Data Wrangling and Data Analysis
Heterogeneous Data Integration (Part B)
Entity Linkage

Hakim Qahtan

Slides prepared by

Prof. Yannis Velegrakis

Department of Information and Computing Sciences

Utrecht University

Utrecht University

I won a trip to L.A.

That is
Lekanopedio **A**ttikis

Not the famous **L**os **A**ngeles !!

How many names, descriptions are used for the same real-world "entity"?

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Londain Londe Londen Londen Londen Londinium
London Londona Londonas Londoni Londono Londra
Londres Londrez Londyn Lontoo Loundres Luân Đôn
Lunden Lundúnir Lunnainn Lunnon لندن لندن لندن لوندون
לאנדאן לונדון Λονδίνο Лёндан Лондан Лондон Лондон
Лондон Լոնդոն 伦敦 …

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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, …

How many names, descriptions are used for the same real-world “entity”?

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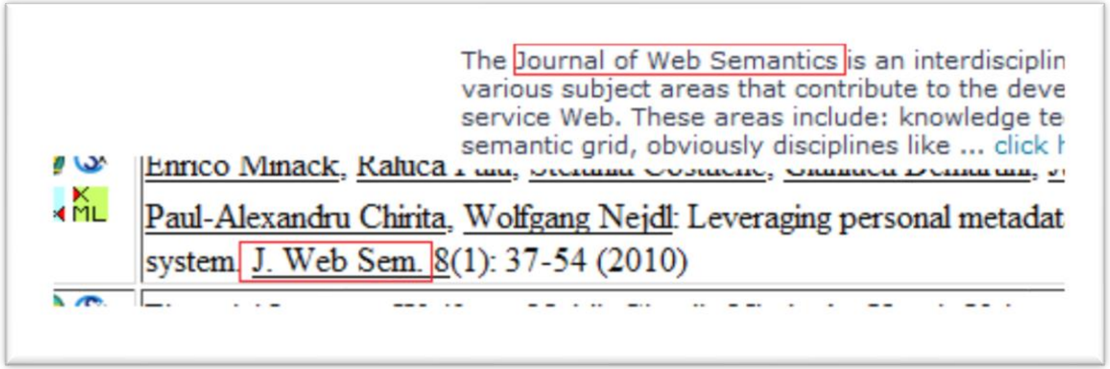
- London, Uninc Shelby County, Shelby, IN
- London, Deerfield, WI
- London, Deerfield, Dane, WI
- London, Uninc Freeborn County, MN
- …

- 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
- …

Reasons of Different Descriptions

- Text variations:
  - Misspellings
  - Acronyms
  - Transformations
  - Abbreviations
  - etc.

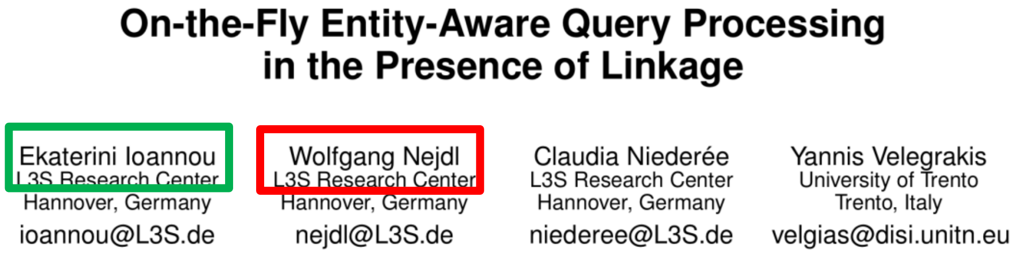


Reasons for Different Descriptions

- Text variations
- Local knowledge:
  - Each source uses different formats
    e.g., person from publication vs. person from email
  - Lack of global coordination for identifier assignment


to You
cc Prof. Nejdl, Iris Zieseniß
E. Ioannou <ioannou@L3S.de> wrote:

Hello Prof. Nejdl,


On-the-Fly Entity-Aware Query Processing in the Presence of Linkage

Ekaterini Ioannou
L3S Research Center
Hannover, Germany
ioannou@L3S.de

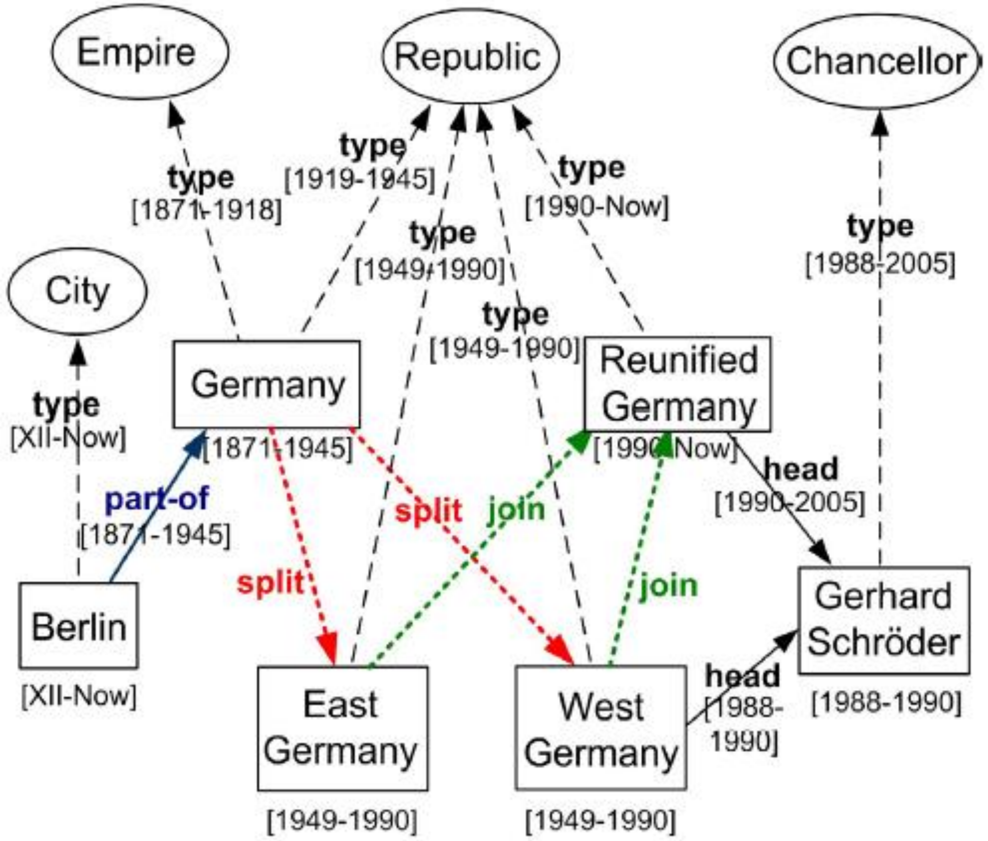
Wolfgang Nejdl
L3S Research Center
Hannover, Germany
nejdl@L3S.de

Claudia Niederée
L3S Research Center
Hannover, Germany
niederee@L3S.de

Yannis Velegrakis
University of Trento
Trento, Italy
velgias@disi.unitn.eu

Reasons for Different Descriptions from [VelegrakisBM09]

- Text variations
- Local knowledge
- Evolving nature of data:
  - Entity alternative names
  - appearing in time
  - Updates in entity data



