Parallel Meta-blocking: Realizing Scalable Entity Resolution over Large, Heterogeneous Data

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Abstract—Entity resolution constitutes a crucial task for many applications, but has an inherently quadratic complexity. Typically, it scales to large volumes of data through blocking: similar entities are clustered into blocks so that it suffices to perform comparisons only within each block. Meta-blocking further increases efficiency by cleaning the overlapping blocks from unnecessary comparisons. However, even Meta-blocking can be time-consuming: applying it to blocks with 7.4 million entities and 2.2·1013 comparisons takes almost 8 days on a modern high-end server. In this paper, we parallelize Meta-blocking based on MapReduce. We propose a simple strategy that explicitly creates the core concept of Meta-blocking, the blocking graph. We then describe an advanced strategy that creates the blocking graph implicitly, reducing the overhead of data exchange. We also introduce a load balancing algorithm that distributes the computationally intensive workload evenly among the available compute nodes. Our experimental analysis verifies the superiority of our advanced strategy and demonstrates an almost linear speedup for all meta-blocking techniques with respect to the number of available nodes.

I. INTRODUCTION

Entity resolution (ER) is the task of mapping different entities to the same real-world object [6]. In the context of Big Web Data, it constitutes a batch process of quadratic complexity that is confronted with two Vs: volume, as it receives a large number of profiles as input, and variety, because the profiles are described by diverse schemata [16], [17] (velocity appears in Incremental ER). Volume is typically addressed by blocking, which places similar profiles into blocks and performs comparisons within each block. Variety is addressed by schema-agnostic blocking methods, which completely disregard attribute names; for instance, Token Blocking [16] creates one block for every token shared by at least two entities. Most of these blocking methods are redundancy-positive, placing profiles into multiple blocks so that the more blocks two profiles share, the more likely they are to be matching [16]. On the flip side, they entail two kinds of unnecessary comparisons: the redundant ones repeatedly compare the same profiles in multiple blocks, while the superfluous ones involve non-matching profiles. For example, the blocks b2 and b4 in Figure 1(a) contain one redundant comparison each, repeated in b1 and b3; assuming that profiles e1 and e2 match with e3 and e4, b5, b6, b7

![Figure 1](image-url)

Figure 1. (a) A set of redundancy-positive blocks, (b) the corresponding blocking graph with Jaccard similarity as edge weight, and (c) one of the possible pruned blocking graphs.

and b5 contain superfluous comparisons. In total, there are 13 comparisons: (4-3/2=)6 in b8 and 1 in each of the 7 remaining blocks; 3 of these comparisons are redundant and 8 superfluous. Such comparisons increase the computational cost without contributing any identified duplicates.

Current state-of-the-art. Block Processing is the task of discarding unnecessary comparisons to enhance the efficiency of block collections. Established approaches include Iterative Blocking [19] and Meta-blocking [17], with the latter consistently outperforming the former in both effectiveness and time efficiency [17]. This is achieved as follows. First, it transforms the input block collection B into a blocking graph \( G_B \) that contains a node \( n_i \) for every profile \( e_i \) in B and an edge \( <n_i, n_j> \) for every pair \( e_i, e_j \) that share at least one block. Every edge \( <n_i, n_j> \) is associated with a weight \( w_{i,j} \in [0, 1] \), analogous to the likelihood that the adjacent profiles are matching. For instance, the graph in Figure 1(b) is extracted from the blocks in Figure 1(a) using Jaccard similarity for weighting the edges. Note that there are no parallel edges, thus eliminating all redundant comparisons at no cost in recall (i.e., without missing any matching comparison). Second, the edges with low weights are discarded according to a pruning criterion so as to eliminate part of the superfluous comparisons. For instance, the graph \( G_B' \) in Figure 1(c) is derived from the graph in Figure 1(b) by discarding the edges with weight lower than the average one (1/4). \( G_B' \) is then transformed into a collection \( B' \) by creating a new block for every retained edge. \( G_B' \) yields 5 blocks, each containing a pair of entities. Out of the 5 comparisons, only 3 are superfluous, as the edges \( <n_1, n_3> \) and \( <n_2, n_4> \) connect matching entities. Compared
to the initial block collection in Figure 1(a), the comparisons were reduced by 62% without missing any pair of duplicates.

**Scalability Limitations.** Theoretically, Meta-blocking involves a linear time complexity with respect to the number of comparisons in the input block collection [17]. In practice, though, its running time depends also on the average number of blocks associated with every profile. The reason is that the edge \(<n_i, n_j>\) is weighted after estimating the intersection of the list of blocks associated with \(e_i\) and \(e_j\). Therefore, the higher the redundancy in a block collection, the more time-consuming the processing of Meta-blocking.

So far, the largest dataset processed by Meta-blocking involves 3.4M profiles (4.0\(\cdot\)10\(^{10}\) comparisons), each placed in 15 blocks on average (\(D_{dbpedia}\) and \(DB_c\) in Tables I and II, respectively) [17]. Using a high-end server with Intel i7 (3.40GHz), 64 GB of RAM and Debian Linux 7, Meta-blocking requires 3 hours to execute. To assess its scalability, we tested it on 7.4M profiles (2.2\(\cdot\)10\(^{11}\) comparisons), each associated with 40 blocks on average (\(D_{freebase}\) and \(FR_P\) in Tables I and II, respectively). Using the same server, the required time raised to 186 hours (~8 days), i.e., a 2x increase in the size of the input resulted in a 62x increase in execution time. Therefore, even as a pre-processing step for ER, Meta-blocking is a heavy computational task with serious efficiency limitations at the scale of the Web. We expect this problem to aggravate over time, as Web Data grow constantly, both in terms of the number of entity profiles and the amount of information inside each profile (see http://stats.lod2.eu). To overcome these limitations of the existing serialized techniques, novel distributed approaches are required.

**Proposed Solution.** In this paper, we adopt MapReduce for parallelizing Meta-blocking and scaling its techniques to voluminous Web Data collections. We provide two strategies. The first one explicitly targets the blocking graph, building and storing all edges along with their weights. Although MapReduce leads to a significant speedup, it bears a high I/O cost that may become the bottleneck, when building very large graphs. The second approach overcomes this shortcoming, by using implicitly the blocking graph; it enriches the input block collection with the necessary information for computing the edges’ weights on demand, without explicitly storing them. To avoid potential bottlenecks associated to the computation-intensive parts of our MapReduce functions, we also introduce a novel load balancing algorithm. It exploits the power law distribution of block sizes in redundancy-positive collections to split them in partitions of equivalent computational cost (i.e., total number of comparisons).

