Supervised Meta-blocking

George Papadakis[$], George Papastefanatos[$], Georgia Koutrika[◇]
[◇] HP Labs, USA koutrika@hp.com
[$] Institute for the Management of Information Systems, Research Center "Athena", Greece
{gpapadis,gpapas}@imis.athena-innovation.gr

ABSTRACT

Entity Resolution matches mentions of the same entity. Being an expensive task for large data, its performance can be improved by blocking, i.e., grouping similar entities and comparing only entities in the same group. Blocking improves the run-time of Entity Resolution, but it still involves unnecessary comparisons that limit its performance. Meta-blocking is the process of restructuring a block collection in order to prune such comparisons. Existing unsupervised meta-blocking methods use simple pruning rules, which offer a rather coarse-grained filtering technique that can be conservative (i.e., keeping too many unnecessary comparisons) or aggressive (i.e., pruning good comparisons). In this work, we introduce supervised meta-blocking techniques that learn classification models for distinguishing promising comparisons. For this task, we propose a small set of generic features that combine a low extraction cost with high discriminatory power. We show that supervised meta-blocking can achieve high performance with small training sets that can be manually created. We analytically compare our supervised approaches with baseline and competitor methods over 10 large-scale datasets, both real and synthetic.

1. INTRODUCTION

Entity Resolution (*ER*) is the process of finding and linking different instances (profiles) of the same real-world entity [9]. It is an inherently quadratic task, since, in principle, each entity profile has to be compared with all others. For Entity Resolution to scale to large datasets, *blocking* is used to group similar entities into blocks so that profile comparisons are limited within each block. Blocking methods may place each entity profile into only one block, forming disjoint blocks, or into multiple blocks, creating redundancy [4].

Redundancy is typically used for reducing the likelihood of missed matches – especially for noisy, highly heterogeneous data [9, 21]. In particular, redundancy-positive blocking is based on the intuition that the more blocks two entities share, the more likely they match [22]. To illustrate, consider the profiles in Figure 1(a): profiles p_1 and p_3 correspond to the same person and so do p_2 and p_4. As an example of a redundancy-based blocking method, let us consider Token Blocking [21], which creates one block for every distinct token

Proceedings of the VLDB Endowment, Vol. 7, No. 14

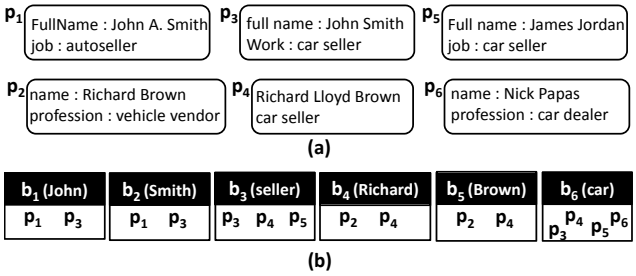


Figure 1: (a) A set of entity profiles, and (b) the redundancy-positive block collection produced by Token Blocking.

that appears in at least two profiles. The resulting block collection is shown in Figure 1(b). We observe that both pairs of matching profiles can be detected, as they co-occur in at least one block.

However, redundancy brings about repeated comparisons between the same entity profiles in different blocks. In the example of Figure 1(b), block b_2 repeats the comparison contained in block b_1, while b_5 repeats the comparison in b_4. Hence, b_2 and b_5 contain one *redundant* comparison each. Furthermore, there are several comparisons between non-matching entities, which we call *superfluous* comparisons. Block b_3 entails 3 superfluous comparisons between the non-matching profiles p_3, p_4 and p_5. In b_6, all 3 comparisons involving p_6 are superfluous, while the rest are redundant, repeated in b_3. Overall, while blocking improves entity resolution times, it still involves unnecessary comparisons that limit its performance: superfluous ones between non-matching entities, and redundant ones, which repeatedly compare the same entity profiles. In our example, the total number of comparisons in the blocks of Figure 1(b) is 13 compared to 15 of the brute-force method. This number could be further reduced – without affecting the recall of blocking-based ER – by avoiding the redundant and the superfluous comparisons.

Meta-blocking is a method that takes as input a redundancy-positive block collection and transforms it into a new block collection that generates fewer comparisons, but keeps most of the detected duplicates [22]. To achieve this, existing meta-blocking techniques operate in two phases. First, they map the input block collection to a graph, called *blocking graph*; its nodes are the entity profiles, while its edges connect two nodes if the corresponding profiles co-occur in at least one block. By definition, the graph eliminates all redundant comparisons: each pair of co-occurring profiles is connected with a single edge, which means that they will be compared only once. In the second phase, meta-blocking techniques use the graph to prune superfluous comparisons. For this task, each edge is assigned a weight leveraging the fundamental property of redundancy-positive block collections that the similarity of two entity profiles is proportional to their co-occurrences in blocks. High

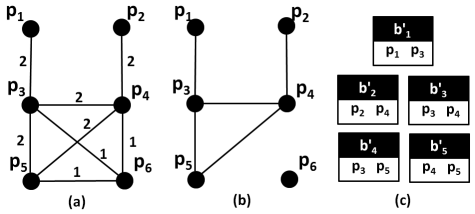


Figure 2: (a) A blocking graph mapping the blocks in Figure 1, (b) possible pruned blocking graph, (c) the derived blocks.

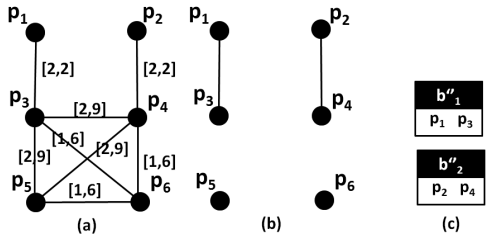


Figure 3: (a) A blocking graph mapping the blocks in Figure 1, (b) a possible pruned blocking graph, (c) the derived blocks.

weights are given to the *matching edges* (i.e., edges likely connecting duplicates) and lower weights to the *non-matching* ones.

As an example, the blocks in Figure 1(b) can be mapped to the blocking graph depicted in Figure 2(a). The edge weights are typically defined in the interval [0,1] through normalization, but for simplicity, we consider that each edge weight in this example is equal to the absolute number of blocks shared by its adjacent entities. Different pruning algorithms can be used to remove edges with low weights and hence discard part of the superfluous comparisons. For example, one such strategy, called Weight Edge Pruning, discards all edges having a weight lower than the average edge weight across the entire graph [22]. For the blocking graph of Figure 2(a), the average edge weight is 1.625. The resulting pruned blocking graph is shown in Figure 2(b). The output block collection is generated from the pruned blocking graph by placing the adjacent entities of every edge into a separate block as shown in Figure 2(c). As the result of meta-blocking, the new block collection contains just 5 comparisons and does not miss any matches.

Existing meta-blocking methods use simple pruning rules such as "`if` *weight<threshold* `then discard edge`" for removing comparisons. Consequently, they face two challenges: assigning representative weights to edges and choosing a good threshold for removing edges. We argue that determining if an edge is a good candidate for removal is in fact a multi-criteria decision problem. Combining these criteria into a single scalar value inevitably misses valuable information. Furthermore, pruning based on a single threshold on the weights is a rather coarse-grained filtering technique that can be conservative (i.e., keeping many superfluous comparisons) or aggressive (i.e., pruning good comparisons). In our example in Figure 2(c), the final block collection retains 3 superfluous comparisons in b'_3, b'_4 and b'_5; increasing the threshold so as to further reduce these comparisons would prune the matching comparisons, as well, because they have the same weight as the superfluous ones.

In this paper, we argue that accurate identification of non-matching edges requires learning composite pruning models from the data. We *formalize meta-blocking as a binary classification task*, where the goal is to identify matching and non-matching edges. We propose *supervised meta-blocking* techniques that compose generic, schema-agnostic information about the co-occurring entities into comprehensive feature vectors, instead of summarizing it into unilateral weights, as unsupervised methods do.

For example, the blocks of Figure 1(b) can be mapped to the blocking graph of Figure 3(a), where each edge is associated with a feature vector $[a_1, a_2]$. The feature a_1 is the number of common blocks shared by the adjacent entities, and a_2 is the total number of comparisons contained in these blocks. The resulting feature vectors are fed into a classification algorithm that learns composite rules (or models) to effectively distinguish matching and non-matching edges. In our example, a composite rule could look like "`if` $a_1 \leq 2$ & $a_2 > 5$ `then discard edge`", capturing the intuition that the more blocks two profiles share and the smaller these blocks are, the more likely the profiles match. Figure 3(b) shows the graph generated by this rule, and Figure 3(c) depicts the resulting blocks; compared to the blocks in Figure 2(c), they have no superfluous comparisons, thus achieving higher efficiency for the same recall.

We identify and examine three aspects that determine the performance of supervised meta-blocking techniques: (*a*) the set of features annotating the edges of the blocking graph, (*b*) the training data, and (*c*) the classification algorithm and its configuration.

Using more features may help make the pruning of the non-matching edges more accurate. However, the computational cost for meta-blocking gets higher. Moreover, the classification features should be generic enough to apply to any redundancy-positive block collection. With these issues in mind, *we propose a small set of generic features that combine a low extraction cost with high discriminatory power* and we evaluate their performance using real data. Furthermore, to facilitate the understanding of the space of possible features, we divide it according to five dimensions.

Selecting training data, we face two issues. The first one is a class imbalance problem: the vast majority of the edges in a blocking graph are non-matching. In order to build representative training sets, we select the most suitable technique for our task among established solutions. The second issue regards the training set size. In general, large training sets increase the accuracy and robustness of the learned model. However, they yield complex, inefficient classifiers that require time-consuming training. In addition, the manual creation of large training sets in the absence of ground-truth is a painful and challenging process. *We show that we can achieve high performance with small training sets that can be manually created* making supervised meta-blocking a practical solution.

We consider a representative sample of state-of-the-art classifiers: Naïve Bayes, Bayesian Networks, Decision Trees and Support Vector Machines. We show that *our supervised techniques are robust with respect to different classifiers and their configurations* by examining their performance over several large-scale datasets.

Finally, we evaluate the performance of supervised meta-blocking by comparing to (*a*) the brute-force Entity Resolution, which executes all comparisons included in the input set of blocks, (*b*) the top-performing unsupervised meta-blocking methods [22], and (*c*) the iterative blocking [25]. Note that the iterative blocking constitutes the only other method in the literature that, similarly to meta-blocking, receives an existing block collection and aims at processing it in a way that improves its original performance: it propagates every detected pair of duplicates to all associated blocks in order to identify additional matches and to save unnecessary comparisons. We perform a scalability analysis, which involves 7 large-scale synthetic datasets of various sizes, ranging from 10 thousand to 2 million entities. Our experiments demonstrate that *our supervised techniques exhibit significantly better time efficiency than the best alternatives, while achieving equivalent recall*.

In summary, this paper makes the following contributions:

• We formalize supervised meta-blocking as a classification problem and we demonstrate how it can be used to significantly enhance the quality of a redundancy-positive block collection.

• We map the space of possible classification features along five dimensions and we select a small set of generic features that combine a low extraction cost with high discriminatory power. We evaluate their performance using real data.
• We show that small training sets, which can be manually created, can achieve high performance, making supervised meta-blocking a practical solution for Entity Resolution.
• We show that our supervised techniques are robust with respect to different classifiers and their configurations by examining their performance over several large-scale datasets.
• We perform a thorough scalability analysis, comparing supervised meta-blocking against the best competitor approaches.

The rest of the paper is structured as follows. Section 2 presents related work, Section 3 provides a brief overview of unsupervised meta-blocking, Section 4 introduces supervised meta-blocking, and Section 5 describes the real-world datasets and the metrics used in the evaluation. Sections 6 and 7 cover feature and training set selection, while in Section 8, we fine-tune the classification algorithms. Section 9 experimentally compares supervised meta-blocking with competitor techniques and finally, Section 10 concludes the paper.

2. RELATED WORK

There is a large body of work on Entity Resolution [9, 19]. Blocking techniques group similar entities into blocks so that profile comparisons are limited within each block. These methods can be distinguished into *schema-based* and *schema-agnostic* ones.

Schema-based methods (e.g., Sorted Neighborhood [12], Suffix Array [7], HARRA [14], Canopy Clustering [17], and q-grams blocking [10]) group entities based on knowledge about the semantics of their attributes. These approaches are only suitable for homogeneous information spaces, like databases, where the quality of the schema is known a-priori. In contrast, schema-agnostic blocking techniques cluster entities into blocks without requiring any knowledge about the underlying schema(ta). For instance, in Token Blocking [21], every token that is shared by at least two entities creates an individual block. Total Description [20] improves on Token Blocking by considering the most discriminative parts of entity URIs instead of all their tokens. In the same category fall Attribute Clustering [21] and TYPiMatch [16]. These techniques are preferred in the context of heterogeneous information spaces, which involve large volumes of noisy, semi-structured data that are loosely bound to various schemata [11].

Both schema-based and schema-agnostic blocking methods usually produce redundancy-positive block collections [22]. Meta-blocking operates on top of them, improving the balance between precision and recall by restructuring the block collection [22].

All the aforementioned approaches rely on an unsupervised functionality. Supervised learning has been applied to blocking-based ER with the purpose of fine-tuning the configuration of schema-based blocking methods: in [1, 18], the authors propose methods for learning combinations of attribute names and similarity metrics that are suitable for extracting and comparing blocking keys. Supervised learning has also been applied to generic ER in order to classify pairs of entities into matching and non-matching, by adapting similarity metrics and the corresponding thresholds to a particular domain [2, 6, 8, 24]. Other works introduce methods for facilitating the construction of the training set [23], while in [3], the authors propose supervised techniques for combining the decisions of multiple ER systems into an ensemble of higher performance. No prior work has applied supervised learning techniques to the task of meta-blocking.

3. PRELIMINARIES

In this section, we introduce the main concepts and notation used in the paper and we provide a brief overview of existing unsupervised meta-blocking techniques. Table 1 summarizes notation.

An *entity profile* p is a uniquely identified collection of information described in terms of name-value pairs. An *entity collection* $\mathcal{E}$ is a set of entity profiles. Two profiles $p_i, p_j \in \mathcal{E}$ are *duplicates* or *matches* ($p_i \equiv p_j$) if they represent the same real-world object.

Entity Resolution comes in two forms. *Clean-Clean ER* receives as input two duplicate-free but overlapping entity collections and returns as output all pairs of duplicate profiles they contain. *Dirty ER* receives as input a single entity collection that contains duplicates in itself and returns the set of matching entity profiles. Blocking can be used to scale both forms of ER to large entity collections by clustering similar profiles into *blocks* so that comparisons are restricted among the entity profiles within each block b_i.

The quality of a *block collection* B can be measured in terms of two competing criteria, namely precision and recall, which are estimated through the following established measures [1, 7, 18, 21]:

(i) Pairs Quality (PQ) assesses precision, i.e., the portion of non-redundant comparisons between matching entities. It is defined as: $PQ(B) = |\mathcal{D}(B)|/\|B\|$, where $\mathcal{D}(B)$ represents the set of detectable matches, i.e. the pairs of duplicate profiles that co-occur in at least one block, and $|\mathcal{D}(B)|$ stands for its size. $\|B\|$ is called *aggregate cardinality* and denotes the total number of comparisons contained in B: $\|B\| = \sum_{b_i \in B} \|b_i\|$, where $\|b_i\|$ is the cardinality of b_i (i.e., the number of pair-wise comparisons it entails). PQ takes values in $[0, 1]$, with higher values indicating higher precision for B, i.e., fewer superfluous and redundant comparisons.

(ii) Pair Completeness (PC) assesses recall, i.e., the portion of duplicates that share at least one block and, thus, can be detected. It is formally defined as: $PC(B) = |\mathcal{D}(B)|/|\mathcal{D}(\mathcal{E})|$, where $\mathcal{D}(\mathcal{E})$ represents the set of duplicates contained in the input entity collection $\mathcal{E}$, and $|\mathcal{D}(\mathcal{E})|$ stands for its size. PC values are in the interval $[0, 1]$, with higher values indicating higher recall for B.

Note that we follow a known best practice [1, 4, 18, 25], examining the quality of a block collection independently of profile matching techniques. In particular, we assume an oracle exists that correctly decides whether two entity profiles match or not. Thus, $\mathcal{D}(B)$ is equivalent to the set of matching comparisons in B. The rationale of this approach is that a block collection with high precision and high recall guarantees that the quality of a complete ER solution is as good as that of the selected entity matching algorithm.

There is a clear trade-off between the precision and the recall of B: as more comparisons are executed (i.e., higher $\|B\|$), its recall increases (i.e., higher $|\mathcal{D}(B)|$), but its precision decreases, and vice versa. The redundancy-positive block collections achieve high PC at the cost of lower PQ, as they place every entity profile into multiple blocks. Meta-blocking aims at improving this balance by restructuring a redundancy-positive block collection B into a new one B' of higher precision but equivalent recall. More formally:

Problem 1 (Meta-blocking). *Given a redundancy-positive block collection B, the goal of meta-blocking is to restructure B into a new collection B' that achieves significantly higher precision, while maintaining the original recall ($PQ(B') \gg PQ(B)$, $PC(B') \approx PC(B)$).*

Existing meta-blocking techniques rely their functionality on the *weighted blocking graph* ($\mathcal{G}_B$), a data structure that models the block assignments in the block collection B. As illustrated in Figure 2(a), $\mathcal{G}_B$ is formed by creating a node for every entity profile in B and an undirected edge for every non-redundant pair of co-occurring profiles. Formally, this structure is defined as follows:

p_i	an entity profile
B, $\|B\|$, $\|\|B\|\|$	a block collection, its size (# of blocks), its cardinality (# of comparisons)
b_i, $\|b_i\|$, $\|\|b_i\|\|$	a block, its size (# of entities), its cardinality (# of comparisons)
G_B, V_B, E_B	the generalized blocking graph of B, its nodes and its edges
G_{v_i}, V_{v_i}, E_{v_i}	the neighborhood of node v_i, its nodes and its edges.
$B_i \subseteq B$, $\|B_i\|$	the set of blocks containing p_i and its size (# of blocks)
$B_{i,j} \subseteq B$	the set of blocks shared by the p_i and p_j ($B_{i,j}=B_i \cap B_j$)
$\|B_{i,j}\|$	the size of $B_{i,j}$, i.e., # of comparisons between p_i and p_j
$\mathcal{D}(B)$,$\|\mathcal{D}(B)\|$	the set of detected duplicates in B and its size
$p_i.comp()$	the set of comparisons entailing p_i (including the redundant ones)

Table 1: Summary of main notation.

Definition 1 (Weighted Blocking Graph). *Given a block collection B, its* weighted blocking graph *is a graph $\mathcal{G}_B = \{\mathcal{V}_B, \mathcal{E}_B, W_B\}$, where $\mathcal{V}_B$ is the set of its nodes such that $\forall p_i \in B\ \exists n_i \in \mathcal{V}_B$, $\mathcal{E}_B \subseteq \mathcal{V}_B \times \mathcal{V}_B$ is the set of undirected edges between all pairs of co-occurring entity profiles in B, and W_B is the set of edge weights that take values in the interval $[0, 1]$ such that $\forall e_{i,j} \in \mathcal{E}_B\ \exists w_{i,j} \in W_B$.*

As explained in Section 1, the blocking graph enhances precision by eliminating all redundant comparisons without any impact on recall, since it contains no parallel edges. Then, meta-blocking applies a pruning algorithm in order to discard part of the superfluous comparisons at a small cost in recall. These algorithms are distinguished into four categories, based on their functionality and the type of threshold they incorporate [22]:

- *Cardinality Edge Pruning* (*CEP*) sorts all edges in descending order of their weight and retains those in the top K ranking positions. Therefore, K constitutes a global cardinality threshold that is applied to the entire graph.
- *Cardinality Node Pruning* (*CNP*) does the same, but retains the top k edges for each node. k is also a global cardinality threshold, but is applied to the neighborhood of each node.
- *Weight Edge Pruning* (*WEP*) discards all edges of the blocking graph that have a weight lower than a global weight threshold (the average edge weight in our case).
- *Weight Node Pruning* (*WNP*) applies a local weight threshold to the neighborhood of each node, discarding those adjacent edges with a weight lower than it.

4. SUPERVISED META-BLOCKING

We consider that a comparison between profiles p_i and p_j can be captured by a feature vector $f_{i,j}=[a_1(p_i, p_j), a_2(p_i, p_j), \ldots, a_n(p_i, p_j)]$, where $\{a_1, a_2, \ldots, a_n\}$ is a set of features, and $a_k(p_i, p_j)\{k = 1...n\}$ is the value of feature a_k for this pair. For instance, the number of common blocks the adjacent profiles share could be such a feature. By replacing edge weights with feature vectors, we extend the weighted blocking graph $\mathcal{G}_B$ into the *generalized blocking graph* G_B, formally defined as follows:

Definition 2 (Generalized Blocking Graph). *Given a block collection B, its* generalized blocking graph *is a graph $G_B = \{V_B, E_B, F_B\}$, where V_B is the set of nodes such that $\forall p_i \in B\ \exists n_i \in V_B$, $E_B \subseteq V_B \times V_B$ is the set of undirected edges between all pairs of co-occurring entity profiles in B, and F_B is the set of feature vectors that are assigned to every edge such that $\forall e_{i,j} \in E_B\ \exists f_{i,j} \in F_B$.*

The elements of F_B are fed to a classifier that labels all edges of the blocking graph as `likely_match` or `unlikely_match`, if they are highly likely to connect two matching or non-matching entity profiles, respectively. We measure the performance of this process using the following notation:

- $TP(E_B)$ denotes the true positive edges of E_B, which connect matching profiles and are correctly classified as `likely_match`.
- $FP(E_B)$ are the false positive edges of E_B, which are adjacent to non-matching profiles, but are classified as `likely_match`.
- $TN(E_B)$ are the true negative edges of E_B, which connect non-matching profiles and are correctly categorized as `unlikely_match`.
- $FN(E_B)$ are the false negative edges of E_B, which connect matching profiles, but are categorized as `unlikely_match`.

After classifying all edges, supervised meta-blocking derives the pruned blocking graph G_B^{cl} by discarding those edges labeled as `unlikely_match` (i.e., $TN(E_B)$ and $FN(E_B)$). The edges retained in G_B^{cl} belong to the sets $TP(E_B)$ and $FP(E_B)$: $E_B^{cl} = TP(E_B) \cup FP(E_B) = E_B - (TN(E_B) \cup FN(E_B))$. The output of supervised meta-blocking is the block collection B_{cl} that is derived from G_B^{cl} by creating a block of minimum size for every retained edge $e_{i,j} \in E_B^{cl}$. Thus, its PC and PQ can be expressed in terms of the edges in E_B^{cl} as follows:

$$PC(B_{cl}) = \frac{|\mathcal{D}(B_{cl})|}{|\mathcal{D}(\mathcal{E})|} = \frac{|TP(E_B)|}{|\mathcal{D}(\mathcal{E})|} = \frac{|\mathcal{D}(B)| - |FN(E_B)|}{|\mathcal{D}(\mathcal{E})|},$$

$$PQ(B_{cl}) = \frac{|\mathcal{D}(B_{cl})|}{||B_{cl}||} = \frac{|TP(E_B)|}{|TP(E_B)| + |FP(E_B)|}.$$

We now formally define the task of supervised meta-blocking as:

Problem 2 (Supervised Meta-blocking). *Given a redundancy-positive block collection B, its generalized blocking graph $G_B = \{V_B, E_B, F_B\}$, the classes $C=\{$`likely_match`, `unlikely_match`$\}$, and a training set $E_{tr} = \{<e_{i,j}, c_k> : e_{i,j} \in E_B \wedge c_k \in C\}$, the goal of supervised meta-blocking is to learn a classification model that minimizes the cardinality of the sets $FN(E_B)$ and $FP(E_B)$ so that the block collection B_{cl} resulting from the pruned graph G_B^{cl} achieves higher precision than B (i.e., $PQ(B_{cl}) \gg PQ(B)$), while maintaining the original recall (i.e., $PC(B_{cl}) \approx PC(B)$).*

4.1 Classification Algorithms

In principle, any algorithm for supervised learning can be used for edge classification in supervised meta-blocking. However, it should have a limited overhead for correctly categorizing most edges of the blocking graph. Further, it should be compatible with the pruning algorithm at hand. Supervised meta-blocking learns global pruning models that apply to the entire blocking graph and not to a specific neighborhood. Thus, it can be applied to *CEP*, *CNP* and *WEP*, substituting their thresholds with a classification model. In the first two cases, though, the output of the classification model should sort the edges of the blocking graph in ascending order of the likelihood that they belong to the class `likely_match`. Given that most classifiers simply produce a category label for every instance, this is only possible with probabilistic classifiers: they associate every instance with the probability that it belongs to every class, thus enabling their sorting. Note, though, that supervised meta-blocking is not compatible with *WNP*: applying a global threshold or classification model to *WNP* renders it equivalent to *WEP*.

Based on the above, we have selected four state-of-the-art approaches that are commonly used in classification tasks [26]: *(i)* Naïve Bayes (NB), *(ii)* Bayesian Networks (BN), *(iii)* C4.5 decision trees, and *(iv)* Support Vector Machines (SVM). For their implementation, we used the open-source library WEKA, version 3.6. Unless stated otherwise, we employ their default configuration, as provided by WEKA.

These approaches encompass two probabilistic classification algorithms that are compatible with *CEP* and *CNP*, namely Naïve Bayes and Bayesian Networks. In addition, they involve functionalities of diverse sophistication. On the one extreme, SVM involves complex statistical learning, while on the other extreme, Naïve Bayes relies on simple probabilistic learning. The latter actually operates as a benchmark for deciding whether the additional computational cost of the advanced classifiers pays off: comparable performance across all algorithms provides strong indication for the robustness of our classification features.

To solve the supervised meta-blocking problem, we need to determine the features to annotate the edges of the blocking graph (Section 6) and the appropriate training set, both in terms of size and composition (Section 7). In Section 5, we introduce the datasets and metrics to be used for the evaluation of the proposed solution.

5. DATASETS & METRICS

Datasets. We consider both Clean-Clean and Dirty ER and we employ the real-world datasets used in the earlier meta-blocking work [22]. Table 2 summarizes the characteristics of the entity collections and their blocks for each dataset.

D_{movies} is a collection of 50,000 entities shared among the individually clean sets of IMDB and DBPedia movies. The ground truth for this dataset stems from the "imdbid" attribute in the profiles of the DBPedia movies. Its blocks were created using Token Blocking (cf. Section 2) in conjunction with Block Purging, which discards blocks containing more comparisons than a dynamically determined threshold [21]. The resulting block collection exhibits nearly perfect recall at the cost of 27 million comparisons. Out of them, 22 million comparisons are non-redundant, forming the edges of the blocking graph.