Jacqueline Lee Bouvier

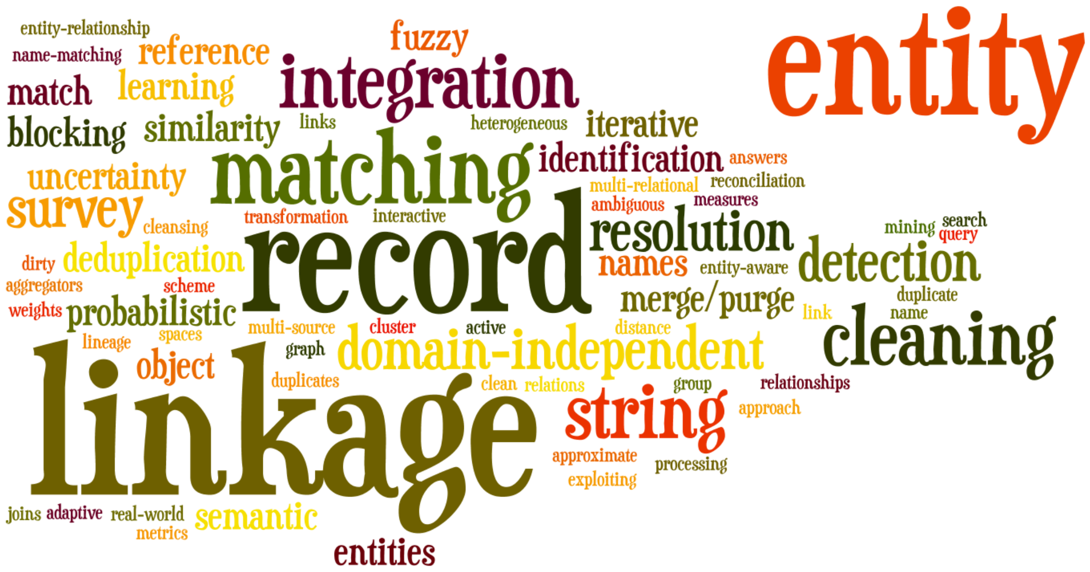
Reasons for Different Descriptions

- Text variations
- Local knowledge
- Evolving nature of data
- New functionality:
  - Import data collections from various applications
    - e.g., Wikipedia data used in Freebase

Entity Resolution

[Dong et al., Book 2015] [Elmagarmid et al., TKDE 2007] :

identify the different structures/records that model the same real-world object.



Why it is useful

- Improves data quality and integrity
- Fosters re-use of existing data sources
- Optimize space

Application areas:

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

Challenges for ER

- Variety – Semantic
  - Semi-structured data → unprecedented levels of heterogeneity
  - Numerous entity types & vocabularies
  - LOD Cloud*: ~50,000 predicates, ~12,000 vocabularies

Outline

1. **Atomic similarity methods**

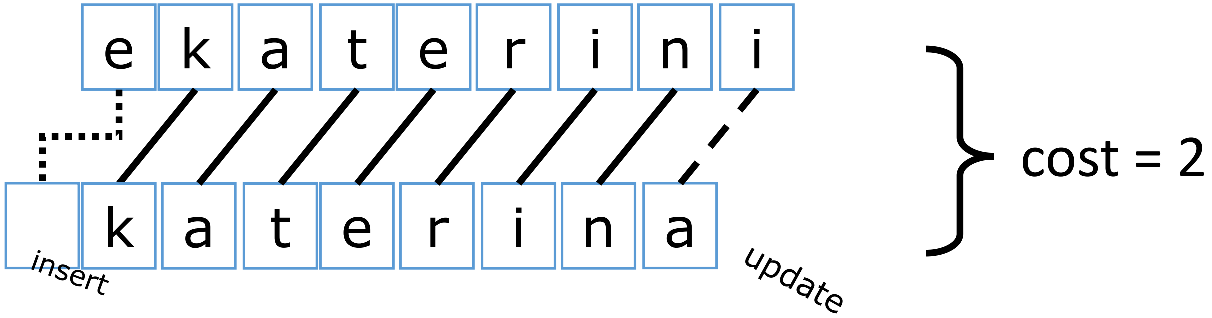
Atomic String Similarity

- Examples of targeting cases:
  - Publication authors: "John D. Smith" vs. "J. D. Smith"
  - Journal names: "Transactions on Knowledge and Data Engineering" vs. "Trans. Knowl. Data Eng."

Edit Distance:

- Number of operations to convert from 1st to 2nd string
- Operations in Levenstein distance [Lev66]

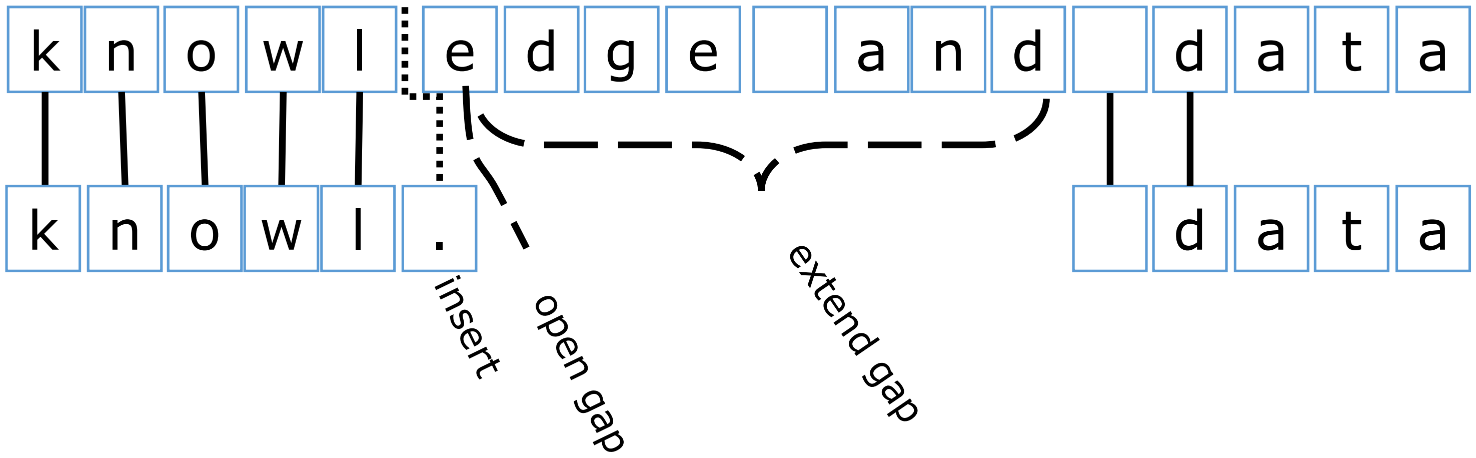
→ delete, insert, and update a character with cost 1



Atomic String Similarity

- Gap Distance:
  - Overcome limitation of edit distance with shortened strings
  - Considers two extra operations [Nav01]

    → open gap, and extend gap (with small cost)



cost = 1 + o + 8e

Atomic String Similarity

- Jaro similarity [Jar89]:
  - Small strings, e.g., first and last names

$$JaroSim(S_1, S_2) = \frac{1}{3}\left(\frac{C}{|S_1|} + \frac{C}{|S_2|} + \frac{C - T}{C}\right)$$

C → common characters in S_1 and S_2

T → transpositions/2 transposition is a k in which $S_1[k] \neq S_2[k]$

<u>Example</u>: "DEIS"vs. "DESI"

C=4, T=2/2, JaroSim= $\frac{1}{3}\left(\frac{4}{4} + \frac{4}{4} + \frac{4-1}{4}\right) = 0.9167$

Atomic String Similarity

- Jaro-Winkler similarity [Win99]:
  - Extension that gives higher weight to matching prefix
  - Increasing it's applicability to names
  - $J_w(S_1, S_2) = JaroSim + P * L * (1 - JaroSim)$
  - P is a scaling factor (0.1 by default)
  - L is the length of the common prefix up to maximum 4
  - Example: Compute $J_w(arnab, aranb)$
    - $JaroSim(arnab, aranb) = \frac{1}{3}\left(\frac{5}{5} + \frac{5}{5} + \frac{4}{5}\right) = 0.933$
    - $J_w(arnab, aranb) = 0.933 + 0.1 * 2 * (1 - 0.933) = 0.9466$

