A Survey of Blocking and Filtering Techniques for Entity Resolution

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Entity Resolution (ER), a core task of Data Integration, detects the different entity profiles that correspond to the same real-world object. Due to its inherently quadratic complexity, a series of techniques have been proposed to accelerate ER and allow it to scale to very large volumes of data. In this survey, we review a large number of works under two different but related frameworks: Blocking and Filtering. The former aims at reducing the computational cost of ER by restricting comparisons to those pairs that are more likely to match, while the latter involves specialized techniques for matching entities represented as strings or sets based on predetermined similarity thresholds. We also elaborate on hybrid approaches that combine different characteristics. For each framework we provide a comprehensive list of the relevant works, discussing them in the greater context. We conclude with the most promising directions for future work in the field.

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1 INTRODUCTION

Entity Resolution (ER) is the task of identifying different entity profiles that describe the same real-world object [27, 43]. It is a core task for Data Integration, applying to any kind of data, from the structured entities of relational databases [22] to the semi-structured entities of the Linked Open Data Cloud[1] [27, 36] and the unstructured entities that are automatically extracted from free text [135]. In essence, ER consists of two parts: (i) the *search step*, which determines the entities that will be compared, and (ii) the *decision step*, which compares the selected entities to determine whether they represent the same real-world object. The latter step is also called *Entity Matching* and involves time-consuming operations, called *pairwise comparisons*, which typically apply string similarity measures to pairs of entities, dominating the overall cost of ER [22, 27, 36].

In this survey, we focus on the search step, which is the crucial part of the process with respect to efficiency and scalability. Without it, ER suffers from a quadratic time complexity, i.e., $O(n^2)$, as every entity profile has to be compared with all others. To reduce its computational cost, numerous techniques have been proposed in the literature, belonging to two dominant frameworks: Blocking and Filtering. The former assumes generic entity profiles represented as attribute-value pairs and,

[1] https://lod-cloud.net

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without knowledge of the matching function (i.e., the decision step), it attempts to identify which entity pairs are likely to match in order to restrict comparisons only between them. The latter represents entities as strings or sets and assumes that two entities match if their similarity is above a specified threshold; based on this, it attempts to quickly discard pairs that are guaranteed to not match, executing comparisons only between the rest. Hence, these two frameworks share the same goal but operate under different settings and assumptions. Although some Blocking methods have used Filtering methods as a baseline for comparison (e.g., [139]), these two lines of research are largely independent from each other. By reviewing them together, this survey attempts to place them under a common context and shed more light to their relation, commonalities and differences. To the best of our knowledge, this is the first survey that jointly reviews these two frameworks.

The rise of Big Data poses new challenges for both Blocking and Filtering approaches [27, 36]: *Volume* requires techniques to scale to millions of entities, while *Variety* calls for techniques that can cope with an unprecedented schema heterogeneity. Both Blocking and Filtering address Volume primarily through paralellization. Existing techniques were adapted to split their workload into smaller chunks that are distributed across different processing units so that they are executed in parallel. This can be done either on a cluster (distributed methods), or using the modern multi-core and multi-socket hardware architectures. Variety, though, is addressed differently in each field. For Blocking, the schema-aware methods are replaced by schema-agnostic techniques, which disregard any schema information, creating blocks of very high recall but low precision. Additionally, a whole new category of methods, called *Block Processing*, intervenes between Blocking and Entity Matching in order to refine the original blocks so as to significantly increase precision at a negligible (if any) cost in recall. For Filtering, techniques that employ more relaxed matching criteria (e.g., fuzzy set matching or local string similarity join) are proposed, while the case of low similarity thresholds is also considered.

To the best of our knowledge, this is the first work to bring these works together and comprehensively cover all the aforementioned aspects. We formally define Blocking, Block Processing and Filtering, introducing a common terminology that facilitates their understanding. For each field, we propose a new taxonomy with categories that highlight the distinguishing characteristics of the corresponding methods. Based on these taxonomies, we provide a broad overview of every field, elucidating the functionality of the main techniques as well as the relations among them. As a result, established techniques are now seen in a different light (e.g., Canopy Clustering [86] may now be viewed as a Block Processing method, in the sense that it can be used to refine an existing set of blocks). We also elaborate on the parallelization methods for each field. Special care is taken to clarify the relation between Blocking and Filtering through the examination of hybrid methods and a novel, detailed qualitative analysis that stresses their commonalities and differences. We also investigate the ER tools that incorporate established efficiency techniques and propose a series of open challenges that constitute promising directions for future research.

Parts of the material included in this survey have been presented in tutorials at WWW 2014 [141], ICDE 2016 [111], ICDE 2017 [140], and WWW 2018 [112]. Among the past surveys that also cover efficiency ER techniques, [23] is restricted to the main schema-aware Blocking methods. The same blocking methods are experimentally evaluated in a schema-agnostic context in [100], while [116] extends their experimental analysis with Block Processing techniques. Other surveys [43] and textbooks [27, 36] provide a holistic overview of ER methods, merely examining the main Blocking and Block Processing techniques. Closer to our work is a recent survey on Blocking [99], but it offers a more limited coverage, while referring neither to parallelization nor to Filtering works. Recent surveys on string and set similarity joins also exist but have a much more limited scope. They focus exclusively on either centralized [60, 84, 167] or distributed approaches [46], with the purpose of experimental comparison, and without covering approximate techniques or methods

that allow for more relaxed matching criteria. Also, none of these surveys considers similarity joins in the broader context of ER.

The rest of the paper is structured as follows: Section 2 provides background knowledge on ER and its efficiency techniques, while Sections 3 and 4 delve into Blocking and Block Processing, respectively. Section 5 is devoted to Filtering, whereas Section 6 elaborates on works that combine Blocking with Filtering. Section 8 provides a high-level discussion of the surveyed works, and Section 7 enumerates the main ER tools that incorporate efficiency methods. Section 9 concludes the paper along with directions for future work.

2 PRELIMINARIES

At the core of ER lies the notion of *entity profile*, which constitutes a uniquely identified description of a real-world object in the form of attribute-value pairs. Assuming infinite sets of attribute names $\mathcal{N}$, attribute values $\mathcal{V}$, and unique identifiers $\mathcal{I}$, an entity profile is formally defined as follows [27, 108]:

Definition 1 (Entity Profile). *An* entity profile $\mathbf{e_{id}}$ *is a tuple* $\langle id, A_{id} \rangle$*, where* $id \in \mathcal{I}$ *is a unique identifier, and* A_{id} *is a set of attribute-value pairs* $\langle n, v \rangle$*, with* $n \in \mathcal{N}$ *and* $v \in (\mathcal{V} \cup \mathcal{I})$*. An* entity collection $\mathcal{E}$ *is a set of entity profiles.*

This model is simple, but flexible enough to accommodate a wide variety of both structured and semi-structured entity representations. For instance, nested attributes can be transformed into a flat set of attribute-value pairs, while links between two entities may be represented by assigning the id of one as the attribute value of the other.

Definition 2 (Entity Resolution). *We say that two entity profiles* e_i *and* e_j match*, if they refer to the same real-world entity, and we denote this by* $\mathbf{e_i \equiv e_j}$*. Matching entities are also referred to as* duplicates*. The task of Entity Resolution (ER) is to find all matching entities within an entity collection or across two or more entity collections.*

In particular, we distinguish between the following two cases:

(1) *Clean-Clean ER* receives as input two entity collections, $\mathcal{E}_1$ and $\mathcal{E}_2$, which are internally clean (i.e., duplicate-free), and produces as output the set of all pairs of matching entity profiles between them, i.e., $\mathcal{D}(\mathcal{E}_1, \mathcal{E}_2) = \{(e_i, e_j) : e_i \in \mathcal{E}_1,\ e_j \in \mathcal{E}_2,\ e_i \equiv e_j\}$.
(2) *Dirty ER* receives as input an entity collection $\mathcal{E}$ and produces as output the set of all pairs of matching entity profiles within $\mathcal{E}$, i.e., $\mathcal{D}(\mathcal{E}) = \{(e_i, e_j) : e_i \in \mathcal{E},\ e_j \in \mathcal{E},\ e_i \equiv e_j\}$.

In the context of structured (i.e., relational) data, Clean-Clean ER is also known as *Record Linkage*, whereas Dirty ER is also called *Deduplication* [22, 23]. ER involving three or more entity collections can be performed by either executing a sequence of pairwise Clean-Clean ER tasks (assuming that each collection is internally clean) or by performing Dirty ER over the union of all collections.

The performance of an ER workflow can be characterized by two main aspects: its *effectiveness* and its *efficiency*. The former refers to how many of the actual duplicates are detected, while the latter refers to the computational cost for detecting them. This cost is typically measured by the number of performed comparisons between entity profiles. We refer to this as *cardinality* and denote it by $||\mathcal{E}||$. The naive, brute-force approach performs all pairwise comparisons between entity profiles. For Clean-Clean ER, $||\mathcal{E}|| = |\mathcal{E}_1| \times |\mathcal{E}_2|$, while for Dirty ER $||\mathcal{E}|| = |\mathcal{E}| \cdot (|\mathcal{E}| - 1)/2$. In other words, the brute-force approach has quadratic complexity, which is not efficient and does not scale to large entity collections.

Blocking tackles this issue, providing a means to trade effectiveness for efficiency. The idea is to reduce the number of performed comparisons, while missing as few matches as possible. Ideally, one would compare only the pairs of duplicates, whose number grows *linearly* with the number of the input entity profiles [49, 140]. To this end, blocking clusters potentially matching entities

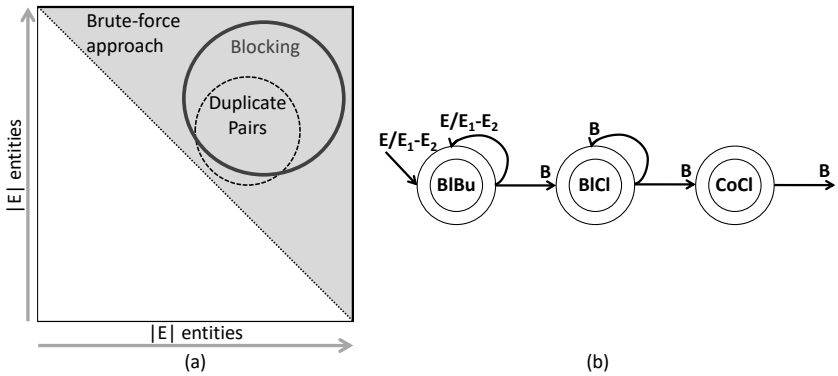

Fig. 1. (a) The relative computational cost for brute-force approach, blocking and ideal solution (duplicate pairs) over Dirty ER. (b) The internal functionality of Blocking modeled as a deterministic finite automaton with three states: Block Building (BlBu), Block Cleaning (BlCl) and Comparisons Cleaning (CoCl).

inside the same block and exclusively compares entity profiles within the same block. As shown in Figure 1(a), Blocking lies between the two extremes of the ideal and the brute-force solution, involving a *super-linear*, but *sub-quadratic* time complexity. In fact, the closer the two circles are, the better is the performance of Blocking: the larger the intersection of the two circles, the less duplicates are missed by Blocking, whereas the relative complement of the Duplicate Pairs in Blocking is analogous to the executed comparisons between non-matching entities. The diagram corresponds to Dirty ER, but can be easily generalized to Clean-Clean ER, as well.

In more detail, a blocking method employs a *blocking scheme*, which when applied to one or more entity collections yields a set of blocks $\mathcal{B}$, also referred to as *block collection*. The cardinality $||\mathcal{B}||$ of a block collection $\mathcal{B}$ denotes the number of comparisons entailed in $\mathcal{B}$, taking into consideration that only entity pairs within the same block are compared, i.e., $||\mathcal{B}|| = \sum_{b_i \in \mathcal{B}} ||b_i||$, where $||b_i||$ stands for the number of comparisons contained in block b_i. We denote the set of *detectable duplicates* in $\mathcal{B}$ as $\mathcal{D}(\mathcal{B})$, while $\mathcal{D}(\mathcal{E})$ denotes all existing duplicates. Since $\mathcal{B}$ reduces the number of performed comparisons, $\mathcal{D}(\mathcal{B}) \subseteq \mathcal{D}(\mathcal{E})$.

Assume that we have an *oracle*, i.e., a perfect matching function that, given a pair of entity profiles e_i and e_j, it can correctly determine whether they match or not. This is a common assumption in the literature [23, 36, 108, 109, 140] that allows for reasoning about the performance of blocking methods independently of matching methods. Using this oracle, a pair of matching entity profiles is detected as long as they share at least one block. There is a clear trade-off between the effectiveness and the efficiency of a blocking scheme [23, 36, 140]: the more comparisons are contained in the resulting block collection $\mathcal{B}$ (i.e., higher $||\mathcal{B}||$), the more duplicate pairs will be detected (i.e., higher $|\mathcal{D}(\mathcal{B})|$). In this way, effectiveness rises at the cost of lower efficiency, and vice versa. A blocking scheme is, therefore, considered successful as long as it achieves a good balance between these two competing objectives. This trade-off is commonly captured by the following three measures [16, 31, 89, 104]:

(1) *Pair Completeness (PC)* corresponds to *recall*, estimating the portion of the detectable duplicates with respect to the existing ones. Given a block collection $\mathcal{B}$, it is defined as: $PC(\mathcal{B}) = |\mathcal{D}(\mathcal{B})|/|\mathcal{D}(\mathcal{E})|$. *PC* takes values in the interval $[0, 1]$, with higher values indicating higher *effectiveness* of the blocking scheme.
(2) *Pairs Quality (PQ)* corresponds to *precision*, estimating the portion of executed comparisons that correspond to real duplicates. Given a block collection $\mathcal{B}$, it is defined as: $PQ(\mathcal{B}) = |\mathcal{D}(\mathcal{B})|/||\mathcal{B}||$. *PQ* takes values in the interval $[0, 1]$, with higher values indicating fewer comparisons between non-matching entities and higher *efficiency* of the blocking scheme.

