Blocking for BIG Data Integration

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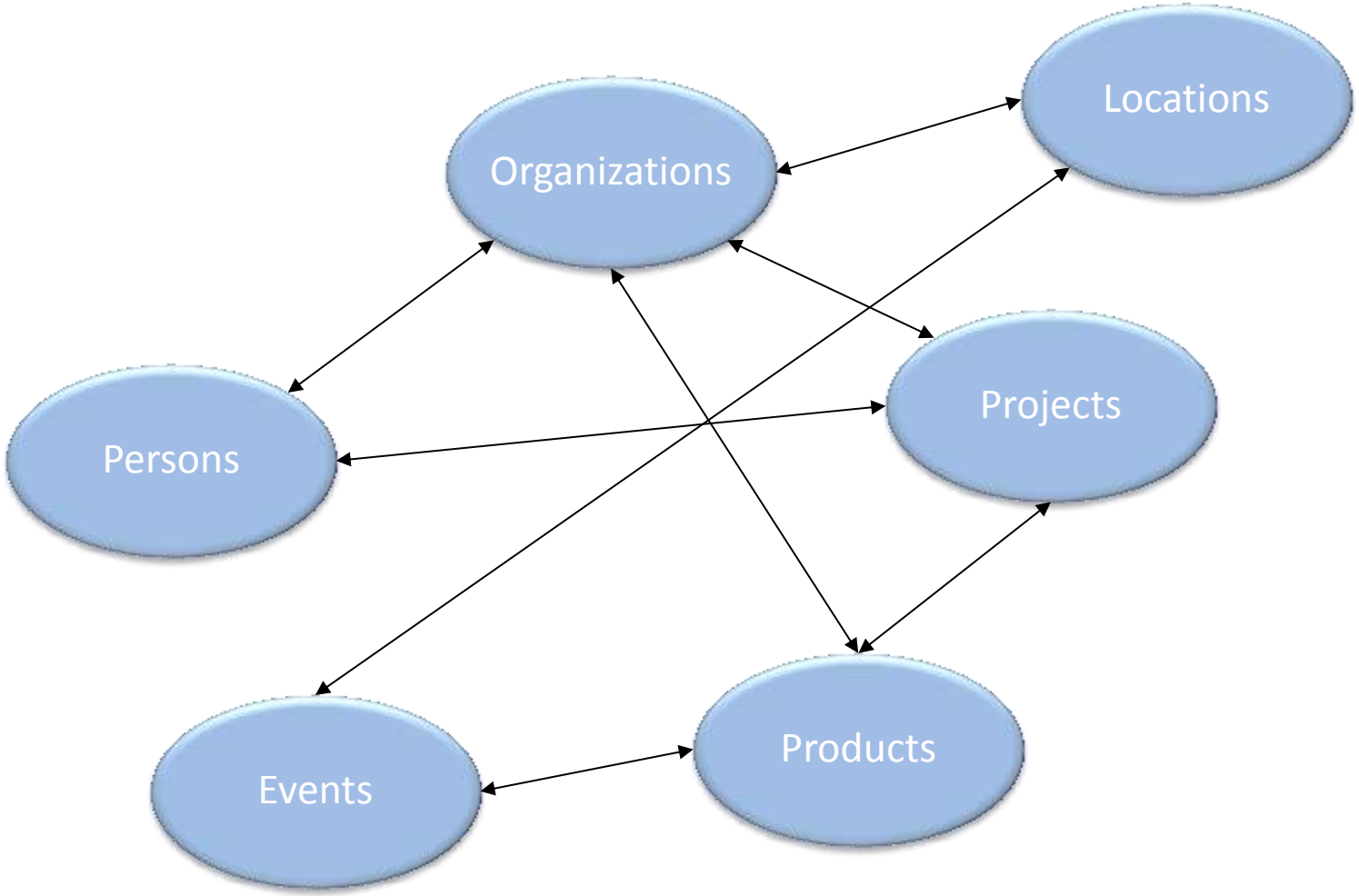
Entities: an invaluable asset

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



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How many names, descriptions or IDs (URIs) are used for the same real-world "entity"?

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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
- …

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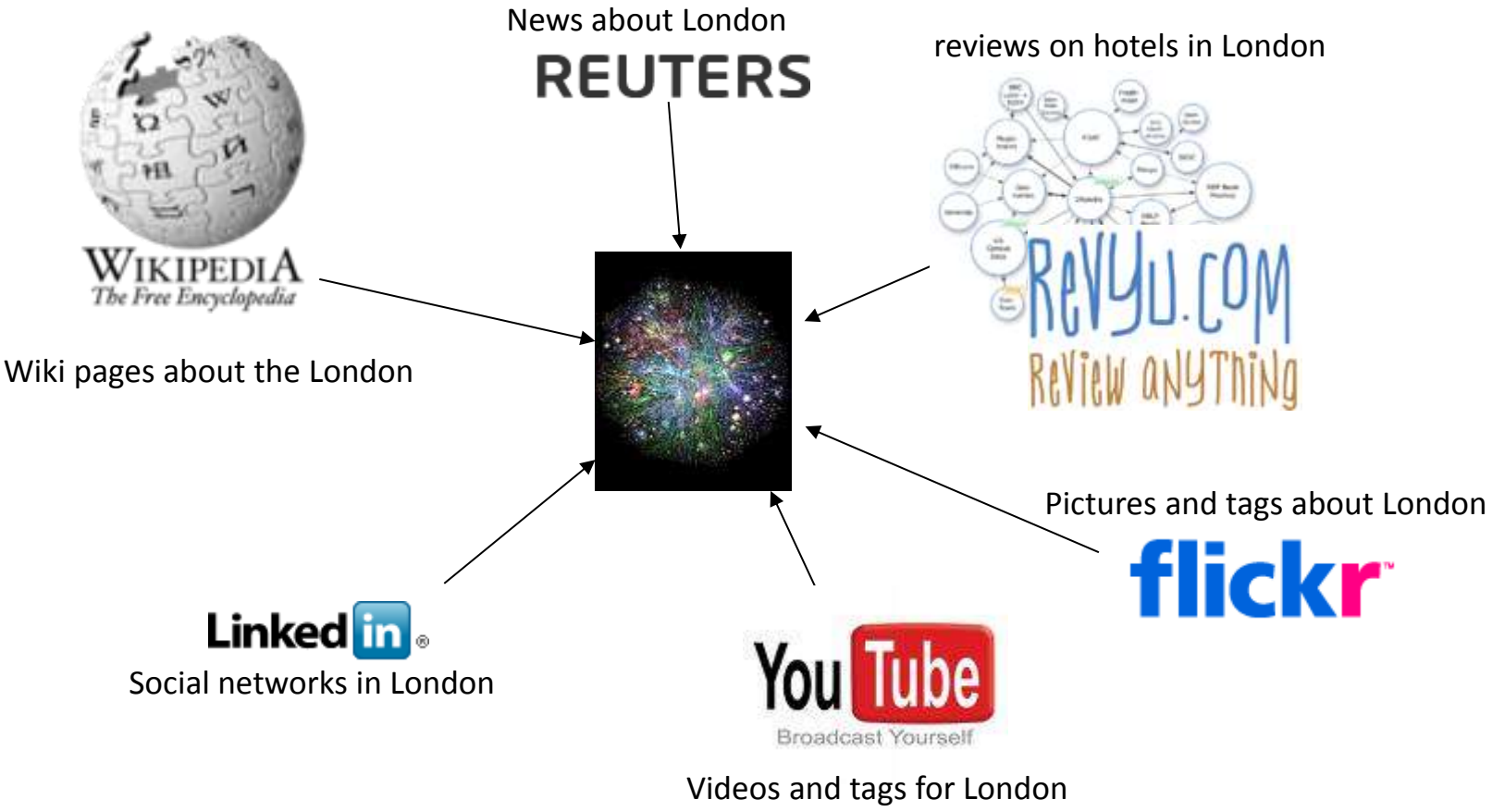
- London, Deerfield, WI
- London, Deerfield, Dane, WI
- London, Uninc Freeborn County, MN
- ...

- 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, TKDE 2011]:

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

Useful because:

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

Application areas:

Linked Data, Social Networks, census data,

price comparison portals, fact-checking, …

Types of Entity Resolution

The input of ER consists of entity collections that can be of two types [Christen, TKDE 2011]:

- 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

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  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 well to large entity collections (e.g., Web Data).

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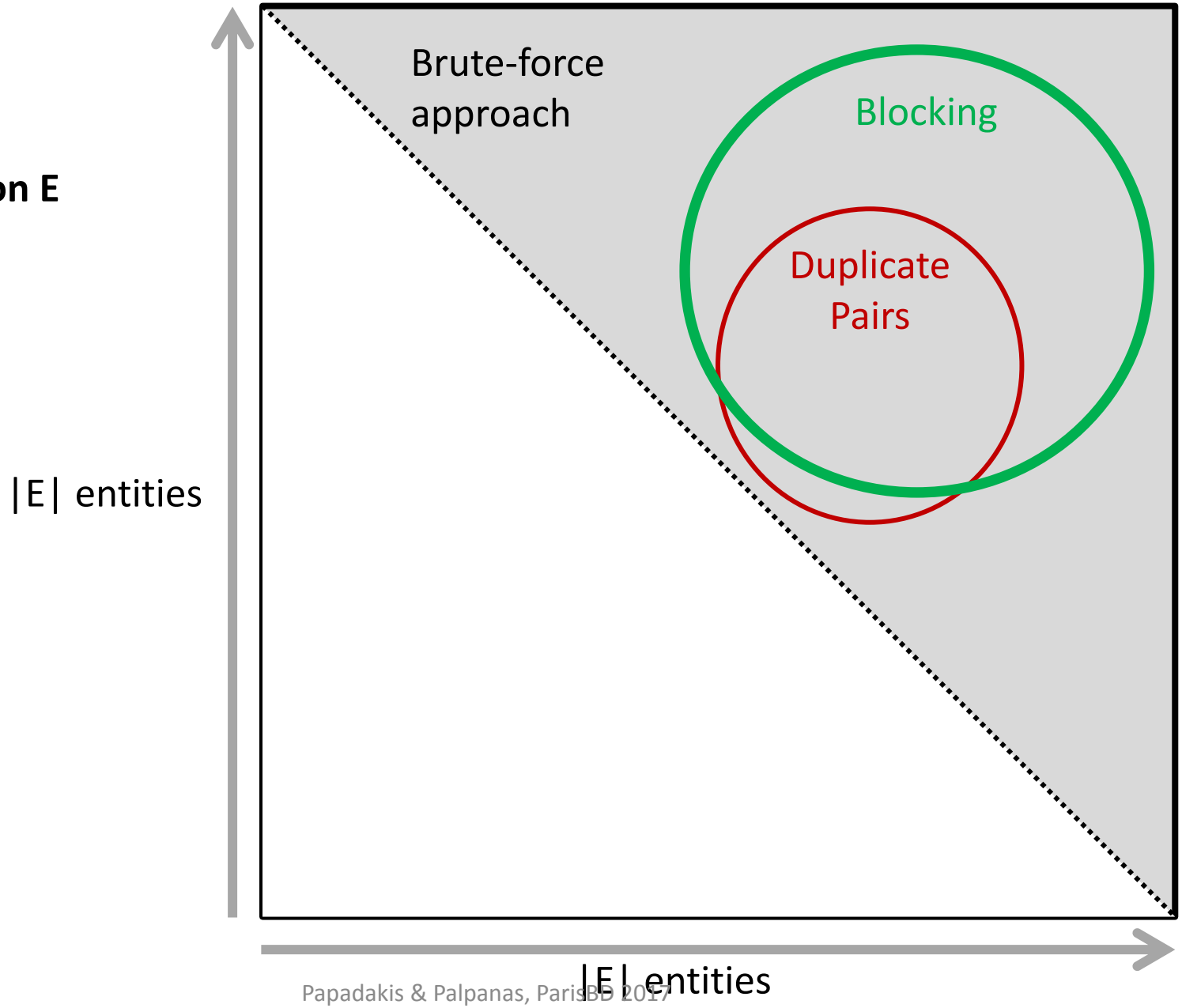
Solution: Blocking

- group similar entities into blocks
- execute comparisons only inside each block
  - complexity is now quadratic to the size of the block (much smaller than dataset size!)

Computational cost

Input:
Entity Collection E



Example of Computational cost

DBPedia 3.0rc ↔ DBPedia 3.4

1.2 million entities ↔ 2.2 million entities

Entity matching: Jaccard similarity of all tokens
Cost per comparison: 0.045 milliseconds (average of 0.1 billion comparisons)

Brute-force approach

Comparisons: $2.58 \cdot 10^{12}$
Recall: 100%
Running time: 1,344 days → **3.7 years**

Outline

1. Introduction to Blocking
2. Blocking Methods for Relational Data
3. Blocking Methods for Web Data
4. Block Processing Techniques
5. Meta-blocking
6. Challenges
7. JedAI Toolkit
8. Conclusions

Part 1:

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 → **entity matching** is an orthogonal problem.