Finally, we provide an extensive experimental evaluation of our methods over the Hadoop environment (https://hadoop.apache.org). We apply the main Meta-blocking configurations to four large-scale, real-world datasets and measure the qualitative performance as well as the corresponding running times. The outcomes exhibit an almost linear speedup with respect to the available nodes. To facilitate other researchers to experiment with parallel Meta-blocking, we have publicly released the data and the implementation of our methods (See https://github.com/vfethym/ParallelMetablocking).

**Contributions.** In summary, these are our contributions:

- We provide a parallelized version of the Meta-blocking workflow based on the MapReduce paradigm. For each stage of the workflow, we offer two alternative strategies: a basic and an advanced one of higher scalability.
- We present a load balancing technique that deals with skewness in the input block collection, splitting it evenly into partitions with the same number of comparisons.
- We demonstrate the high performance and the linear speedup of our techniques through a thorough experimental evaluation over four real, voluminous datasets.

The rest of the paper is organized as follows: Section II describes related work, Section III provides the preliminaries for blocking and Meta-blocking, in Section IV we adapt Meta-blocking to MapReduce and evaluate its performance in Section V. We summarize our findings in Section VI.

**II. Related Work**

ER constitutes a well-studied problem [7], [6], [9]. Due to its quadratic complexity, a bulk of work aims at improving its scalability. **Parallel ER methods**, e.g., [5], [13], [10], exploit the processing power of multiple cores to minimize the ER response time. Recent approaches are based on MapReduce, which offers fault-tolerant, optimized execution for applications, distributed across independent nodes. Its programs consist of two consecutive procedures grouped together into jobs: Map receives a (key, value) pair and transforms it into one or more new pairs; Reduce receives a set of pairs that share the same key and are sorted according to their value, and performs a summary operation on them to produce a new, usually smaller set of pairs. Based on MapReduce, [3] introduces an approach in which a decision about matching two entity profiles triggers further decisions about matching their associated profiles. Similar approaches are used by other iterative techniques, which employ some partial results of the ER process to locate new matches (e.g., [1], [2], [8], [12]).

In a different line of work, approximate techniques aim to achieve a good balance between the number of identified duplicates and the number of executed comparisons. The most prominent technique is blocking [4]; it represents profiles by sets of keys and groups similar profiles into blocks based on similar or identical keys. Comparisons are then executed inside the resulting blocks. More recent methods, e.g., [16], target data of low structuredness, such as those stemming from the Web. Most of these techniques are redundancy-positive, yielding a large number of unnecessary
comparisons when applied to large datasets. Yet, their blocks can be significantly enhanced by Meta-blocking.

This work bridges the gap between the two lines of research for ER over Web data, parallelizing Meta-blocking to achieve even higher scalability. A similar effort for tabular data is made in [14, 15], which adapt Standard Blocking and Sorted Neighborhood, respectively, to MapReduce.

III. Preliminaries

**Blocking.** An entity profile comprises a set of name-value pairs, uniquely identified through a global id; $e_i$ denotes a profile with id $i$. Two profiles that refer to the same object are called duplicates or matches. A set of profiles is called entity collection (E); $D(E)$ stands for the duplicate profiles in $E$, and $|D(E)|$ for the number of duplicates in $E$. A blocking method groups the entities of a collection into clusters, called blocks; $b_i$ is a block with id $i$. The number of entities in $b_i$ is called block size ($|b_i|$), while the number of comparisons it involves is called block cardinality ($|b_i|$). Collectively, a set of blocks is called block collection (B); $|B|$ stands for its size, and $|B|$ for its total cardinality, which is the number of comparisons it involves, i.e., $|B| = \sum_{b \in B} |b_i|$. The set of blocks containing a particular entity $e_i$ is denoted by $B_i(\subseteq B)$, with $|B_i|$ representing its size. Two entities $e_i$, $e_j$ placed in the same block are called co-occurring, and their comparison, $c_{i,j}$, is called matching if $e_i$, $e_j$ are duplicates; $B_{ij}$ represents the set of blocks they co-occur in and its size, $|B_{ij}|$, stands for the number of blocks they share.

Typically, the performance of a block collection is independent of the entity matching method that executes the pair-wise comparisons [4, 17]. The main assumption is that two duplicates are detected as long as they co-occur in at least one block. The set of co-occurring duplicate entities is denoted by $D(B)$, with $|D(B)|$ representing its size. In this context, two established measures are used for assessing the performance of a block collection [4, 16]:

- **Pairs Completeness (PC)** is analogous to recall, estimating the portion of existing pairs of duplicates that are co-occurring: $PC = |D(B)|/|D(E)|$. It is defined in the interval $[0, 1]$, with higher values indicating better recall.

- **Pairs Quality (PQ)** is analogous to precision, estimating the portion of executed comparisons that involve a non-redundant pair of duplicates: $PQ = |D(B)|/|B|$. Defined in the interval $[0, 1]$, higher values indicate better precision.

Ideally, the goal of blocking is to maximize both $PC$ and $PQ$. However, there is a trade-off between these measures: the more comparisons are contained in $B$, the more duplicates are co-occurring and the higher $PC$ gets. Given, though, that $|B|$ increases quadratically for a linear increase in $|D(B)|$ [11], $PQ$ is reduced. For this reason, the goal of blocking methods in practice is to achieve a good balance between the two measures – with an emphasis on recall.

**Meta-blocking.** Redundancy-positive blocking trades high $PC$ for low $PQ$, i.e., it yields a large number of unnecessary comparisons to achieve high recall. Meta-blocking operates on its blocks to tip the balance in favor of precision at a small cost in recall. It restructures a redundancy-positive block collection $B$ into a new one $B'$ such that $PC(B') \approx PC(B)$ and $PQ(B') \gg PQ(B)$ [17]. Its performance depends on two parameters that affect the pruning of the blocking graph: the weighting and the pruning scheme.

The weighting scheme receives as input the entities defining an edge in $G_B$ along with the block collection $B$ and estimates the corresponding weight. We focus on three schemes [17], formally defined in Figure 2. CBS captures the fundamental property that the more blocks two entities share, the more likely they are matching. ECBS improves CBS by discounting the contribution of entities participating in many blocks. Finally, JS estimates the portion of blocks shared by two entities. In all cases, their weights are restricted to $[0, 1]$ through normalization.

