Using Metric Space Indexing for Complete and Efficient Record Linkage

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Abstract. Record linkage is the process of identifying records that refer to the same real-world entities, in situations where entity identifiers are unavailable. Records are linked on the basis of similarity between common attributes, with every pair being classified as a link or non-link depending on their degree of similarity. Record linkage is usually performed in a three-step process: first groups of similar candidate records are identified using indexing, pairs within the same group are then compared in more detail, and finally classified. Even state-of-the-art indexing techniques, such as Locality Sensitive Hashing, have potential drawbacks. They may fail to group together some true matching records with high similarity. Conversely, they may group records with low similarity, leading to high computational overhead. We propose using metric space indexing to perform *complete* record linkage, which results in a parameter-free record linkage process combining indexing, comparison and classification into a single step delivering complete and efficient record linkage. Our experimental evaluation on real-world datasets from several domains shows that linkage using metric space indexing can yield better quality than current indexing techniques, with similar execution cost, without the need for domain knowledge or trial and error to configure the process.

Keywords: Entity resolution; data matching; similarity search; blocking.

1 Introduction

Record linkage, also known as entity resolution, data matching and duplicate detection [3], is the process of identifying and matching records that refer to the same real-world entities within or across datasets. The entities to be linked are often people (such as patients in hospital or customers in business datasets), but record linkage can also be applied to link consumer products or bibliographic records [3]. Record linkage is commonly challenged by the lack of unique entity identifiers (keys) in the datasets to be linked, which prevents the use of a database join. Instead, the linkage of records requires the comparison of the common attributes (or fields) that are available within the datasets. For datasets that contain information about individuals, these attributes include the names, addresses, dates of birth, and so on, of individuals.

To overcome data quality issues such as typographical errors and variations (which are common in name and address values [3]), approximate string comparison functions (such as edit distance, the Jaro-Winkler comparator, or Jaccard

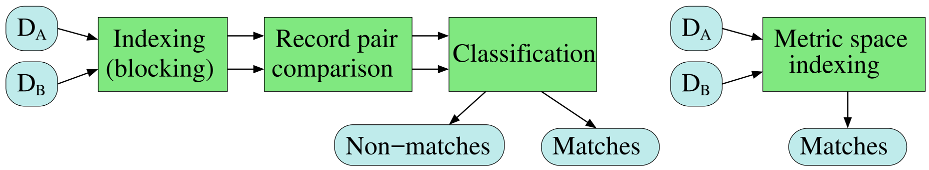


Fig. 1: Overview of the steps of the traditional record linkage process (left side) and our proposed metric space indexing based approach (right side), as described in Sect. 1, where records from two datasets, $\mathbf{D}_A$ and $\mathbf{D}_B$, are being linked.

similarity [3]) are used to compare pairs of records, leading to a vector of similarities (one similarity per attribute compared) for each pair. These similarity vectors are then used to classify the compared record pairs into *links* (where it is assumed both records in a pair correspond to the same real-world entity) and *non-links* (where the records are assumed to correspond to two different entities). Various classification methods have been employed in record linkage [3,6], ranging from simple threshold-based to sophisticated clustering, supervised classification techniques, and active learning approaches [24].

Besides the issues of a lack of unique entity identifiers and data quality (which will affect linkage quality), record linkage is also challenged by the increasing sizes of the datasets to be linked [6]. To avoid full pair-wise comparison of all possible record pairs (quadratic in the sizes of the datasets to be linked), blocking techniques, commonly known as *indexing* [4], are used. These split the datasets into smaller blocks in a computationally efficient way, such that records that are likely to correspond to the same entity are grouped into the same block. Only records within the same block are then compared in more detail.

While indexing techniques facilitate efficient linkage of very large datasets [6], they generally achieve scalability at the cost of reduced linkage quality, because potentially true matching record pairs are removed in the indexing step, leading to a reduction in recall [3]. A variety of indexing techniques, discussed in more detail in the following section, have been proposed, ranging from simple phonetic based blocking [3] and sorting of the datasets [7] to locality sensitive hashing based techniques [12,23]. Techniques for unsupervised [11,20] and supervised [1,16] learning of optimal blocking schemes have also been proposed.