Our second Clean-Clean ER dataset, $D_{infoboxes}$, consists of two different versions of the DBPedia Infobox dataset[1]. They contain all name-value pairs of the infoboxes in the articles of Wikipedia's English version, extracted at October 2007 for $DBPedia_1$ and October 2009 for $DBPedia_2$. The large time period that intervenes between the two collections renders their resolution challenging, since they share only 25% of all name-value pairs among the common entities [21]. As matching entities, we consider those with the same URL. For the creation of blocks, we applied Token Blocking and Block Purging. The resulting block collection entails 40 billion comparisons; 34 billion of them are non-redundant.

Finally, our Dirty ER dataset D_{BTC09} comprises more than 250,000 entities from the Billion Triple Challenge 2009 (BTC09) data collection[2]. Its ground-truth consists of 10,653 pairs that were identified through their identical value for at least one inverse functional property. Its blocks correspond to a subset of those derived by applying the *Total Description* approach [20] (cf. Section 2) to the entire BTC09 data collection (see [22] for more details on how we selected this subset). They achieve very high *PC* at the cost of 130 million comparisons, out of which 78 million are non-redundant.

Metrics. To assess the impact of supervised meta-blocking on *blocking effectiveness*, we consider the relative reduction in *PC*, formally defined as: $\Delta PC = \frac{PC(B_{cl})-PC(B)}{PC(B)} \cdot 100\%$, where $PC(B)$ and $PC(B_{cl})$ denote the recall of the original and the restructured block collection, respectively. Negative values indicate that meta-blocking reduces *PC*, while positive ones indicate higher recall.

To assess the impact of supervised meta-blocking on *blocking efficiency*, we use the following metrics:

- *Classification time CT* is the average time (in milliseconds) required by the learned model to categorize an individual edge of the blocking graph – excluding the time to build its feature vector.
- *Overhead time OT* is the total time required by meta-blocking to process the input blocks, i.e., to train the model, build the feature vectors of all edges, classify them and produce the new blocks.
- *Resolution time RT* is the sum of *OT* and the time required to execute all comparisons that are classified as `likely_match` using an entity matching technique. As such, we employ the Jaccard similarity of all tokens in the values of two entity profiles – regardless of the associated attribute names.

[1] `http://wiki.dbpedia.org/Datasets`

[2] `http://km.aifb.kit.edu/projects/btc-2009`

	D_{movies}		$D_{infoboxes}$		D_{BTC09}
	DBP	**IMDB**	**DBP_1**	**DBP_2**	
Entities	27,615	23,182	$1{,}19{\cdot}10^6$	$2{,}16{\cdot}10^6$	253,353
Name-Value Pairs	186,013	816,012	$1.75{\cdot}10^7$	$3.67{\cdot}10^7$	$1{,}60{\cdot}10^6$
Existing Matches	22,405		892,586		10,653
Blocks	40,430		$1.21{\cdot}10^6$		106,462
PC	99.39%		99.89%		96.94%
Comparisons in Blocks	$2.67{\cdot}10^7$		$3.98{\cdot}10^{10}$		$1.31{\cdot}10^8$
Brute-force *RT*	26 min		~320 hours		64 min
Edges	$2.26{\cdot}10^7$		$3.41{\cdot}10^{10}$		$7.77{\cdot}10^7$
Nodes	$5.06{\cdot}10^4$		$3.33{\cdot}10^6$		$2.53{\cdot}10^5$

Table 2: Overview of the real-world datasets.

- *CMP* denotes the absolute number of comparisons contained in the restructured block collection (i.e., $\|B_{cl}\|$).

For these metrics, the lower their value is, the higher is the efficiency of meta-blocking. Note that *OT* and *RT* do not consider the time to randomly select the training set, due to its negligible computational cost (see Section 7). We also estimate efficiency using *PQ*, with higher values indicating more efficient meta-blocking.

6. FEATURES FOR META-BLOCKING

Features for supervised meta-blocking describe the edges of the generalized blocking graph and should pertain to the corresponding comparisons or to the adjacent entities. These features should adhere to the following principles: (*i*) they should be *generic*, so that they are not tailored to a specific application; (*ii*) they should be *effective*, so that they yield high classification accuracy distinguishing between likely and unlikely matches; (*iii*) they should be *efficient*, involving low extraction cost and overhead, so that the classification time is significantly lower than the comparison time of its adjacent entities, and (*iv*) they should be *minimal*, in the sense that incorporating additional features has marginal benefit on the performance of meta-blocking. Similar principles were defined in [3] for classification tasks related to Entity Resolution (see Section 2).

Feature Categorization. To help understand candidate features for supervised meta-blocking and their appropriateness, we divide their space along five dimensions: schema-awareness, source of evidence, target, complexity and scope (see Figure 4).

Schema awareness. Classification features can be divided into schema-agnostic and schema-based ones.

Schema-agnostic features rely on the structural information of the blocking graph and the characteristics of the blocks.

Schema-based features rely on the quality and the semantics of the attribute names that describe the input entity profiles. Thus, they exclusively consider blocks and parts of the blocking graph that are associated with specific attributes.

Source of evidence. Given a block collection *B*, there are two main sources for extracting classification features: the blocks contained in *B* and the blocking graph G_B. *Block-based* features exclusively consider evidence of the former type, while *graph-based* ones rely on topological information about the blocking graph. *Iterative* features are graph-based features associated with a node that depend on the scores assigned to its neighboring nodes. Similarly to link analysis techniques, such as PageRank, these features may be computed by assigning a prior value to every node (or edge) and iteratively adjusting it, processing the entire blocking graph according to a mathematical formula until convergence.

Target. Depending on the part of the graph they annotate, classification features are divided into *edge-specific*, which pertain to individual edges and *node-specific*, which pertain to individual nodes.

Complexity. Classification features can be categorized into *raw* and *derived* ones. The raw attributes encompass atomic information that is explicitly available in the input block collection or its

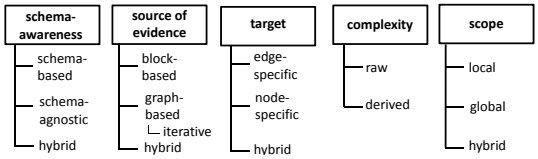


Figure 4: Categorization of classification features.

blocking graph; on the other hand, the *derived* features combine multiple features into a single, composite feature.

Scope. Classification features are *local* when they consider information that is directly related to the annotated item (i.e., the edge or its adjacent nodes). *Global* features consider information from the entire blocking graph.

Most criteria (with the exception of complexity) define two complementary categories. Thus, features from both categories can be combined into *hybrid* ones, which may exhibit higher performance.

6.1 Candidate Features

We introduce our candidate features and explain their appropriateness for our meta-blocking problem (notation is in Table 1).

Common_Blocks. A schema-agnostic, block-based feature is `Common_Blocks`, i.e., the number of blocks shared by two profiles:

$$\texttt{Common\_Blocks}(e_{i,j}) = |B_{i,j}|.$$

This feature captures the inherent trait of redundancy-positive block collections that the more blocks two entity profiles share, the more likely they are to match.

Based on `Common_Blocks`, we could define schema-based features that take into account the subset of common blocks stemming from the values of specific attributes (e.g., $\texttt{Common\_Blocks}_{title}$ for the attribute "Title"). However, such schema-based features are application-specific and have limited generality. In addition, they are crafted for homogeneous information spaces, like databases, and cannot handle heterogeneous ones, characterized by very diverse schemata (e.g., Web of Data) and constituting the most common source of redundancy-positive blocking [22]. Therefore, we focus hereafter on schema-agnostic classification features, which are completely decoupled from the nature and the semantics of the attributes describing the input entity collections.

Entity_Blocks. Another block-based feature is `Entity_Blocks`, which is inversely proportional to the number of blocks containing a specific entity/node:

$$\texttt{Entity\_Blocks}(v_i) = \log \frac{|B|}{|B_i|}.$$

This feature is inspired from the inverse document frequency (IDF) that is commonly used in Information Retrieval (IR). The rationale behind it is that the higher its value is (i.e., lower $|B_i|$), the more likely p_i is to match with one of its co-occurring entity profiles. In contrast, a profile that is contained in an excessively high number of blocks is highly likely to contain noise. For instance, it could be the result of falsely merging several profiles that correspond to different real-world objects.

Node_Degree. This is a graph-based feature and it is equal to the degree of node $v_i \in V_B$:

$$\texttt{Node\_Degree}(v_i) = |V_{v_i}|.$$

In essence, `Node_Degree` is equivalent to the number of non-redundant comparisons involving the entity p_i that corresponds to the node v_i. The intuition here is that the lower its degree is, the more likely p_i is to match with one of its co-occurring entity profiles.

Iterative_Degree. This is an iterative, graph-based feature that is based on the following premise: for every node v_i, the lower the degrees of its neighboring nodes are, the higher is the likelihood that p_i is matching with one of them and, thus, the higher the score of v_i should be. It is similar to `Node_Degree`, as it initially associates every node with a prior score equal to the portion of non-redundant comparisons involving it (i.e., $|V_{v_i}|/|E_B|$). They differ though in that the `Iterative_Degree` gradually modifies the score of a node v_i, $ID(v_i)$, according to the following formula:

$$ID(v_i) = ID_0(v_i) + \sum_{v_k \in V_{v_i}} \frac{ID(v_k)}{|V_{v_k}|},$$

where $ID_0(v_i)$ is the prior score assigned to v_i and $v_k \in V_{v_i}$ are the nodes connected with v_i on the blocking graph. This formula is similar to the one defining PageRank with priors, where the damping factor d, which determines the behavior of the random surfer, is set equal to 0. It can be calculated using a simple iterative algorithm; after converging, nodes connected with many nodes of high degree receive the lowest scores, while the highest scores are assigned to nodes connected with few nodes of low degree.

The extraction of such iterative, graph-based features is computationally expensive and it does not scale well to blocking graphs with millions of nodes and billions of edges. Nevertheless, we include `Iterative_Degree` in our approach and we investigate whether its low efficiency is counterbalanced by high discriminatory power.

Transitive_Degree. A possible surrogate of higher efficiency is the `Transitive_Degree` feature. It lies in the middle of `Node_Degree` and `Iterative_Degree`, considering the aggregate degrees of the nodes that lie within the neighborhood of v_i as follows:

$$\texttt{Transitive\_Degree}(v_i) = \sum_{v_k \in V_{v_i}} |V_{v_k}|.$$

Common_Neighbors. This graph-based feature amounts to the portion of adjacent entity profiles shared by a pair of co-occurring profiles. More formally, it is defined as follows:

$$\texttt{Common\_Neighbors}(e_{i,j}) = \frac{|V_{v_i} \cap V_{v_j}|}{|V_{v_i} \cup V_{v_j}|}.$$

High values indicate that p_i and p_j co-occur with the same entities, either in their common blocks or in blocks they do not share. In the latter case, the common neighbors actually help deal with patterns missed due to noise in entity profiles. For example, consider the entity profiles p_1={<*name*,*John*>, <*surname*,*Smith*>}, p_2={<*name*,*Jon*> , <*surname*, *Smit*>} and p_3={<*name*, *John*>,<*surname*, *Smit*>}, where ($p_1 \equiv p_2$)$\not\equiv p_3$; Token Blocking [21] (cf. Section 2) yields two blocks b_{John}={p_1, p_3} and b_{Smit}={p_2, p_3}, with p_1 and p_2 co-occurring in none of them. Nevertheless, `Common_Neighbors` provides strong evidence for their match.

Jaccard_Similarity. This feature captures the portion of all comparisons (including the redundant ones) that involve a specific pair of entity profiles:

$$\begin{aligned}\texttt{Jaccard\_Sim}(e_{i,j}) &= \frac{|p_i.comp() \cap p_j.comp()|}{|p_i.comp() \cup p_j.comp()|} \\ &= \frac{|B_{i,j}|}{|p_i.comp()| + |p_j.comp()| - |B_{i,j}|}.\end{aligned}$$

Higher values of this ratio indicate a stronger pattern of co-occurrence for p_i and p_j and, hence, the more likely p_i and p_j are to match.

Note that on the target dimension, `Entity_Blocks`, `Node_Degree`, `Iterative_Degree` and `Transitive_Degree` are node-specific, while `Common_Blocks`, `Common_Neighbors` and `Jaccard_Sim` are edge-specific features. Although the distinction between edge- and node-specific features seems trivial, there are two major qualitative differences between them. First, a feature vector has to include two values for every node-specific feature – one for each of the adjacent entities – thus broadening the search space by two dimensions. In contrast, edge-specific attributes are computed only once per feature vector, adding a single dimension to the search space. Second,

	source of evidence			target			complexity		scope		
	block-based	graph-based	iterative	edge-specific	node-specific	hybrid	raw	derived	local	global	hybrid
CF_IBF	✓					✓		✓			✓
Jaccard_Sim	✓			✓				✓	✓		
RACCB	✓			✓				✓	✓		
Node_Degree		✓			✓		✓		✓		
Iterative_Degree			✓		✓			✓		✓	
Transitive_Degree		✓			✓			✓		✓	

Figure 5: Categorization of the features of our approach.

$FS1$:	CF_IBF,RACCB,Node_Degree
$FS2$:	CF_IBF,RACCB,Transitive_Degree
$FS3$:	CF_IBF,RACCB,Node_Degree,Transitive_Degree
$FS4$:	CF_IBF,RACCB,Jaccard_Sim,Transitive_Degree
$FS5$:	CF_IBF,RACCB,Jaccard_Sim,Node_Degree
$FS6$:	CF_IBF,RACCB,Transitive_Degree,Iterative_Degree
$FS7$:	CF_IBF,RACCB,Node_Degree,Iterative_Degree
$FS8$:	CF_IBF,RACCB,Jaccard_Sim,Node_Degree,Transitive_Degree
$FS9$:	CF_IBF,RACCB,Jaccard_Sim,Node_Degree,Iterative_Degree
$FS10$:	CF_IBF,RACCB,Jaccard_Sim,Transitive_Degree,Iterative_Degree

Table 3: Top 10 feature sets selected.

edge-specific features are expected to exhibit higher discriminatory power than the node-specific ones, because every value of the latter participates in as many feature vectors as the degree of the corresponding node; in contrast, every value of the edge-specific features pertains to a single feature vector.

(Reciprocal) Aggregate Cardinality of Common Blocks. From the aforementioned features, only Common_Blocks and Node_Degree are raw. In general, there is no rule-of-thumb for a-priori determining which form of features achieves the best performance in practice. Even different forms of derived features may lead to significant differences in classification accuracy. As an example, consider two edge-specific features that use the same information, but in different forms: the *Aggregate Cardinality of Common Blocks* (ACCB) and the *Reciprocal Aggregate Cardinality of Common Blocks* (RACCB) attributes. The former sums the cardinalities of the blocks shared by the adjacent entities (raw feature): $\texttt{ACCB}(e_{i,j}) = \sum_{b_k \in B_{i,j}} ||b_k||$. The latter sums the inverse of the cardinalities of common blocks (derived feature):

$$\texttt{RACCB}(e_{i,j}) = \sum_{b_k \in B_{i,j}} \frac{1}{||b_k||}.$$

Both features rely on the premise that the smaller the blocks two entities co-occur in, the more likely they are to be matching. Hence, the lower the value of ACCB is, the more likely the co-occurring entities match, and vice versa for RACCB. Preliminary experiments, though, demonstrated that ACCB achieves significantly lower classification accuracy than RACCB, due to its low discriminativeness: it assigns identical or similar values to pairs of co-occurring entities that share blocks of totally different cardinalities. For instance, consider two pairs of entities: the first co-occurs in 3 blocks containing 1,2 and 4 comparisons, while the second shares 2 blocks with 2 and 5 comparisons; ACCB takes the same value for both edges (7), while RACCB amounts to 1.75 and 0.70 for the first and the second pair, respectively, favoring the entities that are more likely to match.

Co-occurrence Frequency-Inverse Block Frequency. Derived features can come in more advanced forms than RACCB, combining multiple features through linear or non-linear functions. However, they should be used with caution for several reasons: (*i*) they involve a higher extraction cost than the comprising raw features; (*ii*) their form might be too complex to be interpretable; (*iii*) they are usually correlated with the raw features they comprise and, thus, are incompatible with them, when applied to classifiers with strong independence assumptions (e.g., Naïve Bayes); (*iv*) some classification algorithms may operate better with raw features, learning themselves the linear or non-linear associations between the input features. For these reasons, the derived features should involve a low extraction cost and transform as few raw features as possible.

Here, we combine Common_Blocks and Entity_Blocks into a feature inspired from the TF-IDF measure employed in IR. We call it Co-occurrence Frequency-Inverse Block Frequency (CF_IBF) and formally define it as:

$$\texttt{CF\_IBF}(e_{i,j}) = |B_{i,j}| \cdot \log \frac{|B|}{|B_i|} \cdot \log \frac{|B|}{|B_j|}.$$

Experiments showed that this form outperforms the individual features, because Entity_Blocks is of limited usefulness when used independently, but it is valuable for extending Common_Blocks, which otherwise suffers from low discriminativeness (it amounts to 1 or 2 for the vast majority of edges). In this way, we also restrict the dimensionality of our approach by two degrees.

Approach Overview. Our approach considers all the candidate features, except for ACCB due to low discriminativeness, and Common_Neighbors, which violates the requirement for generality, as it does not apply to *Clean-Clean ER*. In this case, the resulting blocking graph is bipartite, since every entity of the one collection is exclusively connected with entities from the other collection (only comparisons between different collections are allowed) [22]. As a result, every pair of co-occurring entities shares no neighbors.

On the whole, our approach annotates every edge of the blocking graph with the following nine-feature vector:

[$\texttt{CF\_IBF}(e_{i,j})$, $\texttt{Jaccard\_Sim}(e_{i,j})$, $\texttt{RACCB}(e_{i,j})$,
$\texttt{Node\_Degree}(v_i)$, $\texttt{Node\_Degree}(v_j)$,
$\texttt{Iterative\_Degree}(v_i)$, $\texttt{Iterative\_Degree}(v_j)$,
$\texttt{Trasitive\_Degree}(v_i)$, $\texttt{Transitive\_Degree}(v_j)$].

We selected these features because they cover all feature categories (as illustrated in Figure 5), they are schema-agnostic, applying to any block collection (generality principle), and they form a limited search space that allows for rapidly training classification models of low complexity and overhead (efficiency principle). Most of them also involve a low extraction cost.

Note also that most of the aforementioned features are local with respect to their scope; the exceptions are Entity_Blocks, which involves a hybrid functionality that combines local with global information, and Iterative_Degree and Transitive_Degree, which consider global information about the neighbors of a specific node. In the general case, local features are expected to exhibit higher effectiveness and efficiency than the global ones, because the latter consider more general information and convey a higher extraction cost. As an example, consider a boolean global feature that sorts all edges of E_B in descending order of Common_Blocks and returns true for those ranked in the top 1% positions and false otherwise.

6.2 Feature Selection

To satisfy the minimality principle, we examine the relative performance of each combination of features, called *feature set* (FS), in order to identify the one achieving the best balance between effectiveness and efficiency. There is a clear trade-off here: fewer features mean less complex and less time-consuming learned model (higher efficiency), but lower effectiveness.

The selected features yield 63 combinations. Due to their high number, our feature selection process has two phases. *First*, we extracted the top 10 performing feature sets automatically. *Then*, we selected the best set by examining their relative performance analytically. We use all four classification algorithms over D_{movies}. The models were trained using 1,000 labeled edges, equally partitioned between matching and non-matching edges, that were randomly se-

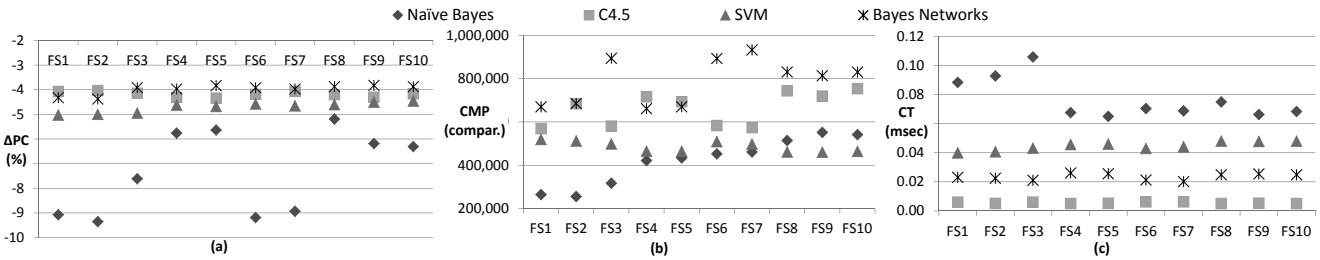


Figure 6: Performance of the feature sets in Table 3 over D_{movies} with respect to (a) the relative reduction in recall (ΔPC), (b) the absolute number of retained comparisons (CMP) and (c) the classification time of an individual edge (CT).

lected from the entire blocking graph. The remaining edges formed the disjoint testing set. To derive accurate performance estimations, we repeated this process 10 times and considered the average value of each metric.

To identify the top 10 performing feature sets, we sort the feature sets in descending order of their total F-measure and select those placed in the top 10 positions. The *Total F-measure* ($TF1$) of a feature set FS_i is the sum of the F-measures corresponding to each classification algorithm: $TF1(FS_i) = \sum_{j \in \{NB,C4.5,SVM,BN\}} F1_j(FS_i)$, where the F-measure for a feature set FS_i and an algorithm j is computed as[3]: $F1_j(FS_i) = 2 \cdot PC \cdot nPQ/(PC + nPQ)$, with nPQ denoting the normalized Pairs Quality across all feature sets for the algorithm j (i.e., $nPQ_j(FS_i) = \frac{PQ_j(FS_i)}{\max(PQ_j(FS_1),PQ_j(FS_2),...,PQ_j(FS_{63}))}$).

The resulting top 10 feature sets are shown in Table 3. Collectively, they involve all features of our approach, a strong indication for the high utility of each feature. Moreover, each feature set comprises at least 3 features, revealing that our features are compatible and complementary, working best when used in conjunction.

To select the best feature set out of the top 10 performing ones, we evaluate their effectiveness through ΔPC and their efficiency through CMP and CT (see Section 5). Figures 6(a), (b) and (c) present ΔPC, CMP and CT, respectively. The horizontal axes correspond to the feature sets. We can identify the optimal feature set by examining their relative performance across the three figures. The closer a feature set is placed to the horizontal axis of each figure across all classification algorithms, the better is its performance.

Figure 6(a) shows that most feature sets exhibit limited variation in ΔPC (between -3.5% and -5% for most algorithms). Only Naïve Bayes is rather unstable, yielding five outliers: $FS1$, $FS2$, $FS3$, $FS6$ and $FS7$ have an unacceptable impact on recall (over -7%) and hence they are not considered any further.

For the remaining sets, Figures 6(a) and 6(b) reveal a trade-off between ΔPC and CMP: the higher ΔPC for a particular feature set and classification algorithm, the lower CMP gets, and vice versa. Hence, none of the feature sets excels in both metrics. To identify the set with the best balance between ΔPC and CMP, we consider their average values across all classifiers. Only $FS4$ and $FS5$ achieve the most stable performance: $FS4$ requires $5.66 \pm 1.25 \times 10^5$ comparisons, and $FS5$ gives $5.65 \pm 1.17 \times 10^5$. They are also the most efficient compared to $FS8$, $FS9$ and $FS10$, which require 12.5% more comparisons, on average.

Finally, to decide between $FS4$ and $FS5$, we compare them in terms of CT. Figure 6(c) shows negligible differences (in absolute numbers) between them – in the order of 1/100 of a millisecond. Given, though, that CT concerns a single edge, these differences become significant when meta-blocking is applied to large blocking graphs with millions of edges. We choose $FS5$ because it learns faster classification models than those of $FS4$ by 3%, on average.

In the following, we exclusively consider the feature set $FS5$, comprising `CF_IBF`, `RACCB`, `Jaccard_Sim` and `Node_Degree`, which combines a low extraction cost with high discriminatory power.

7. TRAINING SET

The quality of the learned classification model also depends on the training set and in particular on its composition and size.

The definition of supervised meta-blocking (Problem 2) makes no assumptions about the training set. However, the vast majority of the edges in the blocking graph connect non-matching entities and thus correspond to superfluous comparisons. If the training set involves the same class distributions as the set of edges, E_B, it will be heavily imbalanced in favor of the `unlikely_match` class. As a result, the classifier would be biased towards assigning every instance to the majority class, pruning most of the edges.

This situation constitutes a *class imbalance problem*, which is typical in supervised learning (as an example, consider the task of spam filtering, where the vast majority of e-mails is not spam) with several solutions [15]: *oversampling* randomly replicates instances of the minority class until the class distribution is balanced, *cost-sensitive learning* incorporates high misclassification cost for the minority class when training the classifier, and *ensemble learning* trains a set of classifiers that collectively take classification decisions through a form of weighted voting. Unfortunately, cost-sensitive and ensemble learning increase the complexity of the classification model, while oversampling yields excessively large training sets prone to overfitting (too many repetitions of the same instances). Instead, we use *undersampling*, which randomly selects a subset of the same cardinality from both classes. The training set is equally partitioned between `likely_match` and `unlikely_match` edges. This approach is best for small training sets, which can be manually labeled in the absence of ground truth.

The size of the training set, called *sample size*, affects both the effectiveness and the efficiency of supervised meta-blocking: the smaller the sample size is, the lower is the complexity of the learned model and the more efficient is its training and its use. However, this comes at the cost of lower classification accuracy, as the simpler the learned model is, the more likely it is to miss patterns. To identify the break-even point in this trade-off, we experimentally perform a sensitivity analysis for the sample size with respect to effectiveness (ΔPC) and efficiency (CT and CMP).

Training Set Selection. We apply the selected feature set to the four classifiers over D_{movies} using training sets of various sizes. Due to undersampling, these training sets were specified in terms of the minority class cardinality (i.e., the number of matching entities in

[3]Note that the F-measure for blocking-based ER is defined as $F1 = \frac{2 \cdot PC \cdot PQ}{PC + PQ}$ [4]. We employ nPQ instead of PQ, because the latter takes very low values for redundancy-positive block collections. In fact, PQ is lower than PC by one or two orders of magnitude, thus dominating $F1$, which ends up assigning high scores to feature sets with a few comparisons and a few detected duplicates.

