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End-to-End Entity Resolution for Big Data: A Survey

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Abstract One of the most important tasks for improving data quality and the reliability of data analytics results is *Entity Resolution* (ER). ER aims to identify different descriptions that refer to the same real-world entity, and remains a challenging problem. While previous works have studied specific aspects of ER (and mostly in traditional settings), in this survey, we provide for the first time an end-to-end view of modern ER workflows, and of the novel aspects of entity indexing and matching methods in order to cope with more than one of the Big Data characteristics simultaneously. We present the basic concepts, processing steps and execution strategies that have been proposed by different communities, i.e., database, semantic Web and machine learning, in order to cope with the loose *structuredness*, extreme *diversity*, high *speed* and large *scale* of entity descriptions used by real-world applications. Finally, we provide a synthetic discussion of the existing approaches, and conclude with a detailed presentation of open research directions.

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1 Introduction

In the Big Data era, business, government and scientific organizations increasingly rely in their day-to-day operations on massive amounts of data collected from both internal (e.g., CRM, ERP) and external data sources (e.g., the Web). Even when data integrated from multiple sources refer to the same real-world entities, they usually exhibit several quality issues such as *incompleteness* (i.e., partial data), *redundancy* (i.e., overlapping data), *inconsistency* (i.e., conflicting data) or simply *incorrectness* (i.e., data errors). A typical task for improving various aspects of data quality and thus increase the reliability of the outcomes of data analytics, is *Entity Resolution* (ER).

ER aims to identify different descriptions that refer to the same real-world entity appearing either within or across data sources, when unique entity identifiers are not available. Typically, ER aims to match structured descriptions (i.e., records) stored in the same (a.k.a. *deduplication*), or two different (a.k.a. *record linkage*) relational tables, although other scenarios are also considered, such as matching semi-structured descriptions across RDF knowledge bases (KB) or XML-files (a.k.a. *link discovery* or *reference reconciliation*). Figure 1 illustrates descriptions of the same movies, directors and places from two popular KBs: DBpedia (blue) and Freebase (red). Each entity description is depicted in a tabular format, where the header row is the URI of the description and the remaining rows are the attribute (left) - value (right) pairs of the description.

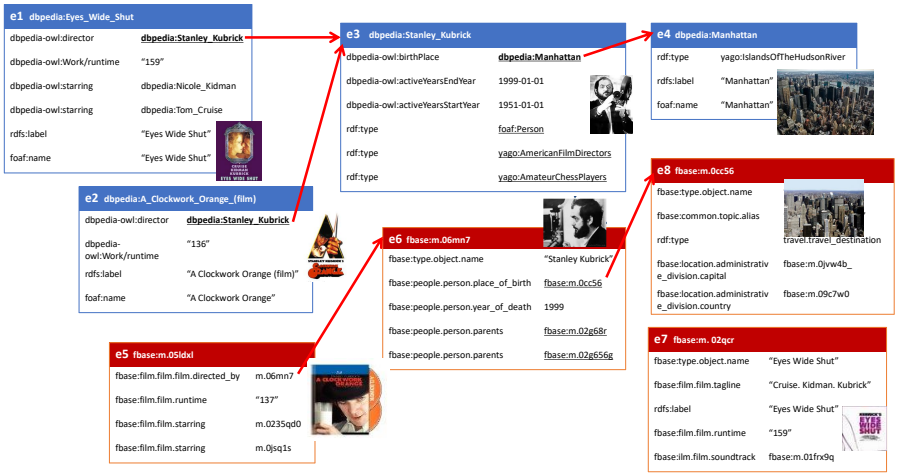

Fig. 1: Movies, Directors, and Locations from DBpedia (blue) and Freebase (red). Note that e_1, e_2, e_3 and e_4 match with e_7, e_5, e_6 and e_8, respectively.

ER aims to classify pairs of descriptions that are assumed to correspond to the same (vs. different) entity into *matches* (vs. *non-matches*). An ER process usually encompasses several steps, including *indexing* or *blocking*, which reduces the number of candidate descriptions to be compared in detail, and *matching*, which assesses the similarity of pairs of candidate descriptions using a set of functions. Several ER frameworks and algorithms for these steps have been proposed during the last three decades in different research communities. In this survey, we present the latest developments in ER, which remains an important and open research problem when processing Big Data. In particular, we explain how the Big Data characteristics call for novel ER frameworks that relax a number of assumptions underlying several methods and techniques proposed in the context of database [29,47,58,108,127], machine learning [71] and semantic Web communities [131].

Our examples are inspired by the Linked Open Data (LOD) initiative [32], which covers only a small fragment of the Web today, but is representative of the challenges raised by Big Data to core ER tasks, namely: (*a*) how descriptions can be effectively compared for similarity, and (*b*) how resolution algorithms can efficiently filter the number of candidate description pairs that need to be compared (readers are referred to [36] for data sources in the Deep Web and to [14,21] for large knowledge graphs underlying Web search engines).

Big Data Characteristics. The following characteristics [46] challenge existing ER techniques and methods across all the steps of traditional ER workflows.

- *Volume.* Not only does the content of each data source never cease to increase, but also the *number of data sources* even for a single domain, has grown to thousands. For example, the LOD cloud alone contains (as of June 2018) almost 1,365 datasets from various sources (this is an x100 growth since its first edition) in 10 domains with ∼200B triples (i.e., $< subject, predicate, object >$) describing more than 60M entities of different types[1]; the life-science domain alone accounts for 334 datasets.
- *Variety.* Data sources (even in the same domain) are extremely heterogeneous both regarding how they structure their data, as well as regarding how they describe the same real-world entity, exhibiting *considerable diversity* even for substantially similar entities. For example, there are ∼2,600 diverse vocabularies in the LOD cloud, but only 109 of them are shared by more than one KB[2].
- *Velocity.* As a direct consequence of the rate at which data is being collected and continuously made available, many of the data sources are *very dynamic*. For example, LOD data are rarely static, with recent studies reporting that 23% of the datasets exhibit infrequent changes, while 8% are highly dynamic in terms of triples additions and deletions[3].
- *Veracity.* Data sources are of *widely differing qualities*, with significant differences in the coverage, accuracy and timeliness of data provided. Even in the same domain various forms of inconsistencies and errors in entity descriptions may arise, due to the limitations of the automatic extraction techniques, or of the crowd-sourced contributions. A recent empirical study [39] shows that there are several LOD quality problems, as their conformance with a number of best practices and guidelines is still open. For example, the two descriptions of "A Clockwork Or-

[1] https://lod-cloud.net
[2] https://lov.linkeddata.es/dataset/lov
[3] http://km.aifb.kit.edu/projects/dyldo

ange" from DBpedia (e_2) and Freebase (e_5) in Figure 1 have different values for the runtime attribute.

Challenges of Big Data Entity Resolution. Individual characteristics of Big Data have been the focus of previous research work in ER. For example, there is a continuous concern for improving the *scalability* of ER techniques using e.g., massively parallel implementations [24], or approximately matching uncertain entity descriptions [47,69]. However, traditional deduplication techniques [30,58] have been mostly conceived for processing structured data of few entity types after being adequately pre-processed in a data warehouse, and hence been able to discover blocking keys of entities and/or mapping rules between their types. We argue that ER techniques are challenged when more than one of the Big Data Vs have to be addressed simultaneously (e.g., Volume or Velocity with Variety).

In essence, the extreme *Variety* of Big Data calls for a paradigm shift in all major steps of ER. Regarding blocking, Variety renders inapplicable the traditional techniques that rely on schema and domain knowledge to maximize the number comparisons that are skipped, because they do not lead to matches [134].

As far as matching is concerned, the extreme Variety requires novel entity matching approaches that go beyond approximate string similarity functions [109]. This is because such functions are typically used for assessing the similarity of the values of specific attributes among pairs of descriptions. Clearly, *schema-based* comparisons cannot be used for *loosely structured and highly heterogeneous entity descriptions*, e.g., as those found in LOD. Similarity evidence of entities can be obtained only by looking at the bag of literals contained in descriptions, regardless of the attributes they appear as values. As the *value-based* similarity of a pair of entities may still be weak due to Big Data *Veracity*, we need to consider additional sources of evidence related to the *similarity of neighboring* entities, i.e., connected via relations.

To clarify this situation, consider Figure 2, which depicts the two types of similarity for entities known to match from 4 benchmark datasets used in the literature, namely Restaurant[4], Rexa-DBLP[5], BBCmusic-DBpedia[6] and YAGO-IMDb[7]. Every dot corresponds to a different matching pair, while its shape denotes its original dataset. The horizontal axis reports the normalized value similarity based on the descriptions common words in a pair (weighted Jaccard [113]), while the vertical one reports the maximum value similarity of

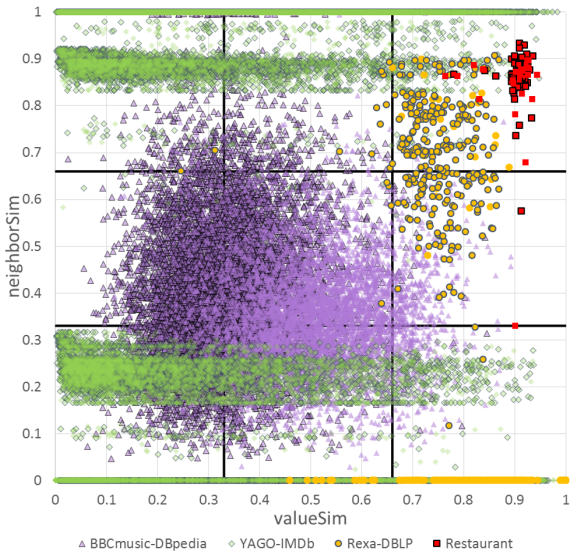

Fig. 2: Value and neighbor similarity distribution of matching entities in 4 established, real-world datasets.

their respective entity neighbors. We can observe that the value-based similarity of matching entities significantly varies across different dataset. For *strongly similar entities* (e.g., with a value-based similarity > 0.5) - hosted in data sources with few entity types - existing duplicate detection techniques work well. However, to resolve *nearly similar entities* (e.g., value similarity < 0.5) - hosted in data sources with a large number of entity types - which cover a large part of the matching pairs of entities, we need advanced ways of exploiting evidence about the similarity of neighboring entities.

Major issues are also raised by the *Velocity* of Big Data. Even though ER is historically framed as an offline, budget-agnostic task that improves data quality in data warehouses upon completion of data integration, many services in the private and public sectors are now requiring to resolve entities under specific efficiency or effectiveness constraints (i.e., w.r.t. a budget), or even in real-time. Such applications strive for new ER workflows that can sacrifice completeness of the resulting matches as long as *budget-aware* (or *progressive* or *pay-as-you-go*)[8] [2,149,189], *query-based* [16,5], or *streaming* [94] execution strategies can be supported.

Contributions. Record linkage and deduplication techniques for structured data in data warehouse settings have been the subject of numerous surveys and benchmarking efforts, such as [29,30,58,80,108,127]. Moreover, uncertain ER has been presented in [69], approximate instance matching have been surveyed in [47], and link discovering algorithms in [131]. Recent efforts to enhance scalability of ER techniques by leveraging

[4] http://oaei.ontologymatching.org/2010/im

[5] http://oaei.ontologymatching.org/2009/instances

[6] http://datahub.io/dataset/bbc-music, http://km.aifb.kit.edu/projects/btc-2012

[7] http://www.yago-knowledge.org, http://www.imdb.com

[8] We use the terms "budget-aware" and "progressive" interchangeably throughout the paper.

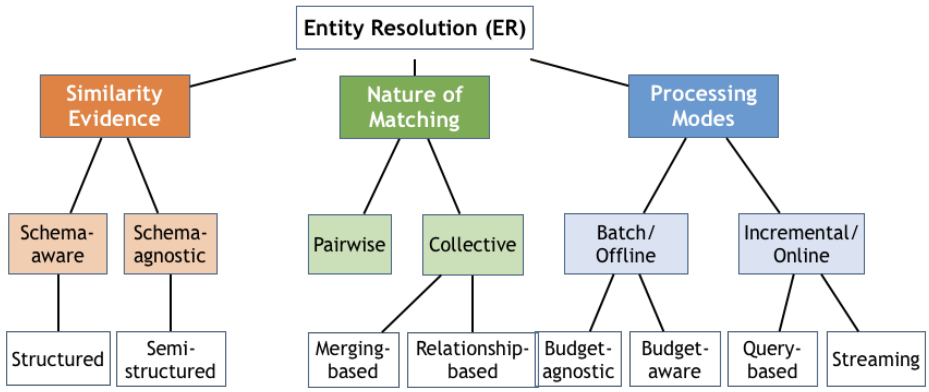

Fig. 3: A non-exhaustive taxonomy of ER settings and approaches based on their key characteristics.

distribution and parallelization techniques have been surveyed in [24].

In contrast, this is the first survey that provides an end-to-end view of modern ER workflows and of the novel aspects of entity indexing and matching methods in order to (simultaneously) cope with the *Volume*, *Variety*, *Velocity* and *Veracity* of Big Data. Throughout this survey, we present the basic concepts, processing steps and execution strategies required to cope with the loose *structuredness*, extreme *diversity*, high *speed* and large *scale* of entity descriptions actually consumed by real applications. We made an effort to cover in a self-contained way representative algorithms proposed by different communities (i.e., database, semantic Web, machine learning) using illustrative examples. This survey is intended to provide a starting point of lecture for researchers, students and developers interested in recent advances of schema-agnostic, budget-ware and incremental ER techniques, enabling to resolve near similar entity descriptions published by numerous data sources. Parts of the material included in this survey has been presented in different tutorials at CIKM 2013 [169], KDD 2013 [72], WWW 2014 [170], ICDE 2016 [143], ICDE 2017 [168] and WWW 2018 [144].

The remaining of this survey is organized as follows. Section 2 presents the core concepts and general processing steps for building ER workflows, explaining how they determine the organization of Sections 3 to 7. Section 8 briefly covers complementary topics for ER, while Section 9 summarizes our understanding about current ER status, presenting directions for future work.

2 ER processing steps and workflows

The core notion of ER is the *entity description*, which comprises a set of attribute-value pairs uniquely identified through a global id. A set of descriptions is called *entity collection*. Two descriptions that correspond to the same real-word object are called *matches* or *duplicates*. Depending on the input and its characteristics, ER is distinguished into [54,140,159,165]:

1. *Clean-Clean ER*, when the input comprises two individually clean (i.e., duplicate-free) entity collections and the goal is to find the matches between them.
2. *Dirty ER*, when the input comprises a single entity collection that contains duplicates in itself and the goal is to identify them.
3. *Multi-source ER*, when more than two entity collections are given as input.

For every ER sub-problem, the general processing steps involved in an end-to-end workflow are illustrated in Figure 4 [56,168,170]. Given that ER is by nature quadratic to the number of input entity descriptions, as every description should be compared to all other descriptions, *blocking* (a.k.a. *indexing*) is typically applied first (targeting Volume). Its goal is to discard as many comparisons as possible without missing any matches. It places similar descriptions into blocks, based on some criteria (typically, called *blocking keys*) so that it suffices to execute comparisons only between descriptions co-occurring in at least one block. In other words, blocking discards comparisons between descriptions that are unlikely to match, quickly splitting the input entity collection into blocks as close as possible to the final ER result.

To address Variety, blocking typically operates in a schema-agnostic fashion (see Figure 3) that considers all attribute values, regardless of the associated attribute names [147]. The key is *redundancy*, i.e., the act of placing every entity into multiple blocks, thus increasing the likelihood that matching entities co-occur in at least one block. On the flip side, the portion of executed comparisons that involve a non-redundant pair of descriptions is extremely big. This is addressed, though, by a second step, called *block processing*. Its task is to restructure an existing block collection so as to minimize the number of comparisons, without any signifi-

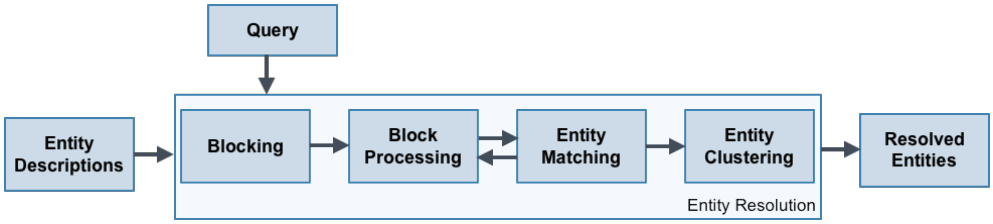

Fig. 4: The general end-to-end Entity Resolution process.

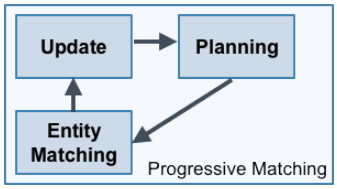

Fig. 5: The progressive matching process.

cant impact on the duplicates that co-occur in blocks. This is achieved by discarding two types of unnecessary comparisons: those repeated across multiple blocks and those involving non-matching entities.

The next step is *matching*, which applies a function M that maps each pair of entity descriptions (e_i, e_j) to $\{true, false\}$, with $M(e_i, e_j) = true$ meaning that e_i and e_j are matches, and $M(e_i, e_j) = false$ meaning that e_i and e_j are not matches. In practice, the match function is defined via a similarity function sim, measuring how similar two descriptions are to each other, according to certain comparison criteria. Finding a similarity function which perfectly distinguishes all matches from non-matches for all entity collections is rather hard. Thus, in reality, we seek a similarity function that will be only good enough, i.e., minimize the number of misclassified pairs.

Note that in the context of Big Data, nearly similar entities are resolved by going beyond *pairwise* ER techniques, which examine each pair of descriptions independently from other pairs. To match imprecise descriptions of the real-world entities, *collective ER techniques* [15] (see Figure 3) are used to increase their matching evidence either by merging the descriptions of partially matched entities or by propagating their similarity to neighbor entities via relationships that will be matched in a next round. These techniques imply several iterations until they converge to a stable ER result (i.e., no more matches are identified). Thus, collective ER is hard to scale in a cross-domain setting involving a very large number of sources and entity types.

Note also that recent works have also proposed using an *iterative ER process*, interleaved with blocking. In such a process, matching is applied to the results of blocking and the results of each iteration potentially alter the existing blocks, triggering a new iteration (see Figure 4). The block modifications are based on the relationships between the matched descriptions and/or on the results of their merging (see Figure 3).

