UNIVERSITY
OF MANNHEIM

Web Data Integration

Identity Resolution

The Data Integration Process

Data Collection / Extraction

↓

Schema Mapping
Data Translation

↓

Identity Resolution

↓

Data Quality Assessment
Data Fusion

Outline

1. Introduction
2. Entity Matching
3. Blocking
4. Evaluation
5. Similarity Measures – In Detail
6. Learning Matching Rules

1. Introduction

Goal of Identity Resolution:
Find all records that refer to the same real-world entity.

DB1	CID1243	Chris Miller	12/20/1982	Bardon Street; Melville	2 sales
DB2	344278	Christian Miller	12/14/1982	7 Bardon St., Melvile	24 sales
	427859	Chris Miller	12/14/1973	Bardon St., Madison	23 sales

– The problem appears whenever
  1. a single data source is cleaned (deduplicated)
  2. data from multiple sources is integrated

Ironically, “Identity Resolution” has Many Synonyms

Duplicate detection

Data matching

Record linkage

Deduplication

Entity resolution

Object identification

Reference matching

Doubles

Householding

Entity clustering

Fuzzy match

Object consolidation

Identity uncertainty

Approximate match

Match

Hardening soft databases

Merge/purge

Reference reconciliation

Mixed and split citation problem

The Two Central Challenges of Identity Resolution

– **Challenge 1: Representations of the same real-world entity are not identical**

- fuzzy duplicates

Chris Miller	12/20/1982	Bardon Street; Melville
Christian Miller	20.12.1982	7 Bardon St., Melvile
Chris Miller (12.14.1973)	NULL	Bardon St., Madison

– Solution: Entity Matching

- compare multiple attributes using attribute-specific similarity measures, after value normalization

– Questions:

1. Which attributes are relevant for the comparison?
2. What is the right similarity measure for each attribute?
3. How to combine the similarity scores of different attributes into a matching decision?

```
488941 britney spears
 40134 brittany spears
 36315 brittney spears
 24342 britany spears
  7331 britny spears
  6633 briteny spears
  2696 britteny spears
  1807 briney spears
  1635 brittny spears
  1479 brintey spears
  1479 britanny spears
  1338 britiny spears
  1211 britnet spears
  1096 britiney spears
   991 britaney spears
   991 britnay spears
   811 brithney spears
   811 brtiney spears
   664 birtney spears
   664 brintney spears
   664 briteney spears
   601 bitney spears
   601 brinty spears
   544 brittaney spears
   544 brittnay spears
   364 britey spears
   364 brittiny spears
   329 brtney spears
   269 bretney spears
   269 britneys spears
   244 britne spears
   244 brytney spears
   220 breatney spears
   220 britiany spears
   199 britnney spears
   163 britnry spears
   147 breatny spears
   147 brittiney spears
   147 britty spears
   147 brotney spears
   147 brutney spears
   133 britteney spears
   133 briyney spears
   121 bittany spears
```

```
29 britent spears
29 brittnany spears
29 britttany spears
29 btiney spears
26 birttney spears
26 breitney spears
26 brinity spears
26 britenay spears
26 britneyt spears
26 brittan spears
26 brittne spears
26 btittany spears
24 beitney spears
24 birteny spears
24 brightney spears
24 brintiny spears
24 britanty spears
24 britenny spears
24 britini spears
24 britnwy spears
24 brittni spears
24 brittnie spears
21 biritney spears
21 birtany spears
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21 bratney spears
21 britani spears
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21 brittinay spears
21 brtany spears
21 brtiany spears
19 birney spears
19 brirtney spears
19 britnaey spears
19 britnee spears
19 britony spears
19 brittanty spears
19 britttney spears
17 birtny spears
17 brieny spears
17 brintty spears
17 brithy spears
```
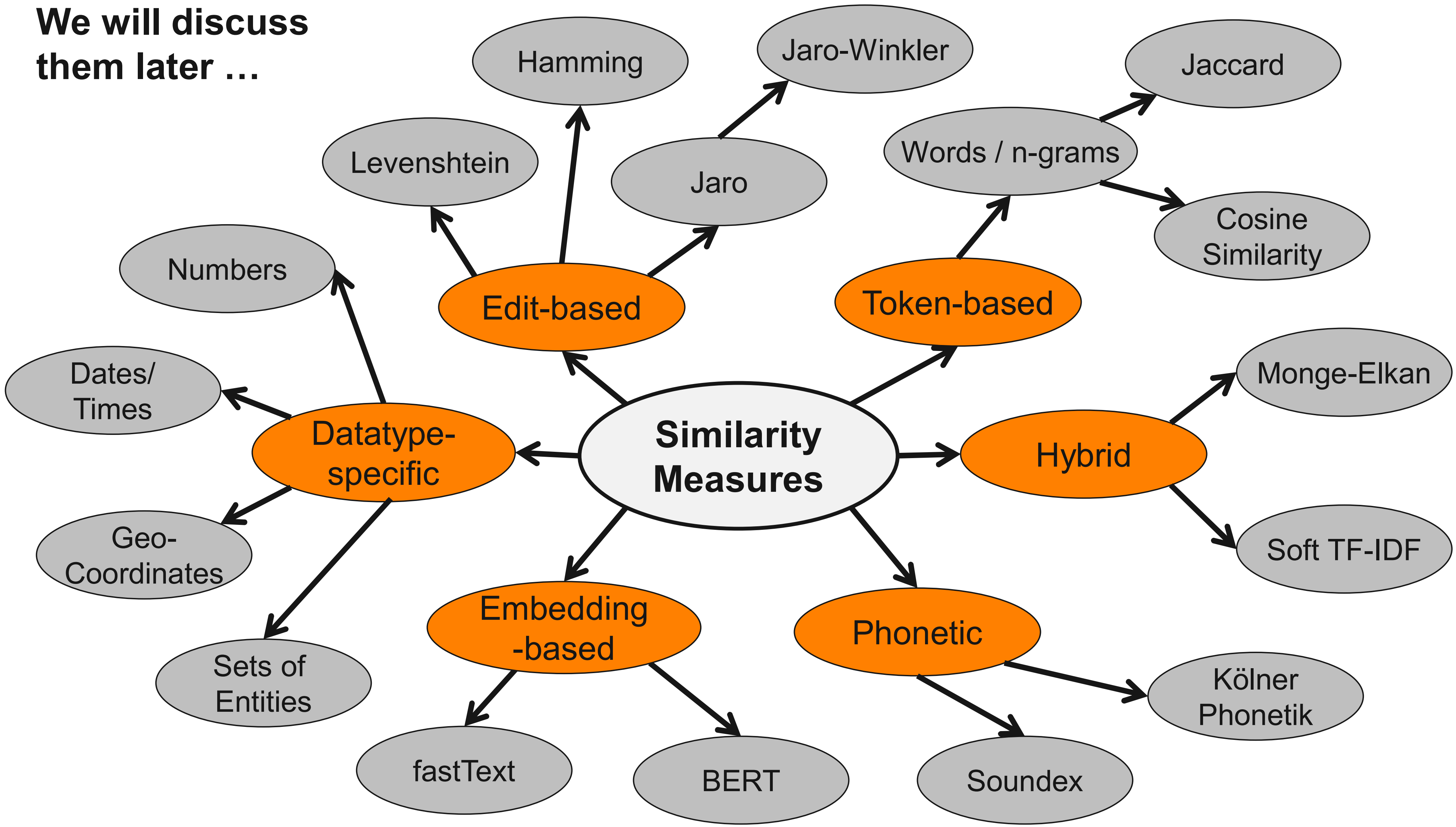
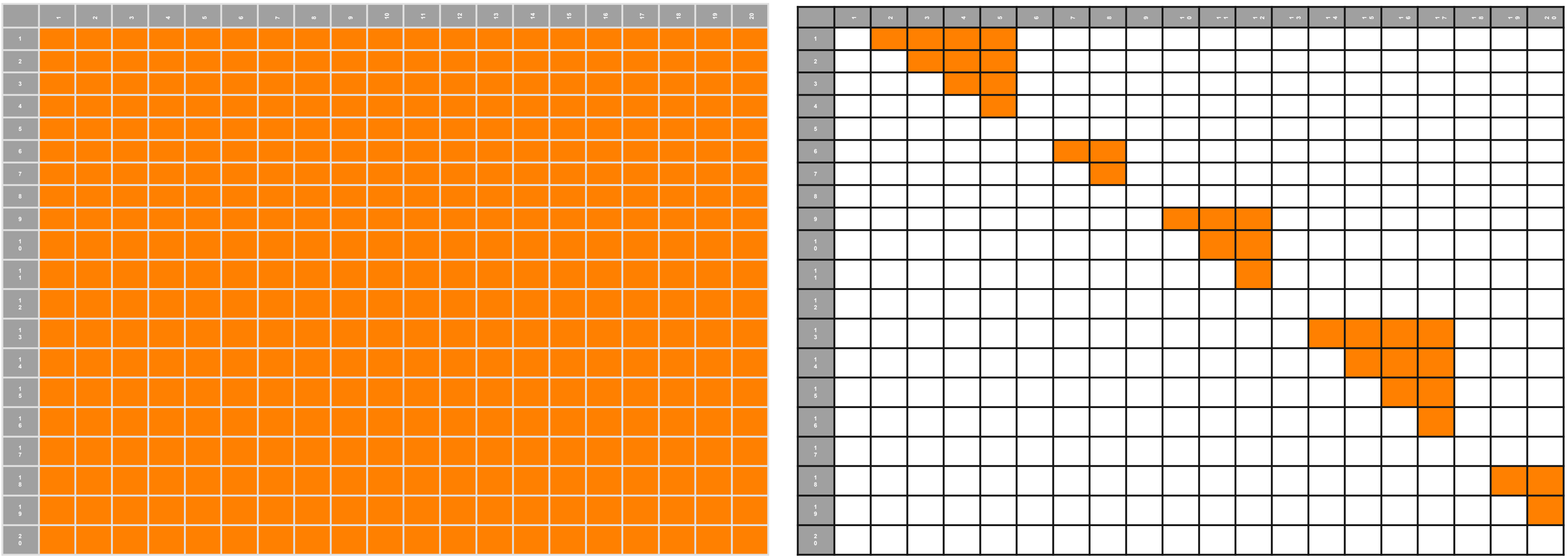

A Wide Range of Similarity Measures Exists

We will discuss them later …



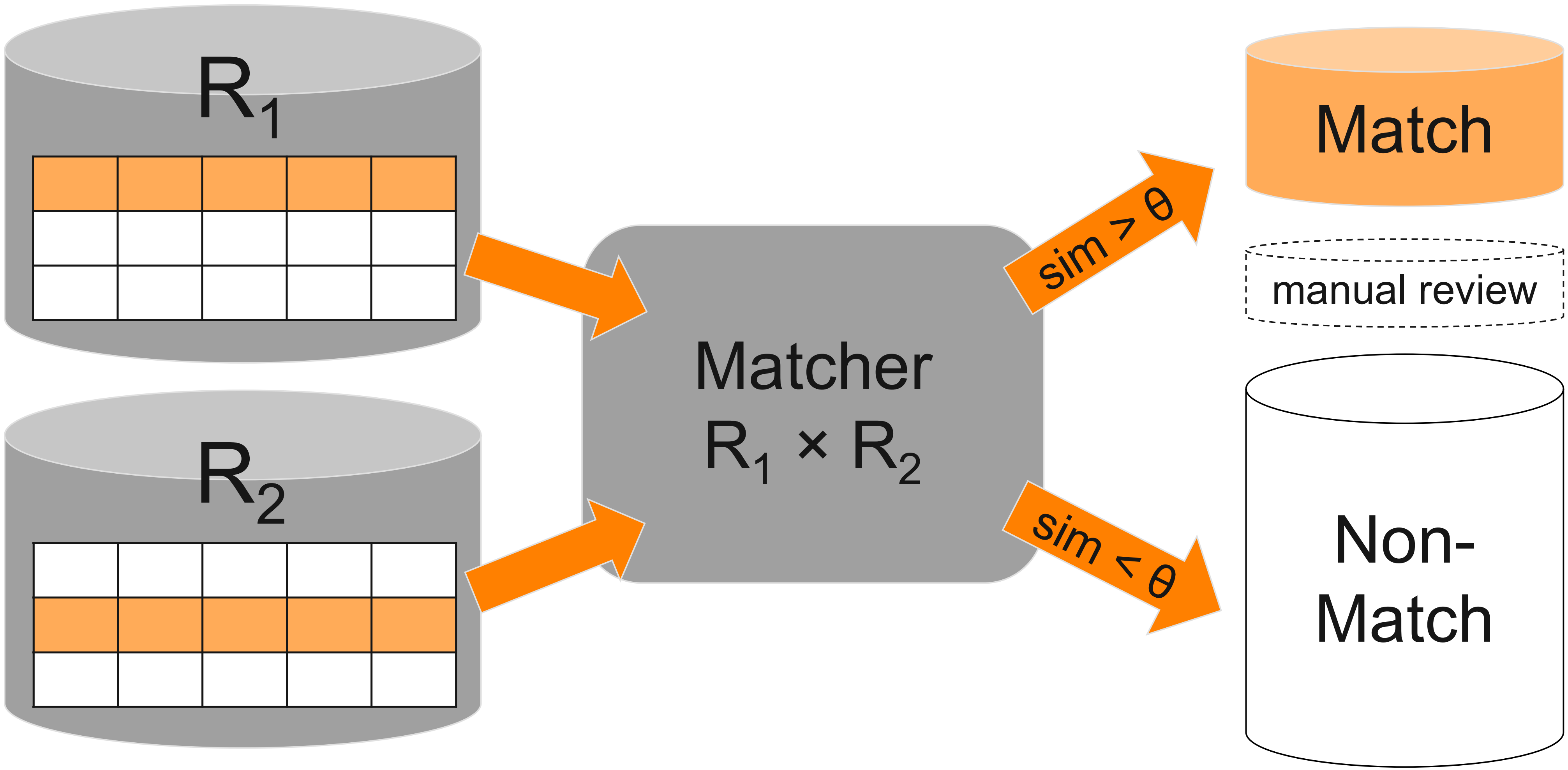
The Two Central Challenges of Identity Resolution

- **Challenge 2: Quadratic Runtime Complexity**
  - Comparing every pair of records is too expensive for larger datasets
- Solution: Blocking methods
  - avoid unnecessary comparisons

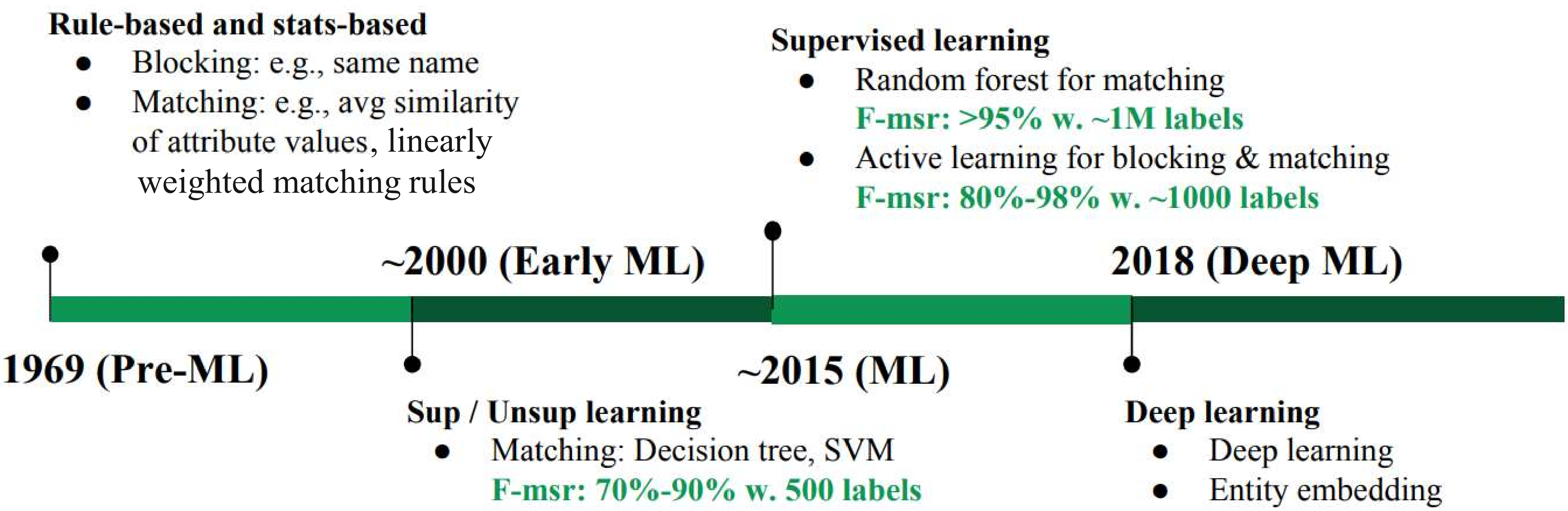


2. Entity Matching

Challenge 1: Representations of the same real-world entity are not identical



50 Years of Entity Matching



Luna Dong: **ML for Entity Linkage. Data Integration and Machine Learning: A Natural Synergy**. Tutorial at SIGMOD 2018. https://thodrek.github.io/di-ml/sigmod2018/sigmod2018.html

2.1 Linearly Weighted Matching Rules

– Compute the similarity score between records x and y as a linearly weighted combination of individual attribute similarity scores

$$sim(x,y) = \sum_{i=1}^{n} \alpha_i * sim_i(x,y)$$

- n is number of attributes in each table
- $sim_i(x,y)$ is similarity score between the i-th attributes of x and y
- $\alpha_i \in [0,1]$ is a pre-specified weight that indicates the importance of the i-th attribute for the matching decision

– We declare x and y matched if $sim(x,y) \geq \beta$ for a pre-specified threshold β, and not matched otherwise

- variation: human manually reviews pair (x,y) if $\alpha \leq sim(x,y) < \beta$.

Example Matching Rule

Table X

	Name	Phone	City	State
x_1	Dave Smith	(608) 395 9462	Madison	WI
x_2	Joe Wilson	(408) 123 4265	San Jose	CA
x_3	Dan Smith	(608) 256 1212	Middleton	WI

(a)

Table Y

	Name	Phone	City	State
y_1	David D. Smith	395 9426	Madison	WI
y_2	Daniel W. Smith	256 1212	Madison	WI

(b)

Matches

(x_1, y_1)
(x_3, y_2)

(c)

$$sim(x,y) = 0.3\ s_{name}(x,y) + 0.3\ s_{phone}(x,y) + 0.1\ s_{city}(x,y) + 0.3\ s_{state}(x,y)$$

$s_{name}(x,y)$: using the Jaro-Winkler similarity measure

$s_{phone}(x,y)$: based on edit distance between x's phone (after removing area code) and y's phone

$s_{city}(x,y)$: based on edit distance

$s_{state}(x,y)$: based on exact match; yes ➔ 1, no ➔ 0

2.2 Non-Linear Matching Rules

- Often better than linear rules but require specific domain knowledge.
- Example 1: Two persons match if names match approximately and their addresses match exactly
  1. if $\mathbf{sim}_{name}(\mathbf{x,y})$ < 0.8 then return "not matched"
  2. otherwise if $\mathbf{equal}_{city}(\mathbf{x,y})$ = true and $\mathbf{equal}_{state}(\mathbf{x,y})$ = true then return "matched"
  3. otherwise return "not matched"
- Example 2: Two genes match if their names match approximately and any of the different, alternative gene identifiers match exactly (deals with missing values)
  - if max ($\mathbf{equal}_{genID}(\mathbf{x,y})$, $\mathbf{equal}_{componentID}(\mathbf{x,y})$, $\mathbf{equal}_{structureID}(\mathbf{x,y})$) = 1
  - and $\mathbf{sim}_{name}(\mathbf{x,y})$ > 0.7
  - then return "matched"
- Non-linear rules can be learned using tree-based learners (Sec. 6)

2.3 Data Gathering for Matching

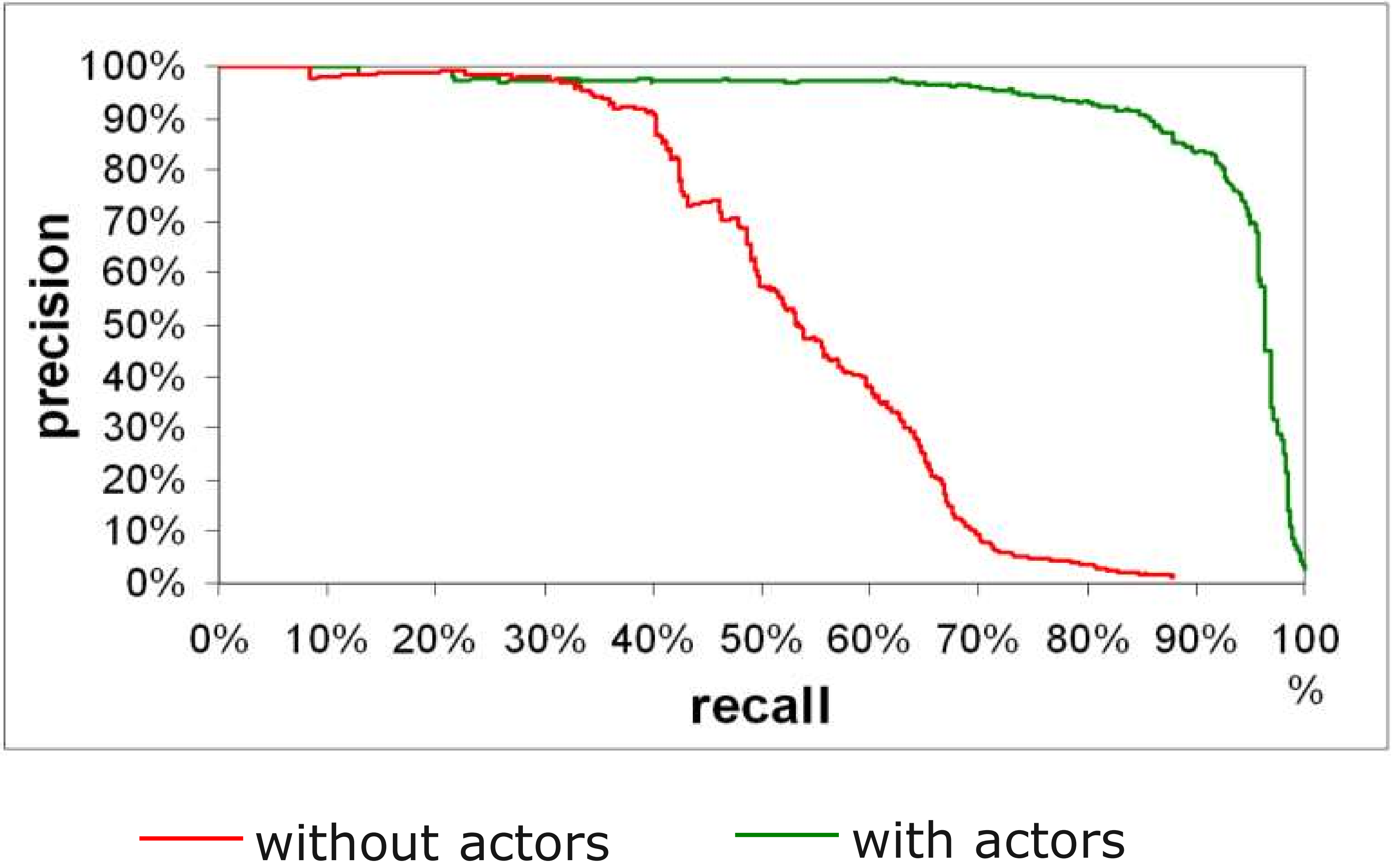
– Not only values of the records to be compared, but also values of related records are relevant for the similarity computation
  - Movies: Actors
  - CDs: Songs
  - Persons: Spouse, children, employer, publications

– Example: The movie names look quite similar to the edit distance measure

ID	Film
1	Star Wars 1
2	Star Wars 4
3	Star War 1

ID	Actor
1	Ewan McGregor
2	Natalie Portman
3	Mark Hamill
4	Harrison Ford
5	Ewan McGregor
6	Natalie Portman

Example: Matching Films using different Thresholds β



2.4 Data Preprocessing for Matching

In order to enable similarity measures to compute reliable scores, the data needs to be normalized.