Atomic String Similarity

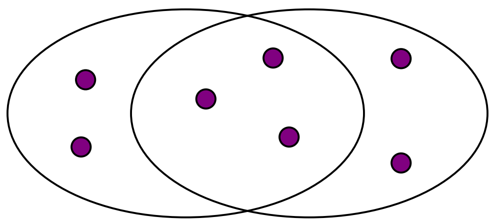
- Soundex:
  - Converts each word into a phonetic encoding by assigning the same code to the string parts that sound the same
  - Similarity is computed between the corresponding phonetic encodings
  - Examples: Meier and Mayer or Smith, Smyth, Smithe, Smeth, Smeeth

- Remarks:
  - Surveys: [CRF03], [Win06]
  - Existing API with these methods:
    - SecondString: http://secondstring.sourceforge.net/
    - SimMetrics: http://www.dcs.shef.ac.uk/~sam/simmetrics.html

Outline

1. Atomic similarity methods
2. **Similarity methods for sets**

Similarity methods for sets



- Jaccard distance/similarity
  - The Jaccard similarity of two sets is the size of their intersection divided by the size of their union:
  - $$sim(C_1, C_2) = |C_1 \cap C_2| / |C_1 \cup C_2|$$
  - Jaccard distance: $d(C_1, C_2) = 1 - |C_1 \cap C_2| / |C_1 \cup C_2|$

3 in intersection
8 in union
Jaccard similarity= 3/8
Jaccard distance = 5/8
Jaccard bag Similarity = 6/10

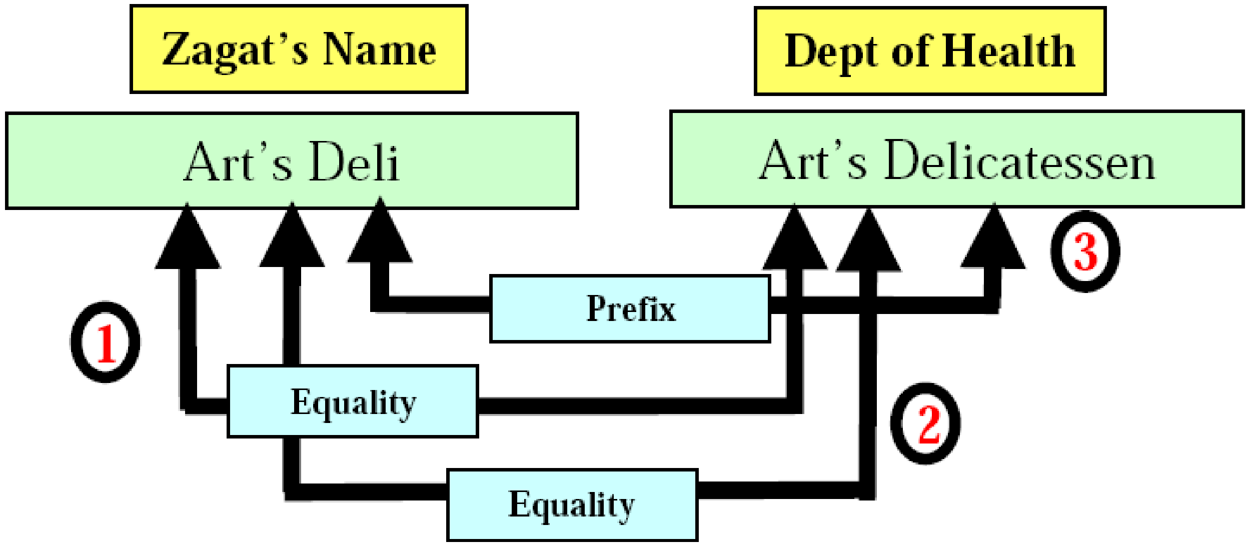
- Similarity between {a, b, c, d} and {a, b, e, f} = 2/6 = 1/3

- Jaccard bag similarity counts the repetition of the elements
- The similarity between {a,a,a,b} and {a,a,b,b,c} = 3/9 = 1/3

Similarity methods for sets

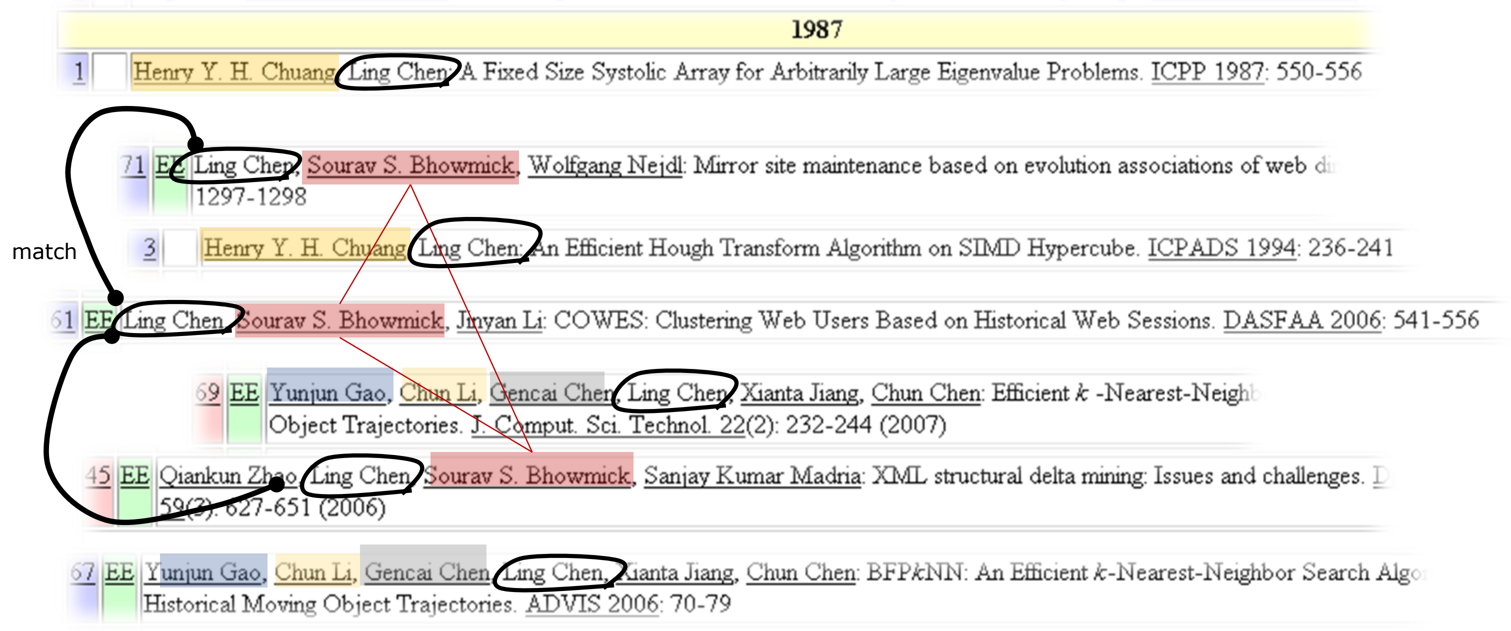
- Using transformations [TKM02]:

1. Analyze data to generate transformations
   - Unary transform:
     - Equality, Stemming, Soundex, Abbreviation (e.g., 3rd or third)
   - N-ary transformations:
     - Initial, Prefix, Suffix, Substring Acronym, Abbreviation
2. Calculate transformation weights
3. Apply on candidate mappings