The final step in the end-to-end ER workflow is *Entity Clustering*, which groups together the identified matches such that all the descriptions placed into the same entity cluster should match. Its goal is actually to infer more duplicates from indirect matching relations, while discarding compared pairs of descriptions that are unlikely to connect duplicates in favor of pairs with higher matching probabilities. Its output comprises disjoint sets of entity descriptions $R = \{r_1, r_2, \ldots, r_m\}$, such that: (i) $\forall e_i, e_j \in r_k$ $M(e_i, e_j) = true$, (ii) $\forall e_i \in r_k \forall e_j \in r_l$ $M(e_i, e_j) = false$, and (iii) $\bigcup_{r_i} r_i \in R = \mathcal{E}$, where $\mathcal{E}$ stands for the input entity collection. This partitioning corresponds to the resulting set of resolved entities in Figure 4.

Each of these four workflow steps is examined in a separate section: blocking in Section 3, block processing in Section 4, matching in Section 5, and clustering in Section 6. Note that all these sections primarily pertain to *budget-agnostic ER* (see Figure 3).

Budget-aware ER is covered in Section 7. Rather than finding all entity matches, its goal is to identify as many matches as possible within a specified cost budget (e.g., time or number of comparisons). Such techniques usually divide the total cost budget into several windows [2] and rely on a known graph of dependencies among structured descriptions [45] to decide (based on the cost/benefit trade-off) for each window which nodes will be resolved next and in what order. To reduce the size of entity dependency graphs existing indexing/blocking methods could be used. As indexing/blocking can be currently supported only offline, progressive techniques usually specify static ER workflows. In this case, the typical ER workflow is extended with a *planning phase*, which is responsible for selecting which pairs of descriptions, that have resulted from blocking, will be compared in the entity matching phase and in what order. The goal of this phase is to favor more promising comparisons, i.e., those that are more likely to increase the targeted benefit. Those comparisons are executed before less promising ones and thus, higher benefit is provided early on in the process. In *dynamic* progressive ER, there is an *update phase*, which

propagates the results of matching, such that a new planning phase will promote the comparison of pairs influenced by the previous matches. This iterative process continues until the cost budget is consumed. Figure 5 illustrates the additional steps of the progressive ER.

Finally, targeting Velocity, an *incremental* (or *online*) approach for ER can be directly applied for resolving the entities provided as streams or queries in real-time (see Figure 4). In the latter case, one description provided by the user is resolved at a time using summarization techniques of stored descriptions [94]. That query description is either added to an existing set of descriptions, corresponding to a distinct real-world entity, or initiates a new set, if it does not match with any other description [16,167,186]. To support this type of ER, we essentially need dynamic techniques for indexing descriptions at varying latencies and thus be able to compare only a small number of high-quality candidate pairs of descriptions arriving in a streaming fashion. Dynamic indexing/blocking techniques are still in their infancy (e.g., using dynamic sorted neighborhood indexing [151] or inverted similarity-aware indexing [153]) and are limited to structured data. Incremental entity matching has been recently framed as a correlation clustering problem, for which polynomial-time approximation algorithms have been proposed to obtain satisfactory quality ER results [77]. Relevant works are covered in Section 5.3.

3 Blocking

As mentioned above, *blocking* aims to reduce the number of comparisons between descriptions that do not match. After blocking, each description can be compared only to others placed within the same block(s). The desiderata of blocking are:

1. to place all matching descriptions in at least one common block, and
2. to minimize the number of suggested comparisons.

The second goal dictates skipping many comparisons, possibly leading to many missed matches, which hampers the first goal. Therefore, blocking should achieve a good trade-off between these two competing goals.

3.1 Preliminaries

Blocking methods are defined over key values that can be used to decide whether or not an entity description could be placed in a block. The "uniqueness" of key values determines the number of entity descriptions that co-occur in blocks and, thus, are considered as *candidate matches*. For structured data, *blocking keys* are typically defined by the value of a specific attribute or a combination of attributes, i.e., they are *schema-aware*. If, for example, the blocking key is defined for the attribute "name", then entity descriptions with same names (or an adequate string transformation function over these names) will end up in the same block.

More formally, a blocking method consists of two components [18]:

- An *indexing function* $h_{key} : \mathcal{E} \rightarrow 2^B$, where B is the set of all blocks, is a unary function that, applied to an entity description $e_i \in \mathcal{E}$ using a specific blocking key, returns as a value the set of blocks under which e_i will be indexed.
- A *co-occurrence function* $o_{key} : \mathcal{E} \times \mathcal{E} \rightarrow \{true, false\}$ is a binary function that, applied to a pair of entity descriptions, returns `true` if the intersection of the sets of blocks, produced by the indexing function on its arguments, is non-empty, and `false` otherwise; $o_{key}(e_k, e_l) = true$ iff $h_{key}(e_k) \cap h_{key}(e_l) \neq \emptyset$.

Note that the co-occurrence function for every pair of descriptions placed in the same block returns `true`, while every pair of descriptions whose co-occurrence function returns `true` shares at least one common block. Also the union of the block elements is the input entity collection, provided that no entity is exclusively associated with *singleton keys*, i.e., blocking keys that appear only once (in case of Dirty ER), or in just one entity collection (in case of Clean-Clean ER). The reason is that by definition, each block should contain at least two descriptions. More formally:

Definition 1 (Atomic Blocking) Given an entity collection $\mathcal{E}$, *atomic blocking* is defined by an indexing function h_{key} for which the generated blocks $B^{key} = \{b_1^{key}, \ldots, b_m^{key}\}$ satisfy the following conditions:

(i) $\forall e_k, e_l \in b_i^{key} : b_i^{key} \in B^{key}, o_{key}(e_k, e_l) = true$,
(ii) $\forall (e_k, e_l) : o_{key}(e_k, e_l) = true, \exists b_i^{key} \in B^{key}, e_k, e_l \in b_i^{key}$,
(iii) $\bigcup_{b_i^{key} \in B^{key}} b_i^{key} = \mathcal{E}$.

In general, the overlap of the resulting blocks determines the *redundancy attitude* of a blocking method, which is characterized as:

1. *partitioning*, if it extracts a single key from each entity (i.e., $\forall e \in \mathcal{E}, |h_{key}(e)| = 1$), and
2. *overlapping*, if it extracts multiple keys per entity (i.e., $\forall e \in \mathcal{E}, |h_{key}(e)| \geq 1$).

The former yield disjoint blocks, while the latter overlapping blocks, which are more robust to noise in blocking keys. On the flip side, they result in a greater number of comparisons, many of which are contained in different blocks, also known as *repeated comparisons* [141]. Depending on the meaning of this redundancy, we distinguish overlapping blocking methods into:

(i) *overlap-positive*, if the number of common blocks between two descriptions is proportional to the likelihood that they are matching, and
(ii) *overlap-neutral*, if the number of common blocks is irrelevant to the matching likelihood.

Typically, the single key per entity that is defined by partitioning methods does not suffice for building effective and efficient blocks [30]. Instead, we need to consider several keys that the indexing function exploits to build different sets of block. Such a composite blocking method is characterized by a disjunctive co-occurrence function that is formally defined as follows [54]:

Definition 2 (Composite Blocking) Given an entity collection $\mathcal{E}$, *composite blocking* is defined by a set of indexing functions H for which the generated blocks $B = \bigcup_{h_{key} \in H} B^{key}$ satisfy the following conditions:

(i) $\forall e_k, e_l \in b : b \in B, o_H(e_k, e_l) = true$,
(ii) $\forall (e_k, e_l) : o_H(e_k, e_l) = true, \exists b \in B, e_k, e_l \in b$,

where $o_H(e_k, e_l) = \bigvee_{h_{key} \in H} o_{key}(e_k, e_l)$.

Atomic blocking can be seen as a special case of composite blocking, consisting of a singular set of indexing functions, i.e., $H = \{h_{key}\}$.

Measures. Given a set M of known matching pairs of descriptions (*ground truth*), we assess the effectiveness of a blocking method through the following measures:

- True Positives (TP) is the number of matching pairs that co-occur in at least one block, i.e., $TP = |\{(e_k, e_l) | o_H(e_k, e_l) = true \wedge (e_k, e_l) \in M\}|$.
- False Positives (FP) is the number of non-matching pairs that co-occur in at least one block, i.e., $FP = |\{(e_k, e_l) | o_H(e_k, e_l) = true \wedge (e_k, e_l) \notin M\}|$.
- True Negatives (TN) is the number of non-matching pairs that have been placed in no common block, i.e., $TN = |\{(e_k, e_l) | o_H(e_k, e_l) = false \wedge (e_k, e_l) \notin M\}|$.
- False Negatives (FN) is the number of matching pairs that have been placed in no common block, i.e., $FN = |\{(e_k, e_l) | o_H(e_k, e_l) = false \wedge (e_k, e_l) \in M\}|$.

Based on these measures, the standard measures used to evaluate the quality of the blocking results [30, 32, 57] are described in Table 1. The range of all measures is $[0, 1]$, with values closer to 1 indicating better performance. Note that RR expresses the relative decrease in computational cost when executing all block comparisons, i.e., $||B||$, instead of an exhaustive comparison of all possible pairs of descriptions, i.e., $||E||$.

Table 1: Quality Measures.

Name	Formula	Description
PC	$\frac{TP}{TP+FN}$	Pairs Completeness (recall)
PQ	$\frac{TP}{TP+FP}$	Pairs Quality (precision)
$F1$	$2\frac{PC \cdot PQ}{PC+PQ}$	F-Measure (harmonic mean PC-PQ)
RR	$1 - \frac{\|\|B\|\|}{\|\|E\|\|}$	Reduction Ratio
$H3R$	$2\frac{RR \cdot PC}{RR+PC}$	Harmonic mean of RR and PC

In general, a good blocking method should have a low impact on recall, i.e., high PC, and a great impact on the number of required comparisons, i.e., high PQ. This trade-off is usually captured by the F-measure ($F1$), the harmonic mean of the two measures. However, $F1$ is typically dominated by the values of PQ, which are usually orders of magnitude lower than those of PC. Moreover, PQ is less important than PC, since the former can be improved by subsequent methods, whereas the latter usually determines the maximum recall of the entire ER process. For this reason, the harmonic mean of recall and RR, namely $H3R$, is also used [32, 95]. $H3R$ gives high values only when both recall (PC) and RR have high values. Unlike $F1$, though, $H3R$ manages to capture the trade-off between effectiveness and efficiency in a more balanced way.

3.2 Blocking for Structured data

The first blocking methods were crafted for structured entities, i.e., relational databases. Given that they typically relied on the schema of the input descriptions, we collectively call them *schema-aware*. As an example, consider a blocking method for census data that suggests candidate matches if two records share the same ZIP code (i.e., they live in the same area). Such conditions are specified either *automatically*, through machine learning, or *manually*, based on expert knowledge. We call methods of the former type *learning-based*, in contrast to the *non-learning* methods of the latter type. In the following, we review each type separately.

3.2.1 Non-learning methods

This type of methods requires no labelled instances for learning their indexing functions. Instead, it presumes manual fine-tuning, i.e., it relies- on expert knowledge for determining combinations and/or transformations

of (parts of) attribute values that offer high distinctiveness together with low levels of noise.

The cornerstone method is *Standard Blocking* [65], which uses a part or a transformation of one or more attribute values as the single blocking key of each entity. Every description is then placed in the block corresponding to its blocking key. This hash-based functionality results in disjoint blocks (partitioning method), thus being quite sensitive to noise in blocking keys: matches without identical blocking keys are missed. To increase its robustness, a multi-pass functionality is applied in practice, i.e., Standard Blocking is combined with several different indexing functions.

Another way to ameliorate this issue is the *Sorted Neighborhood* approach [84]. Its functionality is inherently robust to noise, because it creates blocks based on similar, rather than identical keys (sort-based approach). Initially, the entity descriptions are alphabetically ordered according to their blocking keys. Then, a window of fixed length slides over the ordered descriptions, each time comparing only the contents of the window, i.e., every position of the window forms a new block. In this way, Sorted Neighborhood detects matches with different blocking keys provided that they are lexicographically close. The resulting blocks are overlapping, but their redundancy is independent of matching likelihood (i.e., overlap-neutral). An adaptive variation of Sorted Neighborhood sets the size of the window dynamically [193]. At its core lie the boundary pairs, which correspond to adjacent blocking keys in the sorted order that are significantly different from each other. These boundary pairs mark the positions where one window ends and the next one starts. Hence, this variation creates disjoint blocks through a partitioning, sort-based functionality. Similarly, the *Sorted Blocks* method [49] allows for determining the size of the window as well as the desired degree of overlap.

Q-grams Blocking [76] is an overlap-positive, hash-based method that enhances the noise robustness of Standard Blocking by converting its blocking keys into a list of q-grams, i.e., substrings of q characters. For example, the key "Eiffel" is transformed into the list of bi-grams ["ei","if","ff","fe","el"]; sub-lists are then generated, by recursively removing one q-gram each time, e.g., ["if","ff","fe","el"], ["ei", "ff","fe","el"], and ["ei","ff","el"]. Each sub-list is then converted (by concatenation) into a new blocking key. This way, typographical and spelling errors are excused; e.g., the keys "Eiffel" and "Eifel" yield multiple common blocks.

The same purpose is served by *Suffix Arrays Blocking* [1], which considers the suffixes of Standard Blocking's keys. The suffixes are the sub-strings that are produced by removing some of the first characters, thus ignoring potential errors at the beginning of blocking keys. A separate block is created for each suffix, resulting in a hash-based, overlap-positive functionality. However, very short suffixes lead to excessively large blocks. To prevent this, two thresholds are used: the minimum suffix length and the maximum block size.

A different method for increased noise robustness is *String-Map* [91], which maps blocking keys to objects in a d-dimensional Euclidean space. Each dimension is defined by selecting two pivots, i.e., keys that are as dissimilar as possible according to a string similarity measure. Blocks are then formed by clustering together objects that are close to each other, i.e., within a distance threshold. For high efficiency, String-Map is based on FastMap [62], an algorithm with linear complexity to the number of keys.

Finally, *MFIBlocks* [99] uses maximal frequent itemsets as blocking keys. Each itemset is a collection of concatenated tokens from a specific attribute. The most frequent itemsets, which exceed a predetermined threshold, are treated as keys, thus reducing significantly the number of blocks and matching candidates (i.e., high precision). This may come at the cost of missed matches (lower recall), in case the resulting blocking keys are restrictive for matches with noisy descriptions.

3.2.2 Learning-based methods

This category includes methods that automatically discover effective blocking schemes by leveraging machine learning techniques, i.e., they require labelled data for learning useful patterns. Depending on how the labelled instances are defined, we distinguish them into *supervised* and *unsupervised* methods. The former employ manually curated datasets of high quality, whereas the latter rely on automatically created labelled instances.

Supervised Learning. The first method of this kind is the *Blocking Scheme Learner* [124]. Based on an adaptation of the Sequential Covering Algorithm, it learns blocking schemes that optimize RR, while maintaining recall (PC) above a predetermined threshold. Its output is a disjunction of conjunctions of predicates in the form {`hash-function`,`attribute`}.

A similar approach for learning disjunctive blocking schemes is *ApproxRBSetCover* [18]. It solves a standard weighted set cover problem, where the cover is iteratively constructed by adding the blocking predicate that maximizes the ratio of the previously uncovered matching pairs over the newly covered non-matching pairs. Note that this is a "soft cover", since some matches may remain uncovered.

ApproxDNF [18] alters ApproxRBSetCover so that it learns blocking schemes in Disjunctive Normal Form

(DNF). Instead of individual predicates, the input comprises conjunctions of up to k predicates. These conjunctions are formed in a greedy fashion by iteratively increasing the ratio of matching and non-matching covered training instances. [22] improves ApproxDNF by incorporating samples of the unlabelled instances into the learning process.

C-Block [163] goes beyond these works by combining atomic blocking schemes into a composite one in the form of a hierarchical tree. Every path in this tree is equivalent to applying a conjunctive indexing function to a subset of the input data. The tree is built by a greedy algorithm that maximizes recall, while ensuring that all blocks are smaller than a predetermined threshold: the best indexing function is locally picked at every node where the resulting blocks are expected to violate the size constraint. Blocks that are too small are merged together in order to further increase recall.

Unsupervised Learning. To address the scarcity or lack of labelled instances, an unsupervised approach, called *FisherDisjunctive*, is proposed in [95]. At its core lies a weak training set that is generated by leveraging the TF-IDF similarity between two records: pairs with very low similarities are assigned a negative label (`non-match`), and vice versa for pairs with very high similarities. A boolean feature vector is then associated with every weakly labelled instance. This allows for casting the discovery of DNF blocking schemes in the next stage as a Fisher feature selection problem.

Link-Specific Blocking [96] is a similar approach for heterogeneous structured data described by different schemata (such data can be derived from RDF data using property tables). First, it performs entity mapping on top of TF-weighted vectors. An adapted Hungarian algorithm with linear scalability then produces positive and negative feature vectors. Finally, a heterogeneous version of Blocking Scheme Learner uses bagging to achieve robust performance, as the training sets remain constant and the data grow in size. Another algorithm for the same type of data, called *Extended k-DNF Blocking* [97], combines weighted set covering with an established instance-based schema matcher to learn DNF blocking schemes with at most k predicates.

3.2.3 Hybrid methods

These methods emerged recently as a human-in-the-loop approach that combines expert knowledge with labelled instances to iteratively learn composite blocking schemes of high quality. For instance, *MatchCatcher* [114] relies on user feedback and string similarity joins to detect false negatives, i.e., pairs of matching entities that so far co-occur in no block. The indexing functions are iteratively adapted so that they capture the missed matches, increasing recall.

Fig. 6: Applying Token Blocking to the entities of Figure 1 results in 16 blocks with 47 comparisons, in total.

3.3 Blocking for semi-structured data

Unlike the methods for structured data, blocking methods for semi-structured data make no assumptions about schema knowledge. Instead, they exclusively rely on the content, name or identity of descriptions in order to decide whether they are potentially matches. In this way, they are able to effectively resolve heterogeneous and loosely structured entities across domains, such as those stemming from the Web of Data [137,139,140].

The cornerstone schema-agnostic method for semi-structured data is *Token Blocking* [137]. At its core, lies the assumption that matching descriptions should share at least a common token. Therefore, it uses as blocking keys the set of all tokens in all attribute values of an entity description. Each distinct token t defines a new block b_t, essentially building an inverted index of descriptions. Thus, two descriptions are placed in the same block, if they share a token in their values, regardless of the associated predicates.

Example 1 Figure 6 shows the blocks generated by applying Token Blocking to the entities of Figure 1. All attribute values, including entity URIs, are tokenized on special characters and then lowercased. Tokens like "nicole" and "clockwork" create no blocks, as they appear in just one description (recall that each block contains at least two descriptions). Token Blocking successfully places the duplicate pairs (e_1, e_7), (e_3, e_6) and (e_4, e_8) in at least one common block. It results, though, in a total of 47 comparisons, which exceed those of the brute-force approach (28). The reason is that there are many unnecessary comparisons, such as (e_3, e_4), (e_5, e_6) and (e_7, e_8), as well as many repeated ones, like (e_1, e_7), which is contained in seven different blocks.