For the pruning scheme, there are four options [17]:

- **Weighted Edge Pruning (WEP)** retains all edges with a weight higher than the overall mean one.

- **Cardinality Edge Pruning (CEP)** retains the top-$K$ edges of the entire blocking graph, where $K = \lceil \sum_{b \in B} |b_i|/2 \rceil$.

- **Weighted Node Pruning (WNP)** amounts to the average edge weight of each neighborhood.

- **Cardinality Node Pruning (CNP)** retains, for each neighborhood, the top-$k$ edges with $k = \lceil \sum_{b \in B} |b_i|/|E| - 1 \rceil$.

In this work, we adapt to the MapReduce framework, the combination of all pruning schemes with the CBS, ECBS and JS weighting schemes.

All pruning schemes benefit greatly from Block Filtering [18], which like Meta-blocking cleans a block collection from many unnecessary comparisons. Instead of using a graph, though, it simply removes every entity from the least important of its blocks. The main assumption is that the larger a block is, the less important it is for its entities. In more detail, Block Filtering orders the blocks of $B$ in descending order of cardinality and retains every entity $e_i$ in the top $N_i$ blocks of $B_i$ (i.e., the $N_i$ smallest blocks that contain $e_i$), where $N_i = \lfloor r \times |B_i| \rfloor$ and $r \in [0, 1]$ is the ratio of Block Filtering. In this work, we employ Block Filtering as an integral part of our parallelized approach, setting $r = 0.80$. This value was experimentally verified to prune at least 50% of the blocking graph’s edges, while having a negligible impact on recall [18].

Due to lack of space, we cover the remaining weighting schemes, namely ARCS and EJS, in the extended version of our paper: http://www.csd.uoc.gr/~veltz/thesis/MetaBlockingExtr.pdf.
IV. APPROACH

We now elaborate on the adaptation of Meta-blocking to MapReduce. The serialized workflow consists of two consecutive stages: the first one applies Block Filtering to the input block collection $B$, while the second one applies Meta-blocking to yield the final, restructured collection $B'$. The parallelized counterpart consists of three stages. Again, the first one applies Block Filtering to the input block collection and the last one Meta-blocking. The only difference is in the second stage, which preprocesses the blocks to transform them into a suitable form for Parallel Meta-blocking.

For every stage of the parallelized workflow, we consider two different approaches: (i) a basic strategy, which applies a straightforward adaptation with high I/O between the nodes, and (ii) an advanced strategy, which reduces the overhead of data exchange through a more elaborate processing. We analyse each stage separately, in Sections IV-A to IV-C. In Section IV-D, we introduce a novel algorithm for load balancing that applies to both strategies. In all cases, special care was taken to minimize the I/O between the independent nodes. Part of this effort focused on optimizing our representation model. Instead of using the textual blocking keys and URIs to identify the blocks and the entities, respectively, our model relies exclusively on numbers: blocks and entities are uniquely identified by integer ids; edges are represented by the concatenation of the adjacent entity ids.

A. Stage 1: Block Filtering

The first stage applies Block Filtering to the input blocks in order to reduce the size of the blocking graph. Central to this procedure is the sorting of blocks in ascending order of cardinality, from the smallest to the largest one. Depending on how this sorting is performed, we present two possible approaches for adapting Block Filtering to MapReduce.

The basic strategy orders once and globally all input blocks, using two MapReduce jobs that exploit the automatic sorting of the input to the reduce function. The advanced strategy employs a single MapReduce job that orders locally the blocks associated with every entity at the cost of repeating some computations across the independent nodes.

For both strategies, every $(\text{key}, \text{value})$ pair of the input corresponds to a block $b_i$; the key is the block id, while the value contains the list of the entity ids placed in $b_i$: $\text{key}=k$ and $\text{value}=[i, j, \ldots, m]$ for $b_i=[e_i, e_j, \ldots, e_m]$. The output of both strategies comprises the $N$ most important blocks associated with the individual entities. Every key denotes the id of an entity $e_i$, while the corresponding value contains the list of block ids still containing $e_i$: $\text{key}=i$ and $\text{value}=B'_i$.

1) Basic Strategy: It employs two jobs. The first one sorts all blocks globally in ascending order of cardinality, producing a sorted list $B_{\text{sorted}}$. Specifically, the map function receives a block id $k$ along with the entities contained in $b_k$. It computes the corresponding cardinality, $||b_k||$, and emits a $(||b_k||, k)$ pair. All pairs are sorted in descending order of their keys (i.e., cardinalities), before they are forwarded as input to the single reduce function. The reducer extracts and stores to the disk the values of the sorted input, i.e., the block ids that form $B_{\text{sorted}}$. The second job uses $B_{\text{sorted}}$ to identify the most important blocks for each entity. The map function gets the same input as the first job: a block id along with the entity ids it contains. For every entity $e_i$ contained in the given block $b_k$, it emits a pair $(i, k)$. All pairs having the same key are grouped together so that the reduce function receives as input all block ids assigned to a specific entity $e_i$ (i.e., $\text{key}=i$, $\text{value}=B'_i$). It loads from the disk the sorted list of block ids, $B_{\text{sorted}}$, and uses it to get the ranking position of every block. The $N$ blocks with the highest ranking positions form the list of retained block ids $B'_i$, which are emitted as output: $\text{key}=i$, $\text{value}=B'_i$.

2) Advanced Strategy: It uses a single job that provides the reduce function with the necessary information for sorting the blocks of each entity locally. The map function gets as input the id and the entities of a block $b_k$ and estimates its cardinality, $||b_k||$. For every entity $e_i \in b_k$, it emits a pair with the entity id as the key, while the (composite) value concatenates the id and the cardinality of block $b_k$: $\text{key}=i$ and $\text{value}=k, ||b_k||$. The reduce function gathers all blocks associated with an entity $e_i$ along with their cardinality. It sorts them in ascending number of comparisons and extracts the top $N$ elements from the resulting list to form $B'_i$. Similar to the basic strategy, it then emits a pair $(i, B'_i)$.

