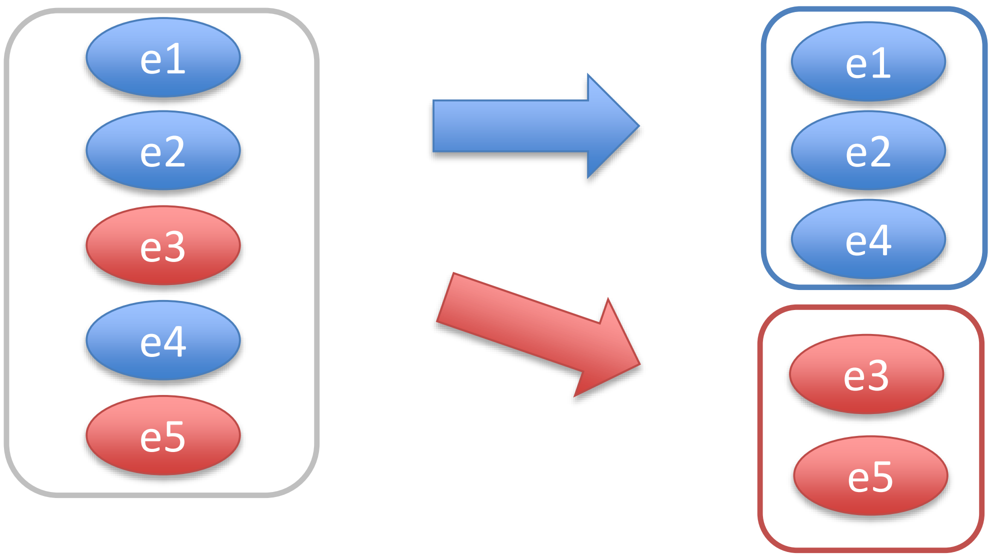
# Blocking

To reduce the number of comparisons:

- Split entity descriptions into blocks
- Compare each description to the descriptions within the same block

Desiderata

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



# Blocking Methodology

Blocking approaches rely on blocking keys

- Criteria on attributes, based on which the descriptions are placed into blocks

Given a blocking key:

The block in which a description will end up is determined by a similarity function on the value of the description for the blocking key

- – Blocking key value (BKV)

Using several blocking keys, places each description in many blocks

- Overlapping

# Standard Blocking [Fellegi & Sunter 1969]

Entity descriptions with the same BKV end up in the same block

E.g. buildings located at the same place are put in the same block

| | Name | Year | Architects | Location |
|---|---|---|---|---|
| $e_1$ | Eiffel Tower | 1889 | Sauvestre | Paris |
| $e_2$ | Statue of Liberty | 1886 | Bartholdi, Eiffel | NY |
| $e_3$ | Lady Liberty | | Eiffel | NY |
| $e_4$ | Eiffel Tower | 1889 | Sauvestre | Paris |
| $e_5$ | White Tower | 1450 | | Thessaloniki |

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| $e_4$ | Eiffel Tower | 1889 | Sauvestre | Paris |
| $e_5$ | White Tower | 1450 | | Thessaloniki |

Generated blocks (partition):

| Paris | NY | Thessaloniki |
|---|---|---|
| $e_1$, $e_4$ | $e_2$, $e_3$ | $e_5$ |

# Sorted Neighborhood Method [Hernandez & Stolfo 1995]

The idea

1. Create <u>key</u>
   – Creates a key value based on relevant attribute values
2. <u>Sort</u>
   – Sort tuples in lexicographical order of their generated keys
3. <u>Merge</u>
   – Slide a window (of fixed size *w*) over the sorted data
   – Limit to comparisons of tuple pairs falling in the same window

# Sorted Neighborhood Method

| ID | Title | Year | Genre |
|---|---|---|---|
| 17 | Mask of Zorro | 1998 | Adventure |
| 18 | Addams Family | 1991 | Comedy |
| 25 | Rush Hour | 1998 | Comedy |
| 31 | Matrix | 1999 | Sci-Fi |
| 52 | Return of Dschafar | 1994 | Children |
| 113 | Adams Family | 1991 | Comedie |
| 207 | Return of Djaffar | 1995 | Children |

(1) create key

| ID | Key |
|---|---|
| 17 | MSKAD98 |
| 18 | DDMCO91 |
| 25 | RSHCO98 |
| 31 | MTRSC99 |
| 52 | RTRCH94 |
| 113 | DMSCO91 |
| 207 | RTRCH95 |

(2) sort

| ID | Key |
|---|---|
| 18 | DDMCO91 |
| 113 | DMSCO91 |
| 17 | MSKAD98 |
| 31 | MTRSC99 |
| 25 | RSHCO98 |
| 52 | RTRCH94 |
| 207 | RTRCH95 |

(3) merge

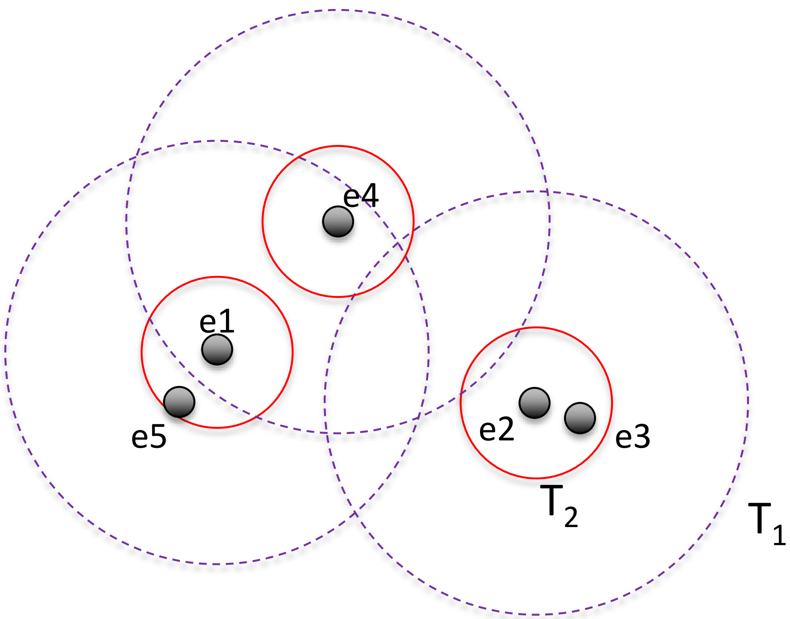
| ID | Key |
|---|---|
| 18 | DDMCO91 |
| 113 | DMSCO91 |
| 17 | MSKAD98 |
| 31 | MTRSC99 |
| 25 | RSHCO98 |
| 52 | RTRCH94 |
| 207 | RTRCH95 |

compare(18,113) → duplicates

compare(52,207) → duplicates

# Canopy Clustering [McCallum et al. 2000]

1. Pick a random entity description $e_i$ from E
2. Create, for $e_i$, a new canopy $C_{ei}$
   Add to $C_{ei}$ the descriptions $e_j$, s.t. $d(e_i, e_j) < T_1$
3. Remove all descriptions $e_j$ from E, s.t. $d(e_i, e_j) < T_2$
4. Return to Step 1, if E is not empty




Generated Blocks:

| e1 | e4 | e2 |
|---|---|---|
| $e_1, e_4, e_5$ | $e_1, e_4$ | $e_2, e_3$ |

*What is the intuition behind thresholds $T_1$, $T_2$?*

# Token Blocking [Papadakis et al. 2011]

Assume two clean sets $E_1$, $E_2$ of entity descriptions – *Clean-Clean Entity Resolution*

- Each distinct token $t_i$ of each value of each description in $E_1 \cup E_2$ corresponds to a block
  - Each block contains all entity descriptions with the corresponding token
  - Pairs originating from the same (clean) set are not compared

*Redundancy!*

- The same pair of descriptions is contained in many blocks
- Many dissimilar pairs are put in the same block

# Token Blocking - Example

$E_1$

| | |
|---|---|
| **name** | **Eiffel Tower** |
| architect | Sauvestre |
| year | 1889 |
| location | Paris |

**e1**

| | |
|---|---|
| **name** | **Statue of Liberty** |
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e2**

| | |
|---|---|
| **about** | **Lady liberty** |
| architect | Eiffel |
| location | NY |

**e3**

$E_2$

| | |
|---|---|
| **about** | **Eiffel Tower** |
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e4**

| | |
|---|---|
| **name** | **White Tower** |
| location | Thessaloniki |
| year-constructed | 1450 |

**e5**

Generated Blocks

| Eiffel | Tower | Statue | Liberty | White | 1889 | Bartholdi |
|---|---|---|---|---|---|---|
| $e_1$, $e_2$, $e_3$, $e_4$ | $e_1$, $e_4$, $e_5$ | $e_2$ | $e_2$, $e_3$ | $e_5$ | $e_1$, $e_4$ | $e_2$ |

| NY | Paris | 1886 | 1450 | Lady | Sauvestre | Thessaloniki |
|---|---|---|---|---|---|---|
| $e_2$, $e_3$ | $e_1$, $e_4$ | $e_2$ | $e_5$ | $e_3$ | $e_1$, $e_4$ | $e_5$ |

# Token Blocking - Example

| name | Eiffel Tower |
|---|---|
| architect | Sauvestre |
| year | 1889 |
| location | Paris |

**e1**

| name | Statue of Liberty |
|---|---|
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e2**

| about | Lady liberty |
|---|---|
| architect | Eiffel |
| location | NY |

**e3**

| about | Eiffel Tower |
|---|---|
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e4**

| name | White Tower |
|---|---|
| location | Thessaloniki |
| year-constructed | 1450 |

**e5**

Generated Blocks

| Eiffel | Tower | ~~Statue~~ | Liberty | ~~White~~ | 1889 | ~~Bartholdi~~ |
|---|---|---|---|---|---|---|
| $e_1$, $e_2$, $e_3$, $e_4$ | $e_1$, $e_4$, $e_5$ | ~~$e_2$~~ | $e_2$, $e_3$ | ~~$e_5$~~ | $e_1$, $e_4$ | ~~$e_2$~~ |

| NY | Paris | ~~1886~~ | ~~1450~~ | ~~Lady~~ | Sauvestre | ~~Thessaloniki~~ |
|---|---|---|---|---|---|---|
| $e_2$, $e_3$ | $e_1$, $e_4$ | ~~$e_2$~~ | ~~$e_5$~~ | ~~$e_3$~~ | $e_1$, $e_4$ | ~~$e_5$~~ |

Blocks containing descriptions from only one collection are discarded

# Token Blocking - Example

| name | Eiffel Tower |
|---|---|
| architect | Sauvestre |
| year | 1889 |
| location | Paris **e1** |

| name | Statue of Liberty |
|---|---|
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY **e2** |

| about | Lady liberty |
|---|---|
| architect | Eiffel |
| location | NY **e3** |

| about | Eiffel Tower |
|---|---|
| architect | Sauvestre |
| year | 1889 |
| located | Paris **e4** |

| name | White Tower |
|---|---|
| location | Thessaloniki |
| year-constructed | 1450 **e5** |

Generated Blocks

| Eiffel | Tower | Liberty | 1889 |
|---|---|---|---|
| $e_1$, $e_2$, $e_3$, $e_4$ | $e_1$, $e_4$, $e_5$ | $e_2$, $e_3$ | $e_1$, $e_4$ |

| NY | Paris | Sauvestre |
|---|---|---|
| $e_2$, $e_3$ | $e_1$, $e_4$ | $e_1$, $e_4$ |

The pair ($e_1$, $e_4$) is contained in 5 different blocks!