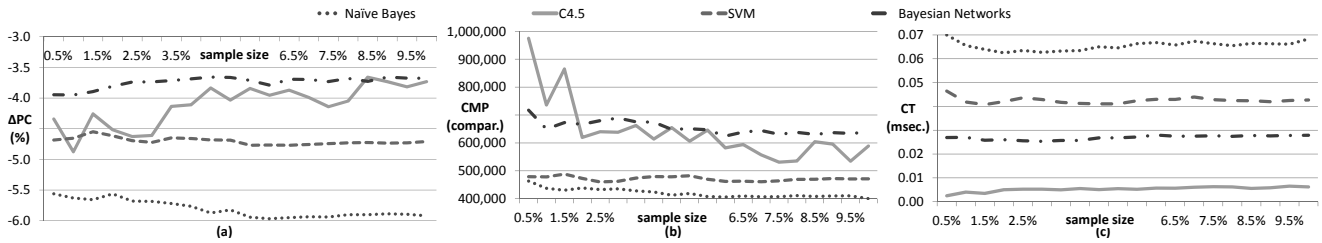


Figure 7: Learning curves of our approach over D_{movies} with respect to (a) ΔPC, (b) CMP and (c) CT. The horizontal axes correspond to the sample size, i.e., the number of training instances expressed as a portion of the minority class cardinality.

the ground truth). Each one was equally partitioned between (randomly selected) matching and non-matching edges, whose number ranged from 0.5% to 10% of the minority class size, with a step of 0.5%. For every sample size, we repeated the process 10 times and considered the average of the aforementioned metrics. Figures 7(a), (b) and (c) depict the learning curves with respect to ΔPC, CMP and CT, respectively.

Figure 7(a) shows that most classifiers exhibit rather stable recall, with a variance at most 1.2%. In all cases, the variance in ΔPC gets lower as the sample size increases. Especially for sample sizes that exceed 5% of the minority class cardinality (i.e., around 1,100 labeled instances per class), there is no variance in practice. These patterns demonstrate that our proposed feature set is comprehensive, robust enough and effective even when trained over small training sets – regardless of the classification algorithm.

Figure 7(b) shows the evolution of CMP with the increase in sample size. Most classifiers start from high values, but gradually converge to lower values as the sample size increases. Similar to ΔPC, the variance in CMP decreases in proportion to the sample size and becomes negligible for sample sizes larger than 5% of the minority class. Regarding CT, Figure 7(c) shows that all classifiers exhibit a relatively stable, good performance regardless of the sample size. The average CT is close to the time observed for the sample size equal to 5%.

Consequently, a sample size equal to 5% of the minority class achieves a performance equivalent to that of much larger ones. In the following, we exclusively consider training sets comprising 5% of the edges labeled as `likely_match` and an equal number of edges labeled as `unlikely_match`.

8. CLASSIFIERS CONFIGURATION

The performance of the selected classification algorithms depends on their internal parameter configuration. Fine-tuning may significantly enhance classification accuracy, but it may also lead to over-fitting, which increases the complexity of the learned model and inflates the overhead of meta-blocking. To assess how their configuration affects the performance of our approach, we perform analytical fine-tuning of their parameters. For each algorithm, we examine two parameters that are fine-tuned in parallel:

• C4.5: we study the maximum number of instances per leaf node, ranging from 2 to 5, and the confidence interval, ranging from 0.1 and 0.5 with a step of 0.05 (36 configurations in total). By default, Weka sets the former parameter to 2 and the latter to 0.25.

• SVM: we consider two kernels, the linear and the RBF, and we vary the complexity parameter C from 1 to 10 with a step of 1 (20 configurations in total). Weka's default configuration incorporates a linear kernel function with the complexity constant C set to 1.

• Bayesian Networks: we use three search algorithms: simulated annealing, hill climbing and genetic search. We use each one with global and with local scope (6 configurations in total). The default configuration of Weka uses the hill climbing search of local scope.

• Naïve Bayes: two boolean parameters that determine the processing of numeric attributes, i.e., use of supervised discretization and of kernel density estimator (4 configurations in total). By default, Weka sets both parameters to `false`.

For each classifier, we apply every possible configuration to 10 randomly selected training sets from the blocking graph of D_{movies} using the sample size and the features determined above. Due to the large number of configurations, we consider only the default, the optimal and the average performance for each classification algorithm and metric. As optimal, we define the configuration with the largest F-measure (again, $F1$ employs nPQ instead of PQ). The following configurations were selected in this way: the use of both supervised discretization and kernel estimator for Naive Bayes; 5 instances per leaf and confidence interval equal to 0.1 for C4.5; linear kernel with C=9 for SVM; simulated annealing with global scope for Bayesian Networks. Figures 8(a) to (c) depict the experimental outcomes with respect to ΔPC, CMP and CT, respectively.

We first investigate the relative *performance* of the default and the optimal configuration. For Naïve Bayes, the optimal one puts more emphasis on effectiveness, increasing ΔPC by executing more comparisons. However, its overall efficiency is significantly increased, as its overhead (CT) is reduced to 1/5. For C4.5 and SVM, the optimal configurations decrease CMP by 5%, while exhibiting practically identical ΔPC and CT with the default ones. On the other hand, the optimal configuration for the Bayesian Networks reduces CMP by 20% for almost the same PC as the default one, but puts a toll on efficiency: CT increases by 25%. Hence, we choose the default configuration for Bayesian Networks, while for the other algorithms we choose the optimal ones, due to their slightly better balance between effectiveness and efficiency.

We now examine the *robustness* of the classification algorithms with respect to their configuration based on the distance between the default, the optimal and the average performance for all configurations. We observe that C4.5 is practically insensitive to fine-tuning, despite the large numbers of configurations considered. The same applies to SVM with respect to ΔPC and CMP; its average CT (2.66 msec), though, is two orders of magnitude higher than the default and the optimal one. This is because the RBF kernels are 10 times slower when classifying an individual edge than the linear ones, which exhibit a rather stable CT. A similar situation appears in the case of Naïve Bayes, where the average CT amounts to 3.80 msec, due to the inefficiency of a single configuration: supervised discretization for numeric attributes without the kernel estimator. The other two metrics, though, advocate that Naïve Bayes is rather sensitive to its configuration. Finally, the Bayesian Networks exhibit significant variance with respect to CMP and CT, but the overall efficiency is relatively stable across all configurations. We can conclude that for the selected feature set and sample size, most classifiers are rather robust with respect to their configuration.

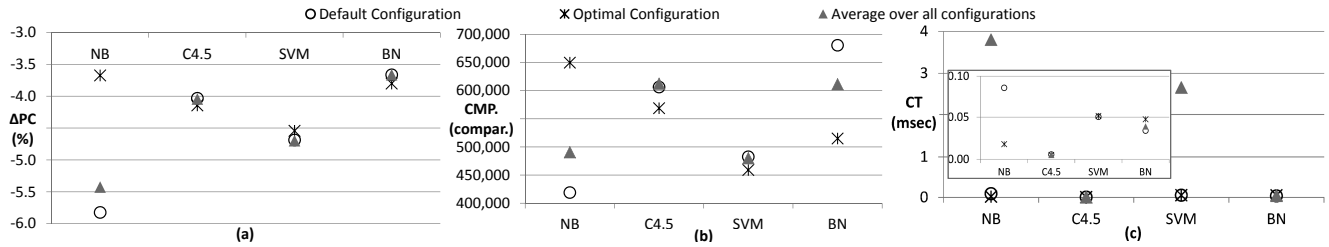


Figure 8: Effect of parameter configuration for each classification algorithm over D_{movies} with respect to (a) ΔPC, (b) CMP and (c) CT. The sub-figure in (c) zooms into the interval $[0, 0.1]$ to highlight differences in CT that are concealed in the interval $[0, 4]$.

9. EXPERIMENTAL EVALUATION

We now compare the performance of our supervised meta-blocking techniques with the best performing unsupervised ones over three pruning algorithms: WEP, CEP and CNP. Remember that WEP is compatible with all classification algorithms, while CEP and CNP are only compatible with Naïve Bayes and Bayesian Networks. To compare the supervised and the unsupervised techniques on an equal basis, we adapted the latter so that they exclude the edges used for training by the former. Hence, we applied them 10 times to each dataset and derived their performance from the average of the relevant metrics (this explains why in some cases their performance is slightly different from that reported in [22]).

We also employ the state-of-the-art approach of Iterative Blocking [25] as an additional baseline method. Given that its performance depends heavily on the processing order of blocks, we apply it to 10 random shuffles of each dataset's blocks and present the average value of each metric. Note that for Clean-Clean ER, we consider the best possible performance of iterative blocking, assuming that all pairs of detected matches are propagated to the subsequently processed blocks so that their entities do not participate in any other comparison.

We implemented our approaches in Java 1.7[4] and tested them on a server with Intel i7-4930K 3.40GHz and 32GB RAM, running Debian 7. Graphs were implemented using the JUNG framework[5].

9.1 In-depth Analysis over Real Datasets

Table 4 presents the performance of the baseline [6] and our supervised techniques with respect to the three pruning algorithms over the datasets of Table 2. For each dataset, we considered the unsupervised meta-blocking in conjunction with the weighting scheme that yields the best trade-off between PC and PQ; for D_{movies} and $D_{infoboxes}$, we used the weighting schemes CBS, EJS and $ECBS$ for WEP, CEP and CNP, respectively, while for D_{BTC09}, we employed the $ARCS$ scheme in all cases (see [22] for more details). We now examine each pruning algorithm separately.

WEP. We observe that supervised meta-blocking consistently achieves a better balance between effectiveness and efficiency over D_{movies} and $D_{infoboxes}$. It executes almost an order of magnitude fewer comparisons than the unsupervised method with a minor increase of PC. As a result, precision consistently increases by at least 4 times. The higher overhead (OT) is counterbalanced by the considerably lower number of comparisons, resulting overall in significantly improved resolution times (RT).

For D_{BTC09}, supervised meta-blocking improves efficiency to a similar extent at the cost of slightly lower recall (the only exception is SVM, whose PC is significantly lower than the unsupervised method by 7.5%). Both the number of comparisons and the overhead time are almost half, leading to significantly better RT.

CEP. For D_{movies} and $D_{infoboxes}$, supervised meta-blocking achieves significantly higher recall, increased by more than 10%. Its overhead time, though, is more than twice that of unsupervised meta-blocking. Given that both approaches execute the same number of comparisons, the classification models exhibit notably increased resolution time. In the case of D_{BTC09}, supervised meta-blocking decreases PC and PQ to a minor extent, while increasing the resolution time by 25%. For each dataset, these patterns are consistent across both probabilistic models.

CNP. For D_{movies} and D_{BTC09}, supervised meta-blocking reduces the number of executed comparisons to a significant extent, at the cost of a lower PC. PQ almost doubles, but the higher overhead than unsupervised meta-blocking leads to an increased resolution time. The same applies to $D_{infoboxes}$, as both OT and RT are significantly higher than unsupervised meta-blocking. In this case, though, the number of comparisons is practically the same, while PQ gets slightly higher, because PC slightly increases.

Iterative Blocking. We observe that iterative blocking achieves the lowest overhead time and the highest recall across all datasets: for the Clean-Clean ER datasets D_{movies} and D_{BTC09}, PC is equal to that of the input block collection, while for the Dirty ER dataset (D_{BTC09}), it increases by 1%. However, this comes at the cost of rather low efficiency; iterative blocking actually executes so many comparisons that its resolution time is practically identical with the brute-force approach of performing all comparisons in the input block collection. For Clean-Clean ER, its run-time lies in the middle between supervised and unsupervised meta-blocking, due to the ideal settings we consider (i.e., none of the matched entities participates in any comparison after their detection). In a more realistic scenario, though, its efficiency is expected to be lower than that of unsupervised meta-blocking. We can conclude, therefore, that Iterative Blocking is only appropriate for applications that place recall in priority and are satisfied with rather conservative savings in efficiency. For the rest of them, supervised meta-blocking offers a better balance between effectiveness and efficiency.

Conclusions. For WEP, our techniques leverage small training samples and feature vectors to significantly increase efficiency at a negligible cost in effectiveness (if any). This consistent behavior is important, since WEP is compatible with practically any blocking-based ER application. It stems from the low computational cost and the comprehensiveness of our features. The latter aspect can be inferred from the performance of Naïve Bayes, which is directly comparable with the more complicated algorithms in all cases. The best performance, though, is achieved when combining supervised

[4]We have publicly released the code of our implementations at `http://sourceforge.net/projects/erframework`.

[5]`http://jung.sourceforge.net`

[6]For unsupervised meta-blocking, OT measures the time required for the creation of the weighted blocking graph and the pruning of its edges. For iterative blocking, OT estimates the time required for the propagation of the detected duplicates to the subsequently processed blocks and the re-processing of the related blocks (in case of Dirty ER).

	D_{movies}						$D_{infoboxes}$						D_{BTC09}					
	CMP (×10^5)	*PQ* (%)	*PC* (%)	Δ*PC* (%)	*OT* (sec)	*RT* (sec)	*CMP* (×10^8)	*PQ* (%)	*PC* (%)	Δ*PC* (%)	*OT* (hours)	*RT* (hours)	*CMP* (×10^6)	*PQ* (%)	*PC* (%)	Δ*PC* (%)	*OT* (min)	*RT* (min)
Brute-force	20.27	1.09	99.39	0	1	89	40.46	0.02	99.89	0	1	34	123.62	0.01	98.22	1.32	1	62
Iterative Blocking	20.27	1.09	99.39	0	1	89	40.46	0.02	99.89	0	1	34	123.62	0.01	98.22	1.32	1	62
Unsupervised	27.04	0.75	94.64	-4.78	13	104	33.97	0.02	95.47	-4.43	12	41	4.14	0.23	94.63	-2.40	6	8
Naive Bayes	6.50	3.14	95.74	-3.67	39	56	3.76	0.22	99.09	-0.80	27	31	2.10	0.45	93.46	-3.58	4	5
C4.5	5.69	3.57	95.27	-4.15	20	40	2.98	0.28	99.00	-0.89	19	21	1.81	0.53	94.01	-3.02	3	4
SVM	4.59	4.40	94.87	-4.54	35	50	4.54	0.18	97.30	-2.60	27	31	2.55	0.35	87.49	-9.75	4	5
Bayesian Networks	6.51	3.13	95.75	-3.66	33	51	3.76	0.22	99.09	-0.80	25	29	2.12	0.45	93.50	-3.54	4	5
(a) WEP																		
Unsupervised	5.70	3.17	84.89	-14.59	9	23	0.26	2.72	82.09	-17.82	11	12	0.94	0.99	92.03	-5.06	3	4
Naive Bayes	5.69	3.56	95.34	-4.08	39	55	0.26	3.06	92.58	-7.32	26	27	0.94	0.96	89.47	-7.70	4	5
Bayesian Networks	5.69	3.56	95.35	-4.07	34	49	0.26	3.08	92.70	-7.20	23	24	0.94	0.96	89.49	7.68	4	5
(b) CEP																		
Unsupervised	11.00	1.87	96.67	-2.74	8	45	0.49	1.64	96.68	-3.21	12	13	1.75	0.53	90.86	-6.27	3	4
Naive Bayes	7.22	2.82	95.46	-3.95	39	59	0.47	1.79	98.38	-1.51	26	27	1.00	0.88	87.40	-9.84	4	5
Bayesian Networks	7.23	2.81	95.47	-3.94	34	54	0.47	1.78	98.38	-1.51	23	24	1.01	0.87	87.41	-9.83	4	5
(c) CNP																		

Table 4: Performance of supervised meta-blocking and the baselines over all datasets with respect to (a) WEP, (b) CEP, (c) CNP.

	Entity Collections		Block Collections			
	Entities	**Duplicates**	**Blocks**	**Compar.**	**PC**	Brute-force **RT**
D_{10K}	10,000	8,615	11,088	3.35×10^5	98.97%	4 sec
D_{50K}	50,000	42,668	40,569	7.42×10^6	98.77%	75 sec
D_{100K}	100,000	84,663	72,733	2.91×10^7	98.73%	5 min
D_{200K}	200,000	170,709	123,648	1.19×10^8	99.02%	23 min
D_{300K}	300,000	254,686	166,099	2.70×10^8	99.09%	45 min
D_{1M}	1,000,000	849,276	441,999	2.94×10^9	99.04%	8 hrs
D_{2M}	2,000,000	1,699,430	863,528	1.17×10^{10}	99.03%	33 hrs

Table 5: Overview of the synthetic datasets.

meta-blocking with C4.5, which reduces the resolution time by 50% across all datasets for practically the same effectiveness.

With respect to *CEP*, which is only suitable for incremental ER, unsupervised meta-blocking exhibits significantly higher efficiency, due to its lower overhead. However, the high *OT* time of the classification models is rendered insignificant, when advanced, time-consuming entity matching methods are used. Then, supervised meta-blocking should be preferred due to its consistently higher recall. For the same reason, it should be used with all applications of incremental ER that place more emphasis on effectiveness.

For *CNP*, we cannot draw any safe conclusions, due to the unstable performance of supervised meta-blocking across the 3 datasets, caused by the incompatibility of its global training information with the local scope of this pruning algorithm. Finally, it is worth stressing that supervised meta-blocking consistently improves the run-time of the brute-force approach by at least 10 times (cf. Table 2).

9.2 Recall and Run-time Scalability

We now examine the scalability of our supervised techniques in relation to the three pruning algorithms. We apply them to seven synthetic datasets that were created by FEBRL [5] and have been widely used in the literature for this purpose [4, 13]. They pertain to Dirty ER and their sizes range from 10 thousand to 2 million entities. To derive redundancy-positive blocks, we applied Token Blocking and Block Purging to each dataset. The technical characteristics of the resulting block collections are presented in Table 5.

As baseline methods, we employ iterative blocking and unsupervised meta-blocking. The latter was combined with the *ECBS* weighting scheme across all pruning algorithms and datasets, as it consistently exhibited the best performance.

We evaluate the performance of all methods using two metrics: Δ*PC* assesses the impact on effectiveness, while *Relative Resolution Time* (*RRT*) assesses the impact on efficiency. In essence, it expresses the portion of the input blocks' resolution time that is required by the meta-blocking method. Formally, it is defined as: $RRT = \frac{RT(B')}{RT(B)} \cdot 100\%$, where $RT(B)$ and $RT(B')$ are the resolution times of the original and the restructured block collections; the lower its value is, the more efficient is the meta-blocking method.

We applied supervised meta-blocking to *WEP*, *CEP* and *CNP*. The outcomes with respect to Δ*PC* are depicted in Figures 9(a)-(c), while *RRT* is presented in Figures 9(d)-(f).

WEP. We observe that iterative blocking consistently achieves the highest effectiveness, increasing *PC* by 1%, at the cost of the worst efficiency across all datasets. In fact, its *RRT* increases monotonically for higher dataset sizes, raising from 1/3 to more than 1/2. On the other extreme lies supervised meta-blocking: it reduces *PC* by at least 3%, but requires at most 1/6 of the original resolution time. It scales well to larger datasets, as its performance is relatively stable across all datasets: for each classification algorithm, the difference between their maximum and minimum Δ*PC* is less than 2%, while for *RRT* it is less than 5%. In the middle of these two extremes lies unsupervised meta-blocking, which reduces recall by less than 3.5%, while requiring half of the resolution time of iterative blocking. Note, though, that it does not scale well to larger datasets, as its *RRT* raises from 1/6 for D_{10K} to 1/3 for D_{2M}.

CEP. For unsupervised meta-blocking, Δ*PC* decreases almost linearly with the increase of the dataset size. In contrast, supervised meta-blocking scales well with respect to recall, as the variance of its Δ*PC* is lower than 7% (note that both classification algorithms exhibit practically identical performances). Equally stable is their efficiency, since their *RRT* is close to 1/8, on average, while its variance is less than 5%. However, the run-time of unsupervised meta-blocking scales better, as its *RRT* decreases from 1/8 for D_{10K} to 1/30 for D_{2M}.

CNP. The efficiency of unsupervised meta-blocking scales well with the increase of dataset size, dropping from 1/5 for D_{10K} to 1/30 for D_{2M}, while its effectiveness decreases. In this case, though, its recall is close to that of supervised meta-blocking, with their maximum difference amounting to 3%. In terms of efficiency, supervised meta-blocking exhibits an unstable behavior, with its *RRT* fluctuating between 1/5 and 1/10.

Conclusions. Overall, we conclude that supervised meta-blocking scales better than the unsupervised one for *WEP* with respect to both effectiveness and efficiency. For *CEP*, it scales better with respect to effectiveness, while unsupervised meta-blocking excels in efficiency in case a cheap entity matching method is employed. The same applies to *CNP*, as well. For this pruning algorithm, though, supervised meta-blocking improves effectiveness only to a minor extent. Compared to iterative blocking, supervised meta-blocking excels in efficiency, requiring a lower resolution time by at least

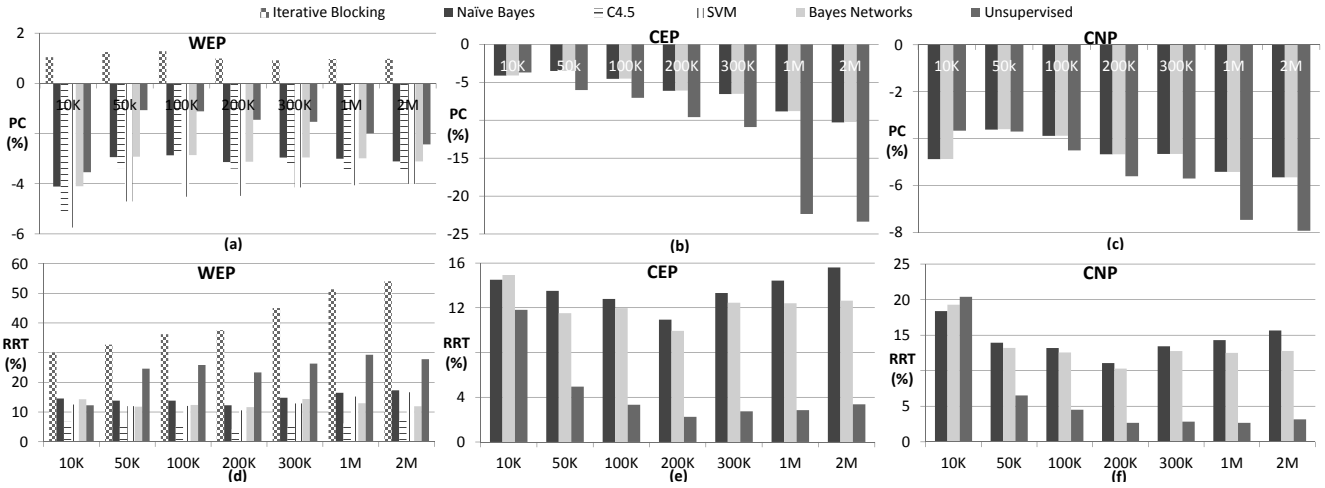


Figure 9: Scalability analysis over the synthetic datasets with respect to (a)-(d) WEP, (b)-(e) CEP and (c)-(f) CNP.

2/3, but achieves significantly lower recall. Compared to the brute-force approach, supervised meta-blocking improves the run-time by at least 5 times, as its *RRT* lies consistently lower than 20%.

10. CONCLUSIONS

In this work, we demonstrated how supervised meta-blocking can be used to enhance the performance of existing, unsupervised meta-blocking methods. For this task, we proposed a small set of generic features that combine a low extraction cost with high discriminatory power. We showed that supervised meta-blocking can achieve high performance with small training sets that can be manually created, and we verified that most configurations of established classification algorithms have little impact on the overall performance. We analytically compared our supervised approaches with baseline and competitor methods.

In the future, we will apply transfer learning techniques to supervised meta-blocking, so that a classification model trained over a labeled set maintains its high performance over another, unlabeled one. In addition, we will explore the use of active learning and crowdsourcing techniques in the creation of training sets.

Acknowledgements. This research has been co-financed by the EU (European Social Fund - ESF) and Greek national funds through the Operational Program "Education and Lifelong Learning" of the National Strategic Reference Framework (NSRF) - Research Funding Program: Thales. Investing in knowledge society through the European Social Fund.

References

[1] M. Bilenko, B. Kamath, and R. J. Mooney. Adaptive blocking: Learning to scale up record linkage. In *ICDM*, pages 87–96, 2006.

[2] M. Bilenko and R. J. Mooney. Adaptive duplicate detection using learnable string similarity measures. In *KDD*, pages 39–48, 2003.

[3] Z. Chen, D. V. Kalashnikov, and S. Mehrotra. Exploiting context analysis for combining multiple entity resolution systems. In *SIGMOD*, pages 207–218, 2009.

[4] P. Christen. A survey of indexing techniques for scalable record linkage and deduplication. *TKDE*, 24(9):1537–1555, 2012.

[5] P. Christen and A. Pudjijono. Accurate synthetic generation of realistic personal information. In *PAKDD*, pages 507–514, 2009.

[6] W. W. Cohen and J. Richman. Learning to match and cluster large high-dimensional data sets for data integration. In *KDD*, pages 475–480, 2002.

[7] T. de Vries, H. Ke, S. Chawla, and P. Christen. Robust record linkage blocking using suffix arrays. In *CIKM*, pages 1565–1568, 2009.

[8] M. G. Elfeky, A. K. Elmagarmid, and V. S. Verykios. Tailor: A record linkage tool box. In *ICDE*, pages 17–28, 2002.

[9] L. Getoor and A. Machanavajjhala. Entity resolution for big data. In *KDD*, 2013.

[10] L. Gravano, P. Ipeirotis, H. Jagadish, N. Koudas, S. Muthukrishnan, and D. Srivastava. Approximate string joins in a database (almost) for free. In *VLDB*, pages 491–500, 2001.

[11] A. Y. Halevy, M. J. Franklin, and D. Maier. Principles of dataspace systems. In *PODS*, pages 1–9, 2006.

[12] M. Hernández and S. Stolfo. The merge/purge problem for large databases. In *SIGMOD*, pages 127–138, 1995.

[13] B. Kenig and A. Gal. Mfiblocks: An effective blocking algorithm for entity resolution. *Inf. Syst.*, 38(6):908–926, 2013.

[14] H. Kim and D. Lee. HARRA: fast iterative hashed record linkage for large-scale data collections. In *EDBT*, pages 525–536, 2010.

[15] R. Longadge, S. Dongre, and L. Malik. Class imbalance problem in data mining: Review. *Int'l Journal of Computer Science and Network (IJCSN)*, 2(1), 2013.