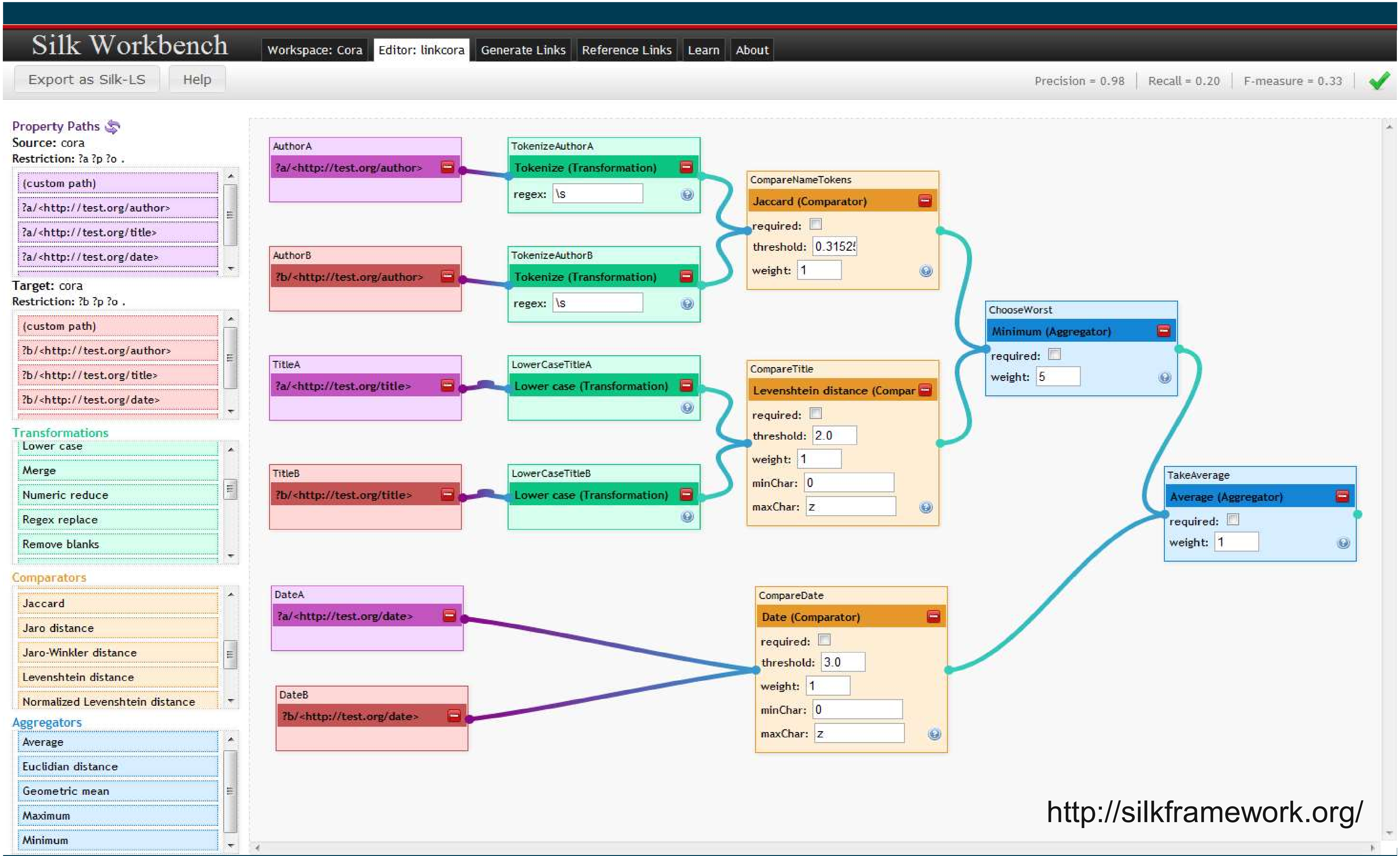
- Normalize spelling
  - lower case everything: Müller and mueller ➔ mueller
  - remove punctuation: U.S.A ➔ usa
- Remove stopwords
  - The Netherlands ➔ netherlands
- Normalize value formats and units of measurement
  - +49 621 181 2677 and (621) 181 2677 ➔ 496211812677
  - 1000 MB and 1 GB ➔ 1000 MB
- Normalize abbreviations and synonyms/surface forms
  - Inc. ➔ Incorporated, Mr.➔ Mister, USA ➔ United State of America
  - using domain-specific lists of abbreviations and synonyms/surface forms

Parsing and Translation

- Information Extraction / Parsing
  - Extract attribute/value pairs from compound descriptions or titles
    - using regular expressions or attribute specific extractors (e.g list of all brands)
  - Often required for e-commerce data or postal addresses:
    - Apple MacBook Air MC968/A 11.6-Inch Laptop
    - Apple MacBook Air 11-in, Intel Core i5 1.60GHz, 64 GB, Lion 10.7
- Translation using external services
  - Geocoding
    - translate addresses into geo-coordinates and compare coordinates afterwards
    - e.g. using Google Geocoding API
  - Translate into target language
    - מנהיים ➔Mannheim
    - e.g. using Google Translate API or other translation software

Kannan, et al: **Matching unstructured Product Offers to structured Product Specifications.** KDD, 2011.

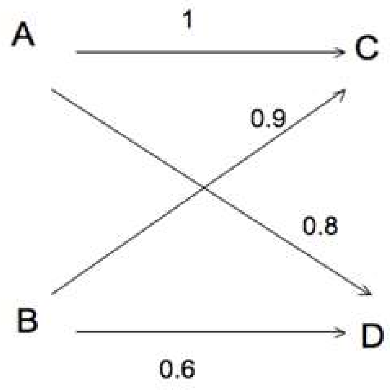
Example: Complex Matching Rule including Preprocessing



http://silkframework.org/

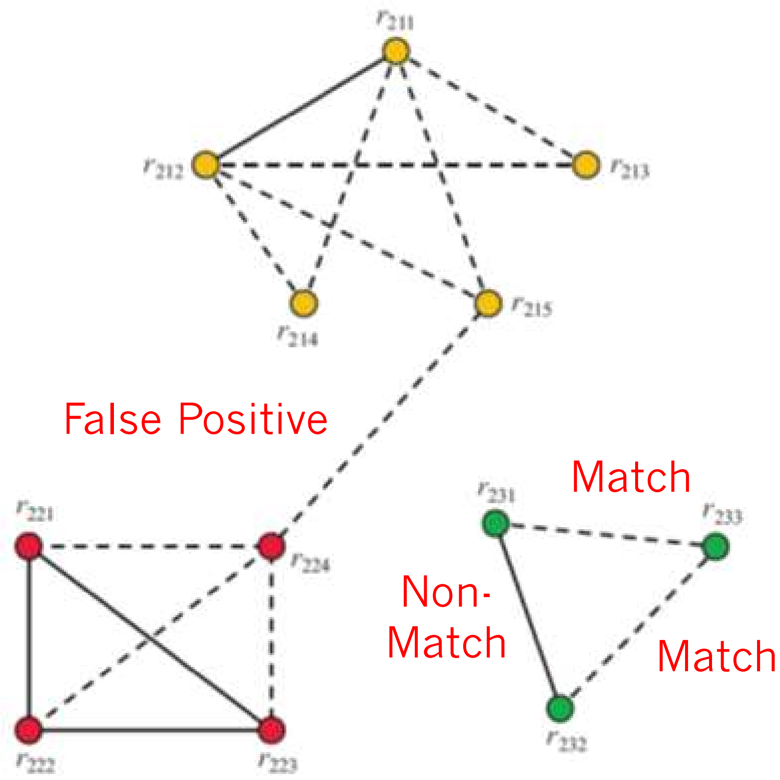
2.5 Local versus Global Matching

– Input: A matrix containing record similarities
– Output: A set of correspondences connecting pairs of matching records
– Local Matching
  - consider all pairs above threshold β as matches
  - implies that one record can be matched with several other records
  - makes sense for duplicate detection within single data source
– Global Matching
  - enforce constraint that one record in data set A should only be matched to one record in data set B
  - makes sense for data sources that do not contain duplicates
  - Approaches:
    1. Bipartite pairs with the maximal sum of similarity values
    2. Stable marriage (see Chapter Schema Mapping)



2.6 Cluster Records using Pairwise Correspondences

- Goal: Create groups of records describing the same real-world entity from pairwise correspondences
  - relevant for matching multiple data sources and for the deduplication of a single source
- Simple Approach: Connected Components
  - transitive closure of pairwise correspondences
  - problem: correspondences might be inconsistent as they result from separate local decisions
- Smarter Approach: Correlation Clustering
  - cuts graph into coherent groups by minimizing disagreement with pairwise correspondences
    - Cohesion penalty: Non-matching records in cluster
    - Correlation penalty: Removing correspondences



Saeedi, et al.: **Comparative Evaluation of Distributed Clustering Schemes for Multi-source Entity Resolution.** ADBIS 2017.
Hassanzadeh, et al.: **Framework for Evaluating Clustering Algorithms in Duplicate Detection.** *VLDB Endowment*, 2009.

Summary: The Entity Matching Process

Gather Data for Matching

Normalize Attribute Values

Crucial, despite being a lot of effort!

Apply Attribute-specific Similarity Measures

Combine Similarity Scores

Decide Match/Non-Match

Cluster Records based on Correspondences

3. Blocking

- Real world data sets are often large
- Problem: Quadratic complexity of matching process
  - comparing every pair of records is too expensive:
    - 100 customers ➔ 10,000 comparisons
    - 10,000 customers ➔ 100 million comparisons
    - 1,000,000 customers ➔ 1 trillion comparisons
  - Each comparison itself is also expensive as it involves calculating various similarity scores
    - calculation of a string similarity score often has quadratic complexity itself
- Solution: Reduce number of pairs of records that are compared by
  1. avoiding unnecessary comparisons (next 3 slides)
     - no negative effect, but faster ☺
  2. applying blocking methods that further reduce the number of comparisons
     - negative effect: True matches might be missed ☹

Number of comparisons: All pairs

Complexity: n^2

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1																				
2																				
3																				
4																				
5																				
6																				
7																				
8																				
9																				
10																				
11																				
12																				
13																				
14																				
15																				
16																				
17																				
18																				
19																				
20																				

20 records

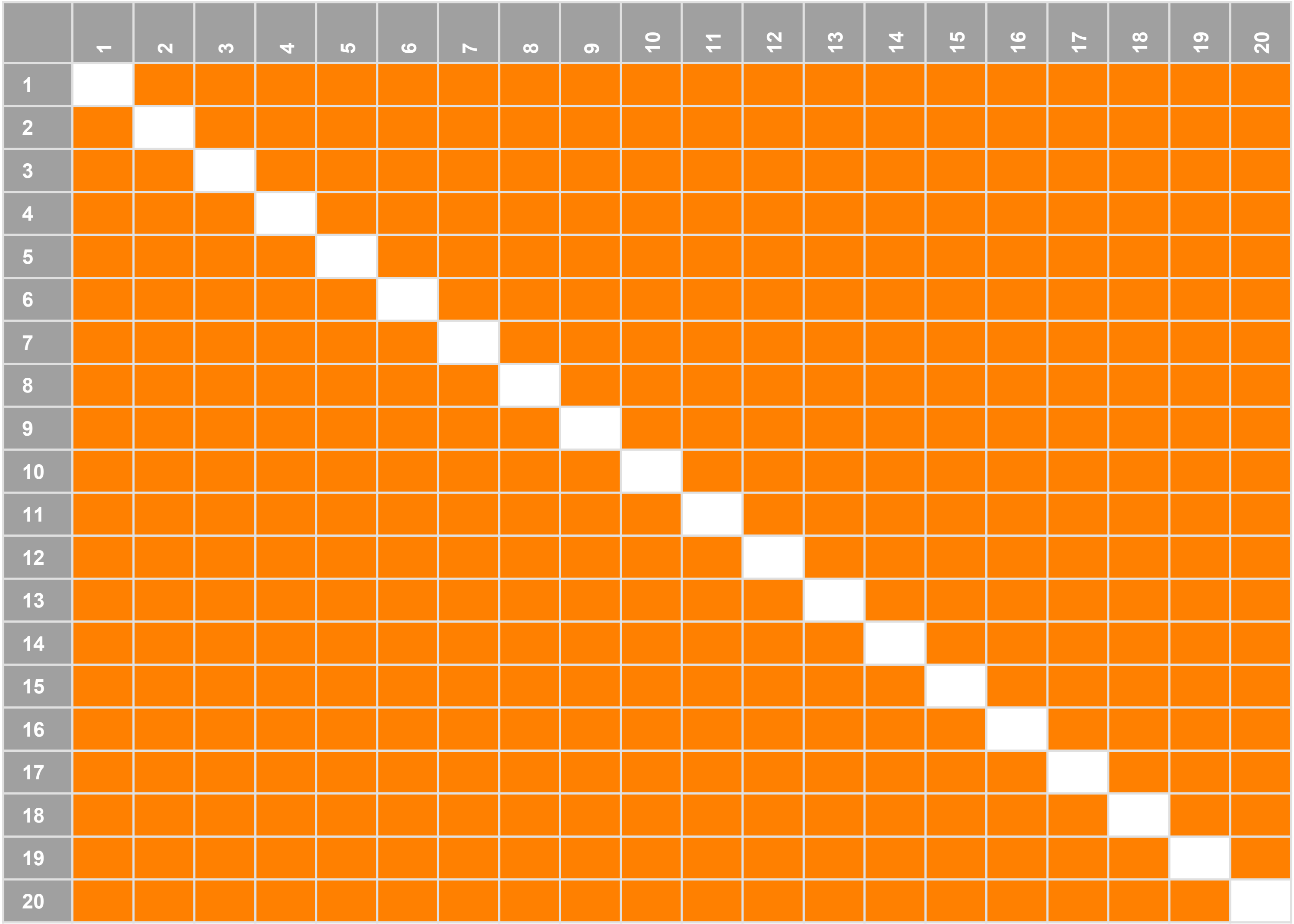
➔

400

comparisons

Reflexivity of Similarity

Complexity: n^2-n



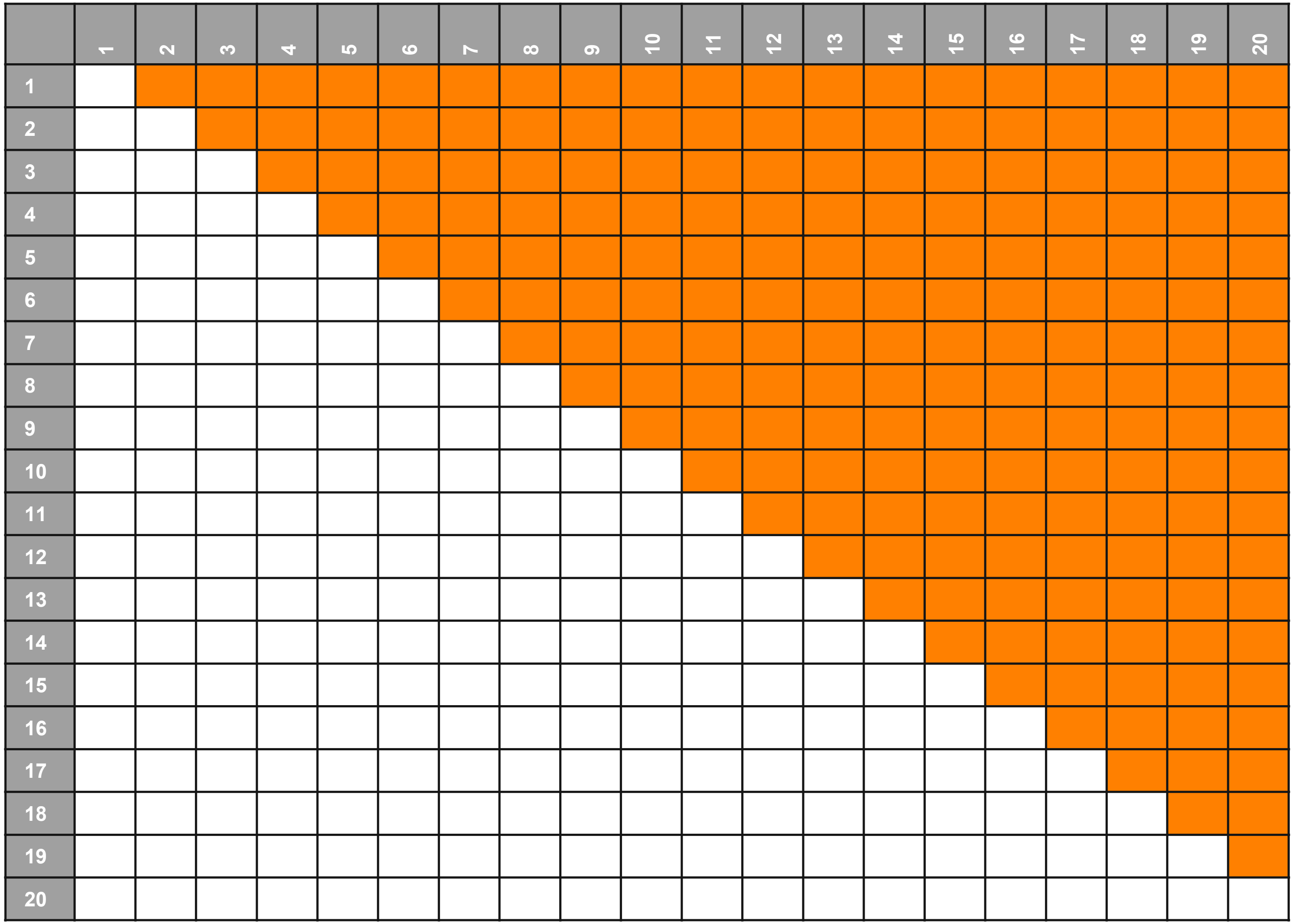
Similarity is reflexive:
sim(x, x) = 1

380 comparisons

- Applies to duplicate detection use case
- but not to two data sources use case

Symmetry of Similarity

Complexity: $(n^2-n) / 2$



Similarity is symmetric: sim(x,y) = sim(y,x)

190 comparisons

Still quadratic ☹

3.1 Standard Blocking

Idea: Reduce number of comparisons by partitioning the records into buckets and compare only records within each bucket.