The crude operation of Token Blocking can be improved by reducing the large number of unnecessary and repeated comparisons without affecting those involving matching entities. This way, precision increases, without any (significant impact on recall). Three methods have been proposed towards this end.

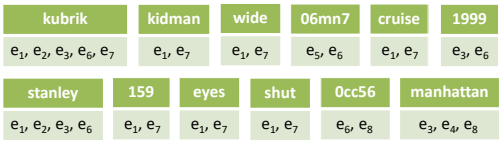

Fig. 7: Applying Prefix-Infix(-Suffix) Blocking to the entities of Figure 1 results in 10 blocks with 14 comparisons, in total.

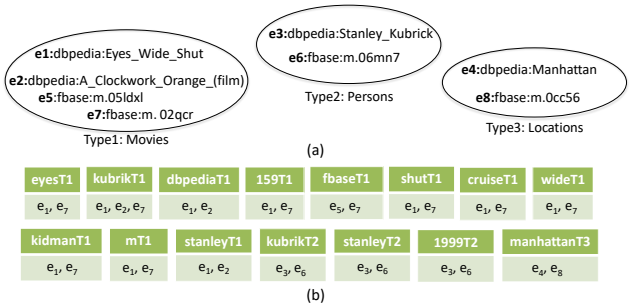

Fig. 8: (a) The types of the entities in Figure 1, (b) Applying TYPiMatch to these entities results in 15 blocks with 17 comparisons, in total.

The first one is *Attribute Clustering Blocking* [140], which requires the common tokens of two descriptions to appear in *syntactically similar attributes*, i.e., in attributes that contain similar values, but are not necessarily semantically matching (unlike Schema Matching). First, it clusters attributes based on the similarities of their aggregate values over the entire dataset. Each attribute is connected to its most similar attribute and the transitive closure of the connected attributes forms disjoint clusters. Then, every token t in the values of the attributes belonging to cluster c defines a block $b_{c.t}$. This way, attribute clustering generates overlapping blocks, but compared to Token Blocking, it produces a larger number of smaller blocks.

A different approach is followed by *Prefix-Infix(-Suffix) Blocking* [139], which exploits the naming pattern in the descriptions' URIs. The *prefix* describes the domain of the URI, the *infix* is a local identifier, and the optional *suffix* contains details about the format, or a named anchor [136]. For example, consider the URI `http://liris.cnrs.fr/olivier.aubert/foaf.rdf#me`; the prefix is `http://liris.cnrs.fr`, the infix is `olivier.aubert` and the suffix is `foaf.rdf#me`. In this context, this method uses as blocking keys the (URI) infixes along with the tokens in the descriptions of literal values. Yet, its applicability is constrained by the extent to which common naming policies are followed within a KB. In a favourable scenario, the infixes allow for detecting matching entities, even if their literal values share no tokens.

Example 2 Figure 7 depicts the blocks generated by applying Prefix-Infix(-Suffix) Blocking to the entities of Figure 1. Compared to the outcomes Token Blocking in Figure 6, there is no block for tokens from URI prefixes, namely "fbase", "m", "dbpedia" and "yago". Also, the entire infix "stanley_kubrik" is used as a blocking key, instead of breaking it into two tokens. This approach saves 33 pairwise comparisons (a reduction by more than 70%), at the cost of missing a pair of duplicates: e_3 and e_6 now co-occur in no block. Only the duplicate pairs (e_1, e_7) and (e_4, e_8) are retained in at least one common block.

The third approach to improving Token Blocking is *TYPiMatch* [118], which classifies the entities of heterogeneous data collections into different, possibly overlapping types; e.g., products in a Web repository can be distinguished into computers, cameras, etc. TYPiMatch applies Token Blocking independently to the descriptions of each entity type. It creates a co-occurrence graph, where every node corresponds to a token in any attribute value and every edge connects two tokens if both conditional probabilities of co-occurrence exceed a predetermined threshold. The maximal cliques from the co-occurrence graph are then extracted and merged if their overlap exceeds another threshold. The resulting clusters correspond to the entity types, with every entity participating in all types to which its tokens belong. However, this approach is time-consuming and rather sensitive to its parameter configuration [147].

Example 3 Figure 8(a) depicts the entity types that are ideally identified among the entities of Figure 1. Based on these entity types, Figure 8(b) illustrates the blocks generated by applying TYPiMatch to their entities. Every blocking key is concatenated with a suffix Tx, $x \in \{1, 2, 3\}$, that indicates the corresponding entity type Type_x. This allows for effectively applying Token Blocking independently inside each type. As a result, large blocks are not split into smaller ones, reducing the number of pairwise comparisons to a significant extent. For example, the block "kubrik", with 5 entities and 10 comparisons, is now split into "kubrikT1" with 3 entities and 3 comparisons and "kubrikT2" with 2 entities and 1 comparison. Compared to the outcomes Token Blocking in Figure 6, TYPiMatch saves 30 pairwise comparisons (a reduction by more than 63%), without missing any pair of duplicates - they all co-occur in at least one block. The main challenge is the accurate detection of entity types in a schema-agnostic way.

A recently proposed approach for schema-agnostic blocking is the combination of LSH with distributed representations (i.e., embeddings) in *DeepER* [50]. Every entity is transformed into a dense, real-valued vector by aggregating all tokens from all attribute values. This vector is then hashed into multiple buckets with LSH, providing probabilistic guarantees for the resulting recall. Multiprobe-LSH [117] is then used for extracting the top-N most likely matches for each entity.

3.4 Parallel Methods

The process itself of creating the blocks and retrieving the candidate pairs suggested by blocking could raise significant scalability concerns when applied to large volumes of entity collections. For this reason, several parallel adaptations of existing blocking methods have been proposed in the literature. They enable blocking in entity collections of massive volumes, without compromising the effectiveness of the original approach.

Most parallelization works rely on the *MapReduce framework* [38], since it offers fault-tolerant, optimized execution for applications distributed across a set of independent nodes. In a nutshell, MapReduce splits the data it receives as input into smaller chunks, which are then processed in parallel. A `Map` function emits intermediate (key, value) pairs for each input split, while a `Reduce` function processes the list of values that correspond to a particular intermediate key, regardless of the mapper that emitted them. These two functions form one MapReduce job, but it is common for a complex procedure to involve multiple jobs.

Blocking for structured data. Among the schema-aware methods, the hash-based, non-learning ones are adapted to MapReduce in a straightforward way: in the `map` phase, a (key, entity) pair is emitted for each description, such that entities with the same key are assigned to the same reduce task. In this way, each reduce task receives a block of descriptions and performs comparisons only between them. Such implementations for various blocking methods are provided by Dedoop [102].

Sorted Neighborhood is adapted to MapReduce in [104]. The `map` function extracts the blocking key(s) from each input entity, while the *partitioning* phase that follows sorts all entities in alphabetical order of their keys based on a specific range partitioning function. The `reduce` function slides a window of fixed size within every reduce partition. Inevitably, entities close to the partition boundaries need to be compared across different reduce tasks. This is achieved by extending the map function so that it replicates those entities, forwarding them to both the respective reduce task and its successor. The same concept can be generalized to the other sort-based non-learning blocking methods.

Blocking for semi-structured data. The MapReduce implementation of the schema-agnostic blocking methods is presented in [32, 55]. Token Blocking builds an inverted index that associates every token with all entities containing it in their attribute values. This is carried out by a single MapReduce job: for every input entity e_i, the `map` function emits a (t, e_i) pair for every token t in the values of e_i; then, all entities sharing a particular token are processed by the same `reduce` function, i.e., they are placed in the same block.

For the parallelization of Attribute Clustering, four MapReduce jobs are required. The first one assembles all values that correspond to each attribute name. The second job computes the similarities between all attributes, even those placed in different data partitions – an approach similar to the non-approximate algorithm in [197] is used for this purpose. The third job associates every attribute with its most similar one. Finally, the fourth job associates every attribute with a cluster id and applies the same process as the MapReduce-based Token Blocking. The only difference is that the `map` function emits pairs of the form ($c_{id}.t$, e_i), where c_{id} is the cluster id of e_i's attribute that contains token t.

Also complex is the parallelization of Prefix-Infix(-Suffix) Blocking, which involves three MapReduce jobs. The first one parallelizes the algorithm that extracts the prefixes from a set of URIs [136]. The second one does the same for the extraction of suffixes from a set of URIs. The third job involves two different mappers that run in parallel: (i) the mapper of Token Blocking, which applies to the literal values, and (ii) a specialized mapper, which emits a pair (i, e_i) for every infix i that is extracted from description's e_i URI, or from the URIs appearing in its values. The final reduce phase ensures that all entities having a common token or infix in their literals or URIs will be placed in the same block.

Load Balancing. A crucial aspect of MapReduce-based methods is the *load balancing algorithm* that distributes evenly the overall workload among the available nodes. This avoids potential bottlenecks in the computation-intensive parts of the implementation. One of the first relevant approaches was *BlockSplit* [103], which splits the bigger blocks into smaller sub-blocks and processes them in parallel. Special care is taken to ensure that every entity is compared not only to all entities in its sub-block, but also to all entities of its super-block, even if their sub-block is initially assigned to a different node. This yields additional network and I/O overhead, as entities of split blocks are processed multiple times. Most importantly, BlockSplit may still lead to an unbalanced workload, due to sub-blocks of different size.

To overcome this issue, *PairRange* [103] splits evenly the comparisons in a set of blocks into a predefined number of partitions, by assigning every comparison to a particular partition id. To this end, it involves a single MapReduce job, whose mapper associates every entity e_i in block b_k with the output key $rid.k.i$, where rid denotes the index of the comparison range, i.e., the partition id. Then, the reducer groups together all entities that have the same rid and block id, reproducing all comparisons of a particular partition.

Two more load balancing algorithms were presented in [194]. Both rely on sketches in order to minimize memory consumption; the one aims to improve the space requirements of BlockSplit and the other of PairRange.

It should be stressed that none of these methods aims to distribute evenly the cost of blocking. Instead, they exclusively balance the computational cost, i.e., the time required for executing the comparisons defined in an existing set of blocks.

The load balancing algorithm presented in [33] shares the same goal, but goes beyond the above methods in that its cost model considers both the computational and the communication cost (e.g., network transfer time, local disk I/O time). The algorithm considers all possible cases of blocking, from disjoint blocks stemming from a single indexing function to overlapping blocks derived from multiple indexing functions. Most importantly, it provides strong theoretical guarantees that the overall maximum cost per reducer is within a small constant factor from the lower bounds.

3.5 Dynamic Methods

All works mentioned above pertain to batch ER, building static, i.e., immutable blocks. To support online ER, a series of recent works examine dynamic indexing techniques, where the contents of blocks are updated, depending on the entities that are posed as queries.

One of the earliest approaches is presented in [31]. The main idea is to pre-calculate similarities between the attribute values that co-occur in blocks in order to avoid similarity calculations at query time and minimize the corresponding response time. At the core of this approach lie three indexes that extend Standard Blocking: one that associates blocking keys with the corresponding attribute values, one that contains the pre-calculated similarities between attribute values that co-occur in a block, and one that associates every distinct attribute value with a record id. This approach is extended by *DySimII* [153] so that all three indexes are updated as query entities arrive. The experimental results demonstrate that both the average record insertion time and the average query time remain practically stable, even when the index size grows. Interestingly, the index size can be reduced, without any significantly loss in recall, by indexing only a certain percentage of the most frequent attribute values.

Another approach to dynamic indexing is to extend the Sorted Neighborhood method. This idea lies at the core of *F-DySNI* [151,152], which converts the sorted list of blocking keys into an index tree that is faster to search. This is actually a braided AVL tree, i.e., a combination of a height balanced binary tree and a double-linked list [157]: every tree node is linked to its alphabetically sorted predecessor node, to its successor node and to the list of ids of all entities that correspond to its blocking key. F-DySNI actually employs a forest of such index trees, with each tree associated with a different blocking key definition. This forest is updated whenever a query entity arrives and is compatible with both a fixed and an adaptive window. The former defines the rigid number of neighboring nodes that are considered, while the latter considers only the neighbors that exceed a predetermined similarity threshold.

3.6 Discussion

Table 2 presents an overview of the serial, static blocking methods discussed in Sections 3.2 and 3.3. They are organized into a taxonomy consisting of the four aforementioned criteria: schema-awareness, complexity and definition of the indexing function, as well as redundancy attitude. All but the last five methods are crafted for structured data. They are schema-aware, with most of them involving composite, hash-based indexing functions. Their majority also results into overlap-positive blocks and entails non-learning indexing functions, i.e., it requires expert knowledge for their definition.

Performance-wise, there is no clear winner among them. They are all quite efficient, requiring few iterations over the input entity descriptions, while thorough experimental studies have verified that their effectiveness depends largely on their parameter configuration [30,134]. In many cases, though, they score an insufficient recall (even <50%), especially when using Standard Blocking, Sorted Neighborhood and their variants as atomic methods, i.e, in combination with a single indexing function [30,134]. Instead, they should be used in a multi-pass manner with several indexing functions.

It is also worth stressing that the non-learning schema-aware methods are *compatible* with the schema-agnostic functionality. They can be easily adapted to it by treating every distinct attribute value token as a primary blocking key, to which they apply their transformation (e.g., sorting, suffix or q-grams extraction) [134]. This adaptation enables traditional schema-aware methods

Table 2: A taxonomy of the blocking methods discussed in Sections 3.2 and 3.3 (in the order of presentation).

	Schema-awareness		Indexing Function Complexity		Indexing Function Definition				Redundancy attitude		
						learning-based				overlapping	
	schema-based	schema-agnostic	atomic	composite	non-learning	supervised	unsupervised	hybrid	partitioning	overlap-positive	overlap-neutral
Standard Blocking [65]	✓		✓		hash-based				✓		
Sorted Neighborhood [84]	✓		✓		sort-based						✓
Adaptive Sorted Neighborhood [193]	✓		✓		sort-based						✓
Sorted Blocks [49]	✓		✓		sort-based						✓
Q-Grams Blocking [76]	✓			✓	hash-based					✓	
Suffix Arrays Blocking [1]	✓			✓	hash-based					✓	
String-Map [91]	✓			✓	hash-based					✓	
MFIBlocks [99]	✓			✓	hash-based				✓		
Blocking Scheme Learner [124]	✓			✓		✓				✓	
ApproxRBSetCover [18]	✓			✓		✓				✓	
ApproxDNF [18]	✓			✓		✓				✓	
C-Block [163]	✓			✓		✓				✓	
FisherDisjunctive [95]	✓			✓			✓			✓	
Link-Specific Blocking [96]	✓			✓			✓			✓	
Extended k-DNF Blocking [97]	✓			✓			✓			✓	
MatchCatcher [114]	✓			✓				✓		✓	
Token Blocking [137]		✓		✓	hash-based					✓	
Attribute Clustering Blocking [140]		✓		✓	hash-based					✓	
Prefix-Infix(-Suffix) Blocking [139]		✓		✓	hash-based					✓	
TYPiMatch [118]		✓		✓	hash-based					✓	
DeepER [50]		✓		✓	hash-based					✓	

to consistently score very high recall ($\gg$80%), while simplifying their configuration to the extent of waiving the requirement for domain knowledge [134]. Most importantly, this adaptation enables them to address not only the Volume of Big Data, but also its Variety. The resulting precision, though, is extremely low [134].

The same applies to the schema-agnostic blocking methods, i.e., the last five ones in Table 2. All of them fall into the same category across all five criteria. They all address schema heterogeneity (i.e., Variety) through composite, schema-agnostic indexing functions that are defined in a non-learning way, independently of domain and expert knowledge. Despite their hash-based functionality, they also tackle Veracity via their overlap-positive blocks, placing every entity into multiple blocks.

Among these five methods, Token Blocking relies on the simplest assumption in order to maximize recall: it merely requires that duplicate entities share at least one common token in their values. Extensive experiments have demonstrated that this assumption holds for KBs in the *center of the LOD cloud* [32,55]. Yet, this coarse-grained approach typically leads to very low precision, since most of the pairs sharing a common word are non-matches. TYPiMatch attempts to raise precision, by categorizing the given entities into overlapping types, but its recall typically drops to a large extent, due to the noisy, schema-agnostic detection of entity types [147].

More effective are the improvements introduced by Attribute Clustering Blocking and Prefix-Infix(-Suffix) Blocking. The former, which is more general and effective, increases precision by further requiring that the common tokens of matching entities appear in semantically similar (not identical) attributes. The latter applies only to RDF data, disregarding most tokens from the URIs of attribute values, considering only their most distinguishing part, i.e., their infix. However, extensive experiments have shown that even these advanced schema-agnostic blocking methods perform poorly when applied to KBs from the *periphery of the LOD cloud* [55,32]. The reason is that they exclusively consider the noisy content of descriptions, disregarding the valuable evidence that is provided by contextual information, such as the neighboring descriptions, i.e., entities of different types connected via important relations. More experiments are needed in order to examine whether this issue can be addressed by the semantics that lie at the core of the latest schema-agnostic method, namely LSH with Distributed Representations.

Conceptually comparing schema-aware with schema-agnostic blocking, we can deduce that they follow a different philosophy. The former aims to maximize recall

and precision at once, in a single procedure, whereas the latter involves two steps [142]: the creation of blocks (Section 3.3), which maximizes recall, and Block Processing (Section 4), which is indispensable for raising the originally low precision by orders of magnitude. This two-step approach has two advantages: it applies to data of any structuredness, from relational data to free-text entities, and it simplifies parameter configuration, involving neither complex combinations of (parts of) attribute values nor labelled instances.

4 Block Processing

The core characteristic of *overlap-positive* blocking methods is that the resulting blocks achieve very high recall at the cost of a large number of *repeated comparisons*, which appear in multiple blocks, as well as *unnecessary comparisons*, which involve non-matching entities. The goal of Block Processing is to discard both types of comparisons in order to enhance the precision of overlap-positive blocks at a limited cost in recall.

We elaborate on the main Block Processing techniques in Section 4.1 and delve into the parallelization of the computationally-intensive ones in Section 4.2.

4.1 Serial Methods

Depending on the granularity of their functionality, we can distinguish the block processing techniques into:

1. The *block-centric methods*, which rely on the coarse-grained characteristics of blocks. Such techniques are efficient, but lack in accuracy, as their crude processing cannot control its impact on recall (in terms of matching comparisons).
2. The *entity-centric methods*, which involve a more fine-grained operation that considers individual entities, assessing the importance of each block independently for each entity it contains.
3. The *comparison-centric methods*, which operate at the level of entity pairs in order to decide whether they should be compared or not (in case of repeated or unnecessary comparisons). Their fine-grained processing is more accurate than the other categories, at the price of a higher computational cost.