[16] Y. Ma and T. Tran. Typimatch: type-specific unsupervised learning of keys and key values for heterogeneous web data integration. In *WSDM*, pages 325–334, 2013.

[17] A. McCallum, K. Nigam, and L. Ungar. Efficient clustering of high-dimensional data sets with application to reference matching. In *KDD*, pages 169–178, 2000.

[18] M. Michelson and C. A. Knoblock. Learning blocking schemes for record linkage. In *AAAI*, pages 440–445, 2006.

[19] F. Naumann and M. Herschel. *An Introduction to Duplicate Detection*. Synthesis Lectures on Data Management. Morgan & Claypool Publishers, 2010.

[20] G. Papadakis, E. Ioannou, C. Niederée, T. Palpanas, and W. Nejdl. Beyond 100 million entities: Large-scale blocking-based resolution for heterogeneous data. In *WSDM*, pages 53–62, 2012.

[21] G. Papadakis, E. Ioannou, T. Palpanas, C. Niederée, and W. Nejdl. A blocking framework for entity resolution in highly heterogeneous information spaces. *IEEE Trans. Knowl. Data Eng.*, 25(12):2665–2682, 2013.

[22] G. Papadakis, G. Koutrika, T. Palpanas, and W. Nejdl. Meta-blocking: Taking entity resolutionto the next level. *IEEE Trans. Knowl. Data Eng.*, 26(8):1946–1960, 2014.

[23] S. Sarawagi and A. Bhamidipaty. Interactive deduplication using active learning. In *KDD*, pages 269–278, 2002.

[24] S. Tejada, C. A. Knoblock, and S. Minton. Learning domain-independent string transformation weights for high accuracy object identification. In *KDD*, pages 350–359, 2002.

[25] S. E. Whang, D. Menestrina, G. Koutrika, M. Theobald, and H. Garcia-Molina. Entity resolution with iterative blocking. In *SIGMOD Conference*, pages 219–232, 2009.

[26] I. H. Witten and E. Frank. *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann, 2005.

Meta-Blocking: Taking Entity Resolution to the Next Level

George Papadakis, Georgia Koutrika, Themis Palpanas, and Wolfgang Nejdl

Abstract—Entity Resolution is an inherently quadratic task that typically scales to large data collections through blocking. In the context of highly heterogeneous information spaces, blocking methods rely on redundancy in order to ensure high effectiveness at the cost of lower efficiency (i.e., more comparisons). This effect is partially ameliorated by coarse-grained block processing techniques that discard entire blocks either a-priori or during the resolution process. In this paper, we introduce meta-blocking as a generic procedure that intervenes between the creation and the processing of blocks, transforming an initial set of blocks into a new one with substantially fewer comparisons and equally high effectiveness. In essence, meta-blocking aims at extracting the most similar pairs of entities by leveraging the information that is encapsulated in the block-to-entity relationships. To this end, it first builds an abstract graph representation of the original set of blocks, with the nodes corresponding to entity profiles and the edges connecting the co-occurring ones. During the creation of this structure all redundant comparisons are discarded, while the superfluous ones can be removed by pruning of the edges with the lowest weight. We analytically examine both procedures, proposing a multitude of edge weighting schemes, graph pruning algorithms as well as pruning criteria. Our approaches are schema-agnostic, thus accommodating any type of blocks. We evaluate their performance through a thorough experimental study over three large-scale, real-world datasets, with the outcomes verifying significant efficiency enhancements at a negligible cost in effectiveness.

Index Terms—Entity Resolution, Redundancy-positive Blocking, Meta-blocking

1 Introduction

Entity resolution (ER) is the task of identifying the same real-world object across different entity profiles. It constitutes an inherently quadratic process, as it requires every entity profile to be compared with all others. Therefore, it typically scales to large data collections through approximate methods that trade off effectiveness (i.e., percentage of detected duplicates) for efficiency (i.e., number of executed pair-wise comparisons). *Data blocking* [13], the most popular of these methods, groups similar entity profiles into *blocks* and exclusively performs the comparisons within each block. Blocking methods are generally distinguished in two categories: those forming non-overlapping blocks (i.e., *redundancy-free*), and those placing every entity profile into multiple blocks (i.e., *redundancy-bearing*).

Redundancy constitutes an indispensable and reliable means of reducing the likelihood of missed matches in the context of highly heterogeneous information spaces (HHIS), such as the Web of Data [4] and Dataspaces [16]. The reason is that HHIS involve extremely large volumes of data, high levels of noise, and loose schema binding. Though beneficial for effectiveness, redundancy comes at the cost of lower efficiency, as it increases the number of required pair-wise comparisons. In this work, we investigate ways of compensating for its effect on efficiency without sacrificing its high effectiveness.

Motivating Examples. As an example, consider the entity collection presented in Figure 1(a), where the entity profiles p_1 and p_2 describe the same real-world objects as profiles p_3 and p_4, respectively. Although the values of the duplicate profiles are relatively similar, every canonical attribute name has a different form in each of them; the name of a person, for instance, appears as "FullName" in p_1, as "name" in p_2 and as "full name" in p_3. This situation is further aggravated by the tag-style values; e.g., the name of person p_4 is not associated with any attribute value. In these settings, redundancy-free blocking methods can only be applied on top of a schema matching method that maps all entity profiles into a canonical schema with attributes of a-priori known quality. However, although schema matching seems straightforward in our example, it is not practical in large-scale collections of user-generated data: Google Base[1] alone encompasses 100,000 distinct schemata corresponding to 10,000 entity types [20]. Thus, in this work we exclusively consider redundancy-bearing blocking methods and aim at improving their efficiency.

Not all of these methods, though, share the same interpretation of redundancy. For the *redundancy-positive* blocking techniques, the number of common blocks between a pair of entity profiles is proportional to their similarity and, thus, the likelihood that they are matching. In this category fall methods that associate each profile with multiple blocking keys, such as q-grams [15], Suffix Array [1], [8], HARRA [18] and schema-agnostic blocking [27], [29]. To illustrate their functionality, consider Figure 1(b), which depicts the blocks that are produced after applying the

- *G. Papadakis is with the National Technical University of Athens, Greece and the L3S Research Center, Germany. E-mail: papadakis@L3S.de, gpapadis@mail.ntua.gr*
- *G. Koutrika is with HP Labs, USA. E-mail: koutrika@hp.com*
- *T. Palpanas is with the University of Trento, Italy. E-mail: themis@disi.unitn.eu*
- *W. Nejdl is with the L3S Research Center, Leibniz University of Hanover, Germany. E-mail: nejdl@L3S.de*

1. http://www.google.com/base

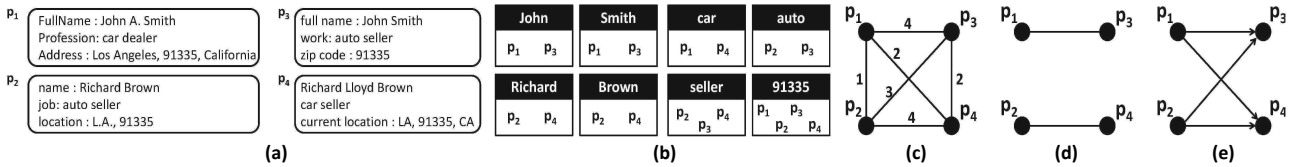


Fig. 1. (a) A noisy, heterogeneous entity collection, (b) the resulting set of attribute-agnostic blocks, (c) the blocking graph corresponding to it, (d) the pruned blocking graph, and (e) an alternative pruned blocking graph, discussed in Section 3.4.

simplest form of schema-agnostic blocking to the entity collection of Figure 1(a). Each block corresponds to a distinct token that has been extracted from at least one attribute value, regardless of the associated attribute name(s). Thus, the more blocks two entity profiles share, the more likely they are to describe the same real-world object.

In contrast, *redundancy-negative* blocking methods regard the high number of common blocks among two entity profiles as a strong indication that they are unlikely to be matching. For them, highly similar profiles share just one block. A typical example of this functionality is Canopy Clustering [22]: after selecting a random seed p_i, the most similar profiles are placed in the same block with p_i and are removed from the pool of candidate matches; thus, they cannot be included in any other block.

In the middle of these two extremes lie *redundancy-neutral* blocking methods, which involve the same number of common blocks across all pairs of entity profiles (e.g., Sorted Neighborhood [17]). In this category also fall methods that are not suitable for drawing conclusions about the matching likelihood of two profiles from the blocks they have in common (e.g., Semantic Blocking [25]).

We observe that redundancy-negative and redundancy-neutral blocking methods are not applicable to HHIS. For example, even though Canopy Clustering and the Sorted Neighborhood approaches are scalable to large entity collections, they require an a-priori known schema in order to create blocks. The same applies to other related methods, such as the Adaptive Sorted Neighborhood [33] and the Sorted Blocks approach [11]. In contrast, the redundancy-positive techniques have been shown to apply to HHIS and scale to millions of entity profiles [18], [27], [29]. Therefore, our work focuses on improving the efficiency of redundancy-positive blocking methods by discarding the unnecessary comparisons of their blocks. In general, comparisons of this kind are distinguished into two categories: (*i*) the *redundant* ones, which repeatedly compare the same entities across different blocks, and (*ii*) the *superfluous* ones, which involve non-matching entities. Continuing our example, we can observe that the blocks of Figure 1(b) involve 9 redundant comparisons in the blocks "Smith", "Brown", "seller" and "91335". They also involve 6 superfluous comparisons between all possible pairs of non-matching entities in the blocks "car", "auto", "seller" and "91335". Skipping comparisons of these types increases blocking efficiency without affecting effectiveness.

Existing block processing techniques enhance the efficiency of redundancy-positive blocking methods mainly by operating at the coarse level of entire blocks. For example, Block Purging [27] a-priori discards *oversized blocks*, which involve an excessively high number of unnecessary comparisons. To illustrate this notion, consider the block of "91335" in Figure 1(b): it contains all possible comparisons of the entity profiles in Figure 1(a) and the only non-redundant comparisons it involves are superfluous. A similar technique is Block Pruning [27], which assumes an ordered set of blocks and terminates their processing as soon as *duplicate overhead* (i.e., the cost of identifying new duplicates) exceeds a predefined threshold dh_{max}. Processing the blocks of Figure 1(b) in their order of appearance, the initial duplicate overhead in block "John" is $dh = 1$ (i.e., one comparison for one pair of duplicates); the second pair of duplicates is identified in the fourth block "Richard" yielding a duplicate overhead $dh = 3$ (i.e., three comparisons for one pair of duplicates). For $dh_{max} = 2$, the remaining blocks will not be examined, thus saving 10 comparisons. Due to the coarse granularity of their functionality, though, existing block processing methods are unable to distinguish the redundant and superfluous comparisons from the matching ones (i.e., those involving a non-redundant pair of duplicate entity profiles). As a result, they enhance efficiency without controlling their impact on effectiveness.

Work Overview and Contributions. In this paper, we introduce *meta-blocking* as the task of developing efficient techniques that operate at the level of individual comparisons. These methods utilize abstract blocking information to achieve maximum efficiency gains for redundancy-positive blocking methods at a small and controllable impact on effectiveness. Meta-blocking goes beyond existing block processing methods by offering principled approaches that consider the information encapsulated in the set of *block assignments* (i.e., the associations between blocks and entity profiles). In essence, it aims at identifying the closest pairs of profiles so as to restructure a given set of blocks into a new one that involves significantly fewer comparisons, while maintaining the original level of effectiveness. Meta-blocking is independent from the underlying blocking method and generic enough to handle any redundancy-positive block collection, regardless of whether it is based on schema information or not.

We note that meta-blocking does not replace but complements the existing blocking methods. It builds on the intrinsic characteristic of redundancy-positive blocking that the similarity of two entity profiles is reflected on their common block assignments. Meta-blocking operates efficiently because it skips the high complexity of computing pair-wise, string-based entity similarities, relying instead on the block-to-entity profile associations of the input set of blocks. Although approximate, this information leads to an

effective and efficient solution.

Based on these ideas, we introduce a family of meta-blocking methods that rely on the *blocking graph*. This is a structure that is extracted from the input block collection and connects with edges those pairs of entity profiles that are compared in at least one block. For instance, the graph corresponding to the blocks of Figure 1(b) is depicted in Figure 1(c); its nodes correspond to the profiles of the input entity collection (Figure 1(a)) and its edges connect the profiles that share at least one block. The edges are naturally undirected, and weighted according to a scheme that determines the trade-off between the computational cost and the gain of comparing the adjacent entity profiles (i.e., the benefit for the recall of the ER process, in case they are matching). In the example of Figure 1(c), we present the simplest scheme, which sets the weight of each edge equal to the number of blocks the adjacent entity profiles have in common. Also applicable are schema-based schemes, which set edge weights according to the values of one or more selected attributes.

The blocking graph forms the basis for enhancing efficiency through *pruning*: edges that do not satisfy a predefined criterion are removed, thus leading to a smaller number of comparisons. In our example, the blocking graph of Figure 1(d) can be derived from that of Figure 1(c) by discarding edges with a weight lower than 2, or by retaining the two edges with the highest weight. In any case, the remaining edges determine a new set of blocks that ideally places every pair of duplicate profiles in a separate block. Every retained edge is actually transformed into a new block that contains only its adjacent entity profiles. In our example, the pruned graph of Figure 1(d) yields two blocks, $b_1 = \{p_1, p_3\}$ and $b_2 = \{p_2, p_4\}$, that achieve the same recall as the blocks of Figure 1(b) with just 2 comparisons.

Overall, the contributions of our work are the following:

- We formalize the problem of meta-blocking and introduce the blocking graph as the cornerstone for a family of solutions that operate independently of the process that created the input blocks.
- We coin five schema-agnostic schemes for weighting the edges of a blocking graph.
- We present two schema-agnostic, orthogonal categories of pruning algorithms along with two orthogonal dimensions for specifying the corresponding pruning criteria.
- We examine the performance of our methods on three large-scale, real-world datasets, with the results validating the exceptional performance of our methods.

The rest of the paper is structured as follows: we formalize the task of meta-blocking in Section 2 and we present several techniques for building and pruning the blocking graph in Section 3. Section 4 analyzes the results of our experimental evaluation, and Section 5 wraps up our work. We discuss the state-of-the-art in blocking-based ER in the Appendix.

2 Problem Definition

Entity Resolution. At the core of entity resolution lie entity profiles describing real-world objects. An *entity profile* is a uniquely identified collection of information in the form of name-value pairs. Assuming an infinite set of identifiers $\mathcal{ID}$, we can formally define an entity profile as follows:

***Definition** 1 (Entity Profile):* An *entity profile* p is a tuple $\langle id, A_p \rangle$, where $id \in \mathcal{ID}$ is a unique identifier, and A_p is a set of name-value pairs $\langle n, v \rangle$.

Naturally, the value v in a name-value pair $\langle n, v \rangle$ of an entity profile p may be unspecified. Similarly, the attribute name n may not be given, thus allowing for the representation of tag-style values, as illustrated in Figure 1(a). In general, the model of Definition 1 is flexible enough to accommodate entity representations of any complexity, such as those employed in Web and Dataspace applications [20]. In the following, we refer to this definition using the terms entity profile, profile and entity interchangeably.

An *entity collection* $\mathcal{E}$ is a set of entity profiles. Two entity profiles contained in $\mathcal{E}$, p_i and p_j, are *duplicates* or *matches*, denoted by $p_i \equiv p_j$, if they represent the same real-world object. Given two input entity collections, $\mathcal{E}_1$ and $\mathcal{E}_2$, the goal of entity resolution is to identify the duplicate entity profiles they contain. Depending on the inputs, we distinguish the following types of ER:

- In *Clean-Clean ER*, both $\mathcal{E}_1$ and $\mathcal{E}_2$ are duplicate-free entity collections.
- In *Dirty-Clean ER*, $\mathcal{E}_1$ is a duplicate-free entity collection, and $\mathcal{E}_2$ is a dirty one (i.e., it contains duplicates in itself).
- In *Dirty-Dirty ER*, both $\mathcal{E}_1$ and $\mathcal{E}_2$ are dirty.

In all cases, the output comprises the pairs of duplicate profiles, $\mathcal{D}^{\mathcal{E}_1 \cup \mathcal{E}_2}$, that are contained in the union of the input entity collections (i.e., the duplicate profiles shared by $\mathcal{E}_1$ and $\mathcal{E}_2$ as well as those contained in the individual entity collections). Note that, for simplicity, we consider the last two sub-problems to be equivalent to *Dirty ER*: the input comprises a single entity collection $\mathcal{E}$ that contain duplicates in itself, as it is formed by the union of the given collections (i.e., $\mathcal{E} = \mathcal{E}_1 \cup \mathcal{E}_2$). In this case, the output comprises the set of matching pairs of entity profiles, $\mathcal{D}^{\mathcal{E}}$, that are contained in $\mathcal{E}$.

Blocking for Entity Resolution. ER constitutes an inherently quadratic task, requiring the pair-wise comparison of all profiles in the input entity collection(s). To make ER scale to large entity collections, blocking restricts the computational cost to comparisons between similar profiles: it clusters them into *blocks* and performs comparisons solely among the entity profiles within each block.

In more detail, block building techniques transform every entity profile into a (set of) *blocking key(s)* that is suitable for clustering. Profiles with the same (or similar) key(s) are grouped together into blocks (Figures 1(a) and (b)). The resulting set of blocks $\mathcal{B}$ is called *block collection*. Depending on the ER problem, its elements may be of two types:

- *Unilateral blocks* contain entity profiles from the same dirty entity collection (i.e., Dirty ER). Thus, they are all candidate matches and should be compared to each other.

- *Bilateral blocks* are internally partitioned in two sub-blocks that individually contain non-matching entity profiles from the same clean input collection (i.e., Clean-Clean ER). Thus, for a bilateral block b_i, comparisons are only allowed between its inner blocks b_i^1 ($\subseteq\mathcal{E}_1$) and b_i^2 ($\subseteq\mathcal{E}_2$).

Improving Blocking through Meta-blocking. The quality of a block collection $\mathcal{B}$ is measured in terms of two competing criteria: efficiency and effectiveness. The former is directly related to its *aggregate cardinality* ($\|\mathcal{B}\|$), i.e., the total number of comparisons it contains: $\|\mathcal{B}\| = \sum_{b_i\in\mathcal{B}} \|b_i\|$, where $\|b_i\|$ is the *individual cardinality* of b_i (i.e., total number of comparisons entailed in block b_i); we have $\|b_i\|=|b_i|\cdot(|b_i|-1)/2$ for a unilateral block b_i and $\|b_j\|=|b_j^1|\cdot|b_j^2|$ for a bilateral block. The effectiveness of $\mathcal{B}$ depends on the cardinality of the set $\mathcal{D}^{\mathcal{B}}$ of detectable matches (i.e., pairs of duplicate profiles compared in at least one block).

There is a clear trade-off between the effectiveness and the efficiency of $\mathcal{B}$: the more comparisons are executed (i.e., higher $\|\mathcal{B}\|$), the higher its effectiveness gets (i.e., higher $|\mathcal{D}^{\mathcal{B}}|$), but the lower its efficiency is, and vice versa. Successful block collections achieve a good balance between these two competing objectives, as estimated by the following, established measures [3], [8], [23], [27].

(i) **Pair Completeness** (*PC*) assesses the portion of duplicates that share at least one block and, thus, can be detected. It is formally defined as: $PC(\mathcal{B}) = |\mathcal{D}^{\mathcal{B}}|/|\mathcal{D}^{\mathcal{E}}|$, where $|\mathcal{D}^{\mathcal{E}}|$ is the number of duplicates in the input entity collection $\mathcal{E}$. *PC* takes values in the interval $[0, 1]$, with higher values indicating higher *effectiveness* for $\mathcal{B}$.

(ii) **Pairs Quality** (*PQ*) estimates the portion of non-redundant comparisons that involve matching entities. Formally, it is defined as: $PQ(\mathcal{B}) = |\mathcal{D}^{\mathcal{B}}|/\|\mathcal{B}\|$. It takes values in $[0, 1]$, with higher values indicating higher *efficiency* for $\mathcal{B}$ (i.e., fewer superfluous and redundant comparisons).

(iii) **Reduction Ratio** (*RR*) measures to which degree efficiency is enhanced with respect to a baseline block collection $\mathcal{B}_{bs}$. It is defined as: $RR(\mathcal{B}, \mathcal{B}_{bs}) = 1 - \|\mathcal{B}\|/\|\mathcal{B}_{bs}\|$ and takes values in the interval $[0, 1]$ (for $\|\mathcal{B}\| \leq \|\mathcal{B}_{bs}\|$), with higher values denoting higher *efficiency* for $\mathcal{B}$.

Meta-blocking aims at restructuring a block collection $\mathcal{B}$ so as to improve its quality. It operates on its elements independently of their type (i.e., unilateral or bilateral blocks), relying primarily on the information encapsulated in their block assignments. Its output comprises a new block collection $\mathcal{B}'$ that maintains comparable levels of effectiveness (i.e., *PC*), while involving lower aggregate cardinality (i.e., higher efficiency). Formally, this task is defined as follows:

***Problem 1** (Meta-blocking):* Given a block collection $\mathcal{B}$, restructure it into a new one $\mathcal{B}'$ that achieves significantly higher levels of efficiency (i.e., $PQ(\mathcal{B}')\gg PQ(\mathcal{B})$ and $RR(\mathcal{B}', \mathcal{B})\gg 0$), while maintaining the original effectiveness (i.e., $PC(\mathcal{B}')\geq PC(\mathcal{B})$).

Note that the type of output blocks does not need to coincide with the input ones. As we will see in Section 3.3, a unilateral block collection can be transformed into a bilateral one, and vice versa. Note also that, in general, the effectiveness of the output block collection can be higher than that of the input one (i.e., $PC(\mathcal{B}') > PC(\mathcal{B})$). However, this can only be achieved by inferring new connections between entities from the original ones. We consider this inference problem to be orthogonal to the task we study in this paper, i.e., how to improve the efficiency of a block collection without affecting its effectiveness.

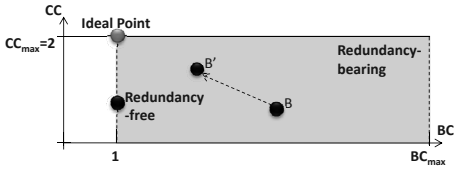


Fig. 2. The *BC-CC* metric space along with its main topological characteristics. The horizontal axis corresponds to Blocking Cardinality, which measures the redundancy of block collections, while the vertical one corresponds to Comparisons Cardinality, which estimates their efficiency.

Metric Space for Blocking Techniques. The goal of meta-blocking is to improve the balance between effectiveness and efficiency that a block collection $\mathcal{B}$ achieves. However, the impact on *PC* and *RR* can only be computed *after* examining analytically all blocks in $\mathcal{B}$ and $\mathcal{B}'$. Instead, we want to estimate their actual values *without* executing any comparison, so as to guide the restructuring process. A close, a-priori approximation of *PC* and *RR* is provided by the orthogonal measures of the *BC-CC* metric space, which was originally introduced in [29] for blocking-based Dirty ER. Here, we extend it to cover blocking-based Clean-Clean ER, as well, by adding the necessary definitions.

As depicted in Figure 2, the horizontal dimension of the *BC-CC* metric space corresponds to *Blocking Cardinality* (*BC*). This measure quantifies the redundancy of a block collection $\mathcal{B}$ as the average number of block assignments per entity of the input collection(s): $BC = \sum_{b_i\in\mathcal{B}} |b_i|/|\mathcal{E}|$, where $|b_i|$ denotes size (i.e., the number of entities) of block b_i. *BC* takes values in the interval $[0, \frac{2\cdot|\mathcal{E}_1|\cdot|\mathcal{E}_2|}{|\mathcal{E}_1|+|\mathcal{E}_2|}]$ for Clean-Clean ER and in $[0, |\mathcal{E}| - 1]$ for Dirty ER. Values lower than 1 indicate block collections that failed to place every entity profile in at least one block, values equal to 1 usually correspond to redundancy-free block collections (black dot in Figure 2), and values over 1 to redundancy-bearing ones (gray sub-plane in Figure 2). In general, the higher *BC* is, the higher is the level of redundancy in $\mathcal{B}$.

The vertical axis measures *Comparisons Cardinality* (*CC*), which estimates the efficiency of a block collection through the number of block assignments that account for each comparison: $CC = \sum_{b_i\in\mathcal{B}} |b_i|/\|\mathcal{B}\|$. *CC* takes values in the interval $[0, 2]$, with higher values corresponding to fewer comparisons per block assignment, and higher efficiency (i.e., smaller blocks, on average). Its maximum value actually corresponds to a block collection that exclusively contains blocks of minimum size (i.e., two entities).

The *BC-CC* mapping of a block collection can be efficiently computed in linear time (i.e., $O(|\mathcal{B}|)$) through a simple inspection of the size and the cardinality of its

elements. It has been experimentally demonstrated that, for redundancy-positive blocking methods, *BC* is highly correlated with *PC* (i.e., higher *BC* values lead to higher effectiveness), while *CC* is directly related to *RR* (i.e., higher *CC* values convey higher efficiency) [29]. In conjunction, they can be used for a-priori comparing the performance of blocking schemes: the closer a blocking method is mapped to point (1,2) (gray dot in Figure 2), the better is its balance between *PC* and *RR* [29]. Indeed, this represents the *Ideal Point* that corresponds to the *optimal blocking method*, i.e., the method that builds a block of minimum size for each pair of duplicates, thus involving neither redundant nor superfluous comparisons. In this context, the goal of meta-blocking is to restructure a block collection so as to move its mapping closer to the *Ideal Point* (from $\mathcal{B}$ to $\mathcal{B}'$ in Figure 2). Section 3.3 explains how this is accomplished.