- Examples:
  - partition customers by first two digits of their zip code
    - results in about 100 partitions for Germany
    - given about 100 customers per partition

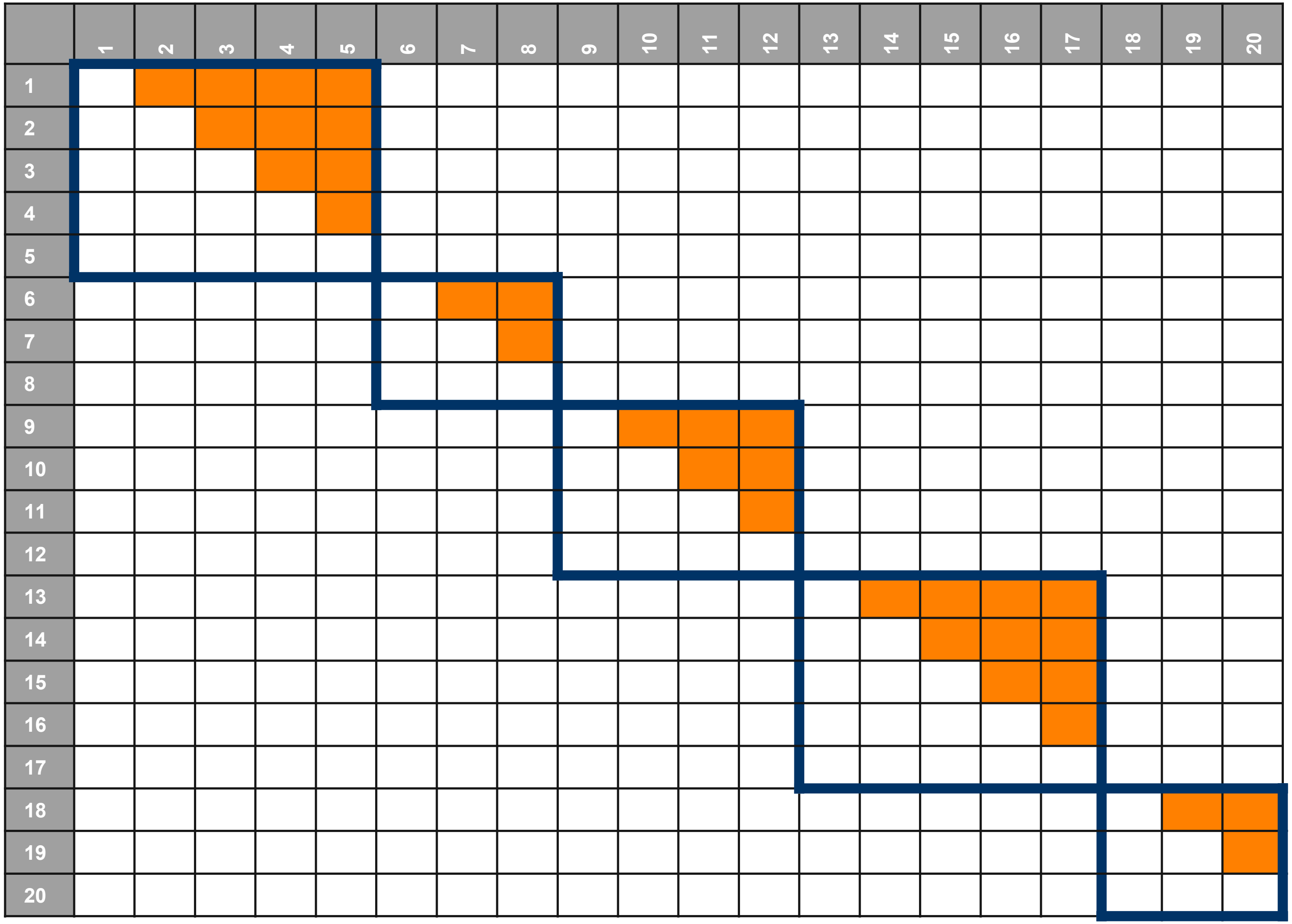
    ➔ 495,000 comparisons instead of 49,995,000

    Positive: algorithm ~100 times faster

    Negative: matches with wrong zip code might be missed
  - partition books by publisher
  - partition people by first two characters of surname
- Blocking is also called hashing or partitioning

Source: wikipedia.de

Standard Blocking



32 comparisons

+ much faster than 190 comparisons

- might miss Matches ☹

Choosing a Good Blocking Key

- Reduction ratio depends on effectiveness of blocking key
  - high: if records are equally distributed over buckets
  - low: if majority of the records end up in one bucket
    - example: 90% of all customers are from Mannheim
  - possible workaround: build sub-buckets using a second blocking attribute
    - block houses by zip first. Afterward, block within each bucket by street name
- Recall depends on actually matching pairs being kept (compared)
  - pairs might not be compared as their blocking key values differ
    - typo in zip code, customer has moved
  - possible workaround: use only first letters as they often contain less typos
- Example combining both workarounds

FirstName	Name	Adresse	ID
Sal	Stolpho	123 First St.	456780
Mauricio	Hernandez	321 Second Ave	123456

Blocking Key
STOSAL
HERMAU

3.2 The Sorted Neighborhood Method (SNM)

Idea: Sort records so that similar records are close to each other. Only compare records within a small neighborhood window.

1. Generate key
   - e.g. first 3 letters of social security number + first 3 letters of surname
2. Sort by key
   - so that similar records end up close to each other
3. Slide window over sorted records
   - match each record with only the next w-1 records, where w is a pre-specified window size

3. Slide window w=2

FirstName	Surname	Address	SSN
Mauricio	Hernandez	321 Second Ave	123456
All	Stolpho	123 First St.	456780
Sal	Stolpho	123 First St.	456780
Sal	Stelfo	123 First Street	456789

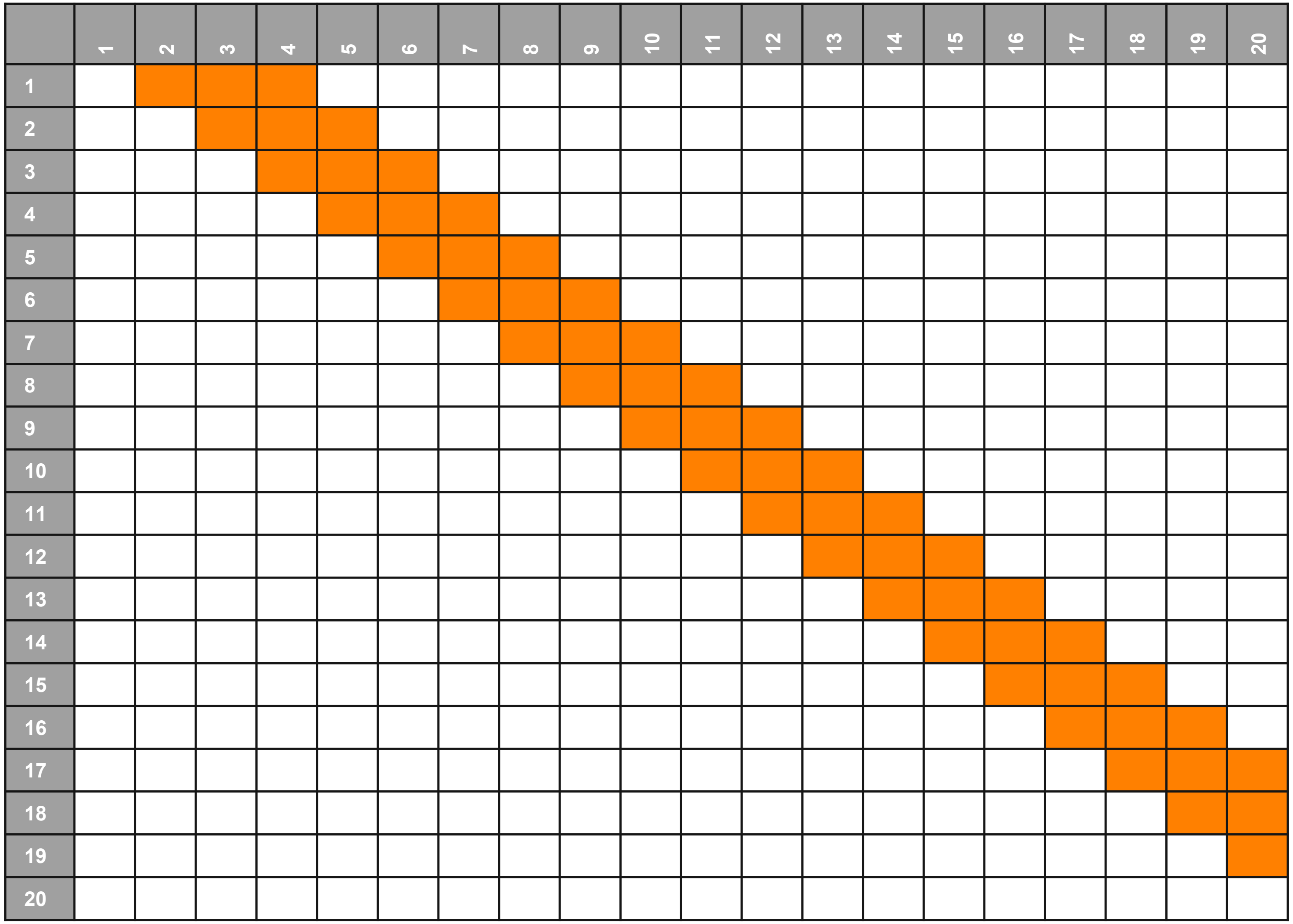
1. Generate key

Key
123HER
456STO
456STO
456STE

2. Sort

The Sorted Neighborhood Method (SNM)

Window size = 4



54 comparisons

\+ no problem with different bucket sizes

Complexity:

1. Key generation: O(n)
2. Sorting: O(n*log(n))
3. Comparisons: O(n*w)

Challenges when Applying the SNM

– Choice of Blocking Key
  - SNM assumes that records that are likely to match fall within the window
  - Thus, key should be **strongly “discriminative”** and bring together records that are likely to match, and pushes apart records that are not
    - example keys: social sec, student ID, two characters of first + surname

– Choice of Window Size
  - Depends on the types and frequency of the errors/typos in the data
  - Practical experience: w = 20 often a good compromise

– Workaround: Use Multi-Pass Approach
  1. Run SNM several times with different blocking keys
     - use simple keys and a small w, e.g. 1. social sec, 2. two characters first + surname
  2. Merge sets of matches found in each run
  - Less efficient, but much more effective than single-pass

3.3 Token Blocking for Textual Attributes

– Identifying attributes are often rather textual, e.g.
  - Product names: Samsung Galaxy S10 SM-G975, 128GB, 8GB RAM
  - Names of local business: Wong Restaurant, Hoy Wong Greenwich
– Token Blocking
  - builds an inverted index that associates every token with all entities containing it in their attribute values
  - using only the identifying attribute or a concatenation of multiple attributes
  - afterwards, all pairs that sharing at least one (or more) tokens are compared
– N-Gram Blocking
  - variation of token blocking that uses character n-grams in order to deal with typos
  - n=3 : men, end, edo, ...

Set X

1: {lake, mendota}
2: {lake, monona, area}
3: {lake, mendota, monona, dane}

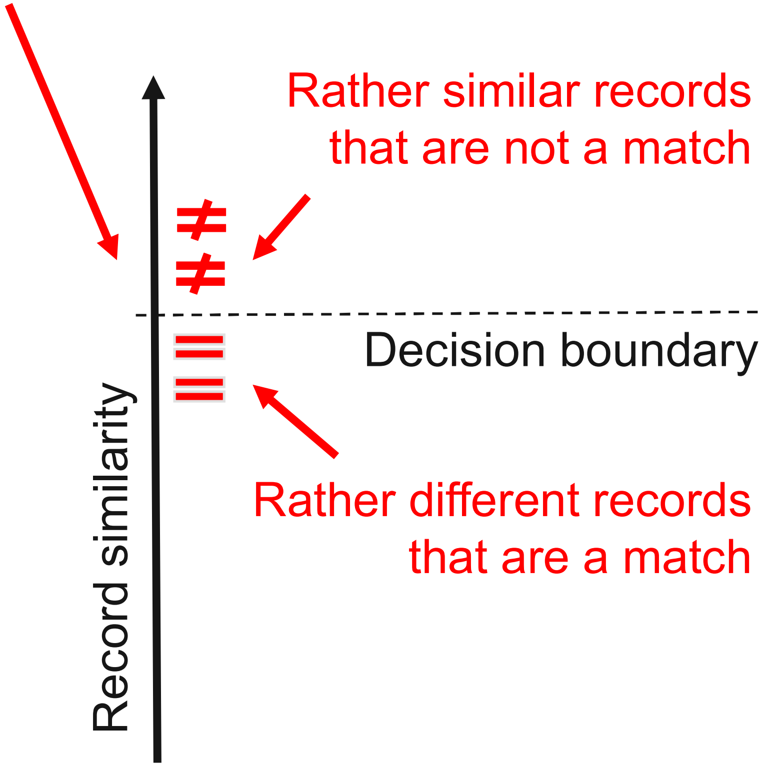
Set Y

4: {lake, monona, university}
5: {monona, research, area}
6: {lake, mendota, monona, area}

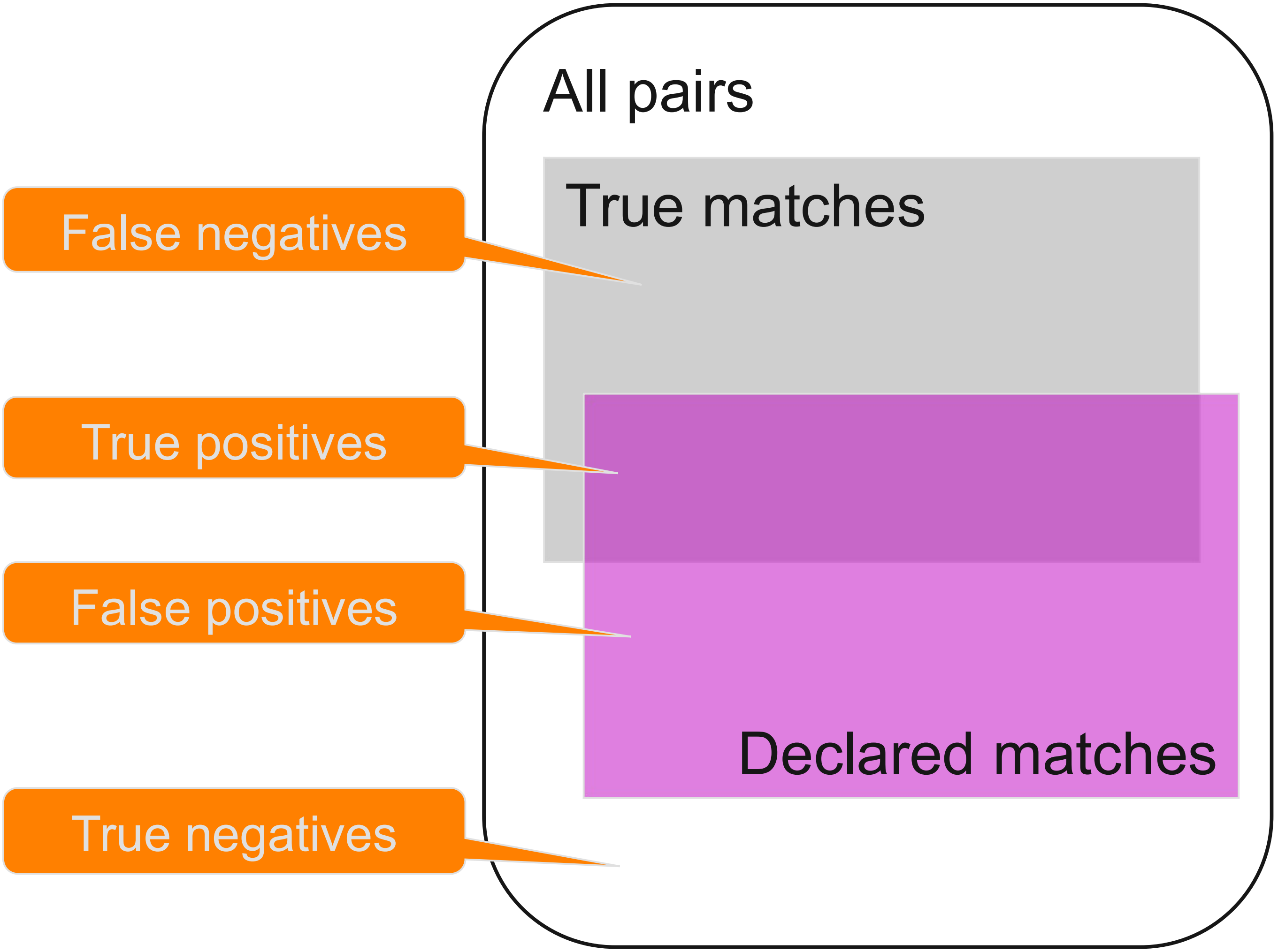
Terms in Y	ID Lists
area	5
lake	4, 6
mendota	6
monona	4, 5, 6
research	5
university	4

4. Evaluation

– You need ground truth (gold standard) for the evaluation
– To create a gold standard, manually label a set of record pairs as matches or non-matches including corner cases
– Rule of thumb for creating a *suitable* gold standard with *acceptable* manual effort:
  1. match records using several simple matching techniques (goal: avoid selection bias) and sort record pairs according to their similarity
  2. if available, use information about likely matches (e.g. ISBN or GTIN numbers that exist in multiple sources)
  3. manually verify a fair amount of the resulting pairs (e.g. >500 pairs) including
     1. matching record pairs (randomly chosen, 20% of GS)
     2. corner case matches and non-matches (30% of GS)
     3. non-matching record pairs (randomly chosen, 50% of GS)



Evaluation Metrics: Precision, Recall & F1



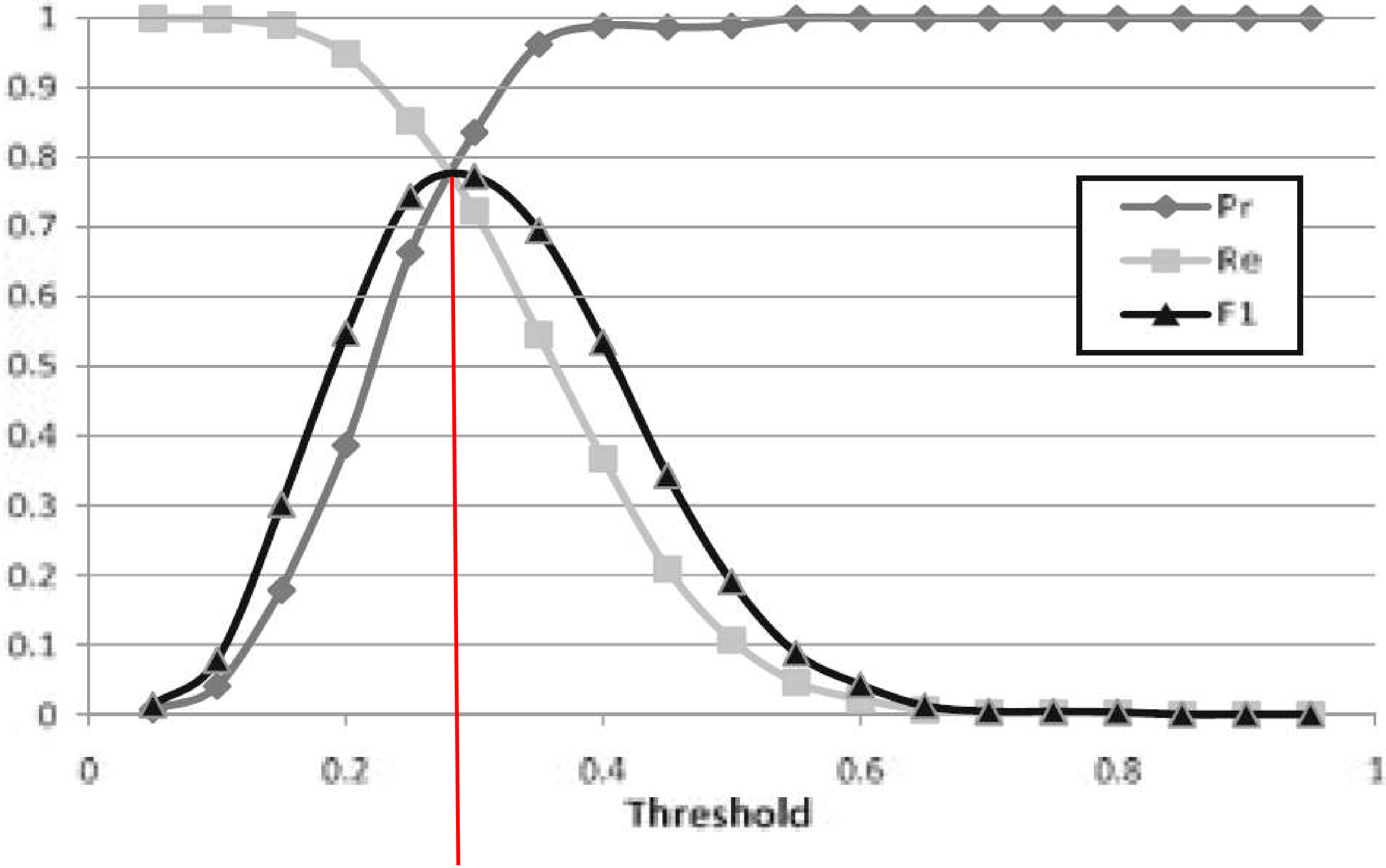
$$\text{Precision} = \frac{\text{True positives}}{\text{Declared matches}}$$

$$\text{Recall} = \frac{\text{True positives}}{\text{True matches}}$$

$$\text{F1-Measure} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy is not a good metric as matching is a strongly unbalanced task
(true negatives dominate overall result)