4. Focus on string values.

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 [Christen, TKDE 2011]:

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

- Pairs Quality: $PQ = \frac{detected\ matches}{executed\ comparisons}$ (pessimistic 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 *Pairs Completeness* (**PC**) and *Pairs Quality* (**PQ**) are maximized.

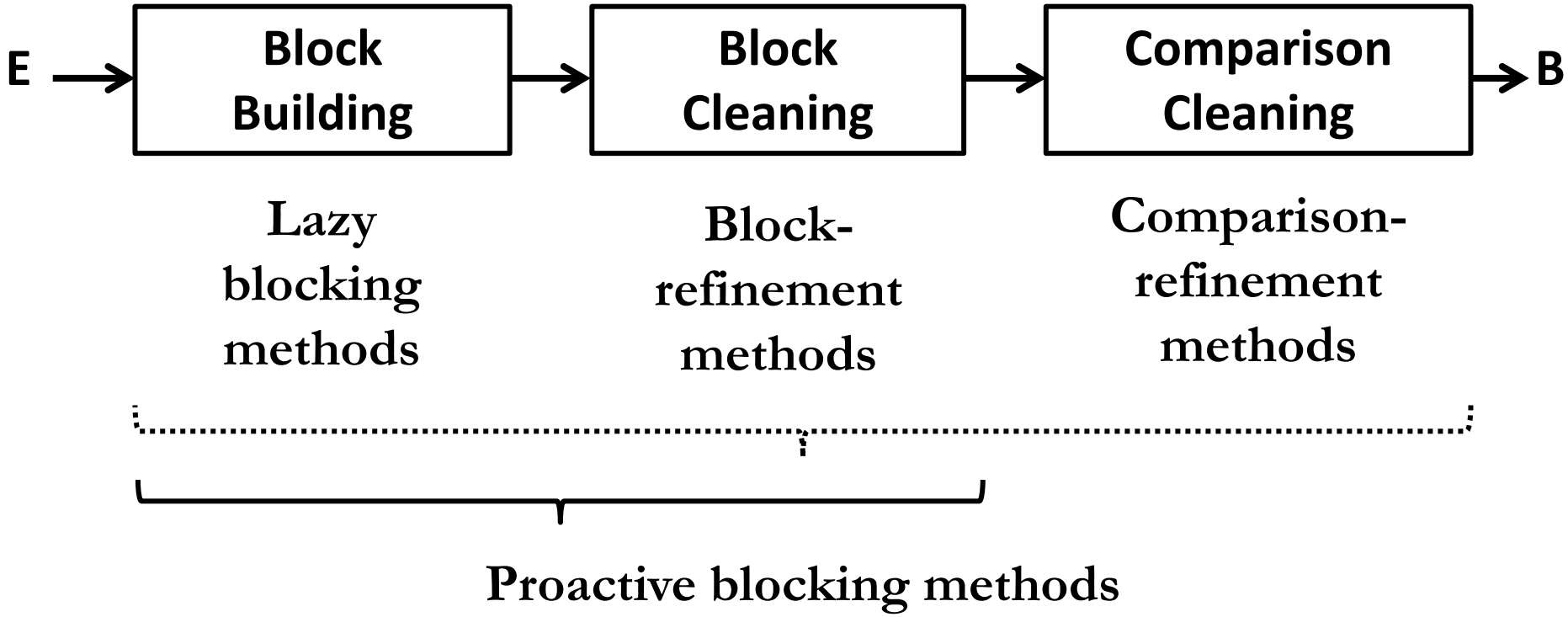
caution:

- Emphasis on Pairs Completeness (PC).
  - if two entities are matching then they should coincide at some block

Blocking Techniques Taxonomy

1. Performance-wise
   - Exact methods
   - Approximate methods
2. Functionality-wise
   - Supervised methods
   - Unsupervised methods
3. Blocks-wise
   - Disjoint blocks
   - Overlapping blocks
     - Redundancy-neutral
     - Redundancy-positive
     - Redundancy-negative
4. Signature-wise
   - Schema-based
   - Schema-agnostic

Blocking Workflow [Papadakis et. al., VLDB 2016]



Blocks- and Signature-wise Categorization of Block Building Methods

	Disjoint Blocks	**Overlapping Blocks**		
		Redundancy-negative	**Redundancy-neutral**	**Redundancy-positive**
Schema-based	Standard Blocking	(Extended) Canopy Clustering	1. (Extended) Sorted Neighborhood 2. MFIBlocks	1. (Extended) Q-grams Blocking 2. (Extended) Suffix Arrays
Schema-agnostic	-	-	-	1. Token Blocking 2. Agnostic Clustering 3. TYPiMatch 4. URI Semantics Blocking

Part 2:

Block Building for Relational Data

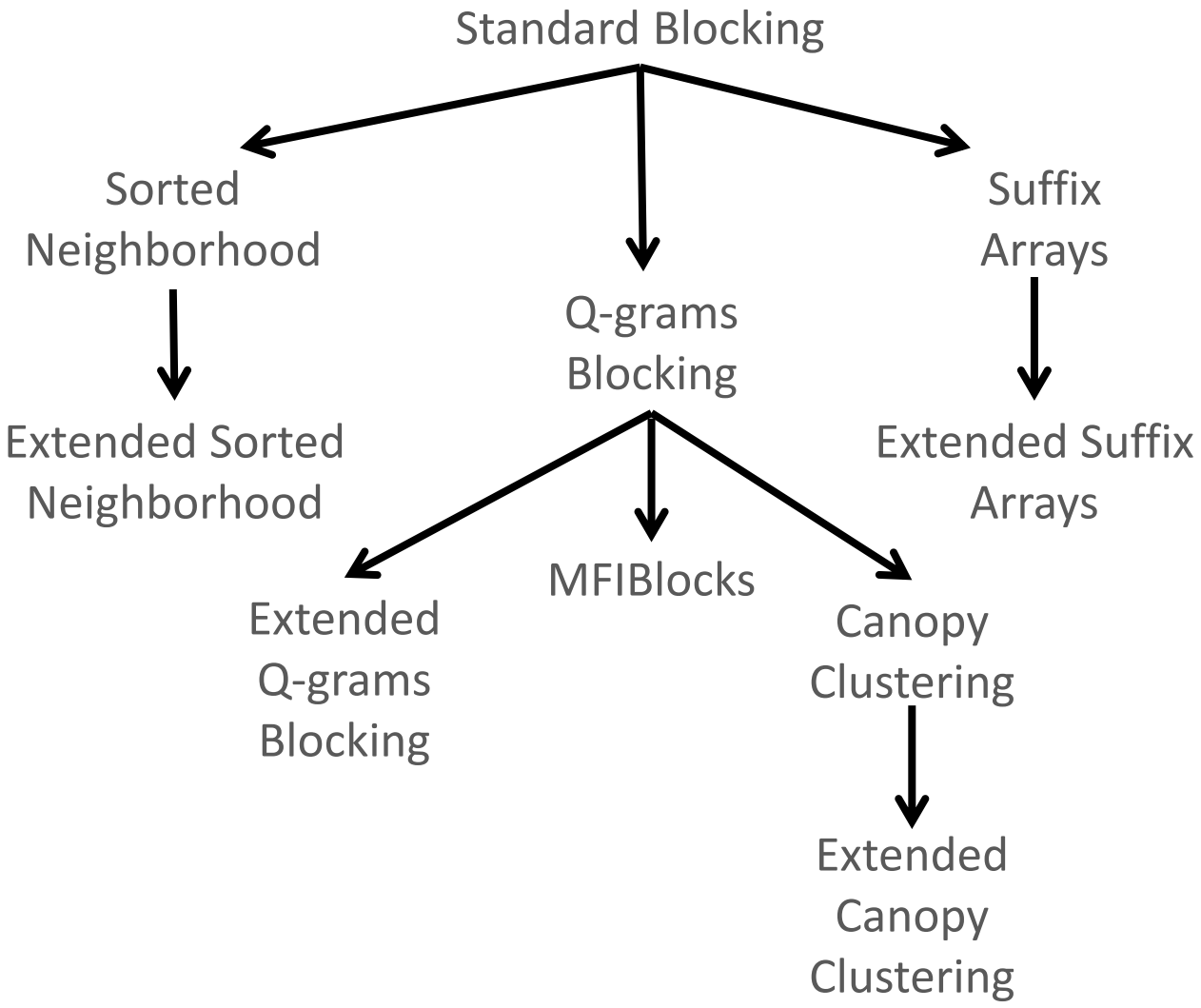
General Principles

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

Overview of Schema-based Methods



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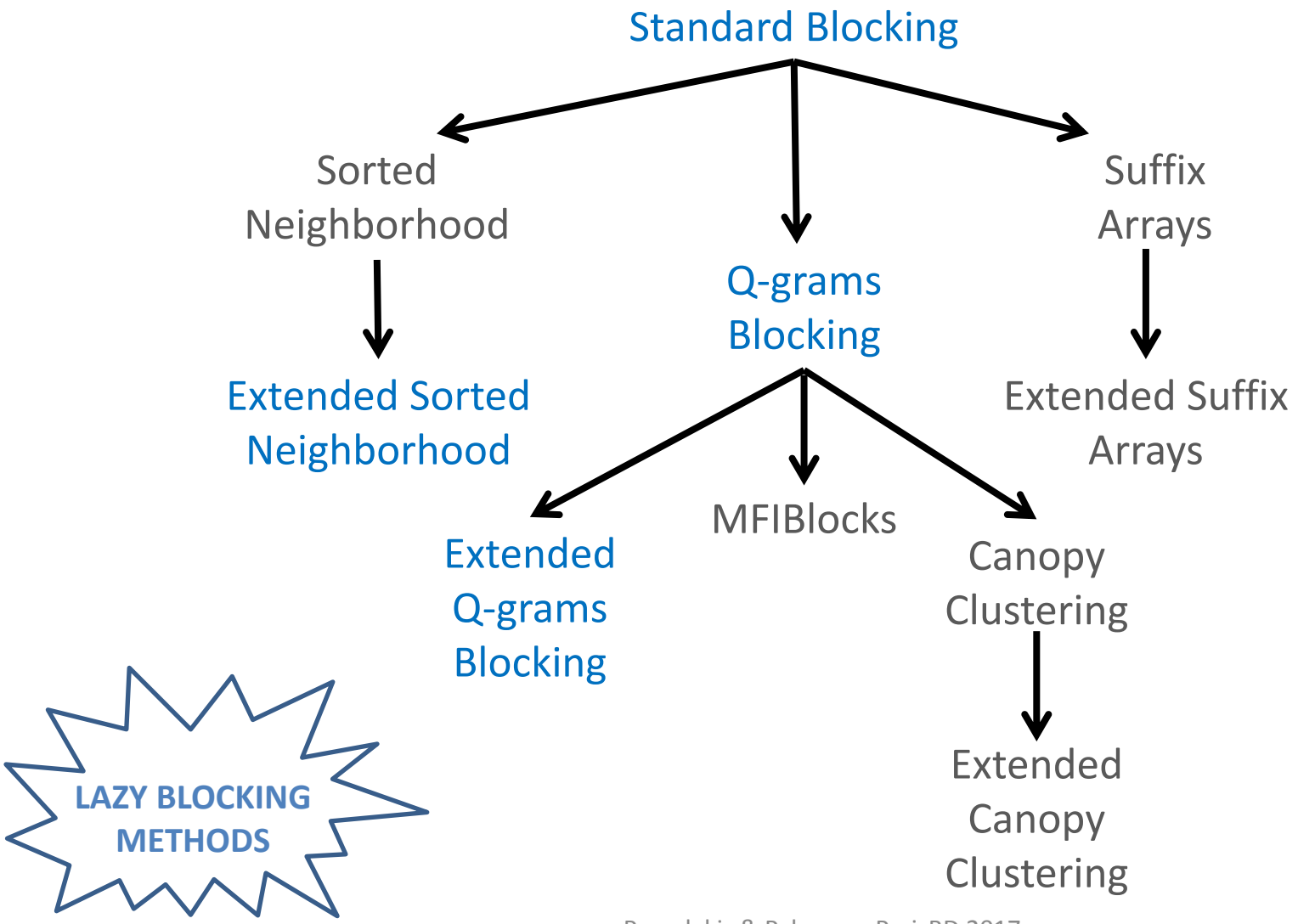