Traditional record linkage systems that perform indexing prior to comparison and classification, as illustrated on the left in Figure 1, add a further practical complexity to the process. Indexing, comparison and classification are often conducted using algorithms and parameters selected based on technical and domain expertise of the user of the record linkage system, followed by a manual assessment (auditing) of the linkage outcomes [3]. If the quality of the resulting links is not good enough for a certain application, the linkage process needs to be repeated with different parameter settings and possibly also alternative algorithms. This can result in a time-consuming and labour-intensive iterative process. A major challenge is often the heuristic nature of indexing, where the choice of a certain indexing technique and its parameters (including which attributes to use in indexing) will determine the final outcome of a linkage.

This paper focuses on approaches that use a similarity threshold to classify links. Such techniques are fundamentally limited by the extent to which true matching records are similar, and true non-matches are dissimilar—this is dataset-dependent. Within this domain, we define a technique to be *complete* if it is guaranteed to identify all record pairs within the specified similarity threshold. Commonly used indexing techniques are incomplete, since they reduce computational cost at the expense of potentially overlooking some true matches. By definition, incomplete techniques yield lower recall than complete techniques. Conversely, and perhaps counter-intuitively, complete techniques can yield lower precision with some datasets. This is discussed further in Sect. 3.

Metric space indexing (MSI) is a complete technique with much lower computational overheads than a brute force approach. It allows indexing, comparison and classification to be combined into a single step, as illustrated in the right-hand side in Fig. 1, making the overall record linkage process simpler, more efficient and more effective than incomplete indexing approaches.

Contribution: The primary contribution of this paper is the novel application of MSI to achieve complete and efficient record linkage, without the need for complex parameter tuning. We evaluate our approach on several real-world datasets from diverse domains and demonstrate its advantages over existing indexing techniques for record linkage.

2 Related Work

We now briefly review relevant work in the areas of indexing for record linkage (for recent surveys see [4,19]), and metric space indexing [25].

Techniques to link records across datasets have been investigated for over five decades [8,18], with the scalability of linking being an ongoing challenge as datasets grow in size and complexity. Traditional blocking [4] uses a set of attributes (known as a *blocking key*) to insert records that share the same value(s) in their blocking key into the same block. Only records within the same block are compared to each other. To overcome variations and misspellings, the values used in blocking keys can be phonetically encoded using functions such as Soundex, NYSIIS, or Double-Metaphone [3]. These convert a string into a code according to its pronunciation, assigning the same code to similar sounding names (such as 'Gail' and 'Gayle'). Multiple blocking keys may also be used to deal with the problem of missing attribute values.

A different approach to indexing is the sorted neighbourhood method [17], where the datasets to be linked are sorted according to a *sorting key* (usually a concatenation of the values from several attributes). A sliding window is then moved over the datasets and only records within the window are compared. Techniques that adaptively shrink or expand the window size based on the characteristics of the sorting key values have been shown to improve both linkage efficiency and quality [7] over approaches that use fixed size windows.

These blocking techniques are heuristics, commonly requiring domain knowledge, such as the choice of appropriate blocking or sorting keys. Poor choices of blocking attributes result in records being inserted into inappropriate blocks, and thus true matches being missed. As a result, such techniques can lead to *incomplete* linkage. Conversely, many of the record pairs compared in a block may turn out to have low similarity, corresponding to non-matches, resulting in *inefficient* linkage.

Locality sensitive hashing (LSH), originally proposed to allow efficient nearest-neighbour search in high-dimensional spaces [10], has been employed in record linkage as an indexing technique where attribute values are hashed multiple times, and blocks are created from those records that share some hash values. *HARRA* [12] is a record linkage approach based on MinHash [2] and LSH which blocks, compares, and then merges linked records in an iterative fashion, where merged records are re-hashed to improve overall linkage quality. [23] evaluates two LSH variations, concluding that in order to get good results, LSH methods must be tuned to the particular datasets being linked. This requires good quality ground truth data which may be unavailable or expensive to obtain.