(3) *Reduction Ratio (RR)* measures the reduction in the number of pairwise comparisons contained in a block collection $\mathcal{B}$ with respect to the brute-force approach. It is defined as: $RR(\mathcal{B}, \mathcal{E}) = 1 - ||\mathcal{B}||/||\mathcal{E}||$, thus taking values in the interval $[0, 1]$, with higher values denoting higher *efficiency* of the blocking scheme.

Note that *PC* provides an optimistic estimation of recall, presuming the existence of an oracle, while *PQ* provides a pessimistic estimation of precision, treating as false positives the redundant comparisons between duplicates (i.e., only the non-redundant duplicate pairs are true positives).

Based on the above, we can define Blocking as follows:

Definition 3 (Blocking). *Given an entity collection $\mathcal{E}$, Blocking clusters similar entities into a block collection $\mathcal{B}$ such that $PC(\mathcal{B})$, $PQ(\mathcal{B})$ and $RR(\mathcal{B}, \mathcal{E})$ are simultaneously maximized.*

This definition refers to Dirty ER, but can be easily extended to Clean-Clean ER. Simultaneously maximizing *PC*, *PQ* and *RR* necessitates that the enhancements in time efficiency do not affect the effectiveness of Blocking, i.e., they stem from the careful removal of comparisons between non-matching entities. Thus, conceptually, Blocking can be viewed as an optimization task. However, this implies that the real duplicate collection $\mathcal{D}(\mathcal{E})$ is known, which is actually what ER tries to compute. Hence, in practice, Blocking is typically treated as an engineering task that aims to provide an approximate solution for the data at hand.

A blocking-based ER workflow may comprise several stages. In addition to *Block Building* (BlBu), which applies a blocking scheme to produce a block collection $\mathcal{B}$ from the given entity collection(s), there is often a second, optional, stage called *Block Processing*. Its purpose is to refine $\mathcal{B}$ through additional optimizations that further reduce the number of performed comparisons. This may involve discarding *entire blocks* that primarily contain unnecessary comparisons, referred to as *Block Cleaning* (BlCl), and/or discarding *individual comparisons* within certain blocks, referred to as *Comparison Cleaning* (CoCl).

Block Building may be repeated several times on the same input in order to apply multiple blocking schemes to achieve a more robust performance in the context of highly noisy data. Similarly, Block Cleaning may be applied repeatedly, each time enforcing a different, complementary method to discard blocks. Comparison Cleaning can be performed only once, since it comprises competitive methods: they serve exactly the same purpose and once applied to a block collection, they alter it in such a way that turns all other methods inapplicable. On this basis, the internal functionality of a blocking workflow can be modelled as a deterministic finite automaton with three states, as shown in Figure 1(b), where each state corresponds to one of the blocking sub-tasks. We delve into Block Building in Section 3, while Block Processing is surveyed in Section 4.

3 BLOCK BUILDING

3.1 Definitions

Block Building receives as input one or more entity collections and produces as output a block collection $\mathcal{B}$. The process is guided by the *blocking scheme*, which determines how entity profiles are assigned to blocks. This scheme typically comprises two parts. Every entity profile is initially processed to extract *signatures* (e.g., tokens, q-grams), such that the similarity of signatures reflects the similarity of the corresponding entity profiles. Based on these signatures, every entity is subsequently mapped to one or more blocks. Let $\mathcal{P}(\mathcal{S})$ denote the power set of a set S, and let $\mathcal{K}$ denote the universe of signatures appearing in entity profiles. We formally define a blocking scheme as follows:

Definition 4 (Blocking Scheme). *Given an entity collection $\mathcal{E}$, a* blocking scheme *is a function $f_B : \mathcal{E} \rightarrow \mathcal{P}(\mathcal{B})$ that maps entity profiles to blocks. It is composed of two functions: (a) a* transformation

function $f_T : \mathcal{E} \rightarrow \mathcal{P}(\mathcal{K})$ *that maps an entity profile to a set of* signatures *(also called* blocking keys*), and (b) an* assignment *function* $f_A : \mathcal{K} \rightarrow \mathcal{P}(\mathcal{B})$ *that maps each signature to one or more blocks.*

This definition applies to Dirty ER, but can be easily extended to Clean-Clean ER. The set of comparisons in the resulting block collection $\mathcal{B}$ is called *comparison collection* and is denoted by $\mathcal{C}(\mathcal{B})$. Every comparison $c_{i,j} \in \mathcal{C}(\mathcal{B})$ belongs to one of the following types [108, 109]:

- *Matching comparison*, if e_i and e_j match.
- *Superfluous comparison*, if e_i and e_j do not match.
- *Redundant comparison*, if e_i and e_j have already been compared in a previous block.

We collectively call the last two types *unnecessary comparisons*, as their execution brings no gain.

Note that once the input entity profiles are mapped to blocks, an *inverted index* is constructed that associates the id of each entity profile with the ids of the blocks that contain it. For this reason, Block Building is also called *Indexing* in the literature [22, 23].

3.2 Taxonomy

To facilitate the understanding of the main methods for Block Building, we organize them into a novel taxonomy that consists of the following dimensions:

- *Key selection* distinguishes between *rule-based* and *ML-based* methods. The former methods assign entities to blocks based on rules derived from expert knowledge or mere heuristics. The latter methods require a training set and use Machine Learning (ML) techniques to learn the best blocking keys for mapping entities to blocks.
- *Schema-awareness* distinguishes between *schema-aware* and *schema-agnostic* methods. The former methods presume schema knowledge for mapping entities into blocks, i.e., they extract blocking keys from specific attributes which are considered to be more appropriate for matching (e.g., more distinctive or less noisy). The latter methods do not rely on schema knowledge, extracting blocking keys from all attributes.
- *Key type* distinguishes between *hash-* or *equality-based* methods, which map a pair of entities to the same block if they have a common key, and *sort-* or *similarity-based* methods, which map a pair of entities to the same block if they have a similar key. There exist also *hybrid* methods, which combine hash- with sort-based functionality.
- *Redundancy-awareness* distinguishes methods into three categories based on the relation between the blocks they create. *Redundancy-free* methods assign every entity to a single block, thus creating disjoint blocks. *Redundancy-positive* methods place every entity into multiple blocks, yielding overlapping blocks. The more blocks two entities share, the more similar their profiles are. The number of blocks shared by a pair of entities is thus proportional to the likelihood that they are matching. *Redundancy-neutral* methods create overlapping blocks, where most pairs of entities share the same number of blocks, or the degree of redundancy is arbitrary, having no implications.
- *Constraint-awareness* distinguishes blocking methods into *lazy*, which impose no constraints on the blocks they create, and *proactive*, which enforce one or more constraints on their blocks, such as maximum block size, or try to refine their comparisons, discarding unnecessary ones.
- *Matching-awareness* distinguishes between *static* methods, which are independent of the subsequent matching process, producing a static block collection, and *dynamic* methods, which intertwine Block Building with Entity Matching, updating or processing their blocks dynamically, as more duplicates are detected.
- *Domain* refers to the type of data a block building method is crafted for, which can be structured (e.g., relational), semi-structured (e.g., XML, RDF), or both (i.e., any data type).

Table 1 maps all methods discussed in Sections 3.3 and 3.4 to our taxonomy.

Table 1. Taxonomy of the Block Building methods discussed in Sections 3.3 and 3.4.

Method	Key type	Redundancy awareness	Constraint awareness	Matching awareness	Domain
Standard Blocking (SB) [45]	hash-based	redundancy-free	lazy	static	structured data
Suffix Arrays Blocking (SA) [3]	hash-based	redundancy-positive	proactive	static	structured data
Extended Suffix Arrays Blocking [23, 100]	hash-based	redundancy-positive	proactive	static	structured data
Improved Suffix Arrays Blocking [31]	hash-based	redundancy-positive	proactive	static	structured data
Q-Grams Blocking [23, 100]	hash-based	redundancy-positive	lazy	static	structured data
Extended Q-Grams Blocking [11, 23, 100]	hash-based	redundancy-positive	lazy	static	structured data
MFIBlocks [67]	hash-based	redundancy-positive	proactive	static	structured data
Sorted Neighborhood (SN) [56, 57, 120]	sort-based	redundancy-neutral	proactive	static	structured data
Extended Sorted Neighborhood [23]	sort-based	redundancy-neutral	lazy	static	structured & XML data
Incrementally Adaptive SN [165]	sort-based	redundancy-neutral	proactive	static	structured data
Accumulative Adaptive SN [165]	sort-based	redundancy-neutral	proactive	static	structured data
Duplicate Count Strategy (DCS) [39]	sort-based	redundancy-neutral	proactive	dynamic	structured data
DCS++ [39]	sort-based	redundancy-neutral	proactive	dynamic	structured data
Sorted Blocks [38]	hybrid	redundancy-neutral	lazy	static	structured data
Sorted Blocks New Partition [38]	hybrid	redundancy-neutral	proactive	static	structured data
Sorted Blocks Sliding Window [38]	hybrid	redundancy-neutral	proactive	static	structured data
(a) Rule-based, schema-aware methods.					
ApproxRBSetCover [16]	hash-based	redundancy-positive	lazy	static	structured data
ApproxDNF [16]	hash-based	redundancy-positive	lazy	static	structured data
Blocking Scheme Learner (BSL) [89]	hash-based	redundancy-positive	lazy	static	structured data
Conjunction Learner [19] (semi-supervised)	hash-based	redundancy-positive	lazy	static	structured data
BGP [44]	hash-based	redundancy-positive	lazy	static	structured data
CBlock [133]	hash-based	redundancy-positive	proactive	static	structured data
DNF Learner [50]	hash-based	redundancy-positive	lazy	dynamic	structured data
FisherDisjunctive [64] (unsupervised)	hash-based	redundancy-positive	lazy	static	structured data
(b) ML-based (supervised), schema-aware methods.					
Token Blocking (TB) [104]	hash-based	redundancy-positive	lazy	static	any data type
Attribute Clustering Blocking [108]	hash-based	redundancy-positive	lazy	static	any data type
RDFKeyLearner [139]	hash-based	redundancy-positive	lazy	static	any data type
Prefix-Infix(-Suffix) Blocking [107]	hash-based	redundancy-positive	lazy	static	RDF data
TYPiMatch [81]	hash-based	redundancy-positive	lazy	static	any data type
Semantic Graph Blocking [97]	-	redundancy-neutral	proactive	static	any data with relations
(c) Rule-based, schema-agnostic methods.					
Hetero [65]	hash-based	redundancy-positive	lazy	static	semi-structured data
Extended DNF BSL [66]	hash-based	redundancy-positive	lazy	static	semi-structured data
(d) ML-based (unsupervised), schema-agnostic methods.					

3.3 Schema-aware Block Building

Schema-aware methods assume that the input entity profiles adhere to a known schema and, based on this schema and respective domain knowledge, one can select those attributes that are most suitable for resolving entities. We distinguish between rule-based methods, reviewed in Section 3.3.1, and ML-based methods, reviewed in Section 3.3.2.

3.3.1 Rule-based Methods. The family tree of the methods in this category is shown in Figure 2(a); a parent-child edge implies that the latter method improves upon the former one. Below, we elaborate on these methods based on their key type.

Hash-based Methods. The seminal method *Standard Blocking* (SB) [45] belongs to this category. SB applies the simplest form of blocking: an expert selects the most suitable attributes, and a transformation function concatenates (parts of) their values to form blocking keys. For every distinct key, a block is created containing all corresponding entities. In short, SB operates as a hash function, conveying two main advantages: (i) it yields disjoint blocks, which contain no redundant comparisons, and (ii) it has a linear time complexity, $O(|E|)$. On the flip side, *PC* depends on the noise in the blocking keys, as the slightest difference in the blocking keys of duplicates places them in different blocks, or no blocks at all. Additionally, SB is a lazy method that imposes no limit on the size of the resulting blocks. Depending on the frequency distribution of attribute values, it may yield large blocks with many superfluous comparisons, i.e., low *PQ* and *RR*.

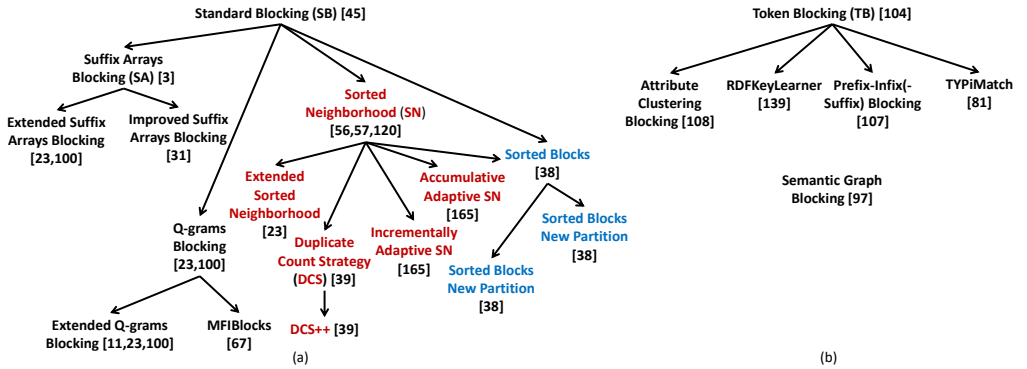

Fig. 2. The genealogy trees of rule-based (a) schema-aware and (b) schema-agnostic Block Building techniques. Hybrid, hash- and sort-based methods are marked in blue, black and red, respectively.