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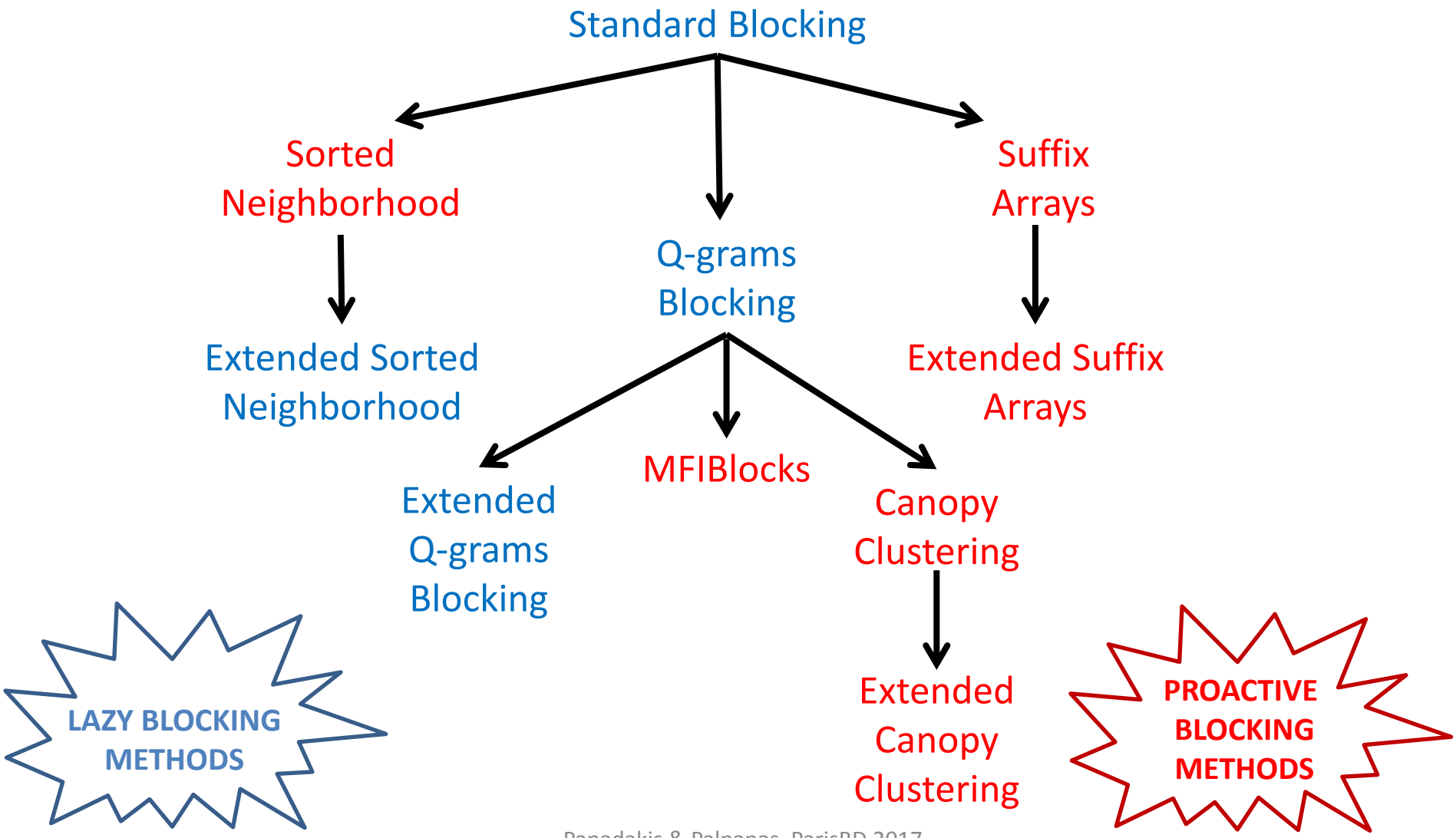

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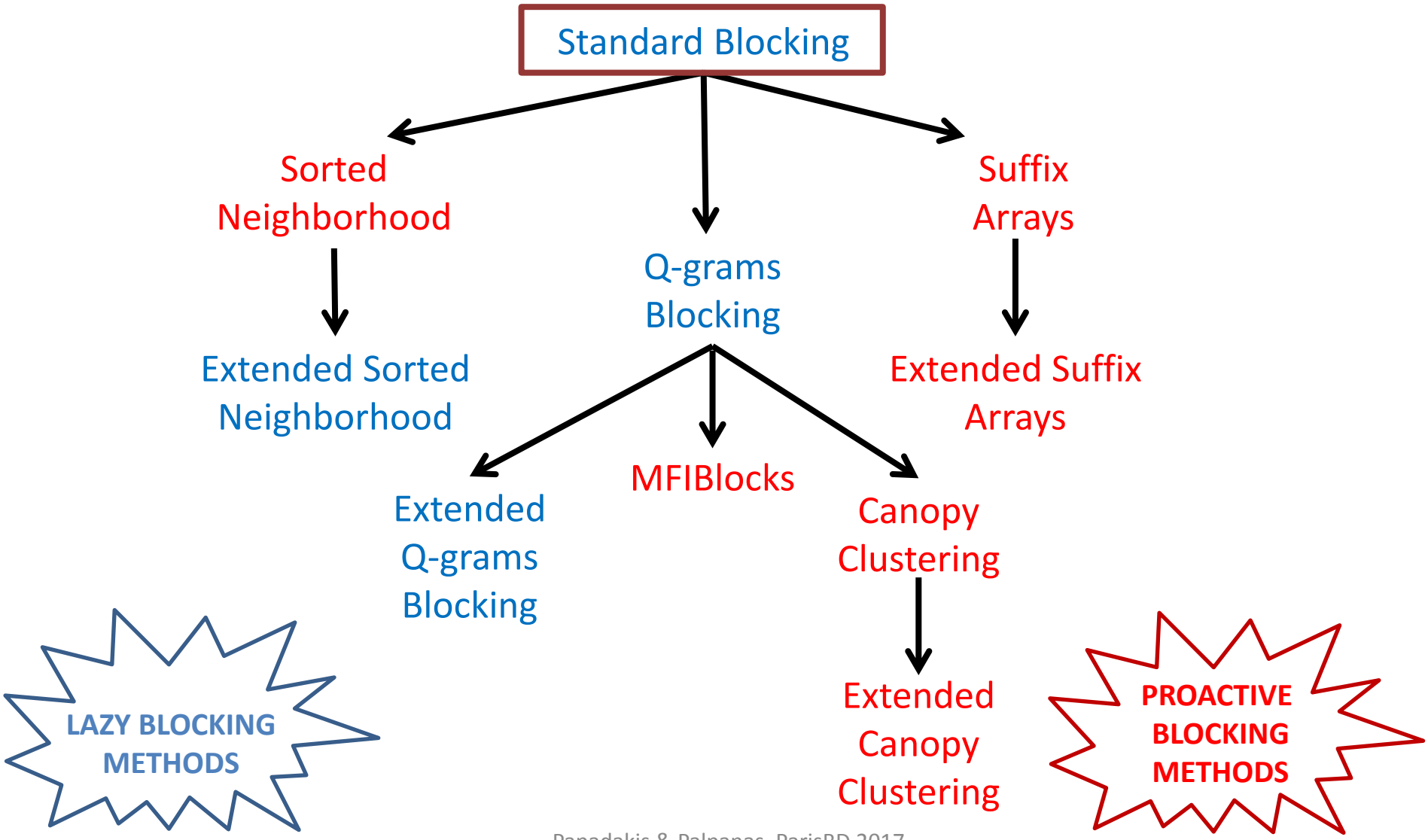


Standard Blocking [Fellegi et. al., JASS 1969]

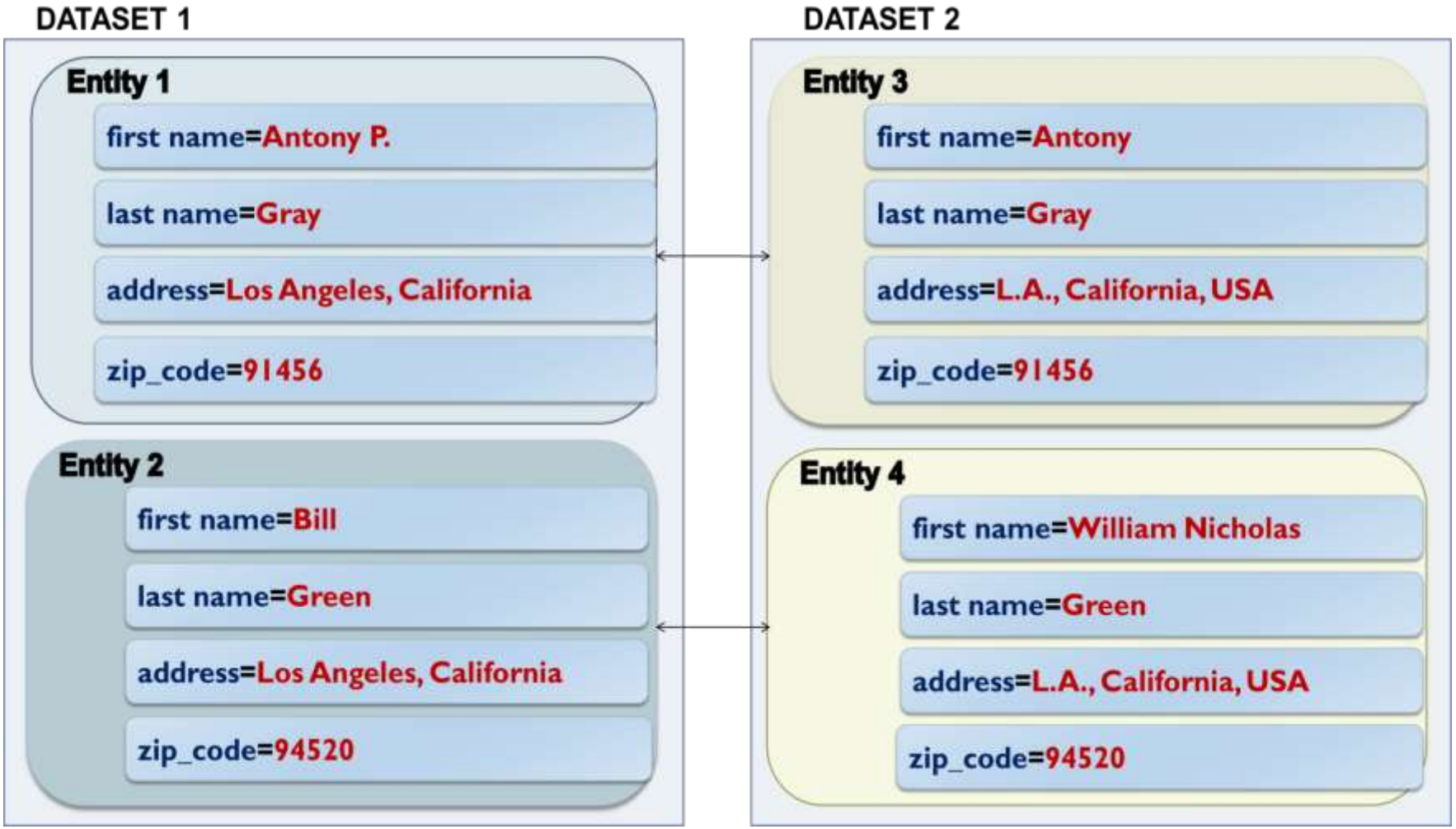
Earliest, simplest form of blocking.

Algorithm:

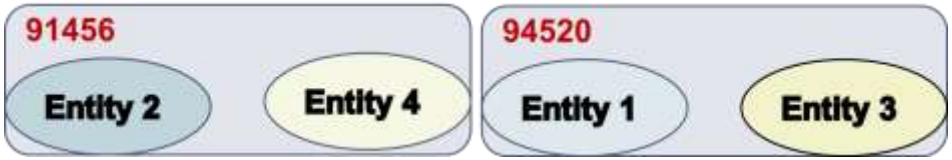
1. Select the most appropriate attribute name(s) w.r.t. noise and distinctiveness.
2. Transform the corresponding value(s) into a Blocking Key (BK)
3. For each BK, create one block that contains all entities having this BK in their transformation.

Works as a hash function! → Blocks on the **equality** of BKs

Example of Standard Blocking



Blocks on zip_code:



Summary of Blocking for Databases [Christen, TKDE2011]

1. They typically employ **redundancy** to ensure higher recall in the context of noise at the cost of lower precision (more comparisons). Still, recall remains low for many datasets.