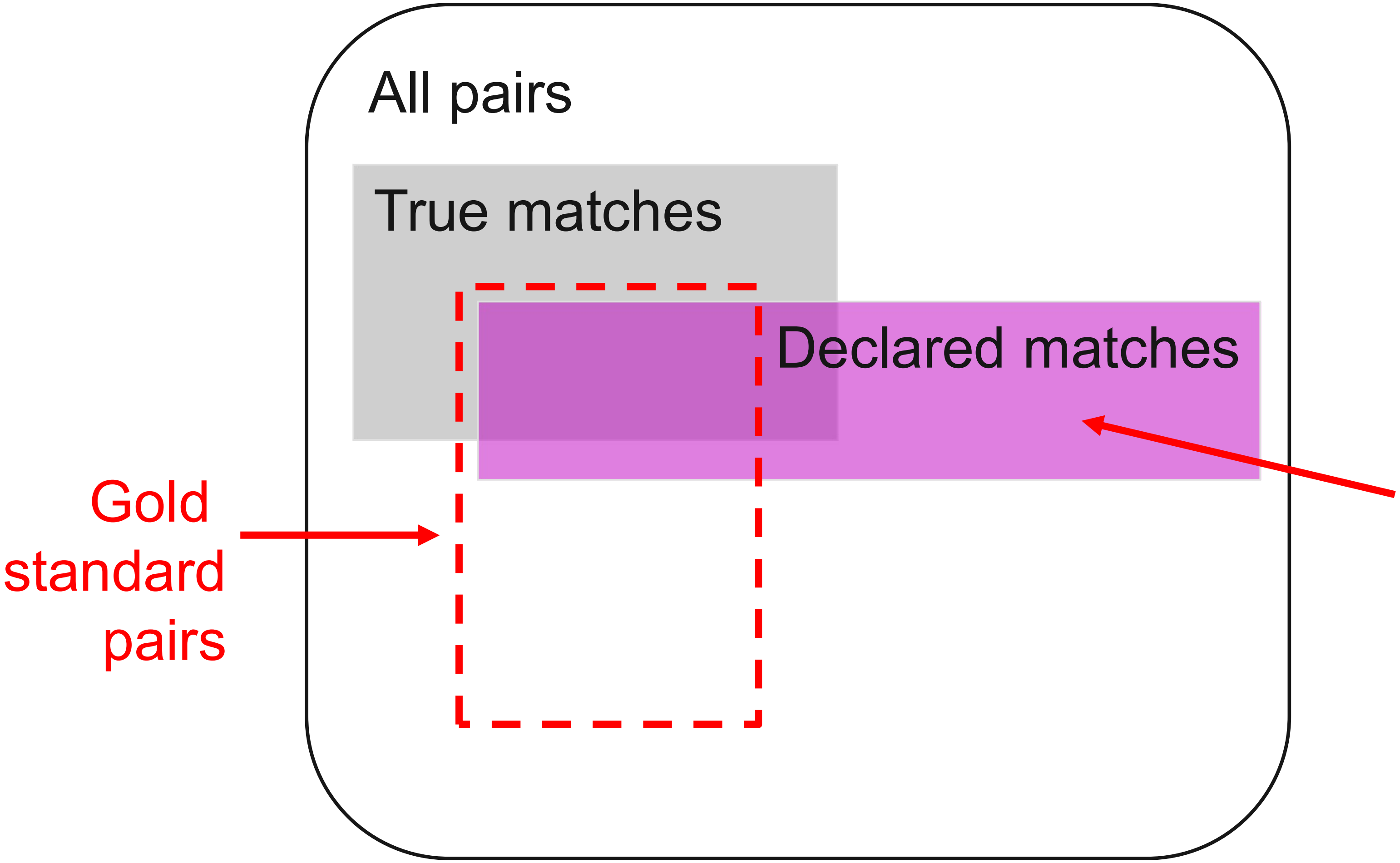
F1-Measure Graph



Optimal threshold β for linearly weighted matching rules

Gold Standard Pairs versus All Pairs

Be aware that the selection bias of the record pairs in gold standard influences the evaluation result (and the data fusion quality).

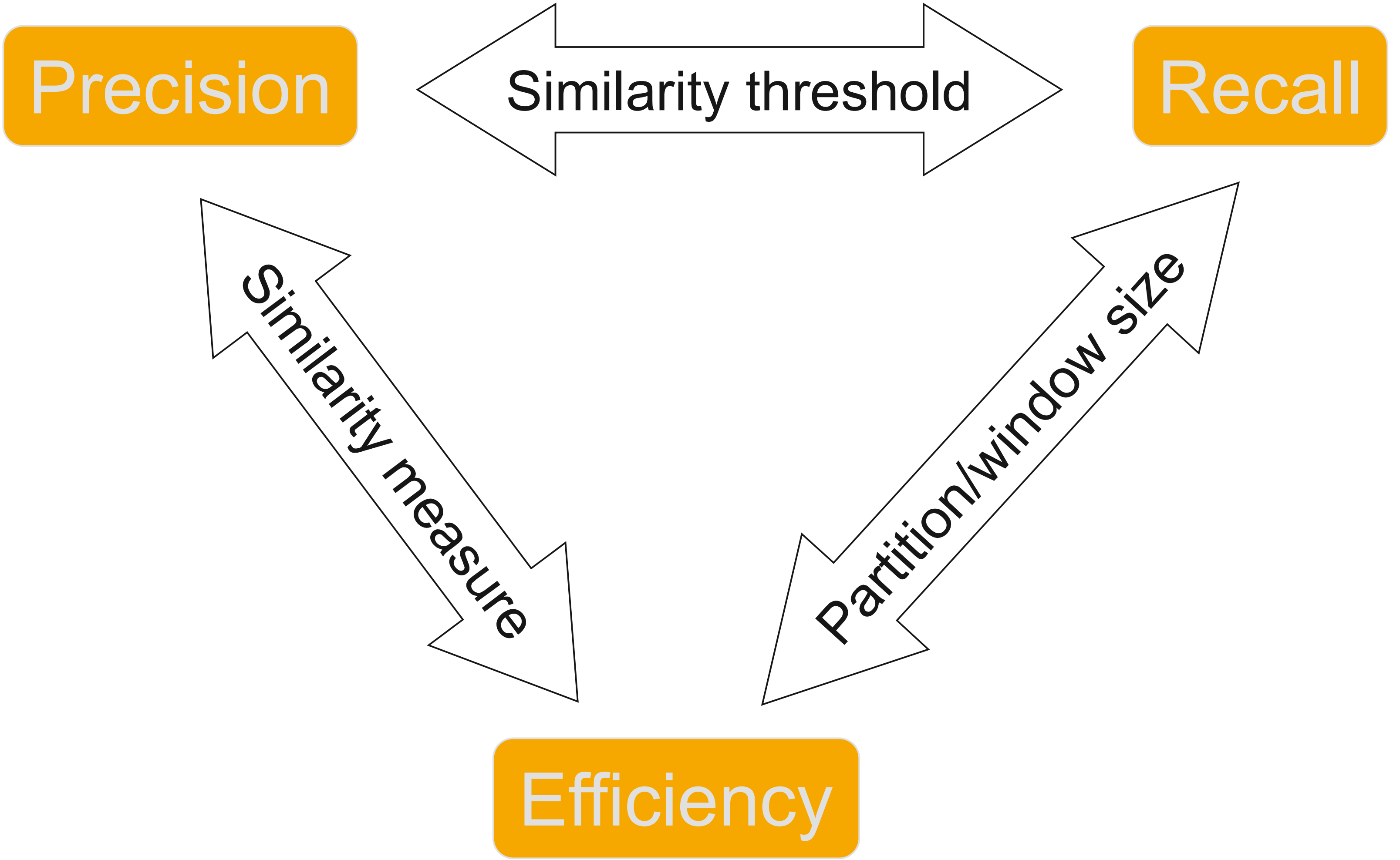


Additional wrong correspondences lead to unnaturally large clusters of records which might confuse the fusion method later

Efficiency Measures

- Besides of the quality of the matching method, the quality of the blocking method is also important
- Option 1: Runtime measurements
  - but: different hardware, replicability problematic
- Option 2: Measure how well/poor the blocking method filters the candidate pairs
  - by which ratio does the blocking method reduce the number of comparisons?
  - how many true positives are missed?
- Reduction Ratio $= 1 - \frac{\text{pairs}_{\text{afterBlocking}}}{\text{pairs}_{\text{beforeBlocking}}}$
- Pairs Completeness $= \text{matches}_{\text{afterBlocking}} / \text{matches}_{\text{beforeBlocking}}$

Tradeoffs between Precision, Recall and Efficiency



Evaluation Datasets

Matching methods should be evaluated using the same datasets in order to make results of different methods comparable.

1. Leipzig Evaluation Datasets

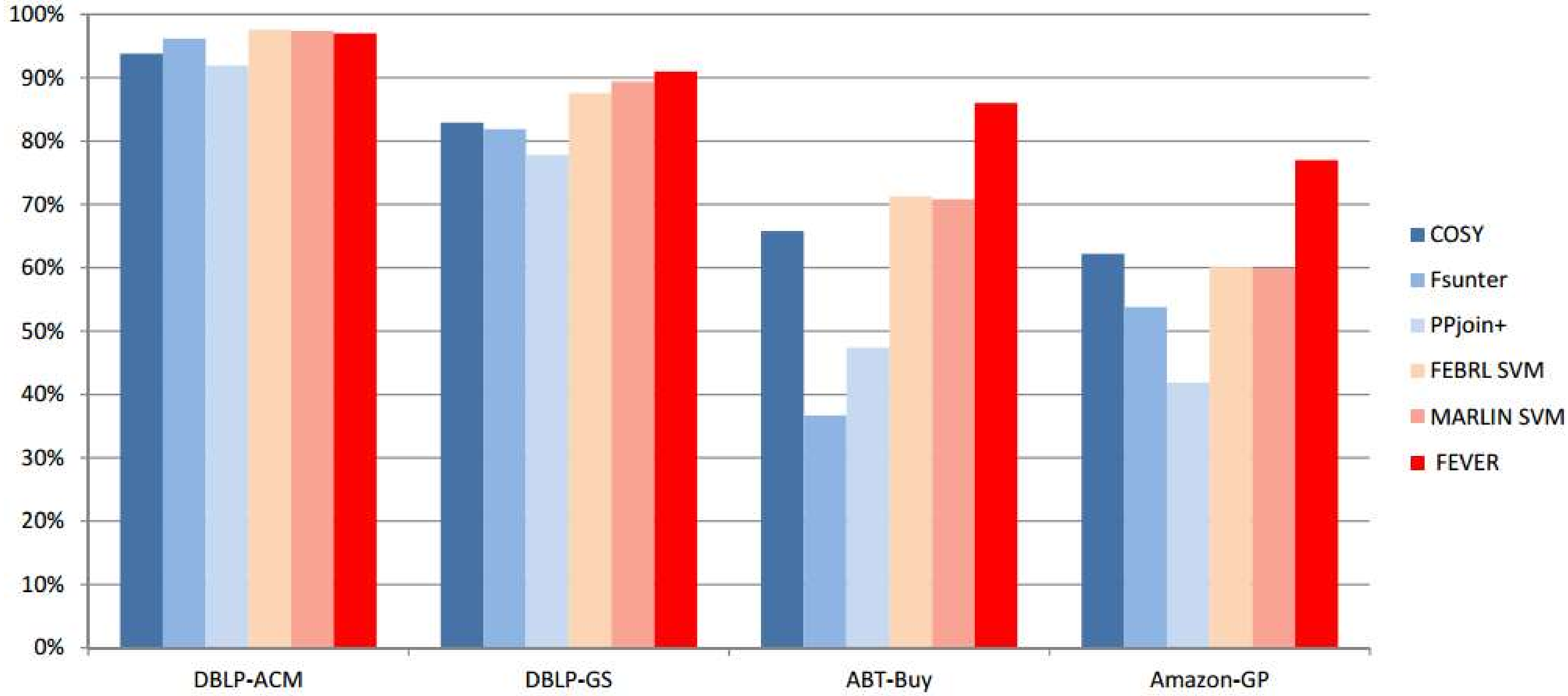
Match task		Source size (#entities)		Mapping size (#correspondences)		
Domain	Sources	Source 1	Source 2	Full input mapping (cross product)	Reduced input mapping (blocking)	perfect match result
Bibliographic	DBLP-ACM	2,616	2,294	6 million	494,000	2224
	DBLP-Scholar	2,616	64,263	168.1 million	607,000	5343
E-commerce	Amazon-GoogleProducts	1,363	3,226	4.4 million	342,761	1300
	Abt-Buy	1,081	1,092	1.2 million	164,072	1097

   – Köpcke, Thor, Rahm: Evaluation of entity resolution approaches. VLDB 2010.

2. DeepMatcher Evaluation Datasets
   – https://github.com/anhaidgroup/deepmatcher/blob/master/Datasets.md

3. WDC Training Dataset and Gold Standard for Large-Scale Product Matching
   – http://webdatacommons.org/largescaleproductcorpus/v2/

F-Measure for Bibliographic and E-Commerce Data (2010)



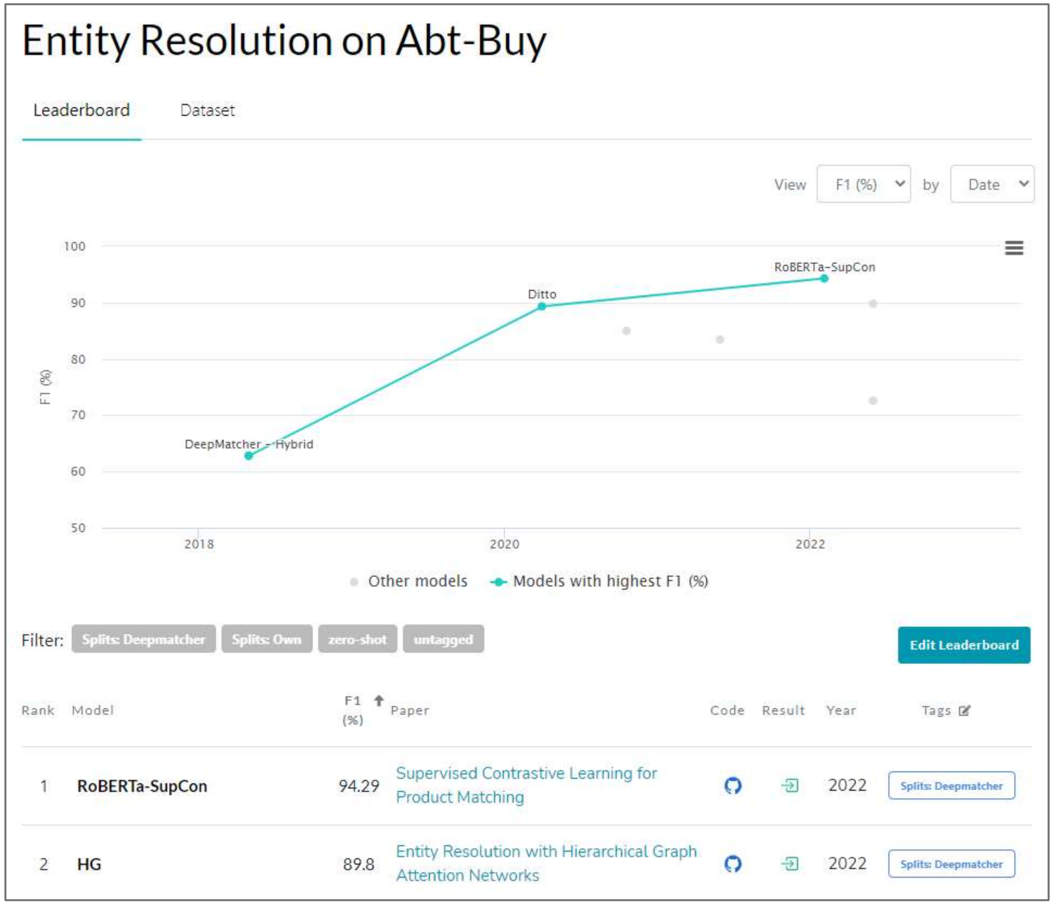
Köpcke, Thor, Rahm: **Evaluation of entity resolution approaches on real-world match problems.** VLDB 2010.

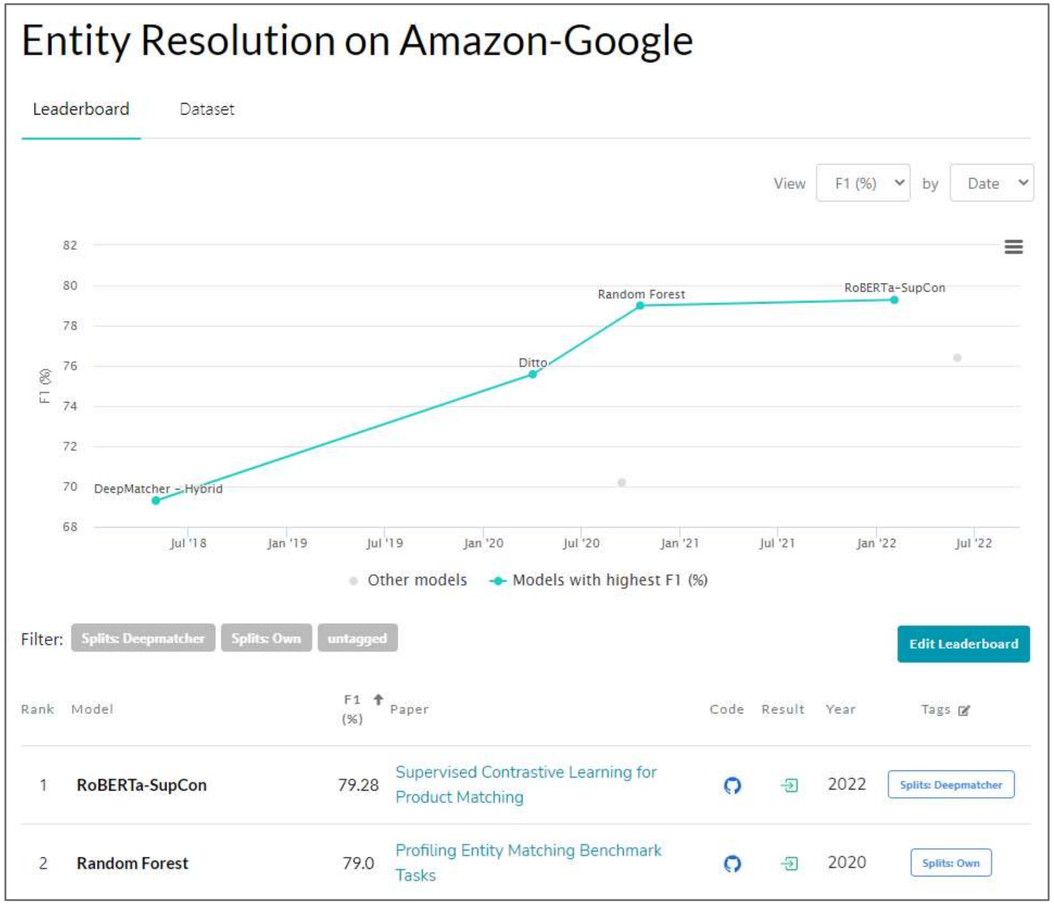
Anna Primpeli, Christian Bizer: **Profiling entity matching benchmark tasks.** CIKM 2020.

F-Measure for E-Commerce Data (2022)

Papers with code collects current benchmark results

- F1 for Abt-Buy dataset: 2010: 86%, 2022: 94% ➔ + 8%*

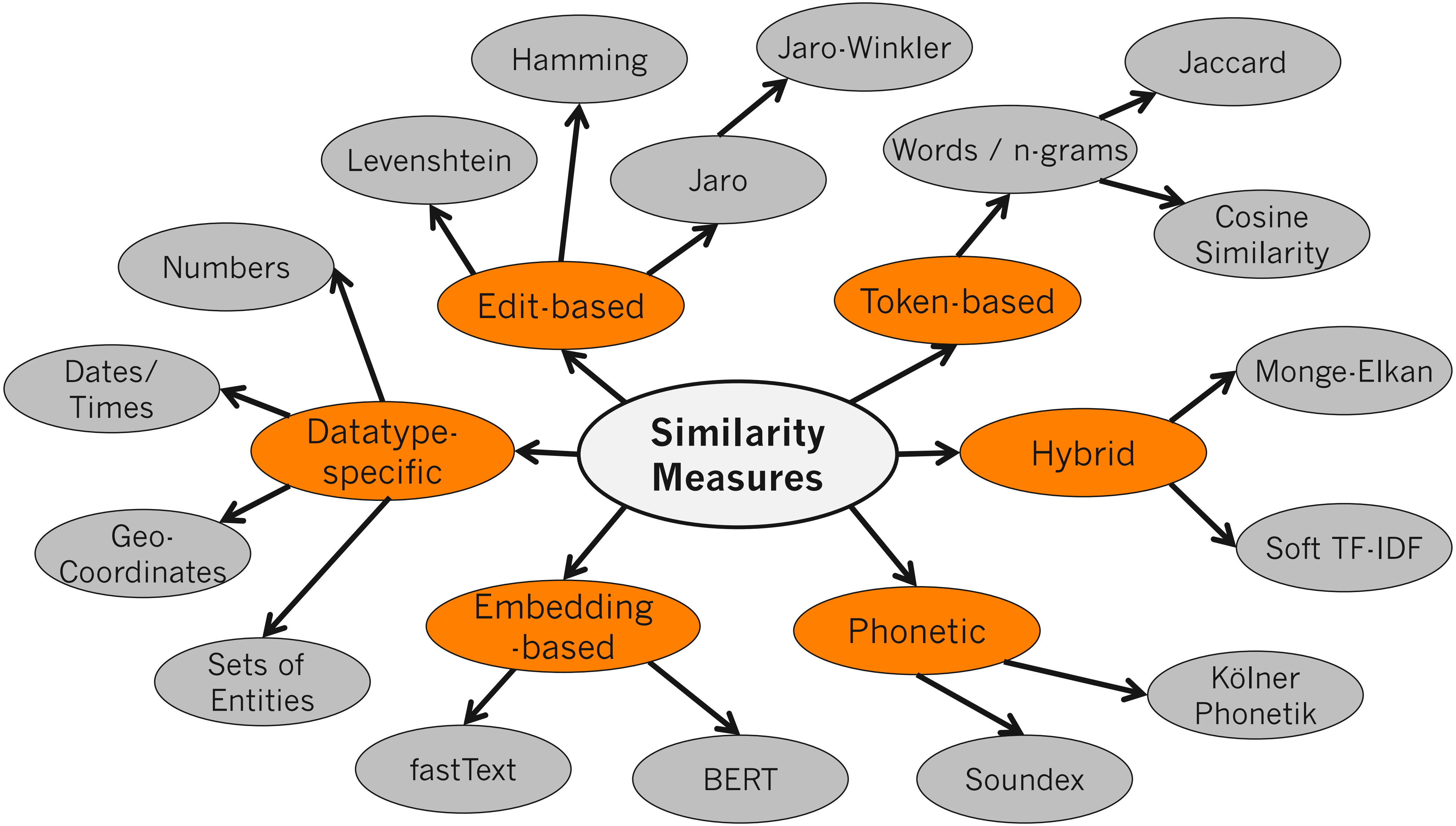




https://paperswithcode.com/sota/entity-resolution-on-abt-buy https://paperswithcode.com/sota/entity-resolution-on-amazon-google

* Assuming that the used splits in development set and test set are comparable

5. Similarity Measures – In Detail



Similarity Measures within the Entity Matching Process

Gather Data for Matching

↓

Normalize Attribute Values

Don‘t forget value normalization!