To address these issues, *Suffix Arrays Blocking* (SA) [3] converts each blocking key of SB into the list of its suffixes that are longer than a predetermined minimum length l_{min}. Then, it defines a block for every suffix that does not exceed a predetermined frequency threshold b_{max}, which specifies the maximum block size. This proactive functionality is necessary, as very frequent suffixes result in large blocks that are dominated by unnecessary comparisons. E.g., the suffix “ing" can be derived from any English verb that is a blocking key, thus designating no semantic similarity.

SA is a popular technique that has spawned a whole family of blocking methods, due to two major advantages [31]: (i) It is very efficient, as it results in a small but relevant set of candidate matches, and it has low time complexity, $O(|E|\cdot log|E|)$ [4]. (ii) It is very effective, due to the robustness to the noise at the beginning of blocking keys and the high levels of redundancy (i.e., it places every entity into multiple blocks). On the downside, SA does not handle noise at the end of SB blocking keys. E.g., two duplicates with SB keys “JohnSnith" and “JohnSmith" have no common suffix if l_{min}=4, while for l_{min}=3, they co-occur in a block only if the frequency of “ith" is lower than b_{max}.

This problem is addressed by *Extended Suffix Arrays Blocking* [23, 100], which supports errors at the end of SB keys by using all their substrings with more than l_{min} characters. This raises *PC* at the cost of a higher number of comparisons, which inevitably lowers both *PQ* and *RR*.

A more advanced solution is provided by *Improved Suffix Arrays Blocking* (ISA) [31], which employs the same blocking keys as SA, but sorts them in alphabetical order, comparing the consecutive ones with a string similarity measure. If the similarity of two suffixes exceeds a predetermined threshold, the corresponding blocks are merged (note that the frequency threshold b_{max} is not applied after the merge of two suffixes). This allows for detecting duplicates even when there is noise at the end of SB keys, or their sole common key is too frequent. For example, ISA detects the high string similarity of the keys “JohnSnith" and “JohnSmith", placing the corresponding entities into the same block. It is theoretically proven that ISA results in a *PC* greater or equal to that of SA, though at the cost of more comparisons and, thus, lower *PQ* and *RR*.

In the context of evolving datasets, where the number of entities increases, the suffix index of ISA, which resides on the disk, is queried for every new entity in order to allocate it to the right blocks. Inevitably, this results in increased disk I/O. To improve its time efficiency, a memory-based Bloom filter is combined with ISA in [32], increasing the time efficiency to a significant extent.

Another family of hash-based methods is inspired from the similarity join technique presented in [53]. The simplest method in this family is *Q-grams Blocking* [23, 100]. Its transformation function converts the blocking keys of SB into sub-sequences of q characters (*q-grams*) and defines a block for every distinct q-gram. For example, for q=3, the key *france* is transformed into the trigrams *fra*,

ran, *anc*, *nce*. This approach is more resilient to noise than SB, yielding higher *PC*, but results in more and larger blocks, thus decreasing both *PQ* and *RR*.

To improve the balance between *PC* and *PQ*/*RR*, *Extended Q-Grams Blocking* [11, 23, 100] uses combinations of q-grams, instead of individual q-grams. Its transformation function concatenates at least l q-grams, where $l = max(1, \lfloor k \cdot t \rfloor)$, with k denoting the number of q-grams and $t \in [0, 1)$ standing for a user-defined threshold. The larger t is, the larger l gets, yielding less keys from the k q-grams. For $T = 0.9$ and q=3, the key *france* is transformed into the following four signatures (k=4 and l=3): [*fra*, *ran*, *anc*, *nce*], [*fra*, *ran*, *anc*], [*fra*, *anc*, *nce*], [*ran*, *anc*, *nce*]. In this way, q-gram-based blocking keys become more distinctive, decreasing the number and the cardinality of the resulting blocks, thus raising *PQ* and *RR* at a limited, if any, cost in *PC*.

A more advanced q-gram-based approach is *MFIBlocks* [67]. Its transformation function concatenates keys of Q-Grams Blocking into itemsets and uses a maximal frequent itemset algorithm for defining new blocking keys. Only the most frequent itemsets that exceed a predetermined support threshold are treated as blocking keys. This reduces significantly the number of blocks and matching candidates (i.e., high *PQ* and *RR*), but it may come at the cost of missed matches (lower *PC*) in case the resulting blocking keys are very restrictive for matches with noisy descriptions.

Sort-based Methods. The cornerstone method of this category is *Sorted Neighborhood* (SN) [56], which operates as follows: first, it sorts all blocking keys in alphabetical order and arranges the associated entities accordingly. Subsequently, a window of fixed size w slides over the sorted list of entities and compares the entity at the last position with all other entities placed within the same window. The underlying assumption is that the closer the blocking keys of two entities are in the lexicographical order, the more likely they are to be matching. Originally crafted for relational data, SN was extended to hierarchical/XML data based on user-defined blocking keys in [120].

SN has three major advantages [23]: (i) it has low time complexity, $O(|E| \cdot log|E|)$, (ii) it results in linear ER complexity, $O(w \cdot |E|)$, and (iii) it is robust to noise, supporting errors at the end of blocking keys. On the flip side, it may place two entities in the same block even if their keys are dissimilar (e.g., the keys "alphabet" and "apple" are considered similar if no other key intervenes between them lexicographically). Its performance also depends heavily on the window size w. Configuring w is quite difficult, especially in Dirty ER, where the matching entities form clusters of varying size [23, 38]; a small w leads to high *PQ* and *RR* but low *PC* and vice versa for a large w.

To ameliorate the effect of the fixed window size, various techniques have been proposed in the literature. The typical solution is the multi-pass version of the algorithm in [57], i.e., applying the core algorithm multiple times, using a different transformation function in each iteration. In this way, more matches can be identified, even if the window is set to low size. Another solution is the *Extended Sorted Neighborhood* [23, 100], which slides a window of fixed size over the sorted list of blocking keys - rather than that of the entities. In this case, variations in the window size have a larger impact on *PQ* and *RR*, affecting the portion of unnecessary comparisons, rather than *PC*. More advanced strategies adapt the window size dynamically in order to optimize the balance between *PC* and *PQ*/*RR*. They are grouped into the following three main categories, depending on the criterion for moving the bottom and the top boundaries of the window [80]:

1) *Key similarity strategy.* The window size increases if the similarity of the blocking keys exceeds a predetermined threshold, which indicates that more similar entities should be expected [80].

2) *Entity similarity strategy.* The window size relies on the similarity of the entities within the current window. *Incrementally Adaptive SN* [165] increments the window size as long as the distance of the first and the last element in the current window is smaller than a predetermined threshold. The actual increase of the window size depends on its current value and the selected threshold. *Accumulative Adaptive SN* [165] creates windows with a single overlapping entity and exploits transitivity to group multiple adjacent windows into the same block, as long as the last

entity of one window is a potential duplicate of the last entity in the next adjacent window. After expanding the window, both algorithms apply a retrenchment phase that decreases the window size until all entities within the block are potential duplicates.

3) *Dynamic strategy.* The window size fluctuates according to the number of identified duplicates, based on the assumption that the more duplicates are found within a window, the more are expected to be found by increasing the current window. *Duplicate Count Strategy* (DCS) [39] defines a window of fixed size w for every entity of SN's sorted list. All comparisons are executed within a window and the ratio d/c is estimated, where d denotes the newly detected duplicates and c the executed comparisons. The window size is then incremented by one position at a time as long as $d/c \geq \phi$, where $\phi \in (0, 1)$ is a predetermined threshold that expresses the average number of duplicates per comparison. DCS++ [39] improves DCS by increasing the window size with the next $w - 1$ entities, even if the new ratio becomes lower than ϕ. It also exploits transitive closure in order to skip some windows, saving part of the comparisons. It is theoretically proven that with an appropriate value for ϕ, DCS++ misses no matches, while being at least as efficient as SN.

Hybrid methods. *Sorted Blocks* [38] combines the benefits of SB's hash-based with SN's sort-based functionality. First, it sorts all blocking keys and their corresponding entities in lexicographical order, just like SN. Then, it partitions the sorted entities into disjoint blocks, just like SB, using a prefix of the blocking keys. Next, all pairwise comparisons are executed within each block. To avoid missing any matches, an overlap parameter o is used to define a sliding window of fixed size. This window starts with the o last entities in the current block together with the first entity of the next block. Then, it slides by one position at a time until reaching the o^{th} entity of the next block. Inside the window, all pairwise comparisons between entities from different blocks are executed.

Sorted Blocks is a lazy approach that does not restrict the size of its blocks. Thus, it may result in large blocks that dominate its processing time. To address this, two proactive variants set a limit on the maximum block size. *Sorted Blocks New Partition* [38] simply creates a new block when the maximum block size is reached for a specific (prefix of) blocking key; the overlap between the blocks ensures that every entity is compared with its predecessors and successors in the sorting order. *Sorted Blocks Sliding Window* [38] avoids executing all comparisons within a block with size larger than the upper limit; instead, it slides a window of size equal to the maximum block size over the entities of the current block. Sorted Blocks New Partition outperforms all other algorithms, including SB and SN. However, Sorted Blocks and its variants include more parameters than SN, involving a more complex configuration.

3.3.2 ML-based Methods. We distinguish these methods into supervised and unsupervised ones. The former rely on a labelled dataset that includes pairs of matching and non-matching entities, called *positive* and *negative instances*, respectively. This dataset is used to learn *blocking predicates*, i.e., combinations of an attribute name and a transformation function (e.g., $\{title, First3Characters\}$). Entities sharing the same output for a particular blocking predicate are considered candidate matches (i.e., hash-based functionality). Disjunctions of conjunctions of predicates, called *supervised blocking schemes*, are learned by optimizing an objective function. To tackle the lack or scarcity of labelled datasets, unsupervised methods have been proposed, as well.

Supervised Methods. One of the first methods of this kind is *ApproxRBSetCover* [16], which learns disjunctive supervised blocking schemes by solving a standard weighted set cover problem. The cover is iteratively constructed by adding in each turn the blocking predicate that maximizes the ratio of the previously uncovered positive pairs over the covered negative pairs. Note that this is a "soft cover", since some positive instances may remain uncovered.

ApproxDNF [16] alters ApproxRBSetCover so that it learns supervised blocking schemes in Disjunctive Normal Form (DNF). Instead of individual predicates, each turn greedily learns a conjunction of up to k predicates that maximizes the ratio of positive and negative covered instances.

A similar approach is *Blocking Scheme Learner* (BSL) [89]. Based on an adaptation of the Sequential Covering Algorithm, it learns supervised blocking schemes that maximize *RR*, while maintaining *PC* above a predetermined threshold. Its output is a disjunction of conjunctions of blocking predicates. BSL is typically faster than *ApproxRBSetCover* and *ApproxDNF*, as it exclusively considers positive instances, thus requiring a smaller training set.

BSL is improved by *Conjunction Learner* [19], which minimizes the candidate matches not only in the labelled, but also in the *unlabelled* data, while maintaining high *PC*. The effect of the unlabelled data is determined through a weight, whose maximum value (1) indicates that they are equally important as the labelled ones, while its minimum value (0) disregards unlabelled data completely, falling back to BSL. This semi-supervised approach requires every supervised blocking scheme to be applied to the large set of unlabelled data, which is impractical. For high scalability, a random sample of the unlabelled data is used in practice.

On another line of research, *Blocking based on Genetic Programming* (BGP) [44] employs a tree representation of supervised blocking schemes, where every leaf node corresponds to a blocking predicate. In every turn, a set of genetic programming operators, such as copy, mutation and crossover, are applied to the initial, random set of supervised blocking schemes. A fitness function is then used to infer their performance from the harmonic mean of *PC* and *RR*. The best schemes identified through this search process are returned as output. Yet, a major disadvantage of BGP is the large number of internal parameters (e.g., probability of mutation), which are hard to fine-tune.

Another approach using a tree representation is *CBLOCK* [133]. In this case, every edge is annotated with a hash (i.e., transformation) function and every node n_i comprises the set of entities that result after applying all hash functions from the root to n_i. *CBLOCK* is the only proactive ML-based method, restricting the maximum size of its blocks. Every node that exceeds this limit is split into smaller, disjoint blocks through a greedy algorithm that picks the best hash function based on the resulting *PC*. To minimize the human effort, a drill down approach is proposed for bootstrapping. *CBLOCK* is also the only ML-based method suitable for the MapReduce framework. Every entity runs through the learned tree and is directed to the machine corresponding to its leaf node.

Finally, *DNF Learner* [50] integrates the learning of supervised blocking schemes with entity matching to address the scarcity of labelled instances. A matching algorithm is applied to a sample of entity pairs to automatically create a labelled dataset. Then, the learning of supervised blocking schemes is cast as a DNF learning problem. To scale it to the exponential search space of possible schemes, their complexity is restricted to manageable levels (e.g., they comprise at most k predicates).

Unsupervised Methods. *FisherDisjunctive* [64] is an unsupervised algorithm that uses a weak training set generated by leveraging the TF-IDF similarity of two entities. Pairs with very low (high) values are considered as negative (positive) instances. A boolean feature vector is then associated with every labelled instance. The discovery of DNF supervised blocking schemes is then cast as a Fisher feature selection problem.

3.4 Schema-agnostic Block Building

These methods are crafted for semi-structured data, i.e., highly heterogeneous and loosely structured entity profiles, such as those stemming from the Web of Data [104, 107, 108]. They inherently support noise both in attribute values and names. They make no assumptions about schema knowledge, disregarding completely attribute names and extracting blocks from all attribute values.

Rule-based Methods. The family tree of this category appears in Figure 2(b). The cornerstone approach is *Token Blocking* (TB) [104]. Assuming that duplicates share at least one common token,

its transformation function extracts all tokens from all attribute values of every entity. A block b_t is then defined for every distinct token t, essentially building an inverted index of entities. Hence, two entities co-occur in block b_t if they share token t in their values, regardless of the associated attribute names. This approach yields very high *PC*, at the cost of very low *PQ* and *RR*.

