Blocking Techniques for Web-scale Entity Resolution

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Outline

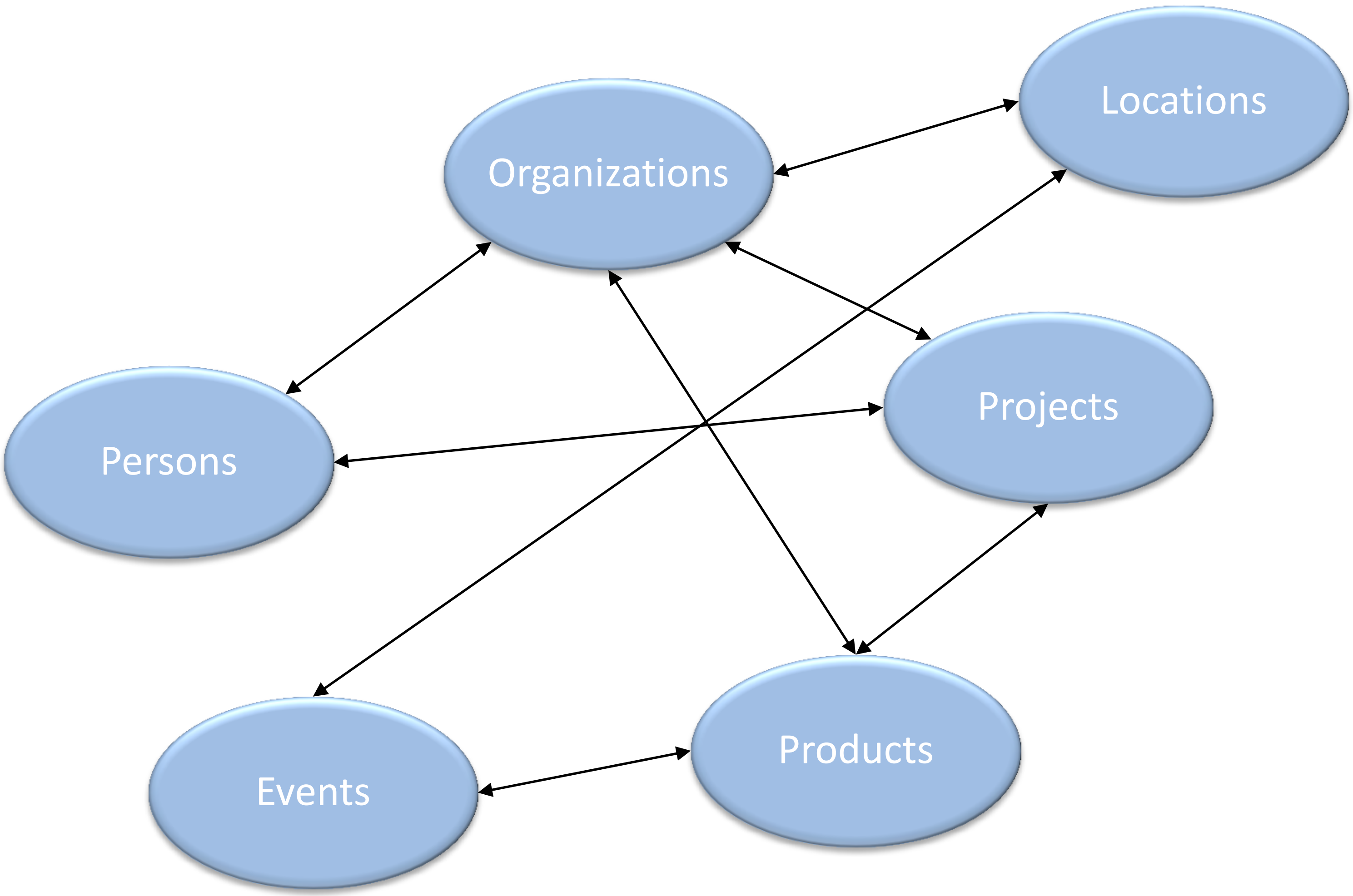
1. Introduction to Entity Resolution
2. Introduction to Blocking
3. Blocking Methods for Databases
4. Blocking Methods for Web Data
5. Meta-blocking
6. Block Processing Techniques
7. ER framework

Part 1:

Introduction to Entity Resolution

Entities: an invaluable asset

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



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capital of UK, host city of the IV Olympic Games, host city of the XIV Olympic Games, future host of the XXX Olympic Games, city of the Westminster Abbey, city of the London Eye, the city described by Charles Dickens in his novels, …

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http://sws.geonames.org/2643743/
http://en.wikipedia.org/wiki/London
http://dbpedia.org/resource/Category:London
…

… or …

How many "entities" have the same name?

- London, KY
- London, Laurel, KY
- London, OH
- London, Madison, OH
- London, AR
- London, Pope, AR
- London, TX
- London, Kimble, TX
- London, MO
- London, MO
- London, London, MI
- London, London, Monroe, MI
- London, Uninc Conecuh County, AL
- London, Uninc Conecuh County, Conecuh, AL
- London, Uninc Shelby County, IN
- London, Uninc Shelby County, Shelby, IN
- London, Deerfield, WI
- London, Deerfield, Dane, WI
- London, Uninc Freeborn County, MN
- ...

… or …

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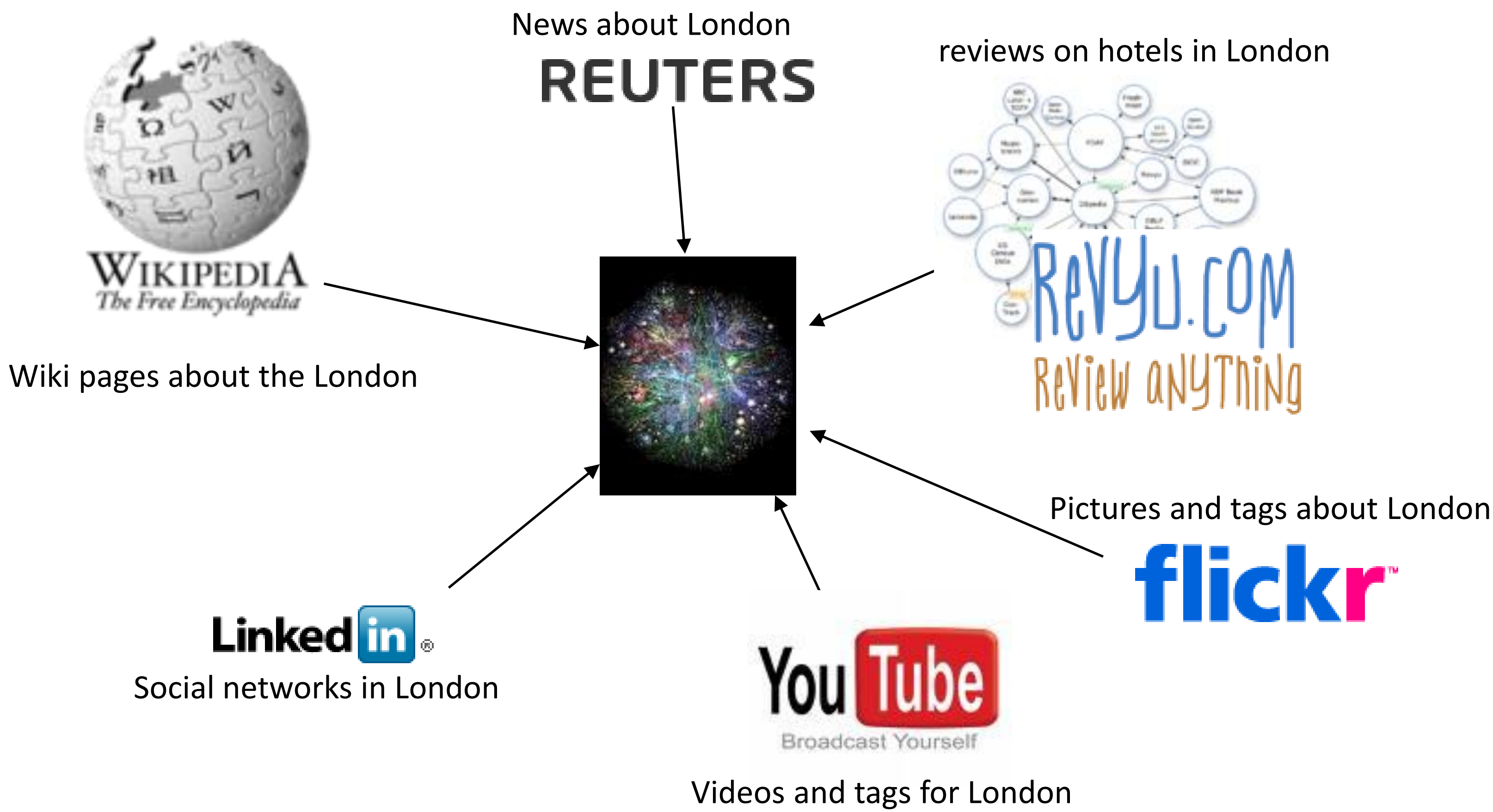
- London, Uninc Shelby County, Shelby, IN
- London, Deerfield, WI
- London, Deerfield, Dane, WI
- London, Uninc Freeborn County, MN
- ...