↓

Apply Attribute-specific Similarity Measures

↓

Combine Similarity Scores

We are here

↓

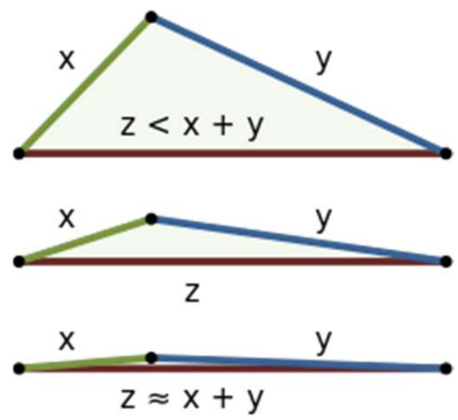
Decide Match/Non-Match

↓

Cluster Records based on Correspondences

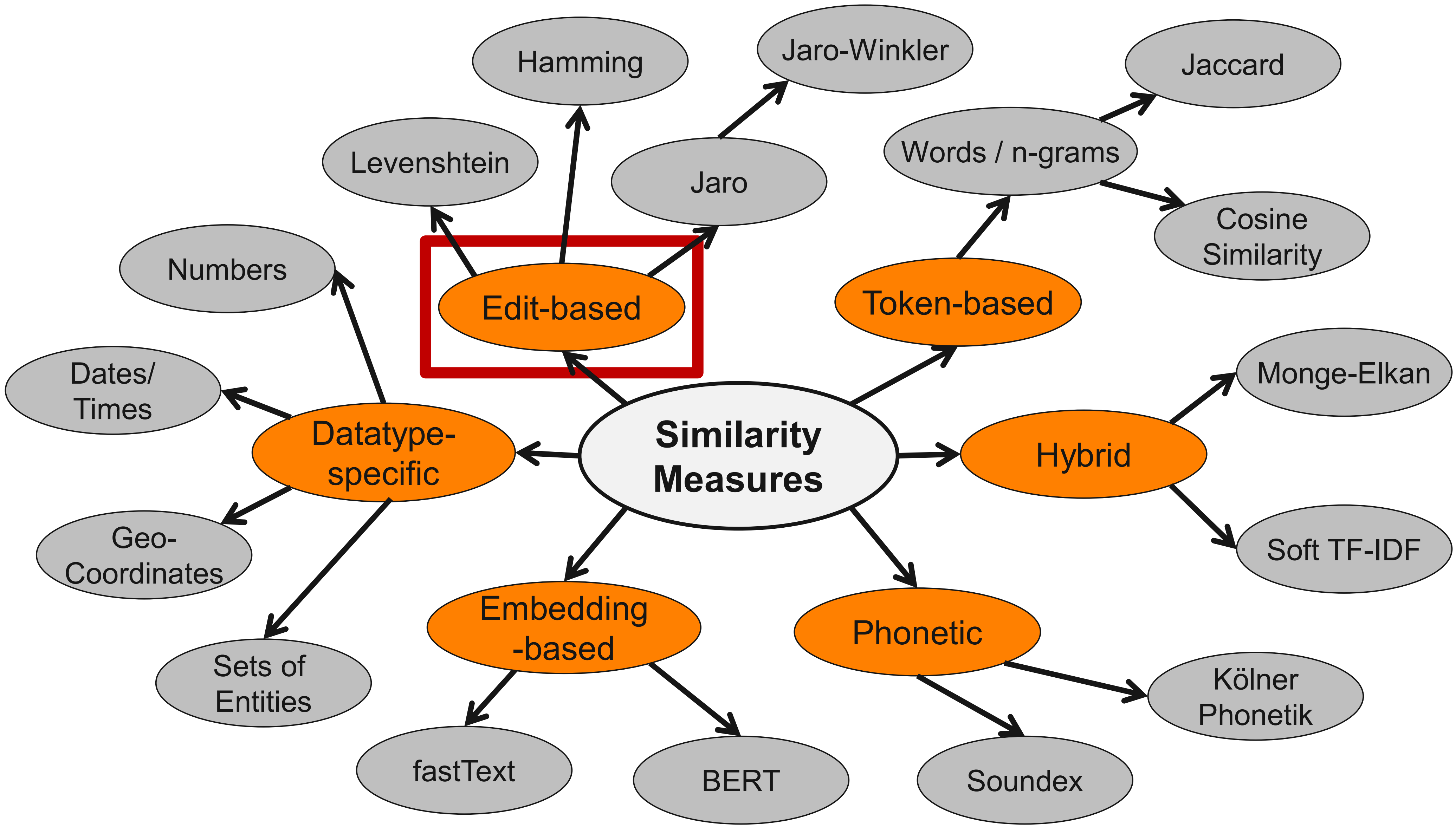
Similarity and Distance Measures

– Similarity is a rather universal but vague concept: sim(x,y)
  - x and y can be strings, numbers, geo coordinates, images, songs, persons, …
– Normalized: $sim(x,y) \in [0,1]$
  - sim(x,y) = 1 for exact match
  - sim(x,y) = 0 for „completely different“ x and y
– Distance measures
  - Positive: $dist(x,y) \geq 0$
  - Reflexive: $dist(x,x) = 0$
  - Symmetric: $dist(x,y) = dist(y,x)$
  - Triangular inequation: $dist(x,z) \leq dist(x,y) + dist(y,z)$



– Converting distances to similarities
  - $sim(x,y) = 1/(dist(x,y)+1)$ if $dist(x,y) \in [0,\infty]$

5.1 Edit-based String Similarity Measures



Levenshtein Distance (aka Edit Distance)

– Measures the dissimilarity of two strings

– Measures the minimum number of edits needed to transform one string into the other

– Allowed edit operations:

  1. insert a character into the string
  2. delete a character from the string
  3. replace one character with a different character

– Examples:

  • levensthein('table', 'cable') = 1 (1 replace operation)
  • levensthein('Chris Bizer', 'Bizer, Chris') = 11 (10 replaces, 1 deletion)

– Levenshtein distance is often called „*edit distance*"

  • as it is the most widely used edit-based measure

Levenshtein Similarity

$$sim_{Levenshtein} = 1 - \frac{LevenshteinDist}{\max(|s_1|, |s_2|)}$$

s_1	s_2	Levenshtein Distance	$sim_{Levenshtein}$
Jones	Johnson	4	0.43
Paul	Pual	2	0.5
Paul Jones	Jones, Paul	11	0

Levenshtein Discussion

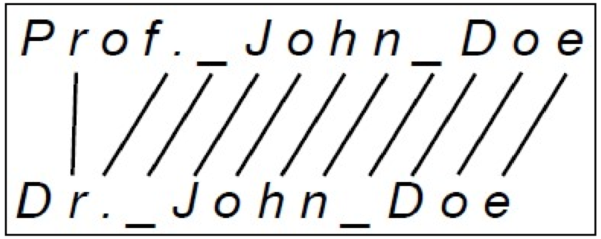
- Good general purpose string similarity measure
  - can deal with typos
  - does not work if parts of string (words) have different order
    - ‘Firstname Surname’ vs. ‘Surname, Firstname’
  - other similarity measures are optimized for specific strings like names
- Has quadratic runtime complexity ☹
  - Levenshtein distance is calculated using dynamic programming
  - runtime complexity $O(|x| \cdot |y|)$

Jaro Similarity

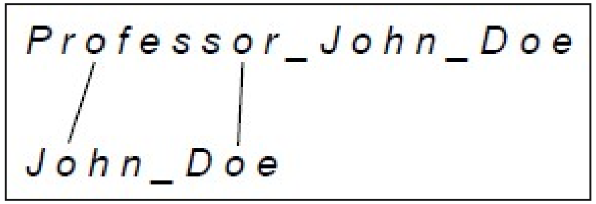
– Specifically designed for matching names at US Census Bureau

– Applies heuristics that empirically proofed to work for names
  - first names, surnames, street names, city names

1. Search for matching characters within a specific distance
   - *m :* number of matching characters
   - search range for matching characters: $\frac{\max(|x|,|y|)}{2} - 1$
   - division by 2 as names often have two parts



2. Look for swapped adjacent characters
   - *transposition: 'pe' vs. 'ep'*
   - *t* : number of transpositions



$$sim_{jaro} = \frac{1}{3}\left(\frac{m}{|x|} + \frac{m}{|y|} + \frac{m-t}{m}\right)$$

Jaro Similarity – Example

$$sim_{jaro} = \frac{1}{3}\left(\frac{m}{|x|} + \frac{m}{|y|} + \frac{m-t}{m}\right)$$

s1	**P**	**A**	**U**	**L**
s2	**P**	**U**	**A**	**L**

$m = 4 \qquad t = 1$

$$sim_{jaro} = \frac{1}{3}\cdot\left(\frac{4}{4} + \frac{4}{4} + \frac{4-1}{4}\right) \approx 0.92$$

s1	**J**	**O**	**N**	E	**S**		
s2	**J**	**O**	H	**N**	**S**	O	N

$m = 4 \qquad t = 0$

$$sim_{jaro} = \frac{1}{3}\cdot\left(\frac{4}{5} + \frac{4}{7} + \frac{4-0}{4}\right) \approx 0.79$$

Winkler Similarity

- Intuition: Similarity of first few letters is more important
  - less typos in first letters
  - dealing with abbreviations
    - ‘Apple Corp.’ vs. ‘Apple Cooperation’
    - ‘Bizer, Christian’ vs. ‘Bizer, Chris’
- Let *p* be the length of the common prefix of x and y.
- $sim_{winkler}(x,y) = sim_{jaro}(x,y) + (1 - sim_{jaro}(x,y))\frac{p}{10}$
  - = 1 if common prefix is $\geq$10

Jaro-Winkler Similarity

– Extension of Jaro similarity considering a common prefix

$$\begin{aligned} &if\ sim_{jaro} \leq 0.7 : sim_{jarowinkler} = sim_{jaro} \\ &otherwise: \quad sim_{jarowinkler} = sim_{jaro} + l \cdot p \cdot (1 - sim_{jaro}) \end{aligned}$$

– *l* : Length of common prefix up to a maximum of 4 characters

– *p* : Constant scaling factor for how much the score is adjusted upwards for having common prefixes (typically *p*=0.1)

– Examples:

$s_1 = PAUL \quad s_2 = PUAL$

$sim_{jaro} = 0.92$

$l = 1$

$p = 0.1$

$sim_{jarowinkler} = 0.92 + 1 \cdot 0.1 \cdot (1 - 0.92) = 0.928$

$s_1 = JONES \quad s_2 = JOHNSON$

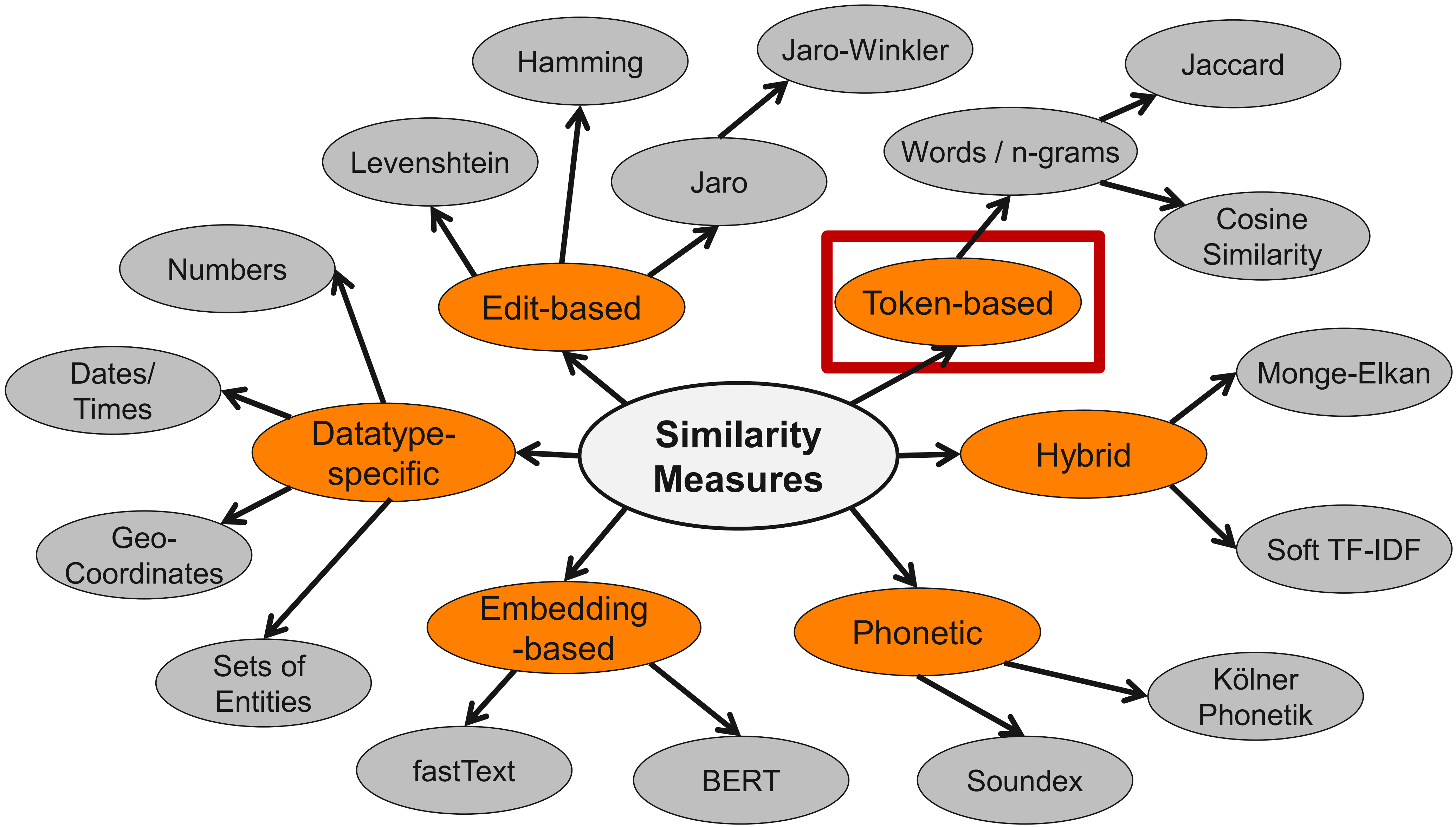
$sim_{jaro} = 0.79$

$l = 2$

$p = 0.1$

$sim_{jarowinkler} = 0.79 + 2 \cdot 0.1 \cdot (1 - 0.79) = 0.832$

5.2 Token-based String Similarity Measures



Token-based Similarity

Token-based measures ignore the order of words which is often desirable for comparing multi-word strings.

- ‘Chris Bizer’ and ‘Bizer, Chris’ do not look similar to edit-based measures
- ‘Processor: Intel Xeon E5620’ vs. ‘Intel Xeon E5620 processor’ vs. ‘Intel Xeon E5620’ consist of similar tokens
- Tokenization
  - forming words from sequence of characters
- General idea: Separate string into tokens using some separator
  - possible separators: space, hyphen, punctuation, special characters
- Alternative: Split string into short substrings
  - n-grams: See next slide

n-grams (aka q-grams)

- Split string into short substrings of length *n*
  - by sliding a length n window over the string
  - *n*=2: Bigrams
  - *n*=3: Trigrams
  - Variation: pad with *n* – 1 special characters
    - Emphasizes beginning and end of string
  - Variation: include positional information in order to weight similarities later
- Goals:
  1. Deal with typos and different order of words
  2. Reduce the time complexity compared to Levenshtein

String	Bigrams	Padded bigrams	Positional bigrams	Trigrams
gail	ga, ai, il	⊙g, ga, ai, il, l⊗	(ga,1), (ai,2), (il,3)	gai, ail
gayle	ga, ay, yl, le	⊙g, ga, ay, yl, le, e⊗	(ga,1), (ay,2), (yl,3), (le,4)	gay, ayl, yle
peter	pe, et, te, er	⊙p, pe, et, te, er, r⊗	(pe,1), (et,2), (te,3), (er,4)	pet, ete, ter
pedro	pe, ed, dr, ro	⊙p, pe, ed, dr, ro, o⊗	(pe,1), (ed,2), (dr,3), (ro,4)	ped, edr, dro

Token-based Similarity Measures

– Can be applied to words or n-grams

– Overlap Coefficient: $sim_{overlap}(x,y) = \dfrac{|tok(x) \cap tok(y)|}{\min(|tok(x)|,|tok(y)|)}$

  • example: useful for attribute label matching if one label might contain additional information, such as units of measurements or years

– Jaccard Coefficient:

$$sim_{jaccard}(x,y) = \frac{|tok(x)\ \cap\ tok(y)|}{|tok(x)| + |tok(y)| - |tok(x)\ \cap\ tok(y)|} = \frac{|tok(x)\ \cap\ tok(y)|}{|tok(x)\ \cup\ tok(y)|}$$

  • focuses of both strings as all unique tokens are considered
  • widely used general purpose similarity measure for tokens

– Speeding up the calculation using an inverted index, see

  • Doan, Halevy: Principles of Data Integration, Chapter 4.3

Cosine Similarity and TF-IDF

– Rare tokens are often more distinguishing and thus more relevant for determining the similarity of two strings

– TF/IDF weighting gives less weight to common tokens (domain-specific stopwords)

	Samsung	Galaxy	S9	S4	32GB	64GB
p1	0	0	0.04	0	0	0.12
p2	0	0	0.04	0	0.04	0
p3	0	0	0	0.12	0.04	0

$$w_{ij} = tf_{ij} \times idf_i$$

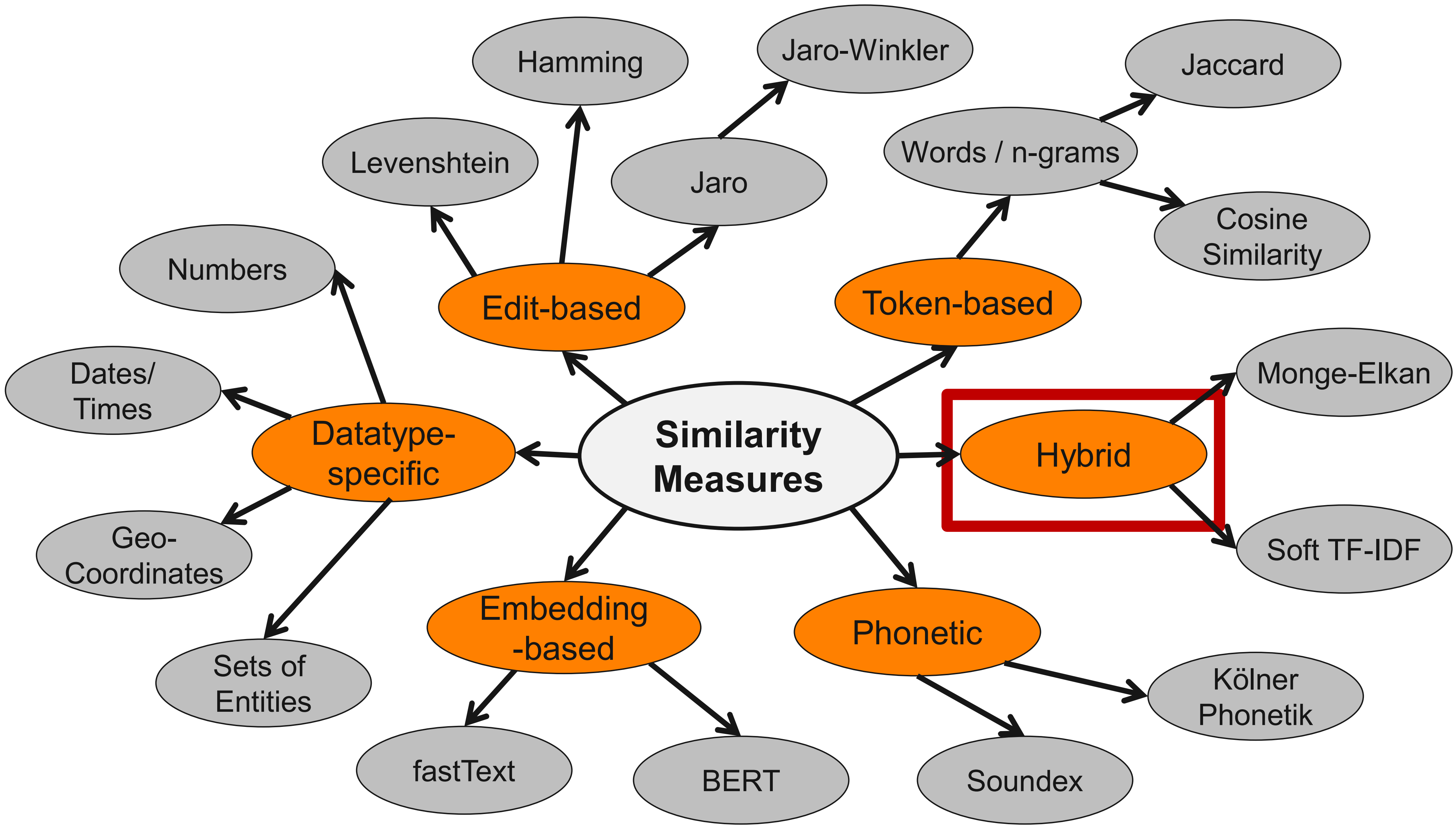
$$idf_i = \log \frac{N}{df_i}$$

– Cosine similarity

- popular similarity measure for comparing weighted term vectors

$$\cos(d_1, d_2) = \frac{d_1 \bullet d_2}{\| d_1 \| \| d_2 \|}$$

5.3 Hybrid String Similarity Measures



Monge-Elkan Similarity

- hybrid similarity measures split strings into tokens and apply internal similarity function to compare tokens
- can deal with typos and different order of words
- Monge-Elkan similarity searches for the best match for each token of the first sting x in the second string y
- $sim_{MongeElkan}(x, y) = \frac{1}{|x|} \sum_{i=1}^{|x|} \max_{j=1,|y|} sim'(x[i], y[j])$
  - $|x|$ is number of tokens in x
  - *sim'* is internal similarity function (e.g. Levenshtein or Jaro depending on the specific requirements of the application)
- focuses on first string x, as length of y does not matter
- runtime complexity: quadratic in number of tokens ☹