Metric space indexing (MSI) techniques [25] provide indexing structures to support the comparison of records in one set with those in another, typically also offering similarity search operations. To create an MSI data structure, it is necessary to define a distance measure between records, with certain properties including the *triangle inequality* [25]. Similarity search operations include *range-search(*$\boldsymbol{q}$*,*d*)*, where all records $\mathbf{r}$ in a database $\mathbf{D}$ within a distance d of a query record $\mathbf{q}$ are identified; *nearest-neighbour(*$\boldsymbol{q}$*)*, returning the record $\mathbf{r} \in \mathbf{D}$ with smallest distance to $\mathbf{q}$; and *nearest-n(*$\boldsymbol{q}$*,*n*)*, returning the n closest records in $\mathbf{D}$ to $\mathbf{q}$. Here we choose one metric space indexing structure, the M-tree [5], and investigate its efficacy for record linkage.

The M-tree is a dynamically balanced tree structure. Every node contains a reference to a record being indexed, a pointer to its parent, the distance to its parent, and the node's radius. The radius of a node is the distance from it to its furthest child. For a parent node with radius r, all its children may be visualised as being contained within a ball of radius r from it.

A threshold-based linkage method using R-trees [9] was described in [14]. It demonstrates that high linkage quality can be achieved using Jaccard similarity over selected record attributes. [5] shows that M-trees are almost always more efficient than R-trees, hence their use in the experiments described in this paper.

3 Approach

We address the following general record linkage problem: for two datasets $\mathbf{D}_A$ and $\mathbf{D}_B$, we wish to find, for each record in $\mathbf{D}_A$, all the records in $\mathbf{D}_B$ that match it with regard to a certain distance threshold, d (i.e. have a distance of d or less). We compare several algorithms for record linkage: traditional blocking, one incomplete similarity search method, LSH-MinHash, and one complete method, M-tree. We also use a simple complete brute force technique as a baseline for comparison, although this can only feasibly be applied to the smallest of our datasets. All experiments have a number of parameters to configure the search space and algorithm behaviour, including a *distance threshold*, d, specifying a maximum distance, equivalent to a minimum similarity, for two records to be classified as a link (i.e. referring to the same entity).

Brute force: Two nested loops are used to compare every record in $\mathbf{D}_A$ with every record in $\mathbf{D}_B$. Each pair is classified as a link if the distance between the records is equal to or less than the threshold d. This approach is guaranteed to identify all links, with complexity $O(|\mathbf{D}_A| \times |\mathbf{D}_B|)$.

Traditional blocking: The parameters of traditional blocking are the set of blocking keys and the (optionally) phonetic encodings applied to each attribute. These are selected as described in [4], exploiting knowledge of the domain and of the records being linked, and chosen with the intention of giving the best possible results for the datasets. Each record in $\mathbf{D}_A$ is placed into the appropriate block based on its blocking key value. The algorithm then iterates over the records in $\mathbf{D}_B$, and for each one, compares it with each of the records from $\mathbf{D}_A$ in the block with the same blocking key value.

LSH-MinHash: The parameters for LSH-Minhash are [2] *shingle size* (l_{ss}), *band size* (l_{bs}) and *number of bands* (l_{nb}). Each record in $\mathbf{D}_A$ is placed in an *LSH-MinHash* data structure. First, all the attributes of the record are concatenated, and the result *shingled* into a set of n-grams with $n = l_{ss}$. Next, a set of deterministically generated hash functions are applied to each n-gram in the set and the smallest result (the MinHash) of each hash application is added to a signature for the record. The number of hashes used, and thus the size of the signature, is set to $l_{nb} \times l_{bs}$. Finally, the signature is split into l_{nb} bands and the values from each band are hashed again to create a number of keys. The original record is added to a map associated with each of the keys.

To perform linkage, the algorithm iterates over the records in $\mathbf{D}_B$. Each record is hashed using the procedure described above, to obtain a set of keys. For each of these keys, the key is looked up in the LSH-MinHash data structure, and the records from $\mathbf{D}_A$ associated with it added to the result set. Finally, the record from $\mathbf{D}_B$ is compared in turn with each record in the result set using the same distance function and threshold, d, as with the other approaches, with the pair being classified as a link or non-link based on their distance.

In some circumstances, incomplete approaches such as traditional blocking and LSH-MinHash can yield higher precision than complete techniques. This can occur when the datasets contain a significant number of non-matches that nonetheless have high similarity. In this situation, the fact that an incomplete technique omits consideration of some potential links can serve to improve precision, since a classification decision based on a certain similarity threshold is incorrect for high-similarity non-matches. By definition, recall can never be higher for incomplete techniques.