- London, Jack
2612 Almes Dr
Montgomery, AL
(334) 272-7005
- London, Jack R
2511 Winchester Rd
Montgomery, AL 36106-3327
(334) 272-7005
- London, Jack
1222 Whitetail Trl
Van Buren, AR 72956-7368
(479) 474-4136
- London, Jack
7400 Vista Del Mar Ave
La Jolla, CA 92037-4954
(858) 456-1850
- ...

Content Providers

How many content types / applications provide valuable information about each of these "entities"?



Preliminaries on Entity Resolution

Entity Resolution [Christen, TKDE2011]:

identifies and aggregates the different entity profiles/records that actually describe the same real-world object.

Application areas:

Linked Data, Social Networks, census data, price comparison portals

Useful because:

- improves data quality and integrity
- fosters re-use of existing data sources.

Types of Entity Resolution

The input of ER consists of entity collections that can be of two types [Christen, TKDE2011]:

- clean, which are duplicate-free

    e.g., DBLP, ACM Digital Library, Wikipedia, Freebase

- dirty, which contain duplicate entity profiles in themselves

    e.g., Google Scholar, Citeseer^X

Types of Entity Resolution

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- dirty, which contain duplicate entity profiles in themselves
  - e.g., Google Scholar, Citeseer^X

Based on the quality of input, we distinguish ER into 3 sub-tasks:

- **Clean-Clean ER** (a.k.a. *Record Linkage* in databases)
- Dirty-Clean ER
- Dirty-Dirty ER

Equivalent to **Dirty ER** (a.k.a. *Deduplication* in databases)

Computational cost

ER is an inherently quadratic problem (i.e., O(n^2)):
every entity has to be compared with all others

ER does not scale to large entity collections (e.g., Web Data).

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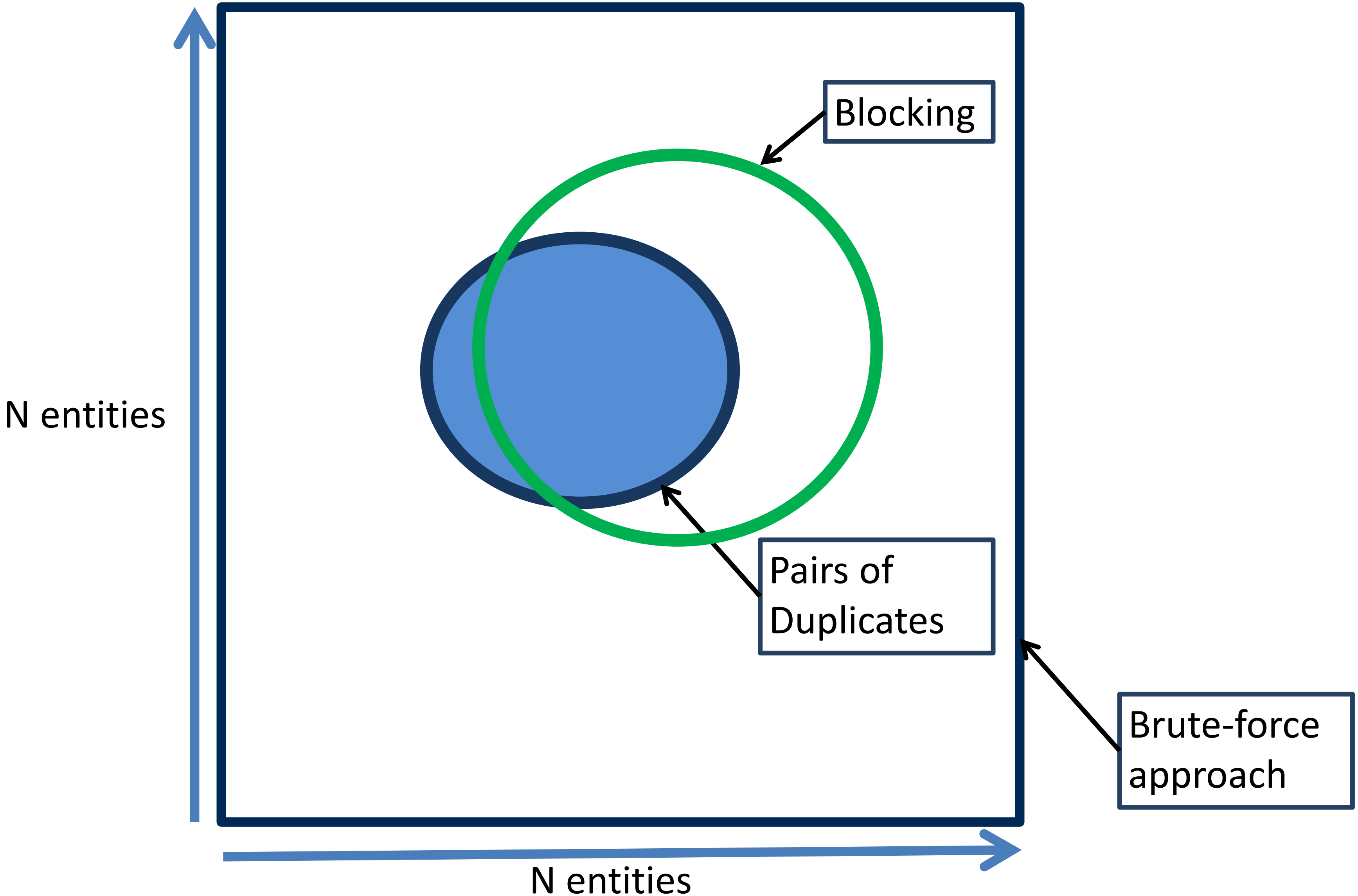
Solution: Blocking

- group similar entities into blocks
- execute comparisons only inside blocks
- approximate solution

Computational cost



Part 2:

Introduction to Blocking

Fundamental Assumptions

1. Every entity profile consists of a uniquely identified set of name-value pairs.

2. Every entity profile corresponds to a single real-world object.

3. Two matching profiles are detected as long as they co-occur in at least one block.

General Principles

1. Represent each entity by *one or more* blocking keys.
2. Place into blocks all entities having the *same or similar* blocking key.

Measures for assessing block quality:

– Pairs Completeness: $PC = \frac{detected\ matches}{existing\ matches}$ (recall)

– Pairs Quality: $PQ = \frac{detected\ matches}{executed\ comparisons}$ (precision)

Trade-off!

Problem Definition

Given one dirty (Dirty ER) or two clean (Clean-Clean ER) entity collections, cluster their profiles into blocks and process them so that both *PC* and *PQ* are maximized.

disclaimer:

Precision of entity matching is dependent on the entity similarity measures, and is orthogonal to the above problem.

Categorization of Blocking Methods

1. Definition of blocking keys
   - Supervised
   - Unsupervised
2. Dependency on schema
   - Schema-based
   - Schema-agnostic
3. Redundancy
   - Disjoint blocks
   - Overlapping blocks
     - Redundancy-positive
     - Redundancy-neutral
     - Redundancy-negative

Unsupervised Blocking Methods

	Disjoint Blocks	Overlapping Blocks		
		Redundancy-negative	**Redundancy-neutral**	**Redundancy-positive**
Schema-based	Standard Blocking	Canopy Clustering	Sorted Neighborhood	1.Q-grams Blocking 2.Suffix Array
Schema-agnostic	-	-	Semantic Indexing	1. Token Blocking 2. Agnostic Clustering 3. URI Semantics 4. TYPiMatch

Part 3:

Blocking Methods for Databases

General Principles

Mostly schema-based techniques.