3 Meta-Blocking Approach

At the core of our approach to meta-blocking lies the notion of *blocking graph*. Given a block collection $\mathcal{B}$, the corresponding blocking graph $\mathcal{G}_\mathcal{B}$ models the block assignments in $\mathcal{B}$: as shown in Figure 1(c), every entity contained in $\mathcal{B}$ is mapped to a node in the blocking graph, and every pair of *co-occurring entities* (i.e., entities that are compared in at least one block) is connected with an undirected edge. Formally, the blocking graph for a unilateral block collection is defined as follows:

***Definition** 2 (Undirected Blocking Graph):* Given a *unilateral* block collection $\mathcal{B}^\mathcal{E}$, the *undirected blocking graph* derived from it is a graph $\mathcal{G}_\mathcal{B} = \{V_\mathcal{B}, E_\mathcal{B}, WS\}$, where $V_\mathcal{B}$ is the set of its nodes, $E_\mathcal{B}$ is the set its undirected edges, and WS is the *weighting scheme* that determines the weight of every edge in the interval $[0, 1]$. $V_\mathcal{B}$ contains all entities of $\mathcal{E}$ that are placed in at least one block of $\mathcal{B}^\mathcal{E}$ (i.e., $\forall v_i \in V_\mathcal{B} : \exists p_i \in \mathcal{E} \wedge b_j \in \mathcal{B}^\mathcal{E} \wedge p_i \in b_j$), while $E_\mathcal{B}$ contains undirected edges between all pairs of co-occurring entities (i.e., $\forall e_{i,j} = \langle p_i, p_j \rangle \in E^\mathcal{E} : p_i \neq p_j \wedge \exists b_k \in \mathcal{B}^\mathcal{E} \wedge p_i \in b_k \wedge p_j \in b_k$).

The blocking graph over a set of bilateral blocks $\mathcal{B}^{\mathcal{E}_1 \times \mathcal{E}_2}$ is defined analogously. The only difference is that it results in a *bipartite* graph, since its set of nodes $V_\mathcal{B}$ is separated into two disjoint sets, $V^1_\mathcal{B}$ and $V^2_\mathcal{B}$, which comprise entities stemming from the entity collections $\mathcal{E}_1$ and $\mathcal{E}_2$, respectively (i.e., $V^1_\mathcal{B} \subseteq \mathcal{E}_1$ and $V^2_\mathcal{B} \subseteq \mathcal{E}_2$). More formally, $\forall v^k_i \in V^k_\mathcal{B} : \exists p_i \in \mathcal{E}_k \wedge b^{1,2}_j \in \mathcal{B}^{\mathcal{E}_1 \times \mathcal{E}_2} \wedge p_i \in b^k_j$, where $k \in \{1, 2\}$. Thus, the set of edges $E_\mathcal{B}$ contains only connections between entities stemming from different entity collections: $\forall e_{i,j} = \langle p_i, p_j \rangle \in E_\mathcal{B} : \exists b^{1,2}_k \in \mathcal{B}^{\mathcal{E}_1 \times \mathcal{E}_2} \wedge p_i \in b^1_k \wedge p_j \in b^2_k$.

Note that for reasons explained in Section 3.3, the edges of a blocking graph can be directed, as well. An edge pointing from entity p_i to p_j is represented by $\vec{e_{i,j}}$ to distinguish it from the undirected edge $e_{i,j}$ that connects the same entities. A blocking graph with directed edges is called *directed blocking graph* and is symbolized as $\vec{\mathcal{G}}_\mathcal{B}$.

The purpose of the blocking graph is to facilitate efficiency improvements over the input block collection. An immediate contribution to this goal is the *elimination of redundant comparisons* without any impact on effectiveness (i.e., *PC*). Redundant comparisons are easily identified during the creation of the blocking graph, as the corresponding entities have already been connected with an edge. In such cases, we simply skip connecting them with an additional edge and, thus, each pair of comparable entities is connected with at most one edge, regardless of the total number of comparisons between them entailed in $\mathcal{B}$. Consequently, each pair of co-occurring (i.e., adjacent) entities is examined only once. While improving efficiency, effectiveness is not affected, since the set of comparable entity pairs remains unchanged.

Additional efficiency enhancements can be achieved through the *pruning* of the blocking graph: edges between *non-matching* entities can be gradually removed from the graph, discarding unnecessary comparisons without affecting *PC*. This process is carried out according to a *pruning algorithm* and theoretically can result in a graph that exclusively contains edges between matching entities, as in Figure 1(d). In practice, though, we can only approximate this ideal case by exploiting the evidence that is encapsulated in the given block collection: how entities are assigned to blocks provides reliable indications for the similarity of adjacent entities, which can be quantified by assigning a weight to the corresponding edge. In the context of redundancy-positive blocking methods, the more blocks two entities share, the more similar they are and the higher the weight of their adjacent edge should be. In this way, the pruning of the blocking graph becomes the process of removing edges with low weights on the grounds that they (are likely to) link dissimilar entities.

In more detail, the weight $e_{i,j}.weight$ of an edge $e_{i,j}$ expresses the utility of the comparison between the profiles p_i and p_j; that is, it quantifies the trade-off between the cost $c_{i,j}$ of comparing the adjacent entities and the gain $g_{i,j}$ of executing this comparison (i.e., $e_{i,j}.weight = g_{i,j}/c_{i,j}$). The cost $c_{i,j}$ pertains to the number of comparisons required by the corresponding edge and is always equal to 1 (since, by definition, each edge in the blocking graph captures one comparison). Thus, the edge weight is always equal to the gain of the corresponding comparison, which is 0 if the compared entities are not matching and 1 if they are duplicates (i.e., $e_{i,j}.weight = 0 \leftrightarrow p_i \not\equiv p_j$ and $e_{i,j}.weight = 1 \leftrightarrow p_i \equiv p_j$).

However, it is not possible to estimate the real value of $g_{i,j}$, and correspondingly $e_{i,j}.weight$, without actually executing the comparison between p_i and p_j. For this reason, we use a *weighting scheme* that a-priori approximates the weight of each edge by considering the features of the blocking graph (e.g., the number of blocks shared by an edge's adjacent entities and the corresponding individual cardinalities). In Section 3.2, we will present five such weighting schemes for redundancy-positive blocking methods (i.e., the more similar two entities are, the higher the weight of the corresponding edge is). Edges with low weights are discarded by a *pruning criterion* that bounds either the number or the weight of the retained edges.

Overall, our approach to meta-blocking involves four successive steps, which are illustrated in Figure 3:

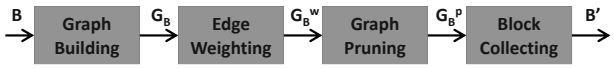


Fig. 3. The internal functionality of our meta-blocking approach.

(i) *Graph Building* receives a block collection $\mathcal{B}$ and derives the blocking graph $\mathcal{G}_\mathcal{B}$ from its block assignments. We elaborate on this process in Section 3.1.

(ii) *Edge Weighting* takes as input a blocking graph $\mathcal{G}_\mathcal{B}$ and turns it into the *weighted blocking graph* ($\mathcal{G}^w_\mathcal{B}$) by determining the weights of its edges. We introduce several weighting schemes for this procedure in Section 3.2.

(iii) *Graph Pruning* receives as input the weighted blocking graph and derives the *pruned blocking graph* ($\mathcal{G}^p_\mathcal{B}$) from it by removing some of its edges. We delve into the pruning algorithms and the pruning criteria involved in this procedure in Section 3.3.

(iv) *Block Collecting* is given as input the pruned blocking graph $\mathcal{G}^p_\mathcal{B}$ and extracts from it a new block collection $\mathcal{B}'$, which actually constitutes the final output of the entire meta-blocking process. We analyze this step in Section 3.4.

Note that the weighting scheme, the pruning algorithm, and the pruning criterion can entail a *schema-dependent*, *schema-agnostic*, or *hybrid* functionality. In the following, we focus on schema-agnostic techniques since they are applicable to any *blocking settings*, i.e., any combination of a blocking scheme and a (pair of) entity collection(s).

3.1 Building the Blocking Graph

The process of extracting the blocking graph from a bilateral block collection $\mathcal{B}$ is outlined in Algorithm 1 (for unilateral blocks, the corresponding algorithm is simpler, and we omit it for brevity). Essentially, for each block in $\mathcal{B}$, we consider every distinct pair of entities it contains (Lines 2-5); for bilateral blocks, this process requires that the considered entities belong to different inner blocks (i.e., $p_i \in b_i^1$ and $p_j \in b_j^2$). For each pair, we add the corresponding nodes to the initially empty blocking graph (Lines 4 and 6) and connect them with an edge (Line 7). The edge weights are specified after the structure of the blocking graph has been settled, because — as explained in the next subsection — it is possible for a blocking scheme to rely on it (Line 8). To restrict them to the interval $[0, 1]$ regardless of the input weighting scheme (cf. Definition 2), we normalize them by dividing with the maximum one (Line 9). The time complexity of this procedure is equal to the aggregate cardinality of $\mathcal{B}$ (i.e., $O(\|\mathcal{B}\|)$).

Graph Materialization. The blocking graph constitutes a conceptual model that aims at facilitating the interpretation and the development of our meta-blocking techniques. In the context of large entity collections with millions of entities (nodes) and billions of comparisons (edges), its materialization actually poses significant technical challenges. For this reason, it can be indirectly implemented in two ways: *(i)* through inverted indices, which associate each entity with the list of the blocks containing it, and *(ii)* with the help of bit arrays, which represent each entity as a vector with a zero value in all places, but those corresponding to the blocks containing it (these are valued 1). Both approaches scale well in the context of HHIS and accommodate all the weighting schemes of Section 3.2.

Algorithm 1: Building the Blocking Graph.

Input: (i) $\mathcal{B}$ a block collection,
(ii) WS a weighting scheme
Output: $\mathcal{G}_\mathcal{B}$ the corresponding blocking graph

1 $V_\mathcal{B} \leftarrow \{\}$; $E_\mathcal{B} \leftarrow \{\}$; `//initially empty graph`
2 **foreach** $b_i \in \mathcal{B}$ **do** `// check all blocks`
3 **foreach** $p_i \in b_i^1$ **do** `// check all comparisons`
4 $V_\mathcal{B} \leftarrow V_\mathcal{B} \cup \{v_i\}$;
5 **foreach** $p_j \in b_i^2$ **do**
6 $V_\mathcal{B} \leftarrow V_\mathcal{B} \cup \{v_j\}$; `//add node for` p_j
7 $E_\mathcal{B} \leftarrow E_\mathcal{B} \cup \{e_{i,j}\}$; `//add edge` $<p_i, p_j>$
8 setEdgeWeights(WS, $\mathcal{B}$, $V_\mathcal{B}$, $E_\mathcal{B}$);
9 normalizeEdgeWeights($E_\mathcal{B}$);
10 **return** $\mathcal{G}_\mathcal{B} = \{V_\mathcal{B}, E_\mathcal{B}, WS\}$;

Efficiency of Construction. Theoretically, the construction of the blocking graph has the same complexity as the naïve method that iterates over all pairs of comparable entities. In practice, though, meta-blocking exhibits a lower running time when implemented on the basis of inverted indices or bit arrays, because it exclusively involves operations with integers. Thus, the computation of edge weights is much faster than the comparison of entity profiles, which invariably relies on string matching algorithms. The reason is that the latter typically have a non-trivial complexity of their own. As an example, consider edit distance, one of the simplest string comparison techniques, whose complexity even for an optimized implementation is $O(n^2/\log n)$, when n is the length for both of the compared strings [21]. We analytically examine the time requirements of our meta-blocking approaches in Section 4.4.

3.2 Edge Weighting

We introduce five schema-agnostic weighting schemes that rely exclusively on evidence drawn from the input block collection. We use the following notations: $\mathcal{B}_i \subseteq \mathcal{B}$ denotes the set of blocks containing the entity p_i, $\mathcal{B}_{i,j} \subseteq \mathcal{B}$ is the set of blocks shared by the entities p_i and p_j (i.e., $\mathcal{B}_{i,j} = \mathcal{B}_i \cap \mathcal{B}_j$), and $|v_i|$ symbolizes the degree of node v_i (i.e., the number of edges connected to it). Next, we describe our weighting schemes and explain the rationale behind them.

(i) *Aggregate Reciprocal Comparisons Scheme* (*ARCS*): This scheme is based on the premise that the more entities a block contains, the less likely they are to match. The reason is that the information forming this block is not distinctive enough to group highly similar entities. For instance, in the case of attribute-agnostic blocking, common words would cluster together a large part of the input entity collection. In this context, the aggregate similarity of two co-occurring entities, p_i and p_j, is defined as the sum of the reciprocal individual cardinalities of their common blocks. Formally, the weight of an edge $e_{i,j}$ is defined as follows:

$$e_{i,j}.weight = \sum_{b_k \in \mathcal{B}_{i,j}} \frac{1}{\|b_k\|}.$$

(ii) *Common Blocks Scheme* (*CBS*): A strong indication of the similarity of two entities is provided by the number of blocks they have in common; the more blocks they share, the more likely they are to match. Therefore, the weight of an edge connecting entities p_i and p_j is set equal to:

$$e_{i,j}.weight = |\mathcal{B}_{i,j}|.$$

(iii) *Enhanced Common Blocks Scheme* ($ECBS$): This scheme improves on CBS by adding contextual information to its weights. Instead of merely considering the number of common blocks, it takes into account the total number of blocks that are associated with each one of the co-occurring entities. Inspired from the IDF metric of Information Retrieval, the fewer blocks an entity is placed in, the higher should be the weights of the edges associated with it. More formally, the weight of an edge is set equal to:

$$e_{i,j}.weight = |\mathcal{B}_{i,j}| \cdot \log \frac{|\mathcal{B}|}{|\mathcal{B}_i|} \cdot \log \frac{|\mathcal{B}|}{|\mathcal{B}_j|}.$$

(iv) *Jaccard Scheme* (JS): Similar to $ECBS$, this scheme aims at enhancing CBS by considering the total number of blocks associated with the co-occurring entities. To this end, it sets the weight of the edge $e_{i,j}$ equal to the Jaccard similarity of the lists of blocks associated with its adjacent entities, p_i and p_j:

$$e_{i,j}.weight = \frac{|\mathcal{B}_{i,j}|}{|\mathcal{B}_i| + |\mathcal{B}_j| - |\mathcal{B}_{i,j}|}.$$

The resulting weights take values in the interval $[0, 1]$, with 0 indicating the absence of common blocks and 1 corresponding to identical block lists. In essence, these weights reveal the percentage of common blocks shared by the adjacent entities.

(v) *Enhanced Jaccard Scheme* (EJS): This scheme improves on JS by adding contextual information to the Jaccard similarity of the associated blocks. Namely, it considers the total number of edges (i.e., comparisons) associated with each one of the adjacent nodes. Based on IDF, the fewer edges connected with a node, the higher should their individual weights be. Thus, we have:

$$e_{i,j}.weight = \frac{|\mathcal{B}_{i,j}|}{|\mathcal{B}_i| + |\mathcal{B}_j| - |\mathcal{B}_{i,j}|} \cdot \log \frac{|E_{\mathcal{B}}|}{|v_i|} \cdot \log \frac{|E_{\mathcal{B}}|}{|v_j|}.$$

Note that the above weighting schemes rely on the principle of redundancy-positive blocking methods that the similarity of block assignments provides a good representation of matching probability. Thus, the more blocks two entities share, the more similar their profiles are expected to be. In Section 4, we experimentally analyze the effect of these weighting schemes on the performance of meta-blocking.

3.3 Pruning the Blocking Graph

This process is based on two essential components: *(i)* the *pruning algorithm*, which specifies the procedure that will be followed in the processing of the blocking graph, and *(ii)* the *pruning criterion*, which determines the edges to be retained. The combination of a pruning algorithm with a pruning criterion forms a *pruning scheme*. In this work, we introduce a series of pruning schemes that rely on schema-agnostic pruning algorithms and criteria, thus being applicable to any blocking graph.

Pruning algorithms. In general, they can be categorized in two classes:

- The *edge-centric algorithms* select the *globally* best comparisons by iterating over the *edges* of a blocking graph in order to filter out those that do not satisfy the pruning criterion.

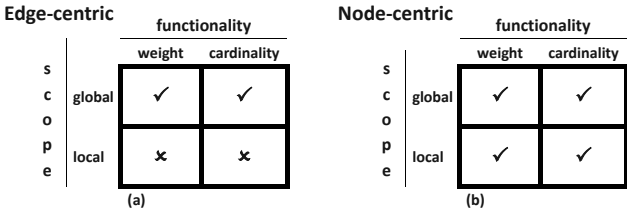


Fig. 4. All possible combinations of our pruning algorithms with our pruning criteria.

- The *node-centric algorithms* iterate over the *nodes* of a blocking graph with the aim of selecting the *locally* best comparisons for each entity (i.e., the adjacent entities with the largest edge weights).

We analytically examine the relative performance of these two types of pruning algorithms in Section 4.2.

Pruning criteria. In general, they can be categorized in a two-dimensional taxonomy formed by the orthogonal but complementary dimensions of functionality and scope. The *functionality* of pruning criteria distinguishes them into *weight thresholds*, which specify the minimum weight for the edges to be retained, and *cardinality thresholds*, which determine the maximum number of retained edges. The *scope* of pruning criteria distinguishes them into *global thresholds*, which define conditions that are applicable to the entire blocking graph (i.e., all the edges of the graph), and *local thresholds*, which specify conditions that apply to a subset of it (i.e., the adjacent edges of a specific node).

Cardinality thresholds should be preferred in applications that have predefined temporal resources (i.e., available processing time), because they allow for a-priori determining the number of executed comparisons. In contrast, weight thresholds are convenient for applications that put more emphasis on controlling effectiveness, since the harshness of their pruning is analogous to their value. Both classes, though, are suitable for incremental ER (a.k.a., Pay-As-You-Go ER) [31], where the goal is to execute most of the matching comparisons in the first iterations, decreasing their number gradually, as ER progresses. For weight (cardinality) thresholds, this can be simply achieved by decreasing (increasing) its value in every iteration.

Pruning Schemes. The composition of pruning schemes is determined by the scope of pruning thresholds. In Figure 4, we illustrate all possible combinations of pruning algorithms with pruning criteria. Starting with the edge-centric algorithms, we observe that they can only be combined with global criteria — regardless of their functionality. The reason is that it is impossible to employ a local threshold, when trying to select the top weighted edges across the entire blocking graph. The combination of edge-centric algorithms with global weight thresholds (i.e., WEP) is analyzed in Section 3.3.1 and their coupling with global cardinality thresholds (i.e., CEP) in Section 3.3.2.

By definition, the node-centric algorithms are compatible with local thresholds — regardless of their functionality. However, they can be combined with global thresholds, as well. Their combination with a global weight threshold is actually identical to WEP, as they both retain the edges that are weighted higher than the given threshold. Their

Algorithm 2: Weight Edge Pruning.

Input: (i) $\mathcal{G}_{\mathcal{B}}^{in}$ the blocking graph, and
(ii) w_{min} the global weight pruning criterion.
Output: $\mathcal{G}_{\mathcal{B}}^{out}$ the undirected pruned blocking graph

```
1 foreach e_{i,j} ∈ E_B do
2     if e_{i,j}.weight < w_min then // discard every edge with
3         E_B ← E_B - { e_{i,j} }; // weight lower than w_min
4 return G_B^out = {V_B, E_B, WS};
```

Algorithm 3: Cardinality Edge Pruning.

Input: (i) $\mathcal{G}_{\mathcal{B}}^{in}$ the blocking graph, and
(ii) K the global cardinality pruning criterion.
Output: $\mathcal{G}_{\mathcal{B}}^{out}$ the undirected pruned blocking graph

```
1 SortedStack ← {}; // sorts edges in descending weight
2 foreach e_{i,j} ∈ E_B do          // add every edge
3     SortedStack.push(e_{i,j}); // in the sorted stack
4     if K < SortedStack.size() then // remove the edge with
5         SortedStack.pop();          // the (K+1)^th top weight
6 foreach e_{i,j} ∈ E_B do          // discard all edges
7     if e_{i,j} ∉ SortedStack then // that are not among the
8         E_B ← E_B - { e_{i,j} }; // the top-K weighted ones
9 return G_B^out = {V_B, E_B, WS};
```

coupling with a global cardinality threshold retains the same number of adjacent edges among all nodes (e.g., the 2 top-weighted edges per node). In contrast, their combination with a local cardinality threshold derives the number of retained edges for each node from its degree (e.g., $|v_i|/10$ of the top weighted edges for every node v_i); this approach is substantially different from CEP, which keeps the top weighted edges across the entire blocking graph. The pruning schemes that combine node-centric algorithms with local weight thresholds (i.e., WNP) are examined in Section 3.3.3, while those coupling them with cardinality thresholds — of any scope — (i.e., CNP) are examined in Section 3.3.4.

Before elaborating on the functionality of the pruning schemes, it should be stressed that the node-centric algorithms yield a directed, pruned blocking graph, unlike the edge-centric algorithms that produce an undirected one.

3.3.1 Weight Edge Pruning (WEP)

This scheme consists of the edge-centric algorithm coupled with a global weight threshold: the minimum edge weight. Its functionality is outlined in Algorithm 2. It iterates over all edges (Line 1) and discards (Line 3) those having a weight lower that the input threshold (Line 2). The remaining edges form the pruned blocking graph of the output. The time complexity of this algorithm is equal to the aggregate cardinality of the original block collection (i.e., $O(\|\mathcal{B}\|)$).

The most critical part of this algorithm is the selection of the minimum edge weight w_{min}. Its precise value depends on the underlying weighting scheme and the resulting distribution of edge weights, in particular. In general, though, the matching entities are expected to be connected with edges of higher weights than the non-matching ones. Thus, the goal is to identify the break-even point that distinguishes the former type of edges from the latter. Experimental evidence with real-world datasets suggests that the average edge weight provides an efficient (i.e., requires just one iteration over all edges) as well as reliable (i.e., low impact on effectiveness) estimation of this break-even point, regardless of the underlying weighting scheme (see Section 4.2 for details).

3.3.2 Cardinality Edge Pruning (CEP) or Top-K Edges

This scheme combines the edge-centric pruning algorithm with a global cardinality threshold K that specifies the total number of edges retained in the pruned graph. The goal is to retain the K edges with the maximum weight. As illustrated in the outline of Algorithm 3, this technique employs a *sorted stack* in order to store the edges in descending order of weights, thus efficiently removing (i.e., pop) the edge with the lowest weight. The algorithm iterates over all edges of the input blocking graph twice: the first iteration (Lines 2-5) identifies the top-K edges and stores them in the sorted stack; the second iteration (Line 6-8) removes from the graph those edges that are not contained in the sorted stack. Similar to WEP, the time complexity of this algorithm is equal to the aggregate cardinality of original block collection (i.e., $O(\|\mathcal{B}\|)$).

To specify the optimal value for K, we employ a technique that relies on the BC-CC mapping of the initial blocking graph and its pruned version. The goal is to map the latter closer to the Ideal Point (1,2) than the former. Given that the pruned graph results in a bilateral block collection with K blocks of size 2 (cf. Section 3.4), its CC takes the maximum value (i.e., CC_{out}=2)[2], while its BC is equal to $BC_{out}=\frac{2K}{|\mathcal{E}|}$, where $\mathcal{E}$ is the size of the input entity collection. Thus, CC_{out} is greater than or equal to CC_{in} of the input blocking graph in all cases and, for an improved BC-CC mapping, it suffices to have: $BC_{out} \leq BC_{in} \Leftrightarrow \frac{2K}{|\mathcal{E}|} \leq BC_{in} \Leftrightarrow K \leq \lfloor \frac{BC_{in} \cdot |\mathcal{E}|}{2} \rfloor$, where BC_{in} stands for the BC value of the input blocking graph. Therefore, the maximum meaningful value for K is specified with respect to the level of redundancy of the input block collection. In cases where $CC_{in} \ll CC_{out}$, we can set $K=\lfloor \frac{BC_{in} \cdot |\mathcal{E}|}{2} \rfloor$ in order to ensure higher redundancy and, thus, higher PC. Although this approach maintains the same levels of redundancy (i.e., the same number of block assignments), efficiency is significantly improved; unlike the input block collection, which contains blocks of various sizes, the output exclusively comprises blocks of minimum size (i.e., two entities per block). This means that CEP minimizes the number of pairwise comparisons for a specific level of redundancy.

3.3.3 Weight Node Pruning (WNP)

This scheme combines the node-centric pruning algorithm with a local weight threshold. In essence, it applies the WEP to the neighborhood of each node v_i, i.e., the subgraph $\mathcal{G}_{v_i}$ that comprises the nodes of $\mathcal{G}_{\mathcal{B}}$ connected with v_i

2. CC expresses the ratio of block assignments over comparisons (i.e., $CC=\sum_{b_i \in \mathcal{B}} |b_i| / \sum_{b_i \in \mathcal{B}} \|b_i\|$. Given that the output of CEP involves only blocks of size 2, there are two block assignments for every comparison, thus leading to $CC_{out}=CC_{max}=2$.

Algorithm 4: Weight Node Pruning.

Input: (i) $\mathcal{G}_{\mathcal{B}}^{in}$ the blocking graph, and
(ii) wt function for defining local weight pruning criteria.
Output: $\mathcal{G}_{\mathcal{B}}^{out}$ the directed pruned blocking graph

1 $E_{\mathcal{B}}^{out} \leftarrow \{\}$; // the set of retained directed edges
2 **foreach** $v_i \in V_{\mathcal{B}}$ **do** // for every node get
3 $\mathcal{G}_{v_i} \leftarrow$ getNeighborhood(v_i, $\mathcal{G}_{\mathcal{B}}$); //its neighborhood and
$t_{v_i} \leftarrow wt(\mathcal{G}_{v_i})$; // its local weight threshold
4 **foreach** $e_{i,j} \in E_{v_i}$ **do** // retain every adjacent
5 **if** $t_{v_i} \leq e_{i,j}.weight$ **then** // edge with weight
6 $E_{\mathcal{B}}^{out} \leftarrow E_{\mathcal{B}}^{out} \cup \{ e_{i,j}^{-} \}$; // higher than t_{v_i}
7 **return** $\mathcal{G}_{\mathcal{B}}^{out} = \{V_{\mathcal{B}}, E_{\mathcal{B}}^{out}, WS\}$;

Algorithm 5: Cardinality Node Pruning.