M-tree: Besides the distance threshold, d, the M-tree linkage algorithm has no additional parameters. In a similar manner to the *LSH-MinHash* approach, each record in $\mathbf{D}_A$ is inserted into an M-tree. To perform linkage, the algorithm

Table 1: Characteristics of datasets used in the experiments.

Dataset name(s)	Records in dataset $\mathbf{D}_A$	Records in dataset $\mathbf{D}_B$	Number of true matching pairs	Entities linked
Cora	1,295	1,295	17,184	Publication–Publication
Isle of Skye	17,612	12,284	2,900	Birth–Death
Kilmarnock	38,430	23,714	8,300	Birth–Death

iterates over each record $\mathbf{b} \in \mathbf{D}_B$. A *range-search(b,d)* operation is performed on the M-tree, passing the distance threshold d as the second parameter. All the returned records are directly classified as links.

4 Experiments and Results

We now describe the datasets we use in our evaluation, the set-up employed to evaluate our proposed metric indexing approach and compare it with traditional blocking techniques, and we then present and discuss our results [1].

We used three datasets from two domains in our experiments, as summarised in Table 1. The first is *Cora* [15], which contains 1,295 records that refer to 112 machine learning publications. Cora is commonly used as a benchmark dataset in the literature for assessing linkage algorithms. Ground truth is provided via a unique *paper_id* identifier of the form "blum1993". In this experiment linkage is performed over the same set of records (i.e. a de-duplication [3]).

The other two datasets are historical Scottish records of vital events (birth, marriages and deaths) one registered on the *Isle of Skye*, a rural district, and the other records from *Kilmarnock*, an industrial town. These datasets were created by historical demographers who extensively curated and linked both datasets [21,22]. Both datasets include the names, gender, addresses of individuals and their parents. Ground truth was generated by the demographers based on their extensive domain knowledge.

In all of our experiments we use a single distance metric which is the sum of the Levenshtein [13] edit distances between the set of attributes being compared.

4.1 Cora Results

In this section, we perform linkage on the Cora dataset using all four approaches presented in this paper: brute force, traditional blocking, LSH and M-tree, using several selected configurations for the blocking and LSH approaches. The distance threshold is varied between $0 \leq d \leq 250$ [2]. For traditional blocking,

[1] The raw data, additional figures and the source code required to run these experiments can be downloaded from: (link removed for double blind review).

[2] Relatively high Levenshtein edit distances are included since Cora includes a number of low-similarity true matches.

the following Cora attributes are used individually as blocking keys: *author*, *title*, *venue*, *location*, *publisher* and *year*. We also use a combined blocking key comprising all attributes.

Figure 2 shows the precision, recall, and F-measure [3] for various thresholds. As expected, low thresholds give high precision and low recall, and the reverse for high threshold values. Brute force and M-tree give identical results, as expected. The best linkage quality, with an F-measure of around 0.7, is achieved by a number of linkers, including brute force, M-tree, blocking on *authors* and blocking on all attributes, and two of the LSH configurations. All of these give similar overall results, apart from blocking on *authors*, which gives much better quality at very high distance thresholds. This is due to the incomplete nature of the approach, avoiding comparisons of significant numbers of high-similarity non-matches and thus avoiding these becoming false positives and keeping precision high.