Rely on two assumptions:

1. A-priori known schema → no noise in attribute names.
2. For each attribute name we know some metadata:
   - level of noise (e.g., spelling mistakes, false or missing values)
   - distinctiveness of values

Standard Blocking

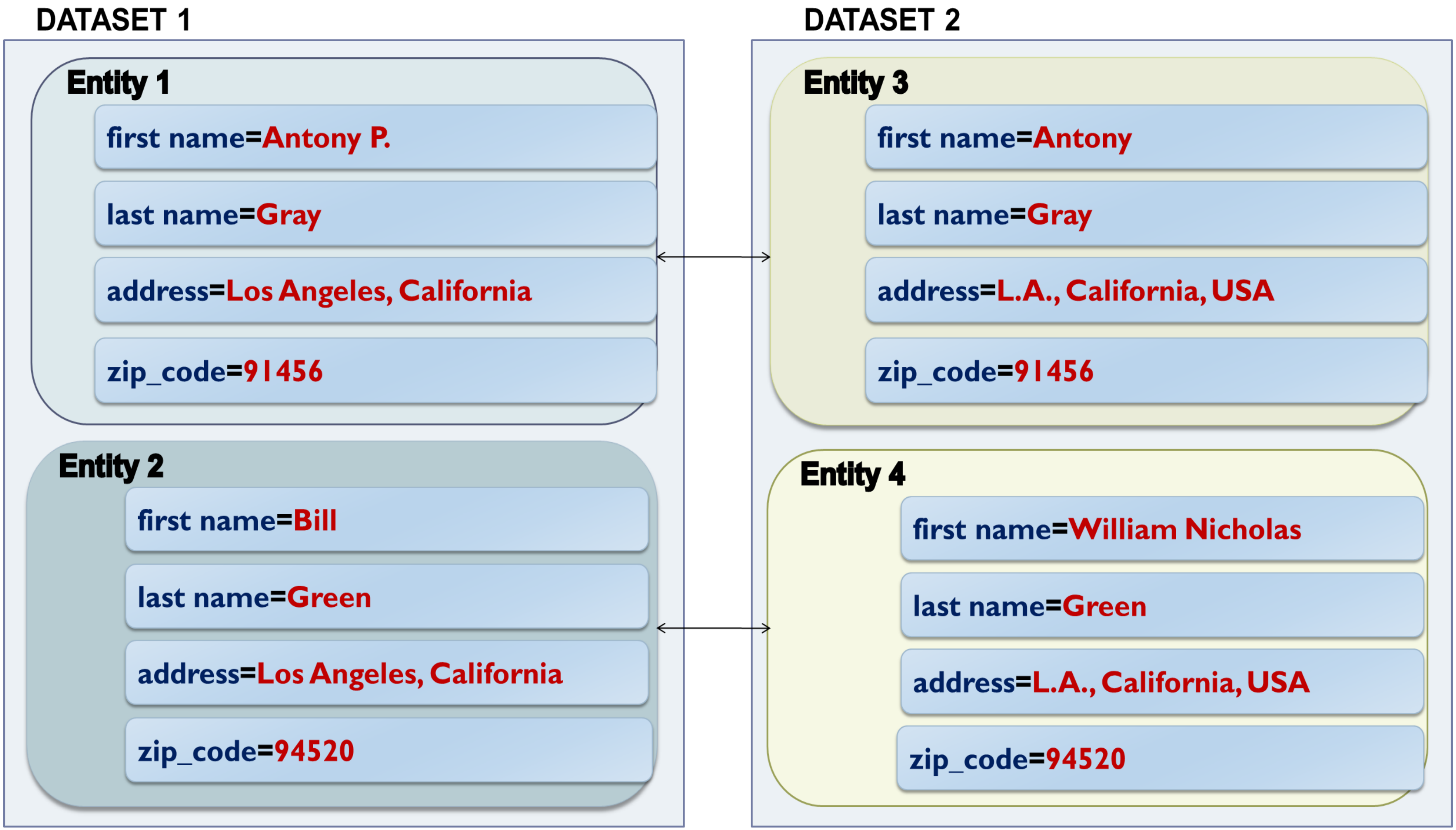
Earliest, simplest form of blocking.

Algorithm:

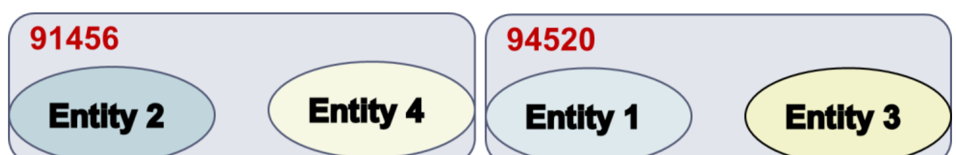
1. Select the most appropriate attribute name w.r.t. noise and distinctiveness.
2. Transform every value into a single Blocking Key (BK)
3. For each BK, create one block that contains all entities having this BK in their transformation.

Works as a hash function!

Example of Standard Blocking



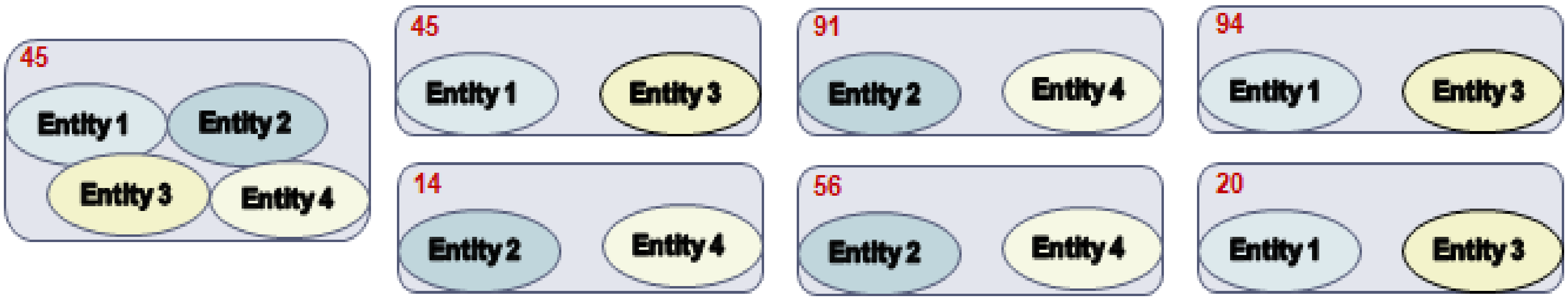
Blocks on zip_code:



Q-grams Blocking [Baxter et. al., KDD 2003] [Gravano et. al., VLDB 2001]

Converts every BK into the list of its *q-grams*.

For *q=2*, the BKs *91456* and *94520* yield the following blocks:



- Advantage:

  robust to noisy BKVs

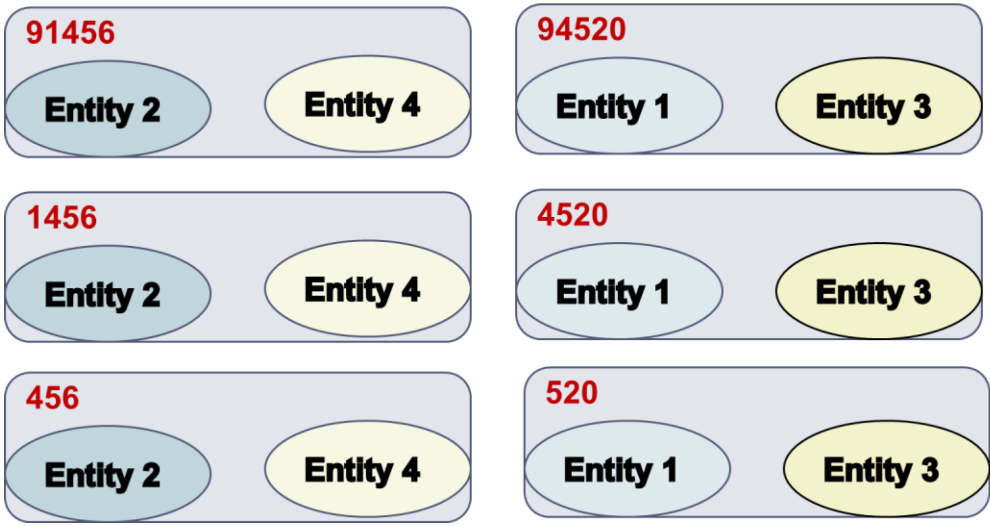
- Drawback:

  larger blocks → higher computational cost

Suffix Array Blocking [Aizawa et. al., WIRI 2005][de Vries et. al., CIKM 2009]

Converts every BKV to the list of its suffixes that are longer than a predetermined minimum length l_{min}.

For $l_{min}=3$, the keys *91456* and *94520* yield the blocks:



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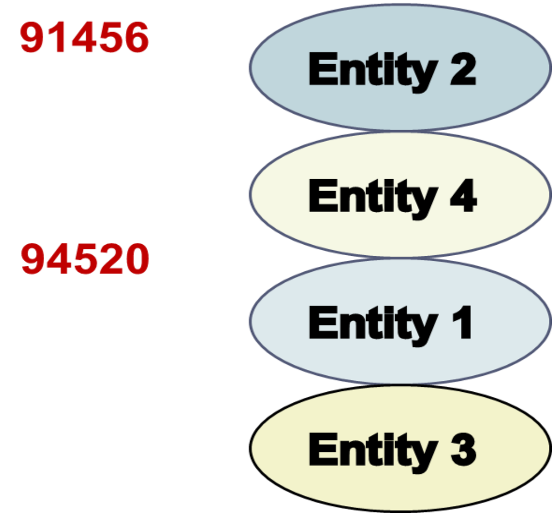
Sorted Neighborhood [Hernandez et. al., SIGMOD 1995]

1. Entities are sorted in alphabetic order of BKs.
2. A window of fixed size slides over the sorted list.
3. At each iteration, it compares the entities that co-occur within the window.