Monge-Elkan – Example

- $sim_{MongeElkan}(x,y) = \frac{1}{|x|} \sum_{i=1}^{|x|} \max_{j=1,|y|} sim'(x[i], y[j])$

- Peter Christen vs. Christian Pedro
  - sim_{jaro}(peter, christian) = 0.3741
  - sim_{jaro}(peter, pedro) = 0.7333
  - sim_{jaro}(christen, christian) = 0.8843
  - sim_{jaro}(christen, pedro) = 0.4417

- $sim_{MongeElkan}(peter\ christen, christian\ pedro) = \frac{1}{2}(0.7333 + 0.8843) = 0.8088$

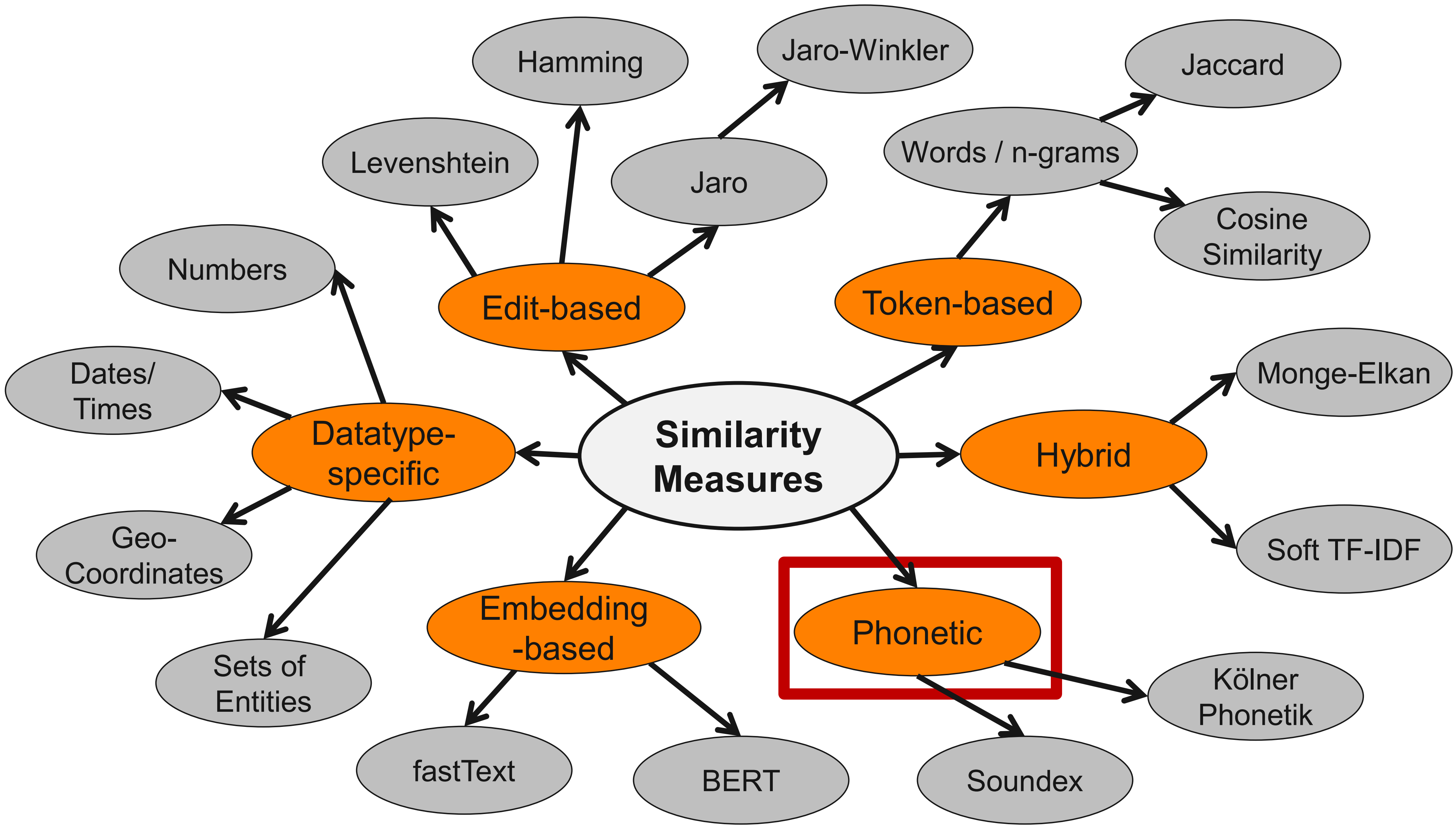
Extended Jaccard Similarity

- uses an internal similarity function (e.g. Levenshtein or Jaro) to calculate similarity between all pairs of tokens
- considers tokens as shared if similarity is above threshold
  - shared tokens: $S = \{(x_i, y_j) | \; x_i \in tok(x) \wedge y_j \in tok(y): sim'(x_i, y_j\,) \geq \theta\}$
  - unique tokens: $U_{tok(x)} = \{x_i | x_i \in tok(x) \wedge y_j \in tok(y) \wedge (x_i, y_j\,) \notin S\}$
- calculates overall similarity as

$$sim_{jaccad\_ext}(x, y) = \frac{|S|}{|U_{tok(x)}| + |U_{tok(y)}| - |S|}$$

- focuses of both strings as all unique tokens are considered
  - as opposed to Monge-Elkan which focuses on tokens of first string

5.4 Phonetic String Similarity Measures



Soundex

- Soundex codes a last name based on the way a name sounds
- Algorithm:
  1. Retain first letter of the name and drop all other occurrences of A, E, H, I, O, U, W, Y
  2. Replace consonants with digits
  3. Two adjacent letters with the same number are coded as a single number
  4. Continue until you have one letter and three numbers. If you run out of letters, pad with 0s
- If a surname has a prefix, such as Van, Con, De, Di, La, or Le, code both with and without the prefix
- Rules have been generated empirically

Digit	Letters
1	B, F, P, V
2	C, G, J, K, Q, S, X, Z
3	D, T
4	L
5	M, N
6	R

- Example
  - PAUL: P400
  - PUAL: P400
  - JONES: J520
  - JOHNSON: J525

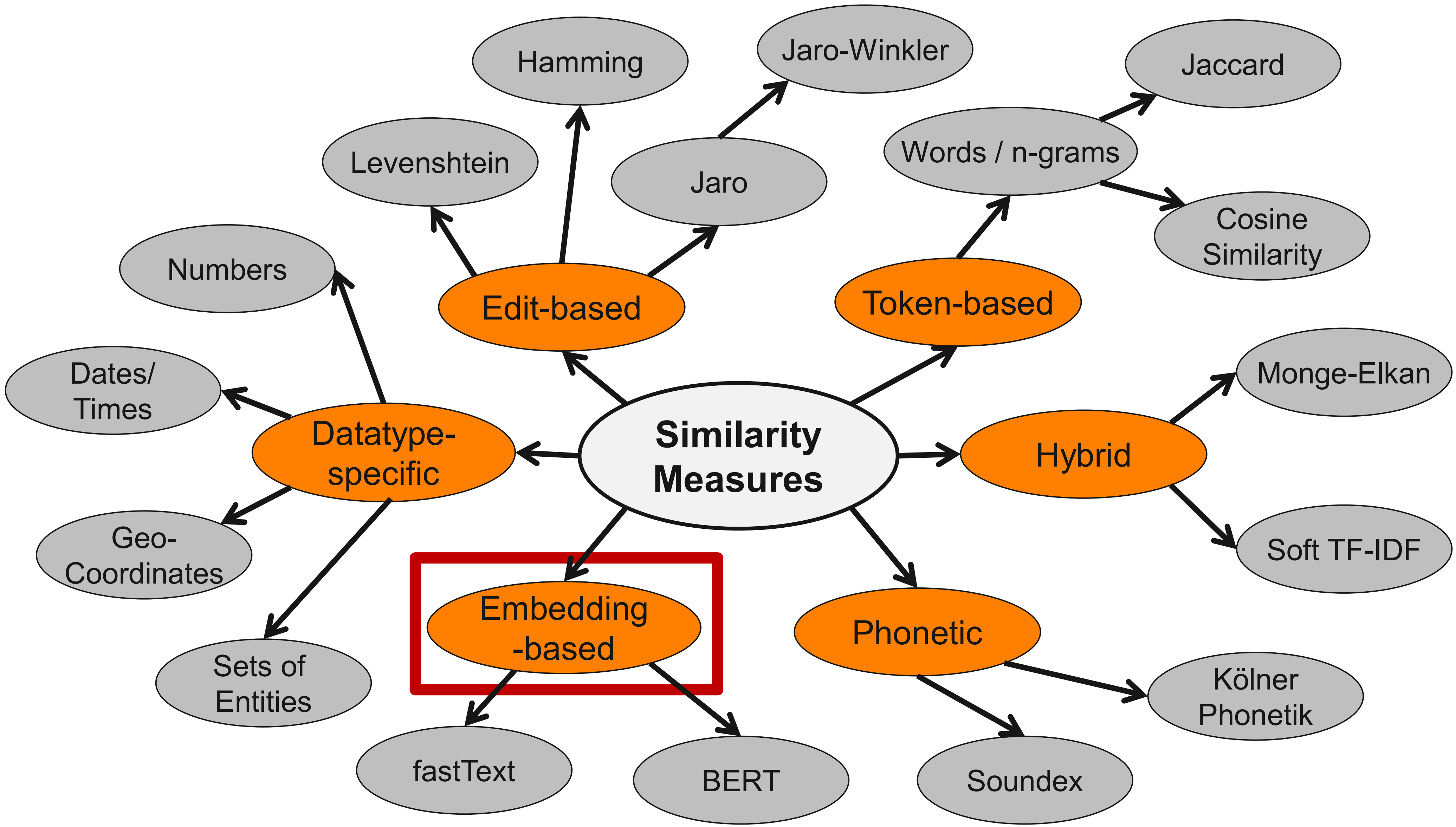
J525 also: Jenkins, Jansen, Jameson

Kölner Phonetik

- Like Soundex, but aimed at German last names
- Letters get different codes based on the context
- Code length is not restricted
- Multiple occurrences of the same code and „0“ are removed
- Examples:
  - PAUL: 15
  - PUAL: 15
  - JONES: 68
  - JOHNSON: 686

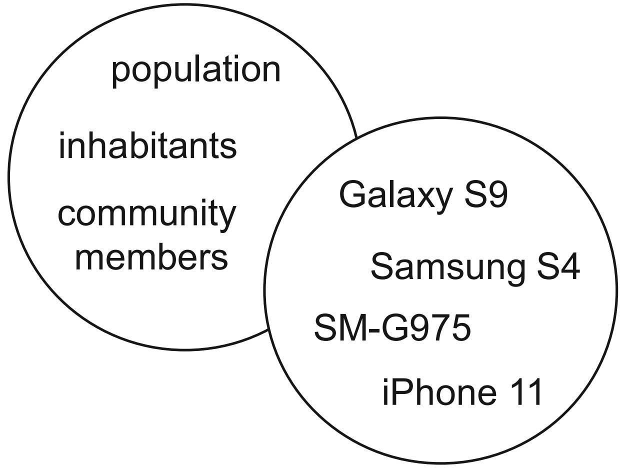
Letter	Context	Code
A, E, I, J, O, U, Y		-
H		-
B		1
P	not before H	1
D, T	not before C, S, Z	2
F, V, W		3
P	before H	3
G, K, Q		4
C	in the initial sound before A, H, K, L, O, Q, R, U, X	4
C	before A, H, K, O, Q, U, X but not after S, Z	4
X	not after C, K, Q	48
L		5
M, N		6
R		7
S, Z		8
C	after S, Z	8
C	in the initial sound, but not before A, H, K, L, O, Q, R, U, X	8
C	not before A, H, K, O, Q, U, X	8
D, T	before C, S, Z	8
X	after C, K, Q	8

5.5 Embedding-based String Similarity Measures

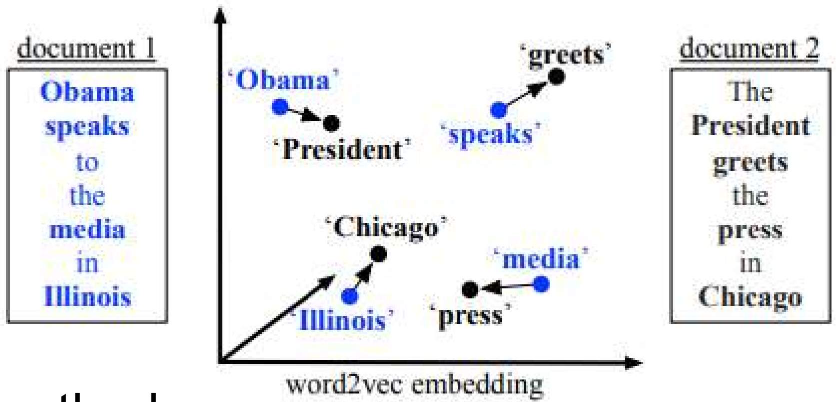


Embedding-based String Similarity

- Embeddings represent words as points in a multidimensional vector space
  - the calculation of embeddings exploits that semantically related words appear in similar contexts in large text corpora (distributional similarity)



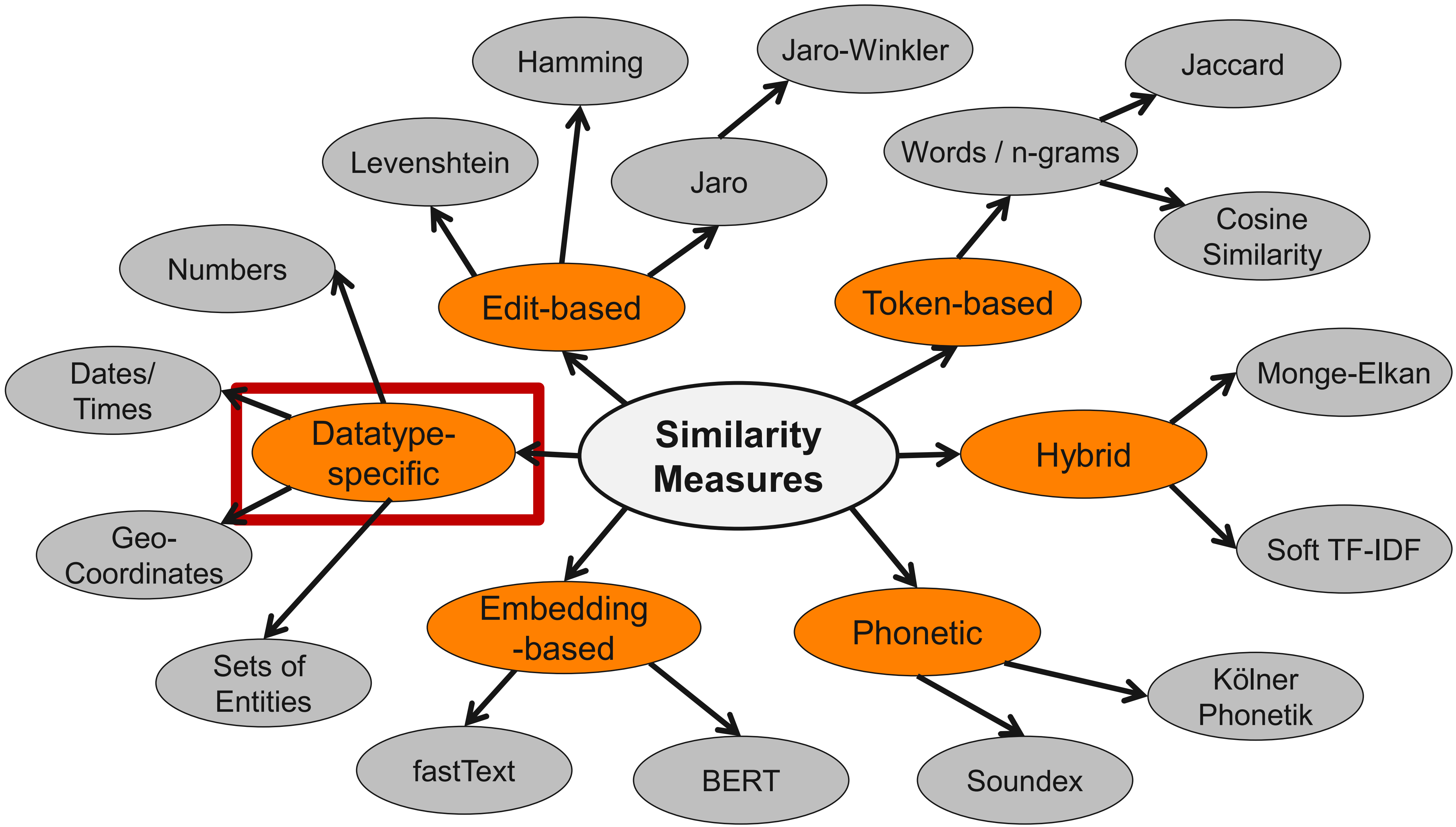
- Similarity of two embeddings
  - cosine similarity, inner product
- Similarity of two sequences of embeddings
  - word movers distance
  - neural networks (LTSMs, BERT, SBERT)



- Embeddings are successfully used for
  - schema matching
  - blocking before entity matching
  - as foundation for supervised entity matching methods

Mudgal, Sidharth: Deep Learning for Entity Matching: A Design Space Exploration. SIGMOD, 2018.
Yuliang, et al: Deep entity matching with pre-trained language models. PVLDB 2021.