Input: (i) $\mathcal{G}_{\mathcal{B}}^{in}$ the blocking graph, and
(ii) ct function for defining local cardinality pruning criteria.
Output: $\mathcal{G}_{\mathcal{B}}^{out}$ the directed pruned blocking graph

1 $E_{\mathcal{B}}^{out} \leftarrow \{\}$; // the set of retained directed edges
2 **foreach** $v_i \in V_{\mathcal{B}}$ **do**
3 $SortedStack_{v_i} \leftarrow \{\}$; //for every node get
4 $\mathcal{G}_{v_i} \leftarrow$ getNeighborhood(v_i, $\mathcal{G}_{\mathcal{B}}$); //its neighborhood and
5 $k \leftarrow ct(\mathcal{G}_{v_i})$; // its local cardinality threshold
6 **foreach** $e_{i,j} \in E_{v_i}$ **do** // add every adjacent
7 $SortedStack_{v_i}$.push($e_{i,j}$); // edge in sorted stack
8 **if** $k < SortedStack_{v_i}.size()$ **then** // remove the
9 $SortedStack_{v_i}$.pop(); // (k+1)th edge
10 **foreach** $e_{i,j} \in E_{v_i}$ **do** // retain every adjacent
11 **if** $e_{i,j} \in SortedStack$ **then** // edge contained in
12 $E_{\mathcal{B}}^{out} \leftarrow E_{\mathcal{B}}^{out} \cup \{ e_{i,j}^{-} \}$; // the SortedStack
13 **return** $\mathcal{G}_{\mathcal{B}}^{out} = \{V_{\mathcal{B}}, E_{\mathcal{B}}^{out}, WS\}$;

— denoted by V_{v_i} — along with the edges connecting them — denoted by E_{v_i}. Its functionality, though, differs from WEP in two aspects: *(i)* it employs a different threshold for each neighborhood, and *(ii)* it replaces the retained, undirected edges with directed ones that point from v_i to a neighboring node. Algorithm 4 presents the pseudo-code for this procedure: it iterates over all nodes of the input blocking graph (Line 2) and extracts the corresponding neighborhood $\mathcal{G}_{v_i}$ (Line 3). Based on this, it specifies the minimum edge weight of the neighborhood according to the input local threshold criterion (Line 4). Then, it iterates over all edges of E_{v_i} (Line 5) and adds one directed edge to the pruned graph for every undirected edge that exceeds the specified local threshold (Lines 6-7). In the worst case, the input blocking graph is a complete one, thus accounting for a time complexity of $O(|V_{\mathcal{B}}|\cdot|E_{\mathcal{B}}|)$; in practice, though, it is significantly lower, as the underlying blocking scheme ensures that not all nodes are connected with each other.

To specify the optimal threshold for each neighborhood, we rely on the same rationale as WEP: weighting schemes assign high values to edges connecting matching entities and low values to edges connecting non-matching nodes. Regardless of the selected scheme, the corresponding break-even point can be approximated by the mean weight of the edges in each neighborhood $\mathcal{G}_{v_i}$.

3.3.4 Cardinality Node Pruning (CNP) or k-Nearest Entities

At the core of this scheme lies the node-centric pruning algorithm in conjunction with a local cardinality threshold. Its goal is to select for each node v_i, the k neighboring nodes that are connected with the top edge weights (i.e., k-nearest entities). To this end, it applies the CEP algorithm to the neighborhood $\mathcal{G}_{v_i}$ of v_i, as depicted in Algorithm 5. In more detail, it iterates over all entities of the input blocking graph (Line 2), extracting their neighborhood (Line 4) and setting the maximum number of retained entities (Line 5). Subsequently, it iterates over the edges of the current neighborhood and places them into the sorted stack (Line 6-9). For each of the selected undirected edges, a new, directed one is added to the pruned blocking graph of the output (Lines 10-12). The time complexity of this algorithm is the same as that of WNP: $O(|V_{\mathcal{B}}|\cdot|E_{\mathcal{B}}|)$.

In general, the cardinality threshold for each neighborhood depends on its size (e.g., k_i=$\lceil 0.1\cdot|E_{v_i}|\rceil$). For simplicity, though, we assume in the following that k takes the same value for each neighborhood. To identify its optimal value, we rely on the *BC*-*CC* mapping of the input and the output blocking graph. Again, the goal is to ensure that the latter is closer to (1,2) than the former. Given that the block collection contains bilateral blocks with inner block sizes of 1 and k (cf. Section 3.4), the CC of the pruned graph is equal to $CC_{out} = \frac{k+1}{k}$, while its BC is equal to BC_{out}=$k+1$. Thus, k is specified with respect to the CC and the BC of the input block collection: $\frac{1}{1-CC_{or}} \leq k \leq BC_{in}$-1. In cases where $CC_{in} \ll 1$, we can safely set k=$\lfloor BC_{in}$-1$\rfloor$, ensuring significantly higher efficiency (CC_{out}>1) at equal levels of redundancy and PC.

3.4 Collecting the new blocks

The procedure for transforming a pruned blocking graph into a new block collection depends on the type of the graph. For the undirected pruned blocking graphs, which are produced by the edge-centric pruning algorithms, block collecting is straightforward: every retained edge lays the basis for creating a bilateral block of minimum size that contains the adjacent entities. As a result, the new block collection is redundancy-free (i.e., non-overlapping blocks). For example, the pruned blocking graph of Figure 1(d) is transformed in the blocks $b_1 = \{\{p_1\}, \{p_3\}\}$ and $b_2 = \{\{p_2\}, \{p_4\}\}$.

For the directed pruned blocking graphs, which are derived from the node-centric pruning algorithms, block collecting creates a bilateral block for every node v_i. Its inner blocks have the following property: one of them contains the entity that is mapped to v_i, while the other contains the entities connected with v_i through the retained, outgoing edges. For instance, the pruned blocking graph of Figure 1(e)[3] is transformed into the blocks $b_1 = \{\{p_1\}, \{p_3, p_4\}\}$ and $b_2 = \{\{p_2\}, \{p_3, p_4\}\}$. In this way, the new block collection involves redundant comparisons, since it is possible for two retained edges with different direction to connect the same entities. This means that its

3. For clarity we have excluded the outgoing edges of nodes p_3 and p_4.

efficiency can be further enhanced with block processing techniques.

4 Evaluation

The goal of our experimental study is manifold: *(i)* to demonstrate the benefits of meta-blocking over existing blocking methods, *(ii)* to compare the edge-centric pruning schemes with the node-centric ones, *(iii)* to compare the weight pruning criteria with the cardinality ones, *(iv)* to compare the weighting schemes for building blocking graphs, *(v)* to compare meta-blocking with the state-of-the-art approach of Iterative Blocking, *(vi)* to examine the robustness of our pruning schemes, and *(vii)* to investigate the time requirements of meta-blocking over large blocking graphs with millions of nodes and billions of edges. Section 4.1 elaborates on the set-up of our experiments, and Section 4.2 examines the objectives *(i)* to *(v)*, analyzing the performance of all meta-blocking settings with respect to *RR*, *PC* and *PQ*. Section 4.3 focuses on goal (*vi*) and Section 4.4 on goal (*vii*). Note that we had to place all figures and tables detailing our experimental results in the appendix, due to lack of space.

4.1 Setup

Our approaches were implemented in Java 1.6 and are publicly available through SourceForge.net[4]. Our experiments were performed on a server with Intel Xeon X5670 2.93GHz and 16GB of RAM, running Scientific Linux 5.8.

Datasets. In our evaluation, we used the same datasets as in our previous works [27], [28], [29], namely D_{movies}, $D_{infoboxes}$ and D_{BTC09}. In this way, we allow for a direct comparison with their outcomes. Note that we have publicly released all datasets, so that they can be used as a benchmark by other researchers[5]. Their technical characteristics are summarized in Table 1.

D_{movies} is a collection of 50,000 entities shared among the individually clean collections of IMDB and DBPedia movies. The ground-truth for this Clean-Clean ER dataset stems from the "imdbid" attribute in the profiles of the DBPedia movies.

Our second Clean-Clean ER dataset, $D_{infoboxes}$, consists of two different versions of the DBPedia Infobox dataset[6]. They contain all name-value pairs of the infoboxes in the articles of Wikipedia's English version, extracted at specific points in time. The older collection, $DBPedia_1$, is a snapshot from October 2007, whereas $DBPedia_2$ dates from October 2009. The large time period that intervenes between the two collections renders their resolution challenging, since only 25% of all name-value pairs is shared among them [27]. As matching entities, we consider those with the same entity URL.

Finally, D_{BTC09} is the Dirty ER dataset of our study, comprising more than 250,000 entities, a subset of those contained in the Billion Triple Challenge 2009 (BTC09) data collection[7]. Its ground-truth consists of 10,653 pairs of matching entities that were identified through their identical value for at least one inverse functional property.

Baseline method. To evaluate the performance of our meta-blocking techniques, the baseline for the two Clean-Clean ER datasets was specified as the attribute-agnostic blocking method in conjunction with Block Purging [27]. For D_{movies}, the resulting blocks exhibit nearly perfect effectiveness (PC = 99.39%) combined with high efficiency (RR = 95.83% with respect to the naïve method of comparing all DBPedia movies with the IMDB ones). The former can be actually attributed to the high levels of redundancy, as each entity is placed in 22 blocks, on average. The corresponding blocking graph is medium-sized, entailing 50 thousand nodes and 22 million edges. Similarly, the resulting block collection for $D_{infoboxes}$ achieves an excellent balance between efficiency and effectiveness (i.e., RR = 98.46% and PC = 99.89%). It involves high redundancy (BC≈15) and produces a large blocking graph with 3.3 million nodes and 34 billion edges.

The blocks of D_{BTC09} were extracted from those produced by *Total Description* [29] when applied to the entire BTC09 data collection. To restrict the originally massive dataset to a moderate block collection that facilitates our thorough experimental analysis, we first purged those blocks that contained none of the ground-truth entities. We then removed the singleton entities, which were associated with just one block after sampling, in order to ensure a redundancy-positive block collection (BC>1) that allows for applying meta-blocking. Finally, we discarded the invalid blocks, which were left with just one entity, and applied Block Purging [29] on the remaining set of blocks. The resulting block collection combines a high RR(>99%) with a high PC(≈97%) and yields a blocking graph with 250 thousand nodes and 77 million edges.

Note that in all datasets, we do not measure the effect of meta-blocking on efficiency against a stand-alone block building method. Instead, we estimate RR with respect to Block Purging, which yields a significant reduction in the aggregate cardinality of the original blocks. In addition, we consider as a baseline the state-of-the-art approach of Iterative Blocking [32]. In essence, this method propagates every new pair of duplicates to all associated blocks (even if they have already been examined) in order to identify additional matches and to save unnecessary comparisons.

To assess the impact of meta-blocking on effectiveness, we consider the relative reduction in PC (ΔPC), which is formally defined as $\Delta PC = \frac{PC(\mathcal{B}')-PC(\mathcal{B})}{PC(\mathcal{B})} \cdot 100\%$, where $PC(\mathcal{B})$ and $PC(\mathcal{B}')$ denote the effectiveness of the original and the restructured block collection, respectively.

4.2 Measuring the blocks of Meta-blocking

In this section, we examine the first five of our evaluation objectives. To this end, we applied all pruning schemes to all blocking graphs (i.e., weighting schemes) that can be derived from D_{movies}, $D_{infoboxes}$ and D_{BTC09}. We categorized the results according to the corresponding pruning scheme and analytically present them in Tables 4(a) to 4(d).

(i) *Effect of meta-blocking on blocking.* Table 4(a) depicts the performance of WEP in conjunction with all weighting

4. http://sourceforge.net/projects/erframework

5. See http://sourceforge.net/projects/erframework/files for instructions on how to download them.

6. http://wiki.dbpedia.org/Datasets

7. http://km.aifb.kit.edu/projects/btc-2009

schemes across all datasets. For D_{movies} and $D_{infoboxes}$, we notice that all weighting schemes convey significant enhancements in efficiency (RR>70%), while incurring moderate reduction in PC (ΔPC<10%). Similar patterns are exhibited for D_{BTC09}: in the worst case $\Delta PC \approx 10\%$, while RR remains higher than 95% for all weighting schemes. The performance of most of them is actually very close over D_{BTC09}. In contrast, for D_{movies} and $D_{infoboxes}$, there is a clear trade-off between RR and PC: the higher the former gets, the lower the latter is and vice versa. Note, though, that the evolution of PQ suggests that RR decreases faster than PC increases.

These patterns can be explained by the weight distribution lying at the core of each weighting scheme. As an example, consider Figures 7(a) and (b), which depict the distribution for every weighting scheme over D_{movies} (similar distributions are exhibited in the other two datasets, as well, but we omit the corresponding diagrams, due to lack of space). In all histograms, the bucket size is set equal to half the average edge weight ($\bar{w}$) of the corresponding scheme across the entire blocking graph (i.e., including the links between matching and non-matching nodes/entities). Thus, the two leftmost bars correspond to the pruned edges and the remaining eight bars to the retained ones. We observe a clear polarization for all weighting schemes: the vast majority of the matching edges is concentrated on the two right-most intervals, with a negligible portion of them lying in the left half (the opposite applies to non-matching edges). In fact, the higher the PC of a weighting scheme over D_{movies} is, the lower is the corresponding number of matching edges in the first two intervals. On the other hand, the higher its RR is, the lower is the portion of non-matching edges placed in the intervals $[1.5\cdot\bar{w},5\cdot\bar{w}]$.

Table 4(b) illustrates the performance of WNP for all weighting schemes over all datasets. Similar to WEP, there is a clear trade-off between effectiveness and efficiency for D_{movies} and $D_{infoboxes}$. It is interesting to note that ranking the weighting schemes in descending order of RR (i.e., ascending order of PC) results in the same order as in Table 4(a). For D_{BTC09}, all weighting schemes achieve similar, high performances with respect to all metrics. Compared to WEP, though, the combination of every weighting scheme with WNP yields significantly higher PC as well as lower RR and PQ.

Table 4(c) presents the performance of CEP in combination with all weighting schemes across the three datasets. By definition, they all achieve the same RR, which amounts to 97.48%, 99.94% and 99.85% for D_{movies}, $D_{infoboxes}$ and D_{BTC09}, respectively. In absolute numbers, this corresponds to 11, 15 and 3 comparisons per entity, respectively, thus requiring 2 orders of magnitude fewer comparisons than the input block collection. Apparently, this is at the cost of lower effectiveness, since PC is reduced in all datasets by more than 14%, regardless of the weighting scheme (the only exception is $ARCS$ for D_{BTC09}). The worst performance usually corresponds to CBS and JS, because there are many pairs of entities that share exactly the same number or portion of blocks, respectively. Again, this behavior can be explained by the normalized histograms in Figures 7(a) and (b), since CEP generally retains the edges of the rightmost interval; the more matching edges and the less non-matching ones it contains, the higher is the PC of the corresponding weighting scheme.

Finally, Table 4(d) presents the performance of CNP for all weighting schemes across all datasets. Similar to its edge-centric counterpart, it exhibits excessively high efficiency for both datasets (i.e., RR>95%). In absolute numbers, this corresponds to 22, 28 and 7 comparisons per entity for D_{movies}, $D_{infoboxes}$ and D_{BTC09}, respectively. Its impact on effectiveness is rather limited, reducing PC at most by 5% for the Clean-Clean ER datasets and less than 14% for the Dirty ER one.

(ii) *Edge-centric vs. node-centric pruning schemes.* The relative performance of these two types of pruning schemes depends on the pruning criteria that lie at their core. Thus, an equal basis comparison requires exactly the same configuration. This is impossible, though, for the weight criteria: WEP can only be combined with a global one, while WNP makes sense only when coupled with a local one (its conjunction with a global threshold renders it identical to WEP).

The configuration of Section 3.3 approximates the ideally equal settings, assuming similar criteria for both algorithms (i.e., average edge weight). For this configuration, our experiments suggest that the edge-centric algorithms perform a deeper pruning that results in the lowest number of comparisons and detected matches (i.e., lowest ΔPC). Nevertheless, they are more accurate in discarding superfluous comparisons, achieving higher PQ across all datasets and weighting schemes. For example, consider the combination of $ARCS$ with WEP and WNP over D_{movies}: PQ suggests that for every 100 comparisons, the former identifies around 1.5 matches and the latter almost half of them.

On the other hand, the node-centric schemes are more conservative in pruning edges, retaining even double as much comparisons. Thus, they have a significantly smaller impact on PC, which is also ensured by the more even distribution of comparisons among entities; unlike the edge-centric algorithms, which completely disregard the entities/nodes that are associated with none of the top weighted edges, they ensure that *every* node remains connected with the most similar of its co-occurring entities.

In the case of cardinality pruning criteria, it is possible to apply the same global threshold to both CEP and CNP. However, these settings merely allow for comparing the relative effectiveness, since they involve the same number of executed comparisons for both algorithms. We put these settings into practice using as threshold for CEP the total number of comparisons required by CNP. The outcomes with respect to PC are presented in Table 2 and confirm that the node-centric algorithms achieve a significantly higher effectiveness than the edge-centric ones, across all datasets and weighting schemes.

In summary, the most appropriate meta-blocking settings for the application at hand depend on its performance requirements and the available resources (assuming the

configuration of Section 3.3). The node-centric pruning schemes are suitable for applications emphasizing on effectiveness, provided that they can afford the high space requirements (these pruning schemes store a threshold or a certain number of comparisons *per entity*). They are also particularly useful for tasks that are inherently expressed in terms of entities (e.g., applications like social networks that seek duplicates for a specific subset of the input entities) and for entity collections that are expected to contain a large portion of duplicate profiles (i.e., there is a matching entity for most of the nodes). In contrast, the edge-centric pruning schemes are suitable for applications like incremental ER that focus on efficiency, especially when the portion of matching entities is expected to be rather low; in these settings, the top weighted edges are more likely to correspond to the few duplicate profiles.

(iii) *Weight vs. cardinality pruning criteria.* There is a clear pattern in the relative performance of weight and cardinality pruning thresholds for the configuration of Section 3.3: the former put more emphasis on effectiveness and the latter on efficiency. In fact, the combination of any weighting scheme with a cardinality threshold requires at least half the comparisons than its combination with the corresponding weight one, regardless of the selected pruning algorithm. In most of the cases, this difference amounts to a whole order of magnitude in the actual number of comparisons. Note, though, that this radical increase in efficiency is accompanied by a moderate difference in effectiveness, due to the efficacy of cardinality thresholds in distinguishing the matching comparisons from the superfluous ones. Comparing the PQ of CEP (CNP) with that of WEP (WNP), we observe that the former is usually higher than the latter by a whole order of magnitude. Still, weight thresholds exhibit higher PC, reducing it — in the worst case — half as much as the corresponding meta-blocking settings with a cardinality criterion. Therefore, there is no dilemma when choosing the appropriate criterion with respect to the application requirements. Note, though, that this decision also depends on the available resources, since the cardinality criteria have higher memory requirements.

(iv) *Comparison between weighting schemes.* For D_{BTC09}, $ARCS$ consistently achieves the highest performance with respect to all block quality metrics, while the rest of the weighting schemes exhibit similar, but lower performance in most of the cases. For the Clean-Clean ER dataset, the choice depends on the functionality of the pruning criterion. In more detail, $ECBS$ offers a balanced choice for the weight pruning criteria, combining high efficiency enhancements with negligible reductions in PC. For the cardinality pruning criteria, where RR remains stable across all weighting schemes, EJS consistently achieves the (nearly) best efficiency-effectiveness balance, scoring the highest PC values in most of the cases.

Of particular interest, though, is the comparison between the plain weighting schemes and their enhanced versions; that is, between CBS and $ECBS$ as well as between JS and EJS. The actual question is whether the more information included in the enhanced schemes leads to a better balance between RR and PC than the plain ones. The weight pruning criteria does not offer a clear answer; we can merely observe that the enhanced schemes offer lower RR and lower PQ at the benefit of higher PC. In contrast, the cardinality pruning criteria allow for a direct comparison: RR is the same across all weighting schemes, but the enhanced ones achieve higher PC in practically all the cases. PQ also takes significantly higher values for $ECBS$ and EJS. We can conclude, therefore, that the enhanced schemes convey significant enhancements in the performance of CBS and JS.

(iv) *Comparison with Iterative Blocking.* Before examining the performance of Iterative Blocking, it is worth clarifying that its functionality in the context of Clean-Clean ER is reduced to discarding part of the superfluous comparisons. In fact, it propagates all detected duplicates to the subsequently processed blocks and merely saves those comparisons that involve at least one entity that has been matched to some other. This approach conveys significant efficiency enhancements when applied to redundancy-positive block collections: its RR exceeds 60% for D_{movies} and 35% for $D_{infoboxes}$. All meta-blocking methods, though, achieve higher efficiency gains, as they have a broader scope, targeting all superfluous comparisons. This is also verified by PQ, which indicates that Iterative Blocking executes the highest portion of superfluous comparisons across both datasets. Its only advantage is that it incurs no impact on effectiveness. In practice, though, this is of minor importance, given that most meta-blocking approaches have limited cost in effectiveness in the context of Clean-Clean ER.

The real strength of Iterative Blocking lies in Dirty ER, especially in applications that involve equivalence classes of high cardinality. In these settings, it puts more emphasis on identifying additional matches, thus yielding the highest PC among all methods. This is exactly the case with D_{BTC09}: although the original PC is already high, amounting to 97%, Iterative Blocking increases it by more than 1%. The re-examination of large blocks, though, increases the number of executed comparisons and prevents significant enhancements in efficiency. Indeed, it merely saves around 1% of all comparisons in the case of D_{BTC09}. Thus, its efficiency is significantly lower than meta-blocking, which again discards more superfluous comparisons.

In summary, Iterative Blocking is only appropriate for applications that place effectiveness in priority and are satisfied with rather conservative savings in efficiency. For the rest of them, meta-blocking offers a better balance between effectiveness and efficiency.

Discussion. In summary, we can conclude that among the weighting schemes, the Enhanced Common Blocks Scheme consistently offers a good balance between effectiveness and efficiency over Clean-Clean ER. For Dirty ER, though, the Aggregate Reciprocal Comparisons Scheme offers the best approach. We also observe that the node-centric approaches perform a shallow pruning that yields lower PQ and RR values than edge-centric ones. This allows them to retain almost intact the original effectiveness, especially

when combined with weight thresholds. Therefore, applications that place more emphasis on effectiveness should opt for node-centric pruning schemes, while those focusing on efficiency should consider the edge-centric ones. Among the two types of pruning criteria, the weight thresholds are more robust with respect to effectiveness, while the cardinality thresholds are appropriate for applications emphasizing on efficiency, such as incremental ER.

4.3 Sensitivity Analysis

As mentioned above, the performance of pruning algorithms depends largely on the underlying pruning criterion — regardless of its scope or functionality. To examine how our pruning schemes behave as a function of their thresholds, we performed sensitivity analyses of *RR* and *PC* for all schemes over the three datasets of our study. In Figures 8(a) to (d), we present the behavior of each pruning algorithm in combination with a specific weighting scheme over D_{movies} (for each algorithm, the rest of the weighting schemes demonstrated similar patterns and, thus, are omitted for brevity. Nevertheless, we tried to cover all of them, considering in each diagram a different one.). Every diagram was derived by incrementing the pruning threshold from $0.1{\cdot}t$ to $1.9{\cdot}t$ with a step of $0.1{\cdot}t$, where t denotes the threshold derived from the configuration of Section 3.3 (e.g., the average edge weight in the case of *WEP*).

In every figure, we observe that there is a clear trade-off between *RR* and *PC*. Higher thresholds increase *RR* and reduce *PC* for the weight pruning criteria, and vice versa for the cardinality ones. In fact, the evolution of *PC* is practically linear for all pruning schemes. The same applies to *RR* for the cardinality criteria, whereas for the weight ones, the linear evolution is preceded by a steep rise for the interval $[0.1{\cdot}t, 0.5{\cdot}t]$. The thresholds of Section 3.3 correspond to the vertical dotted line intersecting the middle of the *x*-axes. We observe that in every case, small variations in the size of t lead to small variations in the resulting performance. This suggests that the threshold we selected for each pruning scheme achieves a good balance between effectiveness and efficiency. Thus, it provides a good basis for adjusting a meta-blocking method to the requirements of the application at hand. For example, an application employing *CEP* could double the threshold specified by our approach in order to rise *PC* by 10% for double as many comparisons.

In summary, the sensitivity analysis of Figures 8(a) to (d) demonstrate that our meta-blocking methods are robust with respect to the threshold configurations of Section 3.3.

4.4 Time Requirements of Meta-blocking

The real usefulness of meta-blocking depends on the relation between the time required for building and pruning the blocking graph and the time consumed while performing the (spared) pairwise comparisons. The goal of this section is to examine whether the former is significantly lower than the latter, thus justifying the use of our approaches. To this end, we evaluate the time requirements of meta-blocking using three measures:

- *Materialization Time* (*MT*) refers to the time required by the first two steps of meta-blocking, i.e., graph building and edge weighting.
- *Restructure Time* (*RT*) corresponds to the last two steps of meta-blocking, i.e., graph pruning and block collecting.
- *Comparison Time* (*CT*) indicates the time required for performing the (retained) pairwise comparisons.

As the baseline method, we consider the one that iterates over the input blocks, executing all the comparisons they entail, without any further processing (i.e., its processing time exclusively corresponds to *CT*, while *MT*=*RT*=0). For all methods, the similarity of entity profiles is defined as the Jaccard coefficient of their tokenized attribute values; any other entity comparison technique is also applicable, but this choice is orthogonal to the proposed method, thus not altering our experimental results.

The outcomes of our experiments are presented in Table 3. We notice the following patterns for the vast majority of meta-blocking approaches across all datasets: first, the overall processing time of the weighting pruning criteria is dominated by *CT*, with *MT* and *RT* merely accounting for a fraction of it. Exception to this rule is *ARCS* in conjunction with *WEP* and *WNP*, as the low discernibility of its weights ($\ll$0.1 in most of the cases) results in a time-consuming meta-blocking process. Second, there is a balance between *CT* and *MT* + *RT* for the cardinality pruning criteria, since they entail a very low number of comparisons with respect to the size of the graph. Again, *ARCS* corresponds to the least efficient meta-blocking process.

We also notice that for every dataset, *MT* and *RT* take almost identical values for all weighting schemes, with the small variations corresponding to the different functionality of each weighting scheme. Regarding *CT*, we observe that it takes significantly lower values for the cardinality pruning criteria than for the weight ones. This overhead is caused not only by the lower number of comparisons retained by the former, but also by the fact that the latter iterate over all edges of the blocking graph during the comparisons phase.

In summary, we observe that all combinations of pruning schemes with a weighting one require significantly less time than the baseline method. For example, the most efficient meta-blocking techniques for D_{movies} (i.e., *CEP* in conjunction with *CBS* or *JS*) are 35 times faster than the baseline. Even the most time-consuming meta-blocking settings for each dataset run at least 2 times faster than the baseline. As explained in Section 3.1, this should be attributed to the efficient materialization of the blocking graph, which involves lower complexity than the string-based techniques for comparing entity profiles.

Note that optimization techniques can be integrated into the implementation of the meta-blocking and the entity comparison methods. For instance, during the pruning of the blocking graph, edges with weights lower than the specified threshold can be identified more efficiently with the help of prefix filtering. No such technique was considered,

though, in our experimental study, since it is orthogonal to our evaluation.