Figure 3 illustrates the functionality of the advanced strategy of Block Filtering. For the three entities $e_1$, $e_2$ and $e_3$ of $b_1$, we emit in the Map phase a pair with each of them as the key and $b_1.3$ as value, since there are three comparisons in this block. In the Reduce phase, we gather all four pairs having $e_1$ as key and keep only the top-3 blocks for this entity. Thus, we discard $b_7$ from the blocks of $e_1$.

B. Stage 2: Preprocessing

This stage prepares the data that will be processed by the pruning algorithm in the third stage. Its output actually determines the complexity of the pruning algorithm: the more computations are performed by Preprocessing and are...
integrated into its output, the simpler is the functionality of the pruning algorithms and vice versa. This trade-off gives rise to two different strategies, which share the same input (i.e., the outcome of Block Filtering), but differ in their output. Basic Preprocessing explicitly creates the blocking graph: it performs all weight computations and stores all edges to the disk in order to simplify the functionality of the pruning algorithm. Advanced Preprocessing defers all weight computations, but facilitates them by enriching the input of the pruning algorithms with all the necessary information. Again, the basic strategy involves two jobs, while the advanced one uses just one job.

1) Basic Strategy: The first job transforms the output of Block Filtering into a block collection. Its map function receives as key the id of an entity \(e_i\) and as value the list of associated blocks, \(B_i\). It swaps values and keys, emitting for every block \(B_k \in B_i\) a pair \((k, i|B_k|)\), where \(k\) and \(i\) are the block and the entity id, respectively, while \(|B_i|\) is the number of blocks containing \(e_i\) after Block Filtering. The reduce function groups together all entities contained in a block \(B_k\) and reproduces all comparisons. For every comparison \(c_{i,j}\) between entities \(e_i\) and \(e_j\), it emits the concatenation of their ids as key \((\text{key}=i,j)\) and \([B_i,|B_j|]\) as value — this information is necessary for the ECBS and JS weighting schemes.

The second job consists of an identity mapper and a reduce function that estimates the weight for every edge of the blocking graph. The value list of its input, \(V\), clusters together the information pertaining to the edge \(\langle n_i, n_j, \rangle\) identified by the input key. Based on them, the reducer computes the corresponding edge weight \(w_{i,j}\) from the formulas in Figure 2. For example, we simply have \(w_{i,j} = |V|\) for CBS, as the size of the value list equals the number of common blocks, \(|B_{i,j}|\). As output, the reducer emits a pair with the id and the weight of the edge: \(\text{key}=i,j,\text{value}=w_{i,j}\).

2) Advanced Strategy: The key to this approach is that every edge \(\langle n_i, n_j, \rangle\) of the blocking graph \(G_B\) corresponds to a non-redundant comparison \(c_{i,j}\) in the block collection \(B\). A comparison \(c_{i,j}\) in \(B_k\) is non-redundant only if it satisfies the Least Common Block Index (LeCoBi) condition. That is, if the id of \(b_k\) equals the least common block id of the entities \(e_i\) and \(e_j\): \(k=\min(B_i \cap B_j)\) [16]. To assess the LeCoBi condition for two entities \(e_i\) and \(e_j\), we need to compare the lists of associated blocks, \(B_i\) and \(B_j\) (for higher efficiency, their elements should be sorted in ascending order of block ids). Advanced Preprocessing integrates this information to its output, so that all edge and weight computations are carried out by the pruning algorithm.

This functionality is performed by one job. The map function receives as input the id of an entity \(e_i\) as key and the associated blocks \(B_i\) as values. First, it sorts \(B_i\) in ascending order of block ids. Then, for every block \(B_k \in B_i\), it emits its id as the key, while the value concatenates the id of \(e_i\), with the entire sorted list \(B_k\): \(\text{key}=k,\text{value}=i|B_k|\). MapReduce then reassembles all blocks, by grouping together all pairs with the same key. The reduce function receives as input the entity list of a specific block along with the blocks that are associated with every individual entity and emits the same \((\text{key}, \text{value})\) pairs as output: \(\text{key}=k\) and \(\text{value}=[i.B_i, j.B_j, \ldots, m.B_m]\).

Figure 4 provides an example for the functionality of the advanced strategy of Preprocessing. For each block \(b_1, b_2\) and \(b_4\), to which \(e_1\) belongs, we emit a pair with their block ids as key and \(e_1\), concatenated with \(b_1, b_2, b_4\) as value in the \(\text{Map}\) phase. In the \(\text{Reduce}\) phase, all the entities of \(b_1\) are grouped together (i.e., \(e_1, e_2\) and \(e_3\)), each accompanied with the block ids in which it belongs. We just concatenate them and emit them as the value of the \(\text{key}=b_1\).

C. Stage 3: Meta-blocking

This stage applies one pruning algorithm to the output of Preprocessing and yields a set of retained edges; every edge corresponds to a new block that is part of the final, restructured block collection. We present two strategies for each algorithm: the basic and the advanced one, applied on top of the basic and the advanced preprocessing outputs.

1) Weighted Edge Pruning: Both strategies employ a single job that estimates the average edge weight in the \(\text{Map}\) phase and discards the edges that do not exceed it in the \(\text{Reduce}\) phase. They use the same \(\text{reduce}\) function and differ only in the \(\text{map}\) function.

Basic Strategy. This identity mapper receives the id of an individual edge \(\langle n_i, n_j, \rangle\) as key \((\text{key}=i,j)\) and its weight \(w_{i,j}\) as value. Before forwarding the input to the reducer, it updates two counters used for estimating the average edge weight: the size of the blocking graph \(|E_G|\) and the total edge weight \(tw\). The reducer receives the id and the weight of an individual edge. If the weight is greater than the mean weight of the graph \((w_{i,j} > tw/|E_G|)\), the input edge is retained and, thus, the input pair \((i,j, w_{i,j})\) is emitted as output.

Advanced Strategy. It operates on the enriched description of an individual block \(b_k\): the input key contains its id \((k)\), while the input value contains a list with the entity ids in \(b_k\) and the blocks ids associated with each entity, i.e., \(\text{value}=[i.B_i, j.B_j, \ldots]\). The map function iterates over all comparisons in \(b_k\) and assesses the LeCoBi condition for the involved entities. For every non-redundant comparison \(c_{i,j}\), it estimates the corresponding edge weight \(w_{i,j}\) and emits it along with the edge id: \(\text{key}=i,j\) and \(\text{value}=w_{i,j}\). It also
updates the two counters that are used in the reduce phase, \(|E_G|\) and \(tw\). As in the Basic strategy, the reducer emits the input pairs \((i, j, w_{ij})\) for which \((w_{ij} > tw/|E_G|)\).