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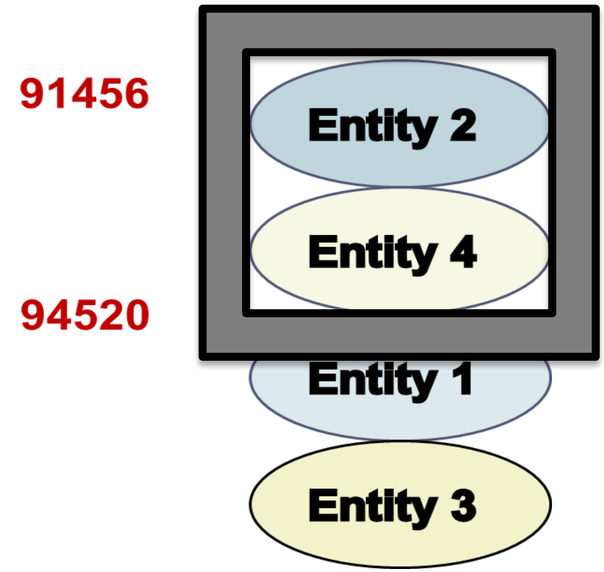

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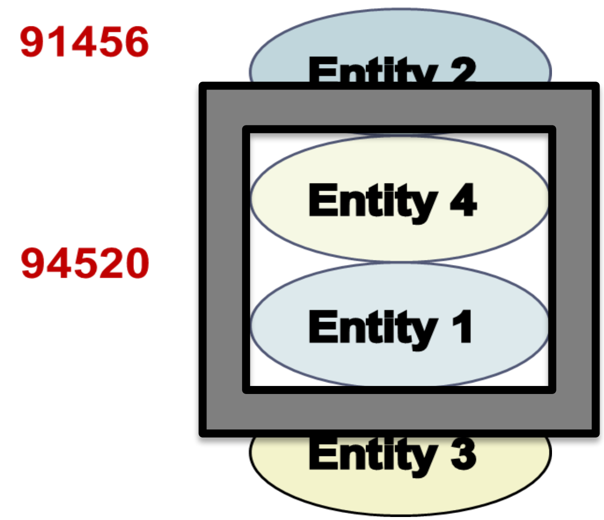

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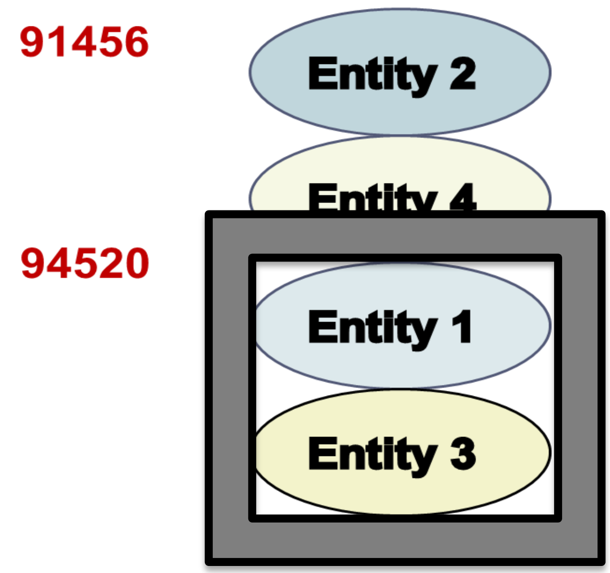
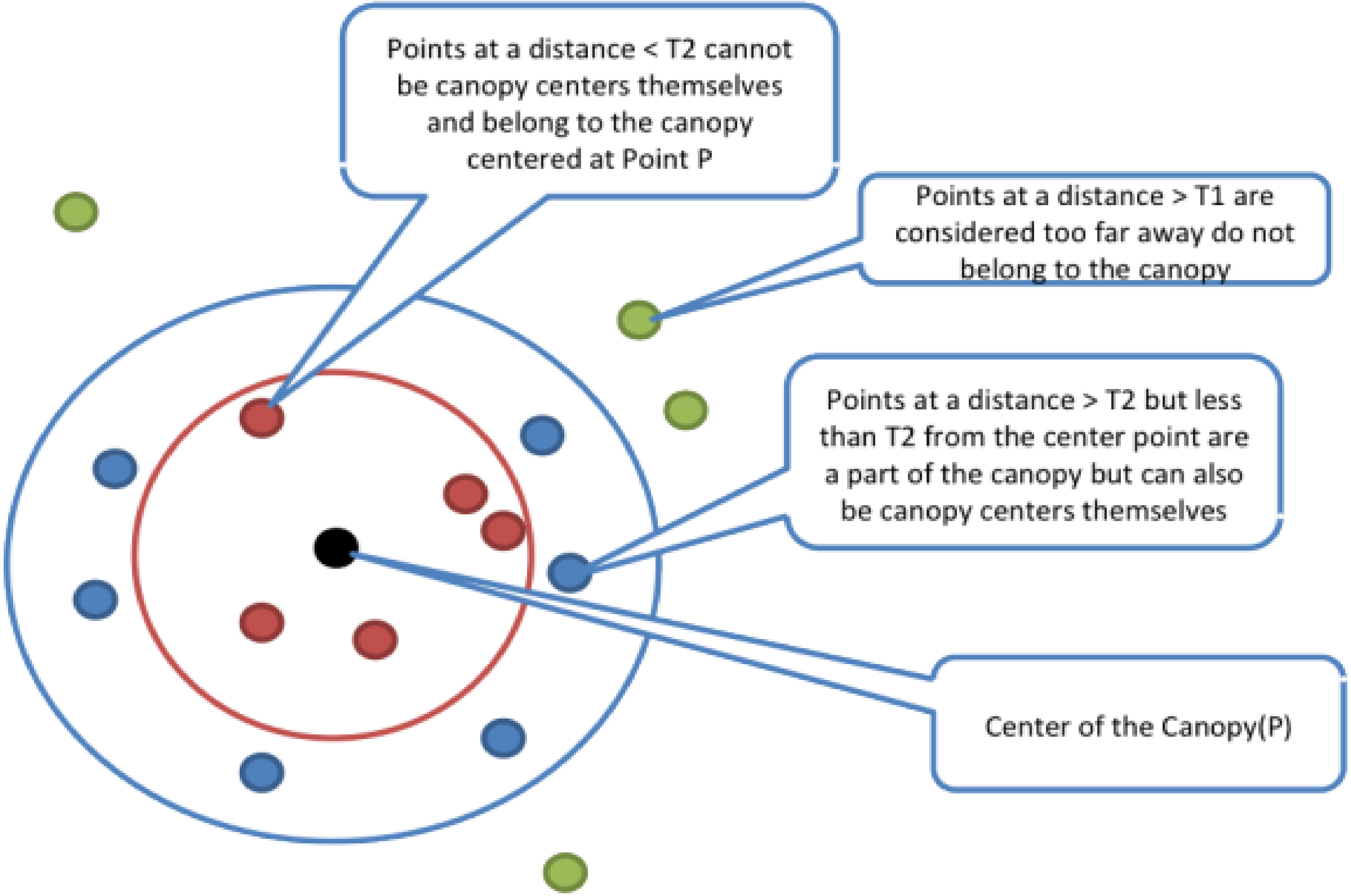


Canopy Clustering [McCallum et. al., KDD 2000]



Summary of Blocking for Databases [Christen, TKDE2011]

They typically employ **redundancy** to ensure robustness in the context of noise at the cost of lower efficiency.

Drawbacks:

1. Too many parameters to be configured

   Canopy Clustering has the following parameters:

   I. String matching method
   II. Threshold t_1
   III. Threshold t_2

2. Schema-dependent

Part 4:

Blocking Methods for Web Data

Characteristics of Web Data

Voluminous, (semi-)structured datasets.