2. Several parameters to be configured

   E.g., Canopy Clustering has the following parameters:

   I. String matching method

   II. Threshold t_1

   III. Threshold t_2

3. Schema-dependent → manual definition of BKs

Improving Blocking for Databases [Papadakis et. al., VLDB 2015]

Schema-agnostic blocking keys

- Use every token as a key
- Applies to all schema-based blocking methods
- Simplifies configuration, unsupervised approach

Performance evaluation

- For lazy blocking methods →
  very high, robust recall at the cost of more comparisons
- For proactive blocking methods →
  relative recall gets higher with more comparisons,
  absolute recall depends on block constraints

Part 3:

Block Building for Web Data

Characteristics of Web Data

Voluminous, (semi-)structured datasets.

- DBPedia 2014: 3 billion triples and 38 million entities
- BTC09: 1.15 billion triples, 182 million entities.

Users are free to add attribute values and/or attribute names

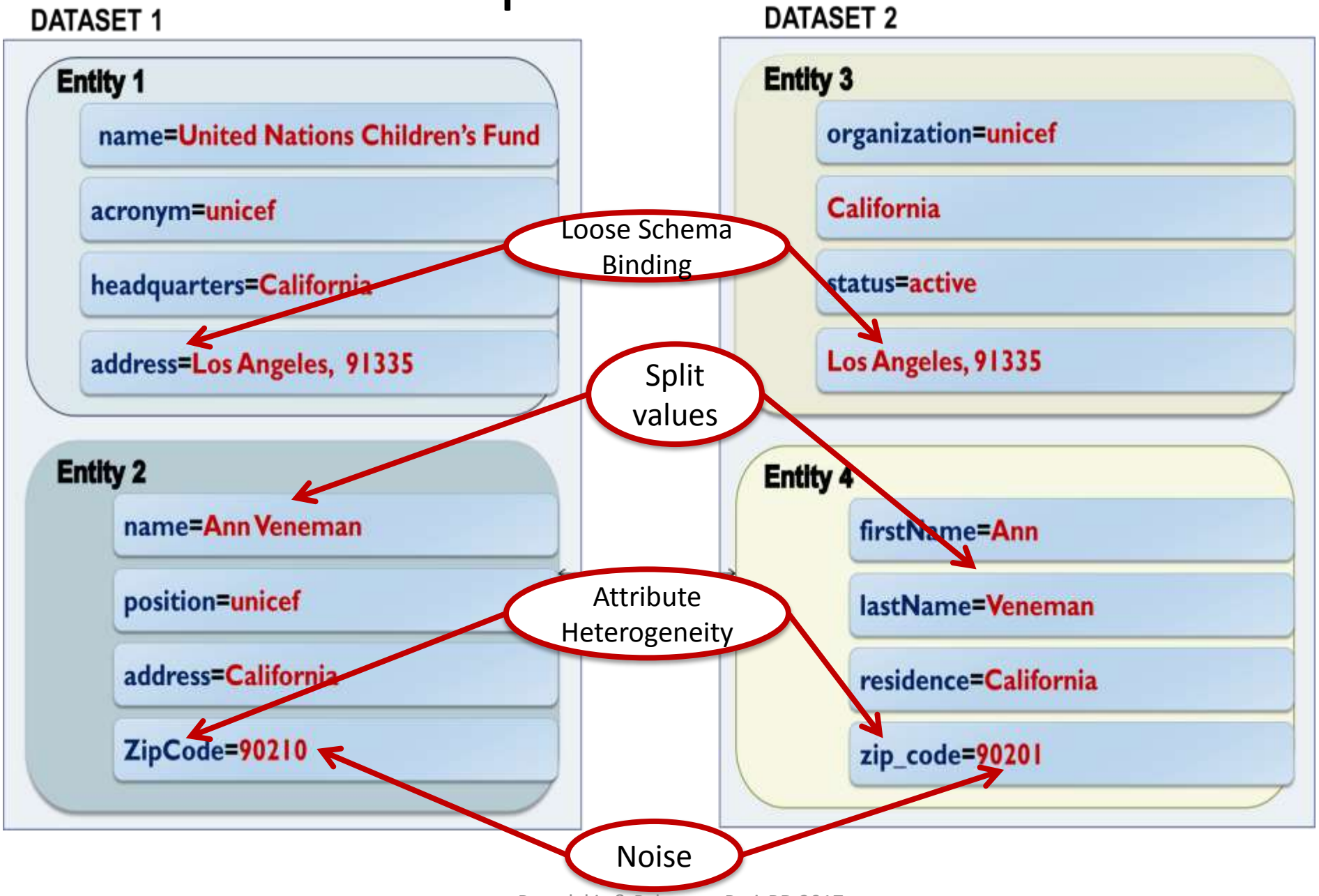
→ unprecedented levels of schema heterogeneity.

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

Several datasets produced by automatic information extraction techniques

→ noise, tag-style values.

Example of Web Data



Token Blocking [Papadakis et al., WSDM2011]

Functionality:

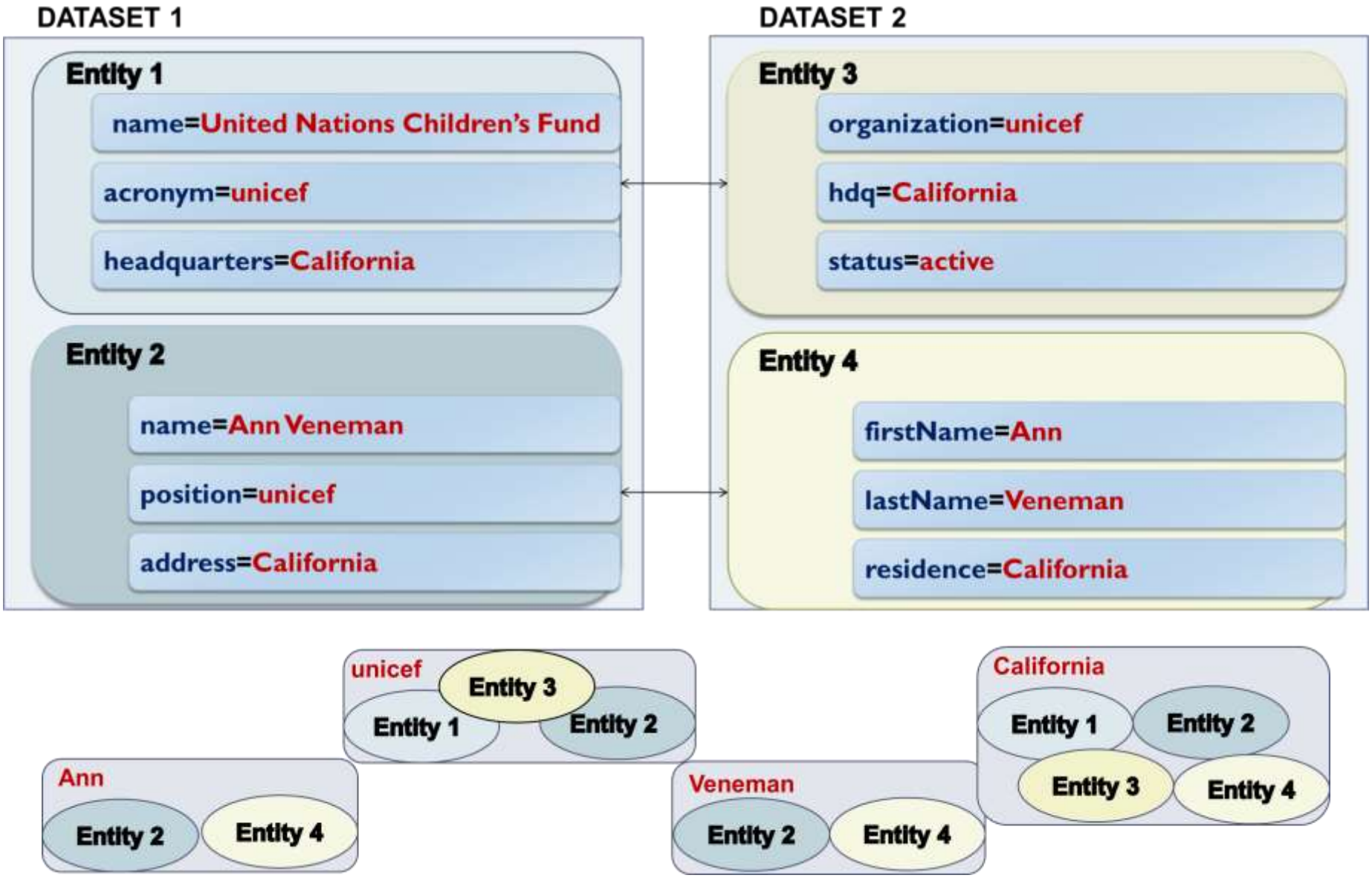
1. given an entity profile, extract all tokens that are contained in its attribute values.
2. create one block for every distinct token → each block contains all entities with the corresponding token*.

Attribute-agnostic functionality:

- completely ignores all attribute names, but considers all attribute values
- efficient implementation with the help of inverted indices
- ***parameter-free***!

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

Token Blocking Example

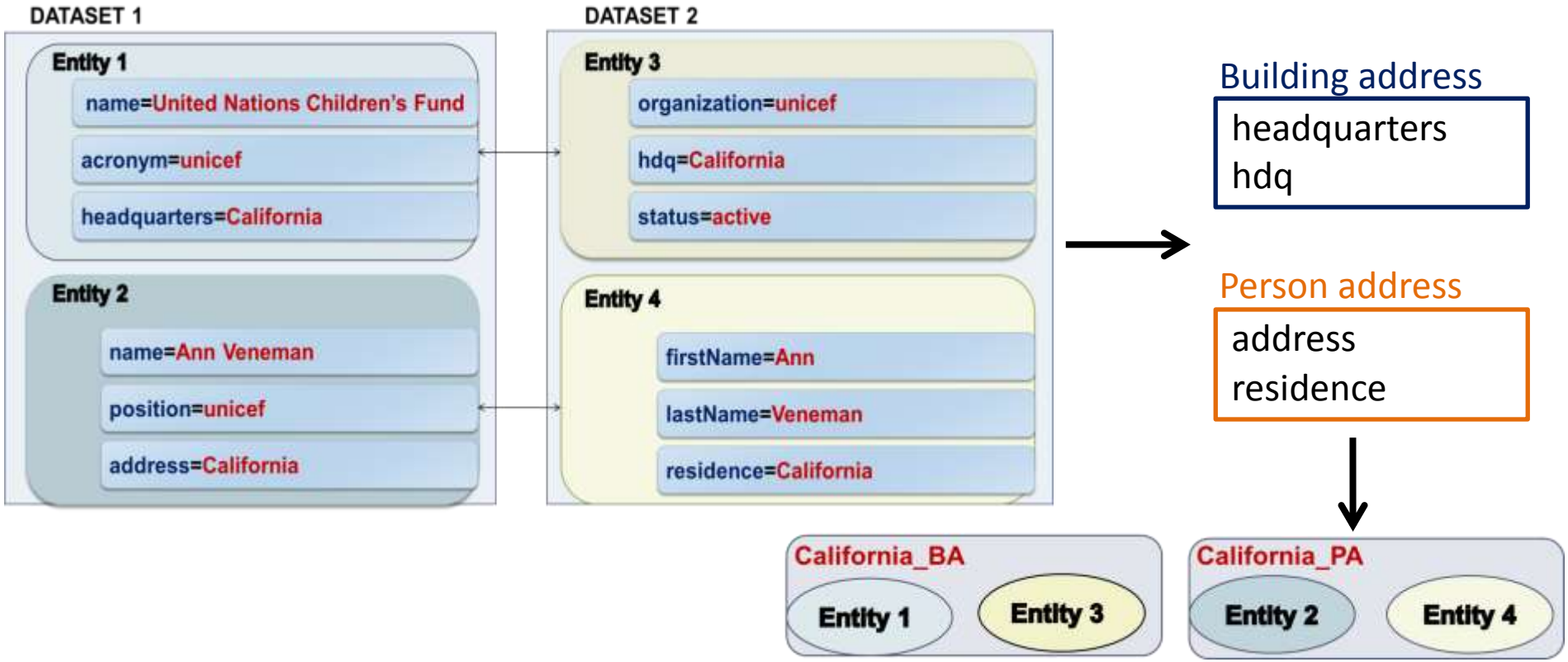


Attribute-Clustering Blocking

[Papadakis et. al., TKDE 2013]

Goal:

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



Attribute-Clustering Blocking

Algorithm

- Create a graph, where every node represents an attribute name and its attribute values
- For each attribute name/node n_i
  - Find the most similar node 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

Parameters

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

Attribute-Clustering vs Schema Matching

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 attribute names are associated with each other

3. Unlike Schema Matching, it scales to the very high levels of heterogeneity of Web Data
   - because of the above simplifying assumptions