In Figure 5, we present the functionality of the advanced strategy of WEP, with an example using the JS weighting scheme. Applying the map function to block \(b_1\), which contains the entity profiles \(e_1, e_2\) and \(e_3\), we output, for every non-redundant comparison the id of the comparison as key (i.e., \(e_1-e_2, e_1-e_3\) and \(e_2-e_3\)) and the weight of the comparisons as value. According to the JS weighting scheme, \(e_1-e_2\) weight is \(1/3\), because the \(e_1, e_2\) entities share only one block (\(b_1\)) from all 3 blocks they belong to. Assuming that the average weight is \(1/3\), in the reduce function we emit only the pairs with a weight above \(1/3\), so we prune the comparisons \(e_1-e_2, e_1-e_3\) and \(e_2-e_3\).

2) Cardinality Edge Pruning: Ideally, we could gather all edges in a single node and sort them in descending weight to retain the top \(K\) ones. In practice, though, this approach does not scale to large blocking graphs with millions of nodes and billions of edges, due to limited memory resources. To overcome this limitation, we convert the global cardinality threshold into a global weight threshold. We use one job to compute the minimum edge weight \(w_{\min}\) such that at least \(K\) edges have a weight greater than or equal to it. Then, a second job outputs exactly \(K\) edges with a weight greater than or equal to \(w_{\min}\). For every job, the two strategies again differ in the mapper, but share the same reducer.

**Basic Strategy.** For both jobs, the mapper receives as input key the id of an individual edge \(\langle n_i, n_j \rangle \) \((i, j)\) and as input value the corresponding weight \(w_{ij}\). The map function of the first job emits a pair \((w_{ij}, 1)\), enabling the reducer to compute the minimum edge weight \(w_{\min}\). The reducer receives as input the list of all distinct weights, sorted in descending order, along with their frequencies (i.e., the number of edges with the same weight). It iterates this list starting from the largest weight and keeps a counter with the number of edges that have a weight greater than or equal to the current one. As soon as the counter reaches \(K\), the reducer stops and stores the current weight \(w_{\min}\) to the disk.

The map function of the second job processes the same input \(\langle n_i, n_j \rangle \) \((i, j)\), \((w_{ij}, 1)\), swaps keys with values and emits a pair \((w_{ij}, i, j)\), only if \(w_{ij} \geq w_{\min}\). It is possible that the overall number of edges \(\langle n_i, n_j \rangle\), with \(w_{ij} \geq w_{\min}\), is larger than \(K\), due to ties. The single reducer of the second job addresses this issue, ensuring that exactly \(K\) edges are retained. It receives as input all pairs of edge weights and ids \((w_{ij}, i, j)\), for which \(w_{ij} \geq w_{\min}\). They are automatically sorted in descending order, from the largest weight to the lowest. The reducer extracts the top \(K\) elements and emits them, after swapping keys and values.

**Advanced Strategy.** For both jobs, the mapper iterates over all comparisons of the input block, using its enriched description. For every non-redundant comparison \(c_{ij}\), it computes the edge weight \(w_{ij}\) from the block ids associated with \(e_i\) and \(e_j\). Then, the map function of the first job emits a pair \((w_{ij}, 1)\), while the map function of the second job emits a pair \((w_{ij}, i, j)\), only if \(w_{ij} \geq w_{\min}\). The reduce function for both jobs is the same with that of the Basic Strategy.

In Figure 6, we provide an example with the functionality of the advanced strategy of CEP, using the same input with Figure 5 and the JS weighting scheme. In the map function of the first job, we process each block and emit the weights of its non-redundant comparisons as keys (e.g., for \(b_1\) the non-redundant comparisons are \(e_1-e_2, e_1-e_3\) and \(e_2-e_3\)) and \(1\) as value. In the reduce function, we retrieve, in descending order of weight, the first \(k\) input pairs and emit the current key as \(w_{\min}\), in our example we assume to be \(1/3\). In the second job, we use the same map function, this time emitting the comparison ids as values, for those comparisons whose weight is greater than or equal to \(w_{\min} = 1/3\). Hence, we prune the comparison \(e_1-e_2\) already from the map phase. In the reduce function, we emit each input pair, sorted in descending order of weight, until we have emitted the \(k\)-th pair, which is \(e_1-e_2\) (pairs with the same weight are sorted randomly).

3) Weighted & Cardinality Node Pruning: Both node pruning schemes use one job with the same map function. They differ in the reduce function, which applies their pruning logic to an individual node neighborhood.
Basic Strategy. The map function takes as input key the id of an individual edge \( <n_i,n_j> \) \((i,j)\) and as input value, the corresponding weight \((w_{i,j})\). To ensure that each reducer gathers all edges adjacent to a specific node, it emits two \((\text{key, value})\) pairs – one for each of the adjacent entities. In each case, the key contains one of the entity ids \((i \text{ or } j)\), while the value concatenates the other entity id with the edge weight \((j.w_{i,j} \text{ or } i.w_{i,j})\).

WNP Reduce Function. Its input key comprises the id \(i\) of an entity \(e_i\) that defines a neighborhood \(N_G(v_i)\) in the blocking graph \(G\). Its input value comprises the adjacent node/entity ids concatenated with the respective edge weights. From them, it estimates the average weight of the neighborhood, \(\bar{w}_i\). Then, it iterates over all adjacent edges and discards those that are assigned a lower weight. For each retained edge \( <n_i,n_j>, \) it emits a pair \((i,j, w_{i,j})\).

CNP Reduce Function. It receives the same input as the WNP reduce function and orders all edges of the neighborhood in descending order of weight. For the top \(k\) ones, it emits their id with their weight – a pair \((i,j, w_{i,j})\).

Advanced Strategy. The map function of the advanced strategy operates on the enriched description of an individual block, iterating over all its comparisons. For every non-redundant comparison, it computes the corresponding edge weight from the associated block ids and emits two \((\text{key, value})\) pairs, one for each of the adjacent entities – just like the basic map function. The aforementioned WNP and CNP Reduce functions process the input.