5 Conclusions

In this paper, we introduced meta-blocking as a generic task that can be applied on top of any blocking method to increase its efficiency at a minor cost in effectiveness. We described a family of techniques, at the core of which lies the blocking graph; they prune its edges with the lowest weight in order to derive a new set of blocks that sacrifices a negligible amount of matches to save a large number of comparisons. We thoroughly evaluated all combinations of the proposed techniques over two large, real-world datasets. The results demonstrate the high efficiency enhancements conveyed by our meta-blocking techniques, with the Weight Node Pruning involving two orders of magnitude less comparisons at a minor cost in *PC* (less than 3% reduction). In absolute values, meta-blocking helps process the original set of blocks 10 to 50 times faster, reducing the required comparisons by a whole order of magnitude.

In the future, we plan to enhance the efficiency of meta-blocking through the incorporation of schema information that depends on the underlying application. We also acknowledge that meta-blocking depends on the level of redundancy entailed by the underlying block collection, which — for some block building methods — can be configured by tuning the corresponding parameter(s). Thus, we intend to investigate the effect of these parameters on the performance of meta-blocking. Last but not least, we will study the interplay of meta-blocking with blocking methods that consider profile merges in the context of Dirty ER, such as HARRA [18] and Iterative Blocking [32].

Acknowledgements. This research has been co-financed by the European Union (European Social Fund - ESF) and Greek national funds through the Operational Program "Education and Lifelong Learning" of the National Strategic Reference Framework (NSRF) - Research Funding Program: Thales. Investing in knowledge society through the European Social Fund.

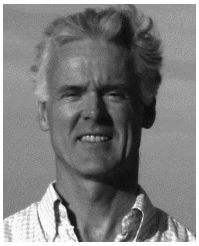
References

[1] A. N. Aizawa and K. Oyama. A fast linkage detection scheme for multi-source information integration. In *WIRI*, pages 30–39, 2005.
[2] R. Baxter, P. Christen, and T. Churches. A comparison of fast blocking methods for record linkage. In *SIGKDD*, volume 3, pages 25–27, 2003.
[3] M. Bilenko, B. Kamath, and R. J. Mooney. Adaptive blocking: Learning to scale up record linkage. In *ICDM*, pages 87–96, 2006.
[4] C. Bizer, T. Heath, T. Berners-Lee, and T. Berners-Lee. Linked data - the story so far. *Int. J. Semantic Web Inf. Syst.*, 5(3):1–22, 2009.
[5] P. Christen. *Data Matching - Concepts and Techniques for Record Linkage, Entity Resolution, and Duplicate Detection*. Data-centric systems and applications. Springer, 2012.
[6] P. Christen. A survey of indexing techniques for scalable record linkage and deduplication. *IEEE Trans. Knowl. Data Eng.*, 24(9):1537–1555, 2012.
[7] W. W. Cohen, P. D. Ravikumar, and S. E. Fienberg. A comparison of string distance metrics for name-matching tasks. In *IIWeb*, pages 73–78, 2003.
[8] T. de Vries, H. Ke, S. Chawla, and P. Christen. Robust record linkage blocking using suffix arrays. In *CIKM*, pages 1565–1568, 2009.
[9] A. Doan and A. Halevy. Semantic integration research in the database community: A brief survey. *AI Magazine*, 26(1):83–94, 2005.
[10] X. Dong, A. Halevy, and J. Madhavan. Reference reconciliation in complex information spaces. In *SIGMOD*, pages 85–96, 2005.
[11] U. Draisbach and F. Naumann. A comparison and generalization of blocking and windowing algorithms for duplicate detection. In *Proceedings of the International Workshop on Quality in Databases (QDB)*, pages 51–56, 2009.
[12] A. Elmagarmid, P. Ipeirotis, and V. Verykios. Duplicate record detection: A survey. *IEEE Trans. Knowl. Data Eng.*, 19(1):1–16, 2007.
[13] I. Fellegi and A. Sunter. A theory for record linkage. *Journal of the American Statistical Association*, pages 1183–1210, 1969.
[14] L. Getoor and C. Diehl. Link mining: a survey. *SIGKDD Expl.*, 7(2):3–12, 2005.
[15] L. Gravano, P. Ipeirotis, H. Jagadish, N. Koudas, S. Muthukrishnan, and D. Srivastava. Approximate string joins in a database (almost) for free. In *VLDB*, pages 491–500, 2001.
[16] A. Y. Halevy, M. J. Franklin, and D. Maier. Principles of dataspace systems. In *PODS*, pages 1–9, 2006.
[17] M. Hernández and S. Stolfo. The merge/purge problem for large databases. In *SIGMOD*, pages 127–138, 1995.
[18] H. Kim and D. Lee. HARRA: fast iterative hashed record linkage for large-scale data collections. In *EDBT*, pages 525–536, 2010.
[19] N. Koudas, S. Sarawagi, and D. Srivastava. Record linkage: similarity measures and algorithms. In *SIGMOD*, pages 802–803, 2006.
[20] J. Madhavan, S. Cohen, X. L. Dong, A. Y. Halevy, S. R. Jeffery, D. Ko, and C. Yu. Web-scale data integration: You can afford to pay as you go. In *CIDR*, pages 342–350, 2007.
[21] W. Masek and M. Paterson. A faster algorithm computing string edit distances. *Journal of Computer and System sciences*, 20(1):18–31, 1980.
[22] A. McCallum, K. Nigam, and L. Ungar. Efficient clustering of high-dimensional data sets with application to reference matching. In *KDD*, pages 169–178, 2000.
[23] M. Michelson and C. A. Knoblock. Learning blocking schemes for record linkage. In *AAAI*, pages 440–445, 2006.
[24] F. Naumann and M. Herschel. *An Introduction to Duplicate Detection*. Synthesis Lectures on Data Management. Morgan & Claypool Publishers, 2010.
[25] J. Nin, V. Muntés-Mulero, N. Martínez-Bazan, and J.-L. Larriba-Pey. On the use of semantic blocking techniques for data cleansing and integration. In *IDEAS*, pages 190–198, 2007.
[26] A. Ouksel and A. Sheth. Semantic interoperability in global information systems: A brief introduction to the research area and the special section. *SIGMOD Record*, pages 5–12, 1999.
[27] G. Papadakis, E. Ioannou, C. Niederée, and P. Fankhauser. Efficient entity resolution for large heterogeneous information spaces. In *WSDM*, pages 535–544, 2011.
[28] G. Papadakis, E. Ioannou, C. Niederée, T. Palpanas, and W. Nejdl. To compare or not to compare: making entity resolution more efficient. In *SWIM Workshop*, 2011.
[29] G. Papadakis, E. Ioannou, C. Niederée, T. Palpanas, and W. Nejdl. Beyond 100 million entities: Large-scale blocking-based resolution for heterogeneous data. In *WSDM*, pages 53–62, 2012.
[30] S. Tejada, C. A. Knoblock, and S. Minton. Learning domain-independent string transformation weights for high accuracy object identification. In *KDD*, pages 350–359, 2002.
[31] S. Whang, D. Marmaros, and H. Garcia-Molina. Pay-as-you-go entity resolution. *IEEE Trans. Knowl. Data Eng. (to appear)*, 2012.
[32] S. E. Whang, D. Menestrina, G. Koutrika, M. Theobald, and H. Garcia-Molina. Entity resolution with iterative blocking. In *SIGMOD*, pages 219–232, 2009.
[33] S. Yan, D. Lee, M.-Y. Kan, and C. L. Giles. Adaptive sorted neighborhood methods for efficient record linkage. In *JCDL*, pages 185–194, 2007.

George Papadakis is a PhD student at the Leibniz University of Hanover. He holds a Diploma in Computer Engineering from the National Technical University of Athens (NTUA) and has worked at the NCSR "Demokritos", NTUA and the L3S Research Center. His research interests include entity resolution and web data mining. He has received the best paper award from ACM Hypertext 2011.

Georgia Koutrika is a senior researcher at HP Labs, Palo Alto. Prior to that, she was a post-doctoral researcher at IBM Almaden Research Center and Stanford University. She holds a PhD in Computer Science from the University of Athens in Greece. Her research interests include personalized search, recommendations, user modeling, social media, information extraction, resolution and integration, and search interfaces.

Themis Palpanas is a professor of computer science at the University of Trento, Italy. Before that he worked at the IBM T.J. Watson Research Center, and has also worked for the University of California at Riverside, Microsoft Research and IBM Almaden Research Center. He is the author of five US patents, three of which are part of commercial products. He has received three best paper awards and is General Chair for VLDB 2013.



Wolfgang Nejdl received M.Sc. and Ph.D. degrees from the Technical University of Vienna. Currently, he is a professor of computer science at the University of Hanover, where he leads the L3S Research Center and the Distributed Systems Institute/Knowledge-Based Systems. His research focuses on information retrieval, peer-to-peer infrastructures, databases, technology-enhanced learning, and artificial intelligence.

APPENDIX
RELATED WORK

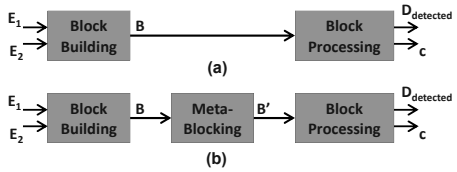


Fig. 5. (a) The process of traditional blocking-based ER, and (b) the blocking-based ER with meta-blocking. In both cases, the input comprises the entity collections to be resolved ($\mathcal{E}_1$ and $\mathcal{E}_2$), while the output consists of the detected duplicates $D_{detected}$ and the computational cost c (i.e., number of executed comparisons).

There is a large amount of work on entity resolution ranging from string similarity metrics [7] to methods relying on transformations [30] and entity relationships [10]. Analytical overviews can be found in these surveys [9], [12], [14], tutorials [19], [26] and books [5], [24]. Due to their quadratic complexity, ER methods typically scale to large data collections through blocking. The blocking-based ER process conceptually consists of two main steps: block building and block processing (see Figure 5(a)).

Block building receives as input two entity collections ($\mathcal{E}_1$ and $\mathcal{E}_2$ in Figure 5(a)) and creates a set of blocks $\mathcal{B}$. Methods of this type are categorized according to two orthogonal criteria: their relation to redundancy and to schema information. The former criterion was analyzed in Section 1, while the latter distinguishes them into *schema-based* and *schema-agnostic* blocking methods; that is, into those techniques that integrate schema information in their functionality and those that completely disregard such evidence. The resulting two-dimensional taxonomy of block building methods is illustrated in Figure 6.

On the one hand, schema-based blocking methods extract from each entity a blocking key that summarizes the values of selected attributes. Entity profiles are then placed in blocks on the basis of equal or similar blocking keys. Schema-based blocking methods include Sorted Neighborhood [17], bi-grams [2] and q-grams [15] blocking, Suffix Array [1], [8], HARRA [18], and Canopy Clustering [22]. A comparative analysis can be found in [6]. As this study points out, one of their major drawbacks is the fine-tuning of multiple parameters [8]. To ameliorate this issue, automatic methods can be trained to select the optimal parameter values [3], [23].

On the other hand, schema-agnostic blocking creates blocks solely on the basis of attribute values, i.e., without knowledge of the input schema(ta). Semantic Indexing [25] creates blocks based exclusively on the relationships between entity profiles. Attribute-agnostic Blocking creates a distinct block for each token shared by at least two input entity profiles [27]. For RDF data, Total Description exploits semantics in the entity URIs, links between entities and tokens in the literal values of every profile [29]. Both techniques do not require tuning (i.e., their functionality is parameter-free) and exhibit high robustness and effectiveness, due to the high levels of redundancy they involve.

Block processing receives as input a set of blocks $\mathcal{B}$ and produces as output the set of detected duplicates $D_{detected}$ along with their computational cost c, in terms of the number of executed comparisons (see Figure 5(a)). Its goal is to process the input set of blocks in such a way that minimizes c without any significant impact on the cardinality of $D_{detected}$. This can be achieved by eliminating the redundant and the superfluous comparisons contained in $\mathcal{B}$. To this end, Block Purging [27] discards the largest blocks, while Block Scheduling [27] sorts blocks according to a probabilistic measure that estimates their likelihood to contain duplicates. Thus, it forms the basis for applying Block Pruning [27] and Duplicate Propagation [32]; the former terminates the entire processing as early as possible, while the latter maximizes the number of superfluous comparisons that can be spared by the early detection of duplicate profiles. On another line of research, *Iterative Blocking* [32] propagates the latest match decisions to all associated blocks: every time two entity profiles are found duplicates, they are replaced by the merged profile in all blocks containing either of them. These blocks are then scheduled for processing, even if they have already been examined. In this way, a block collection is processed iteratively in order to increase the matching accuracy (and, thus, the blocking effectiveness) and to spare repeated comparisons.

The proposed meta-blocking procedure is fundamentally different from both block building and block processing. It is a specialized procedure applicable to redundancy-positive block building methods. Its input comprises the set of blocks $\mathcal{B}$ created by such a method and its output is a new set of blocks $\mathcal{B}'$ that involves fewer comparisons than $\mathcal{B}$, while placing (almost) the same number of matching entity profiles in at least one block. Block Purging and Block Pruning have a similar interface, but their functionality is restricted in discarding some of the input blocks. In contrast, meta-blocking techniques aim at *restructuring* the given block collection $\mathcal{B}$ based on the block-to-entity associations it entails. For this reason, it is performed between block building and block processing, improving the output of the former in order to facilitate the performance of the latter, as shown in Figure 5(b). A similar idea was explored in Comparison Pruning [28], which discards comparisons between entity profiles that share a rather small portion of blocks in the context of redundancy-positive methods. Thus, it can be viewed as a specific instantiation of our meta-blocking framework; in fact, it is equivalent to applying WEP (see Section 3.3.1) on a blocking graph with Jaccard similarities as weights (see Section 3.2).

	Redundancy-free	Redundancy-bearing		
		Redundancy-negative	Redundancy-neutral	Redundancy-positive
Schema-based	Standard Blocking [13]	Canopy Clustering [22]	(Adaptive) Sorted Neighborhood [17,33]	bi-/q-grams blocking [2,15] Suffix Array [1,8] HARRA [18]
Schema-agnostic	-	-	Semantic Indexing [25]	Attribute-agnostic [27] Total Description [29]

Fig. 6. Two-dimensional taxonomy of block building methods.

Experimental Outcomes

	D_{movies}		$D_{infoboxes}$		D_{BTC09}
	DBPedia	**IMDB**	**DBP_1**	**DBP_2**	
Entities	27,615	23,182	$1{,}19{\cdot}10^6$	$2{,}16{\cdot}10^6$	253,353
Name-Value Pairs	186,013	816,012	$1.75{\cdot}10^7$	$3.67{\cdot}10^7$	$1{,}60{\cdot}10^6$
Blocks	40,430		$1.21{\cdot}10^6$		106,462
BC	22.52		15.38		7.45
CC	$4.27{\cdot}10^{-2}$		$1.29{\cdot}10^{-3}$		$1.44{\cdot}10^{-2}$
Brute Force Comp.	$6.40{\cdot}10^8$		$2.58{\cdot}10^{12}$		$3.21{\cdot}10^{10}$
Block Comp.	$2.67{\cdot}10^7$		$3.98{\cdot}10^{10}$		$1.31{\cdot}10^8$
Original *RR*	95.83%		98.46%		99.59%
Existing Matches	22,405		892,586		10,653
Original *PC*	99.39%		99.89%		96.94%
Original *PQ*	$9.83{\cdot}10^{-4}$		$2.24{\cdot}10^{-5}$		$7.89{\cdot}10^{-5}$
Edges	$2.26{\cdot}10^7$		$3.41{\cdot}10^{10}$		$7.77{\cdot}10^7$
Nodes	$5.06{\cdot}10^4$		$3.33{\cdot}10^6$		$2.53{\cdot}10^5$

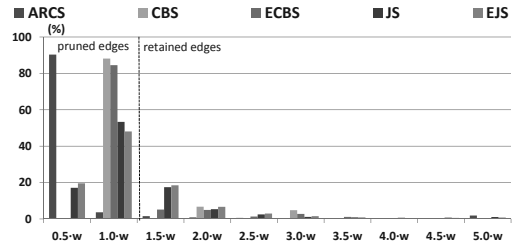
TABLE 1
Overview of the evaluation datasets.

	D_{movies}		$D_{infoboxes}$		D_{BTC09}	
	PC_{CEP}	PC_{CNP}	PC_{CEP}	PC_{CNP}	PC_{CEP}	PC_{CNP}
ARCS	89.16%	**94.13%**	83.82%	**96.87%**	93.22%	**95.60%**
CBS	80.42%	**95.20%**	60.46%	**96.34%**	31.97%	**88.70%**
ECBS	87.17%	**96.69%**	67.85%	**97.72%**	65.78%	**86.25%**
JS	89.22%	**94.93%**	86.02%	**96.86%**	35.97%	**83.79%**
EJS	91.03%	**95.98%**	85.26%	**97.18%**	51.85%	**84.50%**

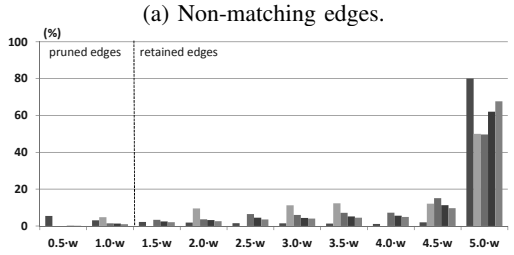
TABLE 2
Comparing effectiveness between CEP and CNP for the same number of comparisons across all datasets.

		D_{movies} (minutes)				$D_{infoboxes}$ (hours)				D_{BTC09} (minutes)			
		MT	*RT*	*CT*	$\sum$	*MT*	*RT*	*CT*	$\sum$	*MT*	*RT*	*CT*	$\sum$
Baseline		.0	.0	14	14	.0	.0	128	128	0	0	111	111
W	*ARCS*	.1	.6	1.0	1.6	3.2	24.4	25.7	53.3	**.2**	**2.5**	**5.9**	**8.7**
	CBS	**.1**	**.1**	**.9**	**1.1**	**3.3**	**7.0**	**21.2**	**31.6**	.2	1.5	19.8	21.5
E	*ECBS*	.1	.2	1.2	1.4	3.1	6.7	30.8	40.6	.2	1.8	17.2	19.2
P	*JS*	.1	.1	2.1	2.3	3.2	6.0	51.2	60.4	.2	1.9	20.2	22.3
	EJS	.1	.2	2.3	2.5	3.2	6.7	52.0	62.0	.2	2.0	20.2	22.4
W	*ARCS*	.1	.6	1.3	1.9	3.5	25.9	28.7	58.1	**.2**	**2.7**	**21.5**	**24.5**
	CBS	**.1**	**.1**	**1.0**	**1.2**	**3.2**	**6.2**	**24.4**	**33.9**	.2	1.7	24.3	26.3
N	*ECBS*	.1	.2	2.1	2.4	3.6	7.5	33.4	44.6	.2	2.1	30.9	33.2
P	*JS*	.1	.1	3.0	3.2	3.5	7.0	55.4	65.9	.2	2.1	37.7	40.1
	EJS	.1	.2	3.6	3.8	3.6	8.0	58.5	70.1	.2	2.4	39.6	42.1
C	*ARCS*	.1	.6	.2	.9	3.2	24.5	.1	27.9	.2	2.6	.8	3.6
	CBS	.1	.1	.2	.4	4.2	7.4	.1	11.7	**.2**	**1.5**	**.8**	**2.5**
E	*ECBS*	.1	.2	.2	.4	4.4	8.0	.1	12.6	.2	1.9	.8	2.9
P	*JS*	.1	.2	.2	.4	4.2	7.5	.1	11.8	.2	1.9	.8	2.9
	EJS	**.1**	**.2**	**.2**	**.4**	**3.2**	**7.1**	**.1**	**10.4**	.2	2.2	.8	3.2
C	*ARCS*	.1	.6	.3	1.0	3.2	24.7	.2	28.1	.2	2.7	1.5	4.4
	CBS	**.1**	**.1**	**.3**	**.5**	3.8	6.7	.2	10.8	**.2**	**1.6**	**1.5**	**3.3**
N	*ECBS*	.1	.2	.3	.6	3.7	6.9	.2	10.9	.2	2.0	1.5	3.6
P	*JS*	.1	.2	.3	.6	**3.2**	**6.3**	**.2**	**9.8**	.2	1.9	1.5	3.6
	EJS	.1	.2	.3	.6	3.2	7.1	.2	10.6	.2	2.3	1.5	4.0

TABLE 3
Processing time for all meta-blocking methods over the three datasets of our experimental study.



(a) Non-matching edges.



(b) Matching edges.

Fig. 7. Normalized histograms of the weight distributions in all blocking graphs of D_{movies}, where w denotes the average edge weight of the blocking graph for each weighting scheme.

	$\mathbf{D_{movies}}$					$\mathbf{D_{infoboxes}}$					$\mathbf{D_{BTC09}}$				
	Comp. ($\times 10^6$)	*RR* (%)	*PC* (%)	ΔPC (%)	*PQ* ($\times 10^{-2}$)	Comp. ($\times 10^8$)	*RR* (%)	*PC* (%)	ΔPC (%)	*PQ* ($\times 10^{-4}$)	Comp. ($\times 10^7$)	*RR* (%)	*PC* (%)	ΔPC (%)	*PQ* ($\times 10^{-4}$)
Iterative Bl.	10.41	61.06	99.39	0	0.21	255.94	35.67	99.89	0	0.35	12.98	0.84	98.22	1.32	0.81
ARCS	1.38	94.82	90.89	-8.55	1.47	2.85	99.28	92.45	-7.45	29.00	**0.41**	**99.35**	**94.77**	**-2.24**	**24.85**
CBS	2.71	89.88	94.68	-4.74	0.78	33.97	91.46	95.47	-4.42	2.51	2.16	96.57	86.84	-10.42	4.29
ECBS	**3.52**	**86.82**	**97.95**	**-1.45**	**0.62**	**57.71**	**85.50**	**99.66**	**-0.23**	**1.54**	1.81	97.12	86.60	-10.67	5.08
JS	6.71	74.90	97.93	-1.46	0.33	112.21	71.80	99.73	-0.16	0.79	2.15	96.58	87.13	-10.12	4.31
EJS	7.34	72.54	98.32	-1.07	0.30	110.14	72.32	99.77	-0.11	0.81	2.13	96.61	89.01	-8.18	4.45
(a) WEP															
ARCS	2.55	90.44	96.55	-2.86	0.85	14.84	96.27	99.41	-0.48	5.98	**2.25**	**96.43**	**95.72**	**-1.26**	**4.54**
CBS	2.86	89.31	97.19	-2.21	0.76	35.65	91.04	99.35	-0.54	2.49	2.69	95.72	91.46	-5.66	3.62
ECBS	**6.92**	**74.10**	**98.64**	**-0.75**	**0.32**	**99.37**	**75.02**	**99.75**	**-0.14**	**0.90**	3.42	94.56	91.13	-5.99	2.84
JS	10.00	62.59	98.68	-0.71	0.22	195.93	50.76	99.87	-0.02	0.46	4.22	93.29	91.43	-5.68	2.31
EJS	11.81	55.77	99.16	-0.23	0.19	199.96	49.74	99.88	-0.01	0.45	4.41	93.00	92.52	-4.56	2.24
(b) WNP															
ARCS	0.57	97.87	82.75	-16.74	3.25	0.26	99.94	79.46	-20.46	276.83	**0.09**	**99.85**	**92.17**	**-4.92**	**103.99**
CBS	0.57	97.87	75.78	-23.75	2.98	0.26	99.94	51.71	-48.37	179.68	0.09	99.85	24.07	-75.17	27.16
ECBS	0.57	97.87	81.58	-17.92	3.20	0.26	99.94	62.14	-37.79	216.49	0.09	99.85	42.81	-56.05	48.07
JS	0.57	97.87	79.12	-20.40	3.11	0.26	99.94	82.09	-17.83	285.98	0.09	99.85	25.77	-99.55	29.07
EJS	**0.57**	**97.87**	**84.87**	**-14.61**	**3.33**	**0.26**	**99.94**	**79.61**	**-20.30**	**277.37**	0.09	99.85	45.85	-52.71	51.73
(c) CEP															
ARCS	1.10	95.88	94.13	-5.39	1.91	0.50	99.88	96.87	-3.02	174.63	**0.18**	**99.72**	**95.60**	**-1.38**	**58.22**
CBS	1.10	95.88	95.20	-3.48	1.95	0.50	99.88	96.34	-3.56	173.68	0.18	99.72	88.70	-8.50	54.02
ECBS	1.10	95.88	96.69	-2.71	1.97	0.50	99.88	97.72	-2.17	176.17	0.18	99.72	84.34	-11.03	52.53
JS	1.10	95.88	94.93	-4.45	1.93	0.50	99.88	96.86	-3.03	174.62	0.18	99.72	83.79	-13.57	51.03
EJS	**1.10**	**95.88**	**95.98**	**-3.43**	**1.95**	**0.50**	**99.88**	**97.18**	**-2.71**	**175.19**	0.18	99.72	84.50	-12.83	51.46
(d) CNP															

TABLE 4
Performance of all pruning schemes in combination with all weighting schemes over the three datasets of our study.

Sentiment Extraction from Tweets: Multilingual Challenges

Nantia Makrynioti(✉) and Vasilis Vassalos

Athens University of Economics and Business, 76 Patission Street, GR10434 Athens, Greece
{makriniotik,vassalos}@aueb.gr

Abstract. Every day users of social networks and microblogging services share their point of view about products, companies, movies and their emotions on a variety of topics. As social networks and microblogging services become more popular, the need to mine and analyze their content grows. We study the task of sentiment analysis in the well-known social network Twitter (https://twitter.com/). We present a case study on tweets written in Greek and propose an effective method that categorizes Greek tweets as positive, negative and neutral according to their sentiment. We validate our method's effectiveness on both Greek and English to check its robustness on multilingual challenges, and present the first multilingual comparative study with three pre-existing state of the art techniques for Twitter sentiment extraction on English tweets. Last but not least, we examine the importance of different preprocessing techniques in different languages. Our technique outperforms two out of the three methods we compared against and is on a par to the best of those methods, but it needs significantly less time for prediction and training.

1 Introduction

Users have integrated microblogging services and social networks in their daily routine, and tend to share through them increasingly more thoughts and experiences of their lives. As a result, platforms, such as Twitter, are a goldmine for the tasks of opinion mining and sentiment analysis, providing valuable information on topics of timeliness or not, by users of varying social, educational and demographic background.

