The Merge/Purge Problem for Large Databases *

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Abstract

Many commercial organizations routinely gather large numbers of databases for various marketing and business analysis functions. The task is to correlate information from different databases by identifying distinct individuals that appear in a number of different databases typically in an inconsistent and often incorrect fashion. The problem we study here is the task of merging data from multiple sources in as efficient manner as possible, while maximizing the accuracy of the result. We call this the *merge/purge* problem. In this paper we detail the *sorted neighborhood* method that is used by some to solve merge/purge and present experimental results that demonstrates this approach may work well in practice but at great expense. An alternative method based upon clustering is also presented with a comparative evaluation to the sorted neighborhood method. We show a means of improving the accuracy of the results based upon a *multi-pass* approach that succeeds by computing the Transitive Closure over the results of independent runs considering alternative primary key attributes in each pass.

1 Introduction

In this paper we study a familiar instance of the *semantic integration* problem[10] or the *instance identification* problem[14], called the *merge/purge* problem. Here we consider the problem over very large databases of information that need to be processed as quickly, efficiently, and accurately as possible. For instance, one month is a typical business cycle in certain direct marketing operations. This means that sources of data need to be identified, acquired, conditioned, and then correlated or merged within a small portion of a month in order to prepare mailings and response analyses. For example, it is common that many magazine subscription databases are purchased for the specific purpose of identifying characteristic interests of people for directed marketing purposes. It is not uncommon for large businesses to acquire scores of databases each month, with a total size of hundreds of millions to over a billion records, that need to be analyzed within a few days.

Merge/purge is ubiquitous in modern commercial organizations, and is typically solved today by expensive *mainframe computing* solutions. Here we consider the opportunity to solve merge/purge on low cost shared-nothing multiprocessor architectures. Such approaches are expected to grow in importance with the coming age of very large network computing architectures where many more distributed databases containing information on a variety of topics will be generally available for public and commercial scrutiny.

The merge/purge problem is closely related to a multi-way join over a plurality of large database relations. The naive means of implementing joins is to compute the Cartesian product, a quadratic time process, and select relevant tuples. The obvious optimizations, as well as parallel variants, for join computation are well known: sort-merge and hash partitioning. These strategies assume a total ordering over the domain of the join attributes (an index is thus easily computable) or a "near perfect" hash function that provides the means of inspecting small partitions of tuples when computing the join. In the case we study here, we cannot assume there exists a total ordering, nor a perfect hash distribution that would lead to a completely accurate result, meaning even slight errors in the data imply all possible "matches" of common data about the same entity may not be found. However, the techniques we study and have implemented are based upon these two strategies for fast execution, with the particular desire to improve their *accuracy*.

The fundamental problem is that the data supplied by various sources typically include identifiers or string data, that are either different among different datasets

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or simply erroneous due to a variety of reasons (including typographical or transcription errors, or purposeful fraudulent activity (aliases) in the case of names). Hence, the equality of two values over the domain of the common join attribute is not specified as a "simple" arithmetic predicate, but rather by a set of equational axioms that define equivalence, i.e., by an *equational theory*. Determining that two records from two databases provide information about the same entity can be highly complex. We use a rule-based knowledge base to implement an equational theory, as detailed in section 2.3.

Since we are dealing with large databases, we seek to partition the database into partitions or *clusters* in such a way that the potentially matching records are assigned to the same cluster. (Here we use the term cluster in line with the common terminology of statistical pattern recognition.) In this paper we first discuss a solution to merge/purge in which sorting of the entire data-set is used to bring the matching records close together in a bounded neighborhood in a linear list. We then explore the approach of partitioning the data into meaningful clusters and then bringing the matching records on each individual cluster close together by sorting. In the second algorithm we need not compute an entire sort of the full data-set, but rather a number of substantially smaller, independent and concurrent sorts that can be performed more efficiently on reduced datasets. However, we demonstrate that, as one may expect, neither of these basic approaches alone can guarantee high accuracy without substantially decreasing the size of the search neighborhood.