5.6 Data Type Specific Similarity Measures



Numerical Comparison

Approach 1: Tolerate absolute difference between values, independently of absolute values

- $sim_{num\_abs}(n,m) = \begin{cases} 1 - \left(\frac{|n-m|}{d_{max}}\right) & if\ |n-m| < d_{max} \\ 0 & else \end{cases}$
  - Linear extrapolation between 0 and d_{max}
  - d_{max} = maximal numeric distance in which numbers should be considered similar
- Example:
  - d_{max} = \$1,000
  - $sim_{num\_abs}(2{,}000,\ 2{,}500) = 1 - \frac{500}{1{,}000} = 0.5$
  - $sim_{num\_abs}(200{,}000,\ 200{,}500) = 1 - \frac{500}{1{,}000} = 0.5$

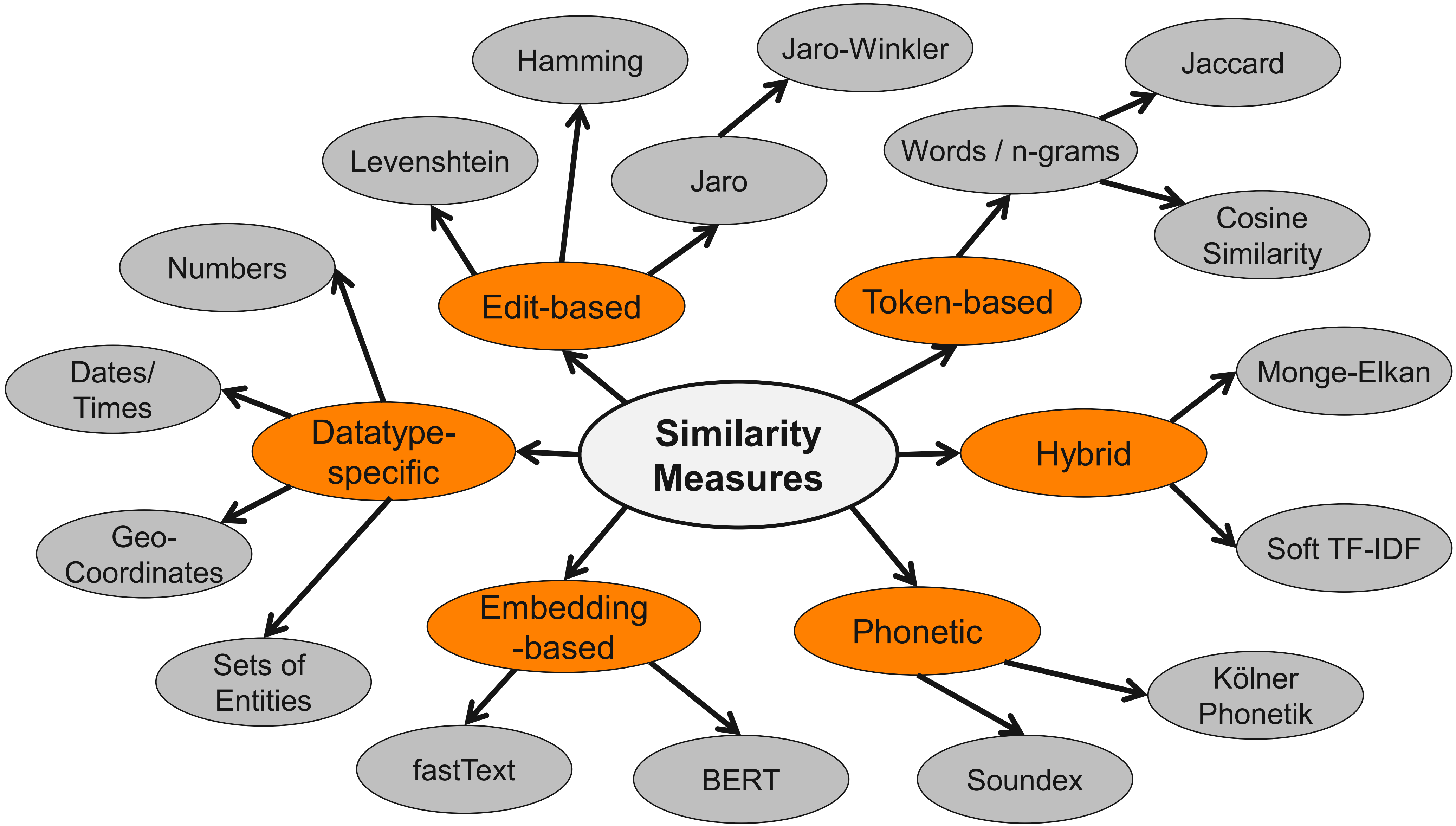
Approach 2: Tolerate difference up to a certain percentage of the absolute values

- $sim_{num\_perc}(n,m) = \begin{cases} 1 - \left(\frac{pc}{pc_{max}}\right) & if\ pc < pc_{max} \\ 0 & else \end{cases}$
  - $pc = \frac{|n-m|}{\max(|n|,|m|)} \cdot 100$ is percentage difference
  - pc_{max} = 33% is the maximal percentage that should be tolerated
  - $sim_{num\_perc}(2{,}000,\ 2{,}500) = 1 - \frac{20}{33} = 0.394$ because $pc = \frac{|2{,}000-2{,}500|}{2{,}500} \cdot 100 = 20\%$
  - $sim_{num\_perc}(200{,}000,\ 200{,}500) = 1 - \frac{0{,}25}{33} = 0.992$ because $pc = \frac{500}{200{,}500} \cdot 100 = 0.25\%$

Time and Space Comparisons

- Dates
  - convert dates into days after year 0 ➔ integer
  - afterwards use sim_{num_abs}
- Geographic Coordinates
  - distance is measured along the surface of the Earth in kilometers or miles
  - compute distance based on geographic projection of coordinates
  - Java package for calculating geographic distances: Geographiclib
  - http://geographiclib.sourceforge.net
- More Similarity Measures for other Data Types
  - Tan, Steinbach, Kumar: Introduction to Data Mining. Chapter 4
  - e.g. shopping baskets ➔ vector of asymmetric binary variables ➔ Jaccard

Summary



Similarity Measures
Edit-based
Levenshtein
Hamming
Jaro
Jaro-Winkler
Token-based
Words / n-grams
Jaccard
Cosine Similarity
Hybrid
Monge-Elkan
Soft TF-IDF
Phonetic
Kölner Phonetik
Soundex
Embedding -based
fastText
BERT
Datatype-specific
Numbers
Dates/ Times
Geo-Coordinates
Sets of Entities

6. Learning Matching Rules

- Problem
  It is hard for humans to write good matching rules, as this requires a lot of knowledge about the data set and matching techniques
  - What kind of typos and other errors are contained in the data?
  - Which string similarity measure fits which attribute?
  - How to normalize attribute values before matching?
  - How to weight different attributes? How to set similarity thresholds?
- Possible solution
  1. Manually label some pairs as matches and non-matches
  2. Use machine learning to generate matching rule from this training data
- Advantage
  - The human does what she is good at: Understand the data
  - The computer does what it is good at: Learn detailed rules from examples

Training Data and Feature Generation

- Training data: $T = \{(\mathbf{x_1},\mathbf{y_1},\mathbf{l}_1), \ldots (\mathbf{x_n},\mathbf{y_n},\mathbf{l}_n)\}$, where
  - each $(\mathbf{x_i},\mathbf{y}_i)$ is a record pair and
  - $\mathbf{l}_i$ is a label: "yes" if $\mathbf{x}_i$ matches $\mathbf{y}_i$ and "no" otherwise
- Feature Generation
  - define a set of features $\mathbf{f}_1, \ldots, \mathbf{f}_m$, each quantifying one aspect of the domain judged possibly relevant to matching the records
  - feature = similarity measure applied to attribute pair
    - after normalizing both values
  - if you want the learning algorithm to decides which similarity measure fits best for a specific attribute pair, you generate multiple features for the pair
    - Levenshtein(x.name, y.name)
    - Jaro(x.name, y.name)
    - Jaccard(tokens(x.name, y.name))
  - Feature engineering requires domain-knowledge, e.g. for value normalization

Example: Feature Generation

<a_1 = (Mike Williams, (425) 247 4893, Seattle, WA), b_1 = (M. Williams, 247 4893, Redmond, WA), yes>
<a_2 = (Richard Pike, (414) 256 1257, Milwaukee, WI), b_2 = (R. Pike, 256 1237, Milwaukee, WI), yes>
<a_3 = (Jane McCain, (206) 111 4215, Renton, WA), b_3 = (J. M. McCain, 112 5200, Renton, WA), no>

match names   match phones   match cities   match states   check area code against city

$v_1 = <[s_1(a_1,b_1), s_2(a_1,b_1), s_3(a_1,b_1), s_4(a_1,b_1), s_5(a_1,b_1), s_6(a_1,b_1)], 1>$

$v_2 = <[s_1(a_2,b_2), s_2(a_2,b_2), s_3(a_2,b_2), s_4(a_2,b_2), s_5(a_2,b_2), s_6(a_2,b_2)], 1>$

$v_3 = <[s_1(a_3,b_3), s_2(a_3,b_3), s_3(a_3,b_3), s_4(a_3,b_3), s_5(a_3,b_3), s_6(a_3,b_3)], 0>$

Label:
Match = 1
Non-Match = 0

- **s_1** and **s_2** use Jaro-Winkler <u>and</u> edit distance
- **s_3** uses edit distance (ignoring area code of a)
- **s_4** and **s_5** return 1 if exact match, 0 otherwise
- **s_6** encodes a heuristic constraint (using a lookup table)

Learn Matching Model M

1. Convert each training example $(\mathbf{x_i}, \mathbf{y_i}, l_i)$ in T to a pair $(\mathbf{v}_i, l_i)$
   - $\mathbf{v}_i = \mathbf{f_1}(\mathbf{x_i},\mathbf{y}_i), \ldots, \mathbf{f_m}(\mathbf{x_i},\mathbf{y}_i)$ is a feature vector that encodes $(\mathbf{x_i},\mathbf{y}_i)$ in terms of the features (list of similarity values)
   - thus T is transformed into T' = $\{(\mathbf{v_1},l_1), \ldots, (\mathbf{v_n},l_n)\}$

2. Apply a learning algorithm to T' to learn a matching model M
   - linear models: logistic regression, linear regression, SVMs
   - non-linear models: decision tree, random forest, XGBoost, neural net

3. Optimize the hyperparameters of the learning algorithm
   - using training, validation, and test set

Example: Learning a Linearly Weighted Matching Rule

- Goal: Learn rule $sim(a,b) = \sum_{i=1}^{6} \alpha_i * s_i(a,b)$
- Perform a least-squares linear regression on training data

v_1 = <[$s_1(a_1,b_1)$, $s_2(a_1,b_1)$, $s_3(a_1,b_1)$, $s_4(a_1,b_1)$, $s_5(a_1,b_1)$, $s_6(a_1,b_1)$], 1>

v_2 = <[$s_1(a_2,b_2)$, $s_2(a_2,b_2)$, $s_3(a_2,b_2)$, $s_4(a_2,b_2)$, $s_5(a_2,b_2)$, $s_6(a_2,b_2)$], 1>

v_3 = <[$s_1(a_3,b_3)$, $s_2(a_3,b_3)$, $s_3(a_3,b_3)$, $s_4(a_3,b_3)$, $s_5(a_3,b_3)$, $s_6(a_3,b_3)$], 0>

to find weights α_i that minimize the squared error

$$\sum_{i=1}^{3} \left(c_i - \sum_{j=1}^{6} \alpha_j * s_j(v_i)\ \right)^2$$

Example: Learning a Decision Tree

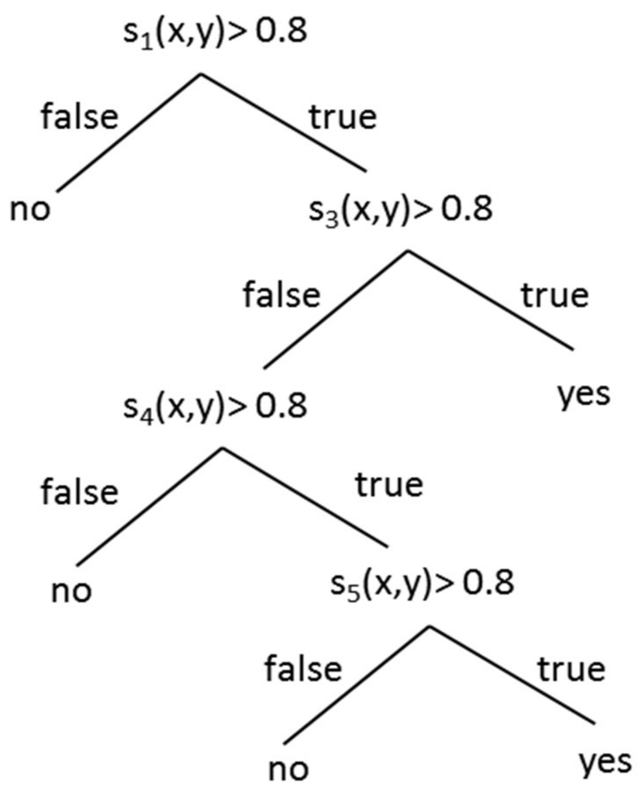
match names | match phones | match cities | match states | check area code against city

v_1 = <[$s_1(a_1,b_1)$, $s_2(a_1,b_1)$, $s_3(a_1,b_1)$, $s_4(a_1,b_1)$, $s_5(a_1,b_1)$, $s_6(a_1,b_1)$], yes>

v_2 = <[$s_1(a_2,b_2)$, $s_2(a_2,b_2)$, $s_3(a_2,b_2)$, $s_4(a_2,b_2)$, $s_5(a_2,b_2)$, $s_6(a_2,b_2)$], yes>

v_3 = <[$s_1(a_3,b_3)$, $s_2(a_3,b_3)$, $s_3(a_3,b_3)$, $s_4(a_3,b_3)$, $s_5(a_3,b_3)$, $s_6(a_3,b_3)$], no>

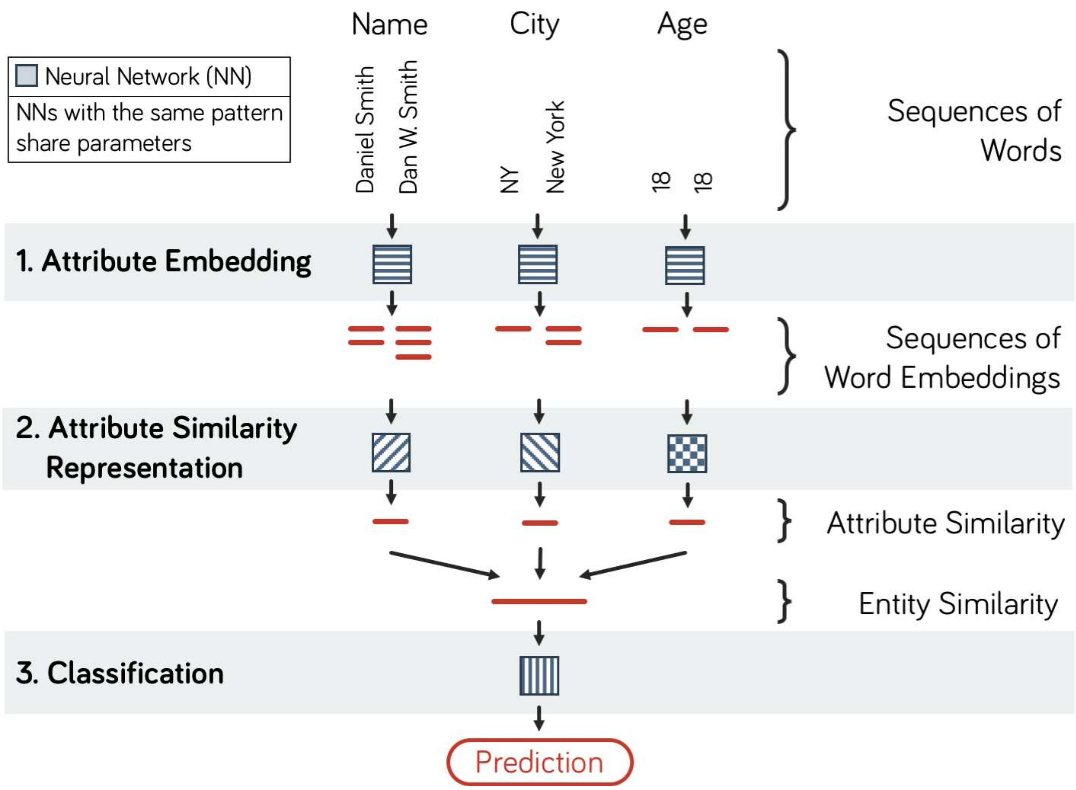
Label:
Match = yes
Non-Match = no



- Tree-based models often perform better than linear models
- The tree learning algorithm automatically selects the most discriminative features
- Always also test random forests and XGBoost

Example: Deep Learning of Matching Models

- Deep learning-based matching models often combine
  1. embeddings for attribute value representation
  2. neural nets for similarity computation, e.g. Siamese networks, and LSTMs, BERT
  3. neural nets for the final matching decision, e.g. fully connected layers on top of concatenated attribute similarity representations



- Deep learning-based models often outperform linear and tree-based matching models
- Example: DeepMatcher (2018)

Mudgal, Sidharth, et al.: Deep Learning for Entity Matching: A Design Space Exploration. SIGMOD, 2018.

Evaluation: DeepMatcher versus Magellan

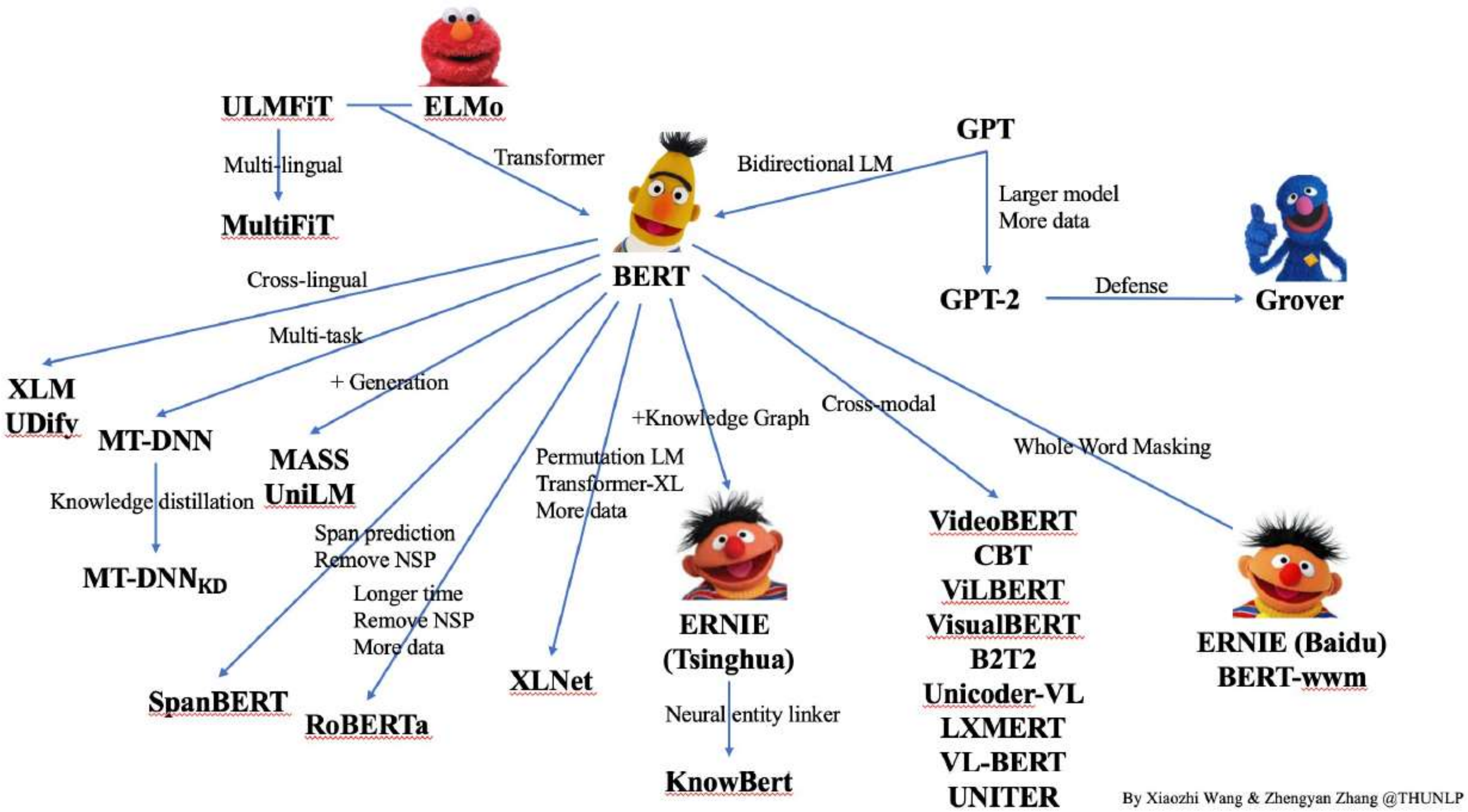
Type	Dataset	Magellan F1	DeepMatcher F1	Difference
Structured	iTunes-Amazon	91.2	88.5	-2.7
	DBLP-ACM	98.4	98.4	+0.0
	DBLP-Scholar	94.7	92.3	+2.4
	Walmart-Amazon	71.9	66.9	-5.0
Textual	Abt-Buy	43.6	62.8	+19.2
	Amazon-Google	49.1	69.3	+20.1
	WDC Computer - Large	64.5	89.5	+25.0
	WDC Computer - Small	57.6	70.5	+12.9

– DeepMatcher outperforms traditional methods on textual data
– mixed results on structured data

Konda, et al.: **Magellan: Toward Building Entity Matching Management**. PVLDB 2016.