Block-centric Methods. *Block Purging* a-priori discards blocks with a size [137] or cardinality [140] higher than a limit. *Block Pruning* [137] orders blocks from the smallest to the largest one, terminating their processing as soon as the cost of identifying new matches exceeds a threshold. Both methods are equivalent to discarding stop-words, i.e., very frequent words that convey little information about an entity, such as "the" or "to". Such words add significant computational cost, without contributing useful evidence to entity similarity.

A similar approach is the dynamic blocking algorithm in [121], which splits large blocks into sub-blocks, "until they are all of tractable size". The same idea lies at the core of *Size-based Block Clustering* [67], a hierarchical clustering approach that transforms a set of blocks into a new one where all block sizes lie within a specified size range. In essence, it merges recursively small blocks that correspond to similar blocking keys, while splitting large blocks into smaller ones. At its core, lies a penalty function that controls the trade-off between block quality and block size.

Entity-centric Methods. For the moment, this category includes only *Block Filtering* [146], which removes every entity from the least important of its blocks. The main assumption is that the larger a block is, the less important it is for its entities. Thus, it orders the input blocks in ascending order of cardinality and retains every entity e_i in the N_i smallest blocks. For every entity e_i, this threshold is *locally* defined as $N_i = \lfloor r \times |B_i| \rfloor$, where $r \in [0, 1]$ is the ratio of Block Filtering. Setting $r = 0.8$ was experimentally verified to significantly raise efficiency, pruning at least 50% of the overall comparisons, while having a negligible impact on recall [146].

Comparison-centric Methods. The earliest method of this type is *Iterative Blocking* [190]. Its functionality depends on the outcomes of the Entity Matching method: whenever a new pair of duplicates is detected, their descriptions are merged and replaced by the unified description in all blocks that contain them. This way, all repeated comparisons of the matched entities are discarded. The already examined blocks that contain either of the matched entities are re-processed in an effort to exploit the new information in the merged description for identifying more duplicates.

Another iterative approach depending on the matching results is *HARRA* [101], which relies on an LSH-based procedure to dynamically hash similar entities into the same buckets (i.e., blocks). Inside every bucket, all pairwise comparisons are executed and pairs of matching entities are merged into new descriptions. The new descriptions are hashed into the existing hash tables so as to optimize memory usage. This procedure runs until convergence (i.e., no entities are merged) or until another, stricter stopping criterion is satisfied (e.g., the portion of merged descriptions drops below a predetermined threshold). In every iteration, special care is taken to avoid repeated and unnecessary comparisons.

All other methods of this granularity are independent of Entity Matching. The simplest one is *Compari-*

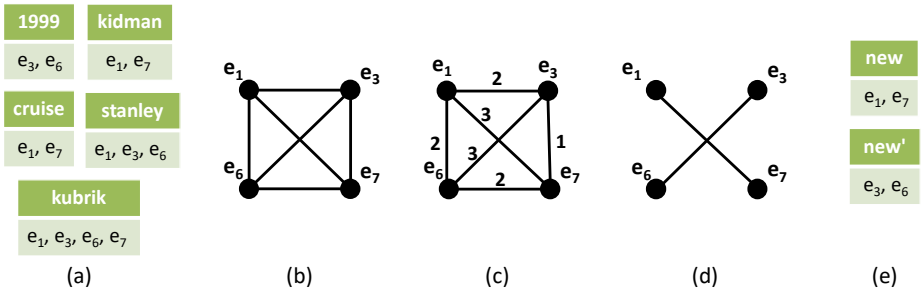

Fig. 9: Applying Meta-blocking: (a) the input set of overlap-positive blocks, (b) the corresponding blocking graph, (c) weighting the edges with CBS, (d) pruning the edges with WEP, and (e) the resulting new set of blocks.

son Propagation [138], which discards all repeated comparisons from any set of blocks without any impact on recall. After comparing two descriptions in a block, this comparison is not performed again in any other block this pair appears.

More advanced techniques belong to the family of *Meta-blocking* methods [141]; they discard all repeated comparisons from any block collection, but go beyond Comparison Propagation, as they also target the majority of unnecessary comparisons. Their functionality consists of two logical steps.

1. The original set of blocks B is transformed into the *blocking graph* G_B, where the nodes correspond to the entities of B, and the edges connect the co-occurring ones. There is at most one edge for every pairwise comparison, regardless of its frequency, thus eliminating all repeated comparisons.
2. Every edge is associated with a weight that is proportional to the likelihood that the adjacent entities are matching. This weight quantifies the evidence that is given by the degree of overlap between the block lists associated with the two entities. Low-weighted edges are less likely to correspond to a match, so they are pruned. The pruned blocking graph G'_B is transformed into a new set of blocks B' by creating a new block for every retained edge.

Various schemes have been proposed for edge weighting [141, 165]. They exclusively consider schema-agnostic information from a block collection, such as the number of common blocks, their size etc. Based on edge weighting, the *pruning scheme* of Meta-blocking decides which edges (i.e., comparisons) will be retained. The main pruning schemes are: (i) *Weighted Edge Pruning* (*WEP*), which retains all edges with a weight higher than the overall mean one. (ii) *Cardinality Edge Pruning* (*CEP*), which retains the top-K edges of the entire blocking graph. (iii) *Weighted Node Pruning* (*WNP*), which retains inside every node neighborhood the edges exceeding the average edge weight in the entire node neighborhood. (iv) *Cardinality Node Pruning* (*CNP*), which retains the top-k edges in each node neighborhood.

Several variations of these algorithms have been proposed in the literature. [198] alters CEP such that it retains the top-weighted edges whose cumulative weight is higher than a specific portion of the total sum of edge weights. *Reciprocal WNP* and *CNP* [146] retain an edge in the blocking graph if it satisfies the pruning criteria in both adjacent nodes' neighborhoods. *BLAST* [165] combines the node-centric pruning algorithm with a weight threshold per edge, which depends on the maximum weights in the adjacent nodes' neighborhoods.

Example 4 The functionality of Meta-blocking is illustrated in Figure 9. The input set of blocks in Figure 9(a) comprises the subset of Token Blocking blocks in Figure 6 that contain the entities e_1, e_3, e_6 and e_7 (note that Meta-blocking applies to the blocks produced by any overlap-positive blocking method, regardless of the type of input data, i.e., structured or semi-structured [146, 147, 165]). Figure 9(b) depicts the respective blocking graph, which contains one node for each input entity and one edge for each pair of co-occurring entities. Note that there are 6 edges, whereas the input blocks involve 12 pair-wise comparisons: the simple blocking graph discards all repeated comparisons, without using edge weights. Weights are added in Figure 9(c) to detect unnecessary comparisons. The weighting scheme annotates every edge with the number of blocks shared by its adjacent entities/nodes. In Figure 9(d), the unnecessary comparisons are discarded using the WEP pruning algorithm: every edge with a weight lower than the average one ($\sim$2.16) is removed. A new block is then created for each retained edge, as shown in Figure 9(e).

Note that *Canopy Clustering* [120] can be considered as a Meta-blocking method, too, even though it was originally proposed for clustering. In short, it works as follows: initially, it places all entities in a pool. In each iteration, an entity is randomly removed from the pool to create a new block. A cheap similarity measure

detects the entities that are most similar to it. Those exceeding a threshold t_{ex} are removed from the pool and placed into the new block. The entities that exceed another threshold t_{in} ($< t_{ex}$) are also placed in the new block, without being removed from the pool.

Canopy Clustering was adapted to blocking in [30], where the keys of Q-grams Blocking were used for deriving a cheap similarity measure. However, there is no restriction for applying it exclusively on top of Q-grams Blocking. We could generalize its cheap similarity to exploit the blocking keys of any overlap-positive blocking method. This approach turns Canopy Clustering into a Meta-blocking technique and as such, it is already implemented in the JedAI Toolkit [148].

Similarly, *Extended Canopy Clustering* [30] can be considered as a Meta-blocking technique, too. It improves Canopy Clustering by ameliorating its sensitivity to its weight thresholds, i.e., the fact that high values for t_{in} and, thus, t_{ex} may leave many entities out of blocks. Instead, Extended Canopy Clustering uses cardinality thresholds: for each randomly selected entity, the n_1 nearest entities are placed in its block, while the $n_2 (\leq n_1)$ nearest entities are removed from the pool.

In all cases, the main restriction of Meta-blocking is that its blocking graph supports a single type of blocks. Yet, composite blocking schemes may also be constructed on different types of blocks, as explained above. To accommodate them, Meta-blocking has been extended with a *Disjunctive Blocking Graph* [54], which has the same set of vertices as the simple blocking graph, but its edges express composite co-occurrence conditions, extending their weights accordingly. Thus, there is an edge $< e_i, e_j >$ for every pair of entities such that $\mathcal{F}(e_i, e_j)$="`true`", where $\mathcal{F}$ is a disjunction of the atomic co-occurrence functions o^k defined along with H. $\lambda : E \rightarrow R^n$ is a labeling function assigning a tuple $[w^1, \ldots, w^n]$ to each edge $\in E$, where w^k is a weight associated with each co-occurrence function $o^k \in H$.

Finally, it is worth noting that we can consider as comparison-centric methods the filtering techniques that are used for accelerating string and set similarity joins (e.g., Prefix, Position and Suffix Filtering [90]). Given a similarity measure in conjunction with a similarity threshold (e.g., Jaccard similarity > 0.8), they filter out those pairs of descriptions that are highly unlikely to satisfy it without performing the actual comparison. In reality, though, these filtering techniques are orthogonal to block processing, as they do not aim to restructure a set of blocks so as to improve its precision without any significant impact on recall. Instead, they are integrated with entity matching, aiming to accelerate the computations that are associated with specific attributes, similarity measures and similarity thresholds. For more details, the interested reader can refer to surveys [195] and experimental analyses of serial [90,66] and parallel implementations [119].

Learning-based Methods. A similar idea lies at the core of *Supervised Meta-blocking* [145], which formalizes WEP, CNP and CEP as binary classification tasks. Supervised Meta-blocking associates every edge with a vector that comprises a set of representative features. Every feature vector is then given as input to a classifier, which labels it as "`likely match`" or "`unlikely match`"; edges with the latter label are discarded from the blocking graph. In this way, the simple, non-learning pruning rules of the form "*if weight < threshold then discard edge*" are replaced by composite pruning models that have been learned from labelled data. To minimize the computational cost, a minimum set of features with high performance was experimentally identified in [145]. To minimize the labelling effort, *BLOSS* [17] introduces an active sampling method that carefully selects a very small set of instances. Labelling them suffices for learning highly accurate pruning schemes.

4.1.1 Discussion

Table 3 presents an overview of the block processing methods discussed above. The resulting taxonomy consists of three criteria: granularity of functionality, *matching awareness* (i.e., whether it depends on the outcomes of Entity Matching method or not) and *pruning definition* (i.e., whether the search space is reduced through a learning process that involves labelled instances or not). Note that schema awareness is not a criterion, because all methods operate in a schema-agnostic fashion that considers exclusively features from the input blocks. In this way, all block processing methods target both the Volume and Variety of Big Data.

We observe that most methods involve a comparison-centric functionality that applies only to overlap-positive blocks. However, these methods are incompatible with each other: at most one of them can be applied to a given set of blocks, since the restructured blocks they produce are not overlapping, i.e., they are deprived of any valuable evidence for further comparison pruning. Thus, BLAST [165] or Disjunctive Blocking Graph [54] should be preferred, as they achieve the top performance among comparison-centric methods. A comparative analysis is required, though, for evaluating the relative performance of these two methods. In any case, there is plenty of room for improving the accuracy of comparison-centric methods, as their precision remains rather low [54,147,165].

The remaining block- and entity-centric methods are complementary with each other, as they target dif-

Table 3: A taxonomy of the block processing techniques discussed in Section 4.1 (in the order of presentation).

	Granularity of Functionality			Matching awareness		Pruning Definition	
	block-centric	comparison-centric	entity-centric	matching-aware	matching-agnostic	non-learning	learning-based
Block Purging [137,140]	✓				✓	✓	
Block Pruning [137]	✓			✓		✓	
Size-based Block Clustering [67]	✓				✓	✓	
Block Filtering [146]			✓		✓	✓	
Iterative Blocking [190]		✓		✓		✓	
HARRA [101]		✓		✓		✓	
Comparison Propagation [138]		✓			✓	✓	
Weighted Edge Pruning [141]		✓			✓	✓	
Cardinality Edge Pruning [141]		✓			✓	✓	
(Reciprocal) Weighted Node Pruning [141,146]		✓			✓	✓	
(Reciprocal) Cardinality Node Pruning [141, 146]		✓			✓	✓	
BLAST [165]		✓			✓	✓	
Disjunctive Blocking Graph [54]		✓			✓	✓	
(Extended) Canopy Clustering [30,120]		✓			✓	✓	
Supervised Meta-blocking [145]		✓			✓		✓

ferent aspects of a set of blocks. Hence, it makes no sense to seek the top performer among them. Instead, every end-to-end ER workflow should involve as many of these methods as possible - they are indispensable for reducing the search space of the selected comparison-centric approach to a significant extent [147].

Regarding matching awareness, only three methods depend on matching: Block Pruning, Iterative Blocking and HARRA. They assume a perfect matcher (oracle), but exploit it in completely different ways. The first one employs the rate of detected duplicates as a signal for prematurely terminating the entire procedure, whereas the other two methods use the matched entities as a means of detecting more matches. A more realistic scenario should involve a noisy matcher, investigating the effect of its errors on the overall performance.

4.2 Parallel Methods

Due to their low computational cost, little effort has been devoted on parallelizing block-centric methods for block processing. The only exception is the sub-block algorithm in [121], which is inherently parallelized on top of the MapReduce framework.

Block Filtering has also been adapted to the MapReduce framework in [51]. The adaptation requires a single job, where the Map function iterates over the input blocks to emit `key-value` pairs of the form `key`="entity id", `value`="block_id.block_cardinality". The Reduce function receives all block ids per entity, sorts them in ascending cardinality and retains the first r%.

Due to its higher computational cost, more effort has been devoted to parallelizing Meta-blocking on top of MapReduce. Three alternative strategies have been proposed in [52]:

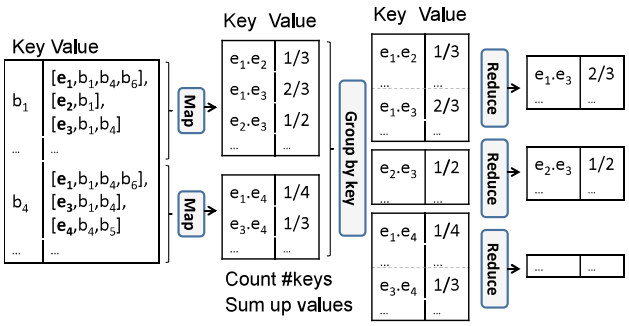

Fig. 10: An example of the comparison-based strategy for WEP, using Jaccard Similarity for edge weighting.

(i) The *edge-based strategy explicitly* builds the blocking graph, storing all the edges along with their weights on the disk. This bears a significant I/O cost that becomes the bottleneck for very large blocking graphs.

(ii) The *comparison-based strategy* offers a more efficient implementation that builds the blocking graph *implicitly*. A pre-processing job enriches every block with the list of block ids associated with every one of its entities. Thus, every edge weight is computed *locally* by the Map function of the next job. This function identifies and ignores all repeated comparisons, reducing significantly the number of edges that are stored on the disk. The pruning of the unnecessary comparisons takes place in the Reduce function of the same job. This is the most efficient strategy for the edge-centric pruning schemes, namely WEP and CEP, as it minimizes the required number of MapReduce jobs.

Example 5 Figure 10 illustrates the comparison-based strategy for parallelizing WEP. Each mapper receives as input a block, where every entity is associated with the list of blocks that contain it. For every non-repeated

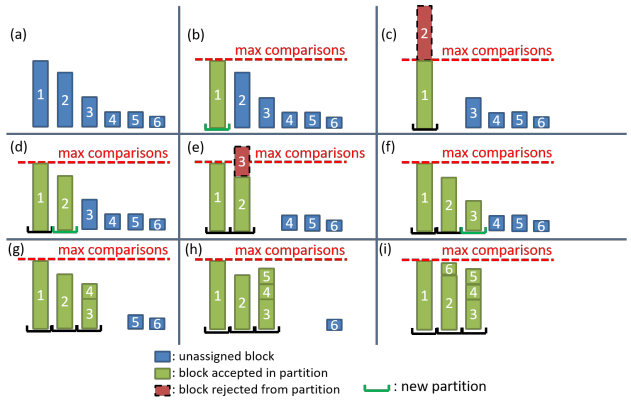

Fig. 11: An example of the MaxBlock algorithm for load balancing. Each block is marked with a different id, while its height is proportional to its cardinality.

comparison in each block, the mapper outputs the id of the comparison as key and the corresponding weight as value. For block b_1 we have $e1.e2$, $e1.e3$ and $e2.e3$, while for b_4 we have only $e1.e4$, $e3.e4$; $e1.e3$ is repeated in b_4. Jaccard Similarity is used as the weighting scheme. Hence, the e_1-e_2 weight is 1/3, since the entities e_1 and e_2 share only one block (b_1) from all three distinct blocks they belong to. Two counters estimate the average edge weight during the Map phase. Assuming that this mean is 1/3, the reducers emit only the pairs with a weight above 1/3; e.g., the comparisons e_1-e_2, e_1-e_4 and e_3-e_4 are pruned.

(iii) The *entity-based strategy* is independent of the blocking graph. It aggregates for every entity the bag of all entities that co-occur with it in at least one block. Then, it estimates the edge weight that corresponds to each neighbor based on its frequency in the co-occurrence bag. This is the most efficient strategy for the node-centric pruning schemes (i.e., WNP, CNP and their variations), since both edge weighting and edge pruning are carried out within the Reduce function of a single job, minimizing the I/O overhead.

To avoid the underutilization of the available resources, a specialized algorithm for Load Balancing, *MaxBlock*, was introduced in [52]. Its functionality is illustrated in Figure 11. It exploits the highly skewed distribution of block sizes in overlap-positive collections in order to split them in partitions of equivalent computational cost (i.e., total number of comparisons). This computational cost is determined by the comparisons of the largest input block. MaxBlock fits easily to the limited memory that is available in each node, due to its *optimized representation model*: every entity is represented by an integer that denotes its id, while every block consists of a list of integers and is itself identified by a unique integer id. The same representation is used by all parallelization strategies described above.

Another approach to parallelizing Meta-blocking is the *multi-core execution* [135], which makes the most of the available processors in a stand-alone system. The key idea is to split the overall computational cost into a set of chunks that are placed in an array, with an index indicating the next chunk to be processed. Following the established fork-join model, every thread retrieves the current value of the index and is assigned to process corresponding chunk.