To improve TB, *Attribute Clustering Blocking* [108] requires the common tokens of two entities to appear in *syntactically similar attributes*. These are attribute names that correspond to 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 input entity collection(s). Each attribute is connected to its most similar attribute and the transitive closure of the connected attributes forms disjoint clusters. A block $b_{k,t}$ is then defined for every token t in the values of the attributes belonging to cluster k. Compared to TB, this results in a much larger number of smaller, redudancy-positive blocks, significantly raising *PQ* at a minor cost in *PC*.

Similarly, *RDFKeyLearner* [139] applies TB independently to the values of specific attributes, which are selected through the following process: all attribute names are initially extracted from the input entity collection(s). Each attribute is then associated with a *discriminability* score, which amounts to the portion of its distinct values over all values in the given dataset. If this is lower than a predetermined threshold, the attribute is ignored due to limited diversity - too many entities have the same value(s). For each attribute with high discriminability, its *coverage* is estimated, i.e., the portion of entities that contain it. The harmonic mean of discriminability and coverage is then computed for all valid attributes and the one with the maximum score is selected for providing blocking keys as long as its score exceeds another predetermined threshold. If not, the attribute with the highest discriminability is combined with all other attributes and the process is repeated.

A different approach is followed by *Prefix-Infix(-Suffix) Blocking* [107], 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 [102]. For example, in the URI `https://en.wikipedia.org/wiki/France#History`, the prefix is `https://en.wikipedia.org/wiki`, the infix is `France` and the suffix is `History`. In this context, this method uses as blocking keys the (URI) infixes along with the tokens in the other attribute values.

Another approach improving TB is *TYPiMatch* [81]. First, it automatically detects the entity types in the input entity collection(s). 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. In the end, it applies TB independently to the profiles of each entity type. However, the detection of entity types is time-consuming and too sensitive to its parameter configuration [116].

Finally, *Semantic Graph Blocking* [97] is based exclusively on the relations between entities, be it foreign keys in a database or links in RDF data. It completely disregards attribute values, building a collaborative graph, where every node corresponds to an entity and every edge connects two associated entities. For instance, the collaborative graph for a bibliographic data collection can be formed by mapping every author to a node and adding edges between co-authors. In this context, blocks are created in the following way: for each node n_i, a new block b_i is formed, containing all nodes connected with n_i through a path, provided that the path length or the block size do not exceed a predetermined limit. This makes it the only proactive schema-agnostic method.

ML-based Methods. An unsupervised approach for semi-structured data is described in [65], called *Hetero*. First, it converts the input data into heterogeneous structured datasets using property tables. Then, it maps every entity to a normalized TF vector, and applies an adapted Hungarian algorithm with linear scalability to produce positive and negative feature vectors. Finally, it applies

FisherDisjunctive [64] with bagging to achieve robust performance, even as the training sets remain constant and the data grow in size. A similar algorithm, called *Extended DNF BSL*, is proposed in [66], combining an established instance-based schema matcher with weighted set covering to learn DNF supervised blocking schemes with at most k predicates.

3.5 Parallelization Approaches

Several parallel adaptations of the above methods have been proposed in the literature, scaling them to massive entity collections without altering their functionality. Most of them rely on the *MapReduce framework* [33], which offers fault-tolerant, optimized execution for applications distributed across a set of independent nodes. In a nutshell, MapReduce splits the input data 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 a MapReduce `job`, with complex procedures typically involving multiple jobs.

Schema-aware methods. The hash-based, rule-based methods are adapted to MapReduce in a straightforward way. The `map` phase implements the transformation function(s), emitting `(key, entity_id)` pairs for each entity. Every reducer creates a block b_t, aggregating all entities with t in their blocking keys. Such implementations for various methods are provided by Dedoop [69].

Among the sort-based methods, Sorted Neighborhood is adapted to MapReduce in [71]. 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. Thus, the `map` function is extended to replicate those entities, forwarding them to the respective reduce task and its successor. This approach can be used as a template for the other sort-based methods.

DCS and DCS++ are adapted to the MapReduce framework in [88], using three jobs. The first one sorts the originally unordered entities of the data partition assigned to each mapper according to the selected blocking keys. It also selects the boundary pairs of the sorted partitions. The second job generates the Partition Allocation Matrix, which specifies the sorted partitions to be replicated, while the third job performs DCS++ locally, to the data assigned to every reducer.

Schema-agnostic methods. Given that Token Blocking builds an inverted index that associates every token with all entities containing it in their attribute values, a single MapReduce job is required for its parallelization [27, 42]. 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 directed to the same `reducer`, which forms a new block.

For Attribute Clustering Blocking, four MapReduce jobs are required [27, 42]. The first assembles all values that correspond to each attribute name. The second computes the similarities between all attribute pairs, even if they are placed in different data partitions. The third connects every attribute name to its most similar one. The fourth associates every attribute name with a cluster id and adapts the MapReduce-based Token Blocking such that the `map` function emits pairs of the form $(k.t, i)$, where k is the cluster id of e_i's attribute name that contains token t.

Finally, the parallelization of Prefix-Infix(-Suffix) Blocking involves three MapReduce jobs [27, 42]. The first parallelizes the algorithm that extracts the prefixes from a set of URIs [102]. The second does the same for the extraction of suffixes from a set of URIs. The third involves two different mappers that run in parallel: (i) the mapper of Token Blocking, which applies to the literal values and (ii) an infix mapper that emits a pair (j, e_i) for every infix j that is extracted from e_i's 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 are placed in the same block.

Load Balancing. This is a crucial aspect of MapReduce, as it distributes evenly the overall workload among the available nodes, avoiding potential bottlenecks. To this end, the following methods distribute the computational cost of processing a block collection $\mathcal{B}$ (i.e., the time required for executing the comparisons in $\mathcal{B}$), rather than the cost of building the blocks.

BlockSplit [70] partitions large 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 an additional network and I/O overhead for the entities of the sub-blocks and may still lead to unbalanced workload, due to sub-blocks of different size.

To overcome this, *PairRange* [70] splits evenly the comparisons in a set of blocks into a predefined number of partitions. It involves a single MapReduce job with a mapper that associates every entity e_i in block b_k with the output key $p.k.i$, where p denotes the index of the comparison range, i.e., the partition id. Then, the reducer groups together all entities that have the same p and block id, reproducing the comparisons corresponding to the partition id.

The space requirements of these two algorithms are improved in [166], which minimizes their memory consumption by adapting them so that they work with sketches.

Finally, *Dis-Dedup* [28] is the only method that takes into account both the computational and the communication cost (e.g., network transfer time, local disk I/O time). Dis-Dedup considers all possible cases, from disjoint blocks produced by a single blocking technique to overlapping blocks derived from multiple techniques. It also provides strong theoretical guarantees that the overall maximum cost per reducer is within a small constant factor from the lower bounds.

4 BLOCK PROCESSING

Block Processing receives as input an existing block collection $\mathcal{B}$ and produces as output a new block collection $\mathcal{B}'$ that improves the balance between effectiveness and time efficiency, i.e., $PQ(B) \ll PQ(B')$, $RR(B', B) \gg 0$, while $PC(B) \sim PC(B')$. We distinguish Block Processing methods into *Block Cleaning* ones, which operate at the coarse level of entire blocks, deciding which ones will be retained or modified, and *Comparison Cleaning* ones, which operate at the finer level of individual comparisons, discarding those deemed as unnecessary.

4.1 Block Cleaning

We classify Block Cleaning methods into two categories: (i) *static*, which are independent of matching results, and (ii) *dynamic*, which are interwoven with the matching process.

Static Methods. *Block Purging* [107, 108] discards extremely large blocks, since they contain few or no unique matches (i.e., matches that share no other block). These blocks are typically produced by lazy schema-agnostic techniques and correspond to stop words. By discarding the blocks that exceed an upper limit on the block cardinality [108] or size [107], Block Purging boosts PQ and RR by orders of magnitude, while exhibiting a low computational cost and a negligible impact on PC.

Block Filtering [115] also relies on the idea that the larger a block is, the less likely it is to contain unique duplicates. Unlike Block Purging, though, it is applied independently to the blocks of every entity, assuming that each block has a different importance for every entity it contains. Block Filtering retains every entity in r% of its smallest blocks, with r typically set to 80% when applied after Block Purging [115] and to 50% when applied right after Block Building [116].

On a different line of research, *Size-based Block Clustering* [47] applies hierarchical clustering to transform a set of blocks into a new one where all block sizes lie within a specified size range. It merges recursively small blocks that correspond to similar blocking keys, while splitting large blocks into smaller ones. A penalty function controls the trade-off between block quality and block size. A similar approach is the MapReduce-based dynamic blocking algorithm in [87], which splits

large blocks into sub-blocks. Another similar, but ML-based approach is *Rollup Canopies* [133]. Given a training set with positive examples, a limit on the maximum block size and a set of disjoint blocks, it employs a greedy algorithm to merge pairs of small blocks, thus increasing *PC*.

Finally, [126] generalizes Meta-blocking (see Section 4.2) to Multi-source Entity Resolution, where the input comprises at least three clean but overlapping entity collections. A graph is constructed, with the nodes corresponding to blocks and the edges connecting blocks whose blocking keys are more similar than a predetermined threshold. The edges are weighted using various functions and all pairs of blocks are then processed in descending edge weight in an effort to maximize the redundant and superfluous comparisons that are skipped.

Dynamic Methods. Assuming that matching is performed by an oracle, these methods exploit the evidence provided by the detected matches in order to adjust the processing of the input block collection $\mathcal{B}$ on-the-fly, attempting to optimize its effectiveness and/or time efficiency.

Iterative Blocking [161] merges any new pair of detected duplicates, e_i and e_j, into a new entity, $e_{i,j}$, and replaces both e_i and e_j with $e_{i,j}$ in all blocks that contain them. If some of these blocks have already been processed, they are reprocessed so that the new entity $e_{i,j}$ is compared with all other entities. The reason is that the new content in $e_{i,j}$ typically results in different similarity values that are capable of identifying previously missed matches. In this way, *PC* rises significantly, while *PQ* and *RR* increase by saving redundant comparisons between matched entities. The ER process terminates when all blocks have been processed without finding new duplicates.

Iterative Blocking applies exclusively to Dirty ER. In Clean-Clean ER, there is no need for merging two matching entities, as no more duplicates may be associated with them, due to the 1-1 restriction. Yet, the detected duplicates should be propagated so as to save the superfluous comparisons with all other entities co-occuring with them in the subsequently processed blocks. The goal is, therefore, to detect all matches as early as possible, thus maximizing the number of saved superfluous comparisons. To this end, *Block Scheduling* aims to optimize the processing order for a collection of bilateral blocks in a non-iterative way. At its core lies the probability $p_i(d)$ that a block b_i contains a pair of duplicates, which is set inversely proportional to block cardinality, i.e., $p_i(d) = 1/||b_i||$ [138], or to the minimum size of the inner block, i.e., $p_i(d) = 1/min|b_{i,1}|, |b_{i,2}|$ [104]. Thus, Block Scheduling orders blocks in ascending order of cardinality or minimum block sizes. The former principle also applies to Iterative Blocking, which does not specify the exact block processing order, even though it significantly affects the resulting performance [116].

Block Pruning [104] extends Block Scheduling by exploiting the decreasing density of detected matches in its block processing order (i.e., the later a block is processed, the less likely it is to contain unique duplicates). Using the same ratio as DCS and DCS++ [39] (see Section 3.3.1), it estimates the average number of executed comparisons for detecting a new pair of duplicates. The ratio is updated after processing the latest block and, as soon as it falls below a specific threshold, Block Pruning terminates the ER process, discarding the remaining comparisons as unnecessary.

4.2 Comparison Cleaning

Rule-based Methods. Figure 3 illustrates the family tree of the methods belonging to this category, with every a parent-child edge indicating that the latter method improves upon the former one. The cornerstone method is *Comparison Propagation* [105], which propagates all executed comparisons to the subsequently processed blocks. In this manner, it eliminates all redundant comparisons in a given block collection without losing any pair of duplicates, thus raising *PQ* and *RR* at no cost in *PC*. This task seems trivial for small datasets, where all executed comparisons can be *explicitly* hashed in memory, but this naive solution fails to scale to large datasets with billions of comparisons. Instead, Comparison Propagation builds an *Entity Index*, an inverted index that points from entity ids to block ids. Then, it compares two entities e_i and e_j in block b_k only if k is their least common

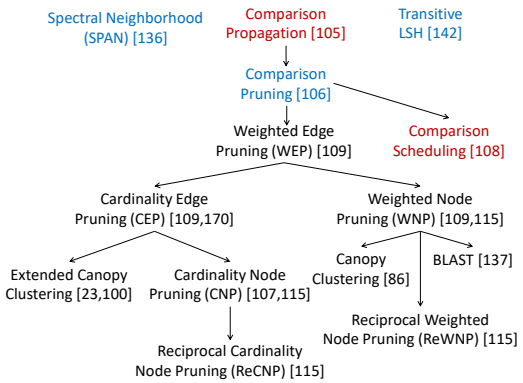

Fig. 3. The genealogy tree of rule-based Comparison Cleaning methods. Methods in black conform to the Meta-blocking framework in Figure 4, methods in blue are Meta-blocking techniques following a (partially) different approach and methods in red are not part of the Meta-blocking framework.

block id, propagating the executed comparisons *implicitly*. For example, consider the blocks in Figure 4(a) and the respective Entity Index in Figure 4(b); the least common block id of e_1 and e_3 is 2 and, thus, they are compared in b_2, but neither in b_4 nor in b_5.

Given a redundancy-positive block collection, the Entity Index allows for identifying the blocks shared by a pair of co-occurring entities. This allows for weighting all pairwise comparisons in proportion to the matching likelihood of the corresponding entities, based on the principle that the more blocks two entities share, the more likely they are to be matching. This gives rises to a family of *Meta-blocking* techniques [109, 115, 137] that go beyond Comparison Propagation by discarding not only all redundant comparisons, but also the vast majority of the superfluous ones.