Transformers started to win all Benchmarks in NLP

- Self-supervised pre-training on large text corpora
- Fine-tuning for downstream tasks



https://**huggingface.co**/docs/transformers/index

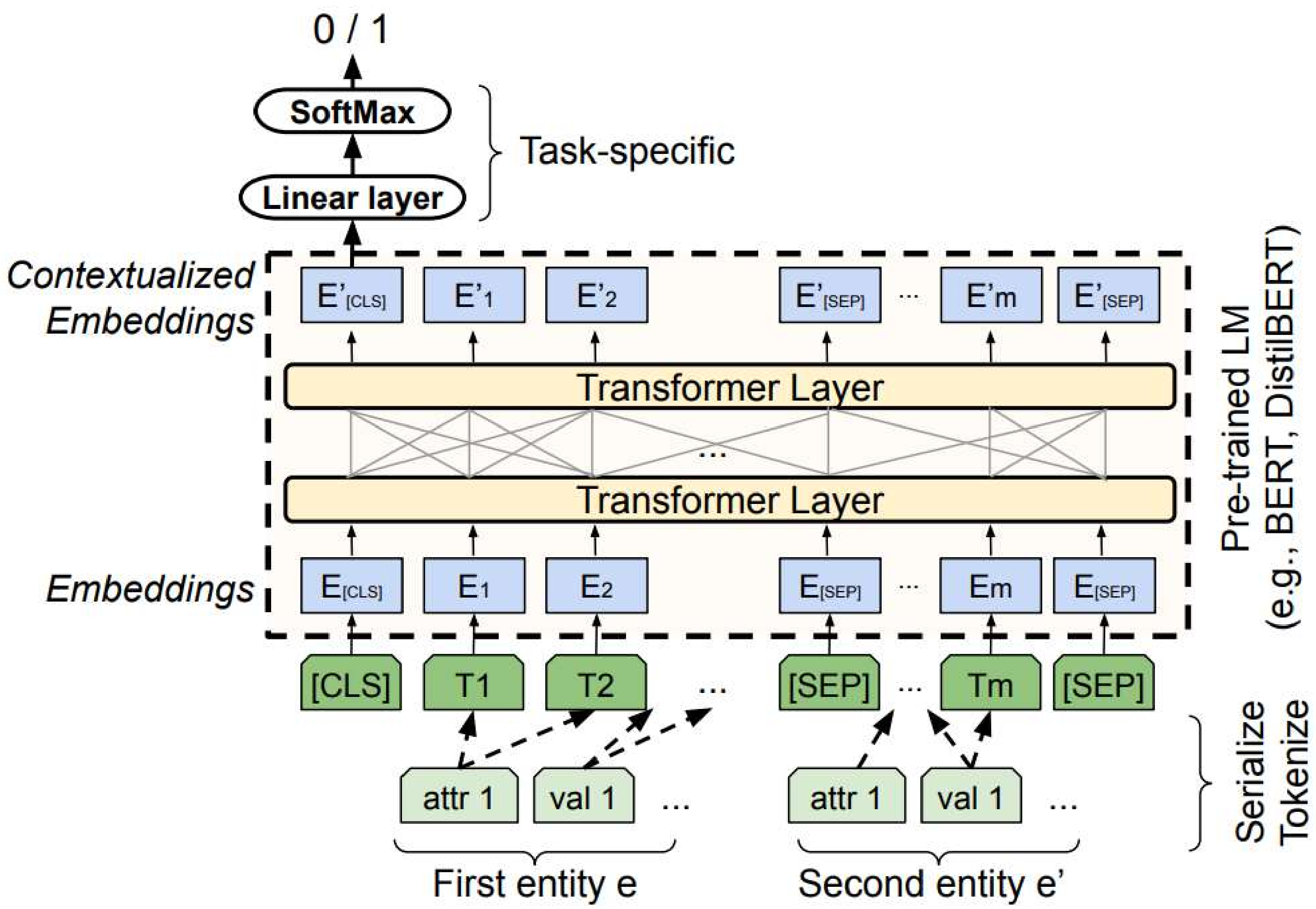
DITTO (2021)

- applies BERT, DistilBERT, RoBERTa for entity matching
- adds methods for entity summarization, highlighting matching clues, training data augmentation

- Entity serialization for BERT
  - Pair of entity descriptions are turned into single sequence
  - [CLS] Entity Description 1 [SEP] Entity Description 2 [SEP]
  - Entity Description = [COL] $attr_1$ [VAL] val_1 . . . [COL] $attr_k$ [VAL] val_k
- Serialization Example
  - [CLS][COL] Name [VAL] Franz Müller [COL] Birthdate [VAL] 20/08/1998[SEP] ...

Yuliang, et al: **Deep entity matching with pre-trained language models.** PVLDB 2021.

DITTO: Architecture



- [CLS] token summarizes the pair of entities
- linear layer on top of [CLS] token for matching decision

DITTO: Evaluation

Type	Dataset	DITTO F1	DeepMatcher F1	Magellan F1
Structured	iTunes-Amazon	97.0	88.5 +8.5	91.2 +5.8
	DBLP-ACM	99.0	98.4 +0.6	98.4 +0.6
	DBLP-Scholar	95.6	92.3 +3.3	94.7 +0.9
	Walmart-Amazon	86.8	66.9 +19.9	71.9 +14.9
Textual	Abt-Buy	89.3	62.8 +26.5	43.6 +45.7
	Amazon-Google	75.6	69.3 +6.3	49.1 +26.5
	WDC Computer - Large	91.7	89.5 +3.2	64.5 +27.2
	WDC Computer - Small	80.8	70.5 +10.3	57.6 +23.2

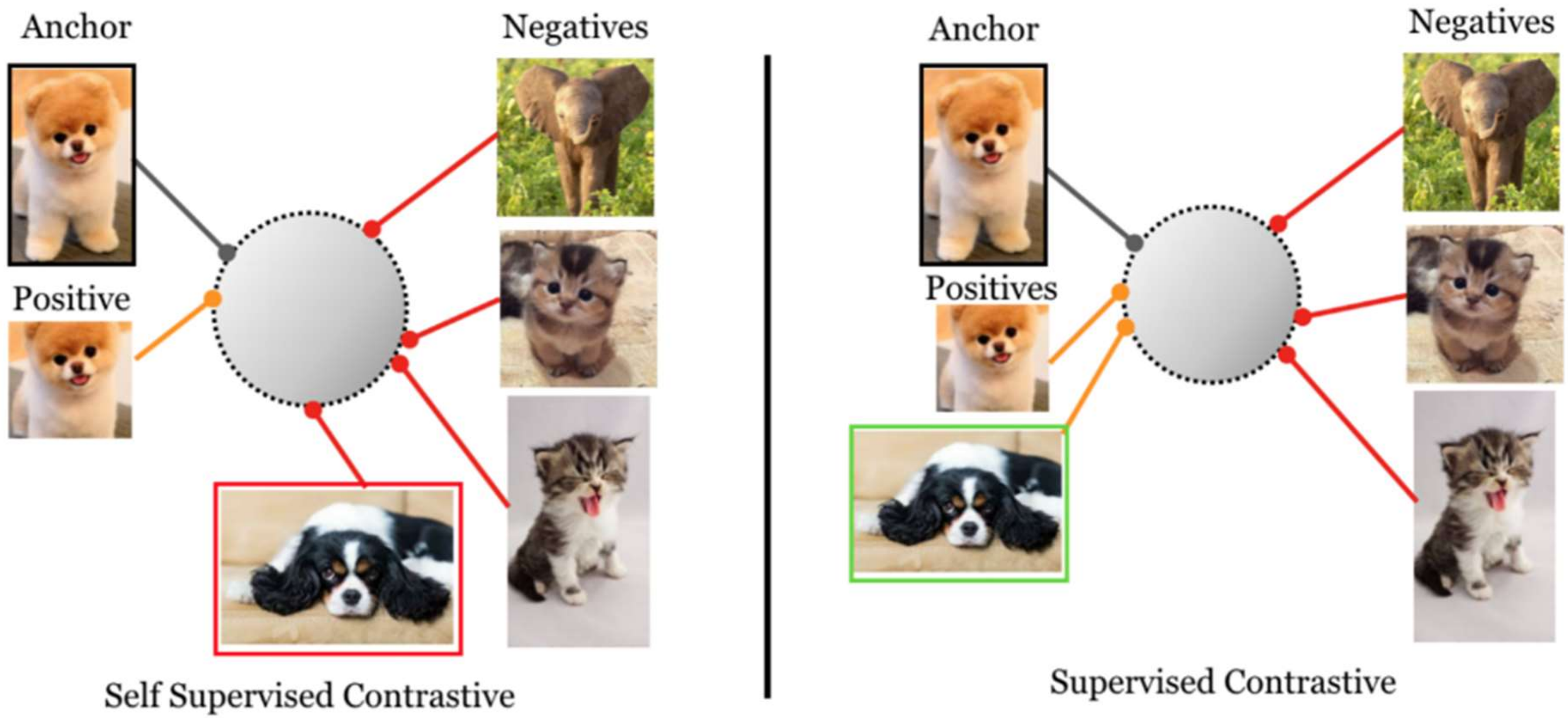
- constant improvement for structured data
- large performance gain for textual data

Potential Reasons for the Performance Gain

- Serialization allows to pay attention to all attributes
  - no strict separation between attributes
- WordPiece tokenizer breaks unknown terms into pieces
  - no problems with out of vocabulary terms
- Transfer learning from pre-training texts
  - different surface forms are already close in embedding space
- Contextualization of the embeddings
  - potentially more suited for capturing differing semantics

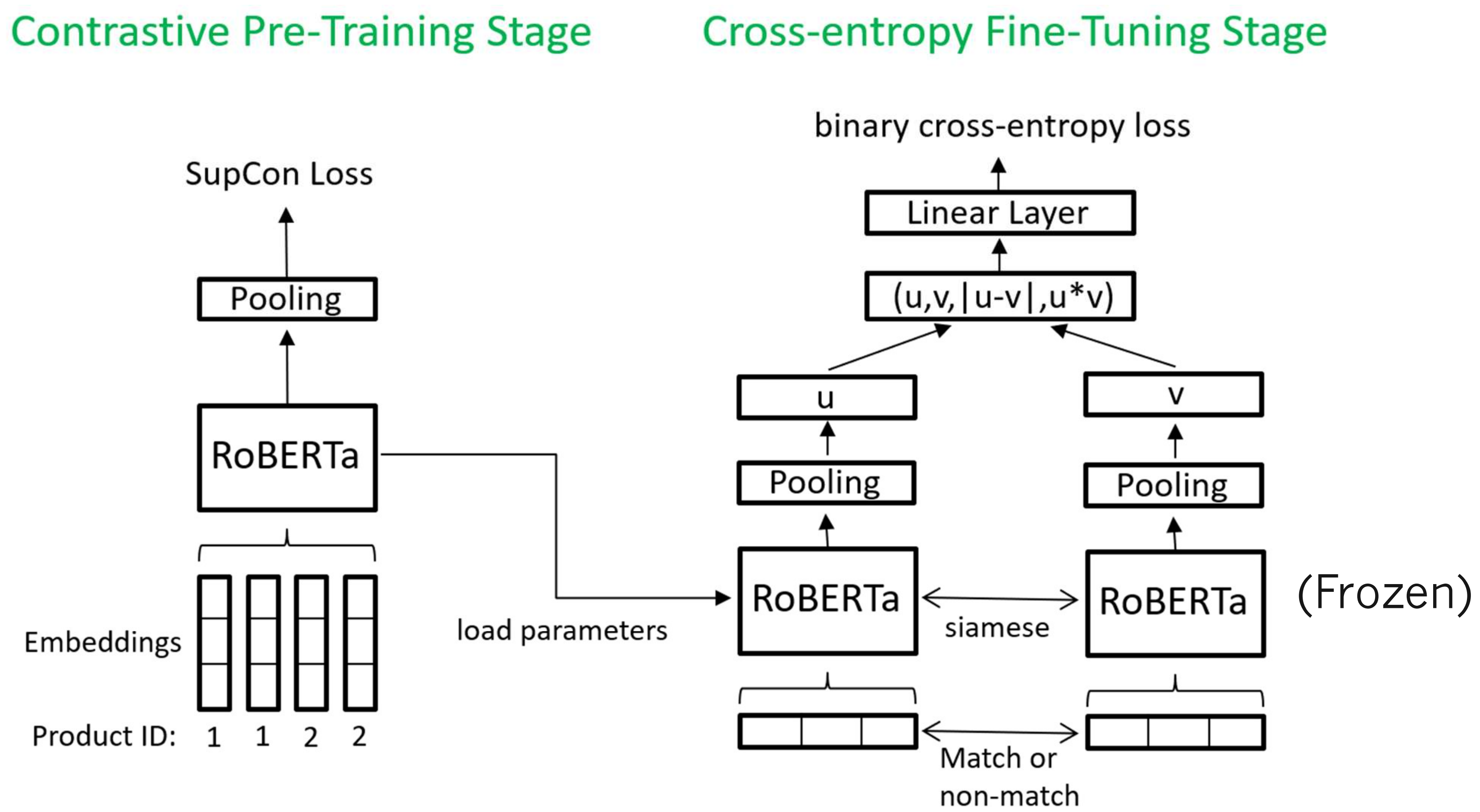
Contrastive Pretraining in Vision

- maximizes distance between classes in the embedding space
- uses large batches containing many positive and negative examples



Khosla, et al.: **Supervised Contrastive Learning**. NeurIPS 2020.

Supervised Contrastive Pretraining for Entity Matching



Input: Batch of n product offers with product IDs

Input: Batch of product offer pairs with match/non-match labels

Peeters, Bizer: **Supervised Contrastive Learning for Product Matching**. WWW Companion 2022.

Supervised Contrastive Pretraining R-SupCon

	Abt-Buy	Amazon-Google	WDC Computers			
# Training Pairs	~7.5K	~9K	~3K (small)	~8K (medium)	~23K (large)	~68K (xlarge)
DeepMatcher	62.80	70.70	61.22	69.85	84.32	88.95
RoBERTa	91.05	74.10	86.37	91.90	94.68	94.73
Ditto	89.33	75.58	80.76	88.62	91.70	95.45
JointBERT	-	-	77.55	88.82	96.90	97.49
R-SupCon	93.70	**79.28**	93.18	97.66	98.16	**98.33**
R-SupCon+augmen	**94.29**	76.14	**95.21**	**98.50**	**98.50**	98.33
Δ to best baseline	+ 3.24	+ 3.70	+ 8.84	+ 6.60	+ 1.60	+ 0.84

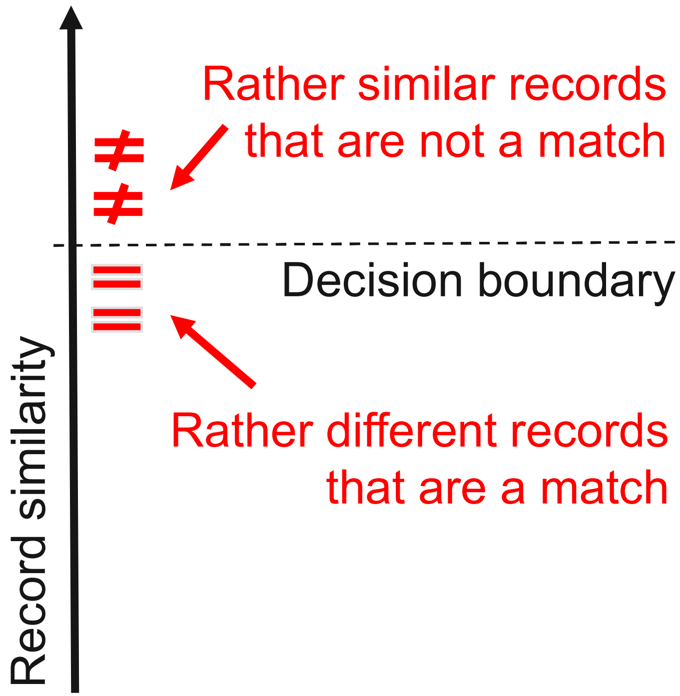
Large improvements for all small training sets ➔ Training data efficient

Summary: Deep Learning for Entity Matching

- Transformer-based matchers boost performance
  - huge increase for textual data
  - significant increases for structured data
- reduced feature engineering effort
  - less value normalization necessary due to pre-training
  - less information extraction effort due to serialization
- requirements for training data
  - pre-training data should be close to the downstream use case
  - all entities should be covered with training examples
  - medium size training sets are enough for fine-tuning

How to Assemble Good Training Data?

– Training data must
  1. be balanced as random pairs would be highly skewed towards non-matches
  2. contain corner cases as they are most informative
     - especially “near-miss” negative examples are more informative for training than randomly selected pairs which tend to be “easy” non-matches.
     - Star Wars 1 vs. Star Wars 2, Mannheim vs. Ludwigshafen
     - rule of thumb: 50% corner cases



– The more training data the better!
  - remember the learning curve
– Try to reduce labeling effort by
  - reusing existing information about matches
    e.g. ISBN or GTIN numbers, owl:sameAs

    = weak supervision as quality is often questionable

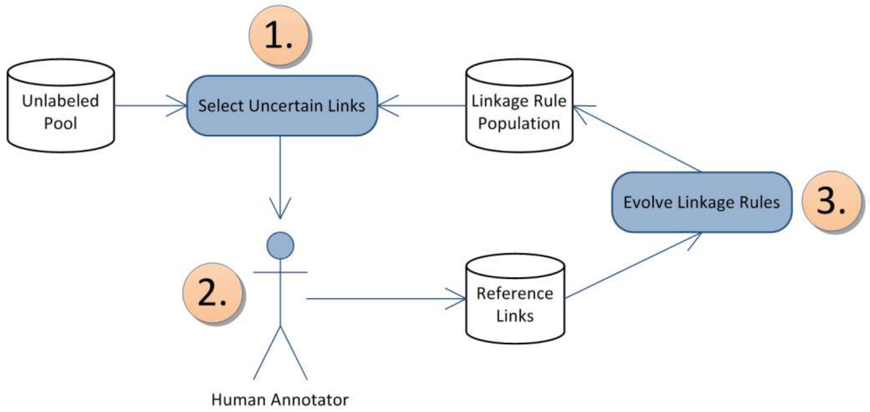
Hanna Köpcke, Erhard Rahm: **Training selection for tuning entity matching.** *QDB/MUD*, 2008.
Ratner, et al.: **Snorkel: Rapid Training Data Creation with Weak Supervision.** VLDB Journal, 2019.

Discussion Learning-based Approaches

– Pros compared to writing matching rules by hand
  - when writing rules by hand, you must manually decide if a particular feature is useful ➔ labor intensive and limits the number of features you can consider
  - learning-based approaches can automatically examine a large number of features

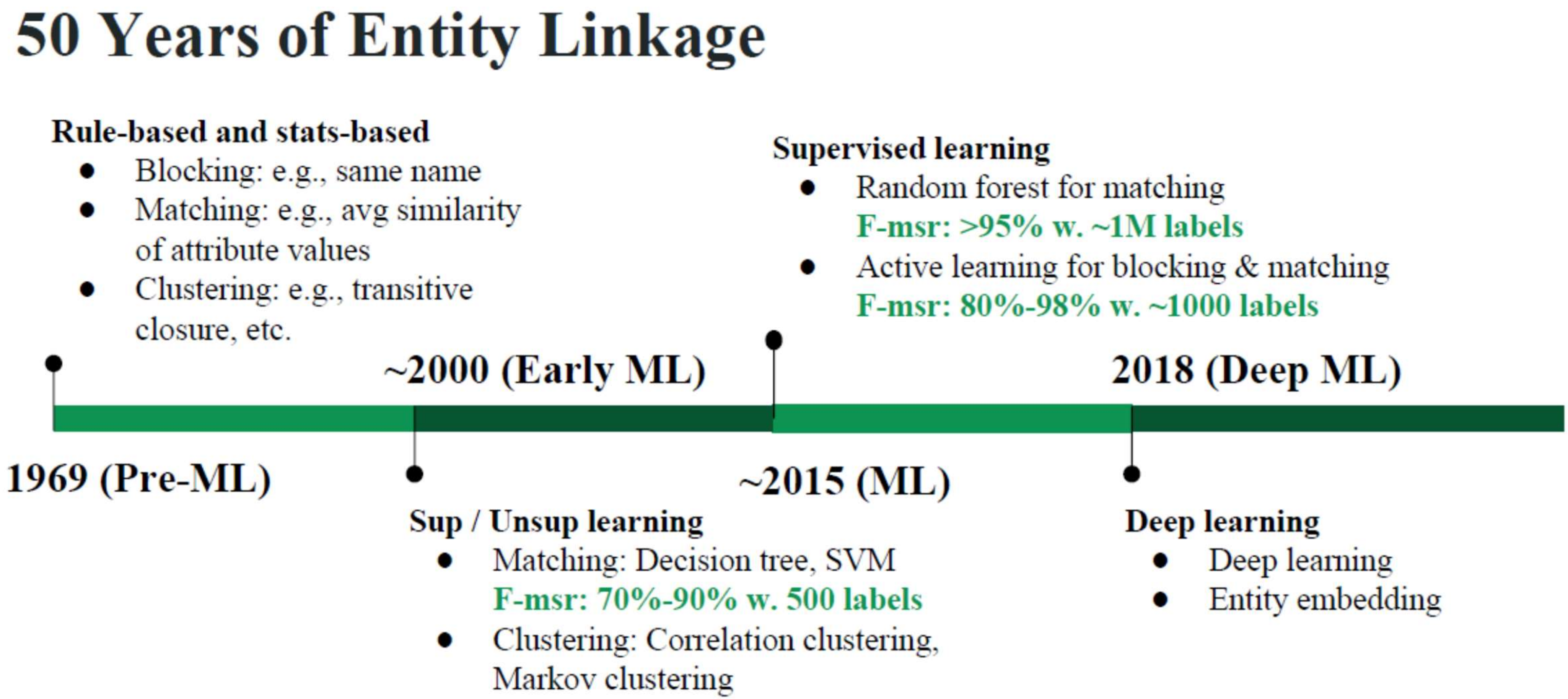
– Cons
  - you need to label training examples
  - you don't know which examples matter to the algorithm and thus might label an unnecessary large amount of examples in order to cover the relevant corner-cases

– Alternative
  - use Active Learning in order to let the algorithm decide which examples matter
  - practical experience: Often F_1 > 0.9 after labeling less than 300 pairs



Isele, Bizer: **Active Learning of Expressive Linkage Rules using Genetic Programming**. Journal of Web Semantics, 2013.

Summary: The Historic Perspective



Luna Dong: **ML for Entity Linkage. Data Integration and Machine Learning: A Natural Synergy**. Tutorial at SIGMOD 2018. https://thodrek.github.io/di-ml/sigmod2018/sigmod2018.html

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- Additional current references: https://paperswithcode.com/task/**entity-resolution**