Similarity methods for sets

- Group Linkage [OKLS07] (Survey [EIV07]):
  - Considers groups of relational records
    - not individual relational records
  - Groups match when:
    1. High similarity between data of individual records
    2. Large fraction of matching records, i.e., no. 1



Outline

1. Motivation: Entity Resolution
2. Atomic similarity methods
3. Similarity methods for sets
4. **Facilitating inner-relationships**

Facilitating inner-relationships

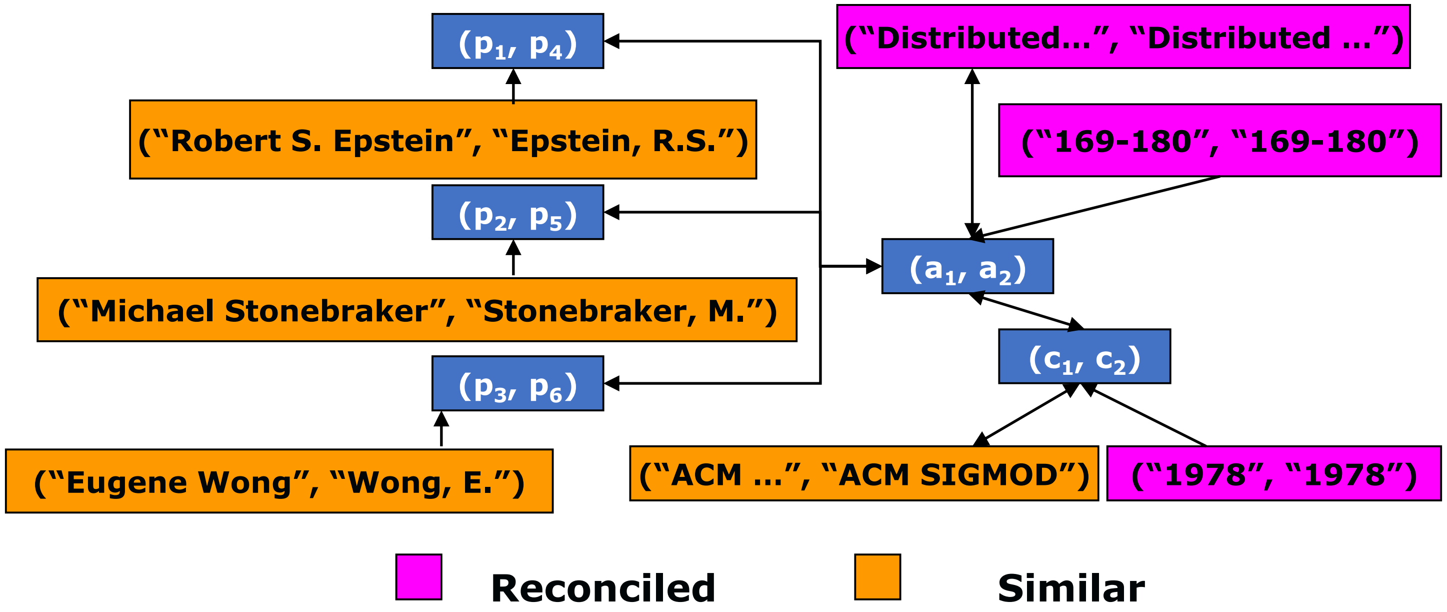
- General idea
  - Heterogeneous data
    - Lack of schema information
    - Variations in entity descriptions
    - Incomplete or missing values
  - Improve effectiveness by considering data semantics
  - Example → Reference Reconciliation

Facilitating inner-relationships

- Reference Reconciliation [DHM05]

1. Build a dependency graph

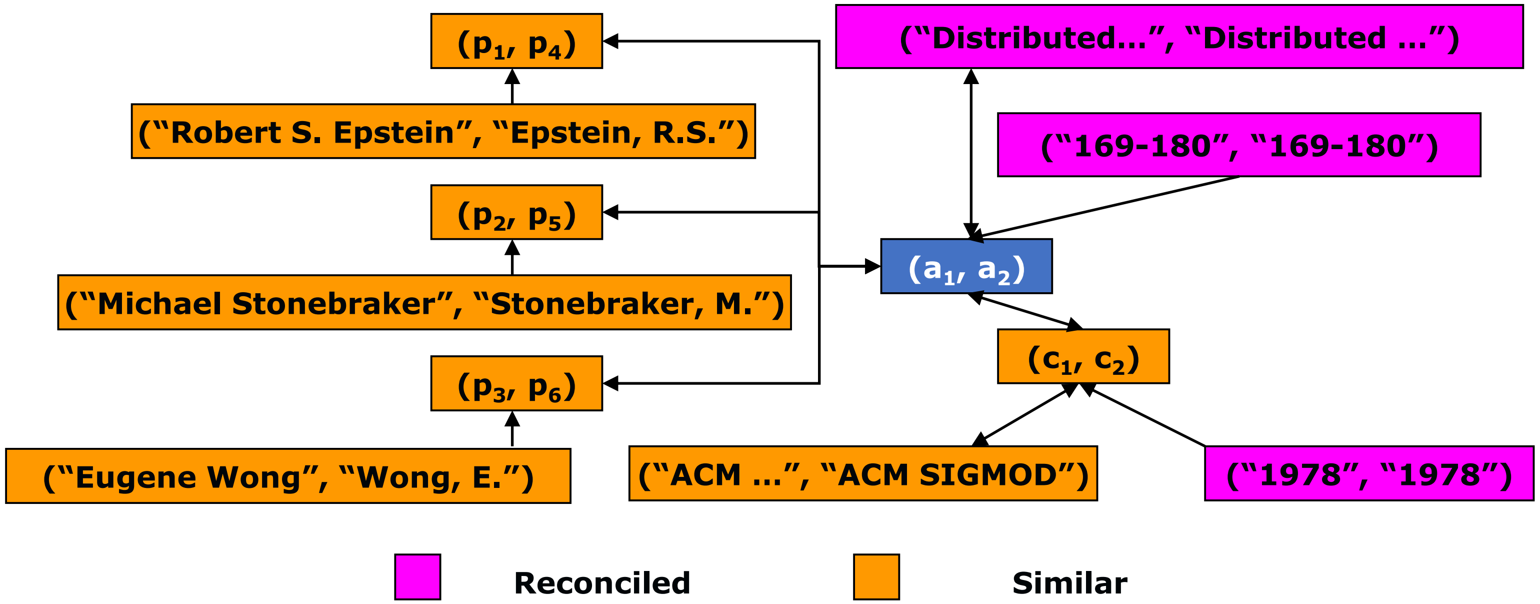
a1: ("Distributed…", "169-180, c1:(1978, "ACM…"), "Robert S. Epstein", "Michael Stonebraker", "Eugene Wong")
a2: ("Distributed…", "169-180, c2:(1978, "ACM SIGMOD"), "Epstein, R.S.", "Stonebraker, M.", "Wong, E.")