5 Matching

At the core of ER lies the *matching* decision: for a given pair of descriptions, decide if they refer to the same real-world entity (i.e., if they match). Having made this decision, ER then splits the descriptions in the input entity collection[9].

5.1 Preliminaries

The matching decision is typically made by a match function M, mapping each pair of entity descriptions (e_i, e_j) to $\{true, false\}$, with $M(e_i, e_j) = true$ meaning that e_i and e_j are matches, and $M(e_i, e_j) = false$ meaning that e_i and e_j are not matches.

In its simplest form, the match function is defined via a similarity function sim, measuring how similar two entities are to each other, according to certain comparison attributes. The employed similarity function can consist of a single similarity measure, like Jaccard similarity, or a complex similarity function, e.g., a linear combination of several similarity functions on different attributes of a description. To specify an equivalence relation among entity descriptions, we need to consider a similarity measure satisfying the non-negativity, identity, symmetry and triangle inequality properties [196], i.e., a similarity *metric*. Given a similarity threshold θ, a simple matching function can be defined as:

$$M(e_i, e_j) = \begin{cases} \text{true, if } sim(e_i, e_j) \geq \theta, \\ \text{false, otherwise.} \end{cases}$$

In more complex ER pipelines, such as when matching rules are manually provided, or learned based on training data, the matching function can be defined as a complex function on several matching conditions (e.g., two person descriptions match if their SSN is identical,

[9] We refer to a set of descriptions as entity collection, regardless of the number of input data sources.

or if their date of birth, zip code and last names are identical, or if their e-mail addresses are identical).

As it becomes clear, finding a similarity metric which can perfectly distinguish all matches from non-matches using simple pairwise comparisons on the attribute values of two descriptions is practically impossible. In particular, similarity metrics are too restrictive to identify nearly similar matches. Thus, in reality, we seek for similarity functions that will be only good enough, i.e., minimize the number of misclassified pairs and rely on collective ER approaches to propagate the similarity of the entity neighbors of two descriptions to the similarity of those descriptions. In this inherently iterative process, the employed match function is based on a similarity that dynamically changes from iteration to iteration, and its results may include a third state, the *uncertain* one. Specifically, given two similarity thresholds θ and θ', with $\theta' \leq \theta$, the match function at iteration n is given by:

$$M^n(e_i, e_j) = \begin{cases} \text{true, if } sim^{n-1}(e_i, e_j) \geq \theta, \\ \text{false, if } sim^{n-1}(e_i, e_j) \leq \theta', \\ \text{uncertain, otherwise.} \end{cases}$$

Based on the characteristics of the entity collections (e.g., structuredness, domain, size), the nature of comparisons (pairwise or collective), the processing mode (offline/batch or incremental/online) as well as the availability of known, pre-labeled matching pairs, different methodologies can be followed to identify an appropriate similarity function and thus, a fitting match function. In what follows, we explore alternative methodologies for the matching task and discuss the cases in which those methodologies are more suited.

5.2 Collective methods

To minimize the number of missed matches, commonly corresponding to nearly similar matches, a collective ER process can jointly discover matches, based on the idea that identifying some matches can help in discovering new candidate description pairs for resolution, even if this inherently iterative process entails additional processing cost. We distinguish between merging-based and relationship-based collective ER approaches. In the former, new matches can be identified by exploiting the merging of the previously located matches, while in the latter, iterations rely on the similarity evidence provided by descriptions being structurally related in the original entity graph.

Example 6 Consider the descriptions in Figure 12 (a), stemming from the knowledge base *KB1*. They all refer to the person Stanley Kubrick. Initially, it is difficult to match *KB1:SKBRK* with any of the other descriptions, since many people named Kubrick may have been born in Manhattan, or died in the UK, respectively. However, it is quite safe to match the first two descriptions (*KB1:Stanley_Kubrick* and *KB1:Kubrick*). By merging the first two descriptions, e.g., using the union of their attribute-value pairs, it now becomes easier to identify that the last description (*KB1:SKBRK*) is also referring to the same person, based on the name, and places of birth and death.

Consider now the descriptions in Figure 12 (b), stemming from the knowledge bases *KB1* and *KB2*. The descriptions on the left (*KB1:SKBRK* and *KB2:SKubrick*) represent Stanley Kubrick, while the descriptions on the right (*KB1:Manhattan* and *KB2:MNHT*) represent Manhattan, where Kubrick was born. Initially, it is difficult to identify the match between the descriptions on the left, based only on the common year of death and last name. However, it is quite straightforward to identify the match between the descriptions of Manhattan, on the right. Having identified this match, a relationship-based collective ER algorithm would reconsider matching *KB1:SKBRK* to *KB2:SKubrick*, since these descriptions are additionally related, with the same kind of relationship (birth place), to the descriptions of Manhattan that were previously matched. Therefore, a relationship-based collective ER algorithm would identify this new match in a second iteration.

The structuredness of the input entity collection to be resolved is also a key factor for the nature of collective approaches. Merging-based methods are typically schema-aware, since structured data make the process of merging easier. On the other hand, collective methods dealing with semi-structured data are typically relationship-based, since merging would require not only deciding on which values are correct for a given attribute, but also, which values are available for similar attributes and can be used to merge two descriptions.

5.2.1 Schema-aware methods

In *merging-based collective ER*, the matching decision between two descriptions triggers a merge operation, which transforms the initial collection by adding the new, merged description and potentially removing the two initial descriptions. This change also triggers more updates in the matching decisions, since the new, merged description needs to be compared to the other descriptions of the collection. Intuitively, the final result of merging-based collective ER is a new set of descriptions which are the results of merging all the matches found in the initial collection. In other words, each real-world

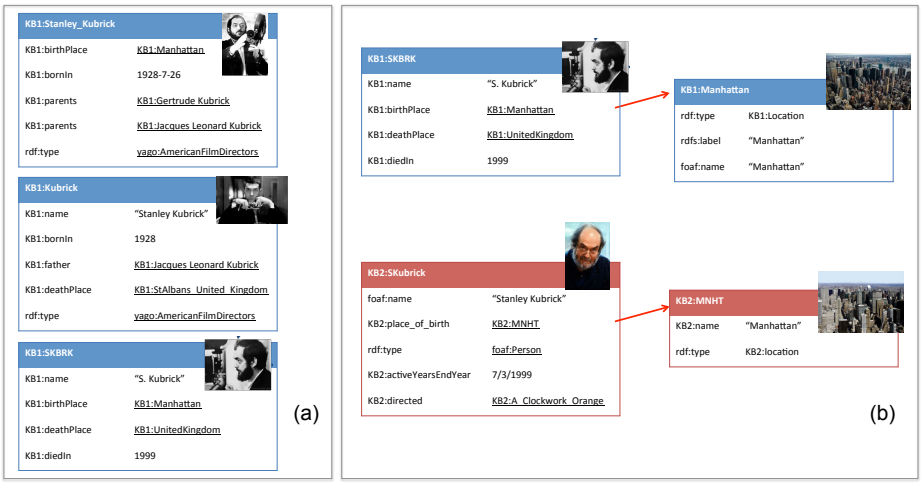

Fig. 12: A merging-based collective ER example (a) and a relationship-based collective ER example (b).

entity described in the input entity collection is represented by a single description in the resolution results and each description in the resolution results represents a distinct real-world entity from the input collection.

Considering the functions of matching M and merging μ as black boxes, *Swoosh* [13] is a family of merging-based collective ER strategies that minimize the number of invocations to these potentially expensive black boxes. Merged entity descriptions are considered as new entity descriptions, being again candidate matches to other descriptions in the collection. In the same line of work, *D-Swoosh* [12] introduces a family of algorithms that distribute the workload of merging-based ER across multiple processors. Since both works consider matching and merging as black boxes, [13] introduces a set of desirable properties that, when satisfied by those functions, lead to higher efficiency. These properties, called $ICAR$ properties for short, are:

- *Idempotence:* $\forall e_i, M(e_i, e_i) = true$ and $\mu(e_i, e_i){=}e_i$.
- *Commutativity:* $\forall e_i, e_j, M(e_i, e_j){=}true \Leftrightarrow M(e_j, e_i){=} true$ and $\mu(e_i, e_j) = \mu(e_j, e_i)$.
- *Associativity:* $\forall e_i, e_j, e_k$, if both $\mu(e_i, \mu(e_j, e_k))$ and $\mu(\mu(e_i, e_j), e_k)$ exist, $\mu(e_i, \mu(e_j, e_k)){=}\mu(\mu(e_i, e_j), e_k)$.
- *Representativity:* If $e_k = \mu(e_i, e_j)$, then for any e_l such that $M(e_i, e_l) = true$, $M(e_k, e_l) = true$.

Regarding the match function, idempotence and commutativity have been already discussed in Section 5.1, as reflexivity and symmetry, respectively, while representativity extends transitivity, by also including the merge function. As a note, consider that if associativity does not hold, it becomes harder to interpret a merged description, since this description depends on the order in which the source descriptions were merged.

One of the algorithms in the Swoosh family exploiting the $ICAR$ properties is *R-Swoosh* [13], which operates as follows. A set $\mathcal{E}$ of entity descriptions is initialized to contain all the input descriptions. Then, at each iteration, a description e is removed from $\mathcal{E}$ and compared to each description e' of the, initially empty, set $\mathcal{E}'$. If e and e' are found to match, then they are removed from $\mathcal{E}$ and $\mathcal{E}'$, respectively, and the result of their merging is placed into $\mathcal{E}$ (exploiting representativity). If there is no description e' matching with e, then e is placed in $\mathcal{E}'$. This process continues until $\mathcal{E}$ becomes empty, i.e., there are no more matches to be found.

In *relationship-based collective ER*, the matching decision between two descriptions triggers discovering new candidate pairs for resolution, or re-considering pairs already compared; matched descriptions may be related to other descriptions, which are now more likely to match to each other.

To illustrate the relationships between the descriptions of an entity collection $\mathcal{E}$, usually, an entity graph $G_{\mathcal{E}} = (V, E)$ is used, in which nodes, $V \subseteq \mathcal{E}$, represent entity descriptions and edges, E, reflect the relationships between the nodes. For example, such a match function could be of the form:

$$M(e_i, e_j) = \begin{cases} true, & \text{if } sim(nbr(e_i), nbr(e_j)) \geq \theta \\ false, & \text{else,} \end{cases}$$

where sim can be a relational similarity function and θ is a threshold value. Intuitively, the neighborhood $nbr(e)$ of a node e can be the set of nodes that contains e and all the nodes connected to e, i.e., $nbr(e) = \{e_j | (e, e_j) \in E\}$, or the set of edges containing e, i.e., $nbr(e) = \{(e, e_j) | (e, e_j) \in E\}$. The first work to coin the term collective ER [15] employs an entity graph, following the intuition that two nodes, i.e., descriptions, are more likely to match, if their edges, reflecting a relationship between the descriptions, connect to nodes corresponding to the same entity. To capture this iterative

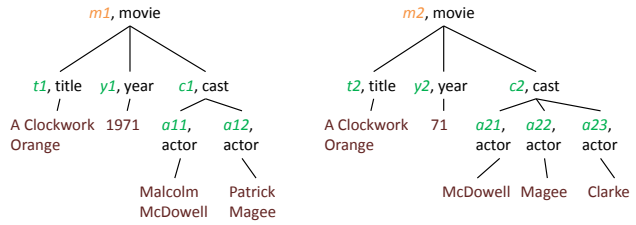

Fig. 13: Two different descriptions of the movie *A Clockwork Orange* and its cast in XML.

intuition, hierarchical agglomerative clustering is performed, where, at each iteration, the two most similar clusters are merged, until the similarity of the most similar clusters is below a threshold. When two clusters are merged, the similarities of their related clusters, i.e., the clusters corresponding to descriptions related to the descriptions in the merged cluster, are updated. To avoid the comparison between all the pairs of descriptions when considering the first merge of clusters, a blocking method (i.e., Canopy Clustering [120]) is used.

Dong et al. [45] present a hybrid approach, based on both partial merging results between descriptions and relations between descriptions, exploiting a graph-based model for collective ER. In this case, a dependency graph is constructed, in which a node represents the similarity between a pair of entity descriptions and an edge represents the dependency between the matching decisions of two nodes. Hence, if the similarity of a pair of descriptions changes, then we know that the neighbors of this pair might need a similarity recomputation. The dependencies between the matching decisions are distinguished between Boolean and real-valued. Boolean dependencies reflect the case in which the similarity of a node only depends on whether the descriptions of its neighbor node match or not, while in real-valued dependencies, the similarity of a node depends on the similarity of the descriptions of its neighbor node. Boolean dependencies are further divided into strong, implying that if a node corresponds to a match, then its neighbor pair should also be a match, and weak, implying that if a node corresponds to a match, then the similarity of its neighbor pair is increased. Initially, all nodes are added to a priority queue. On each iteration, a node is removed from the queue and if the similarity of the node is above a threshold, its descriptions are merged, aggregating their attribute values, to enable further matching decisions. In addition, if the similarity value of this node has increased, its neighbor nodes are added to the priority queue. This iterative process continues until the priority queue becomes empty.

5.2.2 Schema-agnostic methods

[185] studies the problem of collective ER in tree data, and in particular, in XML data. Entity descriptions correspond to XML elements composed by text data or other XML elements, and domain experts specify which XML elements are match candidates, thus, initializing a priority queue of comparisons. The notion of entity dependency here, is used in the following sense: an XML element c depends on another XML element c', if c' is a part of the description of c. Consequently, identifying the matches of c is not independent of identifying the matches of c'. Even if two XML elements are initially considered to be non-matches, they are compared again, if their related elements are found matches. [184] uses a similar approach that is based on the intuition that the similarity of two elements reflects the similarity of their data, as well as the similarity of their children. By following a top-down traversal of XML data, the DELPHI containment metric [6] is used to compare two elements.

Example 7 Figure 13 shows two different descriptions of the movie *A Clockwork Orange* in XML. This representation means that the element *movie* consists of the elements *title*, *year* and *cast*, while the latter further consists of *actor* elements. To identify that the two XML descriptions represent the same movie, we can start by examining the cast of the movies. After we identify that actors a_{11} and a_{21} represent the same person, Malcolm McDowell, the chances that the movies m_1 and m_2 match are increased. They are further increased when we find that actors a_{12} and a_{22} also match, representing Patrick Magee. The same matching process over all the sub-elements of m_1 and m_2 will finally lead us to identify that m_1 and m_2 match.

SiGMa [113] starts with seed matches having identical entity names. Then, it propagates the matching decisions on the compatible neighbors of existing matches. Unique Mapping Clustering is applied for detecting duplicate. For every new matched pair, the similarities of the neighbors are recomputed and their position in the priority queue is updated.

LINDA [20] follows a very similar approach, which differs from SiGMa mainly in the similarity functions used and the lack of a manual relation alignment. LINDA relies on the edit distance of the relations names used in the two KBs to determine if they are equivalent or not. This alignment method makes a strong assumption that descriptions in KBs use meaningful names for relations and similar names for equivalent relations, which is often not true in the Web of Data. Rather than using a similarity threshold, the resolution process in LINDA

terminates when the priority queue is empty, or after performing a predetermined number of iterations.

RiMOM-IM [115,164] initially considers as matches entities placed in blocks of size 2. It also uses a heuristic called "one-left object": if two matched descriptions e_1, e'_1 are connected via aligned relations r and r' and all their entity neighbors via r and r', except e_2 and e'_2, have been matched, then e_2, e'_2 are also considered matches. Similar to SiGMa, RiMOM-IM employs a complex similarity score, which requires the alignment of relations among the KBs.

On another line of research, *PARIS* [172] uses a probabilistic model to identify matching evidence, based on previous matches and the functional nature of entity relations. A relation is considered to be functional if, for a given source entity, there is only one destination entity (e.g., `wasBornIn`). The basic matching idea is that if $r(x, y)$ is a function in one KB and $r(x, y')$ is a function in another KB, then y and y' are considered to be matches. The *functionality*, i.e., degree by which a relation is close to being a function, and the alignment of relations along with previous matching decisions determine the decisions in subsequent iterations. The functionality of each relation is computed at the beginning of the algorithm and remains unchanged. Then, at the first iteration, instances with identical values (for all attributes) are considered matches and based on those matches, an alignment of relations takes place. At the next iteration, instances can be now compared based on the newly aligned relations, and this process continues until convergence. In the last step, an alignment of classes (i.e., entity types) also takes place.

To resolve highly heterogeneous Web entities, *MinoanER* [54,56,53] relies on schema-agnostic similarity metrics that consider the content and neighbors of the entities. For high efficiency, these similarities are extracted from a set of blocks and processed by a non-iterative process that involves four heuristics. First, it identifies matches based on their name (heuristic H1). This is a very effective method that can be applied to all descriptions, regardless of their values or neighbor similarity, by automatically specifying distinctive names of entities from data statistics. Then, the value similarity is exploited to find matches with many common and infrequent tokens, i.e., strongly similar matches (heuristic H2). When value similarity is not high, nearly similar matches are identified based on both value and neighbors similarity using a threshold-free rank aggregation function (heuristic H3). Finally, reciprocal evidence of matching is exploited as a verification of the returned results: only entities mutually ranked in the top matching candidate positions of their unified ranking lists are considered matches (heuristic H4).

5.3 Online methods

Apart from a batch, offline processing of entire entity collections, there have also been interesting approaches that try to resolve only parts of the entity collections that are of interest to a specific user of application online, in real time. We distinguish those approaches between those that try to answer to a user-provided query and those that resolve entities arriving in streams. Note however, that this distinction is not orthogonal, as streaming methods can be also seen as query-based that handle streams of queries instead of a single query (e.g.,[94]).

5.3.1 Query-based methods

One of the applications of ER is that it enables a more complete query answering over an integrated set of KBs. If a better query answering is the only purpose for getting into the trouble of resolving a set of datasets for a specific application, then the following works try to avoid the bulk offline processing of ER on all the entities described in the target datasets and process instead only as much as needed to provide answers to the specific queries in (near) real time. For example, when searching for the publications of Hector Garcia-Molina in DBLP, it is not practical to resolve all the entity descriptions in DBLP. Since the matching needs to be performed at query-time, the process needs to be quick, even if it is not entirely accurate. [16] was the first to introduce the problem of query-driven ER, leveraging existing work in collective ER [15], using a two-stage expand-and-resolve query processing strategy. First, it extracts the related descriptions for a query using two expansion operators, and then resolves the extracted descriptions collectively. Due to the complexity of the collective strategy involved, the approach did not manage to provide real-time answers for large datasets.

[86] introduces a query-driven ER method under data uncertainty. The attribute-level facts for the input entities are associated with a degree of uncertainty, reflecting the case in which those facts are gathered from imperfect extraction tools. Matches are identified using existing ER algorithms and they are also assigned a probability value. At this offline stage, no merging takes place. When a query arrives, the descriptions that need to be merged in order to provide an answer to the query are identified. Then, different possible merging scenarios are explored and the one with minimum uncertainty is selected and returned as an answer.