The contributions of this paper are as follows. We detail a system we have implemented that performs a generic merge/purge process that includes a declarative rule language for specifying an equational theory making it easier to experiment and modify the criteria for equivalence. Alternative algorithms that were implemented for the fundamental merge process are comparatively evaluated and demonstrate that no single pass over the data using one particular scheme as a key performs as well as computing the transitive closure over several independent runs each using a different key for ordering data. We show, for example, that *multiple passes* followed by the computation of the closure consistently dominates in accuracy for only a modest performance penalty. Finally, we discuss the computational costs of these alternative approaches and demonstrate fully implemented parallel solutions to speed up the process over a serial solution. The moral is simply that several distinct "cheap" passes over the data produces more accurate results than one "expensive" pass over the data.

The rest of this paper is organized as follows. In the next section, we will describe the specific details of the merge/purge problem we study, and two solutions based upon sorted neighborhood searching and clustering. Section 3 presents experimental results for our solution method. Finally, parallel processing of these solutions are briefly explored in section 4.

2 The Merge/Purge Problem

2.1 Problem description

Since we are faced with the task of merging very large databases, we presume a pure quadratic time process (i.e., comparing each pair of records) is infeasible under strict time constraints and limited capital budgets for hardware. For pedagogical reasons we assume that each record of the database represents information about "employees" and thus contains fields for a social security number, a name, and an address and other significant information that may be utilized in determining equivalence. Numerous errors in the contents of the records are possible, and frequently encountered. For example, names are routinely misspelled, parts are missing, salutations are at times included as well as nicknames in the same field. In addition, our employees may move or marry thus increasing the variability of their associated records. (Indeed, poor implementations of the merge/purge task by commercial organizations typically lead to several pieces of the same junk mail being mailed at obviously greater expense to the same household, as nearly everyone has experienced.)

There are two fundamental problems with performing merge/purge. First, the size of the data sets involved may be so large that only a relatively small portion of the total available data can reside in main memory at any point in time. Thus, the total database primarily resides on external store and any algorithm employed must be efficient, requiring as few passes over the data set as possible.

Second, the incoming new data is corrupted, either purposefully or accidentally, and thus the identification of matching data requires complex tests to identify matching data. The inference that two data items represent the same domain entity may depend upon considerable statistical, logical and empirical knowledge of the task domain. "Faulty" inferences can be in some cases worse than missing some matching data. The "accuracy" of the result (maximizing the number of correct matches while minimizing the number of false positives) is therefore of paramount importance. It is common that much of the engineering of a merge/purge process is devoted to experiment and comparative evaluation of the accuracy of the overall process, and in particular alternative criteria for matching records.

2.2 The sorted neighborhood method

We consider two approaches to obtaining efficient execution of any solution: partition the data to reduce

the combinatorics of matching large data sets, and utilize parallel processing. We require a means of effectively partitioning the data set in such a way as to restrict our attention to a number of small sets of candidates for matching. Consequently, we can process the candidate sets in parallel. Furthermore, if the candidate sets can be restricted to a very small subset of the data, quadratic time algorithms applied to each candidate set may indeed be feasible in the allotted time frame for processing, leading to perhaps better accuracy of the merge task.

One obvious method for bringing matching records close together is sorting the records over the most important discriminating key attribute of the data. After the sort, the comparison of records is then restricted to a small neighborhood within the sorted list. We call this method *the sorted neighborhood method.* The effectiveness of this approach is based on the quality of the chosen keys used in the sort. Poorly chosen keys will result in a poor quality merge, i.e., data that should be merged will be spread out far apart after the sort and hence will not be discovered. Keys should be chosen so that the attributes with the most discriminatory power should be the principal field inspected during the sort. This means that similar and matching records should have nearly equal key values. However, since we assume the data is corrupted and keys are extracted directly from the data, then the keys will also be corrupted. Thus, we may expect that a substantial number of matching records will not be caught. Our experimental results, presented in section 3, demonstrate this to be the case.

Given a collection of two or more databases, we first concatenate them into one sequential list of N records (after conditioning the records) and then apply the sorted neighborhood method. The sorted neighborhood method for solving the merge/purge problem can be summarized in three phases:

1. **Create Keys** : Compute a key for each record in the list by extracting relevant fields or portions of fields.

2. **Sort Data** : Sort the records in the data list using the key of step 1.

3. **Merge** : Move a fixed size window through the sequential list of records limiting the comparisons for matching records to those records in the window. If the size of the window is w records, then every new record entering the window is compared with the previous $w - 1$ records to find "matching" records. The first record in the window slides out of the window (see figure 1).