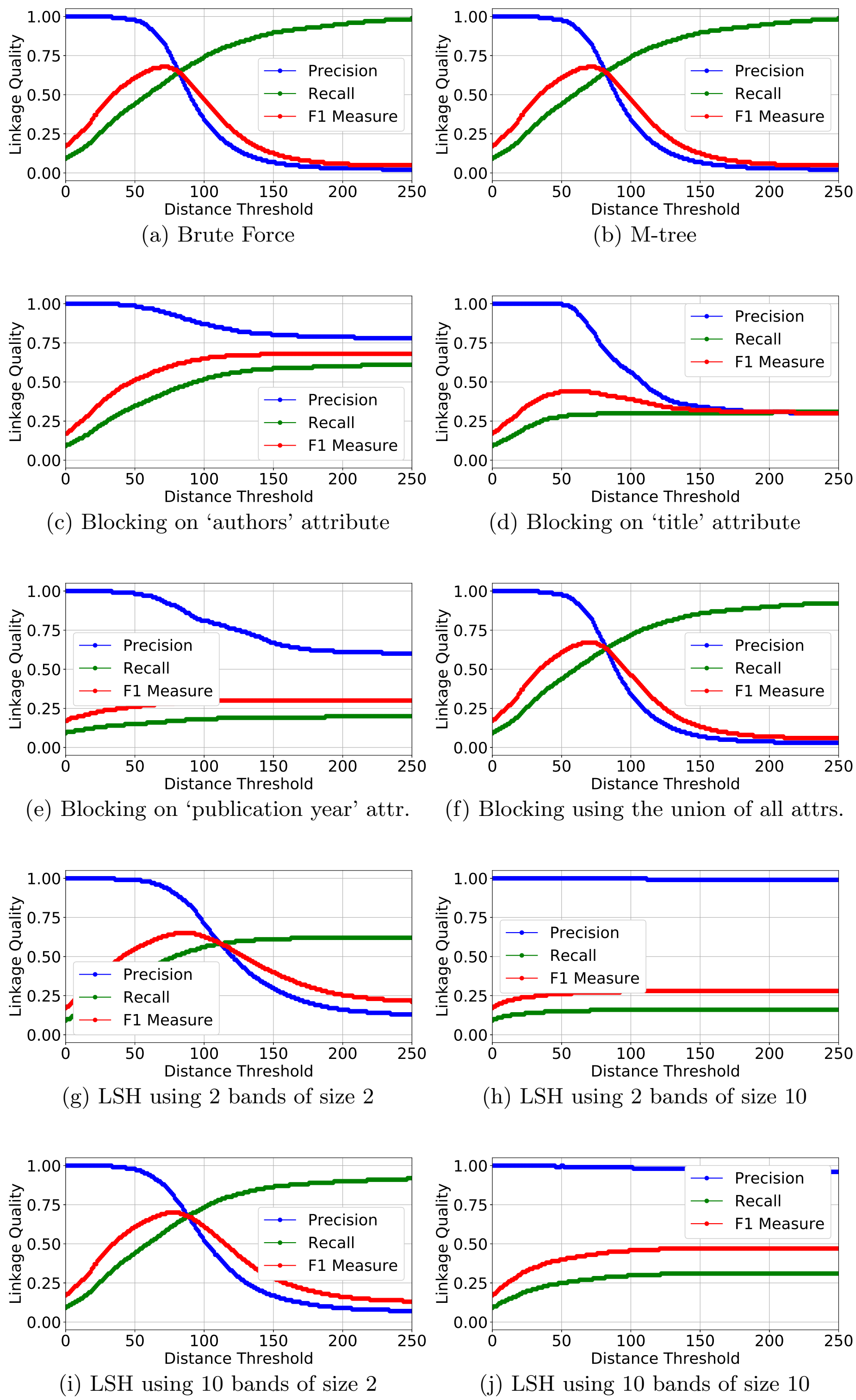
For a more detailed investigation of selected linkers, the brute force approach is used to establish a good threshold value for the Cora dataset. The maximum F-measure is observed at a threshold value of $d = 70$. This value is dataset-dependent; for different datasets the maximum F-measure will occur at different thresholds. In the rest of this section we fix the threshold value at $d = 70$.

Table 2 shows greater detail for selected linkers, showing the parameters for the experiment, the number of distance comparisons made, and the precision, recall and F-measure achieved by each algorithm. In the *Linker* column the algorithm name is followed by its parameters: for LSH the number of the bands followed by the band size, and for traditional blocking the attributes used for blocking. The number of distance comparisons is reported as a machine-independent proxy for execution cost, since code profiling shows that distance calculations are dominant.

M-tree yields the same linkage quality as brute force, although using a significantly lower number of comparisons. This is as expected, since both techniques are complete. Several of the incomplete linkers give similar quality, for example *LSH-2-2*, *LSH-5-2*, *LSH-10-2* and *Block-combined*. These, and a number of other incomplete linkers, give better precision than the complete techniques. This is due to high-similarity non-matches, as discussed in Sect. 3. Although several of the incomplete linkers give as good quality as M-tree, and in some cases at lower cost, this is offset by the need to select appropriate configuration parameters. Some other linkers give very poor results.