UDD [171] is an unsupervised, online ER method which can identify matches from the results of a query over of multiple Web KBs. First, it removes duplicate descriptions stemming from the same KB and then, it

generates a training set which assumes that the results from the same KB are not matches. Based on this set of non-matching examples, as well as a similarity computation between descriptions, it employs two cooperating classifiers, a weighted component similarity summing classifier and an SVM classifier, to iteratively identify matches in the query results.

[180] explores the use of sampling to improve the quality of aggregate numerical queries on large datasets that would be too expensive to resolve online. It performs ER on a small sample of the data and exploits those results to reduce the impact of duplicates on the provided approximate answers of aggregate queries.

QuERy [5] aims to answer join queries over multiple, overlapping data sources, operating on a block level. It identifies which blocks need to be resolved for the requested join and then assumes that any matching method can be applied for the matching step. Complementary to this work, *QDA* [4] tries to reduce the data cleaning overhead and issues the minimum number of necessary steps to answer SQL-like selection queries that do not involve joins, in an entity-pair level. It analyzes which entity pairs do not need to be resolved to identify all entities in a given block that satisfy the selection predicate. To do so, it creates an entity graph for the contents of a block and resolves edges belonging to cliques that may affect the query answer. To support a selection query, QDA performs vestigiality analysis on each block individually to reduce matching steps. This analysis aims to identify matching decisions whose answers are guaranteed to not affect the query answers and thus, need not be performed. As opposed to [180], QDA provides exact query results.

5.3.2 Streaming methods

In the streaming version of entity resolution, the goal is not to find all the matching descriptions between two entity collections, but the matches of descriptions arriving in a streaming fashion against a stored collection of entities, e.g., [94]. For example, consider an application resolving the entities described across news feeds. A journalist using this application could be provided with several facts regarding a breaking news story (e.g., persons, buildings, services affected by an earthquake), as they get published by different agencies or witnesses, enabling him/her to form a complete picture of the events as they occur, in real-time. This would require storing only some parts of the blocking collection, and discarding the rest, as more descriptions are fed to the system. To evaluate which parts of the collection are more useful to keep, we can design different strategies. For example, we may want to keep the latest entities, since new input entities are more likely to be connected to them, and thus, their resolution is more likely to be helped by those latest nodes. Another strategy would be to keep the entities with many relationships with other entities, since they are more likely to influence the matching decision of these entities, and new entities appearing are more likely to be connected to them.

[94] introduces summarization algorithms for speeding up online ER: SkipBloom summarizes the input descriptions, using their blocking keys, enabling fast comparisons between them. Then, BlockSketch summarizes a block to achieve a fixed number of comparisons for a given entity description, during the matching phase, which entails a bounded computational time. To achieve this optimization, BlockSketch splits each block into sub-blocks, reflecting the distances of the block contents from the blocking key. Then, each query description is compared against the sub-block whose contents exhibit the smallest distances from the query description. *SBlockSketch* extends BlockSketch, adapting its functionality to streaming data, using a constant amount of main memory to handle potentially unbounded streams of entity descriptions. It maintains a fixed number of blocks in memory with a time overhead each time any of those blocks need to be replaced with blocks that reside in secondary storage. To minimize this overhead, a selection algorithm is employed to effectively select the blocks to be replaced, considering their selectivity (i.e., how many of the input descriptions are routed to these blocks) and age.

[31] relies on phonetic-similarity-based inverted indices for blocking (more details in Section 3) and the main idea behind enabling a streaming fashion handling of queries is the pre-computation of similarities between attribute values (before the phonetic function is applied) that have been placed into the same block. Those similarities are stored in a similarity index. For each value stored in a block, the similarity index keeps a list of other attribute values in the same block and the similarity between them. In the query phase, there are two possible cases: if the attribute value of the query are available in an index and the similarity to other values have been pre-computed, those values and the descriptions corresponding to those values are retrieved. If the attribute value of the query does not exist in an index, the similarity of the values will have to be calculated.

5.4 Learning-based methods

The first probabilistic model for ER [65] used attribute similarities as the dimensions of comparison vectors, each representing the probability that a pair of descriptions match. Following the same conceptual model, a

large number of works try to automate the process of learning such probabilities based on manually or automatically generated, or even pre-existing training data. We are going to explore different ways of generating and exploiting training data, as well as methods that employ deep learning for ER.

Supervised Learning. [35] proposes an adaptive distance function, combining many attribute similarity functions, which is learned from training data to cluster together descriptions that match. Similarly, *MARLIN* [19] uses labeled data at two levels. First, it can utilize trainable string similarity/distance measures, such as learnable edit distance, adapting textual similarity computations to specific attributes. Second, it uses labeled data to train a classifier that distinguishes pairs between matches and non-matches, using textual similarity values for different attributes as features.

[156] proposes a gradient-based model that can adjust its structure and parameters based on aggregate similarity scores coming from individual similarity functions on different attributes, to efficiently identify matches. The design of this model can potentially allow to locate which similarity functions and attributes are more significant to correctly classify pairs. For training this model, it proposes a performance index that can help learn how to separate descriptions that have already been matched from those that have not yet been matched.

[87] adapts a relationship-based collective ER approach (similar to [45]) to a supervised learning setting. The employed algorithm computes matching probabilities by constructing and maintaining a Bayesian network, which capture cause-effect relationships modeled as directed acyclic graphs, with different matching evidences. In this model, lexical similarity in the values of the descriptions, as well as their links to existing matches constitute positive matching evidence, which incrementally update the employed Bayesian network nodes, similar to the incremental updates that take place in the graph-based dependency model of [45].

GenLink [89] is a supervised, genetic programming algorithm for learning expressive linkage rules from a set of existing labeled matches and non-matches. Linkage rules are defined as functions that assign similarity values to pairs of descriptions, i.e., what we refer to as similarity measures. GenLink generates linkage rules which select important attributes for comparison from the entities, normalizes their attribute values before similarity computations, chooses appropriate similarity measures and thresholds, and combines the results of multiple comparisons using linear, as well as non-linear aggregation functions. It has been incorporated into the Silk Link Discovery Framework [178], which identifies different types of links between RDF datasets.

Deep Learning. The latest developments in deep learning have greatly influenced research in ER, and specifically ER for structured data. The basic constructs of deep learning methods for ER are Recurrent Neural Networks (*RNNs*) [192,59] and word embeddings [11]. RNNs are neural networks with a dynamic temporal behavior. The neurons are fed information not only from the previous layer, but also from their own previous state in time, to process sequences of inputs. Word embeddings are vectorial representations of words, enabling words or phrases to be compared using their vectors. Word embeddings are commonly used with RNNs for speech recognition [123] and similar NLP tasks [27].

DeepER [50] explores two methods to generate entity embeddings, i.e., vectorial representations of entity descriptions, which can be used to identify matches. The first one exploits the word embeddings of the tokens appearing in the values of the descriptions, while the latter uses RNNs to convert each description to a vector. DeepER considers both the cases where pre-trained word embeddings are available [150], and where they are not, presenting ways to create and tune such embeddings, customized for ER. [125] extends the work of DeepER by introducing an architecture template for deep learning methods for ER, consisting of three main modules, for each of which a set of options are available. Those modules are (*i*) the attribute embedding module, which is responsible for converting the sequence of words used in the attribute values of an entity description to word embedding vectors, (*ii*) the attribute similarity representation module, which applies a similarity function on the attribute embeddings of two descriptions to obtain a final similarity value of those descriptions (i.e., this module learns the similarity function), and (*iii*) a classifier module, which uses the similarities between descriptions as features for a classifier that determines if a pair of description is a match (i.e., this module learns the match function). Four such combinations of options (e.g., character-level vs word-level embeddings, pre-trained vs learned embeddings, fixed vs learnable similarity function) are used as representative points for those modules and evaluated, showing the strengths and weaknesses of each.

Weakly Supervised Learning. Arguably, the biggest limitation of supervised approaches is the need for a pre-labeled dataset, based on which the employed machine learning algorithm will learn how to classify new instances, similar to the ones met in the training set. Before we cover unsupervised methods that manage to learn a good classifier without relying on any existing training data, it is worth mentioning some works that still rely on some pre-labeled data.

[173] proposes a *transfer learning* approach for training a machine learning classifier with limited or no available labeled data, i.e., adapting and reusing labeled data from a related dataset. The idea is to use a standardized feature space in which the entity embeddings of the reused and the targeted dataset will be transferred. This way, the existing labeled data from another dataset can be used to train a classifier that can work with the target dataset, even if there are no explicitly labeled data for the target dataset. A similar transfer learning approach is also followed in [158] to infer equivalence links in a linked data setting.

Finally, *Snorkel* [155] is a generic tool that can be used to generate training data for a broader range of problems than ER. It relies on user-provided heuristic rules (e.g., several matching functions) to label some user-provided data and evaluate this labeling using a small pre-labeled dataset. Instead of relying on weighting of attributes in the dataset, reflecting their importance, Snorkel tries to learn the importance of the provided matching functions. This approach of weighting matching rules, instead of features, resembles and complements existing works in ER. For example, [181] tries to identify which similarity measure can maximize a given objective function for an ER task, given a set of matching (i.e., positive) and non-matching (i.e., negative) examples. Those examples can be generated manually one-by-one, or leveraging tools like Snorkel.

Unsupervised Learning. [93] proposes an unsupervised approach to ER, in which an ensemble of automatic self-learning models is generated with different similarity measures. To enhance the automatic self-learning process, it incorporates attribute weighting into the automatic seed selection for each of the self-learning models. To ensure that there is high diversity among the selected self-learning models, it utilizes an unsupervised diversity measure and finally keeps the self-learning models with high contribution ratios, disregarding the ones with poor accuracy from the ensemble.

Rather than relying on domain expertise or manually labeled samples, the unsupervised ER system presented in [98] automatically generates its own heuristic training set. The training set is first used by the system for schema matching to align the properties in the input datasets. The property alignment and training sets are then used to simultaneously learn two functions, one for the blocking step and the other for the matching step. The most interesting step of this approach is the training set generator, which relies on heuristics. Those heuristics generate positive and negative examples for matching. The positive examples are generated from Jaccard similarity of the token sets in the values of the descriptions. Targeting clean-clean ER, having generated the positive example ($e1$, $e2$), where $e1$ belongs to one dataset and $e2$ to the other, for every other positive example ($e3$, $e4$), where $e3$ belongs to the same dataset as $e1$ and $e4$ to the same dataset as $e2$, we can further infer the negative examples ($e1$, $e4$) and ($e3$, $e2$).

For an overview of the latest advances in learning-based ER, we refer to [44].

5.5 Parallelization methods

[154] proposes a framework for scaling collective ER [15] to large datasets. This method assumes the existence of a black-box ER algorithm exploiting a set of rules, used as evidence for matching. To achieve scalability, it runs multiple instances of the ER algorithm in small subsets of the entity descriptions (similar to blocking). Since some rules may require the results of more than one blocks, a message-passing framework is proposed.

In particular, to create the subsets of the descriptions, it uses an extension of blocking, grouping descriptions based on not just their similarity, but also on their relational closeness. The initial blocks are constructed over the similarity of the descriptions using Canopy Clustering [120], and then, they are extended taking the *boundary* of each block with respect to entity relationships. The boundary of a block b is defined as the set of descriptions e', for which there is another description e in b, such that e and e' are related. After the construction of such extended blocks, a simple message-passing algorithm is run, to ensure that the match decisions within a block, which might influence the match decisions in other blocks, are propagated to those other blocks. This algorithm retains a list of active blocks, initially containing all blocks. A black-box ER algorithm is run locally, for each active block, and the newly-identified matches are added in the result set. All the blocks with a description of the newly-identified matches, are set as active. This iterative algorithm terminates when the list of active blocks becomes empty.

LINDA [20] scales out using MapReduce. The pairs of descriptions are sorted in descending order of similarity and stored in a priority queue. Each cluster node holds: (i) a partition of this priority queue, and (ii) the corresponding part of the entity graph, containing the descriptions in the local priority queue partition, along with their neighbors. The iteration step of the algorithm is that, by default, the first pair in the priority queue is considered to be a match and is then removed from the queue and added to the known matches. This knowledge triggers similarity re-computations, which affect the priority queue by enlarging it, when the neighbors of the new match are added again to the queue, reordering it, when the neighbors of the identified match

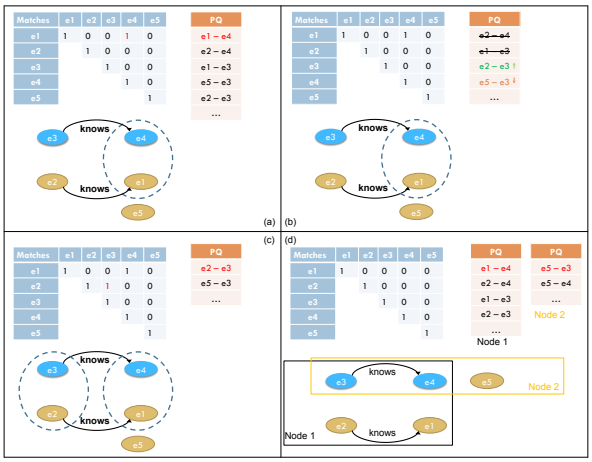

Fig. 14: An execution example of LINDA. (a) PQ initialization, (b) PQ update, (c) new matches are found, (d) distributed version.

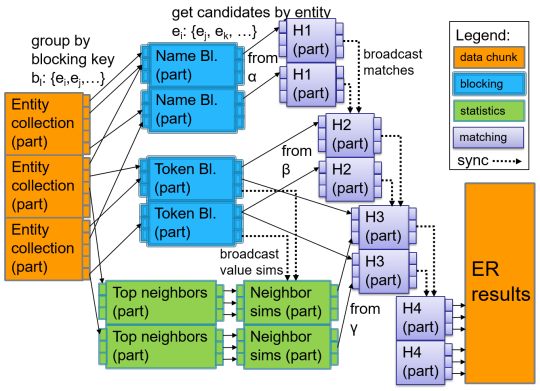

Fig. 15: The architecture of MinoanER in Spark.

move higher in the rank, or shrinking it, by applying transitivity and a unique match per KB constraint. The algorithm stops when the priority queue is empty, or when a specific number of iterations has been reached.

Example 8 Figure 14 shows an execution example of LINDA for the entity graph shown at the bottom, in which e_3, e_4 belong to the same KB, while e_1, e_2, e_5 belong to a second KB. The identified matches are represented by an 1 in the binary matrix, on the top left corners. The entity pair priority queue is initialized and the top pair (e_1, e_4) is considered a match (Figure 14 (a)). This causes the removal of (e_2, e_4) and (e_1, e_3) from PQ, because of the unique match per KB constraint (Figure 14 (b)). The new match causes a re-ordering of PQ. E.g., the similarity between e_2, e_3 is increased, since e_2 is a neighbor of e_1 and e_3 is a neighbor of e_4. In Figure 14 (c), the top pair (e_2, e_3) is considered a match. This causes (e_5, e_3) to be removed. Finally, PQ becomes empty and the algorithm returns the matches shown in Figure 14 (c). A possible initialization of the parallel algorithm is shown in Figure 14 (d), assuming that the algorithm is run on a 2-node cluster. PQ is divided into two partitions, based on a modulo operation on the first description of each pair. Each node also gets the corresponding partition of the entity graph, containing all the descriptions of its PQ partition, along with their immediate neighbors (Figure 14 (d)). The same algorithm then runs locally, on each node of the cluster, sharing the knowledge of the identified matches.

Finally, Figure 15 shows the architecture of *MinoanER* [54] in Spark. Each process is executed in parallel for different chunks of input, in different Spark workers. Each dashed edge represents a synchronization point, at which the process has to wait for results produced by different data chunks (and different Spark workers). MinoanER applies name blocking, while running token blocking and the extraction of top similar neighbors per entity. Then, it synchronizes the results of the last two processes: it combines the value similarities computed by token blocking with the top neighbors per entity to estimate the neighbor similarities for all entity pairs with neighbors co-occurring in at least one block. To minimize the overall run-time, heuristic H1 (finding matches based on their name) starts right after name blocking, H2 (finding strongly similar matches) after H1 and token blocking, H3 (finding nearly similar matches) after H2 and the computation of neighbor similarities, while H4 (the reciprocity filter) runs last, providing the final, filtered set of matches. During the execution of every heuristic, each Spark worker contains only the partial information of the blocking graph that is necessary to find the match of a specific node.

5.6 Discussion

Table 4 presents an overview of the matching methods discussed in this section. They are organized based on schema-awareness (schema-aware or schema-agnostic), nature of comparisons (pairwise or collective), processing mode (batch or online), and algorithmic foundations (learning-based or non-learning). Collective methods are further refined as merging-based (MB) or relationship-based (RB), online methods as query-based (QB) or streaming (STR), and learning-based methods as supervised (S), weakly supervised (WS), unsupervised (U) and deep learning (DL).

We observe that all schema-agnostic methods that have been proposed are collective, and more specifically, relationship-based. This happens because, un-

Table 4: Taxonomy of the matching methods discussed in Section 5. MB: Merging-based, RB: Relationship-based, QB: Query-Based, STR: Streaming, S: Supervised, WS: Weakly Supervised, U: Unsupervised, DL: Deep Learning.

	Schema awareness		Nature of comparisons		Processing mode		Algorithmic foundations	
	Schema-aware	Schema-agnostic	Pairwise	Collective	Batch	Online	Learning-based	Non-learning
Swoosh [13]	✓			MB	✓			✓
D-Swoosh [12]	✓			MB	✓			✓
CollectiveER [15]	✓			RB	✓			✓
Large-scale collectiveER [154]	✓			RB	✓			✓
Hybrid collective [45]	✓			MB,RB	✓			✓
Adaptive matching [35]	✓		✓		✓		S	
MARLIN [19]	✓		✓		✓		S	
Gradient-based [156]	✓		✓		✓		S	
BN-based collectiveER [87]		✓		RB	✓		S	
GenLink [89]		✓	✓		✓		S	
DeepER [50]	✓		✓		✓		S,DL	
DL design space [125]	✓		✓		✓		S,DL	
Transf. learning [173]	✓		✓		✓		WS,DL	
Transf. learning for RDF [158]		✓		RB	✓		WS,DL	
Unsup. ensemble [93]	✓		✓		✓		U	
Unsup. for RDF [98]	✓		✓		✓		U	
Matching rule selection [181]	✓		✓		✓			✓
Query-driven collectiveER [16]	✓			RB		QB		✓
Query-based w/ uncertainty [86]	✓			MB		QB		✓
UDD [171]	✓		✓			QB	U	
Sample-and-clean [180]	✓		✓			QB		✓
QuERy [5]	✓		✓			QB		✓
QDA [4]	✓		✓			QB		✓
SBlockSketch [94]	✓		✓			STR		✓
Pre-computed sim [31]	✓		✓			STR		✓
Collective for XML [185]		✓		RB	✓			✓
SiGMa [113]		✓		RB	✓			✓
LINDA [20]		✓		RB	✓			✓
RiMOM [115,164]		✓		RB	✓			✓
PARIS [172]		✓		RB	✓			✓
MinoanER [54,56,53]		✓		RB	✓			✓

like schema-aware methods, schema-agnostic methods cannot rely on attribute-level similarities for attributes that are not known in advance, or it is not known if they are actually used by the descriptions. Hence, those methods propagate the information provided by entity neighbors as matching evidence whenever possible. Consequently, as a rule of thumb depending on the nature of the input data, we recommend merging-based collective ER methods that are schema-aware for data coming from a single dirty data source (e.g., for the deduplication of a dirty customer data base) and relationship-based collective ER methods that are schema-agnostic for data coming from multiple, curated data sources (e.g., for finding equivalent descriptions among two or more Web KBs).