Sorting and then merging within a window is the essential approach of a *Sort Merge Band Join* as

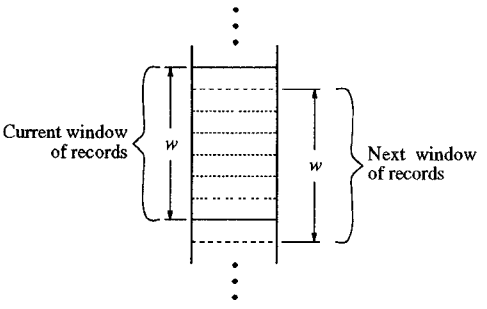


Figure 1: Window Scan during the Merge Phase

described by DeWitt [5]. As described in that paper, the sort and merge phase can be combined in one pass. The differences from this previous work and ours in the use of a complex function (the equational theory) to determine if records under consideration "match", and our concern for the accuracy of the computed result since matching records may not appear within a common "band". In [9], we describe the sorted-neighborhood method as a *generalization of band joins* and provide an alternative algorithm for the sorted-neighborhood method based on the *duplicate elimination* algorithm described in [3]. This *duplicate elimination* algorithms takes advantage of the fact that "matching" records will come together during different phases of the **Sort** phase. Due to space limitations, we will not describe this alternative solution here.

When this procedure is executed serially as a main-memory based process, the create keys phase is an $O(N)$ operation, the sorting phase is $O(N \log N)$, and the merging phase is $O(wN)$, where N is the number of records in the database. Thus, the total time complexity of this method is $O(N \log N)$ if $w < \lceil \log N \rceil$, $O(wN)$ otherwise. However, the constants in the equations differ greatly. It could be relatively expensive to extract relevant key values from a record during the create key phase. Sorting requires a few machine instructions to compare the keys. The merge phase requires the application of a potentially large number of rules to compare two records, and thus has the potential for the largest constant factor.

Note, however, that it may be the case, that for very large databases the dominant cost will be disk I/O, i.e., the number of passes over the data set. In this case, at least three passes would be needed, one pass for conditioning the data and preparing keys, at least a second pass, likely more, for a high speed sort like, for example, the AlphaSort [13], and a final pass for window processing and application of the rule program for each record entering the sliding window. Depending upon the complexity of the rule program, the last pass may indeed be the dominant cost. Later we consider the means of improving this phase by processing "parallel

windows" in the sorted list.

2.2.1 Clustering the data first

Although sorting the data may not be the dominant cost of merge/purge, we consider here an alternative to sorting based upon first partitioning the dataset into independent clusters using a key extracted from the data. Observe that we do not need a completely sorted database, but rather we desire a means of partitioning the data into independent subsets of data in such a fashion that we are assured as much as possible that matching records appear in each cluster. Then we apply the sorted-neighborhood method to each individual cluster independently and in parallel ideally as a main-memory based process. We call this approach the *clustering method.*

Given a group of two or more databases, we first concatenate them into one sequential list of N records. The clustering method can be summarized as the following two phase process:

1. **Cluster Data**: We scan the records in sequence and for each record we extract an n-attribute key and map it into an n-dimensional cluster space. For instance, the first three letters of the last name could be mapped into a 3D cluster space from our example database of names.

2. **Sorted-Neighborhood Method**: We now apply the sorted-neighborhood method independently on each cluster. We do not need, however, to recompute a key (step 1 of the sorted neighborhood method). We can use the key extracted above for sorting. Furthermore, we desire a cluster to be main memory-based when analyzed.

When this procedure is executed serially, the cluster data phase is an $O(N)$ operation, and assuming we partition the data into C equal sized clusters, the sorted-neighborhood phase is $O(N \log \frac{N}{C})$.

Clustering data as described above raises the issue of how well partitioned the data is after clustering. We use an approach that closely resembles the multidimensional partitioning strategy of [7]. If the data from which the n-attribute key is extracted is distributed uniformly over its domain, then we can expect all clusters to have approximately the same number of records in them. But real-world data is very unlikely to be uniformly distributed, i.e. skew elements and other hot spots will be prevalent, and thus, we must expect to compute very large clusters and some empty clusters.