# Token Blocking - Example

| name | Eiffel Tower |
|---|---|
| architect | Sauvestre |
| year | 1889 |
| location | Paris |

**e1**

| about | Eiffel Tower |
|---|---|
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e4**

| name | Statue of Liberty |
|---|---|
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e2**

| about | Lady liberty |
|---|---|
| architect | Eiffel |
| location | NY |

**e3**

| name | White Tower |
|---|---|
| location | Thessaloniki |
| year-constructed | 1450 |

**e5**

Generated Blocks

| Eiffel | Tower | Liberty | 1889 | NY | Paris | Sauvestre |
|---|---|---|---|---|---|---|
| $e_1$, $e_2$, $e_3$, $e_4$ | $e_1$, $e_4$, $e_5$ | $e_2$, $e_3$ | $e_1$, $e_4$ | $e_2$, $e_3$ | $e_1$, $e_4$ | $e_1$, $e_4$ |

Redundant comparisons are performed between ($e_1$, $e_3$), ($e_2$, $e_4$), ($e_1$, $e_5$)

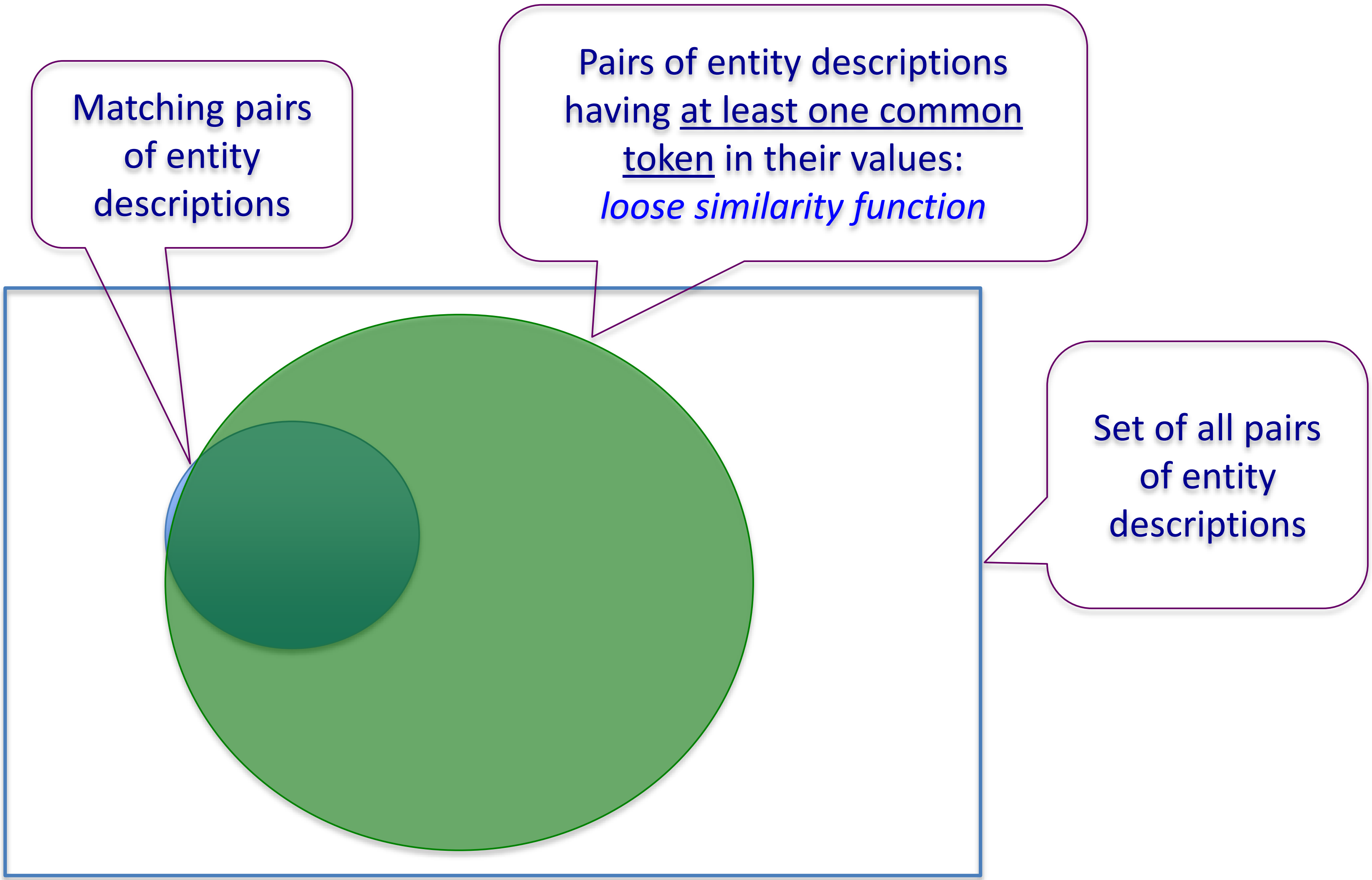
Token blocking achieves:

High recall at the cost of low precision and low efficiency:

- Most true matches are placed in the same block
- Many non-matches are also placed in the same block
- The same pair of descriptions is contained in many blocks

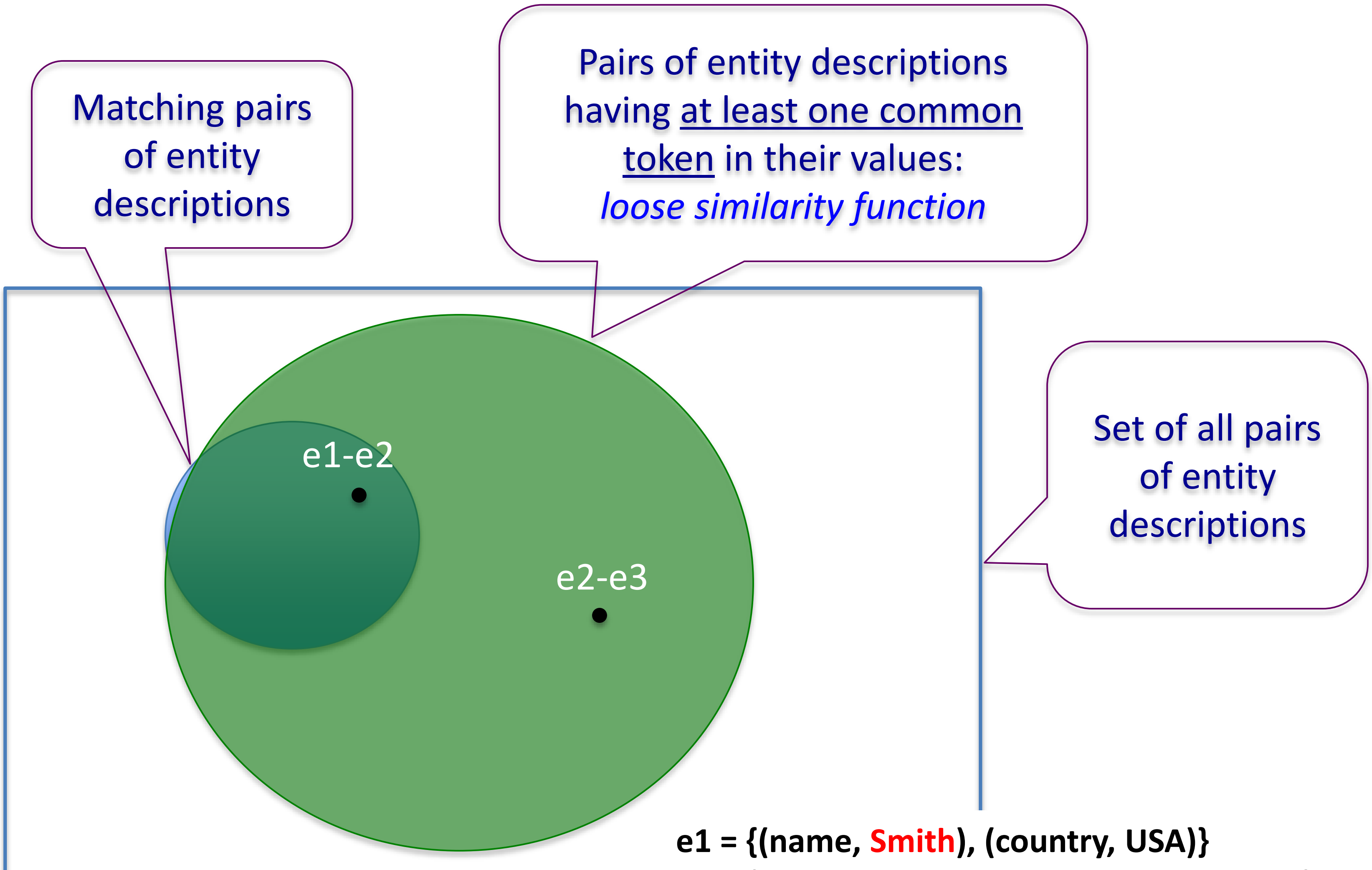
*Token blocking totally ignores the valuable information of attribute names*

# Token Blocking - Evaluation




A single common token in the set of values is enough to place two descriptions in the same block

# Token Blocking - Evaluation




**e1 = {(name, Smith), (country, USA)}**
**e2 = {(about, R. Smith), (livesIn, California)}**
**e3 = {(title, California Dreamin'), (length, 2:34)}**

# *Is this enough*?

*Token blocking totally ignores the valuable information of attribute names*

To improves this, attribute clustering considers patterns in the values

[Papadakis et al. 2013 (a)]

# Attribute Clustering Blocking [Papadakis et al. 2013 (a)]

*The goal again is to identify matches between two datasets, $D_1$ and $D_2$, each containing no duplicates – Clean-Clean Entity Resolution*

Two main steps:

1. Similar attributes are placed together in non-overlapping clusters
2. Token blocking is performed on the descriptions of each cluster

# Creating Clusters of Attributes

1. For each attribute of dataset $D_1$:
   - Find the most similar attribute of dataset $D_2$
2. For each attribute of dataset $D_2$:
   - Find the most similar attribute of dataset $D_1$
3. Compute the transitive closure of the generated pairs of attributes
4. Connected attributes form clusters
5. All single-member clusters are merged into a common cluster

*Similarities between attributes are computed wrt. the string similarities of the values appearing in these attributes*