Facilitating inner-relationships

- Reference Reconciliation [DHM05]

1. Build a dependency graph
2. Exploit information and relationships



Facilitating inner-relationships

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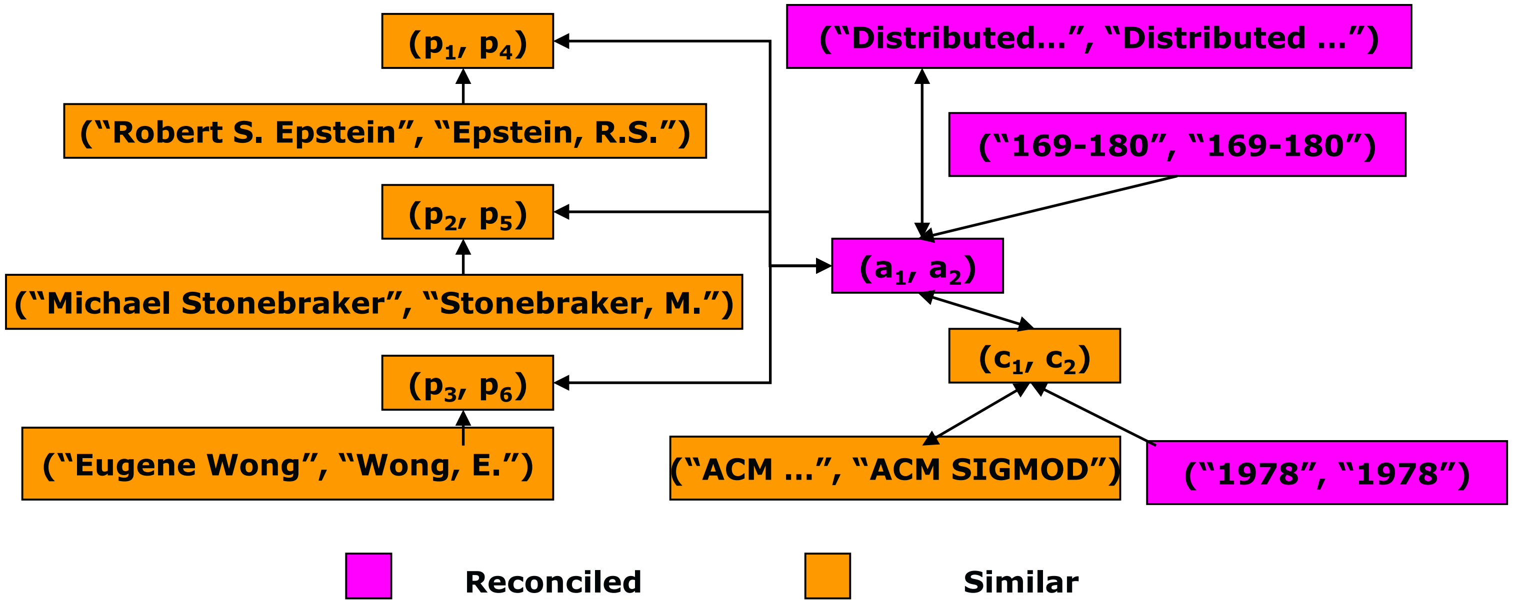

Facilitating inner-relationships

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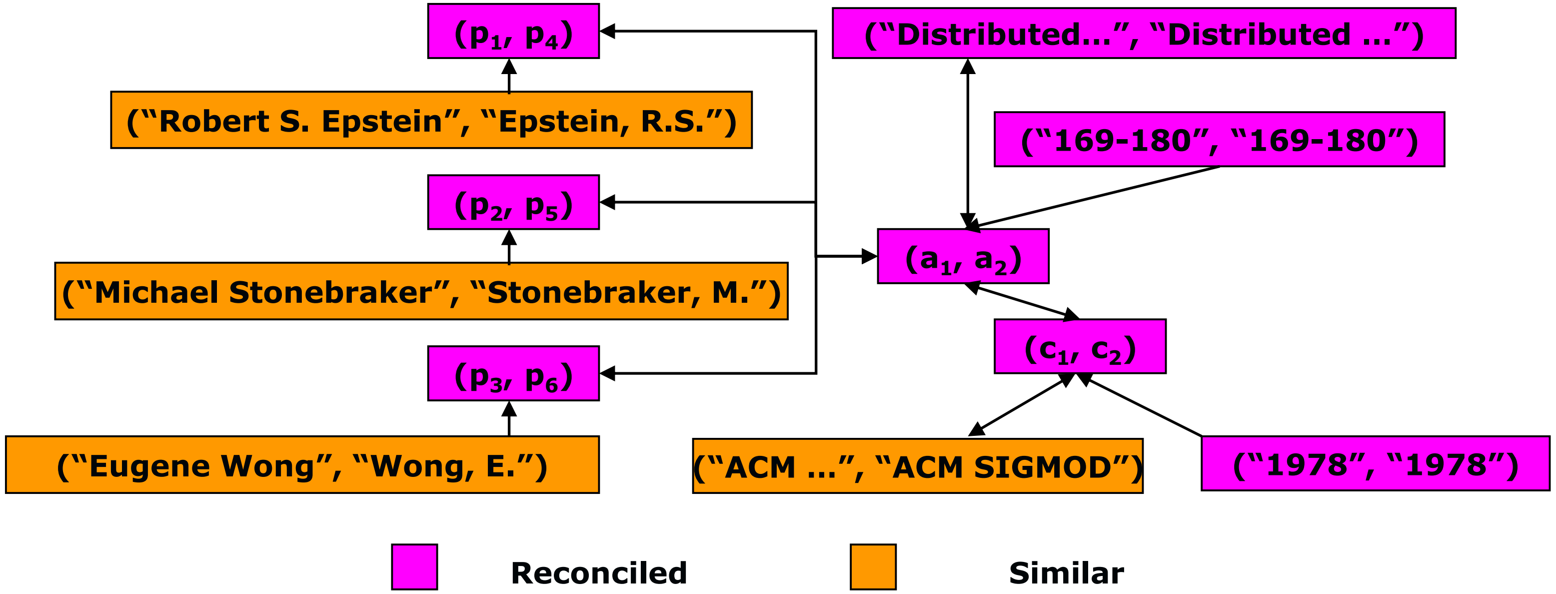


Outline

1. Motivation: Entity Resolution
2. Atomic similarity methods
3. Similarity methods for sets
4. Facilitating inner-relationships
5. **Methods in uncertain data**

Methods in uncertain data

- General idea:

- Keep conflicting relations, e.g., [AFM06], [RDS07], [DS07a], [DHY07]
  - Lack of resolution rules to correctly resolve and merge relations
  - No merging, but maintain results in the database
  - Relations are alternative representations of the same real world object
- Entity representation with probability – indicates...
  - Reliability of the source
  - Output of the matching process
  - Etc.