Figure 7 shows an example of the advanced strategy of WNP to the same input as that of Figures 5, 6, using JS. In the map function, for the comparison \(e_1\rightarrow e_2\), we emit the pairs \((e_1,e_2,1/3)\) and \((e_2,e_1,1/3)\). In the Reduce phase, we group all the pairs with key \(e_1\) and calculate, for this group, a local weight threshold (e.g., 1/3). Then, for the group of \(e_1\), we emit only the pairs with a weight higher than 1/3, i.e., \(e_1\rightarrow e_3\), which has a weight of 2/3. Accordingly, the advanced strategy of CNP differs only in the last step, in which we emit only the top-\(k\) pairs of each group. If we assume that we want the top-2 comparisons that involve \(e_1\), out of the three comparisons shown in the group of \(e_1\), we would emit \((e_1.e_3, 2/3)\) and \((e_1.e_2, 1/3)\).

D. Load Balancing

The default load balancing of Hadoop creates a predetermined number of partitions using a hash function. It involves a negligible overhead and is expected to work fine for jobs that entail linear processing of the input data. This applies to most of the functions defined above, but they are expected to account for a small portion of the overall computational cost. The main computational cost pertains to functions with quadratic complexity: they receive an individual block and iterate over all the comparisons it contains, estimating (part of) the corresponding edge weights. These are the reduce function in the first job of the basic strategy for Stage 2 and all map functions of the advanced strategies for Stage 3. For these functions, the default partitioning disregards the block cardinalities and leads to significant skews in the workload distribution (see Section V).

To address this issue, we developed a specialized algorithm for load balancing. Our goal is to split the input blocks into partitions that share almost the same number of comparisons. The key idea is to exploit the power law distribution of block cardinalities that appears in redundancy-positive block collections: the vast majority of blocks involves one or two comparisons and the frequency of blocks decreases with larger cardinalities [16], [17]. For better results, the number of partitions is determined dynamically.

The functionality of our approach is outlined in Algorithm 1. It sorts the block collection in descending cardinality (Line 1) and removes the first and largest block, \(b_0\), from it (Line 2). The maximum computational cost of each partition, \(maxCost\), is set equal to the cardinality of \(b_0\) (Line 3). A partition is created for \(b_0\) (Line 4) and placed in the priority queue \(Q\), which sorts partitions in ascending order of comparisons (Line 5); this means that the head of \(Q\) always corresponds to the partition with the smallest computational cost.
cost so far. Subsequently, our algorithm iterates over the remaining blocks and examines whether the current block fits into the partition at the head of the queue, \( P_{\text{head}} \) (Lines 6-10); that is, it checks whether their combined cardinality is lower than \( \text{maxCost} \). If so, the current block is added to \( P_{\text{head}} \) (Line 11); otherwise, it is placed in a new partition that is added to the queue (Lines 13-14). Then, \( P_{\text{head}} \) is placed again in \( Q \) (Line 15). The time complexity of our approach is dominated by the sorting of blocks, thus having a complexity of \( O(|B| \log |B|) \). This means that our approach scales well to large block collections, involving a low overhead.

V. EXPERIMENTS

Setup. All approaches were implemented in Java v7, using Apache Hadoop v1.2.0 on a cluster\(^2\) with 15 Ubuntu 12.04.3 LTS servers, one master and 14 slaves, each having 8 AMD 2.1 GHz CPUs and 8 GB of RAM. Each node can run 4 map or reduce tasks simultaneously, assigning 1024 MB to each task. The available disk space (4 TB) was equally partitioned to the nodes. Each time measurement was repeated twice and the average value was considered to eliminate external factors effects (e.g., network overhead). For Load Balancing, we employed the default mechanism of Hadoop for map and reduce functions with linear complexity; for those with a quadratic complexity, we partitioned the relevant blocks to the available nodes using Algorithm 1.

Datasets. We employ the largest datasets that have been applied to Meta-blocking. Their characteristics are presented in Table I. \( D_{\text{dbpedia}} \) involves entities from two snapshots of DBPedia\(^3\) infoboxes, which chronologically differ by 2 years – v3.0rc for \( D_1 \) and v3.4 for \( D_2 \). In total, there are 3.3M entities, of which less than 900,000 are common, having the same URL. This dataset has been employed widely in the literature \cite{16, 17}. \( D_{\text{freebase}} \) contains entities from the Billion Triple Challenge 2012\(^4\). In this case, \( D_1 \) encompasses entities from DBPedia and \( D_2 \) entities from Freebase\(^5\). To avoid noisy profiles, we disregard URIs that appear in just one triple. 7.4M entities were left, of which 1.3M are common according to the \( \text{owl:sameAs} \) statements.

Both datasets are suitable for Clean-Clean ER, where the goal is to identify the matching entities shared by two duplicate-free collections \( D_1 \) and \( D_2 \). We use them for Dirty ER, as well, merging \( D_1 \) and \( D_2 \) into a single collection with duplicates in itself; the goal is to partition the resulting collection into clusters of matching entities. To derive redundancy-positive block collections, we used Token Blocking and Block Purging \cite{16}, which simply discards the blocks that contain more than half the input entities. The characteristics of the resulting blocks are presented in Table II. In total, we have four block collections, two for each ER task, that vary significantly in their characteristics.

Measures. To assess the quality of the restructured block collections, we employ the established measures of Pairs Completeness \( PC \) (recall) and Pairs Quality \( PQ \) (precision) – see Section III. To assess the time efficiency of the Meta-blocking workflow, we use the Overhead Time \( (O\text{Time}) \). This is the time (in minutes) that intervenes between receiving a redundancy-positive block collection as input and returning the restructured blocks as output. The lower its value is, the more efficient is the corresponding workflow.

Load Balancing. We compare the performance of Algorithm 1 to the default Hadoop balancer through the distribution of partition cardinalities they produce (i.e., the total number of comparisons in the blocks of each partition). We summarize these distributions using minimum, maximum, median and mean partition cardinalities. The closer these measures are to each other, the more balanced the workload of each node. We applied both approaches to the input of Stage 2 and present the experimental outcomes in Table III.

Algorithm 1 produces a set of partitions with a practically constant distribution of cardinalities across all datasets. The four measures have identical values, while the standard deviation of the distribution is lower than 1. This means that the partitions differ by a handful of comparisons in the worst case. In contrast, the default balancer yields distributions with much larger variance. The standard deviation is an order of magnitude lower than the other measures for \( DB_C \) and \( DB_P \), while for \( FR_C \) and \( FR_D \) it is almost equal to the average cardinality. The difference between the minimum and the maximum cardinality raises to four and one orders of magnitude for \( FR_C \) and \( FR_D \). Thus, serious bottlenecks are expected to rise in all datasets. For this reason, we did not try to measure the actual running time of the default balancer.