The first relevant method is *Comparison Pruning* [106]. It *a-priori* decides whether two entities are matching or not by computing the Jaccard co-efficient of their lists of blocks. This is compared with a conservative threshold that depends on the average number of blocks per entity. Comparisons weighted below this threshold are pruned, as they designate an unlikely match.

Meta-blocking was formalized into a more principled approach in [109]. The given redundancy-positive block collection $\mathcal{B}$ is converted into a blocking graph G_B, where the nodes correspond to entities and the edges connect every pair of co-occurring entities - see Figure 4(c). Given that no parallel edges are allowed, all redundant comparisons are discarded by definition. The edges are then weighted proportionately to the likelihood that the adjacent entities are matching. In Figure 4(d), the edge weights indicate the number of common blocks. Edges with low weights are pruned, because they correspond to superfluous comparisons. In Figure 4(e), all edges with a weight lower than the average one are discarded. The resulting pruned blocking graph $G_{B'}$ is transformed into a restructured block collection $\mathcal{B}'$ by forming one block for every retained edge - see Figure 4(f). As a result, $\mathcal{B}'$ exhibits a much higher efficiency, $PQ(B') \gg PQ(B)$ and $RR(B', B) \gg 0$, for similar effectiveness, $PC(B') \sim PC(B)$; in our example, the 12 comparisons in the input blocks of Figure 4(a) are reduced to the two matching comparisons in the output blocks in Figure 4(f).

Four main pruning algorithms exist: (i) *Weighted Edge Pruning* (WEP) removes all edges that do not exceed a specific threshold, e.g., the average edge weight [109]; (ii) *Cardinality Edge Pruning* (CEP) retains the globally K top weighted edges, where K can be static [109] or dynamic [170], determined as the number of top-weighted edges with a cumulative weight higher than a specific portion of the total sum of edge weights; (iii) *Weighted Node Pruning* (WNP) retains in each node neighborhood the entities that exceed a local threshold, which may be the average edge weight of each neighborhood [109], or the average of the maximum weights in the two adjacent node neighborhoods, as in *BLAST* [137]; (iv) *Cardinality Node Pruning* (CNP) retains the top-k weighted

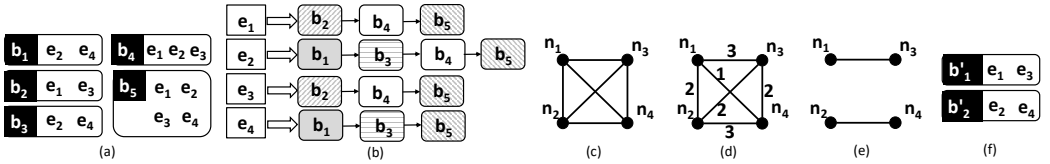

Fig. 4. (a) A block collection B with $e_1 \equiv e_3$ and $e_2 \equiv e_4$, (b) the corresponding Entity Index, (c) the corresponding blocking graph G_B, (d) the weighted G_B, (e) the pruned G_B, and (f) the new block collection B'.

edges in each node neighborhood [109]. For WNP and CNP, special care is taken to avoid redundant comparisons in the restructured blocks, while *Reciprocal WNP* and *CNP* [115] apply an aggressive pruning that retains edges satisfying the pruning criteria in both adjacent node neighborhoods. WNP and WEP are combined through the weighted sum of their thresholds in [9].

Note that the notion of Meta-blocking covers established methods that were previously considered as Block Building ones. Given that Block Building is equivalent to indexing [23], any method based on indexes is in fact a Meta-blocking technique. This applies to *Transitive LSH* [142], which converts the blocks extracted from LSH into an unweighted blocking graph. A community detection algorithm such as [29] is then applied to partition the graph nodes into disjoint clusters, which will become the new blocks. The process finishes when the size of the largest cluster is lower than a predetermined threshold. This approach can be applied to any block building method, not just LSH.

Most importantly, the generalization principle applies to *Canopy Clustering* [86], which was originally proposed for clustering high-dimensional data. Initially, it places all entities in a pool; in every iteration, an entity e_i is randomly removed from the pool to create a new cluster (i.e., block). Using a cheap similarity measure, all entities still in the pool are compared with e_i; those exceeding a threshold t_{ex} are removed from the pool and placed into the new block. Entities exceeding another threshold t_{in} ($< t_{ex}$) are also placed in the new block, without being removed from the pool. This approach was adapted to Block Building in [23]. As a cheap similarity measure, the similarity of Q-grams blocking keys was used. However, no restriction requires applying Canopy Clustering exclusively on top of Q-grams Blocking. We could generalize its cheap similarity to exploit the blocking keys of any redundancy-positive Block Building method, thus turning Canopy Clustering into a pruning algorithm for Meta-blocking. This implementation is already provided by JedAI [117].

Similarly, *Extended Canopy Clustering* [23, 100] may also be employed as a pruning algorithm. It improves Canopy Clustering by ameliorating its high sensitivity to weight thresholds, i.e., the fact that high values for t_{in} and, thus, t_{ex} may leave many entities out of blocks and vise versa for low thresholds. Instead, it 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.

All these pruning algorithms can be coupled with any of the available schema-agnostic *edge weighting schemes* [109]. ARCS sums the inverse cardinalities of the common blocks, giving higher weights to comparisons involving entities that co-occur in smaller blocks. CBS counts the number of blocks shared by two entities, as in Figure 4(c), with ECBS extending it by discounting the contribution from entities placed in many blocks. JS corresponds to the Jaccard coefficient of two block lists, while EJS alters it by discounting the contribution from entities appearing in many non-redundant comparisons. Finally, BLAST employs a composite weighting scheme that consists of two parts [137]: (i) the aggregate attribute entropy associated with the tokens forming every block shared by two entities, and (ii) Pearson's chi-squared test χ^2, which assesses whether two adjacent entities appear independently in blocks.

On another line of research, [136] converts a block collection into a matrix M, where the rows correspond to entities and the columns to the tf-idf of blocking keys (tokens or q-grams). Then, the entity-entity matrix is defined as $A = MM^T$. A spectral clustering algorithm is applied to A

to convert it into a binary tree, where the root node contains all entities and every leaf node is a disjoint subset of entities. The Newman-Girvan modularity is used as the stopping criterion for the bipartition of the tree. Blocks are then derived from a search procedure that carries out pairwise comparisons based on the blocking keys, inside the leaf nodes and across the neighboring ones.

Finally, the sole dynamic rule-based method depending on Entity Matching and its oracle is *Comparison Scheduling* [108], which adapts Block Scheduling to the level of individual comparisons. Its goal is to detect most matches as early as possible so as to maximize the number of superfluous comparisons that are skipped, due to the 1-1 restriction. To this end, it orders all comparisons in decreasing matching likelihood, i.e., edge weight. Then, it executes a comparison only if none of the involved entities has already been matched.

ML-based Approaches. *Supervised Meta-blocking* [113] is the only Comparison Cleaning method that learns its pruning rules from a labelled dataset. Its core idea is that edge pruning is a multi-criteria decision problem that can be cast as a binary classification problem, where every edge is labelled "`likely match`" or "`unlikely match`". A set of schema-agnostic features is proposed, with four of them forming the most effective feature vectors per edge: ARCS, ECBS, JS and Node Degree of the adjacent entities. Undersampling is employed to tackle the class imbalance problem: the training set comprises just 5% of the minority class ("`likely match`") and an equal number of majority class instances. Several established classification algorithms are used for WEP, CEP and CNP, with all of them exhibiting robust performance with respect to their internal configuration.

The main obstacle in using Supervised Meta-blocking is the labelling effort. The cost of manually checking 5% of the expected matches is large. To overcome this issue, *BLOSS* [15] proposes a method for carefully selecting a much smaller training set that retains the original performance. It uses the *ECBS* weights to partition the unlabelled instances into similarity levels. Then, it applies rule-based active sampling inside every level and refines the resulting labelled set by removing non-matching outliers with high *JS* weights. In this way, it reduces the size of the training set by up to 40 times.

Parallelization Approaches. Due to its high computational cost, Meta-blocking has been adapted to the MapReduce framework through three alternative strategies [41]. (i) The *edge-based strategy* builds the blocking graph *explicitly*, storing all weighted edges on the disk. This bears a significant I/O cost when building very large blocking graphs. (ii) The *comparison-based strategy* builds the blocking graph *implicitly*. A pre-processing job enriches every block with the list of block ids associated with every entity. This allows for computing the edge weights and discarding all redundant comparisons in the Map phase of the second job. Superfluous comparisons are pruned in the Reduce phase of the same job. This strategy maximizes the efficiency of WEP and CEP, requiring just 2 and 3 jobs, respectively. Its adaptation to Apache Spark is presented in [9]. (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 approach offers the best implementation for WNP and CNP (and their variations), requiring just 2 jobs.

To avoid the underutilization of the available resources, these strategies employ *MaxBlock* [41] for load balancing. Based on the highly skewed distribution of block sizes in redundancy-positive block collections, it splits the input blocks into partitions of equivalent computational cost (i.e., total number of comparisons), which is equal to the computational cost of the largest input block.

The *multi-core parallelization* of Meta-blocking was examined in [101]. The input is split 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 the corresponding chunk. Depending on the definition of chunks, three alternative strategies were proposed: (i) *Naive Parallelization* treats every entity as a separate chunk, ordering all entities in decreasing computational cost (i.e., the aggregate number of comparisons in

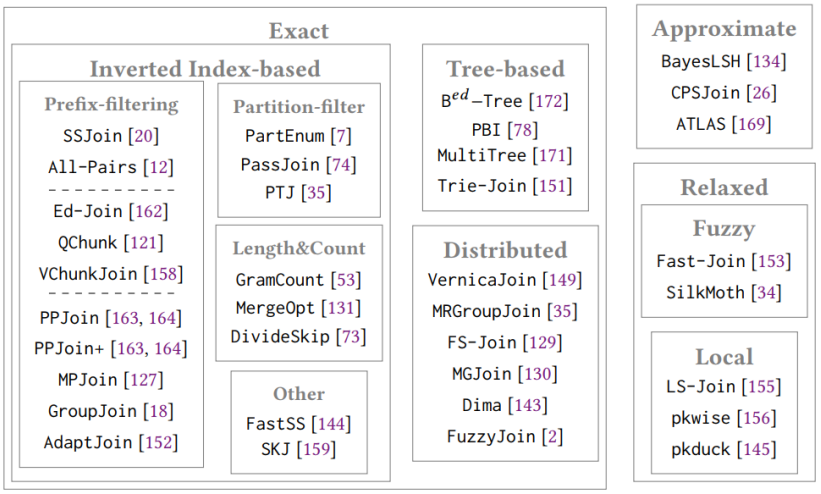

Fig. 5. Taxonomy of the main string and set similarity join techniques in the literature.

the associated blocks). (ii) *Partition Parallelization* uses MaxBlock to group the input entities into an arbitrary number of disjoint clusters with identical computational cost. (iii) *Segment Parallelization* extends the previous approach so that the number of clusters equals the number of available cores.

5 FILTERING TECHNIQUES FOR SIMILARITY JOINS

We now present an overview of the filtering techniques for string and set similarity joins, based on the taxonomy in Figure 5. We introduce the basic concepts and we outline the main filtering methods employed by the state-of-the-art algorithms.

5.1 Similarity Joins and the Filter-Verification Framework

Given two entity collections, E_1 and E_2, a similarity function $f_S : E_1 \times E_2 \rightarrow \mathbb{R}$ that measures the similarity between a pair of entities, and a similarity threshold τ, the goal of similarity join is to identify all pairs of entities in E_1 and E_2 that have a similarity at least τ. Formally, this can be stated as: $E_1 \bowtie_\tau E_2 = \{(e_i, e_j) \in E_1 \times E_2 : f_S(e_i, e_j) \geq \tau\}$.[2]

Similarity joins are often used for ER. In particular, ER can be cast as a similarity join problem under the assumption that two entities match if their similarity is sufficiently high. To this end, one needs to specify: (i) an appropriate representation for each entity, (ii) an appropriate similarity function between pairs of entities under this representation, and (iii) an appropriate similarity threshold above which two entities are considered as duplicates.

Approaches for similarity joins typically follow a *filter-verification* framework to avoid exhaustive pairwise comparisons between all pairs of entities, raising efficiency and scalability [10, 60, 84]. The *filtering* step aims at efficiently finding, for each entity e_i, a relatively small subset of candidate entities that may have a similarity to e_i higher than the threshold τ, while pruning the rest. It typically relies on a signature-based technique, which represents every entity by signatures such

[2]Similarity joins have been studied for a wide variety of entity types and representations, including strings (e.g., entity names), sets (e.g., tokens extracted from entity profiles), binary vectors (e.g., feature vectors extracted from image or audio objects), graphs (e.g., biological structures), data series (e.g., time series, trajectories), etc [10]. Based on the entity type and representation, a wide variety of similarity and distance functions can be used, such as string edit distance, set overlap, Hamming distance, graph edit distance, Euclidean distance, etc. Furthermore, the similarity threshold depends on the data characteristics and the application requirements, and is typically assumed to be provided as input to the similarity join task.