4.2 Demographic Dataset Results

Birth records were linked to death records, separately for the Skye and Kilmarnock datasets, using M-tree and a range of LSH configurations. It was not computationally feasible to run the brute force linker. Of the incomplete linkers, LSH was selected as it gave slightly better results for Cora. The shingle size was set to $l_{ss} = 2$ for all the LSH experiments reported, as this was found to give good results and LSH was not especially sensitive to this parameter. Results for other shingle sizes are omitted from this paper for brevity. A lower range of distance thresholds was explored, based on domain knowledge of the datasets.



(a) Brute Force
(b) M-tree
(c) Blocking on 'authors' attribute
(d) Blocking on 'title' attribute
(e) Blocking on 'publication year' attr.
(f) Blocking using the union of all attrs.
(g) LSH using 2 bands of size 2
(h) LSH using 2 bands of size 10
(i) LSH using 10 bands of size 2
(j) LSH using 10 bands of size 10

Fig. 2: Linkage results on the Cora dataset.

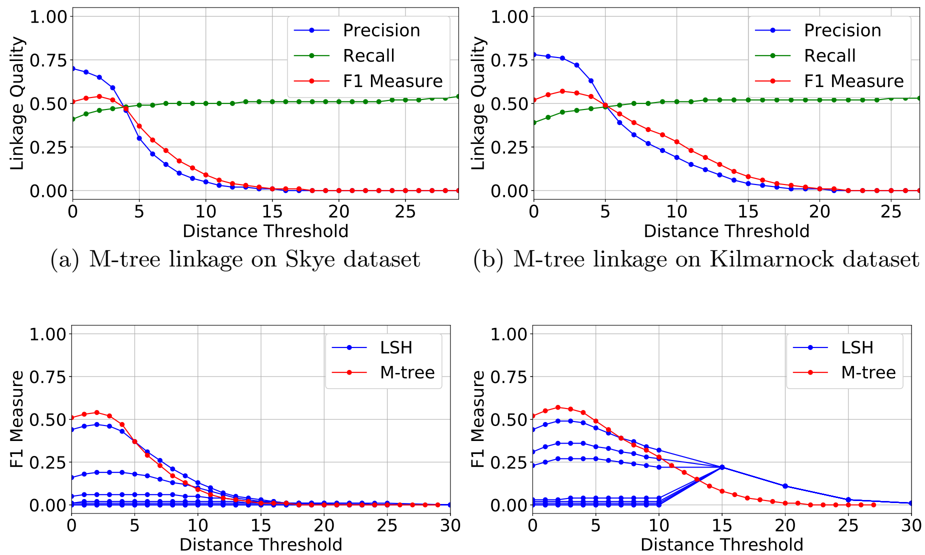
Table 2: Linkage quality on Cora dataset with distance threshold $d = 70$.

Linker	Comparisons	Precision	Recall	F1 Measure
Brute Force	1,677,025	0.84	0.57	0.68
M-tree	902,693	0.84	0.57	0.68
LSH-2-2	192,199	0.95	0.47	0.63
LSH-5-2	342,849	0.91	0.55	0.69
LSH-10-2	513,947	0.88	0.57	0.69
LSH-2-5	14,329	0.99	0.28	0.43
LSH-5-5	22,057	0.99	0.36	0.53
LSH-10-5	26,167	0.98	0.4	0.57
LSH-2-10	4,711	1	0.15	0.27
LSH-5-10	6,501	1	0.19	0.32
LSH-10-10	10,627	0.99	0.27	0.43
Block-year	115,893	0.99	0.35	0.51
Block-authors	11,039	0.94	0.16	0.28
Block-title	27,407	0.95	0.42	0.58
Block-venue	36,647	0.85	0.29	0.44
Block-location	1,009,957	0.83	0.43	0.57
Block-publisher	833,079	0.85	0.44	0.58
Block-combined	1,214,269	0.84	0.56	0.67

Figure 3 plots (a) and (b) show the M-tree precision, recall, and F-measure for various thresholds. In both datasets, the best F-measure values are obtained with a low distance threshold of $d = 2$. Plots (c) and (d) compare the F-measure curves for M-tree with those obtained from a range of LSH configurations. The best F-measure value for M-tree is higher than that of any of the LSH configurations, for both datasets. This demonstrates both the competitiveness of M-tree with respect to linkage quality, and its important characteristic of being parameter-free—the linkage quality is obtained without the need to tune for the dataset.