On the whole, we conclude that Algorithm 1 outperforms the default balancer of Hadoop. The only advantage of the latter is its low overhead, as it is integrated and optimized for Hadoop. However, our approach is quite scalable and

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\(^2\) okeanos (https://okeanos.grnet.gr) GRNET cloud service

\(^3\) http://dbpedia.org

\(^4\) https://km.aifb.kit.edu/projects/btc-2012

\(^5\) https://www.freebase.com

**Table I** The heterogeneous entity collections we employed in our experiments.

<table>
<thead>
<tr>
<th>( D_{\text{dbpedia}} )</th>
<th>( D_{\text{freebase}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entities (</td>
<td>E</td>
</tr>
<tr>
<td>Triples</td>
<td>1.69 \times 10^8</td>
</tr>
<tr>
<td>Attribute Names</td>
<td>30,757</td>
</tr>
<tr>
<td>Triples per Entity</td>
<td>14.19</td>
</tr>
<tr>
<td>Duplicates (</td>
<td>D[E]</td>
</tr>
<tr>
<td>BF Comparisons</td>
<td>2.58 \times 10^{12}</td>
</tr>
</tbody>
</table>

**Table II** The block collections that were used as input to Meta-blocking.

<table>
<thead>
<tr>
<th>( D_{\text{dbpedia}} )</th>
<th>( D_{\text{freebase}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blocks</td>
<td>( DB_C )</td>
</tr>
<tr>
<td>Triples per Entity</td>
<td>1.239,424</td>
</tr>
<tr>
<td>Triples</td>
<td>4.23 \times 10^8</td>
</tr>
<tr>
<td>Entities</td>
<td>891,708</td>
</tr>
<tr>
<td>Pairs</td>
<td>15.30-16.08</td>
</tr>
<tr>
<td>Completeness ( PC )</td>
<td>0.999</td>
</tr>
<tr>
<td>Quality ( PQ )</td>
<td>2.11 \times 10^{-4}</td>
</tr>
</tbody>
</table>
Table III

The distribution of partition cardinalities produced by Algorithm 1 and the default load balancer of Hadoop.

<table>
<thead>
<tr>
<th>Partitions</th>
<th>DBc Algorithm 1</th>
<th>DBc Default</th>
<th>DBD Algorithm 1</th>
<th>DBD Default</th>
<th>FRc Algorithm 1</th>
<th>FRc Default</th>
<th>FRD Algorithm 1</th>
<th>FRD Default</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum Part. Cardinality</td>
<td>2.71·10^7</td>
<td>4.18·10^7</td>
<td>5.74·10^7</td>
<td>7.88·10^7</td>
<td>1.45·10^7</td>
<td>3.21·10^4</td>
<td>3.76·10^7</td>
<td>9.81·10^6</td>
</tr>
<tr>
<td>Maximum Part. Cardinality</td>
<td>2.71·10^7</td>
<td>8.20·10^7</td>
<td>5.74·10^7</td>
<td>1.48·10^8</td>
<td>1.45·10^7</td>
<td>2.35·10^8</td>
<td>3.76·10^7</td>
<td>9.81·10^6</td>
</tr>
<tr>
<td>Median Part. Cardinality</td>
<td>2.71·10^7</td>
<td>5.83·10^7</td>
<td>5.74·10^7</td>
<td>9.59·10^7</td>
<td>1.45·10^7</td>
<td>2.02·10^7</td>
<td>3.76·10^7</td>
<td>9.01·10^7</td>
</tr>
<tr>
<td>Average Part. Cardinality</td>
<td>2.71·10^7</td>
<td>5.87·10^7</td>
<td>5.74·10^7</td>
<td>9.68·10^7</td>
<td>1.45·10^7</td>
<td>3.14·10^7</td>
<td>3.76·10^7</td>
<td>5.84·10^7</td>
</tr>
<tr>
<td>St. Dev. Part. Cardinality</td>
<td>0.48</td>
<td>7.59·10^6</td>
<td>0.19</td>
<td>9.98·10^6</td>
<td>0.48</td>
<td>3.01·10^7</td>
<td>0.27</td>
<td>4.64·10^7</td>
</tr>
</tbody>
</table>

Table IV

Overhead Time in minutes for all Meta-blocking techniques.

<table>
<thead>
<tr>
<th>Block Filtering</th>
<th>DBc Basic</th>
<th>DBc Advan.</th>
<th>DBD Basic</th>
<th>DBD Advan.</th>
<th>FRc Advan.</th>
<th>FRD Advan.</th>
<th>FRc Advan.</th>
<th>FRD Advan.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEP</td>
<td>CBS</td>
<td>222</td>
<td>22</td>
<td>250</td>
<td>22</td>
<td>158</td>
<td>184</td>
<td>188</td>
</tr>
<tr>
<td></td>
<td>ECBS</td>
<td>240</td>
<td>38</td>
<td>278</td>
<td>20</td>
<td>235</td>
<td>188</td>
<td>235</td>
</tr>
<tr>
<td></td>
<td>JS</td>
<td>223</td>
<td>28</td>
<td>279</td>
<td>39</td>
<td>209</td>
<td>234</td>
<td>397</td>
</tr>
<tr>
<td>CNP</td>
<td>CBS</td>
<td>491</td>
<td>301</td>
<td>559</td>
<td>527</td>
<td>1488</td>
<td>2144</td>
<td>2514</td>
</tr>
<tr>
<td></td>
<td>ECBS</td>
<td>555</td>
<td>383</td>
<td>639</td>
<td>633</td>
<td>1949</td>
<td>3058</td>
<td>3058</td>
</tr>
<tr>
<td></td>
<td>JS</td>
<td>534</td>
<td>363</td>
<td>618</td>
<td>620</td>
<td>1637</td>
<td>2546</td>
<td>2546</td>
</tr>
<tr>
<td>WEP</td>
<td>CBS</td>
<td>220</td>
<td>38</td>
<td>250</td>
<td>63</td>
<td>271</td>
<td>89</td>
<td>271</td>
</tr>
<tr>
<td></td>
<td>ECBS</td>
<td>219</td>
<td>36</td>
<td>254</td>
<td>40</td>
<td>271</td>
<td>55</td>
<td>271</td>
</tr>
<tr>
<td></td>
<td>JS</td>
<td>219</td>
<td>41</td>
<td>254</td>
<td>90</td>
<td>371</td>
<td>55</td>
<td>371</td>
</tr>
<tr>
<td>WNP</td>
<td>CBS</td>
<td>498</td>
<td>304</td>
<td>569</td>
<td>539</td>
<td>1534</td>
<td>2674</td>
<td>2674</td>
</tr>
<tr>
<td></td>
<td>ECBS</td>
<td>568</td>
<td>389</td>
<td>658</td>
<td>644</td>
<td>1971</td>
<td>3046</td>
<td>3046</td>
</tr>
<tr>
<td></td>
<td>JS</td>
<td>553</td>
<td>373</td>
<td>641</td>
<td>644</td>
<td>1636</td>
<td>2790</td>
<td>2790</td>
</tr>
</tbody>
</table>