In this paper, we examine sentiment analysis in Twitter with emphasis on tweets written in Greek and we suggest a method based on supervised learning. Sentiment analysis is defined as the task of classifying texts, in case of Twitter these correspond to tweets, into categories depending on whether they express

This research has been co-financed by the European Union (European Social Fund – ESF) and Greek national funds through the Operational Program "Education and Lifelong Learning" of the National Strategic Reference Framework (NSRF) – Research Funding Program: Thales. Investing in knowledge society through the European Social Fund.

S. Madria and T. Hara (Eds.): DaWaK 2015, LNCS 9263, pp. 136–148, 2015.
DOI: 10.1007/978-3-319-22729-0_11

positive or negative emotion or whether they enclose no emotion at all. As a consequence, sentiment analysis solves two classification tasks, the identification of objective and subjective tweets and the categorization of the latter according to their polarity. Given a number of tweets, our task is to categorize them in three classes, positive, negative and neutral depending on the presence of features that indicate emotion or not, as most of the times this is consistent with the sentiment of the message [12].

Although recently many papers study the task of sentiment analysis and many approaches have been proposed, almost all of them regard English text and work for other languages is limited. Moreover, many studies do not report results from comparisons with other pre-existent methods and each technique is usually evaluated on a single dataset. Evaluation on different datasets, including data of more than one languages, is an interesting process, which cross-checks the performance of the methods among languages.

The contributions of our paper are summarized below:

1. We propose a novel method for classification of tweets into three categories, positive, negative and neutral, and we evaluate our classifier on real Greek and English tweets. Our method outperforms two of the three compared approaches while giving statistically indistinguishable results to the third but with significant less time.
2. We present a case study of sentiment analysis in the context of the Greek language, unlike English that are much more studied and understood. For this purpose we collected and manually annotated a corpus of posts in Greek from Twitter, in order to be used as training and test data.[1]
3. We present extensive evaluation results and comparisons to three existing methods developed for English on a Greek as well as an English dataset. The purpose of these experiments is to provide the first comparative study of different state of the art techniques over Greek data, and examine their generalizability to address multilingual challenges. We also examine the contribution of specific preprocessing and postprocessing steps through ablation tests that demonstrate the degree to which certain steps of the proposed method improve the accuracy of the system with regard to Greek or English.

The rest of the paper is organized as follows. Section 2 presents some representative approaches on the problem of sentiment analysis and sect. 3 analyzes the data used for training and testing. In Sect. 4 at first we give an overview of our method and then we describe in detail every step of it. Results from the evaluation of the classifier and the comparative analysis are reported in Sect. 5. Finally, Sect. 6 concludes and presents ideas for future work.

2 Related Work

The mining and analysis of unstructured data from social networks has attracted considerable attention in recent years. Go et al. [9] dealt with sentiment analysis

[1] Data are available by emailing the authors.

in Twitter, but their work was limited to positive and negative sentiments, and does not involve the recognition of objective (neutral) tweets. The machine learning algorithms that were applied are Multinomial Naive Bayes, Support Vector Machines (SVM) [24] and Maximum Entropy, whereas unigrams, bigrams as well as the combination of these two were used as features. Maximum accuracy reached 83 % and was achieved with Maximum Entropy and both unigrams and bigrams. Pak and Paroubek [20] emphasized the preprocessing of tweets before classification and adopted bigrams, trigrams, negation and part-of-speech tags as features. They used entropy and introduced a variant of it called "salience" to select the most representative features. Their results show that bigrams outperform trigrams and salience discriminated n-grams better than entropy. The method described in [5] divides the classification of tweets into two stages. The first stage classifies subjective and objective tweets, while the second categorizes subjective tweets into positive and negative. Part-of-speech tags are used as features in this paper too. Dictionaries of subjective terms and syntax features of Twitter, such as hashtags, links, punctuation and words in capital letters, were also employed. The classifier used SVM and maximum error rate for the first stage reached 18.1 %, whereas for the second stage it reached 18.7 %.

Even though the paper by Pang et al. [21] is not about Twitter, it is a benchmark and a comparison point with all the studies mentioned above. The paper addresses the task of sentiment analysis in movie reviews. Features include unigrams, bigrams and negation. Multinomial Naïve Bayes and Maximum Entropy were tested, but SVM achieved 82.9 %, which was the maximum accuracy. Finally, a very recent approach by Mohammad et al. [17], which used a variety of features, including ngrams, syntax, lexicon and negation features, achieved the highest average F-score (69.02 %) with a SVM classifier in SemEval 2013 (International Workshop on Semantic Evaluation) and the task of sentiment analysis in Twitter [18]. Our work falls into the same category with the aforementioned studies, but apart from the certain difference of experimenting on Greek data, we apply a different combination of features and preprocessing steps, followed by a novel postprocessing negation identification step, which attempts to recognize the structure of negation in text and reverse the given prediction, rather than affect the features used for classification. Moreover, we reproduce published methods and present comparisons of them on a multilingual fashion, experimenting on datasets from two languages, Greek and English. All the above approaches belong to the category of supervised learning, but many studies have also performed unsupervised sentiment analysis. Due to limited space, we do not mention them here.

As stated earlier, there is lack of studies concerning other languages than English and the task is not sufficiently examined from this perspective. The paper by Atteveldt et al. [4] presents a system for automatically determining the polarity of relations between actors, e.g. politicians and parties, and issues, such as unemployment and healthcare, in Dutch text. To determine the polarity of relations, the authors use existing techniques for sentiment analysis in English and show that these methods can be translated to Dutch. Another study

that addresses the multilingual perspective of the task is presented by Boiy and Moens [6]. The authors propose a supervised method for sentiment analysis and perform experiments on English, Dutch and French blog reviews and forum texts. There is also work about sentiment analysis on Modern Standard Arabic at the sentence level [2]. Arabic is a morphologically-rich language in contrast to English and the authors propose some Arabic-specific features along with the more commonly used and language-independent ones. Another work by Abbasi et al. [1] performs sentiment analysis on hate/extremist group forum postings in English and Arabic, and evaluates a variety of syntactic and stylistic features for this purpose. A method on Chinese data is also proposed by Zhao et al. in [26]. We are aware of a paper regarding reputation management on Greek data [22], but it presents a commercial product very briefly and in the abstract, and cannot be reproduced. Thus, our method not only is described extensively and in detail, but is also compared with other methods in the literature.

Finally, with regard to papers that compare methods and systems of sentiment analysis, such as [10] and [3], we take a step further and present comparisons in more than one languages.

3 Data

In this section we describe the datasets that are used for training and testing. Details about the size and contents of each dataset are given by Table 1. The Greek training data were collected between August 2012 and January 2015. Part of positive and negative tweets are based on subjective terms and around 20 % of neutral tweets were gathered from accounts of newspapers and news sites. The rest were streamed randomly. Respectively, Greek test set consists of random tweets posted between October 2013 and January 2015. We used Twitter Search and Streaming API[2] for the collection. Both training set and test set were labeled by three annotators. The calculated Fleiss' kappa [7] for the training set is 0.83, which is interpreted as almost perfect agreement, whereas for the test set is 0.691, which denotes substantial agreement. We will refer to the Greek training and test set as GR–train and GR–test.

For experiments on English we use training and test data provided by the organizers of SemEval 2013 [18] for the task of sentiment analysis in Twitter. The organizers collected tweets according to popular topics, which included

Table 1. Datasets

Dataset	Positive	Negative	Neutral	Total
GR–train	1870	2940	3190	8000
GR–test	261	249	378	888
Sem–train	3287	1601	4175	9063
Sem–test	1572	601	1640	3813

[2] https://dev.twitter.com/.

named entities previously extracted by a Twitter-tuned NER system [23], and used Mechanical Turk for annotation. We will refer to SemEval training and test set as Sem–train and Sem–test respectively.

4 Overview of Approach

The approach we adopt consists of three main steps: (1) Preprocessing of data. (2) Feature engineering. (3) Reversal of classifier's prediction for a tweet due to negation identification. The proposed method takes into account not only inflection but also word stress, both characteristics of morphologically-rich languages, and suggests a novel technique to reduce the negative effect of the combination of both in classification performance. Moreover, it treats identification of negation as a postprocessing step and attempts to capture its structure, which is a much different approach than adding a special suffix to bag-of-words features that most methods do until now. The aforementioned steps are described in detail in the following sections.

4.1 Preprocessing

Preprocessing is applied to both training and test set. The first step of preprocessing is the removal of noise from the data. Elements that do not indicate the polarity of a tweet are considered as noise. Such elements are listed below. (1) URL links. (2) Mentions of other users. (3) The abbreviation RT, which indicates that a tweet is a retweet of another one. (4) Stop words, including articles and pronouns. Stop words are extremely common words, which appear to be of little value in deciding the sentiment of a text.

Because users use plethora of emoticons/hashtags, we choose to replace positive emoticons[3] with the emoticon ":)" and negative emoticons[4] with the emoticon ":(". A number of hashtags, such as #fail and #win, are also replaced with the former two emoticons. The aim of this step is to group the emoticons/hashtags in two categories and to avoid the need of importing tweets in the training set for each one of them. In addition to the above replacements, possible repetitive vowels encountered in a word are reduced to one, whereas repetitive consonants are reduced to two.

Capitalization and removal of accent marks are the next steps. An accent mark over the vowel in the stressed syllable is used in Greek to denote where the stress goes, e.g. 'καλημέρα' (good morning). In order to avoid mistakes due to omission of stress marks and incorrect use of capital letters versus lowercase letters, we remove these marks from tweets and transform them to uppercase. Stemming is the third and last step, and is used mostly to compensate for data sparseness. Stems are generated by George Ntais' Greek stemmer [19] for Greek and by Lovins stemmer [15] via the Weka data mining software [11] for English.

[3] List of positive emoticons: :-), :), :o), :], :3, :c), :>, =], 8), =), :}, :^), <3, ^_^, ;>, (:, ;), (;, :d, :D.

[4] List of negative emoticons: >:[, :-(, :(, :-c, :c, :-<, :<, :-[, :[, :{, :'(, :/ .

The previous steps are applied to the test set too. However, the preprocessing of test set involves an additional step: part-of-speech tagging. It takes place before stemming and is an auxiliary step for the process of negation identification (Sect. 4.3), which follows classification. After the replacements, we annotate the words of each tweet with part-of-speech tags, which are not taken into account by the classifier to predict the class, but are used in patterns whose intention is to detect negation. A Greek part-of-speech tagger [13] is used for the tagging process in Greek, whereas in English the Carnegie Mellon University (CMU) Twitter Natural Language Processing (NLP) tool was selected [8].

4.2 Features

Feature engineering follows the bag-of-words representation with unigrams and term presence. Due to the limit in the number of characters that compose a tweet, a unigram is enough to denote the sentiment in most of the cases. For some unigrams there is a dependency with a particular class, while others do not give any information under any circumstances about the polarity. We decided to keep only a subset of them in order to eliminate noisy features and build a simpler model. We experimented with two methods, Information Gain and Chi Squared [14]. They both gave equally good results, so Information Gain is chosen arbitrarily for the experiments displayed in sections below.

Apart from word ngrams, lexicons of subjective terms, which contain terms with association to positive and negative sentiments, may provide various features for sentiment analysis. There are plenty of subjective lexicons in English, but we are not aware of any such lexicons in Greek. Nonetheless, we attempted to create manually two simple Greek subjective lexicons, one with positive words and one with negative words according to their prior polarity. Words were derived from random tweets, not contained in GR–train or GR–test, or translated from subjective English lexicons. The positive lexicon contains 199 words and the negative one consists of 292 words. We use two simple features, the presence of positive/negative terms of such lexicons in Greek tweets and more sophisticated features, such as those proposed in [17], for English data. In the aforementioned paper, lexicon-based features proved to be useful for the task of sentiment analysis. We present our conclusions about this kind of features in Sect. 5.

4.3 Negation Identification and Polarity Reversal

Negation identification is based on patterns of part-of-speech tags combined with negation words. We attempt to identify these patterns in each tweet and store the token that is negated. For example, the Greek word 'δεν' (not) followed by a verb and an adjective constitutes a negation pattern. If a tweet contains the phrase 'Η ταινία δεν ήταν καλή' (The movie wasn't good), the former negation pattern will be identified due to the word 'δεν', the verb 'ήταν' (both correspond to wasn't) and the adjective 'καλή' (good). Then the token 'καλή', which is the one that is negated, will be stored. Nine frequent patterns are recognized for Greek and eight for English. The detection of negation aims to reverse the prediction

given by the classifier for a tweet from positive to negative or from negative to positive. If the prediction is neutral, no change is made. So following the decision of the classifier, we first check if a negated token is stored for the tweet. If yes, then we examine if this token belongs to the features that are present in the tweet. Suppose we have the aforementioned tweet for which we have kept the token 'καλή' as the negated token. If the unigram 'καλή' is one of the features and its value is 1, which indicates that this feature is present in the tweet, then the appropriate reversal of polarity will be performed. Otherwise, it will not.

4.4 Challenges of the Greek Language

The Greek language has a highly inflective nature that reduces the effectiveness of usual bag-of-words features. Greek verbs and adjectives are inflected for person, number and gender, which affects mostly the suffixes of the words. The various suffixes due to inflection increase ngram features, many of which are not contained in the training set. Hence, classification performance decreases. As a countermeasure to the inflective nature of Greek, the words of each tweet are replaced by their stems, assuming that stems are enough to denote the sentiment of a tweet in most cases.

Except from inflected verbs and adjectives, stress marks used in Greek make things even more complicated. Twitter users often forget to add these marks or they add them at the wrong syllable, creating this way a number of different versions of the same word (e.g. 'καλημέρα' is a different unigram from 'καλημερα'). As stated earlier, we chose to remove accent marks in order to reduce ngram features, but in case of stemming this choice may lead to mistaken predictions. Specifically, although stemming operates positively and helps the method to generalize better on unseen data (a conclusion that is drawn from the ablation tests included in Sect. 5.4), there is a case where it operates negatively: the stem of two words is the same whereas their polarities are different. For example the Greek words 'συμφωνώ' (agree) and 'σύμφωνα' (according to) have completely different meaning. The first word has positive polarity, whereas the second is neutral. Since the stem of both words is 'συμφων', there is no information to reveal the original word before stemming. As unigrams are used for predictions after stemming, the above case may be handled incorrectly. The described phenomenon can be frequently seen in Greek, even with words that are spelled exactly the same, but because they are stressed differently, their meaning changes. Note that these words are not homonyms as the word "like" for example, which serves both as verb and as proposition. In fact, purely homonyms with different polarity are extremely rare if non existent in the Greek language.

In order to handle the particular cases properly, a database is created with each record storing the following information: (i) stem, (ii) part-of-speech tag, (iii) polarity. The presence of unigrams (if any), on which the classifier based each prediction, are stored. If one of them, along with its part-of-speech tag, exists in the database, it is replaced with another one that has the same polarity. Specifically, if the unigram that exists in the database is positive, it will be replaced with the emoticon ":)", whereas if it is negative, it will be replaced with

the emoticon ":(". Finally, if the unigram is neutral, an article will replace it. At the moment, seven such cases are identified and stored in the database. However, this database can be continually improved by a user feedback mechanism.

The described particularities show that depending on language, different preprocessing steps may improve the performance of the classifier and thus it is not trivial to suggest a method that proves to be best for every language.

5 Experiments

There are two versions of the proposed method that are developed for the experiments. The first one uses SVM as the classification algorithm and we will refer to it as #Sentiment_v1. The second version is called #Sentiment_v2 and uses Logistic Regression. SVM uses linear kernel and the value of parameter C is 1.0. The implementations of both algorithms are provided by the Weka data mining software. The section of experiments is divided in two parts. The first part presents the results of the evaluation on the Greek dataset collected by us, whereas the second includes results of experiments on English data provided by SemEval 2013. In those subsections we also compare the proposed method to three pre-existing methods developed for English [5,9,17], which we followed and implemented according to the descriptions in the corresponding papers. We will refer to these methods as Go_method, Mohammad_method and Barbosa_method according to the first author. Due to space restrictions we do not describe these methods, but of course we provide the corresponding references for details.

The evaluation metrics we report in the experiments are average precision, recall and F-score, i.e. the sum of the corresponding metrics for each class divided by the number of classes. We also use McNemar's test [16] to check the statistical significance of the difference in performance between systems in each experiment.

5.1 Greek Data

The experiments of this section concern the evaluation on Greek data gathered by us, i.e. the GR–test. We present a comparison between the two versions of our system and the three pre-existing methods described above. For Barbosa_method we implement only two lexicon features, number of positive and number of negative words, as all other lexicon features depend on the structure of the MPQA lexicon [25], which is separated into strong subjective and weak subjective terms (this distinction does not exist in current Greek lexicons). Figure 1 displays the evaluation results of the five systems, #Sentiment_v1, #Sentiment_v2, Go_method, Mohammad_method and Barbosa_method on Greek data. As far as our method is concerned, the difference in F-score between #Sentiment_v1 and #Sentiment_v2 on GR–test is statistically significant, which means that SVM outperforms Logistic Regression. However, our performance is statistically indistinguishable from Mohammad_method. The other two methods by Go and Barbosa achieve much lower average F-scores.

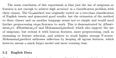


Fig. 1. Results on Greek data (GR-train for training and GR-test for testing)

The main conclusion of this experiment is that just the use of unigrams as features is not enough to achieve high accuracy in a classification problem with three classes. The Go_method was originally tested on a two-class classification of English tweets and generated good results, but the extension of the method to three classes and on another language seems not so simple and would need further preprocessing steps/features to work. This is demonstrated by #Sentiment_v1, #Sentiment_v2 and Mohammad_method, which also support the use of unigrams, but extend it with lexicon features, more preprocessing, such as stemming or feature selection, and achieve to reach higher average F-scores. Mohammad_method addresses inflection by keeping all ngram features, which however means a much larger model and more training time.

5.2 English Data

This section is dedicated to experiments on English data provided by the organizers of SemEval 2013. Again we present a comparison between the system proposed (only #Sentiment_v1, which is the best version according to the previous experiments) and the other three methods.

The evaluation results on the SemEval dataset (Sem-train and Sem-test) are displayed in Fig. 2. #Sentiment_v1 and Mohammad_method are again statistically indistinguishable and give the highest F-scores. Again methods that include both ngram and lexicon features, along with preprocessing and feature selection techniques, perform better on English data.

Fig. 2. Results on SemEval data (Sem-train for training and Sem-test for testing)

5.3 Time Consumption

In this section we present time performance results of the methods using the number of predicted tweets per second and training time. All methods ran on a single machine with an Intel Core i5 processor at 2.6 GHz and 16 GB of RAM. Details about time consumption of each method are given by Table 2.

Table 2. Time consumption

Method	Predicted tweets/sec	Training time (minutes)
#Sentiment_v1	16 tweets/sec	8.45 min
Mohammad_method	9 tweets/sec	14.91 min
Go_method	807 tweets/sec	5.9 min
Barbosa_method	8 tweets/sec	15 min

Although #Sentiment_v1 and Mohammad_method are indistinguishable in terms of F-score, #Sentiment_v1 needs 43 % less prediction and training time. This difference in time performance is reasonable, since Mohammad_method generates more features, such as part-of-speech and Twitter syntax features (RTs, hashtags, e.g.), which based on the experimental results they do not contribute that much to accuracy, but they increase processing time. Go_method is by far the fastest method. This is because it only involves unigram features, which are quickly generated. Nevertheless, they fail to predict test data effectively as experimental results demonstrated.

5.4 Sensitivity Analysis

We also performed ablation tests in order to check how the omission of different steps of our method affects performance. Table 3 shows the effect of negation identification, feature selection and stemming on Greek and English data. The remarkable change in F-score in Greek after the omission of stemming is expected due to the inflective nature of the language. Notably, negation identification does not seem to matter a lot. This is probably due to the fact that many tweets are neutral and their polarity is not reversed, but also that the technique suffers from low recall. It tends to be quite precise and correctly reverse polarity when a negation pattern is captured and the negated token is one of the classification features. However, in many cases the negated token does not belong to the features and even though the pattern is again captured, no reversal takes place.

Table 3. Results of sensitivity analysis

Modification	Avg F-score on Greek	Avg F-score on English
No modification	68.6%	64.2%
Without negation identification	68.7%	64.1%
Without feature selection	66.7%	62.2%
Without stemming	63.1%	62.2%

6 Conclusion and Future Work

We present a method for sentiment analysis in Twitter focused on the Greek language. We perform the first multilingual comparative analysis and report comparison results to three leading existing methods, from experiments on two different datasets (Greek and English). Our method clearly outperforms two of the three methods we compared against in sentiment extraction, while being statistically indistinguishable from the third. However, the proposed method needs 43% less time for predictions and training. These experiments reveal that the generalization of a method to different languages or from a two to a three class classification problem is not trivial. Moreover, they give evidence about the effect of different preprocessing steps and features, such as stemming, in performance for Greek and English. An interesting idea to pursue in the future is the assignment of sentiment to the correct entity in the tweet.

References

1. Abbasi, A., Chen, H., Salem, A.: Sentiment analysis in multiple languages: feature selection for opinion classification in web forums. ACM Trans. Inf. Syst. **26**(3), 12:1–12:34 (2008)

2. Abdul-Mageed, M., Diab, M.T., Korayem, M.: Subjectivity and sentiment analysis of modern standard arabic. In: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: Short Papers . HLT 2011, vol. 2, pp. 587–591. Association for Computational Linguistics, Stroudsburg, PA, USA (2011)
3. Annett, M., Kondrak, G.: A comparison of sentiment analysis techniques: polarizing movie blogs. In: Bergler, S. (ed.) Canadian AI. LNCS (LNAI), vol. 5032, pp. 25–35. Springer, Heidelberg (2008)
4. Atteveldt, W.V., Ruigrok, N., Schlobach, S.: Good news or bad news? conducting sentiment analysis on dutch text to distinguish between positive and negative relations. J. Inf. Technol. Polit. **5**(1), 73–94 (2008)
5. Barbosa, L., Feng, J.: Robust sentiment detection on twitter from biased and noisy data. In: Proceedings of the 23rd International Conference on Computational Linguistics: Posters, pp. 36–44. Association for Computational Linguistics (2010)
6. Boiy, E., Moens, M.F.: A machine learning approach to sentiment analysis in multilingual web texts. Inf. Retrieval **12**(5), 526–558 (2009)
7. Fleiss, J., et al.: Measuring nominal scale agreement among many raters. Psychol. Bull. **76**, 378–382 (1971)
8. Gimpel, K., Schneider, N., O'Connor, B., Das, D., Mills, D., Eisenstein, J., Heilman, M., Yogatama, D., Flanigan, J., Smith, N.A.: Part-of-speech tagging for twitter: annotation, features, and experiments. In: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: short papers. HLT 2011, vol. 2, pp. 42–47 (2011)
9. Go, A., Bhayani, R., Huang, L.: Twitter sentiment classification using distant supervision. Processing **150**(12), 1–6 (2009)
10. Gonçalves, P., Araújo, M., Benevenuto, F., Cha, M.: Comparing and combining sentiment analysis methods. In: Proceedings of the First ACM Conference on Online Social Networks. pp. 27–38. COSN '13, ACM, New York, NY, USA (2013)
11. Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H.: The weka data mining software: an update. SIGKDD Explor. Newsl. **11**(1), 10–18 (2009)
12. Hu, X., Tang, J., Gao, H., Liu, H.: Unsupervised sentiment analysis with emotional signals. In: Proceedings of the 22nd International Conference on World Wide Web. WWW 2013 (2013)
13. Koleli, E.: A new Greek part-of-speech tagger, based on a maximum entropy classifier. Master's thesis, Athens University of Economics and Business (2011)
14. Liu, H., Setiono, R.: Chi2: Feature selection and discretization of numeric attributes. In: 1995 Proceedings of Seventh International Conference on Tools with Artificial Intelligence, pp. 388–391. IEEE (1995)
15. Lovins, J.B.: Development of a stemming algorithm. Mech. Translation Comput. Linguist. **11**, 22–31 (1968)
16. McNemar, Q.: Note on the sampling error of the difference between correlated proportions or percentages. Psychometrika **12**(2), 153–157 (1947)
17. Mohammad, S., Kiritchenko, S., Zhu, X.: Nrc-canada: building the state-of-the-art in sentiment analysis of tweets. In: Second Joint Conference on Lexical and Computational Semantics (*SEM), Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013), vol. 2, pp. 321–327 (2013)

18. Nakov, P., Rosenthal, S., Kozareva, Z., Stoyanov, V., Ritter, A., Wilson, T.: Semeval-2013 task 2: sentiment analysis in twitter. In: Second Joint Conference on Lexical and Computational Semantics (*SEM), Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013), vol. 2, pp. 312–320 (2013)
19. Ntais, G.: Development of a Stemmer for the greek Language. Master's thesis, Stockholm's University (2006)
20. Pak, A., Paroubek, P.: Twitter as a corpus for sentiment analysis and opinion mining. In: Proceedings of the Seventh Conference on International Language Resources and Evaluation (LREC 2010). European Language Resources Association (ELRA) (2010)
21. Pang, B., Lee, L., Vaithyanathan, S.: Thumbs up?: sentiment classification using machine learning techniques. In: Proceedings of the ACL-02 Conference on Empirical Methods in Natural Language Processing, vol. 10, pp. 79–86. Association for Computational Linguistics (2002)
22. Petasis, G., Spiliotopoulos, D., Tsirakis, N., Tsantilas, P.: Sentiment analysis for reputation management: mining the Greek web. In: Likas, A., Blekas, K., Kalles, D. (eds.) SETN 2014. LNCS, vol. 8445, pp. 327–340. Springer, Heidelberg (2014)
23. Ritter, A., Clark, S., Mausam, Etzioni, O.: Named entity recognition in tweets: an experimental study. In: Proceedings of the Conference on Empirical Methods in Natural Language Processing, pp. 1524–1534. EMNLP 2011 (2011)
24. Vapnik, V.: Statistical Learning Theory. Wiley, New York (1998)
25. Wilson, T., Wiebe, J., Hoffmann, P.: Recognizing contextual polarity in phrase-level sentiment analysis. In: Proceedings of the Conference on Human Language Technology and Empirical Methods in Natural Language Processing. HLT 2005, pp. 347–354 (2005)
26. Zhao, J., Dong, L., Wu, J., Xu, K.: Moodlens: an emoticon-based sentiment analysis system for chinese tweets. In: Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data mining, pp. 1528–1531. KDD 2012 (2012)