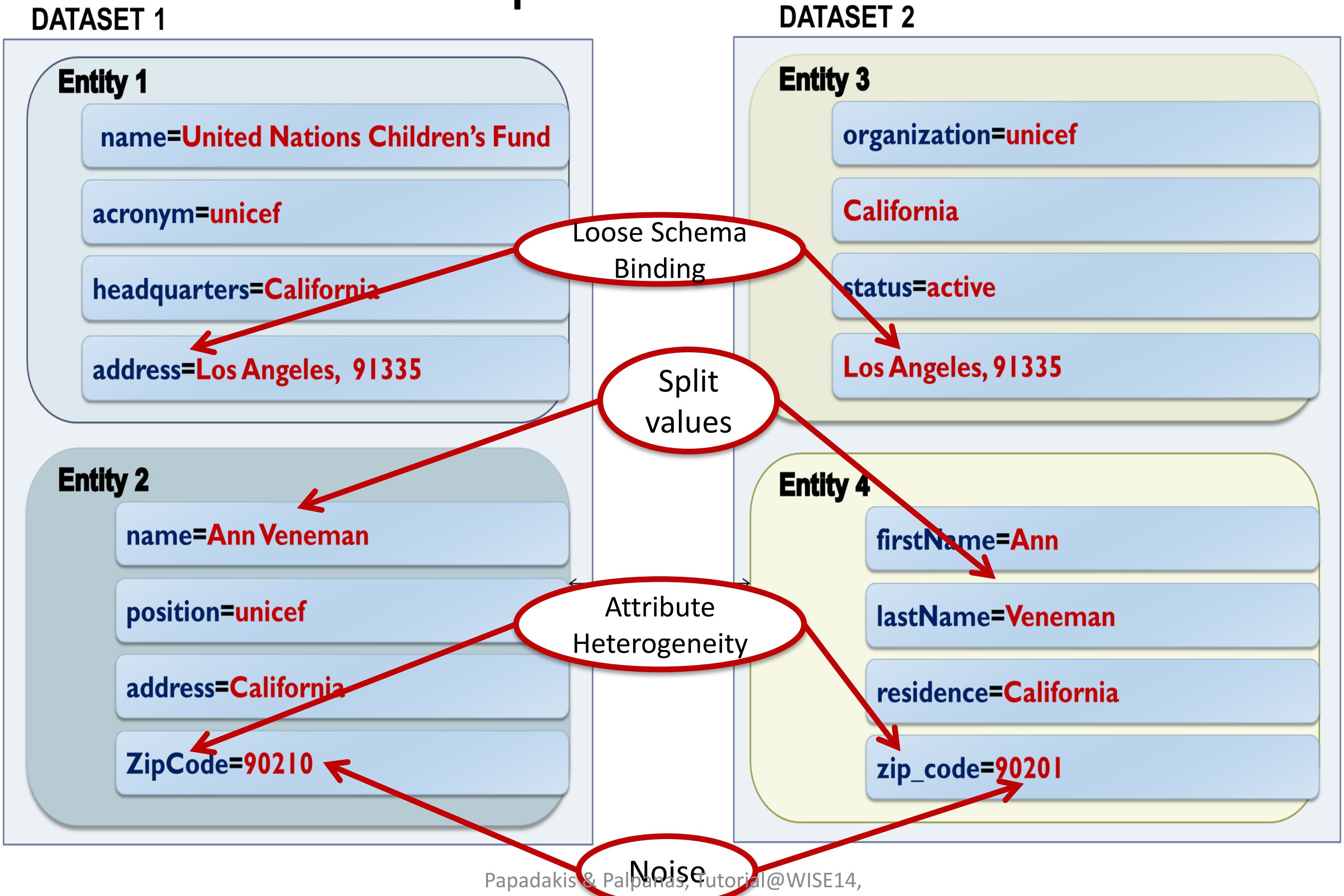
- DBPedia 3.4: 36.5 million triples and 2.1 million entities
- BTC09: 1.15 billion triples, 182 million entities.

Users are free to insert not only attribute values but also attribute names → high levels of heterogeneity.

- DBPedia 3.4: 50,000 attribute names
- Google Base:100,000 schemata for 10,000 entity types
- BTC09: 136K attribute names

Large portion of data originating from automatic information extraction techniques → noise, tag-style values.

Example of Web Data



Token Blocking [Papadakis et al., WSDM2011]

Functionality:

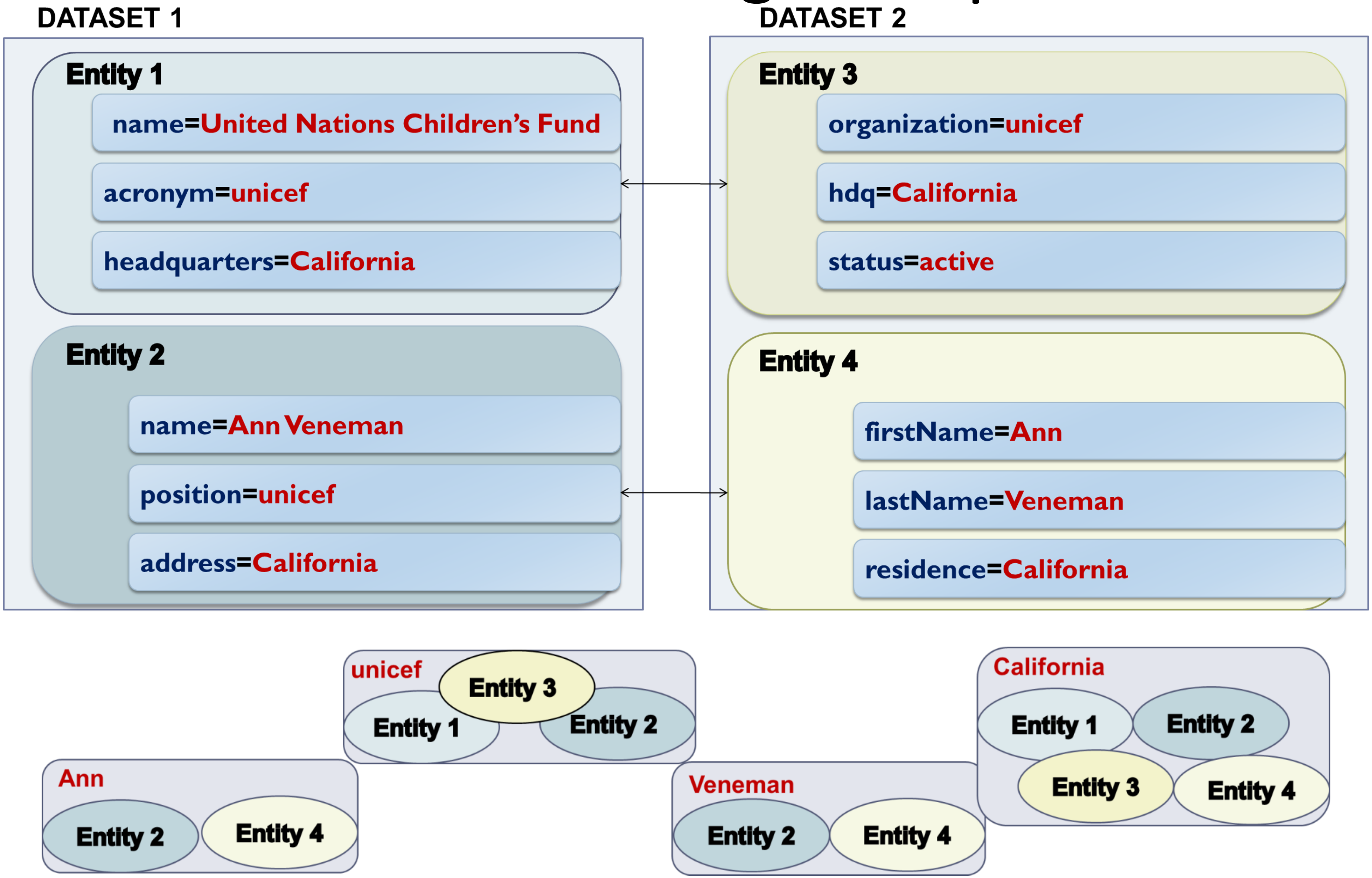
1. given an entity profile, it extracts all tokens that are contained in its attribute values.
2. creates one block for every distinct token → each block contains all entities with the corresponding token*.

Attribute-agnostic blocking scheme:

- completely ignores attribute names
- considers all attribute values
- redundancy-positive blocks
- parameter-free!

**Each block should contain at least two entities.*

Token Blocking Example



Attribute-Clustering Blocking [Papadakis et. al., TKDE2013]

Goal:

group attribute names into clusters s.t. we can apply Token Blocking independently inside each cluster, without affecting effectiveness → smaller blocks, higher efficiency.

Algorithm:

- Create a graph with a node for every attribute name
- For each attribute name n_i
  - Find the most similar n_j
  - If $sim(n_i,n_j) > 0$, add an edge $<n_i,n_j>$
- Extract connected components
- Put all singleton nodes in a “glue” cluster

Attribute-Clustering Blocking [Papadakis et. al., TKDE2013]

Parameters:

1. Representation model
   – Character n-grams, Character n-gram graphs, Tokens
2. Similarity Metric
   – Jaccard, Graph Value Similarity, TF-IDF

Similar to Schema Matching, but fundamentally different:

1. Associated attribute names do not have to be semantically equivalent. They only have to produce good blocks.
2. All singleton attributes are associated with each other.
3. Unlike Schema Matching, it scales to the extreme levels of heterogeneity of Web Data.