Summary of Blocking for Web Data

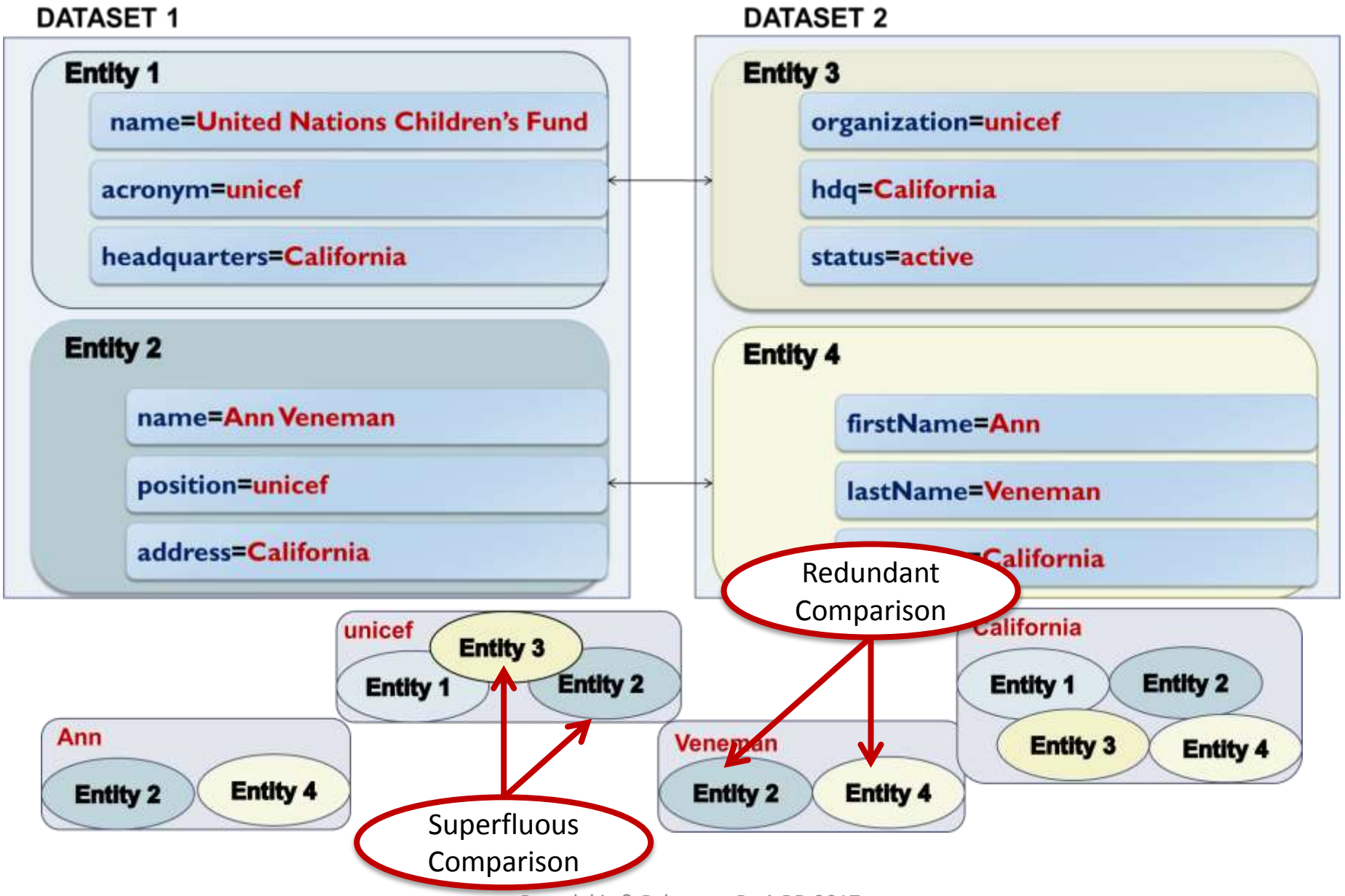
High Recall in the context of noisy entity profiles and extreme schema heterogeneity thanks to:

1. redundancy that reduces the likelihood of missed matches.
2. attribute-agnostic functionality that requires no schema semantics.

Low Precision because:

- the blocks are overlapping → redundant comparisons
- high number of comparisons between irrelevant entities → superfluous comparisons

Token Blocking Example



Part 4:

Block Processing Techniques

Outline

1. Introduction to Blocking
2. Blocking Methods for Relational Data
3. Blocking Methods for Web Data
4. Block Processing Techniques
   - Block Purging
   - Block Filtering
   - Block Clustering
   - Comparison Propagation
   - Iterative Blocking
5. Meta-blocking
6. Challenges
7. ER framework

General Principles

Goals:

1. eliminate *all* redundant comparisons
2. avoid *most* superfluous comparisons

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

Depending on the granularity of their functionality, they are distinguished into:

1. Block-refinement
2. Comparison-refinement
   - Iterative Methods

Block Purging

Exploits power-law distribution of block sizes.

Targets **oversized blocks** (i.e., many comparisons, no duplicates)

Discards them 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.

Block Filtering [Papadakis et. al, EDBT 2016]

Main ideas:

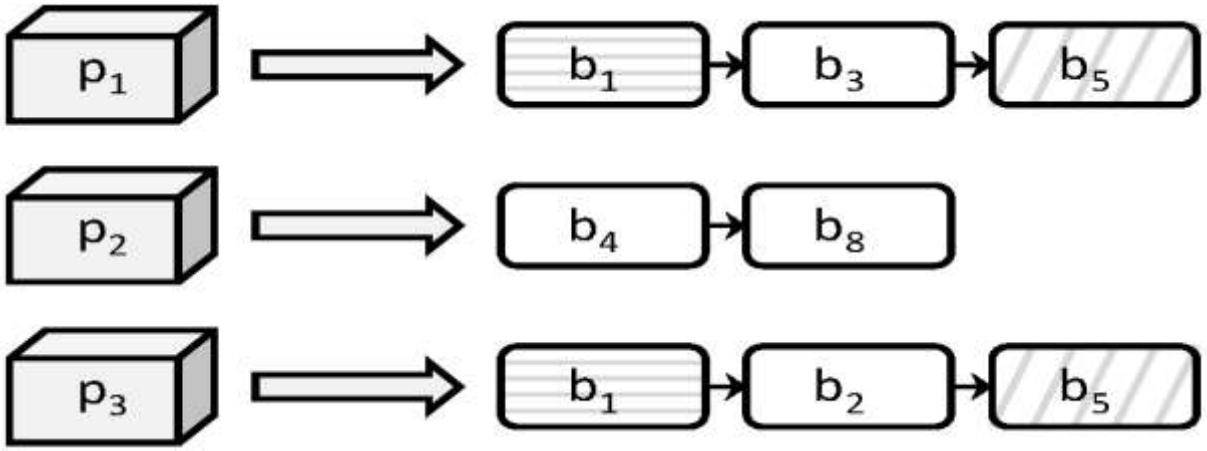
- each block has a different importance for every entity it contains.
- Larger blocks are less likely to contain unique duplicates and, thus, are less important.

Algorithm

- sort blocks in ascending cardinality
- build Entity Index
- retain every entity in **r%** of its smallest blocks
- reconstruct blocks

Comparison Propagation [Papadakis et al., JCDL 2011]

- Eliminate all redundant comparisons at no cost in recall.
- Naïve approach does not scale.
- Functionality:
  1. Build Entity Index
  2. Least Common Block Index condition.



Part 5:

Meta-blocking

Motivation

DBPedia 3.0rc ↔ DBPedia 3.4

1.2 million entities ↔ 2.2 million entities

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Brute-force approach

Comparisons: $2.58 \cdot 10^{12}$

Recall: 100%

Running time: 1,344 days → **3.7 years**

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Token Blocking + Block Filtering + Comparison Propagation

Overhead time: <30 mins

Comparisons: $3.5 \cdot 10^{10}$

Recall: 99%

Total Running time: **19 days**

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Token Blocking + Block Filtering + **??**

Meta-blocking [Papadakis et. al., TKDE 2014]

Goal:

restructure a **redundancy-positive** block collection into a new one that contains substantially lower number of redundant and superfluous comparisons, while maintaining the original number of matching ones ($\Delta PC \approx 0$, $\Delta PQ >> 1$) →

Meta-blocking [Papadakis et. al., TKDE 2014]

Goal:

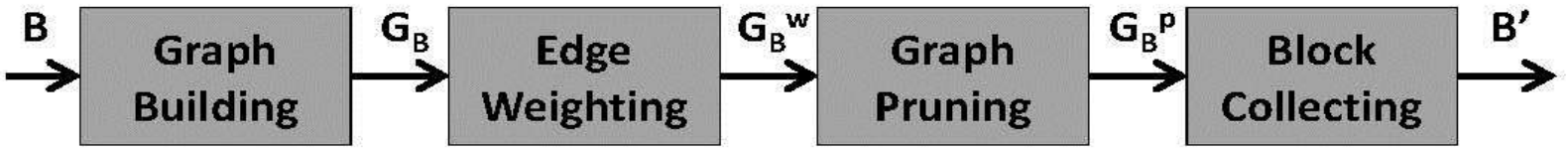
restructure a **redundancy-positive** block collection into a new one that contains substantially lower number of redundant and superfluous comparisons, while maintaining the original number of matching ones ($\Delta PC \approx 0$, $\Delta PQ >> 1$) →

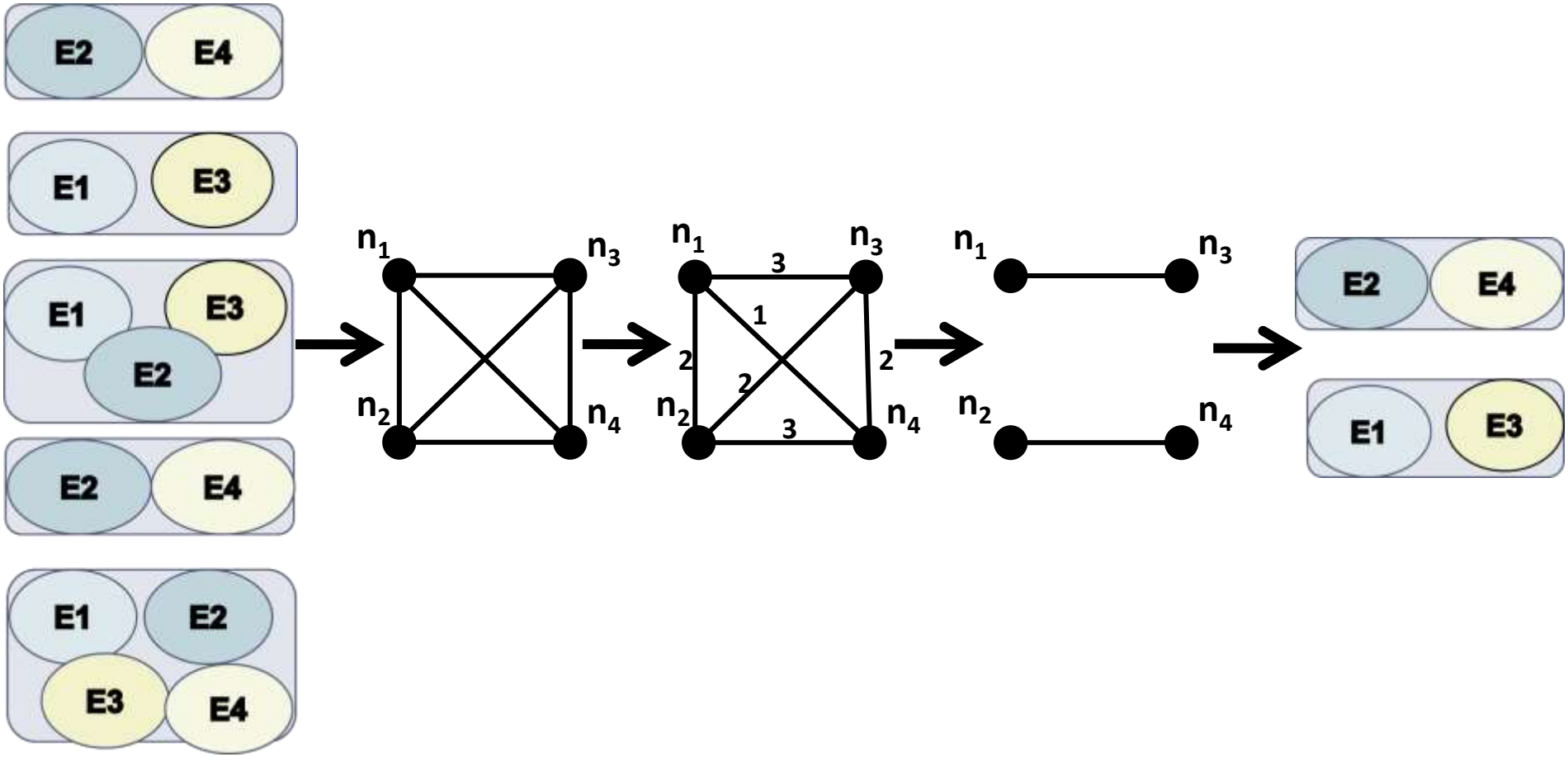
Main idea:

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





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.