Another point worth mentioning is that learning-based methods can be seen as either pairwise, as at their core, they try to learn the probability that two descriptions match, based on previous examples of similar pairs, or collective, as models are trained on sets of pairs, or even on vectorial representations of entity descriptions, or the words used in the values of those descriptions. For completeness, in Table 4 we classify them as pairwise, following the traditional learning approach, and also because their collective nature cannot be easily labeled as merging-based or relationship-based. We believe that learning-based methods, and especially deep learning-based methods are gaining ground as new and more effective ways to represent individual or groups of entity descriptions appear. The emergence of weakly supervised and transfer-learning methods seem to alleviate the long-lasting problem of generating a labeled set for training data. Therefore, we recommend that when labeled examples are available (as is or through transfer learning) or easy to generate using existing tools (e.g., [155]) and the test data are not expected to deviate considerably from the training data, then those methods seem to be more promising. Before choosing learning-based or non-learning methods, one should also consider the desired frequency of re-training a new classification model, the memory footprint of each method (whether the whole model needs to reside in memory or not) and the time needed for training and classification.

In general, even if some efforts have been made in the past (e.g., [88,106,108]), we notice the lack of a systematic benchmarking of matching methods, and perhaps more importantly end-to-end ER tools, which will involve the effectiveness, i.e., quality of the output matches, time and space efficiency, i.e., the time required for preprocessing, training, and matching, the memory and disk space required by each method, and scalability, i.e., using the same computational and storage resources, what is the data limit that each method can handle.

We have noticed that due to the lack of works in streaming ER, existing methods compare against works in progressive ER, as those in Section 4. We distinguish those approaches, seeing streaming ER as a subset of progressive ER, in which resolved entities can be returned in real time, not necessarily covering the whole input entity collections, but only a subset of them, perhaps related to a user-defined query. We strongly recommend such methods in cases where ER requires only resolving a small set of descriptions, such as only those needed to answer a user's query, in which resolving the whole input set of descriptions would be unnecessarily costly in terms of time and resources.

6 Clustering methods

Typically, clustering constitutes the final step in the end-to-end ER workflow, following matching. Its input comprises the *similarity graph*, where the nodes correspond to the descriptions, while the edges connect descriptions that have been compared during matching (i.e., they indicate pairs of likely matches). Clustering aims to infer more edges from indirect matching relations, while discarding edges that are unlikely to connect duplicates in favor of edges with higher matching probabilities. Hence, its end result is a set of *entity clusters*, each of which comprises all descriptions that correspond to the same, distinct real-world object.

In the simplest case, *Connected Components* [80, 159] is applied to compute the transitive closure of the detected matches. This naive approach increases recall, but is rather sensitive to noise. False positives have a significant impact on precision, leading to entity clusters that are dominated by non-matching descriptions. For this reason, more advanced clustering techniques have been proposed to leverage the weighted edges in the similarity graph, whose score, typically in $[0, 1]$, is analogous to the matching likelihood. In general, these techniques are distinguished into three categories, according to the input of the ER task at hand:

1) For Clean-Clean ER, clustering typically relies on the 1-1 correspondence between the input data sources. The most popular technique is *Unique Mapping Clustering*, which first sorts all edges in decreasing weight. At each iteration, the top edge is considered a match, if none of the adjacent descriptions has already been matched. The process ends when the top edge has a similarity lower than a threshold t. Essentially, this approach provides an efficient solution to the *Stable Marriage* problem for unequal sets [122], given that Clean-Clean ER forms a (usually unbalanced) bipartite similarity graph. The *Hungarian algorithm* is also applicable, though at a much higher computational cost, unless an approximation is used (e.g., [42,110]).

2) For Dirty ER, the core characteristic of clustering algorithms is that they produce a set of disjoint entity clusters without requiring as input the number of clusters or any labelled dataset for training [80]. *Center Clustering* [82] iterates once over all edges and creates clusters around nodes that are selected as centers. Its functionality is enhanced by *Merge-Center Clustering* [81], which merges together clusters with centers similar to the same node. *Star Clustering* [8] begins with sorting all similarity graph nodes in descending order of degree. Then, the top node becomes the center of a cluster that includes all its direct neighbors. The same process is repeatedly applied to the remaining nodes, until all nodes belong to a cluster. The resulting clusters are overlapping, unless post-processing assigns each node to a single cluster. *Ricochet Clustering* [191] comprises a family of techniques based on two alternating stages: the first one determines the centers of clusters (similar to Star Clustering), while the second one (re-) assigns nodes to cluster centers (similar to K-Means).

Other techniques focus on the relative strength of links inside and across clusters, i.e., *intra-* and *inter-cluster* edges. *Markov Clustering* [174] uses random walks to strengthen the intra-cluster edges, while weakening the inter-cluster ones. *Cut clustering* [68] iteratively identifies the minimum cut of maximum flow paths from a similarity graph node to an artificial sink node. This way, it detects small inter-cluster cuts, while strengthening intra-cluster links. *Correlation Clustering* [10] solves an optimization task, where the goal is to maximize the sum of the intra-cluster edges, while minimizing the sum of the inter-cluster ones. This is an NP-hard problem that is typically solved through approximations, such as *Clustering Aggregation* [73] and *Restricted Correlation Clustering* [111]. The latter is a semi-supervised approach that leverages a small labelled dataset carefully selected via an efficient sampling procedure based on LSH. The performance of these methods has been experimentally evaluated in [80]. As expected, Connected Components exhibits the worst accuracy. Ricochet Clustering performs well only over data sources with uni-

formly distributed duplicates, while Markov Clustering consistently achieves top performance. Surprisingly enough, the highly scalable, single-pass algorithms like Center and Merge-Center clustering provide comparable, if not better, results than more complex techniques, like Cut and Correlation Clustering.

3) Most algorithms for Dirty ER are also applicable to Multi-source ER [159]. However, the multitude of input data sources calls for specialized clustering methods. The main ones are *SplitMerge* [130] and *CLIP* [161]. SplitMerge applies Connected Components clustering and cleans the resulting clusters by iteratively removing entities with low similarity to other cluster members. Then, it merges similar clusters that are likely to correspond to the same real-world entity. For higher efficiency, its functionality is massively parallelized through Apache Flink in [129]. CLIP assumes duplicate-free data sources as input. First, it computes the transitive closure of strong links, i.e., the edges that correspond to the maximum weight per source for both adjacent nodes. The remaining graph is cleaned from weak links, i.e., edges that do not correspond to the maximum weight per source for neither adjacent node. Finally, the transitive closure is computed and its clusters are processed to ensure that they contain at most one description per source. The relative performance of these algorithms has been thoroughly examined in [159, 160], using their parallel adaptation in Apache Flink. The results of the extensive experiments demonstrate that SplitMerge and CLIP achieve the top performance for Multi-sourcee ER, with the latter providing a better balance between effectiveness and time efficiency.

In practical ER applications it is difficult and costly to obtain ground truth data of high quality and enough size, to train learning-based ER classifiers or assess the overall quality of ER. To tackle this problem, [182] proposes an interactive learning algorithm that exploits the cluster structure in similarity vectors calculated from compared record pairs. Then, informative training examples are selected to assess the purity of clusters, and recursively split clusters until clusters pure enough for training are found. Two aspects of active learning that are significant in practical applications have been considered: (a) a limited budget for the number of manual classifications that can be done, and (b) a noisy oracle where manual labeling might be incorrect.

7 Progressive Entity Resolution

Unlike the budget-agnostic functionality of the above methods, Progressive ER operates in a budget-aware way: its goal is to provide the best possible *partial solution*, when the response time, or the available computational resources are limited. It is driven by modern *pay-as-you-go* applications that do not require the complete solution to produce useful results, as the number of data sources and the amount of available data multiply. For example, the number of high-quality HTML tables on the Web is in the hundreds of millions, while the Google dataset search system alone has indexed ∼26 billion datasets [75]. Such a huge volume of data can only be resolved in a pay-as-you-go fashion, especially for applications with strict time requirements.

Typically, progressive methods rely on blocking as a pre-processing step that identifies similar entity descriptions. They differ, though, on how they leverage blocks to prioritize the execution of comparisons (Planning in Figure 5). They are classified into 4 categories with respect to the granularity of their functionality [166]:
1. The *block-centric methods* produce a list of blocks sorted in descending order of the likelihood they include duplicates among their descriptions. In every call, all the comparisons for each block are generated, one block at a time, following that ordered list; all comparisons in the same block have the same matching likelihood.
2. The *comparison-centric methods* provide a list of entity pairs sorted in descending order of matching likelihood. With every method call, these descriptions pairs are emitted, one at a time, following that ordered list.
3. The *entity-centric methods* provide a list of entities sorted in descending order of duplication likelihood. In every call, all comparisons of every entity are generated, one entity at a time, following that ordered list.
4. The *hybrid progressive methods* combine characteristics from two or all of the previous categories.

Progressive methods are further classified into two categories according to the functionality of blocking keys (this categorization is orthogonal to the one defined by the granularity of the methods) [166]:
1. The *sort-based methods* rely on the similarity of blocking keys. They produce a list of entities by sorting all descriptions alphabetically, according to the blocking keys that represent each of them. They assume that the matching likelihood of any two profiles is analogous to their proximity after sorting.
2. The *hash-based methods* consider identical blocking keys. Most of them rely on overlap-positive blocks, assuming that the similarity of two descriptions is proportional to the number of blocks they share.

Below, we examine separately the methods that have been proposed for structured and semi-structured data.

7.1 Methods for structured data

The progressive methods that are suitable for structured data rely on schema. This means that their per-

formance depends heavily on the attribute(s) that provide the schema-aware blocking keys they leverage, typically requiring domain experts to fine-tune them.

In this context, the core comparison-centric method is *Progressive Sorted Neighborhood* (PSN) [189]. Based on Sorted Neighborhood [84], it associates every description with a schema-aware blocking key. Then, it produces a *sorted list of descriptions* by ordering all blocking keys alphabetically. Comparisons are progressively defined through a sliding window, w, whose size is *iteratively incremented*: initially, all descriptions in consecutive positions (w=1) are compared, starting from the top of the list; then, all descriptions at distance w=2 are compared and so on, until the processing is terminated. In case of low recall, the entire process is repeated, using multiple blocking keys per description.

The above approach produces a *static* list of comparisons, in the sense that it remains immutable, regardless of the duplicates that are identified. In other words, PSN cannot react to the skewed distribution of duplicates. To ameliorate this issue, a *dynamic* version of the algorithm was proposed in [149]. Its functionality is integrated with Matching to adjust the processing order of comparisons on-the-fly. Arranging the sorted entities in a two-dimensional array A, if the position $A(i, j)$ corresponds to a duplicate, the processing moves on to check the positions $A(i+1, j)$ and $A(i, j+1)$, too.

The same principle lies at the core of the dynamic, block-centric method *Progressive Blocking* [149]. Initially, a set of blocks is created and its elements are arranged in a two-dimensional array A. Then, all comparisons are executed inside every block, measuring the number of duplicates per block. Starting from the block with the highest density of duplicates in position $A(i, j)$, its entities are compared with those in the blocks $A(i+1, j)$ and $A(i, j+1)$ in order to identify more matches.

A static, block-centric method is the *Hierarchy of Record Partitions* [189]. Essentially, it builds a hierarchy of blocks, such that the matching likelihood of two descriptions is proportional to the level in which they co-occur for the first time: the blocks at the bottom of the hierarchy contain the descriptions with the highest matching likelihood, and vice versa for the top hierarchy levels. Thus, the hierarchy of blocks can be progressively resolved, level by level, from the leaves to the root. Note, though, that this method presumes that the distance of two records can be naturally estimated through a certain attribute (e.g., product price) [189]. A variation of this approach is adapted to MapReduce for even higher efficiency in [3]. It divides every block into a hierarchy of child blocks and uses an advanced strategy for optimizing their parallel processing.

An entity-centric improvement of the Hierarchy of Record Partitions is the *Ordered List of Records* [189]. This method converts the hierarchy of blocks into a list of records sorted by their likelihood to produce matches. In this way, it involves a lower memory consumption than the Hierarchy of Record Partitions, but results in slightly worse performance.

Finally, [2] proposes a progressive solution in the context of Multi-source ER over different entity types. It uses a graph in which nodes are entity pairs and every edge indicates that the resolution of a node influences the resolution of another node. During the scheduling phase, it divides the total cost budget into several windows of equal cost. For each window, a comparison schedule is generated, by choosing the one with the highest expected benefit among those with a cost lower than the current window. The cost of a schedule is computed by considering the cost of finding the description pairs and the cost of resolving them. Its benefit is determined by how many matches are expected to be found by this schedule, and how useful it will be to declare those nodes as matches, in identifying more matches within the cost budget. After a schedule is executed, the matching decisions are propagated to all the influenced nodes, whose expected benefit now increases and have, thus, higher chances of being chosen by the next schedule. The algorithm terminates when the cost budget has been reached.

7.2 Methods for semi-structured data.

Unlike the aforementioned approaches, methods of this category rely on an inherently *schema-agnostic* functionality that completely disregards any schema information. Most importantly, they are independent of expert knowledge and require no labeled data for learning how to rank comparisons, blocks or entities.

In this context, the cornerstone of sort-based methods is the *Neighbor List* [166], i.e., the list of entities created by schema-agnostic adaptation of Sorted Neighborhood [134]: every token in any attribute value is considered as a blocking key and all entities are sorted alphabetically according to these keys; thus, each entity appears in the Neighbor List as many times as the number of its distinct tokens. The naive progressive approach would be to slide a window of increasing size along this list, incrementally executing the comparisons it defines, as in PSN[10]. This approach, however, results

[10] All comparisons are valid in this approach: in case of Clean-Clean ER, a comparison is valid only if the two entities stem from different entity collections, whereas for Dirty ER, the comparison should involve different entities.

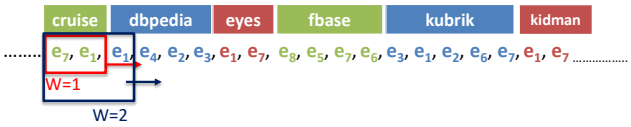

Fig. 16: Part of the Neighbor List corresponding to the entities of Figure 1.

in many repeated comparisons and suffers from *coincidental proximity*, since the ordering of entities with identical keys is practically random.

To ameliorate this issue, *Local Schema-agnostic PSN* [166] enriches the Neighbor List with weights based on the assumption that the closer the blocking keys of two descriptions are, when sorted alphabetically, the more likely they are to be matching. Every comparison defined by the current window size is associated with a numerical estimation of the likelihood that it involves a pair of matching descriptions through the following schema-agnostic weighting function: $\frac{fr_{j,i}}{fr_i+fr_j-fr_{i,j}}$, where fr_k is the number of blocking keys associated with entity e_k (i.e., how many times it appears in the Neighbor List), while $fr_{j,i}$ denotes the frequency of the comparison $< e_i, e_j >$ within the current window. This approach eliminates all repeated comparisons within every window. Its main drawback, is its inability to remember past emissions, i.e., it defines an execution order for a specific window size, without preventing the same comparison to be emitted multiple times, for two or more different window sizes. To address this drawback, *Global Schema-agnostic PSN* [166] defines a global execution order for all comparisons in a predetermined range of window sizes $[1, w_{max}]$, using the same function.

Example 9 Figure 16 depicts part of the Neighbor List for the entities of Figure 1. First, the attribute value tokens are sorted in alphabetical order (first row) and then, the corresponding entities per token are placed in arbitrary order (second row). The naive schema-agnostic PSN slides a window of fixed size w over the sorted entities, starting with w =1 and incrementing it in every iteration. For a particular window size, the same pair of entities might appear multiple times; e.g., for size $w = 1$, we encounter the pair e_1-e_7 three times in this part of the Neighbor List. Local Schema-agnostic PSN leverages this frequency of co-occurrence to identify the most promising entity pairs per window size. However, Local Schema-agnostic PSN cannot consider cases where the distance of entities belonging to consecutive tokens is arbitrary; e.g., e_5 from "fbase" and e_2 from "kubrik" co-occur in a window of size 6, but their distance could range from 1 to 9. To mitigate this issue, Global Schema-agnostic PSN considers co-occurrence patterns within a range of window sizes.

A different approach is implemented by the hash-based method *Progressive Block Scheduling* [166]. First, the input blocks are ordered in increasing cardinality such that the fewer comparisons a block entails, the higher it is ranked. Then, the sorted list of blocks is processed, starting from the top-ranked (i.e., smallest) block. Inside every block, one of Meta-blocking's weighting schemes is used to specify the processing order of comparisons, from the highest weighted to the lowest one. During this process, all repeated comparisons are discarded before computing their weight.

Finally, *Progressive Profile Scheduling* [166] is a hybrid method that relies on the notion of *duplication likelihood*, i.e., the likelihood of an individual entity to have one or more matches. This is estimated as the average edge weight of its node in the corresponding blocking graph. This method processes the input entities in decreasing duplication likelihood, starting from the entity with the highest likelihood of having a match. For each entity, all comparisons that entail it are ordered in decreasing weight, as estimated through a Meta-blocking weighting scheme. Among the non-repeated comparisons, the top-k weighted ones are emitted.

7.3 Discussion

To tackle the Velocity of Big Data, the progressive methods apply ER in a pay-as-you go manner. To address Volume, they all rely on blocking methods. The schema-agnostic progressive methods are also capable of addressing Variety. Table 5 organizes all methods discussed above into a taxonomy formed by the four aforementioned criteria: schema-awareness, functionality of blocking keys, granularity of functionality and type of ordering. We observe that there is no dynamic schema-agnostic method that adapts its processing order as more duplicates are identified. More research is required towards this direction. A noisy matching method should be used, instead of the ideal one that is currently considered by dynamic schema-aware methods. Intelligent ways for tackling the errors introduced by noisy matchers are indispensable for a realistic progressive scenario.