customer

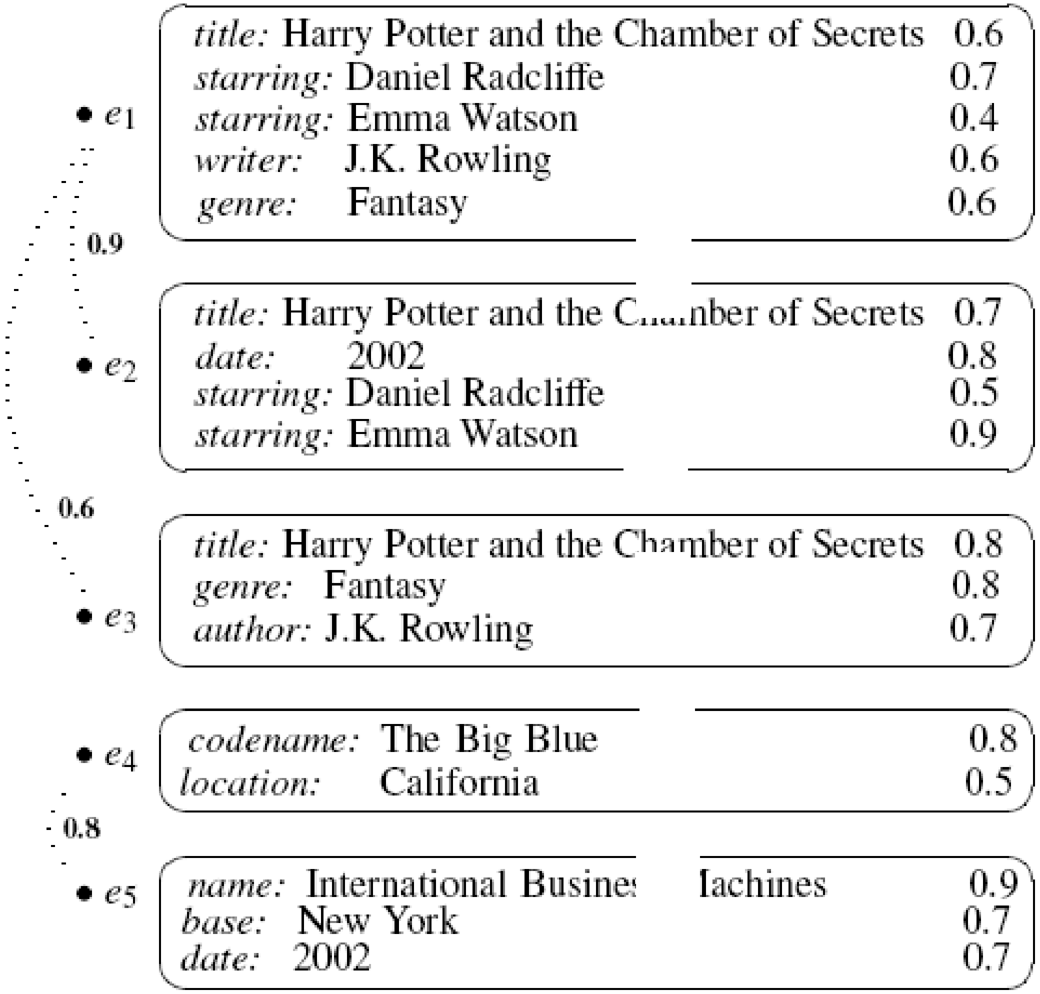
	custId	name	income	prob
s_1	c1	John	\$120K	0.9
s_2	c1	John	\$80K	0.1
s_3	c2	Mary	\$140K	0.4
s_4	c2	Marion	\$40K	0.6

Methods in uncertain data

- Entity-Aware querying over prob. linkages (different perspectives)

[Ioannou & Velegrakis 2010]

  - Not merging the entities using threshold
  - Keep probabilistic linkages alongside the original data
  - Use them during query processing
  - The idea of possible Worlds



- Query:
  - “J. K. Rowling” movies in “2002”
- Assume no linkages:
  - zero results
- Possible answer with linkages:
  - merge(e_1, e_2)
  - merge(e_1, e_2, e_3)

Similarity Methods for Sets

The case of documents

A Common Metaphor

- Many problems can be expressed as finding “similar” sets
  - Find near-neighbors in high-dimensional space
- Examples:
  - Pages with similar words
    - For duplicate detection, classification by topic, plagiarism
  - Customers who purchased similar products (e.g. Movies)
  - Products with similar customer sets (e.g. fans)
  - Images with similar features
    - Users who visited similar websites

Documents as High-Dim Data

- **Converting documents to set**
  - **Simple approaches:**
    - Document = set of words appearing in document
    - Document = set of "important" words

- **Need to account for ordering of words!**
- A different way: **Shingles!**

Define: Shingles

- A *k*-shingle (or *k*-gram) for a document is a sequence of *k* tokens that appears in the doc
  - Tokens can be characters, words or something else, depending on the application
  - Assume tokens = characters for examples

- **Example: k=2**; document $\mathbf{D_1}$ = abcab
  Set of 2-shingles: $\mathbf{S(D_1)}$ = {ab, bc, ca}
  - **Option:** Shingles as a bag (multiset), count ab twice: $\mathbf{S'(D_1)}$ **=** {ab, bc, ca, ab}

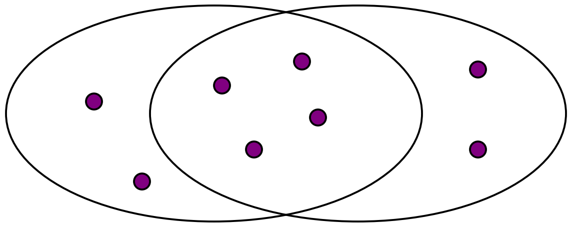
Compressing Shingles

- To **compress long shingles**, we can **hash** them to (say) 4 bytes
- **Represent a document by the set of hash values of its *k*-shingles**
  - **Idea:** Two documents could (rarely) appear to have shingles in common, when in fact only the hash-values were shared
- **Example:** **k=2**; document $\mathbf{D_1}$= abcab
  Set of 2-shingles: $\mathbf{S(D_1)}$ = {ab, bc, ca}
  Hash the shingles: $\mathbf{h(D_1)}$ = {1, 5, 7}

Similarity Metric for Shingles

- **Document D_1 is a set of its k-shingles C_1=S(D_1)**
- Equivalently, each document is a 0/1 vector in the space of *k*-shingles
  - Each unique shingle is a dimension
  - Vectors are very sparse
- **A natural similarity measure is the Jaccard similarity:**

$$sim(D_1, D_2) = |C_1 \cap C_2| / |C_1 \cup C_2|$$



Working Assumption

- **Documents that have lots of shingles in common have similar text, even if the text appears in different order**
- **Caveat:** You must pick ***k*** large enough, or most documents will have most shingles
  - ***k*** = 5 is OK for short documents
  - ***k*** = 10 is better for long documents

Challenges for ER

- Variety – Semantic
  - Semi-structured data → unprecedented levels of heterogeneity
  - Numerous entity types & vocabularies
  - LOD Cloud*: ~50,000 predicates, ~12,000 vocabularies
- Volume - Performance
  - Millions of entities
  - Billions of name-value pairs describing them
  - LOD Cloud*: >$5{,}5 \cdot 10^7$ entities, ~$1{,}5 \cdot 10^{11}$ triples
  - **Too many documents, Too few memory**

Motivation

- **Suppose we need to find near-duplicate documents among $N = 1$ million documents**

- Naïvely, we would have to compute **pairwise Jaccard similarities** for **every pair of docs**
  - $N(N-1)/2 \approx 5*10^{11}$ comparisons
  - At 10^5 secs/day and 10^6 comparisons/sec, it would take **5 days**

- For $N = 10$ million, it takes more than a year…

Find pairs of similar docs

Main idea: Candidates

Instead of keeping a count of each pair, only keep a count of candidate pairs!

-- Pass 1: Take documents and hash them to buckets such that <u>documents that are similar hash to the same bucket</u>

-- Pass 2: Only compare documents that are **candidates** (i.e., they hashed to a same bucket)

Benefits: Instead of $O(N^2)$ comparisons, we need $O(N)$ comparisons to find similar documents