Sometimes the distribution of some fields in the data is known, or can be computed as the data is inserted into the database. For instance, from a directory database we may compute the distribution of the first three letters of every name[1]. If we do not have access to such a list, we can randomly sample the name field of our database to have an approximation of the distribution of the first three letters. This information can be gathered off-line before applying the clustering method.

Now let us assume we want to divide our data into C clusters using a key extracted from a particular field. Given a frequency distribution histogram with B bins for that field ($C \leq B$), we want to divide those B bins (each bin represents a particular range of the field domain) into C subranges. Let b_i be the normalized frequency for bin i of the histogram ($\sum_{i=1}^{B} b_i = 1$). Then for each of the C subranges we must expect the sum of the frequencies over the subrange to be close to $\frac{1}{C}$ (e.g., if bins s to e, $1 \leq s \leq e \leq B$, are assigned to one cluster then we expect $\sum_{i=s}^{e} b_i \simeq \frac{1}{C}$). Each subrange will become one of our clusters and, given a record, we extract the key from the selected field, and map the key into the corresponding subrange of the histogram. The complexity of this mapping is, at worst, $\log B$.

2.3 Equational theory

The comparison of records, during the merge phase, to determine their equivalence is a complex inferential process that considers much more information in the compared records than the keys used for sorting. For example, suppose two person names are spelled nearly (but not) identically, and have the exact same address. We might infer they are the same person. On the other hand, suppose two records have exactly the same social security numbers, but the names and addresses are completely different. We could either assume the records represent the same person who changed his name and moved, or the records represent different persons, and the social security number field is incorrect for one of them. Without any further information, we may perhaps assume the later. The more information there is in the records, the better inferences can be made. For example, `Michael Smith` and `Michele Smith` could have the same address, and their names are "reasonably close". If gender and age information is available in some field of the data, we could perhaps infer that `Michael` and `Michele` are either married or siblings, rather than a misspelling.

What we need to specify for these inferences is an equational theory that dictates the logic of domain equivalence, not simply value or string equivalence. Users of a general purpose merge/purge facility benefit from higher level formalisms and languages permitting ease of experimentation and modification. For these reasons, a natural approach to specifying an equational theory and making it practical would be the use of a declarative rule language. Rule languages have been

[1] That is, we have a cluster space of $27 \times 27 \times 27$ bins (26 letters plus the space).

effectively used in a wide range of applications requiring inference over large data sets. Much research has been conducted to provide efficient means for their compilation and evaluation, and this technology can be exploited here for purposes of solving merge/purge efficiently.

As an example, here is a simplified rule in English that exemplifies one axiom of our equational theory relevant to merge/purge applied to our idealized employee database:

```
Given two records, r1 and r2.
IF the last name of r1 equals the last name of r2,
   AND the first names differ slightly,
   AND the address of r1 equals the address of r2
THEN
   r1 is equivalent to r2.
```

The implementation of "`differ slightly`" specified here in English is based upon the computation of a *distance function* applied to the first name fields of two records, and the comparison of its results to a threshold to capture obvious typographical errors that may occur in the data. The selection of a distance function and a proper threshold is also a knowledge intensive activity that demands experimental evaluation. An improperly chosen threshold will lead to either an increase in the number of falsely matched records or to a decrease in the number of matching records that should be merged. A number of alternative distance functions for typographical mistakes were implemented and tested in the experiments reported below including distances based upon *edit distance*, *phonetic distance* and *"typewriter" distance*. The results displayed in section 3 are based upon edit distance computation since the outcome of the program did not vary much among the different distance functions for the particular databases used in our study.

For the purpose of experimental study, we wrote an OPS5[6] rule program consisting of 26 rules for this particular domain of employee records and was tested repeatedly over relatively small databases of records. Once we were satisfied with the performance of our rules, distance functions, and thresholds, we recoded the rules directly in C to obtain speed-up over the OPS5 implementation[2].

It is important to note that the essence of the approach proposed here permits a wide range of "equational theories" on various data types. We chose to use string data in this study (e.g., names, addresses) for pedagogical reasons (after all everyone gets "faulty" junk mail). We could equally as well demonstrate the concepts using alternative databases of different typed objects and correspondingly different rule sets.