Motivation

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Token Blocking + Block Filtering + **Meta-blocking**

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Comparisons: $3.5 \cdot 10^{10}$

Recall: 99%

Total Running time: **19 days**

Token Blocking + Block Filtering + **Meta-blocking**

Overhead time: 4 hours

Comparisons: $8.95 \cdot 10^{6}$

Recall: 92%

Total Running time: **5 hours**

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Recall: 99%

Total Running time: **19 days**

Token Blocking + Block Filtering + **Meta-blocking**

Overhead time: 4 hours

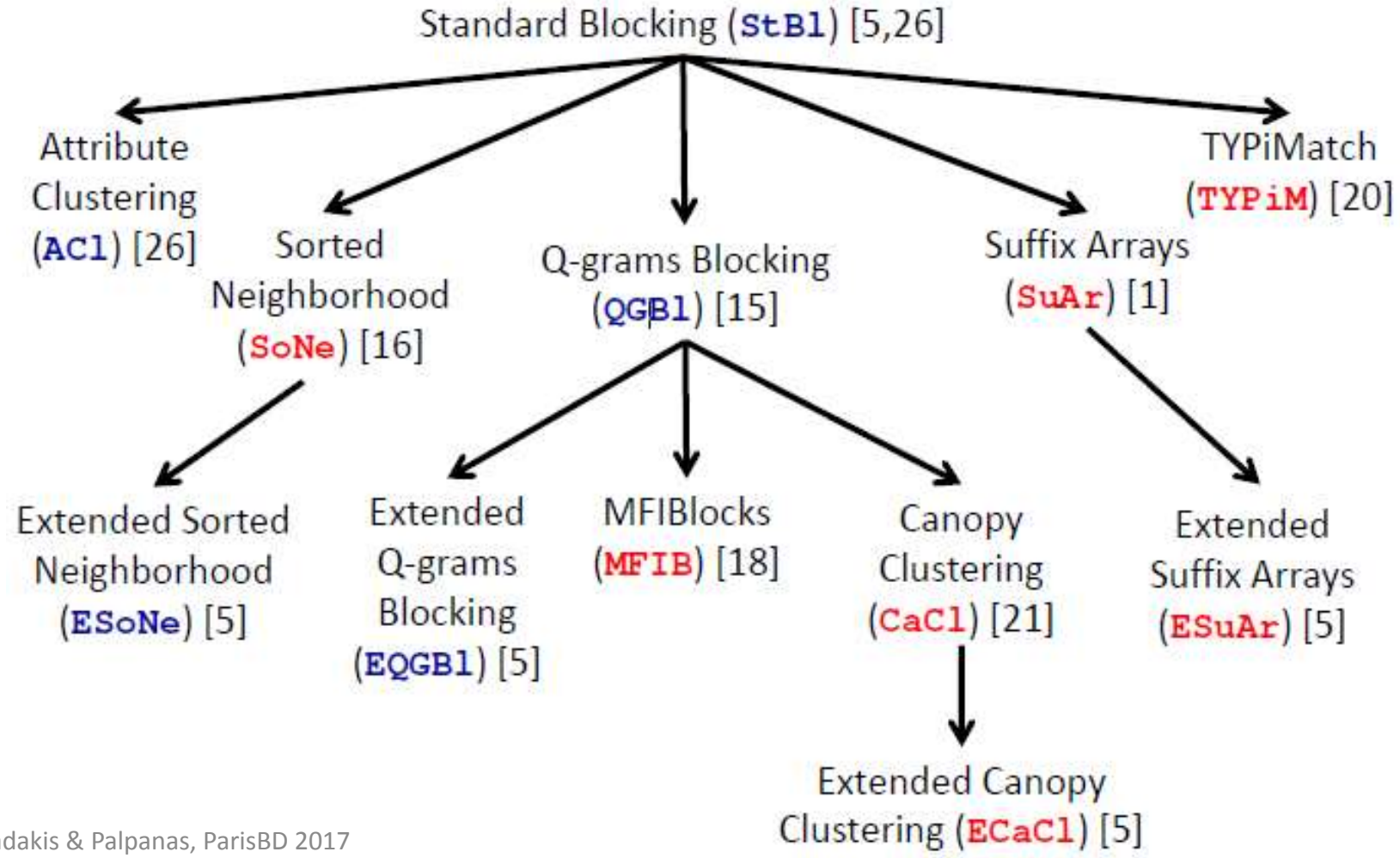
Comparisons: $8.95 \cdot 10^{6}$

Recall: 92%

Total Running time: **5 hours**

Comparative Analysis of Approximate Blocking Techniques [Papadakis et. al., VLDB 2016]

- considered 5 lazy and 7 proactive blocking methods



Experimental Analysis Setup

- Block Cleaning methods:
  1. Block Purging
  2. Block Filtering

- Comparison Cleaning methods:
  1. Comparison Propagation
  2. Iterative Blocking
  3. Meta-blocking

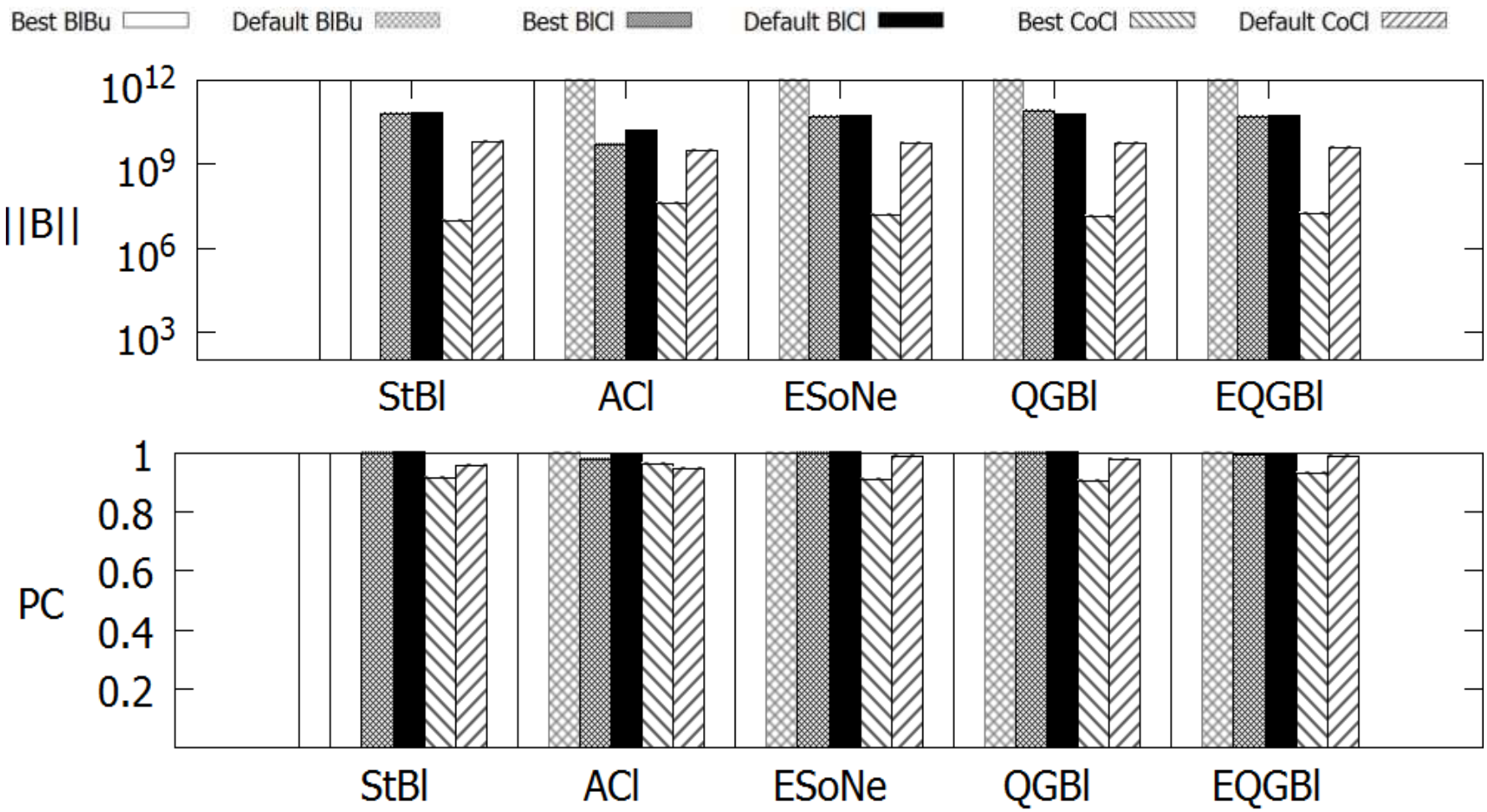
Experimental Analysis Setup

- Exhaustive parameter tuning to identify two configurations for each method:
  1. Best configuration per dataset → maximizes
  $$\boldsymbol{a}(\boldsymbol{B},\boldsymbol{E}) = \boldsymbol{RR}(\boldsymbol{B},\boldsymbol{E}) \cdot \boldsymbol{PC}(\boldsymbol{B},\boldsymbol{E})$$
  2. Default configuration → highest average $\boldsymbol{a}$ across all datasets

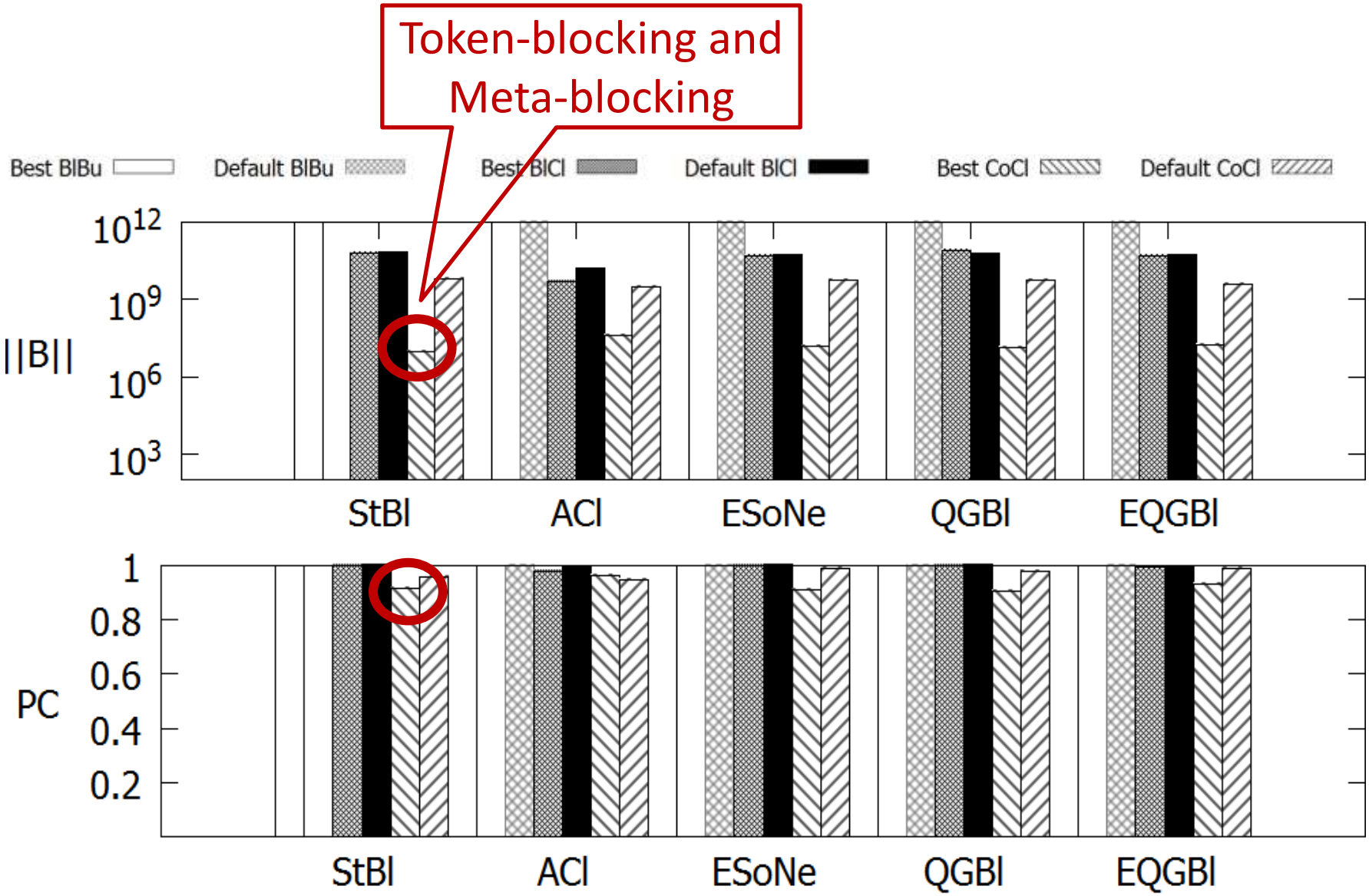
- Extensive experiments measuring effectiveness and time efficiency over **5 real** datasets (up to 3.3M entities).