Evidence for Semantic Web Blocking

For Semantic Web data, three sources of evidence create blocks of lower redundancy than Token Blocking:

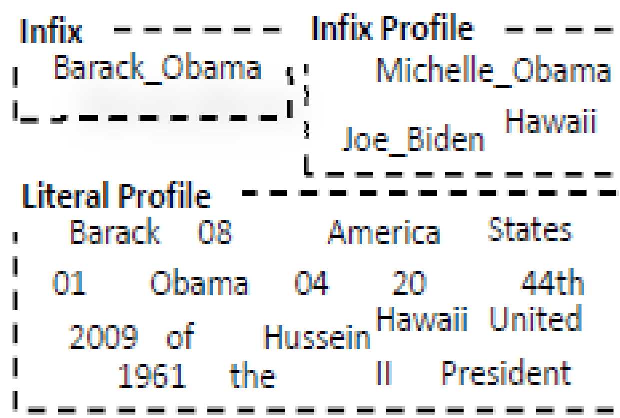
1. Infix [Papadakis et al., iiWAS 2010]

Prefix	Infix	Suffix
http://dblp.l3s.de/d2r/resource/publications/books/sp/wooldridgeV99	/ThalmannN99	
http://bibsonomy.org/uri/bibtexkey/books/sp/wooldridgeV99	/ThalmannN99	/dblp

2. Infix Profile

3. Literal Profile

URL:	**<http://dbpedia.org/resource/Barack_Obama>**
birthname:	"Barack Hussein Obama II"
dateOfBirth:	"1961-08-04"
birthPlace:	"Hawaii" <http://dbpedia.org/resource/Hawaii>
shortDescription:	"44th President of the United States of America"
spouse:	<http://dbpedia.org/resource/Michelle_Obama>
Vicepresident:	<http://dbpedia.org/resource/Joe_Biden>



URI Semantics Blocking [Papadakis et al., WSDM2012]

The above sources of evidence lead to 3 parameter-free blocking methods:

1. **Infix Blocking**
   every block contains all entities whose URI has a specific Infix
2. **Infix Profile Blocking**
   every block corresponds to a specific Infix (of an attribute value) and contains all entities having it in their Infix Profile
3. **Literal Profile Blocking**
   every block corresponds to a specific token and contains all entities having it in their Literal Profile

Individually, these atomic methods have limited coverage and, thus, low effectiveness (e.g., Infix Blocking does not cover blank nodes). However, they are complementary and can be combined into composite blocking methods for higher robustness and effectiveness.

Summary of Blocking for Web Data

attribute-agnostic functionality → no *schema semantics* so as to handle any level of heterogeneity

redundancy to reduce the likelihood of missed matches → high recall

redundancy-positive blocks

Drawbacks:

- the blocks are overlapping (i.e., repeated comparisons)
- high number of comparisons between irrelevant entities → low precision

Part 5:

Meta-blocking

Meta-blocking [Papadakis et. al., TKDE]

Goal:

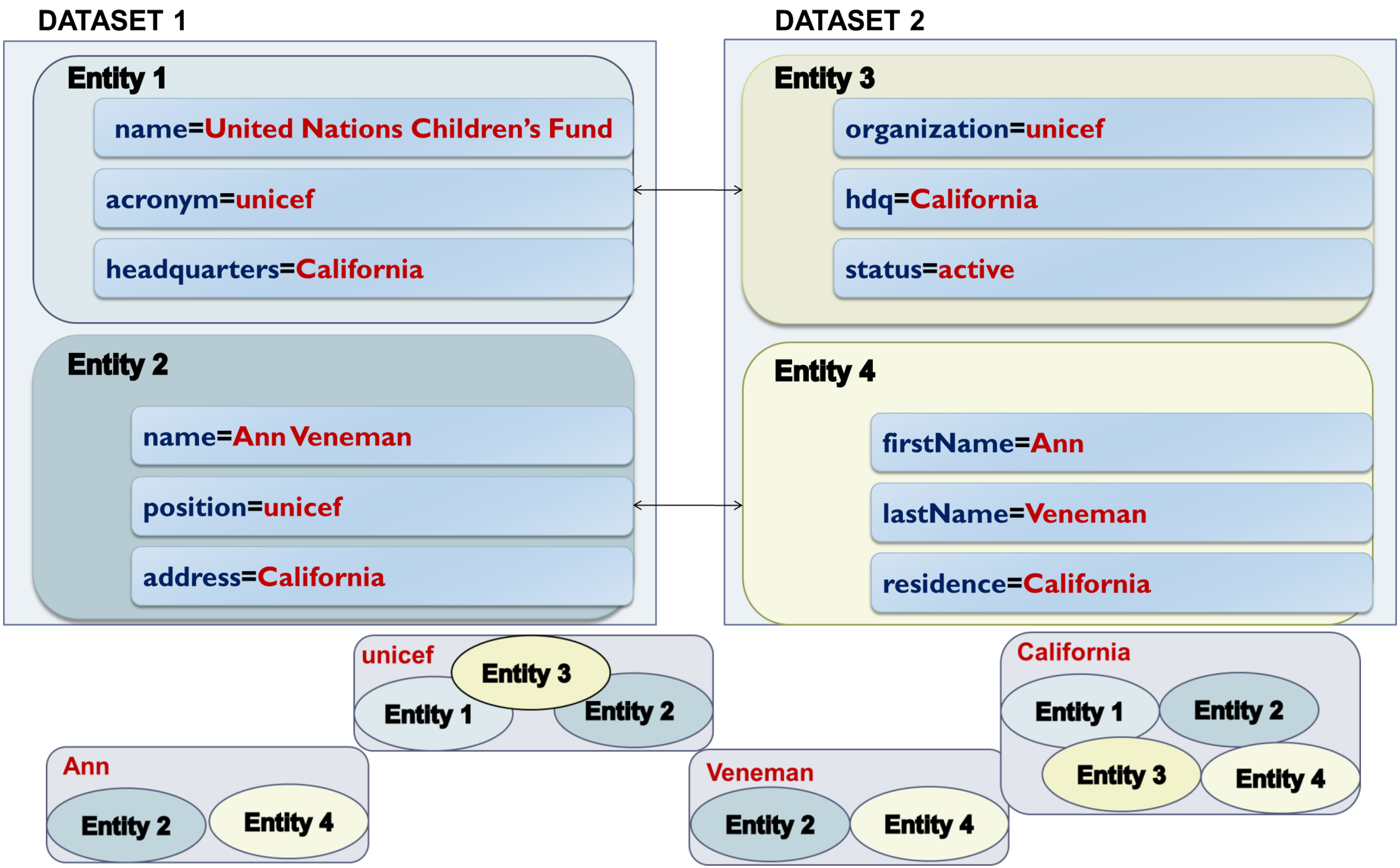
restructure a **redundancy-positive** block collection into a new one that contains a substantially lower number of comparisons, while being equally effective ($\Delta PC \approx 0$, $\Delta PQ \gg 0$).

Type of pair-wise comparisons

Every comparison between entity profiles p_i and p_j belongs to one of the following types:

1. **Matching** if $p_i \equiv p_j$.
2. **Redundant** if p_i and p_j co-occur and will be compared in another block.
3. **Superfluous** if p_i or p_j or both of them have been matched to some other entity (Clean-Clean ER).
4. **Non-matching** if $p_i \neq p_j$ and the comparison is not redundant (for Dirty ER). For Clean-Clean ER, it should not be superfluous either.

Token Blocking Example



Meta-blocking [Papadakis et. al., TKDE]

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restructure a **redundancy-positive** block collection into a new one that contains substantially lower number of redundant and non-matching comparisons, while maintaining the original number of matching ones ($\Delta PC \approx 0$, $\Delta PQ \gg 0$).

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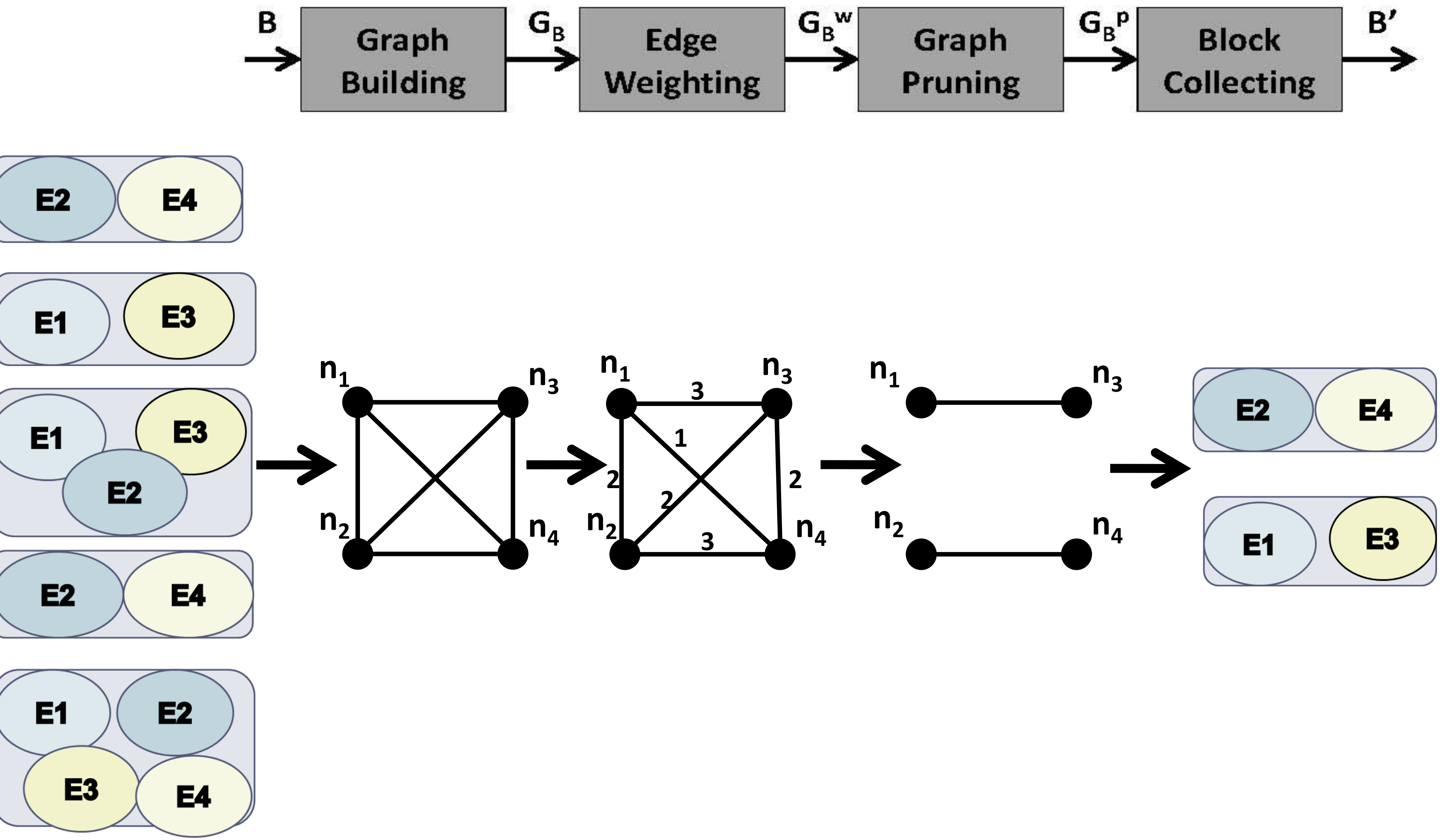
Goal:

restructure a **redundancy-positive** block collection into a new one that contains substantially lower number of redundant and non-matching comparisons, while maintaining the original number of matching ones ($\Delta PC \approx 0$, $\Delta PQ \gg 0$).

Main idea:

common blocks provide valuable evidence for the similarity of entities → the more blocks two entities share, the more similar and the more likely they are to be matching

Outline of Meta-blocking



Graph Building

For every block:

- for every entity → add a node
- for every pair of co-occurring entities → add an undirected edge

Blocking graph:

- It eliminates all redundant comparisons → no parallel edges.
- Low materialization cost → implicit materialization through inverted indices or bit arrays.

Edge Weighting

Five generic, attribute-agnostic weighting schemes that rely on the following evidence:

- the number of blocks shared by two entities
- the size of the common blocks
- the number of blocks or comparisons involving each entity.

Computational Cost:

- In theory, equal to executing all pair-wise comparisons in the given block collection.
- In practice, significantly lower because it does not employ string similarity metrics.

Weighting Schemes

1. Aggregate Reciprocal Comparisons Scheme (ARCS)

$$w_{ij} = \sum_{b_k \in B_{ij}} \frac{1}{||b_k||}$$

2. Common Blocks Scheme (CBS)

$$w_{ij} = |B_{ij}|$$

3. Enhanced Common Blocks Scheme (ECBS)

$$w_{ij} = |B_{ij}| \cdot \log \frac{|B|}{|B_i|} \cdot \log \frac{|B|}{|B_j|}$$

4. Jaccard Scheme (JS)

$$w_{ij} = \frac{|B_{ij}|}{|B_i| + |B_j| - |B_{ij}|}$$

5. Enhanced Jaccard Scheme (EJS)

$$w_{ij} = \frac{|B_{ij}|}{|B_i| + |B_j| - |B_{ij}|} \cdot \log \frac{|V_G|}{|v_i|} \cdot \log \frac{|V_G|}{|v_j|}$$

Graph Pruning

Pruning algorithms

1. Edge-centric
2. Node-centric

   they produce directed blocking graphs

Pruning criteria

Scope:

1. Global
2. Local

Functionality:

1. Weight thresholds
2. Cardinality thresholds

Edge-centric

scope \ functionality	weight	cardinality
global	WEP	CEP
local	x	x

(a)

Node-centric

scope \ functionality	weight	cardinality
global	x	CNP
local	WNP	CNP

(b)

Thresholds for Graph Pruning

Experiments show robust behavior of the following configurations:

1. **Weighted Edge Pruning** (WEP)
   threshold: average weight across all edges
2. **Cardinality Edge Pruning** (CEP)
   threshold: $K = BPE \cdot |E|/2$
3. **Weighted Node Pruning** (WNP)
   threshold: for each node, the average weight of the adjacent edges
4. **Cardinality Node Pruning** (CNP)
   threshold: for each node, $k=BPE-1$

Block Collecting

Transform the pruned blocking graph into a new block collection.

For undirected blocking graphs:

every retained edge creates a block of minimum size

For directed blocking graphs:

for every node (with retained *outgoing* edges), we create a new block containing the corresponding entities

Part 6:

Block Processing Techniques

General Principles

Goals:

1. eliminate repeated comparisons,
2. discard superfluous comparisons,
3. avoid non-matching comparisons.

without affecting matching comparisons (i.e., effectiveness).

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Taxonomy of techniques:

Comparison's Type

Granularity	Repeat Method	Superfluity Method	Non-match method	Scheduling method
Block-refinement	-	-	1. Block Purging 2. Block Pruning	Block Scheduling
Comparison-refinement	Comparison Propagation	Duplicate Propagation	Comparison Pruning	Comparison Scheduling

Block Purging [Papadakis et al., WSDM2011] & [Papadakis et al., WSDM2012]

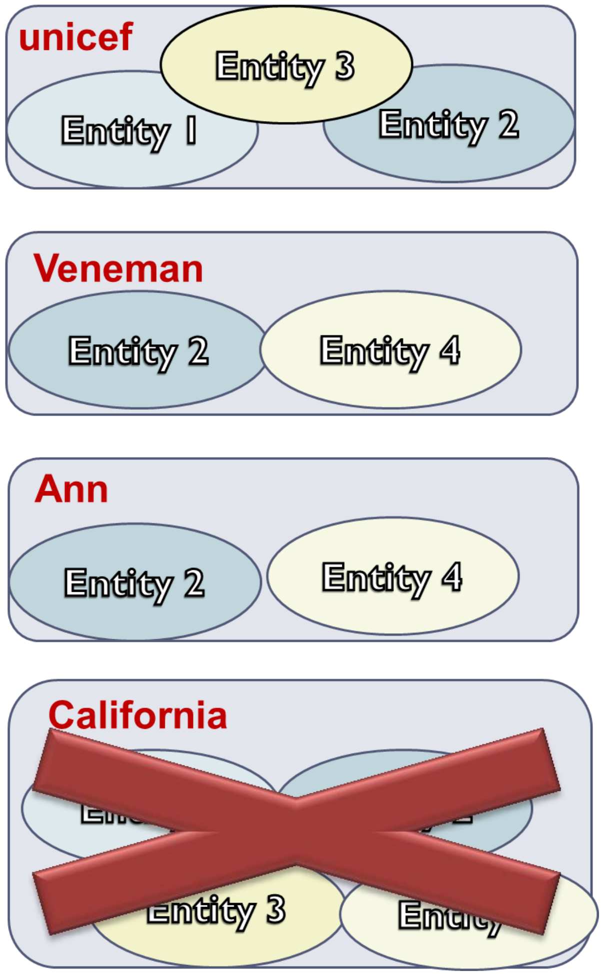
Oversized blocks: many, unnecessary comparisons (redundant, non-matching, superfluous).

Block Purging: discards oversized blocks by setting an upper limit on:

- the size of each block [Papadakis et al., WSDM 2011],
- the cardinality of each block [Papadakis et al., WSDM 2012]

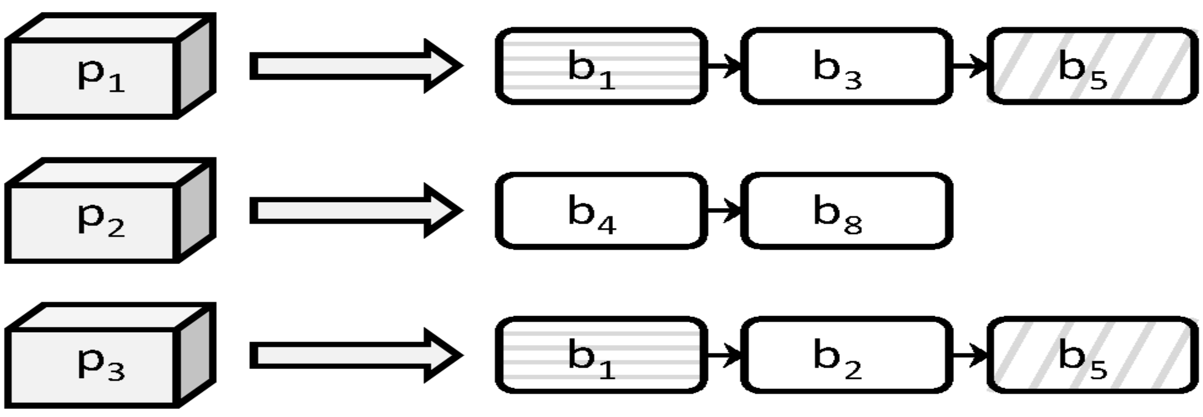
Core method:

- Low computational cost.
- Low impact on effectiveness.
- Boosts efficiency to a large extent.