Type of Joins	Measure	Definition	Equivalent Overlap Threshold
character-based	Edit Distance	# character transformations	$\max(\|x\|, \|y\|)+1-(1+\boldsymbol{\theta}) \times q$
token-based	Overlap	$\|\mathbf{x} \cap \mathbf{y}\|$	$\boldsymbol{\theta}$
	Cosine	$\|\mathbf{x} \cap \mathbf{y}\|/\sqrt{\|x\| \cdot \|y\|}$	$\boldsymbol{\theta} \times \sqrt{\|x\| \cdot \|y\|}$
	Dice	$2 \cdot \|\mathbf{x} \cap \mathbf{y}\|/(\|x\| + \|y\|)$	$\boldsymbol{\theta} \times (\|x\| + \|y\|)/2$
	Jaccard	$\|\mathbf{x} \cap \mathbf{y}\|/(\|x\| + \|y\| - \|\mathbf{x} \cap \mathbf{y}\|)$	$\boldsymbol{\theta} \times (\|x\| + \|y\|)/(1 + \boldsymbol{\theta})$

Fig. 6. Definition of the main similarity measures used by string and set similarity join algorithms, and how the input threshold θ for each measure can be transformed into an equivalent overlap threshold.

that if two entities have a similarity above the given threshold then their signatures should overlap. The *verification* step subsequently filters out the false positives among those candidates.

The filter-verification process involves a tradeoff: spending more time on the filtering step may reduce the number of candidates to be verified in the verification step. However, if verification is relatively inexpensive, as has been shown in the case of set similarity joins [84], then more elaborate filtering techniques may not pay off in practice. Furthermore, in *exact* approaches, the filtering step allows only for false positives, which are then removed by the verification step. Instead, *approximate* methods increase the efficiency of the filtering step at the cost of allowing both false positives and false negatives, thus missing some matches [10].

The filtering step depends on the chosen similarity function and similarity threshold. In this survey, we focus on string and set similarity joins, since we address ER over entities described by one or more string-valued attributes. String similarity joins can be *character-* or *token-based*. The former joins compare two strings by representing them as sequences of characters and considering the character transformations required to transform one string into the other. The latter joins transform the strings into sets, typically via tokenization or q-gram extraction, and then compare strings using a set-based similarity measure. Hence, the token-based string similarity join becomes a set similarity join task.

For character-based similarity joins, the most commonly used measure is Edit Distance, which measures the minimum number of edit operations (insertions, deletions, substitutions) required to transform one string to the other [10]. For token-based similarity joins, the most commonly used similarity measures include Overlap, Jaccard, Cosine or Dice. The last three are normalized variants of the Overlap. Typically, join algorithms do not operate directly with these normalized variants, but first translate the given threshold θ into an equivalent set overlap threshold τ that depends on the size of the sets, as shown in Figure 6. Notice that a similar transformation is also possible for edit distance, implying that token-based similarity join algorithms may be applied to this measure as well [10].

5.2 Inverted Index-based Algorithms

These techniques extract signatures from each string or set such that candidate pairs can be filtered by checking whether their corresponding signatures overlap. An inverted index is then constructed over the signatures, and the inverted lists are searched to generate candidate pairs. Next, we briefly present the main filtering criteria and the corresponding algorithms.

Length and Count filtering. *Length filtering* states that for a string or set r to be similar to another string or set s, the length of r should be within certain bounds of that of s. For edit distance threshold τ, the condition is $|s| - \tau \leq |r| \leq |s| + \tau$, while for Jaccard similarity threshold δ it is $\delta \cdot |s| \leq |r| \leq |s|/\delta$; similar conditions apply to other similarity measures. This filtering condition is rather simple and straightforward, hence it is often used alongside other more advanced filters. Moreover, position-enhanced length filter is proposed in [83], establishing a tighter upper bound.

Count filtering states that if r is similar to s, its signature must share at least T common elements with that of s. E.g., for q-grams and edit distance threshold τ, $T = |s| + 1 - q - q \cdot \tau$, while for Jaccard similarity threshold δ, $T = \lceil \delta \cdot |s| \rceil$.

`GramCount` [53] was the first algorithm to propose length and count filtering, utilizing them to support edit distance on strings using q-grams. The focus was on incorporating approximate string matching capabilities inside a DBMS. `MergeOpt` [131] proposed various optimizations for applying count filtering, supporting both character-based and token-based similarity measures. `DivideSkip` [73] relied also on count filtering, proposing efficient techniques for merging the inverted lists of signatures.

Prefix filtering and its extensions. *Prefix filtering* applies to sets, but may also be used for strings represented as sets of q-grams. The elements of each set are first sorted in increasing order of frequency. The π-prefix of each set is subsequently formed, containing its π first elements in that order. For two sets to be similar, their prefixes must contain at least one common element. The prefix size π of r is determined based on the similarity measure and threshold being used. E.g., for edit distance threshold τ, $\pi = q \cdot \tau + 1$, while for Jaccard similarity threshold δ, $\pi = \lfloor (1 - \delta) \cdot |r| \rfloor + 1$.

Prefix filtering was first proposed by `SSJoin` [20], which, like `GramCount`, focused on supporting similarity joins inside a DBMS. The first main memory algorithm to employ prefix filtering was `All-Pairs` [12]. Numerous subsequent algorithms have adopted prefix filtering and proposed various optimizations and extensions over it for edit distance and set similarity joins.

For edit distance, `Ed-Join` [162] proposed two optimizations: one that is most effective against non-clustered edit errors and one designed for clustered edit errors. The locations and contents of mismatching q-grams are analyzed to further reduce the prefix length by removing unnecessary elements. `QChunk` [121] introduced the concept of *q-chunks*. The q-chunks of a string r are substrings of length q that start at $1 + i \cdot q$ positions in the string, for $0 \leq i \leq (|r| - 1)/q$. Given a pair of strings r and s, QChunk extracts q-grams from the one and q-chunks from the other as signatures. Appropriate bounds are then derived for the minimum required overlap between the sets of q-grams and q-chunks of the two strings. Specifically, the intersection between the q-grams of r and the q-chunks of s should be at least $\lceil |s|/q \rceil - \tau$, while the intersection between the q-chunks of r and the q-grams of s should be at least $\lceil |r|/q \rceil - \tau$. `VChunkJoin` [158] uses non-overlapping substrings called *chunks*, ensuring that each edit operation destroys at most two chunks. This yields a tight lower bound on the number of common chunks shared by two strings with edit distance lower than the threshold.

For set similarity joins, `PPJoin` [163, 164] improved prefix filtering by combining it with *positional filtering*. In addition to searching for common tokens in the two prefixes, positional filtering also examines the positions where these common tokens occur. Based on them, it derives an upper bound for the overlap between the two sets, which may allow to prune this pair. `PPJoin+` [163, 164] additionally uses *suffix filtering*: following a divide-and-conquer strategy, the suffix of the one set is partitioned into two subsets of similar sizes. The token separating the two partitions is called *pivot* and is used to split the suffix of the other set. This allows to calculate the maximum number of tokens in each pair of corresponding partitions between the two sets that can match.

`MPJoin` [127] added a further optimization over `PPJoin` which allows to dynamically prune the length of the inverted lists. This aims at reducing the computational cost of candidate generation rather than the number of candidates. `GroupJoin` [18] extended `PPJoin` with group filtering, which groups together sets with identical prefixes, treating them as a single set during candidate generation. Multiple candidates may thus be pruned in batches. Finally, `AdaptJoin` [152] proposed adaptive prefix filtering, which generalizes prefix filtering by adaptively selecting an appropriate prefix length for each set. It supports longer prefixes dynamically, extending their length by $n - 1$,

and then prunes a pair of sets if they contain less than n common tokens in their extended prefixes. Prefix filtering is a special case where $n = 1$.

Partition filtering. This is a different approach to prefix filtering based on the pigeonhole principle. Each string or set is partitioned into multiple segments in such a way that matching pairs have at least one common segment. For instance, for edit distance threshold τ, each string is partitioned into $\tau + 1$ segments. `PartEnum` [7] proposes a partitioning scheme for Hamming distance. Since Hamming distance applies to vectors having the same length, the algorithm also relies on length filtering to group strings together based on their length. `PassJoin` [74] proposes an efficient technique to minimize the number of segments required to find the candidates pairs. `PTJ` [35] proposes an approach to increase the pruning power of partition-based filtering by using a mixture of the subsets and their 1-deletion neighborhoods, which are subsets derived from a set after eliminating one element.

Other. A different approach is the *deletion neighborhood filtering*, which is proposed by the FastSS algorithm [144]. This is specifically tailored to edit distance and it is practical only for short strings. For each string s, it generates a deletion neighborhood, which contains substrings of s derived by deleting a certain number of characters. These are then used as signatures for filtering.

Finally, a different perspective for speeding up set similarity joins is proposed in [159]. The idea is based on the following observation: existing approaches examine each set individually when computing the join. However, it turns out that it is possible to improve efficiency through computational cost sharing by exploiting related sets. The proposed algorithm, called `SKJ`, leverages this fact by combining an index-level skipping technique, which groups related sets in the index into blocks, with an answer-level skipping technique, which incrementally generates the answer of one set from an already computed answer of another related set.

5.3 Tree-based Algorithms

Algorithms in this category employ tree-based indexes instead of inverted indexes. `Trie-Join` [151] is a trie-based technique for string similarity joins with edit distance. Each trie node represents a character in the string. Thus, strings with a common prefix share the same ancestors. The algorithm is based on the concept of *active node*. A trie node is called an active node of a string s if their edit distance is not larger than the given threshold. This leads to a technique called *subtrie pruning*. According to it, given a trie T and a string s, if node n is not an active node for every prefix of s, then n's descendants cannot be similar to s.

B^{ed}`-Tree` [172] is a B^+-tree based index for string similarity search using edit distance. It relies on a mapping from the string space to the integer space to support efficient searching and pruning. `PBI` [78] also uses a B^+-tree index, and exploits the fact that edit distance is a metric. The string collection is partitioned according to a set of selected reference strings. Then, the strings in each partition are indexed based on the distances of these strings to their corresponding reference strings. The proposed approach supports both range and k-NN queries and can be integrated inside a DBMS. `MultiTree` [171] is another index structure based on B^+-tree. Each element in a set is represented as a vector and is mapped to an integer according to a defined global ordering, which is then used to insert the element in the index. Searching for similar elements is then done via a range query on the index.

5.4 Distributed Algorithms

Parallel and distributed algorithms based on the MapReduce paradigm have been proposed to tackle scalability issues when dealing with very large numbers of entities. `VernicaJoin` [149] is based on prefix filtering. It computes prefix tokens and builds an inverted index on them. Then, it generates candidate pairs from the inverted lists, using additionally the length, positional and suffix

filters to prune candidates. A deduplication step is finally employed to remove duplicate result pairs generated from different reducers. MRGroupJoin [35] is a MapReduce extension of PTJ [35]. It applies a partition-based technique, where records are grouped by length and are partitioned in subrecords, such that matching records share at least one subrecord. The process is performed in a single MapReduce job. FS-Join [129] sorts the tokens in each set in increasing order of frequency, and then splits each set into disjoint subsets using appropriate pivot tokens. These subsets are then grouped together so that subsets from different groups are non-overlapping. MGJoin [130] follows a similar approach to VernicaJoin, but introduces multiple prefix orders and a load balancing technique that partitions sets based on their length.

These parallel algorithms for set similarity joins are compared in a recent experimental study [46]. VernicaJoin achieved the best performance in most experiments, followed by MRGroupJoin, FS-Join and MGJoin. Interestingly, none of the examined algorithms scales sufficiently to very large datasets. Furthermore, in several experiments, these distributed algorithms were outperformed by non-distributed ones. To some extent, this can be attributed to the overhead introduced by the MapReduce framework. However, the analysis showed that it is also due to reasons related to high or skewed data replication between map and reduce tasks, thus pointing out that it is an inherent limitation of the algorithms and cannot be overcome by simply increasing the number of nodes in the cluster. Moreover, besides dataset size, the algorithms were found to often behave poorly when dealing with very frequent tokens or low similarity thresholds.

Similarly, different strategies for performing similarity joins using MapReduce have been studied in [2]. The focus is on algorithms that can operate in a single map-reduce step in order to avoid the overhead associated with initiating multiple MapReduce jobs. The authors present a theoretical analysis of different methods, showing that different algorithms provide different tradeoffs with respect to map cost, reducer cost and communication cost.

Finally, a distributed in-memory system, called Dima, is built on top of Spark, supporting both similarity search and similarity join, with both set-based and character-based similarities [143]. It relies on signature-based global and local indexes for efficiency. The proposed signatures are adaptively selectable based on the workload, which allows to balance the workload among partitions. Dima extends the Catalyst optimizer of Spark SQL to introduce cost-based optimization of similarity search and join queries. However, no experimental comparison with other approaches is provided.

5.5 Approximate Algorithms

When the number of entities is very large or the similarity measure is costly to compute, it may be preferable in practice to apply approximate techniques. The most popular solution in this case is hashing, which transforms an item to a low-dimensional representation [154]. Locality sensitive hashing (LSH) [51] is typically used for similarity search and join. LSH has the property that similar items have much higher probability to be mapped to the same hash code than dissimilar ones. Thus, LSH can be exploited in the filtering phase to generate candidates [30, 79, 146]. The basic idea is that each object is hashed several times using randomly chosen hash functions. Hence, candidates are those pairs of objects that have been hashed to the same code by at least one hash function.

BayesLSH [134] combines Bayesian inference with LSH in a principled manner, allowing to estimate similarities to a user-specified level of accuracy. It uses LSH not only for filtering but also during the verification phase, for estimating similarities and pruning candidates. The method provides probabilistic guarantees on the quality of the output, both in terms of accuracy and recall.

CPSJoin [26] is a randomized algorithm for set similarity joins. It uses a recursive filtering technique, building upon a previously proposed index for set similarity search [25], as well as sketches for estimating set similarity. The algorithm has 100% precision and provides a probabilistic guarantee on recall. The experiments conducted by the authors show that CPSJoin is much faster

than BayesLSH as well as MinHash LSH [51]. CPSJoin is also compared against All-Pairs. CPSJoin is found to perform well on datasets where tokens are contained in a large number of sets on average, but fails to improve upon All-Pairs on datasets with many rare tokens.