[2] At the time the system was built, the public domain OPS5 compiler was simply too slow for our experimental purposes. Another OPS5C compiler [12] was not available to us in time for these studies. The OPS5C compiler produces code that is reportedly many times faster than previous compilers. We captured this speed advantage for our study here by hand recoding our rules in C.

2.4 Computing the transitive closure over the results of independent runs

The effectiveness of the sorted neighborhood method highly depends on the key selected to sort the records. A key is defined to be a sequence of a subset of attributes, or substrings within the attributes, chosen from the record. For example, we may choose a key as the last name of the employee record, followed by the first non blank character of the first name sub-field followed by the first six digits of the social security field, and so forth.

In general, no single key will be sufficient to catch all matching records. Attributes that appear first in the key have a higher priority than those appearing after them. If the error in a record occurs in the particular field or portion of the field that is the most important part of the key, there may be little chance a record will end up close to a matching record after sorting. For instance, if an employee has two records in the database, one with social security number `193456782` and another with social security number `913456782` (the first two numbers were transposed), and if the social security number is used as the principal field of the key, then it is very unlikely both records will fall under the same window, i.e. the two records with transposed social security numbers will be far apart in the sorted list and hence they may not be merged. As we will show in the next section, the number of matching records missed by one run of the sorted neighborhood method can be large.

To increase the number of similar records merged, two options were explored. The first is simply widening the scanning window size by increasing w. Clearly this increases the computational complexity, and, as discussed in the next section, does not increase dramatically the number of similar records merged in the test cases we ran until w becomes excessively large.

The alternative strategy we implemented is to execute several independent runs of the sorted neighborhood method, each time using a different key and a *relatively small window*. We call this strategy the *multi-pass approach*. For instance, in one run, we use the address as the principal part of the key while in another run we use the last name as the principal part of the key. Each independent run will produce a set of pairs of records which can be merged. We then apply the transitive closure to those pairs of records. The results will be a union of all pairs discovered by all independent runs, with no duplicates, plus all those pairs that can be inferred by transitivity of equality.

The reason this approach works for the test cases explored here has much to do with the nature of the

errors in the data. Transposing the first two digits of the social security number leads to unmergeable records as we noted. However, in such records, the variability or error appearing in another field of the records may indeed not be so large. Therefore, although the social security numbers in two records are grossly in error, the name fields may not be. Hence, first sorting on the name fields as the primary key will bring these two records closer together lessening the negative effects of a gross error in the social security field.

It is clear that the utility of this approach is therefore driven by the nature and occurrences of the errors appearing in the data. Once again, the choice of keys for sorting, their order, and the extraction of relevant information from a key field is a knowledge intensive activity that must be explored prior to running a merge/purge process.

In the next section we will show how the *multi-pass* approach can drastically improve the accuracy of the results of only one run of the sorted neighborhood method with varying large windows. Of particular interest is the observation that only a small search window was needed for the *multi-pass* approach to obtain high accuracy while no individual run with a single key for sorting produced comparable accuracy results with a large window (other than window sizes approaching the size of the full database). These results were found consistently over a variety of generated databases with variable errors introduced in all fields.

3 Experimental Results

3.1 Generating the databases

All databases used to test the sorted neighborhood method and the clustering method were generated automatically by a database generator that allow us to perform controlled studies and to establish the accuracy of the solution method. This database generator provides a large number of parameters including, the size of the database, the percentage of duplicate records in the database, and the amount of error to be introduced in the duplicated records in any of the attribute fields. Each record generated consists of the following fields, some of which can be empty: social security number, first name, initial, last name, address, apartment, city, state, and zip code. The names were chosen randomly from a list of 63000 real names. The cities, states, and zip codes (all from the U.S.A) come from publicly available lists.

The errors introduced in the duplicate records range from small typographical changes, to complete change of last names and addresses. When setting the parameters for the kind of typographical errors, we used known frequencies from studies in spelling correction algorithms [11]. For this study, the generator selected from 10% to 50% of the generated records for duplication with errors, where the error was controlled according to published statistics found for common real world datasets.