Tables 3 and 4 show greater detail for selected linkers. In both cases the F-measure achieved is better for M-tree than any of the LSH linkers. The better linkage quality achieved by M-tree is largely due to recall for M-tree being much higher than for any of the LSH configurations. In most cases, LSH out-performs M-tree in terms of precision. More significantly, LSH linkage quality is heavily dependent on the configuration parameters. For plausible settings for the number of bands and band size, F-measure varies from 0.01 (extremely poor) to 0.47 (relatively good) for Skye and from 0.03 to 0.49 for Kilmarnock. In both cases *LSH-10-2* performs best, but since this is data-dependent there is no guarantee that these parameters would work well with another dataset.

The number of distance comparisons varies dramatically among the various linkers. M-tree always performs the most comparisons, since they are intrinsic to the *range-search* algorithm. The core part of the LSH linker performs Jaccard similarity comparisons and hashing; distance comparisons are only performed in



(a) M-tree linkage on Skye dataset

(b) M-tree linkage on Kilmarnock dataset

(c) F1 Measure on Skye dataset with M-tree and all LSH configurations

(d) F1 Measure on Kilmarnock dataset with M-tree and all LSH configurations

Fig. 3: Linkage results on the demographic datasets.

the final step to determine whether a candidate pair is a link. The LSH configurations yielding the best results perform distance comparisons of the same order of magnitude as M-tree. This indicates that the good LSH linkers return many candidates beyond the distance threshold. Thus, in order to get good results, LSH tends towards a brute force search over the candidate results. Despite this, LSH is faster due to the efficiency of the hashing process.

5 Conclusions and Future Work

In this paper we have demonstrated the efficacy of MSI in achieving complete and efficient record linkage, without the need for complex parameter tuning. In conclusion, this claim deserves some careful unpacking. It is always possible to achieve high quality linkage using a brute force approach. However the quadratic complexity of this approach prevents its practical application for datasets of even moderate size. We have shown that MSI techniques such as M-tree can deliver high precision, high recall results that are the same as those delivered by brute force. Furthermore this is achieved with fewer distance comparisons, and consistently without the need for complex parameter tuning.

We contrast this to traditional blocking and LSH-based approaches. Their major drawback is that whilst they can produce extremely good results, they can also produce extremely poor results. It was our observations of low recall given by these approaches that originally led us to experiment with M-trees.

Table 3: Linkage quality on Skye dataset with distance threshold $d = 2$.

Linker	Comparisons	Precision	Recall	F1 Measure
M-tree	102,318,525	0.65	0.46	0.54
LSH-2-2	3,109,250	0.63	0.03	0.06
LSH-5-2	10,412,496	0.64	0.11	0.19
LSH-10-2	53,874,127	0.68	0.36	0.47
LSH-5-5	36,566	0.76	0.01	0.01
LSH-10-5	129,873	0.72	0.01	0.02

Table 4: Linkage quality on Kilmarnock dataset with distance threshold $d = 2$.

Linker	Comparisons	Precision	Recall	F1 Measure
M-tree	514,871,153	0.76	0.45	0.57
LSH-2-2	99,145,887	0.81	0.16	0.27
LSH-5-2	130,721,338	0.79	0.23	0.36
LSH-10-2	177,168,848	0.79	0.36	0.49
LSH-5-5	239,368	0.84	0.01	0.02
LSH-10-5	855,431	0.87	0.02	0.03

We note that the good results yielded by both traditional blocking and LSH are partly due to the fact that (in the limit) they tend towards brute force as the number of records in the block increase. A second, unexpected, result is that illustrated in Table 2, namely that incomplete approaches such as LSH can in some cases yield higher precision than that achieved by a complete method such as M-tree. This is due to the incomplete linker masking the inability of a classifier based solely on record similarity to correctly classify high-similarity non-matches or low-similarity matches.

The observation that LSH can yield results quickly at the cost of some recall suggests that hybrid algorithms may be a potentially profitable future direction for exploration. We hypothesise that it may be possible to use an incomplete technique like LSH to form indices into a data structure such as an M-tree. In this manner, M-tree nodes could be used as the starting point for range-search queries and, in so doing, prune the search space considerably to yield high quality results quickly. We plan to develop such hybrid indexing approaches with the aim to achieve fully automated, complete and efficient record linkage.

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