# Creating Clusters of Attributes

**e11**

| | |
|---|---|
| about | Eiffel Tower |
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e12**

| | |
|---|---|
| about | Statue of Liberty |
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e13**

| | |
|---|---|
| about | Auguste Bartholdi |
| born | 1834 |

**e14**

| | |
|---|---|
| about | Joan Tower |
| born | 1938 |

**e15**

| | |
|---|---|
| work | Lady Liberty |
| artist | Bartholdi |
| location | NY |

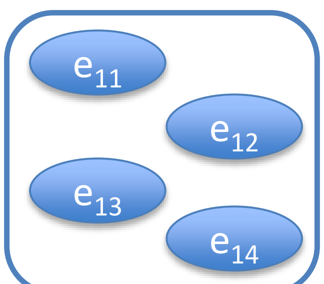
**e16**

| | |
|---|---|
| work | Eiffel Tower |
| year-constructed | 1889 |
| location | Paris |

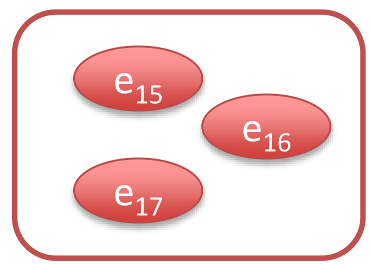
**e17**

| | |
|---|---|
| work | Bartholdi Fountain |
| year-constructed | 1876 |
| location | Washington D.C. |

D1




D2



# Clustering Attributes: Example

| | |
|---|---|
| about | Eiffel Tower |
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e11**

| | |
|---|---|
| work | Lady Liberty |
| artist | Bartholdi |
| location | NY |

**e15**

| | |
|---|---|
| about | Statue of Liberty |
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e12**

| | |
|---|---|
| about | Auguste Bartholdi |
| born | 1834 |

**e13**

| | |
|---|---|
| work | Eiffel Tower |
| year-constructed | 1889 |
| location | Paris |

**e16**

| | |
|---|---|
| about | Joan Tower |
| born | 1938 |

**e14**

| | |
|---|---|
| work | Bartholdi Fountain |
| year-constructed | 1876 |
| location | Washingt on D.C. |

**e17**

Finding the attribute of D2 that is the most similar to the attribute "about" of D1:

values of about: {Eiffel, Tower, Statue, Liberty, Auguste, Bartholdi, Joan}

compared to (with Jaccard similarity) :

values of <u>**work**</u>: {Lady, Liberty, Eiffel, Tower, Bartholdi, Fountain} → **Jaccard = 4/9**

values of artist: {Bartholdi} → Jaccard = 1/8

values of location: {NY, Paris, Washington, D.C.} → Jaccard = 0

values of year-constructed: {1889, 1876} → Jaccard = 0

# Clustering Attributes: Example

| | |
|---|---|
| about | Eiffel Tower |
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e11**

| | |
|---|---|
| about | Statue of Liberty |
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e12**

| | |
|---|---|
| about | Auguste Bartholdi |
| born | 1834 |

**e13**

| | |
|---|---|
| about | Joan Tower |
| born | 1938 |

**e14**

| | |
|---|---|
| work | Lady Liberty |
| artist | Bartholdi |
| location | NY |

**e15**

| | |
|---|---|
| work | Eiffel Tower |
| year-constructed | 1889 |
| location | Paris |

**e16**

| | |
|---|---|
| work | Bartholdi Fountain |
| year-constructed | 1876 |
| location | Washington D.C. |

**e17**

D1

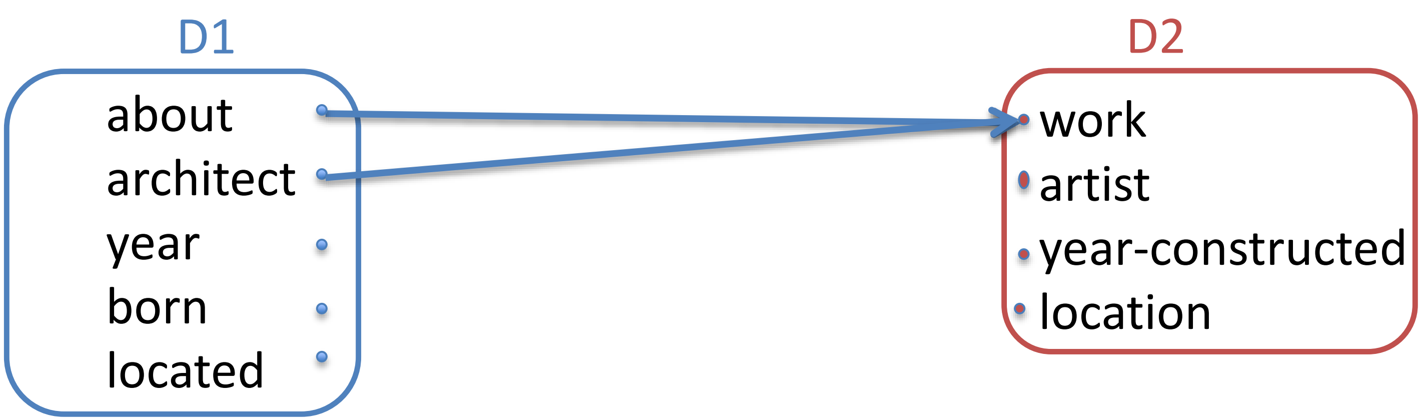
- about
- architect
- year
- born
- located