Table V

The block collections after Block Filtering.

<table>
<thead>
<tr>
<th>DBc</th>
<th>DBD</th>
<th>FRc</th>
<th>FRD</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>1.239·10⁶</td>
<td>1.499·10⁷</td>
<td>1.308·10⁷</td>
</tr>
<tr>
<td>B⁰</td>
<td>1.20·10¹⁰</td>
<td>2.17·10¹⁰</td>
<td>2.96·10¹⁰</td>
</tr>
<tr>
<td>BPE</td>
<td>12.12·12.68</td>
<td>11.72</td>
<td>57.28·3.86</td>
</tr>
<tr>
<td>PC</td>
<td>0.998</td>
<td>0.998</td>
<td>0.996</td>
</tr>
<tr>
<td>PQ</td>
<td>7.44·10⁻⁵</td>
<td>4.11·10⁻⁵</td>
<td>4.38·10⁻⁵</td>
</tr>
</tbody>
</table>

in the introduction.

Note also that there is a considerable variance between the efficiency of the two strategies, which designates that the parallelization of Meta-blocking is not a trivial task. The basic approach is consistently slower than the advanced one and their difference is particularly intense in the case of WEP and CEP. The inferior performance of the basic strategy should be attributed to the more jobs it employs and the higher I/O it yields between the independent nodes of the cluster: it creates a distinct edge for all comparisons, even the redundant ones, whereas the advanced approach creates a distinct edge only for the non-redundant comparisons; this means around 30% less comparisons in our datasets.

For the advanced strategy, CEP is the fastest algorithm in most cases, partly because it outputs the lowest number of comparisons. WEP follows in close distance, due to its similarly simple processing. CNP and WNP exhibit similar overhead times, as there are minor differences in the computational cost of their processing. They are the most time-consuming algorithms by far, since they process every edge twice, inside the neighborhoods of both adjacent nodes. They also retain significantly more comparisons than CEP and WEP, respectively (see RR below).

Qualitative Performance. To assess the quality of the restructured blocks produced by Meta-blocking, we consider the performance of the four pruning algorithms with respect to PC (recall), PQ (precision) and RR, namely the Reduction Ratio. RR expresses the relative decrease in the number of comparisons conveyed by Meta-blocking. Formally, \( RR = 1 - ||B'||/||B|| \), where \( B \) is the original and \( B' \) the restructured block collection [4]. For all measures, we estimated the average value and the standard deviation across the five weighting schemes per dataset. The outcomes are presented in Figures 8(a) to (c). In all diagrams, the higher a bar is, the better the corresponding performance.

Figure 8(a) demonstrates that the relative recall of the pruning algorithms remains the same across all datasets: the node-centric schemes, CNP and WNP, are more robust and...
detect more duplicates than their edge-centric counterparts. CEP and WEP. The cardinality-based schemes, CEP and CNP, consistently achieve lower PC than the weight-based ones, WEP and WNP, which exceed 0.8 across all datasets. This means that they reduce the original PC by less than 10%, despite the significant enhancements in efficiency they convey. Indeed, Figure 8(b) shows that WEP achieves an RR close to 0.8, thus saving 80% of the original comparisons. The pruning of WNP is more shallow, as it retains at least one edge per node. Its RR fluctuates between 0.46 and 0.65, thus saving around half the original comparisons. For CEP and CNP, RR is consistently higher than 0.99. In fact, they perform such a deep pruning that they reduce the pairwise comparisons by 2 to 3 orders of magnitude across all datasets (still CNP retains twice as many comparisons as CEP, on average). This explains their poor recall. Yet, CEP and CNP achieve significantly higher precision across all datasets (Figure 8(c)). There is actually a trade-off between precision and recall for the four pruning algorithms: the higher PQ is for a specific method and dataset, the lower is the corresponding PC and vice versa. These patterns are in accordance with earlier findings about the relative performance of the pruning algorithms [17].

Scalability. Finally, we examined the scalability of the advanced strategy with respect to the available nodes. We applied all WEP to DBc in combination with the 3 weighting schemes using 4, 9 and 14 slave nodes – including the master node. Figure 9 presents the speedup results along with the ideal case, in which the speedup is linear to the number of nodes (similar patterns were exhibited for the other datasets and are omitted for brevity). We observe that all the weighting schemes show a speedup close to the ideal one. For 14 slave nodes, it fluctuates between 11.8 and 12.3. This means that using more cluster nodes than we did in our experiments will improve the overhead time of the advanced strategy of Meta-blocking almost proportionally.

VI. Conclusions

We proposed two parallel versions of Meta-blocking based on MapReduce and equipped them with a load balancing algorithm that distributes the workload evenly among the cluster nodes. Our approaches dramatically increase the time efficiency of the serialized version, enabling blocking-based Entity Resolution in voluminous datasets. We observe that the basic parallelization strategy leads to significantly higher space requirements and is consistently slower than the advanced one, especially in the case of edge-centric algorithms. Our advanced strategy offers an optimized implementation that reduces the overhead of data exchange, leading to a speedup with the number of cluster nodes that is close to the ideal – regardless of the weighting scheme.

Acknowledgements. This work was partially supported by EU H2020 BigDataEurope (#644564) and PARTHENOS (#654119), and MEDA project (GSRTs KRIPIIS action, Greece & European Regional Development Fund of EU).

References