- Scalability analysis over **7 synthetic** datasets (up to 2M entities).

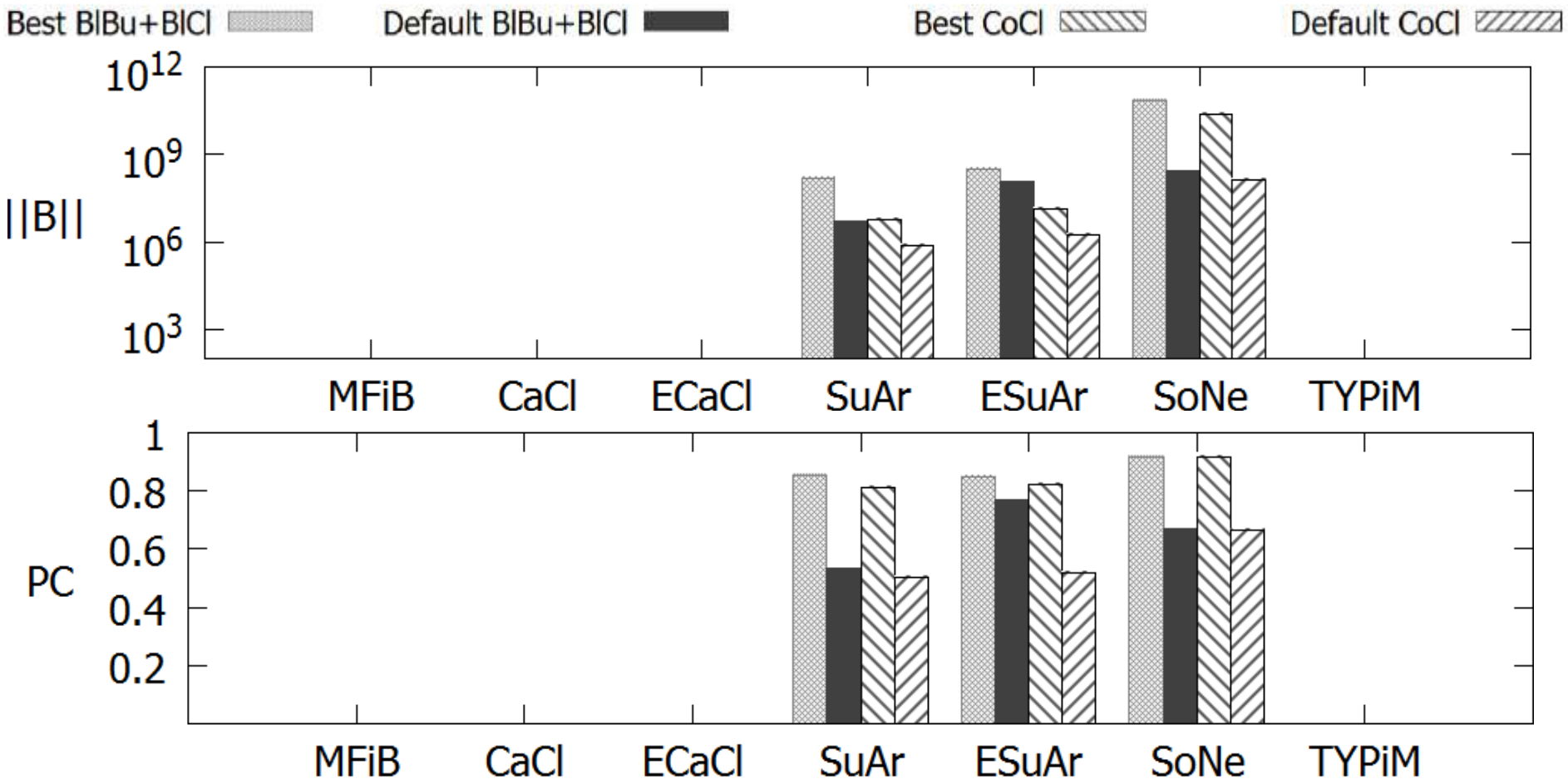
Effectiveness of Lazy Methods on DBPedia



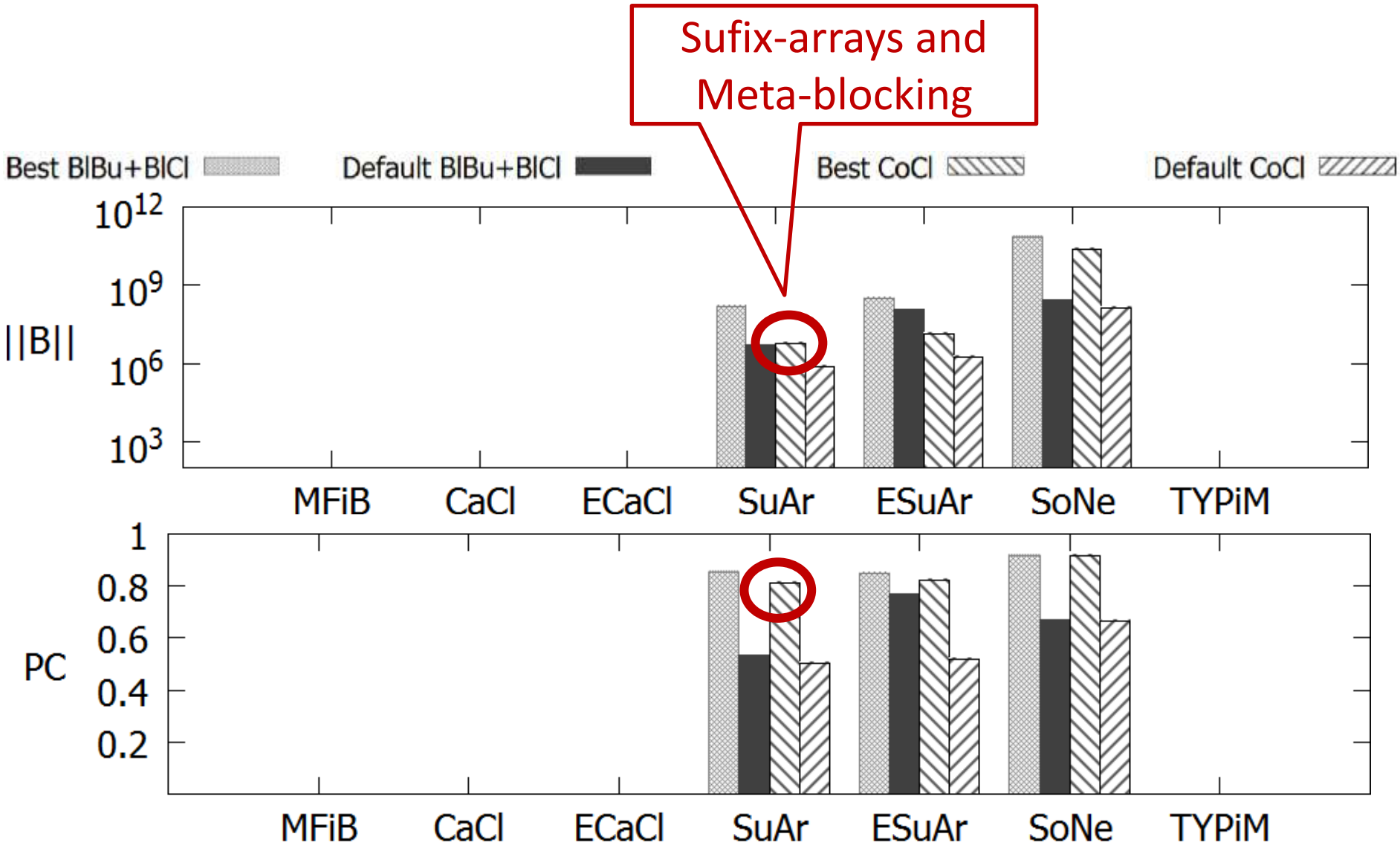
Effectiveness of Lazy Methods on DBPedia



Effectiveness of Proactive methods on DBPedia



Effectiveness of Proactive methods on DBPedia



Part 6:

Challenges

Automatic Configuration

Facts:

- Several parameters in every blocking workflow
  - Both for lazy and proactive methods
- Blocking performance sensitive to internal configuration
  - Experimentally verified in [Papadakis et. al., VLDB 2016]
- Manual fine-tuning required

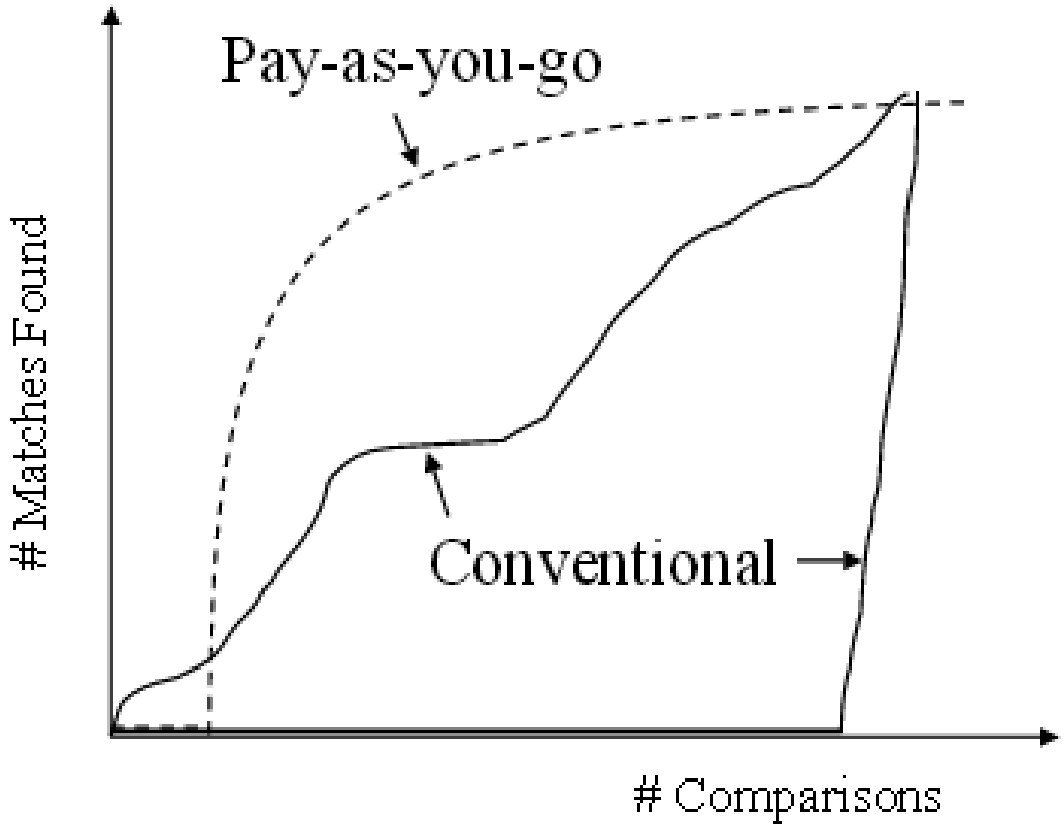
Open Research Directions:

- Plug-and-play blocking
- Data-driven configuration

Progressive Blocking

Facts:

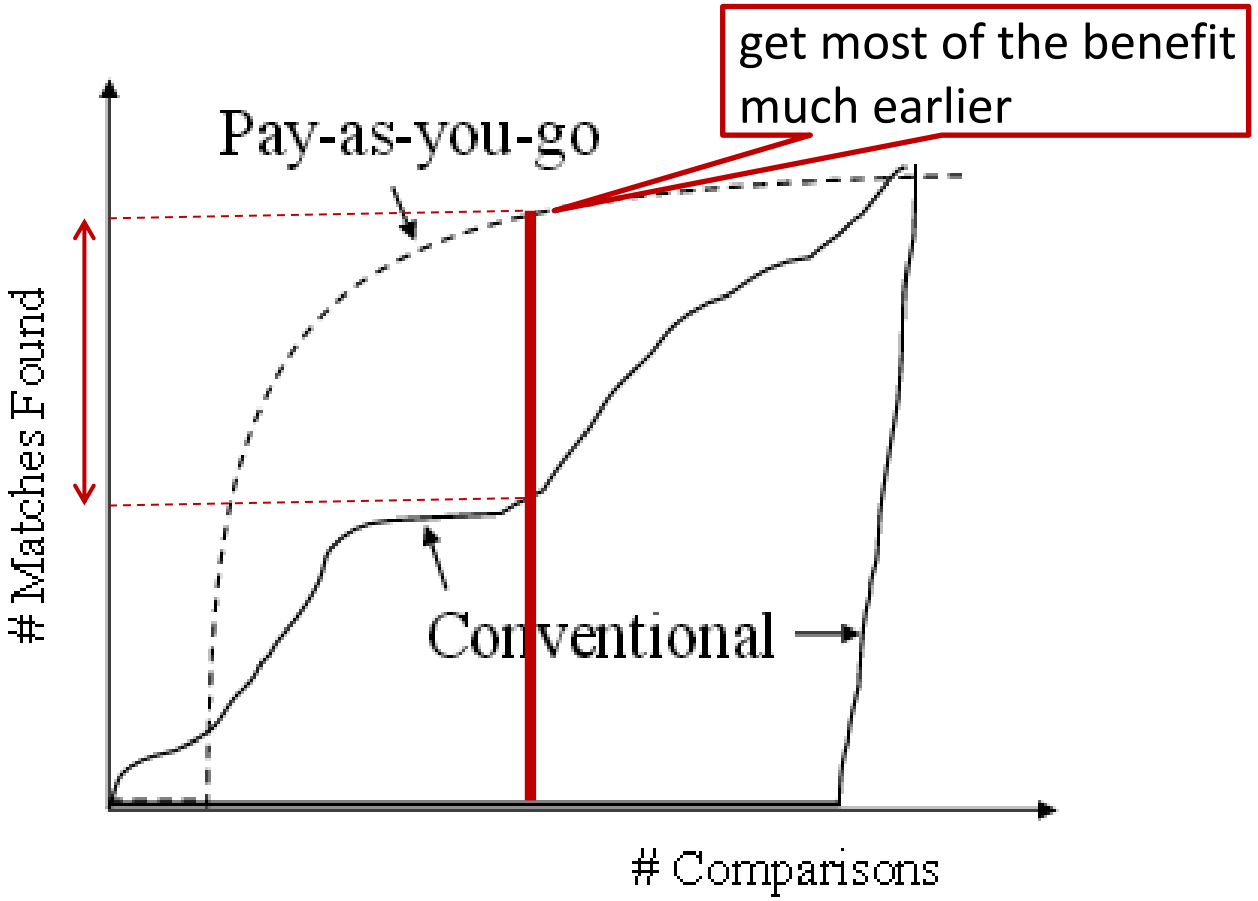
- Progressive, or Pay-as-you-go ER comes is useful



Progressive Blocking

Facts:

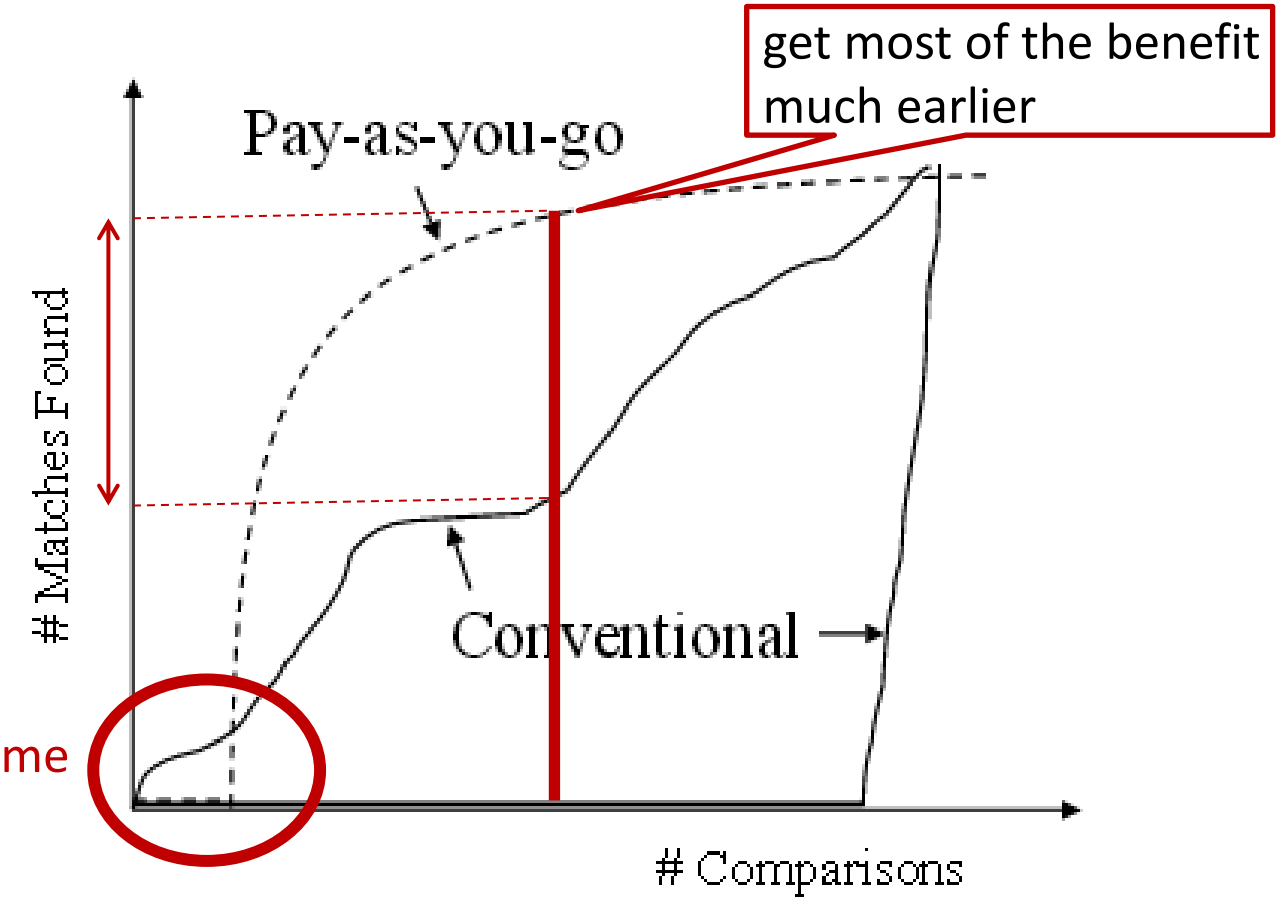
- Progressive, or Pay-as-you-go ER comes is useful



Progressive Blocking

Facts:

- Progressive, or Pay-as-you-go ER comes is useful



may require some pre-processing

Privacy Preserving Blocking

Facts:

- several applications ask for privacy-preserving ER
- lots of interest in this area [Christen, PADM 2006][Karakasidis et al., 2012][Ziad et al, BTW 2015]

Open Research Directions:

- What is the role of blocking workflow techniques?
  - block building, block filtering, comparison cleaning
- How can existing blocking techniques be adjusted?
- Novel blocking methods for this context

Part 7:

JedAI Toolkit

JedAI:
The Force behind Entity Resolution

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SCIFY
SCIENCE FOR YOU

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PARIS
DESCARTES

Manolis Koubarakis

National and Kapodistrian
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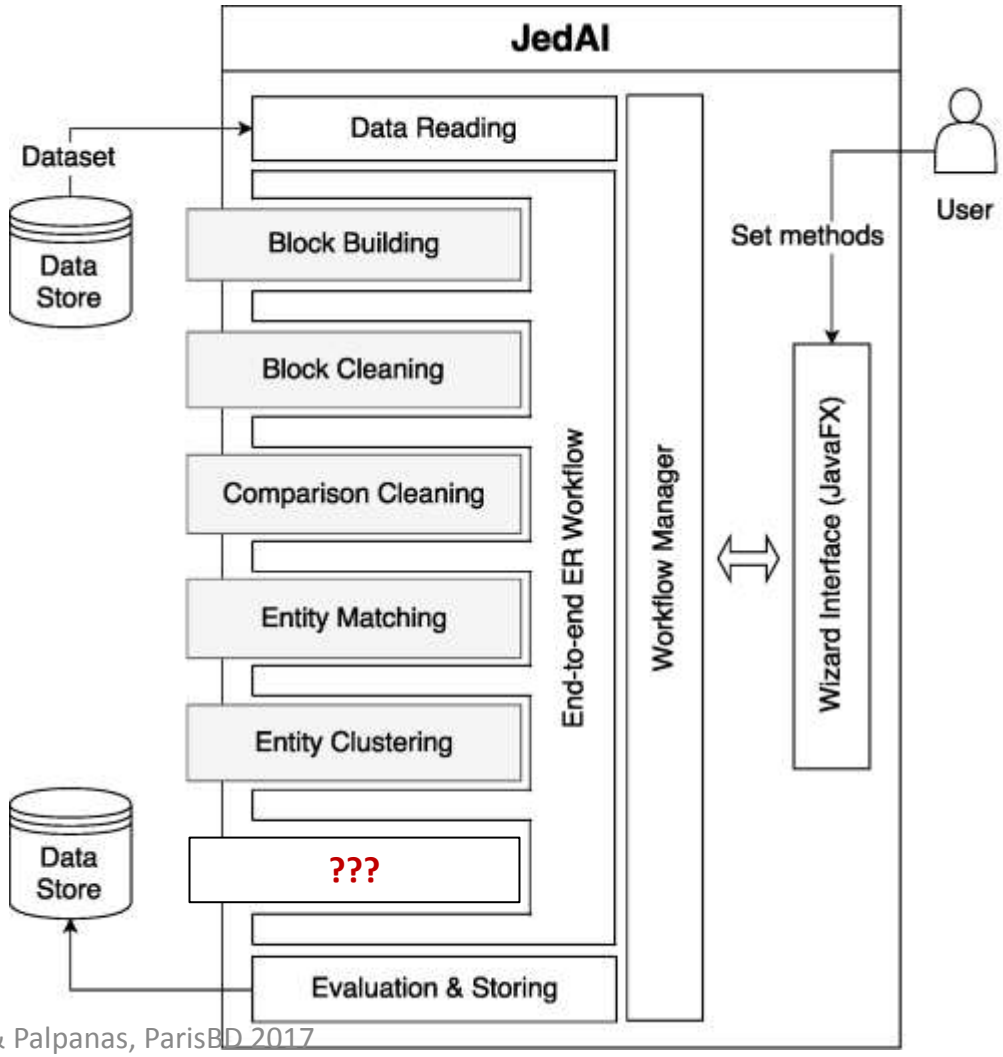
What is the JedAI Toolkit?

JedAI can be used in three ways:

1. As an open source library that implements numerous state-of-the-art methods for all steps of an established end-to-end ER workflow.
2. As a desktop application for ER with an intuitive Graphical User Interface that is suitable for both expert and lay users.
3. As a workbench for comparing all performance aspects of various (configurations of) end-to-end ER workflows.

How is JedAI Toolkit built?

- Modular architecture: one module per workflow step.
- Extensible architecture (e.g., ontology matching)



Where can I find JedAI Toolkit?

- Project website: http://jedai.scify.org .
- Github repository of JedAI Library:
  - https://github.com/scify/JedAIToolkit .
- Github repository of JedAI Desktop Application and Workbench:
  - https://github.com/scify/jedai-ui .
  - All code is well documented.
- Several datasets are available for testing at https://github.com/scify/JedAIToolkit .

Part 8:

Conclusions

Conclusions – Block Building

- Traditional proactive blocking methods only suitable for **relational data**
  - background schema knowledge is available for their configuration
- Recent lazy blocking methods scale well to heterogeneous, semi-structured **Big Data**
  - **Variety** is addressed with schema-agnostic keys
  - **Volume** is addressed with Block and Comparison Cleaning methods → they trade slightly lower recall, for much higher precision

Conclusions – Comparison Cleaning

- Fine-grained functionality:
  - operate at the level of individual comparisons → computationally intensive process
- Apply to both lazy and proactive methods

- Meta-blocking is the current state-of-the-art
  - Discards both superfluous and redundant comparisons
  - Necessary for reducing comparisons to manageable levels for single-threaded ER workflows
    - **reduces comparisons by orders of magnitude, with recall > 98%**
  - Naturally parallelizable

thank you!

questions?

google: themis palpanas

full version: publications -> tutorials

http://www.mi.parisdescartes.fr/~themisp/publications/PapadakisPalpanas-TutorialScaDS-LeipsigSummerSchool2016.pptx

Big Data Research (BDR) Journal

http://www.journals.elsevier.com/big-data-research/

- New Elsevier journal on topics related to big data
  - advances in big data management/processing
  - interdisciplinary applications
- Editor in Chief for BDR
  - submit your work
  - propose special issues
- google: bdr journal

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