D2

- work
- artist
- year-constructed
- location

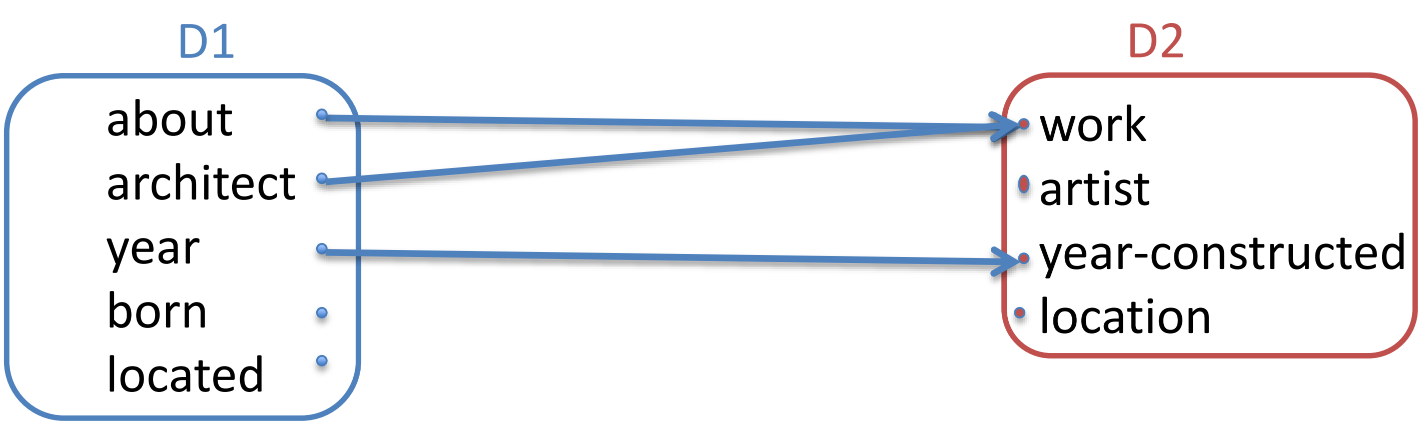
# Clustering Attributes: Example

Similarly for the rest of the attributes…



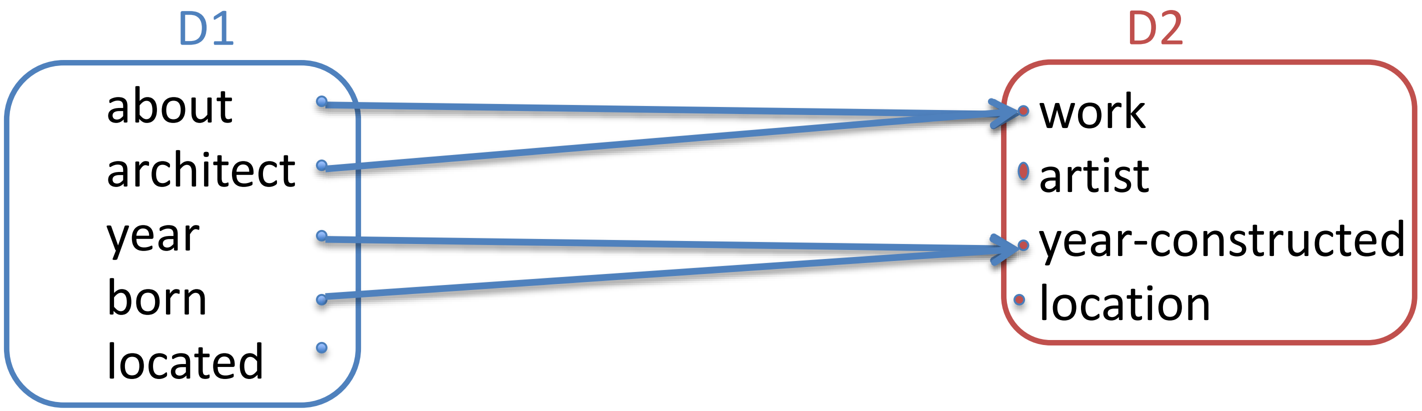
# Clustering Attributes: Example

Similarly for the rest of the attributes…



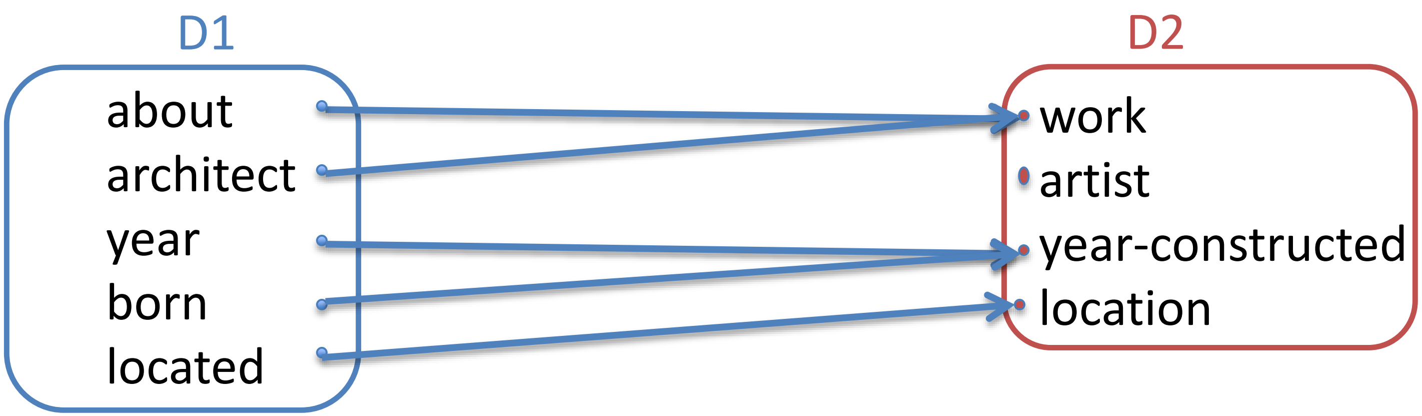
# Clustering Attributes: Example

Similarly for the rest of the attributes…



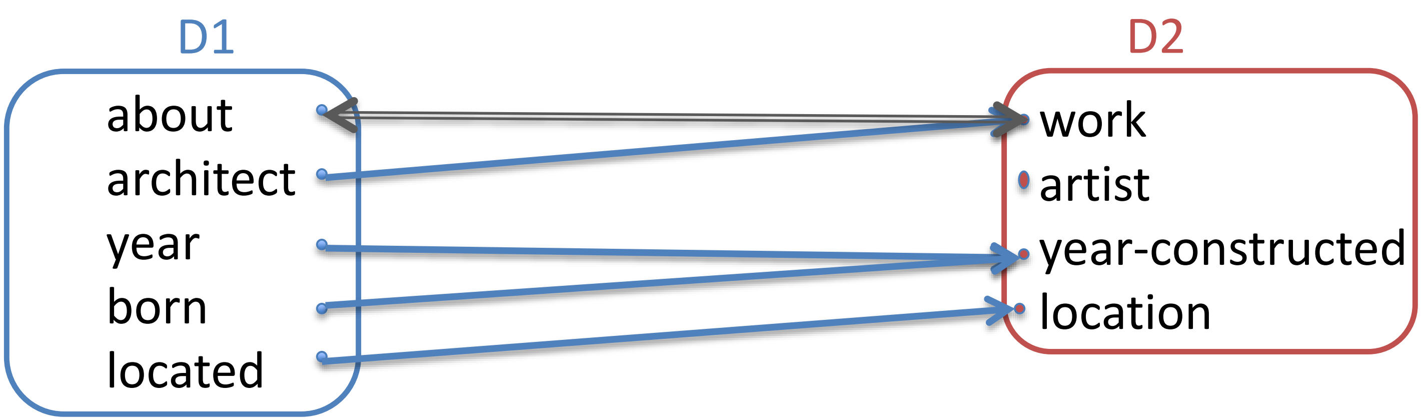
# Clustering Attributes: Example

Similarly for the rest of the attributes…



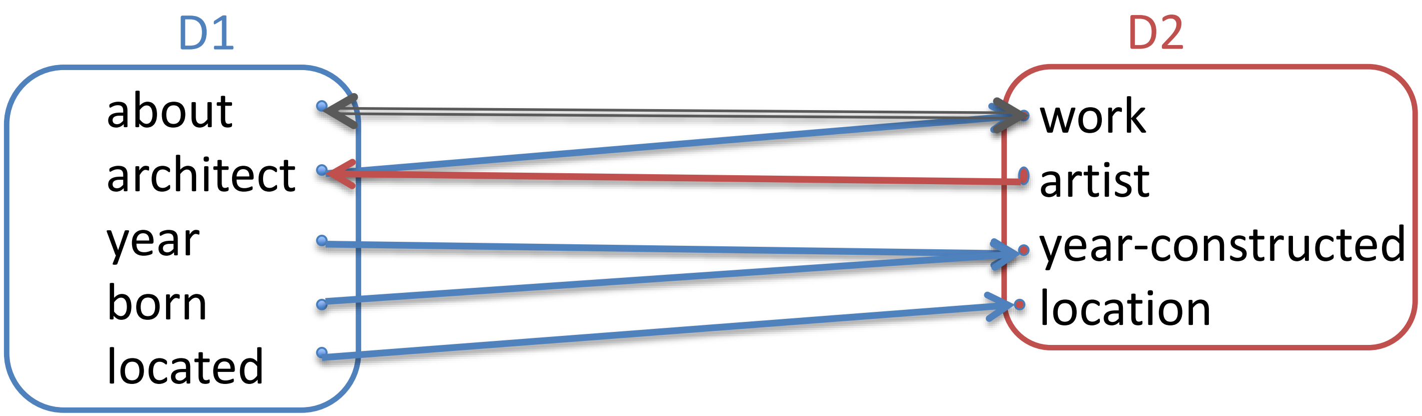
# Clustering Attributes: Example

Similarly for the rest of the attributes…



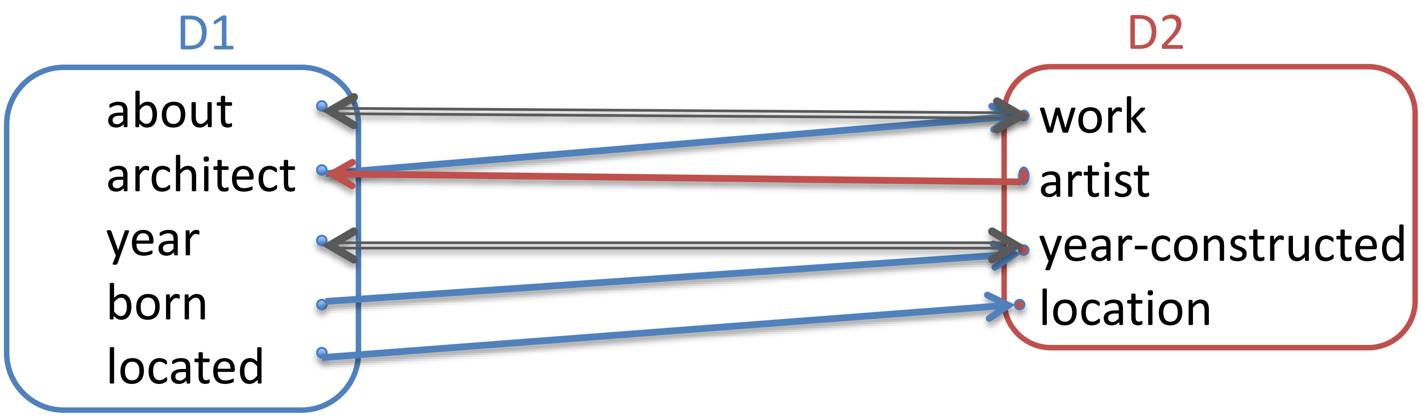
# Clustering Attributes: Example

Similarly for the rest of the attributes…



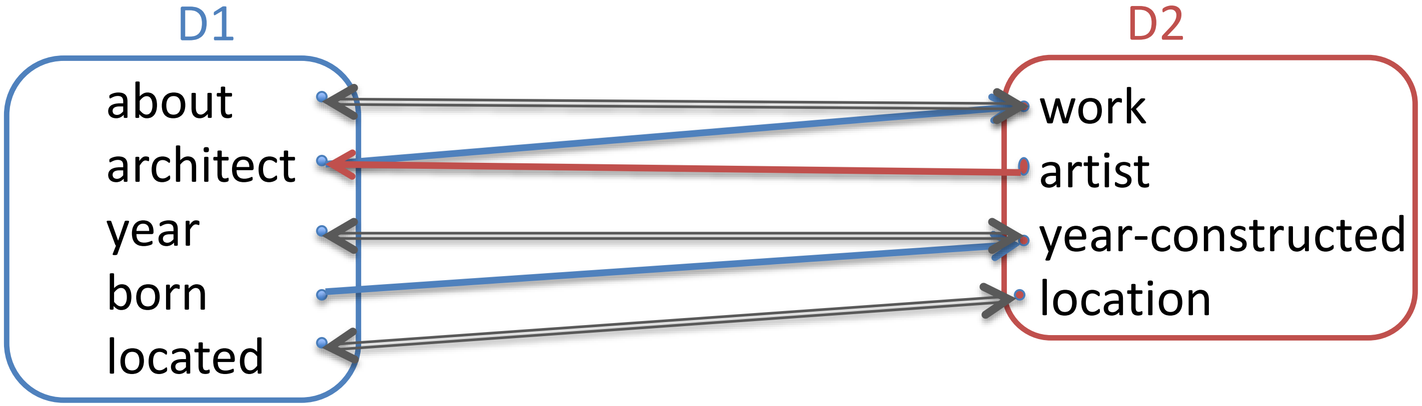
# Clustering Attributes: Example

Similarly for the rest of the attributes…



# Clustering Attributes: Example

Similarly for the rest of the attributes…



# Clustering Attributes: Example

| | |
|---|---|
| about | Eiffel Tower |
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e11**

| | |
|---|---|
| about | Statue of Liberty |
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e12**

| | |
|---|---|
| about | Auguste Bartholdi |
| born | 1834 |

**e13**

| | |
|---|---|
| about | Joan Tower |
| born | 1938 |

**e14**

| | |
|---|---|
| work | Lady Liberty |
| artist | Bartholdi |
| location | NY |

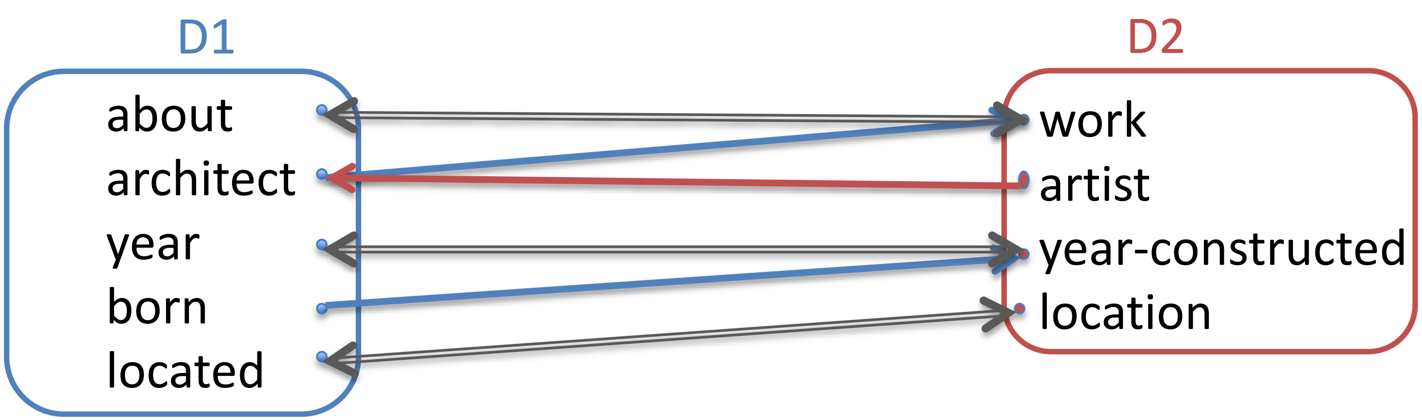
**e15**

| | |
|---|---|
| work | Eiffel Tower |
| year-constructed | 1889 |
| location | Paris |

**e16**

| | |
|---|---|
| work | Bartholdi Fountain |
| year-constructed | 1876 |
| location | Washington D.C. |