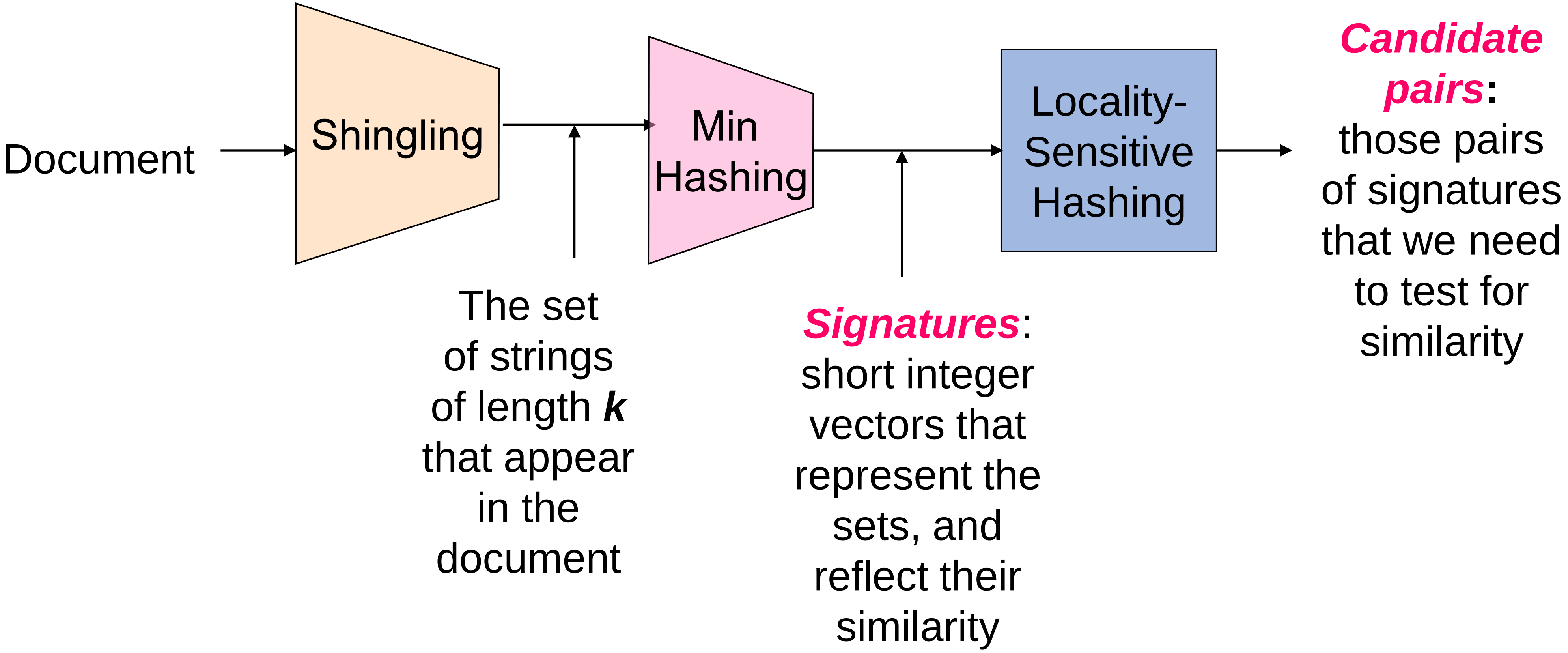
3 Essential Steps for Similar Docs

1. ***Shingling:*** Convert documents to sets

2. ***Min-Hashing:*** Convert large sets to short signatures, while preserving similarity

3. ***Locality-Sensitive Hashing:*** Focus on pairs of signatures likely to be from similar documents
   - **Candidate pairs!**

The Big Picture



Distance Measures

- **Goal: Find near-neighbors in high-dim. space**
  - We formally define "near neighbors" as points that are a "small distance" apart
- For each application, we first need to define what "**distance**" means

From Sets to Boolean Matrices

- **Rows** = elements (shingles)
- **Columns** = sets (documents)
  - 1 in row ***e*** and column ***s*** if and only if ***e*** is a member of ***s***
  - Column similarity is the Jaccard similarity of the corresponding sets (rows with value *1)*
  - **Typical matrix is sparse!**
- **Each document is a column:**
  - **Example: sim(C_1 ,C_2) = ?**
    - Size of intersection = 3; size of union = 6, Jaccard similarity (not distance) = 3/6
    - **d(C_1,C_2) = 1 – (Jaccard similarity) = 3/6**

Documents

Shingles

1	1	1	0
1	1	0	1
0	1	0	1
0	0	0	1
1	0	0	1
1	1	1	0
1	0	1	0

Finding Similar Columns

- **So far:**
  - Documents $\rightarrow$ Sets of shingles
  - Represent sets as Boolean vectors in a matrix
- **Next goal: Find similar columns while computing small signatures**
  - **Similarity of columns == similarity of signatures**

Hashing Columns (Signatures)

- **Key idea:** "hash" each column C to a small ***signature*** $h(C)$, such that:
  - **(1)** $h(C)$ is small enough that the signature fits in RAM
  - **(2)** $sim(C_1, C_2)$ is the same as the "similarity" of signatures $h(C_1)$ and $h(C_2)$
- **Goal: Find a hash function $h(\cdot)$ such that:**
  - If $sim(C_1,C_2)$ is high, then with high prob. $h(C_1) = h(C_2)$
  - If $sim(C_1,C_2)$ is low, then with high prob. $h(C_1) \neq h(C_2)$
- **Hash docs into buckets. Expect that "most" pairs of near duplicate docs hash into the same bucket!**
- **Clearly, the hash function depends on the similarity metric:**
  - Not all similarity metrics have a suitable hash function
- **There is a suitable hash function for the Jaccard similarity:** It is called **Min-Hashing**

Min-Hashing

- Imagine the rows of the Boolean matrix permuted under **random permutation** π

- Define a **"hash" function** $h_\pi(C)$ = the index of the **first** (in the permuted order π) row in which column C has value **1**:

$$h_\pi(C) = \min_\pi \pi(C)$$

- Use several (e.g., 100) independent hash functions (that is, permutations) to create a signature of a column

Min-Hashing Example

2nd element of the permutation is the first to map to a 1

Permutation π | **Input matrix (Shingles x Documents)**

π_1	π_2	π_3				
2	4	3	1	0	1	0
3	2	4	1	0	0	1
7	1	7	0	1	0	1
6	3	2	0	1	0	1
1	6	6	0	1	0	1
5	7	1	1	0	1	0
4	5	5	1	0	1	0

Signature matrix *M*

2	1	2	1
2	1	4	1
1	2	1	2

4th element of the permutation is the first to map to a 1

Similarity for Signatures

- We know: $\Pr[h_\pi(C_1) = h_\pi(C_2)] = sim(C_1, C_2)$
- Now generalize to multiple hash functions

- **The *similarity of two signatures* is the fraction of the hash functions in which they agree**

- **Note:** Because of the Min-Hash property, the similarity of columns is the same as the expected similarity of their signatures

Min-Hashing Example

Permutation π

2	4	3
3	2	4
7	1	7
6	3	2
1	6	6
5	7	1
4	5	5

Input matrix (Shingles x Documents)