Finally, ATLAS [169] is a probabilistic algorithm that is based on random permutations both to generate candidates and to estimate the similarity between candidate pairs. It also proposes a method to efficiently detect cluster structures within the data, which are then exploited to search for similar pairs only within each cluster. ATLAS is particularly suited to binary vectors with high dimensions (in the order of 10^5 to 10^8) and low similarity thresholds.

5.6 Relaxed Matching

The works considered so far for set similarity joins assume binary matching between the tokens in the compared sets. That is, the overlap between two sets is based on the portion of tokens that match exactly. Moreover, the investigated string similarity join methods compare pairs of strings considering them in their entirety when measuring their similarity. In practice, these two matching criteria may be too strict. Instead, it may be desirable to increase the tolerance in matching by allowing elements in two sets to match approximately or by allowing portions of strings to match each other. We discuss such approaches in the following.

Fuzzy token matching. In the case of set similarity joins, *fuzzy token matching* allows elements between two sets to match approximately rather than exactly. Fast-Join [153] measures the similarity between two sets by representing their elements as vertices of a bipartite graph, where edge weights denote the edit similarity between pairs of matching elements. The similarity of two sets is then computed as the maximum weight matching in this bipartite graph. The proposed method follows the filter-verification framework, creating a signature for each set, such that related sets must have overlapping signatures. The signature of a set comprises a subset of its tokens.

In the same direction, SilkMoth [34] generalizes and improves upon this work, providing a formal characterization of the space of valid signatures. After showing that finding the optimal signature for a set is NP-complete, it proposes heuristics to select signatures. To further reduce the number of generated candidates, SilkMoth adds a refinement step which directly compares each set with its candidates, rejecting those for which certain bounds do not hold. These bounds depend not only on the reference set but also on the candidates, hence they can only be computed at this stage. SilkMoth supports both character-based edit similarity and set-based Jaccard similarity for measuring the similarity between a pair of elements.

Local similarity join. In the case of string matching, *local similarity join* refers to finding pairs of strings that contain similar substrings. Local similarity under edit distance constraints can be defined as matching any l-length pattern with k errors. The approach proposed by LS-Join [155] is based on the observation that if two strings are locally similar, they must share at least one common q-gram, for a suitably calculated gram length q. The method uses an inverted index which is populated incrementally during the search. For every examined string, its grams are generated and the candidates are retrieved from the index by finding those strings that have matching grams. The candidates are then verified. Finally, the index is updated with the grams of the current string.

pkwise [156] addresses another variant of the local similarity search problem. Given a document collection, it detects documents that share similar *sliding windows*. A sliding window of size w is a multiset containing w consecutive tokens of a given document. The similarity between two sliding windows is defined as the overlap of those sets. The proposed method is based on prefix filtering but with a novel extension. Instead of relying on single tokens to build the signatures, it proposes *k-wise signatures*, which comprise combinations of k tokens. Larger values of k increase the signatures' selectivity, reducing the size of the postings lists in the inverted index and thus the number of generated candidates; however, they also increase the cost of signature generation. To

strike a better balance, the token universe is partitioned based on token frequency, and signatures with different number of tokens are generated for each partition. An additional optimization is to share common signatures across adjacent windows.

Finally, pkduck [145] proposes a method for approximate string joins with abbreviations. It designs a new similarity measure that estimates the similarity between two strings taking abbreviations into account. Then, it proposes an appropriate signature scheme that extends prefix filtering and can generate signatures without iterating over all derived strings from a given abbreviation.

6 JOIN-BASED BLOCKING METHODS

We now elaborate on Block Building and Block Processing methods that incorporate techniques from the Filtering framework, converting Blocking into a nearest neighbor search.

A large family of Block Building techniques in this category relies on LSH [51], operating as follows: given an entity collection $\mathcal{E}$, the values of selected attribute names are converted into a bag of *k-shingles*, i.e., k consecutive words or characters. Then, a matrix M of size $K \times |\mathcal{E}|$ is formed, with the rows corresponding to the K distinct shingles that appear in all attribute values and the columns to the input entities. The value of every cell $M(i, j)$ indicates whether the entity e_j contains the shingle s_j, $M(i, j)$=1, or not, $M(i, j)$=0. Given that M is a sparse matrix, p random minhash functions are used to reduce its dimensionality: they are applied to each column, deriving a new matrix M' of size $p \times |\mathcal{E}|$. The p rows are then partitioned into b non-overlapping bands and a hash function is applied to every band of each column. The resulting buckets are the blocks, which provide probabilistic guarantees that every pair co-occurs in at least one block.

LSH is combined with K-Means in [142]. KMeans is applied to the low-dimensional columns of M', which represent the input entities. The resulting clusters form a disjoint block collection $\mathcal{B}$, with $|\mathcal{B}|$ determined by the desired average number of entities per block.

DeepER [40] applies LSH to the distributed representations (i.e., embeddings) of the input entities. Every entity is transformed into a dense, real-valued vector by aggregating the embeddings of all attribute value tokens, which are pre-trained by word2vec [90], Glove [119] etc. This vector is then hashed into multiple buckets with LSH. A block is then created for every entity containing its top-N most likely matches, which are detected using Multiprobe-LSH [79].

LSH is combined with a novel semantic similarity in [157]. A taxonomy tree is used to model the concepts that describe the input entity collection. The semantic similarity of two entities is inversely proportional to the length of the paths that connect the corresponding concepts and their children: the longer the paths, the lower the semantic similarity. The concepts of every entity are converted into a hash signature through a semantic hashing algorithm. The resulting low-dimensional signatures are directly combined with the Minhash signatures that are extracted from the n-grams of selected attribute values, capturing the textual similarity of entities. However, the construction of the taxonomy tree requires heavy human intervention.

LSH is combined with R-Swoosh [14] for Entity Matching in [82] through a MapReduce-based parallelization. First, a job is used for defining the blocks using LSH. Then, a graph-parallel Pregel-based platform, like Apache Giraph[3], is used for iteratively executing the non-redundant comparisons in the blocks and computing the transitivity closure of the detected duplicates.

HARRA [68] is another method that combines LSH with Entity Matching. LSH hashes 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 profiles. The new profiles are hashed into the existing hash tables and the process is repeated until no entities are merged or another

[3] http://giraph.apache.org

stopping criterion is met (e.g., the portion of merged profiles drops below a predetermined threshold). In every iteration, special care is taken to avoid repeated and unnecessary comparisons.

Another family of methods in this category relies on exact filtering techniques. A simple approach is to combine Prefix Filtering with Token Blocking, creating one block for every token that appears in the prefix of at least two entities [27]. Another approach is *Adaptive Filtering* [55], which couples schema-aware, rule-based Block Building techniques with two filtering methods. First, blocks are created by extracting keys from specific attributes. In every block with a size exceeding a predetermined threshold, Length and Count Filtering are applied for Comparison Cleaning, using an edit distance threshold on an attribute that is not considered by the transformation function.

Another Block Building technique that relies on filtering is *MultiBlock* [58], which is part of the system Silk [150] (see Section 7). MultiBlock essentially optimizes the execution of complex matching rules that comprise special similarity functions for textual, geographic and numeric values. A block collection is created for every function such that similar entities share multiple blocks. E.g., edit distance is supported for textual values and blocks are created for character q-grams such that entity pairs satisfying the distance threshold co-occur in a sufficient number of blocks. Then, all block collections are aggregated into a multidimensional one in a way that respects the co-occurrence patterns of similar entities and guarantees no false dismissals (i.e., PC=1).

Another approach is to use spatial joins for Block Building. *StringMap* [61] converts schema-aware blocking keys to a similarity-preserving Euclidean space, whose dimensionality d is heuristically derived from a random sample (typically, $d \in [15, 25]$). For each dimension, a linear algorithm initially selects two pivot attribute values that are (ideally) as far apart as possible. Subsequently, the co-ordinates of all other attribute values are determined through a comparison with the pivot strings. Using an R-tree or a grid-based index in combination with two weight or cardinality thresholds [23], similar attribute values are clustered together into overlapping blocks.

This approach is extended by the *Double embedding Scheme* [1]. The input entities are initially mapped to the same d-dimensional Euclidean space. Next, the embedded attribute values are mapped to another Euclidean space of lower dimensionality $d' < d$. A similarity join is performed in the second Euclidean space using a KDTree index. The resulting candidate matches are then clustered in the first, d-dimensional Euclidean space. The experimental study suggests that the d'-dimensional space significantly reduces the runtime of StringMap by 30% to 60%.

7 BLOCKING AND FILTERING IN ENTITY RESOLUTION SYSTEMS

We now present the main systems that address ER, examining whether they incorporate any of the aforementioned methods to improve the runtime and the scalability of their workflows. We analytically examined the 18 non-commercial and 15 commercial systems listed in the extended version of [72][4] along with the 10 Link Discovery frameworks surveyed in [93]. Table 2 summarizes the characteristics of 12 open-source ER systems that include at least one Blocking or Filtering method.

We observe that all systems include blocking methods, with Standard Blocking (SB) and Sorted Neighborhood (SN) being the most popular ones. Note that the first four systems are Link Discovery frameworks that implement custom approaches: KnoFuss and SERIMI apply Token Blocking only to the literal values of RDF tiples, Silk implements MultiBlock (see Section 6) and LIMES provides a lossless method that operates only on metric spaces [95]. It relies on the triangle inequality in order to approximate the distance between entities based on previous comparisons. Utilizing sets of entities as reference points, called *exemplars*, this method computes lower and upper bounds to filter out superfluous comparisons before their execution. Note also that Febrl and JedAI offer the largest variety of established techniques. The former provides their original, schema-aware

[4]The extended version of [72] is available here: http://pages.cs.wisc.edu/~anhai/papers/magellan-tr.pdf.

Table 2. Blocking and Filtering methods in open-source systems for Entity Resolution.

Tool	Blocking	Filtering	GUI	Language	Data Formats
KnoFuss [96]	Literal Blocking	-	No	Java	RDF, SPARQL
SERIMI [8]	Literal Blocking	-	No	Ruby	SPARQL
Silk [150]	Multiblock	-	Yes	Scala	RDF, SPARQL, CSV
LIMES [95]	custom methods	PPJoin+, Ed-Join, custom methods, e.g., ORCHID [94]	Yes	Java	RDF, SPARQL, CSV
Dedupe [17]	SB with learning-based techniques	-	No	Python	CSV, SQL
DuDe [37]	SB, SN, Sorted blocks	-	No	Java	CSV, JSON, XML, BibTex, Databases(Oracle, DB2, MySQL and PostgreSQL)
Febrl [21]	SB, SN, Sorted Blocks, Suffix Arrays, Extended Q-Grams, Canopy Clustering, StringMap	-	Yes	Python	CSV, text-based
FRIL [62]	SB, SN	-	Yes	Java	CSV, Excel, COL, Database
OYSTER [92]	SB	-	No	Java	text-based
RecordLinkage [132]	SB (with SOUNDEX)	-	No	R	Database
Magellan [72]	SB, SN, it also supports user-specified blocking methods	Overlap, Length, Prefix, Position, Suffix	Yes	Python	CSV
JedAI [117]	SB, SN, Extended SN, Suffix Arrays, Extended Suffix Arrays, LSH, Q-Grams, Extended Q-Grams + Block Processing	to be added in the forthcoming version	Yes	Java	CSV, RDF, SPARQL, XML, Database

implementation, while the latter provides their schema-agnostic adaptations. For this reason, JedAI is the only tool that implements Block Processing techniques, as well.

Surprisingly, only two systems currently include filtering algorithms for improving the runtime of their matching process: LIMES and Magellan. The latter actually offers the largest variety of established techniques through the package `py_stringsimjoin`.

Half of the tools offer a graphical user interface and are implemented in Java. Regarding the type of the input data, most systems support structured data. The only exceptions are the three Link Discovery frameworks, which are crafted for semi-structured data. JedAI is the only tool that applies uniformly to both structured and semi-structured data.

Note that Block Building is part of the ER workflow in several commercial systems, such as IBM Infosphere and Informatica Data Quality [72]. These systems are generally required to handle diverse types of data, focusing on data exploration and cleaning. They typically provide variations of SB, which allow users to extract blocking keys from specific attributes, guided by statistics and data analysis via a sophisticated GUI. As a result, users' expertise and experience with specific domains is critical for the performance of these systems' blocking components.

8 DISCUSSION

Starting with the Block Building methods, it is worth stressing that all ML-based techniques are primarily evaluated with respect to effectiveness. Their time efficiency is usually neglected, thus requiring a deeper investigation. The supervised methods also suffer from the scarcity of labelled datasets; even if a training set is available for a particular dataset, it cannot be directly used for learning supervised blocking schemes for another dataset. Instead, a complex transfer learning procedure is typically required [91, 147].

The rule-based schema-aware methods have two drawbacks: they apply exclusively to structured data and they are quite parameter-sensitive. Even small changes parameter value modifications may yield significantly different performance [23, 31, 98, 100]. Their most important parameter is the definition of the blocking keys, which requires fine-tuning by an expert. Even so, their *PC* remains insufficient in many cases, placing less than half of the duplicates in at least one common

block [23, 100]. This applies even to methods that employ redundancy for higher recall. The reason is that the schema-based methods try to simultaneously maximize *PC*, *PQ* and *RR*.

These shortcomings are ameliorated by schema-agnostic methods, which apply both to structured and semi-structured data, consistently achieving very high *PC* in both contexts. They also simplify the configuration of Block Building, reducing its sensitivity through the automatic definition of blocking keys [100, 116]. Rather than human intervention or expert knowledge, their robustness emanates from the high levels of redundancy they employ, placing every entity in a multitude of blocks. On the downside, they yield a considerably higher number of comparisons, resulting in very low *PQ* and *RR*. Both, however, can be significantly improved by Block Processing [110, 116].