**e17**



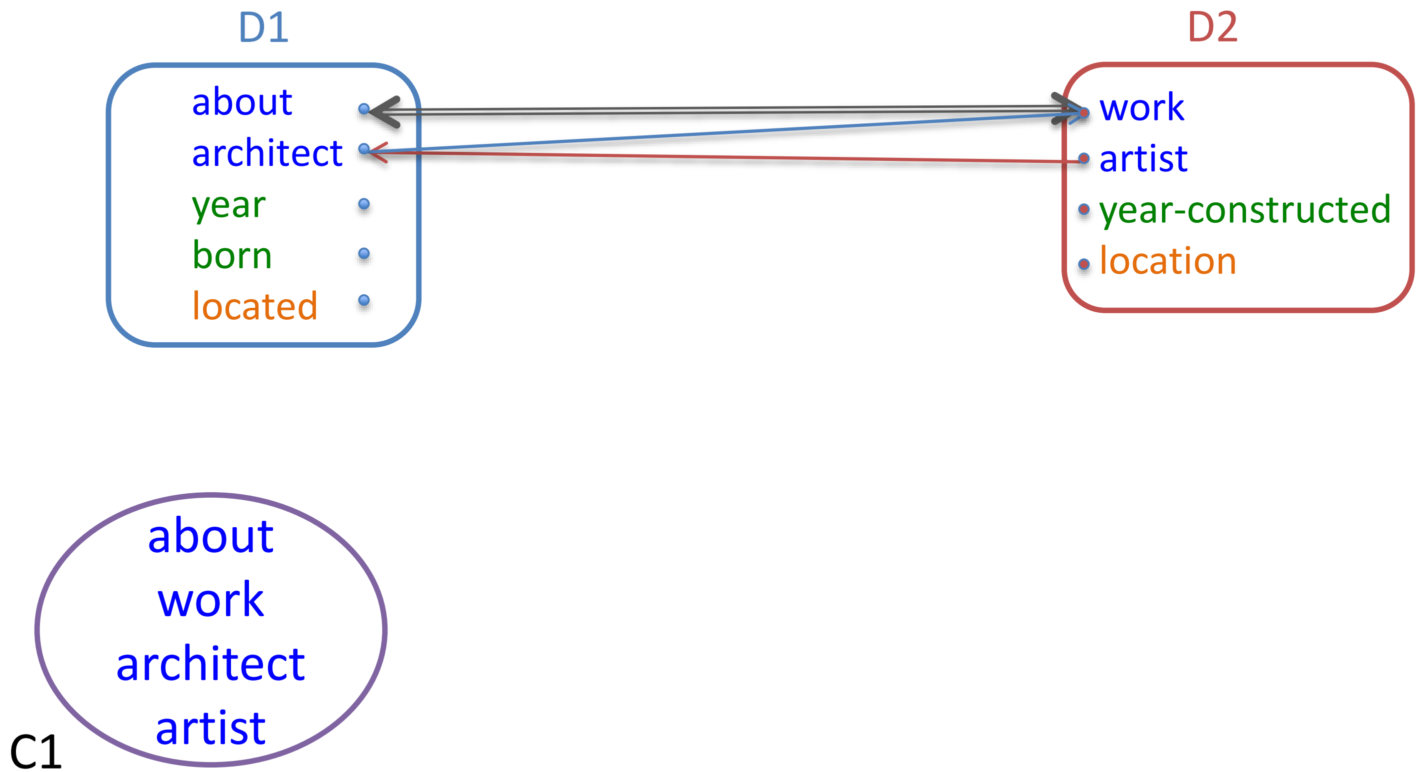
# Clustering Attributes: Example

Compute the transitive closure of the generated attribute pairs

- Connected attributes form clusters

Pairs: (about, work), (work, about), (artist, architect), (architect, work)

Transitive closure:



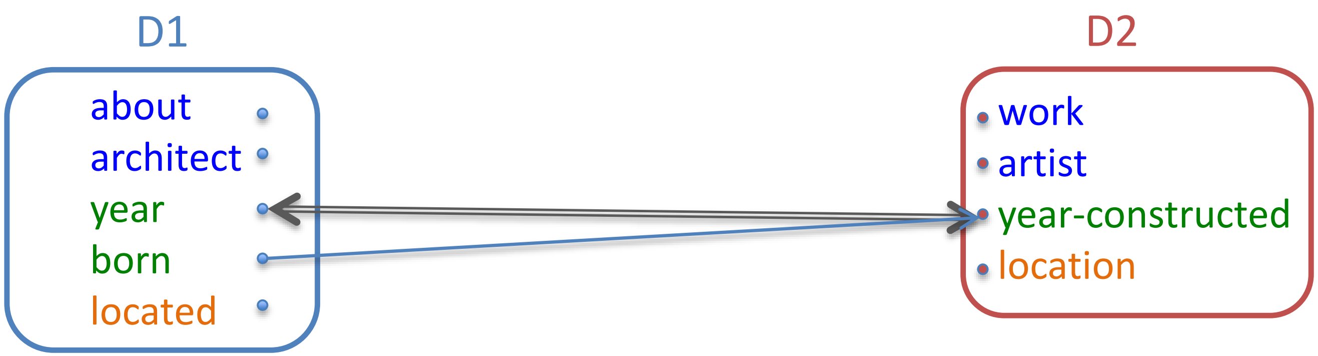
# Clustering Attributes: Example

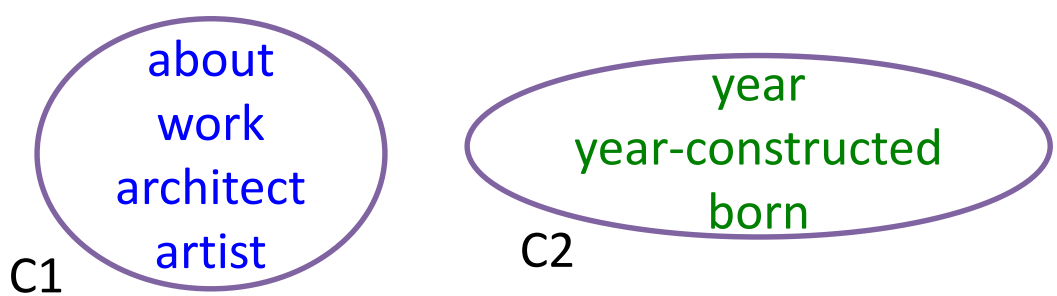
Compute the transitive closure of the generated attribute pairs

- Connected attributes form clusters

Pairs: (year, year-constructed), (year-constructed, year), (year-constructed, born)

Transitive closure:



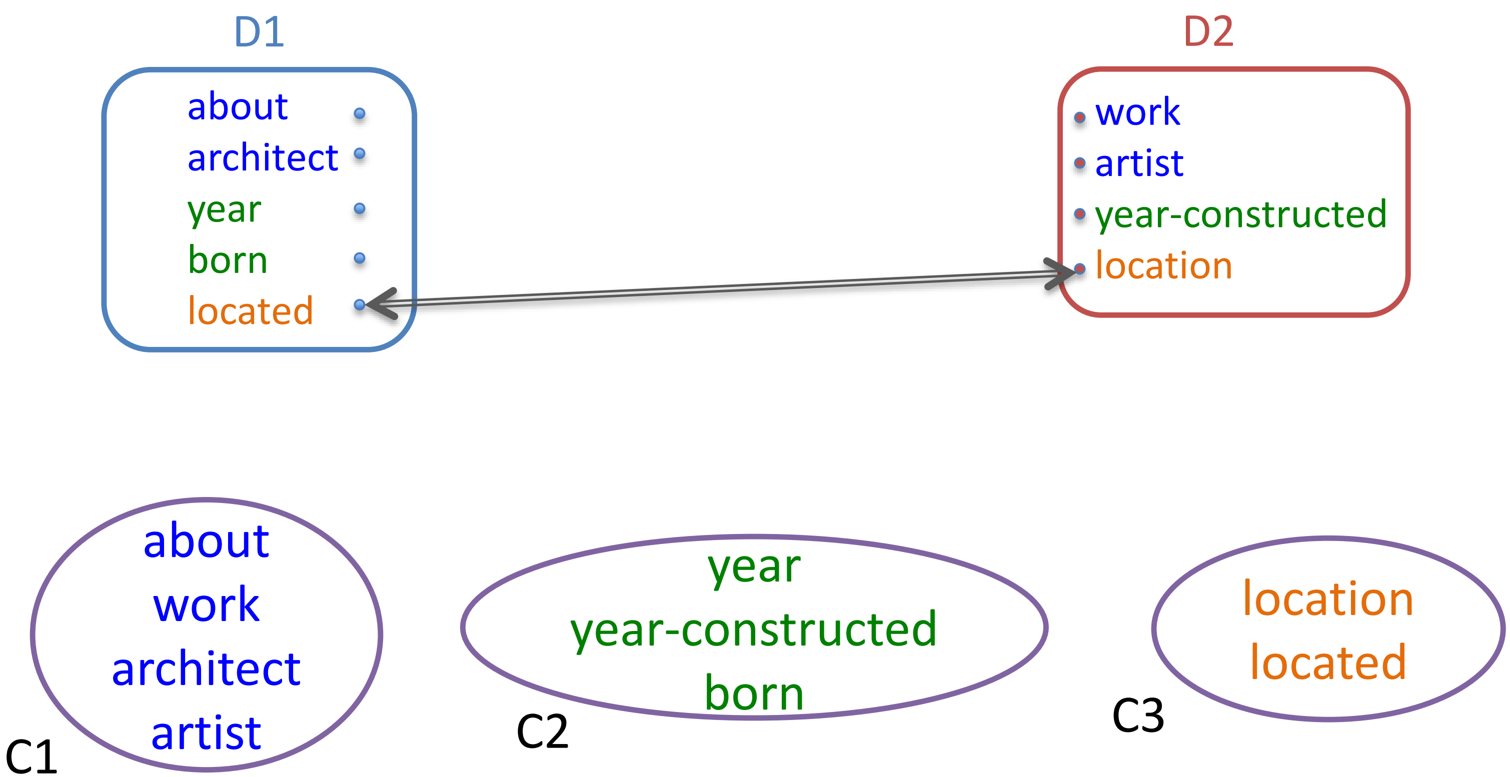
# Clustering Attributes: Example

Compute the transitive closure of the generated attribute pairs

- Connected attributes form clusters

Pairs: (located, location), (location, located)