1	0	1	0
1	0	0	1
0	1	0	1
0	1	0	1
0	1	0	1
1	0	1	0
1	0	1	0

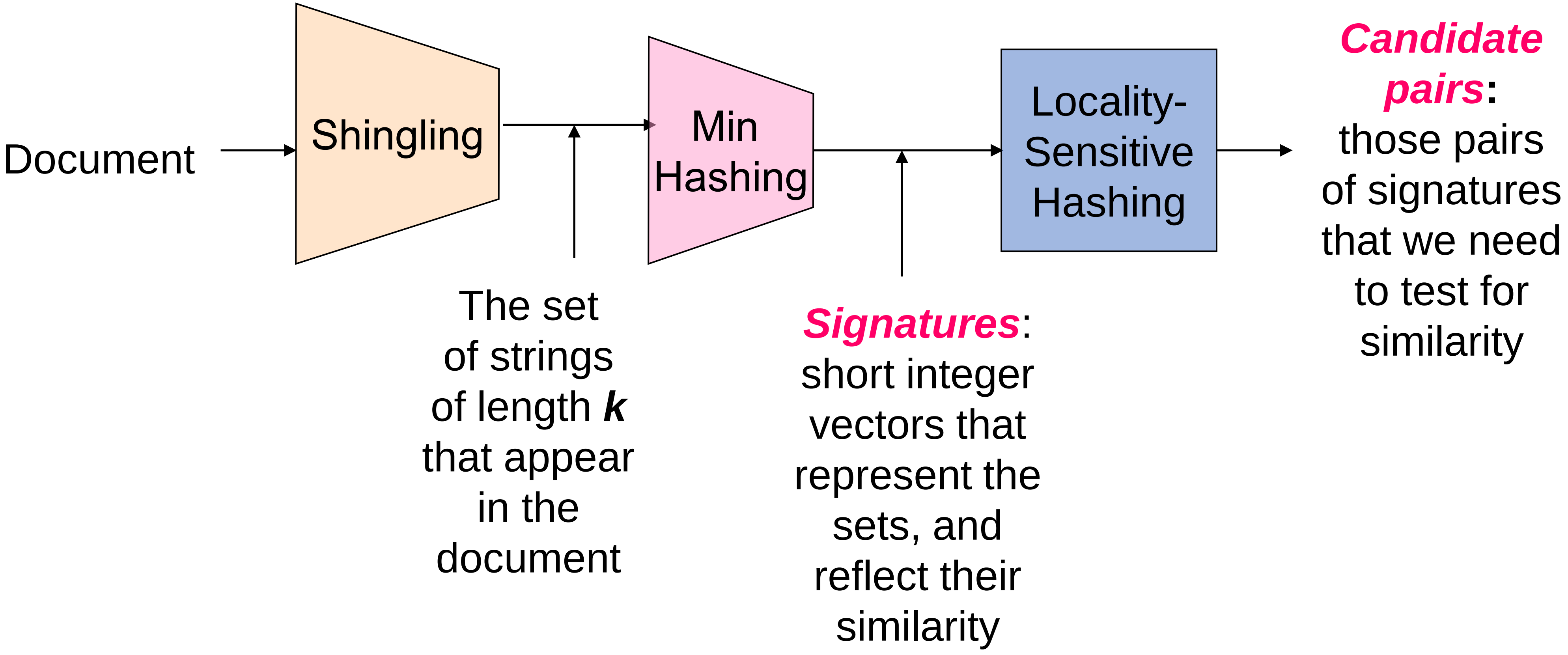
Signature matrix *M*

2	1	2	1
2	1	4	1
1	2	1	2

Similarities:

	1-3	2-4	1-2	3-4
Col/Col	0.75	0.75	0	0
Sig/Sig	0.67	1.00	0	0

Locality-Sensitive Hashing



- **Step 3:** ***Locality-Sensitive Hashing:***
  Focus on pairs of signatures likely to be from similar documents

LSH for Min-Hash

- **Big idea: Hash columns of signature matrix *M* several times**
- Arrange that (only) **similar columns** are likely to **hash to the same bucket**, with high probability
- **Candidate pairs are those that hash to the same bucket**
- (Blocking)

Performance

- Merge-purge [HS95],[HS98]:
- Idea: same entities with share information
- Create a key for each relation (e.g., email)
- Sort relations according to key
- Compare only a limited set of relations in each iteration

Standard Blocking

Earliest, simplest form of blocking.

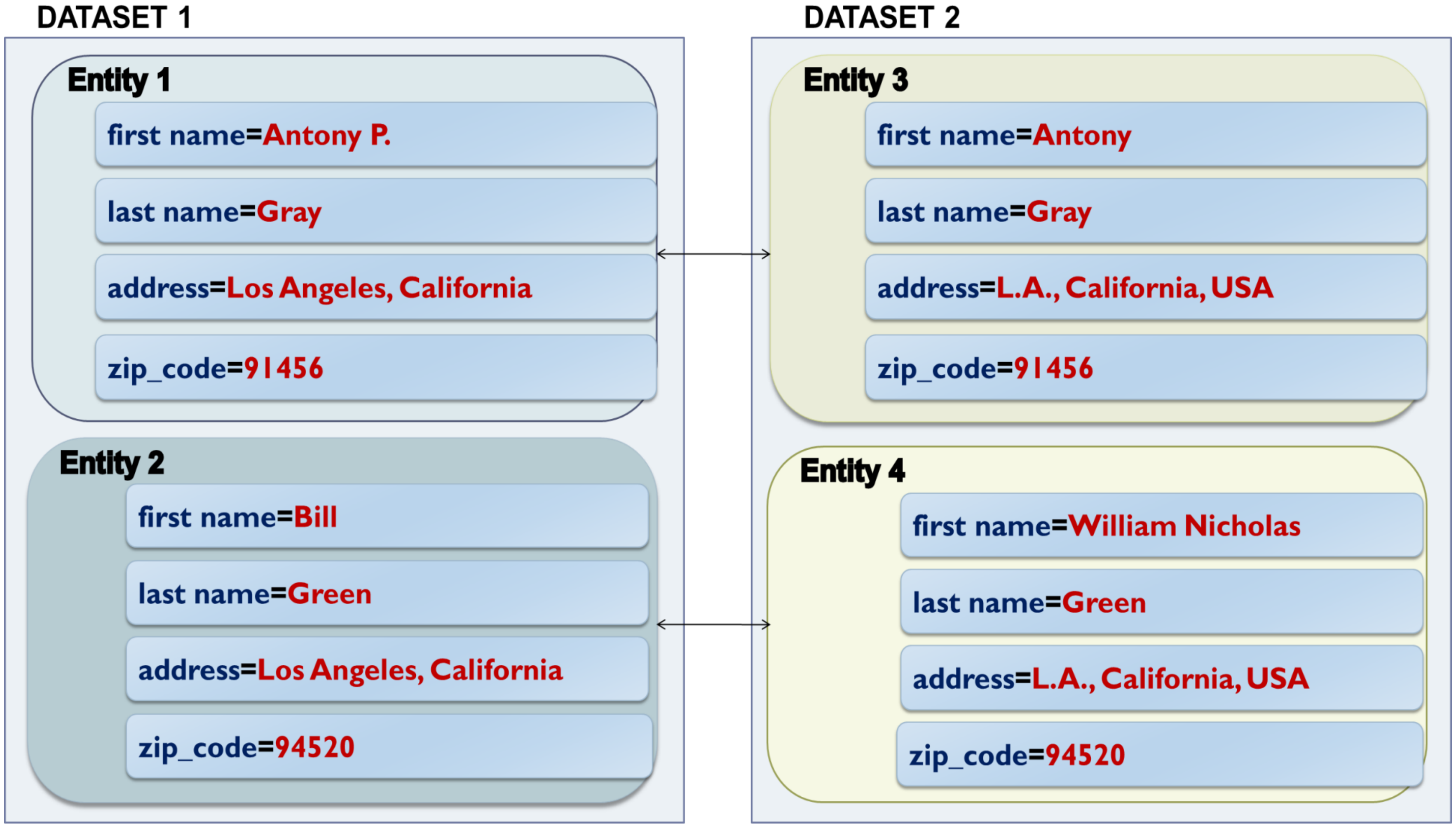
[Fellegi et. al., JASS 1969]

Algorithm:

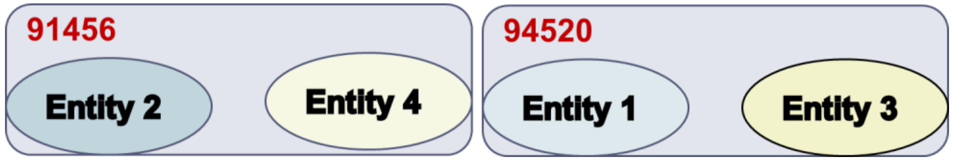
1. Select the most appropriate attribute name(s) w.r.t. noise and distinctiveness.
2. Transform the corresponding value(s) into a Blocking Key (BK)
3. For each BK, create one block that contains all entities having this BK in their transformation.

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

Example of Standard Blocking



Blocks on zip_code:



Thank you for your attention!

Questions?