The core characteristic of Block Processing methods is that they are schema-agnostic; they all rely exclusively on the characteristics of blocks, such as their size, cardinality and overlap. This is no surprise, as they are primarily crafted for boosting the performance of schema-agnostic Block Building methods. In fact, extensive experiments have demonstrated that Block Processing is indispensable for these methods, raising *PQ* and *RR* by whole orders of magnitude, at a minor cost in *PC* [108, 114, 116].

Recall, though, that there is a fundamental difference between Block and Comparison Cleaning methods, apart from their different granularity. The former are complementary and, thus, multiple Block Cleaning methods can be applied consecutively in a single blocking workflow - see Figure 1(b). For example, Block Filtering is typically applied after Block Purging [114]. In contrast, Comparison Cleaning methods are incompatible with each other, because applying any of them to a redundancy-positive block collection deprives it from its co-occurrence patterns and renders all other techniques inapplicable. Hence, at most one Comparison Cleaning method can be part of a blocking workflow.

Regarding Filtering techniques, interesting insights were drawn from a series of experimental studies. The following algorithms were experimentally compared in [60]: `DivideSkip`, `FastSS`, `All-Pairs`, `Ed-Join`, `QChunk`, `AdaptJoin`, `VChunkJoin`, `PassJoin`, `PartEnum`, `PPJoin` and `PPJoin+`. The results showed that `PassJoin` is the best algorithm for string similarity joins with edit distance, being surpassed only by `FastSS` in the case of short strings. For set similarity joins using Jaccard, Cosine and Dice similarities, `AdaptJoin` and `PPJoin+` were reported as the best algorithms. Yet, these conclusions contradict a more recent experimental study [84], which focused on set similarity joins, comparing `All-Pairs`, `PPJoin`, `PPJoin+`, `MPJoin`, `AdaptJoin` and `GroupJoin`. These experiments indicated that the plain prefix filtering, i.e., `All-Pairs`, is still quite competitive, being the winner in the majority of cases. Instead, more sophisticated filters were found to provide only moderate improvements or even to negatively affect performance. `PPJoin` and `GroupJoin` were reported as having the best median and average performance, with `GroupJoin` being also the most robust algorithm. The discrepancy between the two studies was attributed to the more efficient process that performed the verification step in [84]; reducing the cost of verification means that employing a complex filter to reduce the number of candidate pairs may not pay off. Another interesting finding is that leveraging set relations can improve the performance of the filtering algorithms; `SKJ` was found to consistently outperform `PPJoin`, `PPJoin+`, `AdaptJoin` and `PTJ` in [159].

Finally, we qualitatively compare the Blocking framework with the Filtering-verification one. Beginning with their commonalities, we observe that both frameworks serve the same purpose: they increase ER efficiency by reducing the number of performed comparisons. To this end, both employ a stage producing candidate matches, which are subsequently verified to remove false positives. Both usually operate either on two clean but overlapping data collections (Clean-Clean ER for Blocking, Cross-table Join for Filtering) or on a single dirty data collection (Dirty ER for Blocking, Self-join for Filtering). Both extract signatures such that the similarity of two entities is reflected in the similarity of their signatures. Both also apply similar implementation-level optimizations, representing signatures with integer ids, instead of strings, so as to reduce the memory footprint

and facilitate in-memory execution. Moreover, both frameworks include character- and token-based methods. For Blocking, the former methods mainly pertain to schema-aware techniques that apply character-level transformations to blocking keys (e.g., q-grams, suffixes etc), while token-based methods primarily pertain to schema-agnostic methods. For Filtering, similarity measures can also be distinguished between character-based (e.g., edit similarity) and token-based ones (e.g., Jaccard), even though many algorithms can be adapted to handle both. Last but not least, in both cases textual data have been combined with other types of data, particularly with spatial or spatio-temporal data, including [94] for Blocking and [13, 18, 48, 59] for Filtering.

On the other hand, Blocking and Filtering have several distinguishing characteristics. By definition, a blocking scheme applies to a single entity, considering all its attribute values (schema-agnostic methods), or combinations of multiple values (schema-aware techniques); in contrast, Filtering usually applies to a pair of values from the same attribute of two entities. Blocking relies on positive evidence, clustering together similar entities, while Filtering relies on negative evidence, detecting dissimilar entities early on. Blocking is typically independent of Entity Matching, whereas Filtering is interwoven with it, as its goal is to optimize the execution of a matching rule. Blocking is an inherently approximate procedure that falls short of perfect recall (*PC*), even when providing probabilistic guarantees (e.g., LSH Blocking in DeepER [40]); in contrast, most Filtering methods provide an exact solution, returning all pairs of values that exceed the predetermined threshold along with false positives. Blocking trades recall (*PC*) for precision (*PQ*), while Filtering trades filtering power for filtering cost. Blocking may be modelled as a learning problem where the goal is to define supervised blocking schemes that simultaneously optimize *PC*, *PQ* and *RR*, but Filtering requires no labelled set for learning to mark a comparison as true negative. Instead, it relies on a theoretical analysis based on the given similarity measure and threshold. Finally, preserving privacy is orthogonal to Filtering, with very few works examining privacy-preserving similarity joins [63, 76, 168]. In contrast, Blocking constitutes an integral part of privacy-preserving ER, with several relevant works (for details, refer to a recent survey [148]).

8.1 Future Directions

There are many promising directions for future work, from deep learning [40] and dynamic blocking methods for Incremental Entity Resolution [54] to blocking methods that exploit entity evolution [103]. The following are more mature fields, having assembled a critical mass of methods already.

Progressive Entity Resolution. With the constant increase of data volumes, new *progressive* (or *pay-as-you-go*) applications of Entity Resolution have emerged. Their goal is to provide the best possible *partial solution* within a limited budget of computational or time resources. As an example, consider the Google dataset search system, which has indexed ~26 billion datasets [52]; inevitably, its entities can be resolved only progressively. In these Progressive ER applications, Block Building is followed by a *prioritization* step, which schedules the processing of entities, comparisons or blocks through a weight that is analogous to the likelihood that they involve duplicates. We distinguish the relevant techniques into schema-aware and schema-agnostic progressive methods.

The schema-aware methods are suitable for structured data [118, 160], with *Progressive Sorted Neighborhood* (PSN) constituting the cornerstone approach. It operates like SN, creating a sorted list of entities, but uses an incremental window size w: starting from the top of the list, all entities in consecutive positions (w=1) are compared; then, all entities at distance w=2 are compared and so on and so forth, until reaching the user-defined budget. *Dynamic PSN* [118] extends this static approach by adjusting the processing order of comparisons on-the-fly, according to the results of an oracle utilized for matching. It arranges the sorted entities in a two-dimensional array A, and if $A(i, j)$ corresponds to a duplicate, the processing moves on to check $A(i + 1, j)$ and $A(i, j + 1)$, as well. The same principle is applied to a block collection through *Progressive Blocking* [118]. Another

static method is the *Hierarchy of Record Partitions* [160], which creates a hierarchy of blocks, such that the matching likelihood of two entities is proportional to the level in which they co-occur for the first time. This hierarchy of blocks is then progressively resolved, level by level, from leaves to root. A variation of this approach is adapted to the MapReduce parallelization framework for even higher efficiency in [6]. The *Ordered List of Records* [160] converts the hierarchy of blocks into a list of entities that are sorted by their likelihood to produce matches. Finally, a progressive solution for multi-source ER over different entity types is proposed in [5].

The schema-agnostic progressive methods are suitable for both structured and semi-structured data. They are distinguished into two categories [138]: (i) Inspired by schema-agnostic SN, the *sort-based methods* sort all entities alphabetically, according to their attribute value tokens. *Local Schema-agnostic Progressive SN* [138] slides an incremental window over the sorted list of entities. For each window size, it aggregates all distinct comparisons and orders them through a schema-agnostic weighting scheme that considers the number of blocking keys per entity along with the co-occurrence frequency of entity pairs for the current window size. All redundant comparisons for each window size are discarded in this way. *Global Schema-agnostic Progressive SN* [138] does the same, but for a predetermined range of windows, eliminating all redundant comparisons they contain. (ii) Inspired by Meta-blocking, the *hash-based methods* leverage the *blocking graph* for the prioritization step. *Progressive Block Scheduling* [138] orders the blocks in ascending number of comparisons and then prioritizes all comparisons in the current block, by ordering them in decreasing edge weight, whereas *Progressive Profile Scheduling* [138] orders entities in decreasing average weight of the corresponding node neighborhood in the blocking graph and then orders all comparisons of the current entity in decreasing edge weight.

The schema-agnostic methods outperform the schema-based ones with respect to both recall and precision [138]. Yet, they exclusively support *static* prioritization, defining an immutable processing order that disregards the detection of duplicates. More research is needed, though, for developing *dynamic schema-agnostic* progressive methods.

Real-time Entity Resolution. Real-time ER is the task of matching an entity that is given as query to the available entity collections in (ideally) sub-second run-time. To meet this goal, several specialized *dynamic indexing* techniques have been proposed in the literature. An early approach is presented in [24]. The core idea is to pre-calculate similarities between the attribute values of entities co-occurring in the blocks of Standard Blocking, thus avoiding similarity calculations at query time. Three indexes are created for this purpose, containing all the necessary information. This approach is extended by *DySimII* [125] 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.

Another family of dynamic indexing techniques extends the Sorted Neighborhood. For example, *F-DySNI* [122, 124] converts the sorted list of blocking keys into an index tree that is faster to search. In fact, it creates a braided AVL tree [128], which is a combination of a height balanced binary tree and a double-linked list, where every 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 employs one tree for each blocking key definition, updating it whenever a query entity arrives. The window is either fixed, considering a specific number of neighboring nodes, or adaptive, considering as neighbors only the nodes that exceed a predetermined similarity threshold. F-DySNI is extended in [123] with an automatic approach for selecting blocking keys; the weak training set of [64] is combined with a scoring function that for each blocking key assesses how high is its coverage and how low are the average block size and the variance of block sizes. Finally, a hybrid approach that combines MinHash LSH with Sorted Neighborhood is presented in [77].

When searching for the nearest neighbors of a query entity, the entities in large LSH blocks are sorted via a custom scoring function and a window of fixed size slides over the sorted list of entities.

All these methods are crafted for structured data, assuming a fixed schema of known quality. New techniques are required, though, for the noisy, heterogeneous entities of semi-structured data.

Parameter Configuration. A major issue regarding the use of blocking methods is their parameter configuration. Except Token Blocking, which is parameter-free, all other methods involve at least one internal parameter that affects their performance to a large extent [23, 116]. This also affects their relative performance, rendering the selection of the best performing method for the data at hand into a non-trivial task.

To mitigate this issue, parameter fine-tuning is modelled as an optimization problem in [85]. The large, heterogeneous space of possible configurations is searched through a genetic algorithm, whose fitness function exploits the labels of part of the candidate matches (i.e., `match` vs `non-match`). The typical series of genetic operators (i.e., mutation, crossover, elite capture and parental selection) is applied for a specific number of generations. The configuration maximizing the fitness function is selected as optimal. However, this approach involves a large number of parameters itself.

MatchCatcher [75] implements a human-in-the-loop approach combining expert knowledge with labelled instances in order to learn composite blocking schemes of high quality. Using string similarity joins, false negatives (i.e., duplicates sharing no block) are efficiently detected. To capture them, the expert user adapts the transformation and assignment functions iteratively.

On another line of research, a method's performance over several labelled datasets is used for fine-tuning its parameter for a given unlabelled dataset in [85]. At its core lies a two-dimensional metric space formed by the F-Measure (vertical axis) and the running time (horizontal axis) of the overall ER process. The closer a method is mapped to the ideal point (0,1), the better is its performance. A graph is then built such that every node corresponds to a different configuration or blocking method, while a directed edge points from node n_i to n_j if n_j is closer to (0,1). The node with no outgoing edges or the largest difference between incoming and outgoing edges corresponds to the best performing method or configuration. However, this is a rather time-consuming approach, as it performs an end-to-end ER workflow for every configuration or method.

None of the above methods satisfies the requirement for automatic, data-driven, a-priori parameter configuration of blocking methods, which thus remains an open problem.

Filtering for Entity Resolution. Although some Blocking-based ER techniques have used Filtering techniques as a baseline for comparison, the latter have been developed independently of ER, constituting a separate line of research. Having reviewed the Blocking and Filtering frameworks jointly, we believe that opportunities exist for transferring ideas and approaches between them. In particular, we have considered similarity joins as a special case of ER, where entity profiles are represented by strings or sets and the matching function is based on a similarity threshold. It is interesting to investigate in practical settings to what extent similarity joins suffice for ER. We expect that techniques supporting relaxed matching criteria and/or lower similarity thresholds will be required to achieve high recall. Still, as presented in Section 5, relatively few of the existing similarity join techniques are designed for these cases. Moreover, as shown in the experimental survey of [46], scalability remains an open challenge for string and set similarity joins. Finally, there is a need for extensible, open-source ER tools that incorporate the majority of established Blocking and Filtering methods and apply seamlessly to structured, semi-structured and unstructured data [52].

9 CONCLUSIONS

Efficiency techniques are an integral part of Entity Resolution, since its infancy. In this survey, we organized the bulk of works in the field into Blocking, Filtering and hybrid techniques, facilitating their understanding and use. We also provided an in-dept coverage of each category, further

classifying the corresponding works into novel sub-categories. Lately, the efficiency techniques have received more attention, due to the rise of Big Data. This includes large volumes of semi-structured data, which pose challenges not only to the scalability of efficiency techniques, but also to their core assumptions: the requirement of Blocking for schema knowledge and of Filtering for high similarity thresholds. The former led to the introduction of schema-agnostic Blocking in conjunction with Block Processing techniques, while the latter led to more relaxed criteria of similarity. Our survey covers these new fields in detail, putting in context all relevant works.

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