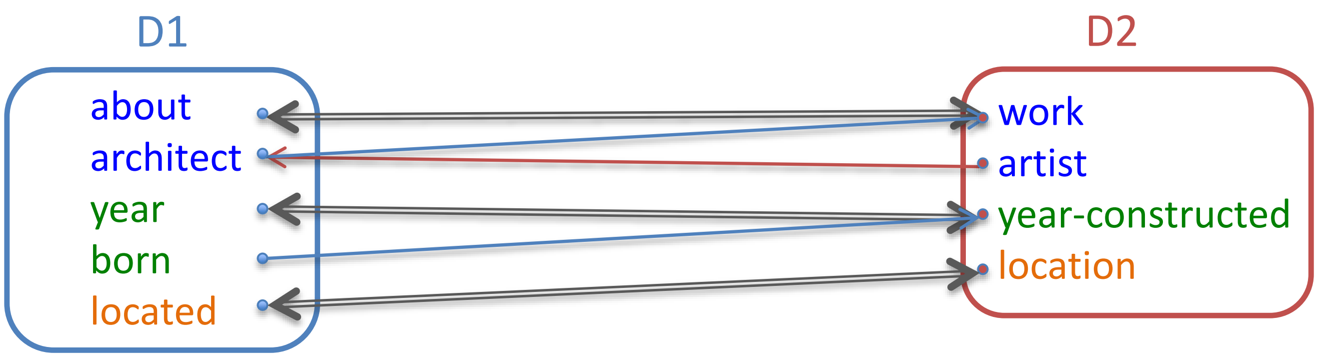
Transitive closure:



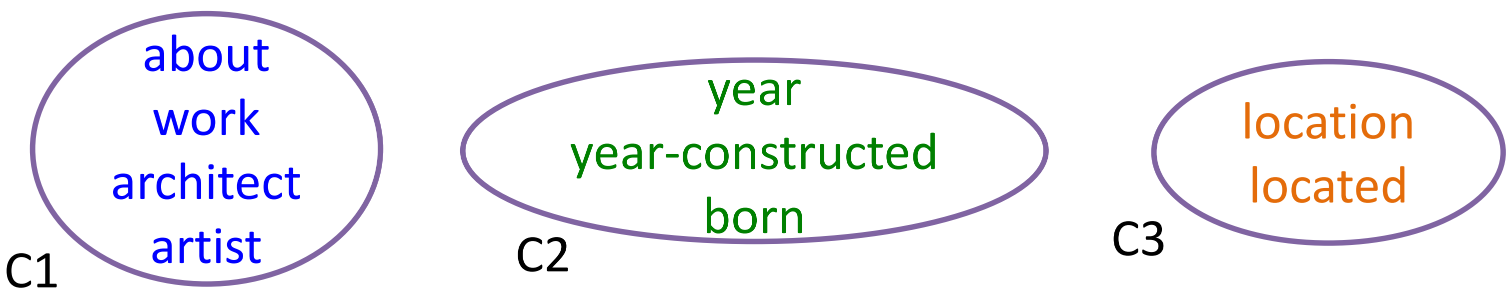
# Clustering Attributes: Example

Compute the <u>transitive closure</u> of the generated attribute pairs

– Connected attributes form clusters




Generated attribute clusters:



# Token Blocking for Each Cluster

| | |
|---|---|
| about | Eiffel Tower |
| architect | Sauvestre |
| year | 1889 |
| located | Paris |

**e11**

| | |
|---|---|
| about | Statue of Liberty |
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e12**

| | |
|---|---|
| about | Auguste Bartholdi |
| born | 1834 |

**e13**

| | |
|---|---|
| about | Joan Tower |
| born | 1938 |

**e14**

| | |
|---|---|
| work | Lady Liberty |
| artist | Bartholdi |
| location | NY |

**e15**

| | |
|---|---|
| work | Eiffel Tower |
| year-constructed | 1889 |
| location | Paris |

**e16**

| | |
|---|---|
| work | Bartholdi Fountain |
| year-constructed | 1876 |
| location | Washington D.C. |

**e17**

C1: about, work, architect, artist

C2: year, year-constructed, born

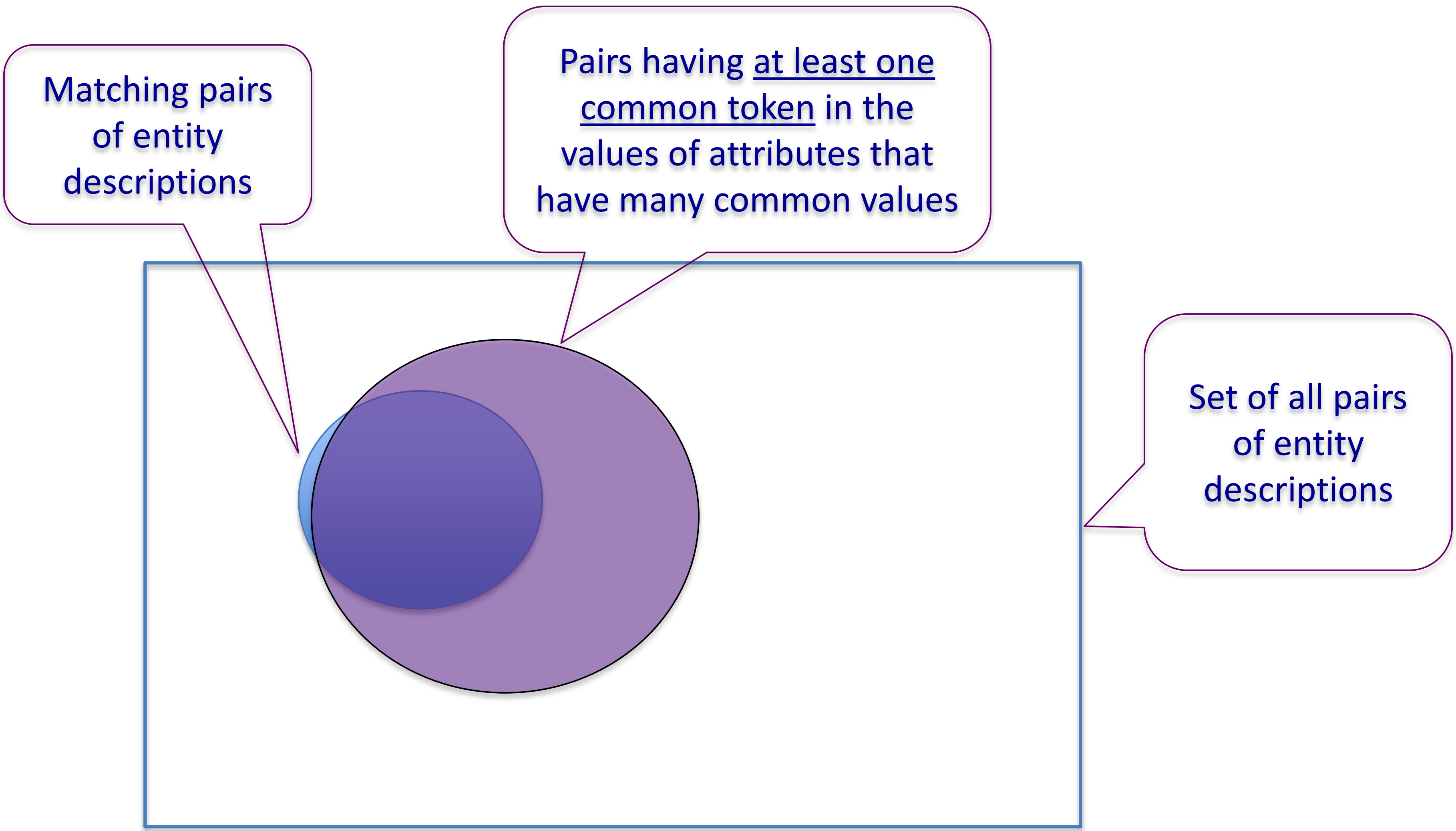
C3: location, located

Some of the generated blocks:

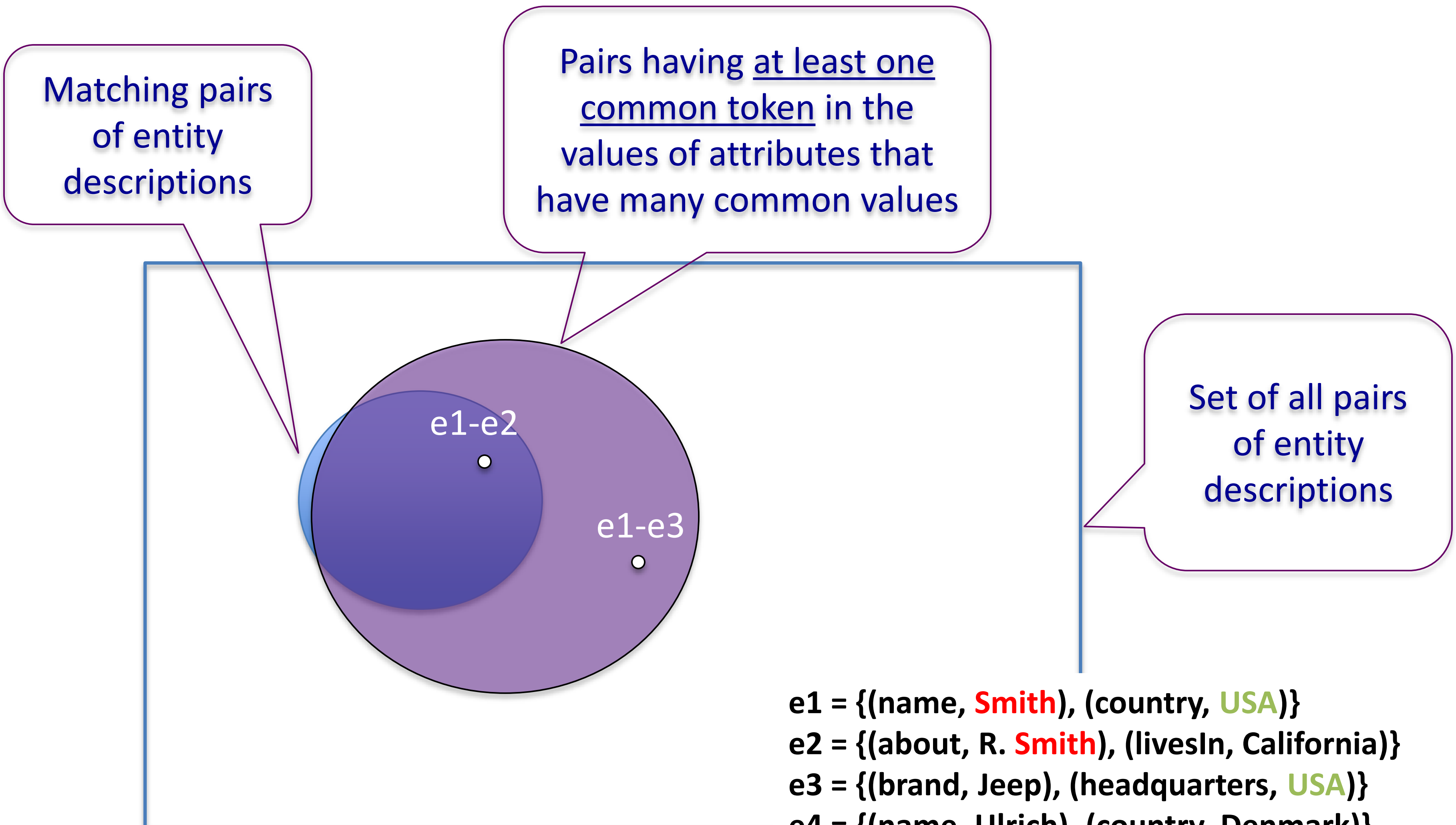
| C3.NY | C1.Tower | C1.Bartholdi |
|---|---|---|
| $e_{12}$, $e_{15}$ | $e_{11}$, $e_{14}$, $e_{16}$ | $e_{12}$, $e_{13}$, $e_{15}$, $e_{17}$ |