Regarding the relative performance of static methods, the schema-agnostic ones consistently outperform the schema-aware ones over several established structured datasets [166]. Among the schema-agnostic methods, the two sort-based ones, i.e., Local and Global Schema-agnostic PSN, achieve the best performance for structured datasets. The difference between them is statistically insignificant and thus, the choice depends on the available memory resources: Local PSN is more suitable in cases of limited memory, with all other settings calling for Global PSN, given that it avoids multiple

Table 5: A taxonomy of the progressive methods discussed in Section 7 (in the order of presentation).

	Schema-awareness		Key Functionality		Granularity of Functionality			Type of Ordering	
	schema-aware	schema-agnostic	hash-based	sort-based	block-centric	comparison-centric	entity-centric	static	dynamic
Progressive Sorted Neighborhood (PSN) [189]	✓			✓		✓		✓	
Dynamic PSN [149]	✓			✓		✓			✓
Progressive Blocking [149]	✓		✓		✓				✓
Hierarchy of Record Partitions [189]	✓		✓		✓			✓	
Ordered List of Records [189]	✓		✓				✓	✓	
Progressive Relational Entity Resolution [2]	✓		✓			✓			✓
Local Schema-agnostic PSN [166]		✓		✓		✓		✓	
Global Schema-agnostic PSN [166]		✓		✓		✓		✓	
Progressive Block Scheduling [166]		✓	✓		✓	✓		✓	
Progressive Profile Scheduling [166]		✓	✓			✓	✓	✓	

emissions of the same comparisons. For large, heterogeneous datasets, Progressive Profile Scheduling exhibits the overall best performance, with Progressive Block Scheduling following in close distance.

8 Other Topics

In this section, we briefly cover topics that are complementary to the methods presented above.

8.1 Crowdsourcing-based methods

In general, crowdsourcing is a costly procedure that can effectively generate or enrich a training set for a learning-based ER algorithm to identify matches, or to evaluate the results of an ER approach. Putting a human in the loop makes ER much more accurate, as in general, computers identify the easy matches for which there is little uncertainty and humans can help in the more difficult cases. However, the main challenges in crowdsourcing-based ER are how this process can scale to big datasets, how erroneous decisions may affect the result and how cost-efficient the whole process can be.

[188,175] try to reduce the cost of crowdsourcing, by minimizing the number of questions posed to humans, selecting each time the question with the highest expected benefit. Benefit can be defined in terms of the most informative question, as the question that will cause the greatest change in the current clustering, after the answer for that question is retrieved [188], or can be based on Maximum Likelihood [175]. Extending this work on minimizing the interaction with the user, [100] reduces the cost of crowdsourcing-based ER methods by involving the crowd's decisions for matching attribute names, and then asking for matching judgments only between descriptions with similar sets of attribute names. Differently, Waldo [176] is an interface that combines pairwise with multi-item questions for matches. The core idea is that difficult matching decisions can be asked to the user explicitly as pairwise questions, while the rest can be given as multi-item tasks.

ZenCrowd [40,41] uses a semi-automatic ER framework, in which decisions not associated with a high confidence score are propagated to humans to improve the quality of the links, by dynamically generating microtasks on an online crowdsourcing platform. It relies on a probabilistic framework to decide how to incorporate manual matching, and to more effectively integrate inconsistent results obtained by arbitrary sets of human workers. Using its probabilistic framework, ZenCrowd is also able to identify, and thus ignore, unreliable human decisions. On the opposite side, in CrowdER [179], descriptions are initially resolved by machines and then people only verify the most certain matches, while Vesdapunt et al. [177] exploit the transitivity of the equivalence relation to infer as many matches as possible, based on the ER answers that were verified by humans.

Most of the existing crowdsourcing-based approaches try to label as many candidates as possible without human involvement, e.g., by creating matching rules, blocking rules, training sets, and only resort to human labeling when necessary. Recently, Corleone [74] suggested the exact opposite direction, namely to crowdsource the whole ER process without using pre-defined matching, blocking, or quality estimation rules. It provides a sample of the data to be matched to the human annotator for building the blocking rules. Using active learning, the human decisions are turned into a random forest, i.e., a set of decision trees on different entity attributes. A sample of the candidates generated from those blocking rules are then sent for evaluation, again by humans, which further refine the blocking strategy. Using a similar approach for matching as in blocking, a sample of the candidates are selected and given to

humans for labeling, using active learning. A big disadvantage of Corleone, and most crowdsourcing-based works on ER, is scaling to large datasets. Falcon [37] improves the scalability of Corleone by using RDBMS-like query execution and optimization over a Hadoop cluster. For related surveys, please refer to [43, 23].

8.2 Rule-based methods

Apart from crowdsourcing methods, which mostly rely on human involvement for specific matching decisions in question, ER can also leverage the manual effort of domain experts who can provide some generic initial rules (e.g., "if two descriptions have a similar address values, then they are matches") that will help an ER method find some / all matches in a given task.

HIL [83] is a high-level scripting language for ER, aiming to provide the core logic for complex ER pipelines. A HIL program captures the overall integration flow through a combination of SQL-like rules that link, map, fuse and aggregate entities. HIL makes uses of logical indices in its data model to facilitate the modular construction and aggregation of complex entity descriptions. Another feature is the presence of a flexible, open type system that allows HIL to handle irregular, sparse or partially known input data.

Manually specifying effective matching rules is often unlikely. Therefore, reasoning and discovery techniques are developed for obtaining more matching rules. [64, 63] complement existing ER methods by providing dependency-based reasoning techniques to help decide keys for matching and blocking. The central notion in those works is that of matching dependencies (MDs), which allow to infer matches, based on the similarity of structured descriptions (database records) on some predefined fields (attributes in relational schemas). MDs are not only used directly to infer matches, but also, they can be extended and used to infer new MDs, leading to more matches, in an effective and efficient way, minimizing manual effort. MDs can be used in both the blocking and the matching steps, complementing the methods that we have already covered.

Even if MDs are looser versions of the strict functional dependencies in traditional relational databases, [183] argues that MDs are still too strict in practice, and therefore introduce the conditional MDs, which bind MDs to only a certain subset of descriptions in a relational table. Compared to MDs, conditional MDs have more expressive power for declaring constraints with conditions and allow a wider range of real applications.

Certus [112] introduces graph differential dependencies (GDDs) as an extension of MDs and CMDs to enable approximate matching of values. It adopts a graph model for entity descriptions which enables formal representation of entities even in unstructured sources. It investigates a special discovery of GDDs for ER by designing an algorithm for generating a non-redundant set of GDDs in labelled data. Then, Certus employs the learned GDDs for improving the accuracy of ER results. Unlike MDs and CMDs, which operate only on structured data, Certus can identify matches irrespective of structure and with no assumed schema.

8.3 Temporal ER methods

In many cases, temporal information in the form of timestamps [26, 126], e.g., user log data or sensor data, or temporal validity of properties [85], e.g., population, marital status, affiliation, is often associated with entity descriptions. ER methods exploiting such temporal information may show better performance than those not [25]. Such methods, rather than deciding if two descriptions match, try to decide if a new description matches with a set descriptions that have been already identified as matches. [25] focuses on the probability of a value re-appearing over time. Intuitively, an entity might change its attribute values in a way that is dependent on previous values. For example, if a persons location has taken the values Los Angeles, San Francisco, San Jose in the past, then these values may be more likely to appear in this persons future location than Athens or Cairo. [26] follows a slightly different approach, coined SFDS (static first, dynamic second), in which it is assumed first that all entities are static, i.e., not evolving over time, and they are grouped into clusters, which are later merged in the dynamic phase, if it is found that the different clusters correspond to the same entities that have evolved over time.

8.4 Open-source ER tools

We now elaborate on the main systems that are crafted for end-to-end Entity Resolution. We examined the 18 non-commercial and 15 commercial tools that are listed in the extended version of [105][11] along with the 10 Link Discovery frameworks surveyed in [131]. However, the closed code systems (e.g., Dedoop [102] and FEVER [107]) and the commercial ones provide insufficient information about their internal functionality and/or the algorithms they implement. For this reason, we exclusively consider open-source ER tools.

A summary of these systems appears in Table 6. For each system, we examine whether it involves one or

[11] http://pages.cs.wisc.edu/~anhai/papers/magellan-tr.pdf

Table 6: The main open-source ER Tools (a feature in parenthesis is partially supported).

Tool	Blocking	Block Processing	Matching	Clustering	Parallelization	Bugdet-awareness	GUI	Language
Dedupe [19]	✓	-	✓	-	multi-core	-	-	Python
DuDe [48]	✓	-	✓	-	-	-	-	Java
Febrl [28]	✓	-	✓	-	multi-core	-	✓	Python
FRIL [92]	✓	-	✓	-	-	-	✓	Java
OYSTER [128]	✓	-	✓	-	-	-	-	Java
RecordLinkage [162]	✓	-	✓	-	-	-	-	R
Magellan [105]	✓	-	✓	-	(Apache Spark)	-	✓	Python
FAMER [159]	-	-	-	✓	Apache Flink	-	-	Java
Silk [89]	✓	-	✓	-	Apache Spark	-	✓	Scala
LIMES [132]	✓	-	✓	-	(multi-core)	-	✓	Java
KnoFuss [133]	✓	✓	-	-	-	-	-	Java
SERIMI [7]	✓	✓	-	-	-	-	-	Ruby
MinoanER [54]	✓	✓	✓	-	Apache Spark	-	-	Java
JedAI [148]	✓	✓	✓	✓	(multi-core)	-	✓	Java

more methods for each step of the general end-to-end ER workflow (see Figure 4), whether it supports parallelization, budget-aware methods, and graphical user interface (GUI) as well as its programming language. To facilitate their understanding, we have grouped all systems into three categories, depending on their input data: (i) systems for structured data, (ii) systems for semi-structured data, and (iii) hybrid systems.

The tools for structured data include Dedupe [19], FRIL [92], OYSTER [128], RecordLinkage [162], DuDe [48], Febrl [28], Magellan [105] and FAMER [159]. All of them include at least one method for Blocking and Matching, while disregarding Clustering. The only exception is FAMER, which exclusively focuses on Clustering, implementing several established techniques in Apache Flink. Febrl involves the richest variety of non-learning blocking methods, which can be combined with several similarity measures and top-performing classifiers for supervised matching. Magellan offers the richest variety of state-of-the-art similarity join techniques for accelerating matching, while conveying a Deep Learning module, which is a unique feature among all ER tools. Most systems are implemented in Java or Python, with just 3 of them offering a GUI.

The systems for semi-structured data receive as input RDF dump files or SPARQL endpoints. The most prominent ones are *Silk* [89] and *LIMES* [132], which are crafted for the Link Discovery problem (i.e., the generic task of identifying relations between entities). Restricting them to the discovery of `sameAs` relations renders them suitable for ER. Both systems involve custom blocking techniques along with a large variety of character- and token-based similarity measures. Combinations of these similarity measures are learned in a (semi-)supervised way for effective Matching. For ease of use, each tool offers an intuitive GUI. In contrast, the remaining tools of this category, *SERIMI* [7] and *KnoFuss* [133], lack a GUI. They both focus on Matching, providing effective, but custom techniques, and apply Token Blocking to literal values for higher efficiency.

The hybrid tools MinoanER [54] and JedAI [148] apply uniformly to both structured and semi- structured data. This is possible due to the schema-agnostic functionality of their methods. In fact, they implement various state-of-the-art non-learning techniques for blocking, matching and clustering. They are also the only systems that offer Block Processing techniques. They are complementary, as JedAI constitutes a desktop application, while MinoanER relies on massive parallelization through Apache Spark. Note that MinoanER supports any data input format describing entities as sets of attribute-value pairs, loaded as Apache Spark RDDs. Currently, only RDF parsers are provided.

Overall, we observe that all open-source systems focus on Matching, conveying a series of string similarity measures for the comparison of attribute values. More effort should be spend on covering more adequately all workflow steps of the general end-to-end ER workflow. Most importantly, no system supports budget-aware (i.e., progressive) ER or any other processing mode apart from budget-agnostic. This shortcoming should be addressed in the future.

9 Conclusions

Although ER has been studied for more than three decades in different computer science communities, it still remains an active area of research. The problem has enjoyed a renaissance during recent years, with the avalanche of data-intensive descriptions of real-world entities provided on by government, scientific, corporate or even user-crafted data sources. Reconciling different entity descriptions in the Big Data era poses new challenges both at the algorithmic and system level. In this survey, we have mainly focused on relevant blocking and matching algorithms reflecting the majority of recent publications. We share, however, the view of ER

as an engineering task by nature, and hence, we cannot just keep developing ER algorithms in vacuum [105]. We attempted to explain the impact of certain blocking algorithms based on the content similarity of descriptions to matching decisions of nearly similar entities requiring additionally to asses neighbor similarity. In the Big Data era, we opt for *open-world ER systems* that allow to plug-and-play different blocking and matching algorithms and can easily integrate with third-party tools for data exploration (e.g., sampling), data cleaning (e.g., outlier detection), or data analytics.

9.1 Directions for Future Work

As we have just begun to realize the need for *Entity Resolution Management Systems* [105], we next highlight few critical research directions for future work aiming to support advanced services for specifying, maintaining and making accountable complex ER workflows.

Multi-modal ER. In the Big Data era, multi-modal entity descriptions are becoming more and more common. Factual, textual or image-based descriptions of the same real world entities are becoming available from different sources and at different temporal or spatial resolutions. Each modality carries a specific piece of information about an entity and offers some type of added value that cannot be obtained from any of the other modalities. Recent years have witnessed a surge of need in jointly analyzing of multi-modal descriptions [199]. Finding the semantically similar descriptions from different modality is one of the heart problems of multi-modal learning. Most current approaches presume that there is a linear or non-linear projection between multi-modal data. These methods focus on how to utilize extrinsic supervised information to project one modality to the other or map both two modalities into a commonly shared space. The performance of these methods heavily depends on the richness of training samples. However, in real-world applications, obtaining the matched data from multiple modalities is costly or even impossible [70]. Therefore, it is urgently needed to develop a sample-insensitive method for multi-modal ER, and in this respect, we can leverage recent advances in multi-model ML techniques [9].

Debugging and Repairing ER workflows. Current ER research mainly focuses on developing accurate and efficient blocking and matching techniques which in reality are constrained by a number of factors, such as low quality of entity descriptions, ambiguity or domain knowledge, limited ground truth. Hence, it becomes difficult to guarantee the quality of ER workflows at specification time. To support a *continuous* specification of ER workflows, an iterative approach is needed to refine ER workflows by identifying and analyzing the mistakes (false matches and non-matches) of ER enactments at each iteration step. Debugging ER workflows requires to (a) understand the mistakes made by blocking or matching algorithms; (b) diagnose root-causes of these mistakes (e.g., due to dirty data, problematic feature sets, or even tuning parameters of algorithms); and (c) prioritize mistakes and take actions to fix them [105]. We should stress that not all categories of mistakes have the same impact on the end-to-end quality of ER workflows. For example, the removal of outliers from the input data often leads to overfitting problems of learning-based matchers. Recognizing patterns of mistakes reproduced under similar conditions can provide valuable insights in order to repair ER workflows. Clearly, the primary focus of ER work so far was in preventing rather than repaing mistakes in ER results. Recent work on debugging and repairing Big Data analytics pipelines can be leveraged in this respect [34,116,78].

Algorithmic Transparency of ER processes.

- *Fairness in Long Tail Entities Resolution.* The reported accuracy scores of several ER approaches are fairly high, giving many times the impression that the problem is well-understood and solved. At the same time, recent existing works (e.g., [60,61]) claim that traditionally, entity resolution systems base their performance on the entities popularity, counting for example popularity with respect to the number of relationships an entity has with others, while performance highly drops when focusing on the rare long tail entities. However, the lack of formal definitions regarding what is popular and long tail entities for the entity resolution task prevents the identification of the difficult cases for entity resolution for which systems need to be adapted or new approaches need to be developed. Better understanding such cases, as well as addressing them explicitly will be helpful for entity resolution, since unlike popular entities, knowledge about long tail entities is less accessible, not redundant and hard to obtain.
- *Diversity of Matching Entities.* Works in progressive ER focus typically on maximizing the reported matches, given a limited computational budget, by potentially exploiting the partial matching results obtained so far in an iterative process. In this setting, it will be interesting to measure the complementary knowledge, similar to the notion of diversity used in information retrieval, that the ER process could achieve after merging the matches. Our intuition is that merges resulting from somehow similar entities are more beneficial in this respect compared to merges from strongly similar entities (i.e., duplicates). Thus, given a constraint in the number of possible merges, the goal is to perform those that contribute most in diversifying the knowledge encoded

in the result. Complementary knowledge can be measured by the number of relationships of a merged entity with other entities; we consider such relationships as a unit of knowledge increase. Specifically, when two relationships represent two different knowledge units, then they are both useful, whereas, when they overlap they represent the same knowledge unit, so we do not gain anything by knowing both of them.

• *Bias in Entity Resolution.* Similarity measures are in the core of the matching task of the entity resolution approaches. However, it is well known that not all similarity measures are appropriate for all types of data (e.g., strings, locations, and videos), or even, when focusing on particular types of measures, e.g., measures for string matching, we do not know beforehand which is the ideal measure for counting similarities with respect to the semantics of the strings to be compared. For instance, we possibly need different measures for computing similarities between American names than for Chinese names. In such scenarios, we typically exploit some solid empirical evidence, which, based on some of the characteristics that our data have, leads us to select, not intentionally, a particular measure. This fact can be considered as algorithmic bias [79]. As a first step, for achieving unbiased and fair entity resolution results, it is important to experimentally study if there is bias in our algorithms for entity resolution. Moving forward, for the next generation of entity resolution approaches, we need to propose solutions and provide guidelines that make entity resolution algorithms fair.

• *Entity Resolution Privacy Concerns.* The process of ER may raise concerns regarding the privacy protection of individuals, whose descriptions are resolved. Two major issues with respect to privacy, when personal information is matched across organizations, arise: (i) typical systems require all data to be available (not only those that are eventually resolved), and (ii) entity resolution results, using descriptions from different organizations, can reveal sensitive information that is not available to a single organization [29]. [187] proposes the practice of disinformation, i.e., deliberately injecting false information into the descriptions, in order to protect the privacy of individuals from potential threats posed by entity resolution systems. By adding false information to a description, it becomes less similar to descriptions with which it should match and hence, it is more difficult for a system to identify those descriptions as matching. Seen differently, disinformation techniques can be used to evaluate the robustness of an entity resolution system. For a complete survey of privacy-preserving entity resolution, we refer to [29].

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