Comparison Propagation [Papadakis et al., SWIM 2011]

- Eliminates all redundant comparisons at no cost in recall → naïve approach does not scale
- Enumerates Blocks
- Least Common Block Index condition.



Part 7:

ER Framework

ER-Framework

- Offers a suite of blocking methods for benchmarking.
- Code in Java (Netbeans project) available at: http://sourceforge.net/projects/erframework .
- Continuous updates.
- Plan to add GUI, documentation and more methods by the end of 2015.
- Established real-world and synthetic datasets available.

Home / DirtyERDatasets / Profiles

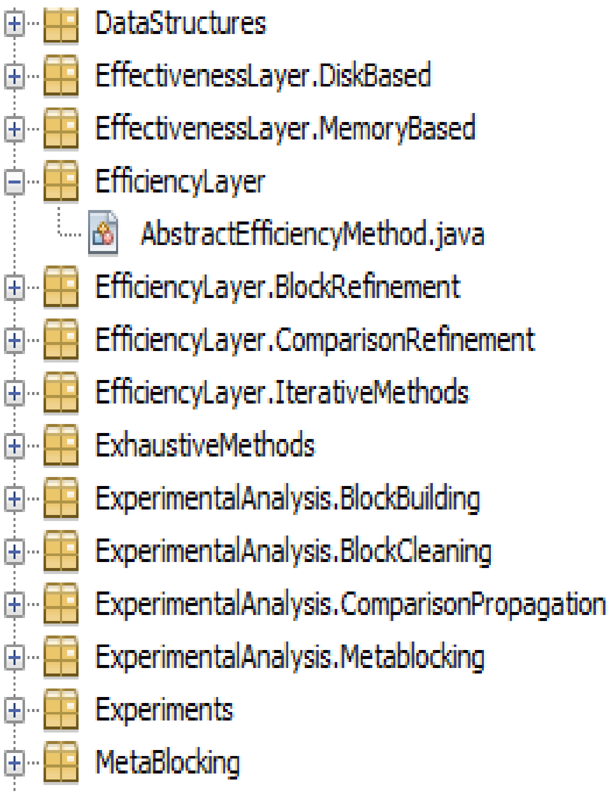
Name ≑	Modified ≑	Size ≑
Parent folder		
300Kprofiles	2014-07-01	77.1 MB
200Kprofiles	2014-07-01	51.3 MB
100Kprofiles	2014-07-01	25.6 MB
10Kprofiles	2014-07-01	2.6 MB
50Kprofiles	2014-07-01	12.8 MB
2Mprofiles	2014-07-01	515.5 MB
1Mprofiles	2014-07-01	257.4 MB
Totals: 7 Items		942.3 MB

Home / CleanCleanERDatasets

Name ≑	Modified ≑
Parent folder	
MoviesUpdated	2014-07-01
AmazonGoogleProducts	2014-07-01
DblpAcm	2014-07-01
DblpGoogleScholar	2014-07-01
AbtBuy	2014-07-01
Totals: 5 Items	

Structure of the ER-Framework

- Effectiveness Layer
  - Disk-based Methods
  - Memory-based Methods
- Efficiency Layer
  - Block-refinement
  - Comparison-refinement
  - Meta-blocking
- Utilities, Data Structures,…



Effectiveness Layer

- Common interface for all methods imposed by AbstractBlockingMethod.
  - Input: dataset 1, dataset 2 (null for Dirty ER) in the form of List<EntityProfile> and parameters, depending on the approach
  - Output: block collection of the form List<AbstractBlock> returned by buildBlocks().
    - It contains objects of type UnilateralBlock for Dirty ER and of type BilateralBlock for Clean-Clean ER.
- Disk-based methods: first store blocks as a Lucene index on a specified directory.

Efficiency Layer

Common interface for all methods imposed by AbstractEfficiencyMethod.

- Input: a block collection of the form List<AbstractBlock>.
- Output: changes to the elements of the input block collection.
- Functionality implemented by applyProcessing().

Measuring Performance

Ground-truth of the form Set<IdDuplicates>, where *IdDuplicates* contains a pair of entity ids.

Class BlockStatistics measures the performance of a block collection wrt:

– PC, PQ, $||B||$, $|D_B|$, BC, CC.

Thank You!

References – Part A

[Aizawa et. al., WIRI 2005] Akiko N. Aizawa, Keizo Oyama, "A Fast Linkage Detection Scheme for Multi-Source Information Integration" in WIRI, 2005.

[Baxter et. al., KDD 2003] R. Baxter, P. Christen, T. Churches, “A comparison of fast blocking methods for record linkage”, in Workshop on Data Cleaning, Record Linkage and Object Consolidation at KDD, 2003.

[Bilenko et. al., ICDM 2006] M. Bilenko, B. Kamath, R. Mooney, “Adaptive blocking: Learning to scale up record linkage”, in ICDM, 2006.

[Christen, TKDE 2011] P. Christen, " A survey of indexing techniques for scalable record linkage and deduplication.” in TKDE 2011.

[de Vries et. al., CIKM 2009] T. de Vries, H. Ke, S. Chawla, P. Christen, “Robust record linkage blocking using sux arrays”, in CIKM, 2009.

[Gravano et. al., VLDB 2001] L. Gravano, P. Ipeirotis, H. Jagadish, N. Koudas, S. Muthukrishnan, D. Srivastava, “Approximate string joins in a database (almost) for free’, in VLDB, 2001.

[Hernandez et. al., SIGMOD 1995] M. Hernandez, S. Stolfo, “The merge/purge problem for large databases”, in SIGMOD, 1995.

References – Part B

[Jin et. al., DASFAA 2003] L. Jin, C. Li, S. Mehrotra, "Efficient record linkage in large data sets", in DASFAA, 2003.

[Kim et. al., EDBT 2010] H. Kim, D. Lee, "HARRA: fast iterative hashed record linkage for large-scale data collections", in EDBT, 2010.

[Madhavan et. al., CIDR 2007] J. Madhavan, S. Cohen, X. Dong, A. Halevy, S. Jeffery, D. Ko, C. Yu, "Web-scale data integration: You can afford to pay as you go", in CIDR, 2007

[McCallum et. al., KDD 2000] A. McCallum, K. Nigam, L. Ungar, "Efficient clustering of high-dimensional data sets with application to reference matching", in KDD, 2000.

[Michelson et. al., AAAI 2006] M. Michelson, C. Knoblock, "Learning blocking schemes for record linkage", in AAAI, 2006.

[Papadakis et al., iiWAS 2010] G. Papadakis, G. Demartini, P. Fankhauser, P. Karger, "The missing links: discovering hidden same-as links among a billion of triples", in iiWAS 2010.

[Papadakis et al., WSDM 2011] G. Papadakis, E. Ioannou, C. Niederee, P. Fankhauser, "Efficient entity resolution for large heterogeneous information spaces", in WSDM 2011.

References – Part C

[Papadakis et al., JCDL 2011] G. Papadakis, E. Ioannou, C. Niederee, T. Palpanas, W. Nejdl, "Eliminating the redundancy in blocking-based entity resolution methods", in JCDL 2011.

[Papadakis et al., SWIM 2011] G. Papadakis, E. Ioannou, C. Niederee, T. Palpanas, W. Nejdl, "To Compare or Not to Compare: making Entity Resolution more Efficient", in SWIM workshop (collocated with SIGMOD), 2011.

[Papadakis et al., WSDM 2012] G. Papadakis, E. Ioannou, C. Niederee, T. Palpanas, W. Nejdl, "Beyond 100 million entities: large-scale blocking-based resolution for heterogeneous data", in WSDM 2012.

[Papadakis et. al., TKDE2013] George Papadakis, Ekaterini Ioannou, Themis Palpanas, Claudia Niederee, Wolfgang Nejdl, "A Blocking Framework for Entity Resolution in Highly Heterogeneous Information Spaces", in IEEE TKDE (to appear).

[Papadakis et. al., TKDE2014] George Papadakis, Georgia Koutrika, Themis Palpanas, Wolfgang Nejdl, "Meta-Blocking: Taking Entity Resolution to the Next Level", in IEEE TKDE (currently under revision).

[Yan et. Al., JCDL 2007] Su Yan, Dongwon Lee, Min-Yen Kan, C. Lee Giles, "Adaptive sorted neighborhood methods for efficient record linkage", in JCDL 2007.