→ *compare Lady Liberty to Auguste Bartholdi*

# Attribute Clustering Blocking- Evaluation

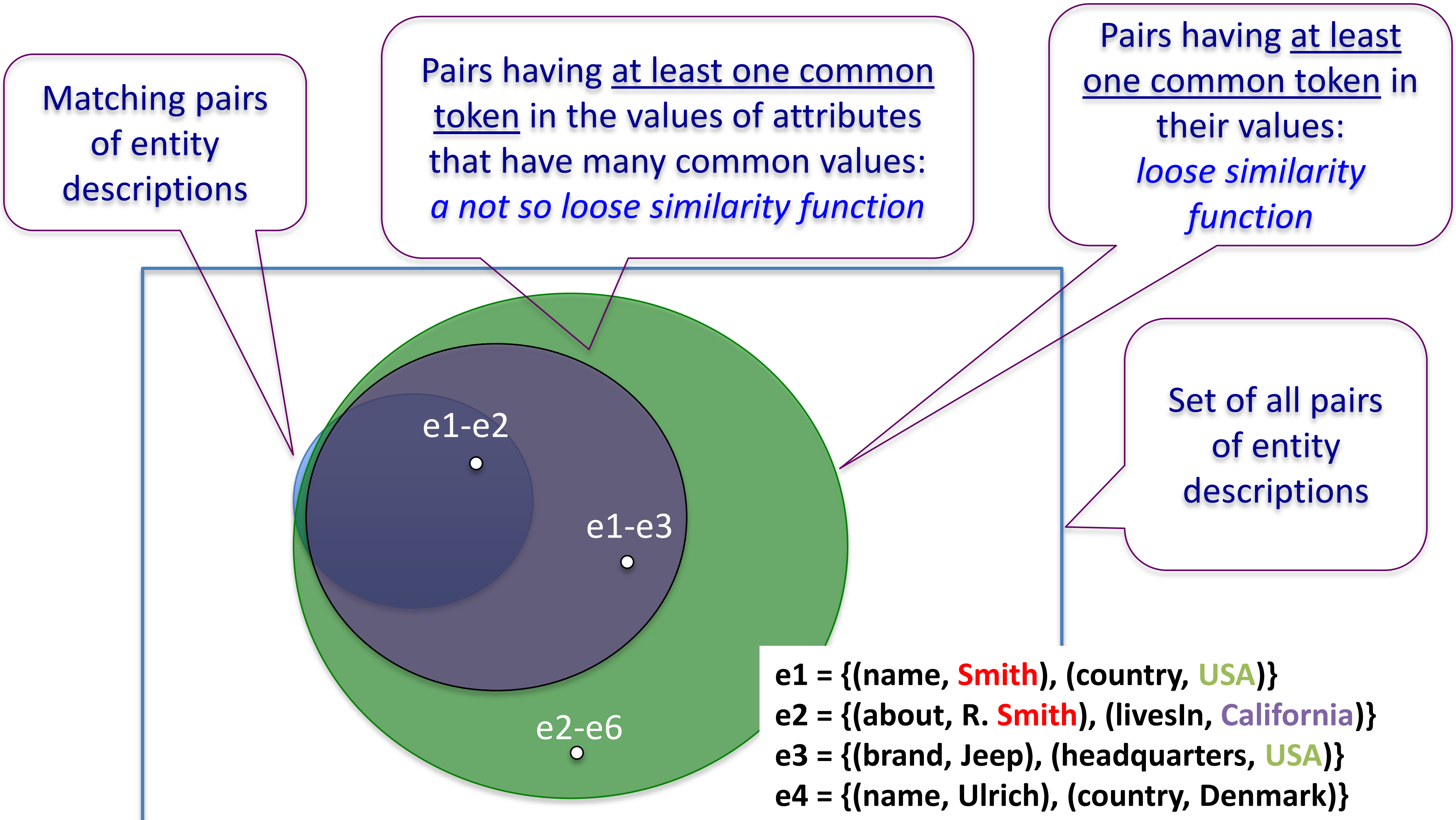


# Attribute Clustering Blocking- Evaluation




**e1 = {(name, Smith), (country, USA)}**
**e2 = {(about, R. Smith), (livesIn, California)}**
**e3 = {(brand, Jeep), (headquarters, USA)}**
**e4 = {(name, Ulrich), (country, Denmark)}**
**e5 = {(about, D. Brunson), (livesIn, Nevada)}**

# Attribute Clustering Blocking vs Token Blocking




e1 = {(name, Smith), (country, USA)}
e2 = {(about, R. Smith), (livesIn, California)}
e3 = {(brand, Jeep), (headquarters, USA)}
e4 = {(name, Ulrich), (country, Denmark)}
e5 = {(about, D. Brunson), (livesIn, Nevada)}
e6 = {(title, California Dreamin'), (length, 2:34)}

# Attribute Clustering Blocking vs Token Blocking

In attribute clustering:

- High recall
- Better efficiency compared to token blocking (save many redundant comparisons)
- Low precision

Many non-matches are placed in the same block

The same pair of descriptions is contained in many blocks

Much more expensive to build the blocks, than just performing token blocking

*Again, it ignores the valuable semantics that attributes and entity relationships offer*

# ZenCrowd [Demartini et al. 2013]

A different approach to attribute clustering

Three-stage blocking:

1. Token blocking on the labels of the descriptions

2. Rank description pairs within blocks, based on the Jaccard similarity of the values of matching attribute pairs
   - Attribute matching is based on the number of exact string matches that two attributes have in their values (within block)

3. Ask humans for the low-ranked pairs (crowdsourcing)

**Find this Target Entity:**
Spoleto (Italy)

- ○ Ariulf of Spoleto
- ○ Spoleto Festival, Italy
- ○ Spoleto
- ○ Spoleto Festival (taped in Italy): Sir John Gielgud; Eileen Farrell
- ○ Winiges of Spoleto

☐ No Result is the same as the Target Entity

# ZenCrowd - Example

| name | Statue of Liberty |
|---|---|
| architect | Bartholdi Eiffel |
| year | 1886 |
| located | NY |

**e1**

| about | Lady liberty |
|---|---|
| architect | Eiffel |
| location | NY |

**e2**

| about | Eiffel Tower |
|---|---|
| architect | Sauvestre |
| year | 1889 |
| location | Paris |

**e3**

1. token blocking on the labels of the descriptions

| Statue | Liberty | Lady | Eiffel | Tower |
|---|---|---|---|---|
| $e_1$ | $e_1, e_2$ | $e_2$ | $e_3$ | $e_3$ |

=> Pairs: $\{(e_1, e_2)\}$

2. attribute matching (only between $e_1$ and $e_2$):
   - #exact string matches(name, about) = 1 ("Liberty")
   - #exact string matches(architect, architect) = 1 ("Eiffel")
   - #exact string matches(architect, location) = 0
   - #exact string matches(year, architect) = 0
   - …
   - #exact string matches(located, location) = 1 ("NY")
     - matching attribute-pairs:
       (name, about), (architect, architect), (located, location)

J(name, about) =
J({Statue, Liberty}, {Lady, Liberty})
= 1/3

similarity($e_1$, $e_2$)=(J(located, location) + J(architect, architect) + J(name, about)) /3
= (1 + 1/2 + 1/3) / 3 = 0.61

# *Blocking* in the Web of Data

| Technique | Put two descriptions in a common block, when they have… |
|---|---|
| Token Blocking | a common token in their values |
| Attribute Clustering Blocking | a common token in the values of attributes that have similar values in overall |
| ZenCrowd | on average, similar values for attributes that have similar values in overall |

*An entity resolution task can also receive only one (Dirty) entity collection as input*

*Can we exploit the way data are published on the Web?*

Many URIs contain semantics

- Use them as indications of matches between descriptions

[Papadakis et al. 2010]

E.g. 66% of the 182 million URIs of BTC09 follow the scheme: Prefix-Infix(-Suffix)

- Prefix describes the source, i.e. domain, of the URI
- Infix is a local identifier
- The optional Suffix contains details about the format, e.g. .rdf and .nt, or a named anchor

http://km.aifb.kit.edu/pro jects/btc-2009/

# Prefix-Infix(-Suffix) [Papadakis et al. 2012]

*Token blocking on the Infixes/literals appearing in the values of descriptions*

http://en.wikipedia.org/wiki/Linked_data#Principles

- **Prefix:** describes the source (domain)
- **Infix:** local identifier
- **Suffix** (optional): details about the format, or a named anchor

Techniques:

Infix blocking

- The blocking key is the infix of the URI of the entity description

Infix profile blocking

- The blocking keys are the infixes in the values of each entity description

# Infix Blocking

The blocking key is the infix of the URI of the entity description

yago:Statue_of_Liberty

| | |
|---|---|
| skos:prefLabel | Statue of Liberty |
| yago:isLocatedIn | yago:Liberty_Island **e1** |

dbpedia:Statue_of_Liberty

| | |
|---|---|
| rdfs:label | Statue of Liberty |
| dbprop:location | dbpedia:Liberty_Island **e2** |

fb:m.072p8

| | |
|---|---|
| fb:official_name | Statue of Liberty |
| fb:contained_by | fb:m.026kp2 |
| ex:location | ex:Liberty_Island **e3** |

geonames:5139572

| | |
|---|---|
| geonames:name | Statue of Liberty |
| geonames:nearby | geonames:5124330 **e4** |

yago:Tina_Brown

| | |
|---|---|
| skos:prefLabel | Tina Brown |
| yago:linksTo | yago:Liberty_Island **e5** |

Generated blocks:

| Statue_of_Liberty | m.072p8 | 5139572 | Tina_Brown |
|---|---|---|---|
| $e_1$, $e_2$ | $e_3$ | $e_4$ | $e_5$ |

# Infix Profile Blocking

The blocking keys are the infixes in the values of each entity description

e1

| | |
|---|---|
| skos:prefLabel | Statue of Liberty |
| yago:isLocatedIn | yago:Liberty_Island |

e2

| | |
|---|---|
| rdfs:label | Statue of Liberty |
| dbprop:location | dbpedia:Liberty_Island |

e3

| | |
|---|---|
| fb:official_name | Statue of Liberty |
| fb:contained_by | fb:m.026kp2 |
| ex:location | ex:Liberty_Island |

e4

| | |
|---|---|
| geonames:name | Statue of Liberty |
| geonames:nearby | geonames:5124330 |

e5

| | |
|---|---|
| skos:prefLabel | Tina Brown |
| yago:linksTo | yago:Liberty_Island |

pros: (e1, e3) correctly identified
cons: (e1, e5) mistakenly identified

Generated blocks:

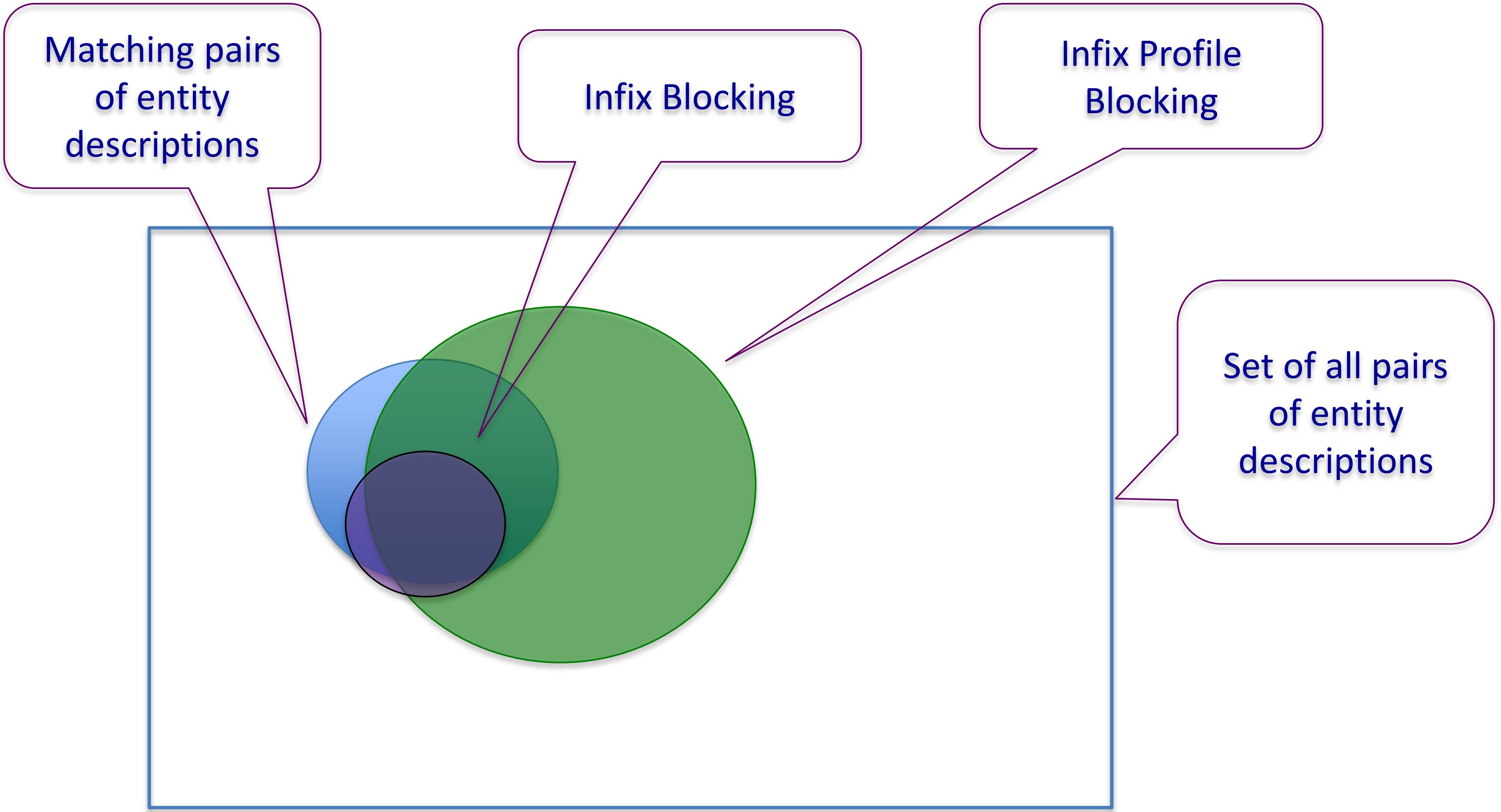
| Liberty_Island |
|---|
| $e_1$, $e_2$, $e_3$, $e_5$ |

| m.026kp2 |
|---|
| $e_3$ |

| 5124330 |
|---|
| $e_4$ |

Drawback!
The effectiveness of these approaches relies on the good naming practices of the data

# Prefix-Infix(-Suffix) - Evaluation



# *Blocking* in the Web of Data

| Technique | Put two descriptions in a common block, when they have… |
|---|---|
| Token Blocking | a common token in their values |
| Attribute Clustering Blocking | a common token in the values of attributes that have similar values in overall |
| ZenCrowd | on average, similar values for attributes that have similar values in overall |
| Prefix-Infix(-Suffix) | a common token in their literal values, or a common URI |

# 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*)**

Still, many redundant comparisons are performed!

- Can we also use the structural type of the descriptions?

*For further enhancing efficiency of entity resolution*

# Block Post-Processing

# Block Post-Processing

STEP 1

Block Building

STEP 2

Block Post-Processing

The goal: *Reduce further the number of comparison*

# Block Post-Processing

- Remove oversized blocks
  - Threshold on the number of descriptions in a block
- Order blocks
  - Examine first the blocks which are more likely to contain matches
    - Wrt. the number of superfluous comparisons spared in subsequently examined blocks
- Remove low-order blocks
  - We do not gain much by examining them
- Order comparisons
  - Perform first the comparisons that are more likely to result in matches
    - Based on the number of blocks they appear together [Papadakis et al. 2011b]
- Remove low-order comparisons [Whang et al. 2013, Papadakis et al. 2011b]
  - Similar to removing low-order blocks

# Meta-Blocking

| STEP 1 | STEP 2 | STEP 3 |
|---|---|---|
| Block Building | Meta-Blocking | Block Post-Processing |

# Meta-blocking [Papadakis et al. 2013 (b)]

A generic procedure for block re-construction

- Create blocks resulting in fewer comparisons
- Preserve effectiveness

Blocking graph: abstract graph representation of the original set of blocks

- Nodes: entity descriptions
- Edges: connect descriptions co-occurring in blocks

Use the blocking graph for discarding redundant comparisons

- i.e. comparisons already performed

Prune edges, not satisfying a criterion, for discarding superfluous comparisons

- i.e. comparisons between non-matches

# Meta-blocking - Example

| | | |
|---|---|---|
| name | **Eiffel Tower** | |
| architect | Sauvestre | |
| year | 1889 | |
| location | Paris | **e1** |

| | | |
|---|---|---|
| name | **Statue of Liberty** | |
| architect | Bartholdi Eiffel | |
| year | 1886 | |
| located | NY | **e2** |

| | | |
|---|---|---|
| about | **Lady liberty** | |
| architect | Eiffel | |
| location | NY | **e3** |

| | | |
|---|---|---|
| about | **Eiffel Tower** | |
| architect | Sauvestre | |
| year | 1889 | |
| located | Paris | **e4** |

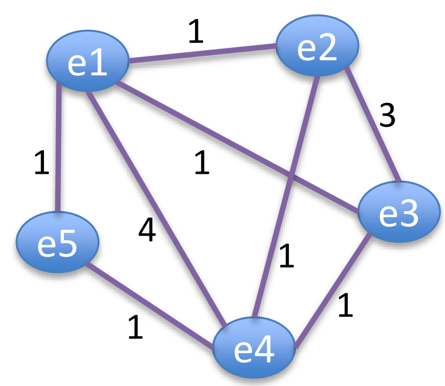
| | | |
|---|---|---|
| name | **White Tower** | |
| location | Thessaloniki | |
| year-constructed | 1450 | **e5** |

Blocks:
(with token blocking)

| **Eiffel** | **Tower** | **Liberty** |
|---|---|---|
| $e_1$, $e_2$, $e_3$, $e_4$ | $e_1$, $e_4$, $e_5$ | $e_2$, $e_3$ |
| **NY** | **Paris** | **1889** |
| $e_2$, $e_3$ | $e_1$, $e_4$ | $e_1$, $e_4$ |

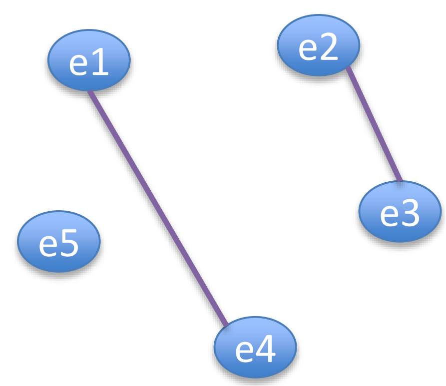
**13** comparisons
to identify 2 matches

Blocking graph:




edge weights = #common blocks

Pruned blocking graph:
(remove edges with weight < 2)




**2** comparisons
to identify 2 matches

# Conclusions of Part I

# Partitioning vs. Overlapping Blocks

Blocking approaches can be distinguished between:

- Partitioning: Each description is placed in exactly one block
  - Fewer comparisons
- Overlapping: Each description is placed in more than one block
  - More identified matches

*Selecting a good blocking key is more important than the blocking technique*

[Christen 2012]

In the Web of Data, selecting a (good) blocking key is not straightforward!

# Discussion on Blocking

In overlapping approaches, *the number of common blocks between two descriptions can be an indication of their similarity*

- Overlap-positive: many common blocks → very similar
- Overlap-negative: few common blocks → very similar
- Overlap-neutral: #common blocks is irrelevant

Overlapping approaches return more matches

- Trade-off between the number and the size of the blocks:
  - Few, large blocks vs. many, small blocks
    - More comparisons vs. more missed matches

  *Overlap-positive: lower misclassification cost*
    - *Seem more appropriate for the Web of data*

# A Classification of Blocking Approaches

| Approach | Partitioning | Overlapping | | |
|---|---|---|---|---|
| | | positive | negative | neutral |
| Fellegi & Sunter 1969 | • | | | |
| Hernandez & Stolfo 1995 | | | | • |
| Yan et al. 2007 | • | | | |
| Draisbach & Naumann 2009 | | | | • |
| McCallum et al. 2000 | | | • | |
| Christen 2012 | | | • | |
| Gravano et al. 2001 | | • | | |
| Aizawa & Oyama 2005 | | • | | |
| Jin et al. 2003 | | • | | |
| Kolb et al. 2011, 2012 | • | | | |
| Papadakis et al. 2011 | | + | | |
| Papadakis et al. 2013 (a) | | + | | |
| Papadakis et al. 2013 (b) | | + | | |
| Papadakis et al. 2012 | | + | | |

•: tabular data
+ : graph data

# Tutorial Overview

- Iterative entity resolution approaches
  - Coffee break!

What follows in Part II:

- Continue on iterative entity resolution approaches
- Large scale entity resolution using MapReduce
- Conclusions

# 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

# Tutorial Overview

What follows in Part II:

- Continue on iterative entity resolution approaches
- Large scale entity resolution using MapReduce
- Conclusions