3.2 Pre-processing the database

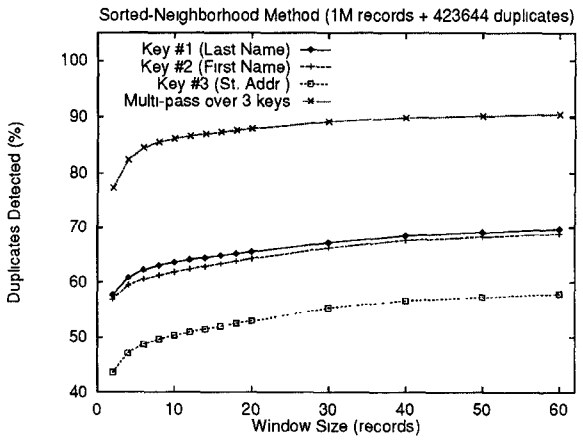
Pre-processing and conditioning the records in the database prior to the merge/purge operation might increase the chance of finding two duplicate records. For example, names like `Joseph` and `Giuseppe` match in only three characters, but are the same name in two different languages, English and Italian. A nicknames database or name equivalence database is used to assign a common name to records containing identified nicknames.

Since misspellings are introduced by the database generator, we explored the possibility of improving the results by running a spelling correction program over some fields. Spelling correction algorithms have received a large amount of attention for decades [11]. Most of the spelling correction algorithms we considered use a corpus of correctly spelled words from which the correct spelling is selected. Since we only have a corpus for the names of the cities in the U.S.A. (18670 different names), we only attempted correcting the spelling of the city field. We chose the algorithm described by Bickel in [2] for its simplicity and speed. Although not shown in the results presented in this paper, the use of spell corrector over the city field improved the percent of correctly found duplicated records by only 1.5% - 2.0%. Most of the effort in matching resides in the equational theory rule base.

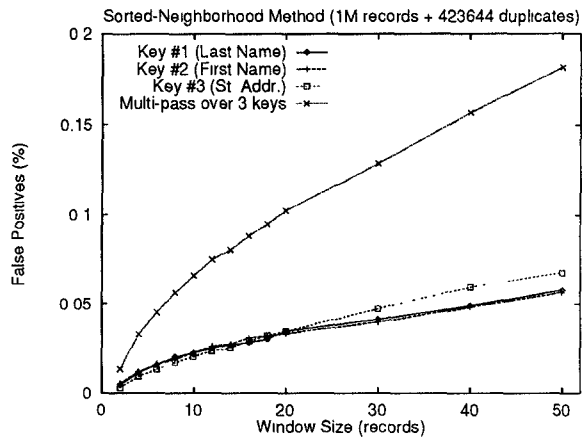
3.3 Initial results on accuracy

The purpose of this first experiment was to determine baseline accuracy of the sorted-neighborhood method. We ran three independent runs of the sorted neighborhood method over each database, and used a different key during the sorting phase of each independent run. On the first run the last name was the principal field of the key. On the second run, the first name was the principal field, while in the last run, the street address was the principal field. Our selection of the attribute ordering of the keys was purely arbitrary. We could have used the social-security number instead of, say, the street address. We assume all fields are noisy (and under the control of our data generator to be made so) and therefore it does not matter what field ordering we select for purposes of this study.

Figure 2 shows the effect of varying the window size from 2 to 50 records in a database with 1,000,000 records and with an additional 1423644 duplicate records with varying errors. A record may be duplicated more than once. Notice that each independent run found from 50% to 70% of the duplicated pairs. Notice also that increasing the window size does not help much and taking in consideration that the time complexity of the



(a) Percent of correctly detected duplicated pairs



(b) Percent of incorrectly detected duplicated pairs

Figure 2: Accuracy results for a 1,000,000 records database

procedure goes up as the window size increases, it is obviously fruitless at some point to use a large window.

The line marked as *Multipass over 3 keys* in figure 2 shows our results when the program computes the transitive closure over the pairs found by the three independent runs. The percent of duplicates found goes up to almost 90%. A manual inspection of those records not found as equivalent revealed that most of them are pairs that would be hard for a human to identify without further information.

As mentioned above, our equational theory is not completely trustworthy. It can mark two records as similar when they are not the same real-world entity (false-positives). Figure 2 shows the percent of those records incorrectly marked as duplicates as a function of the window size. The percent of false positives is almost insignificant for each independent run and grows slowly as the window size increases. The percent of false positives after the transitive closure is also very small, but grows faster than each individual run alone. This suggests that the transitive-closure may not be as accurate if the window size of each constituent pass is very large!

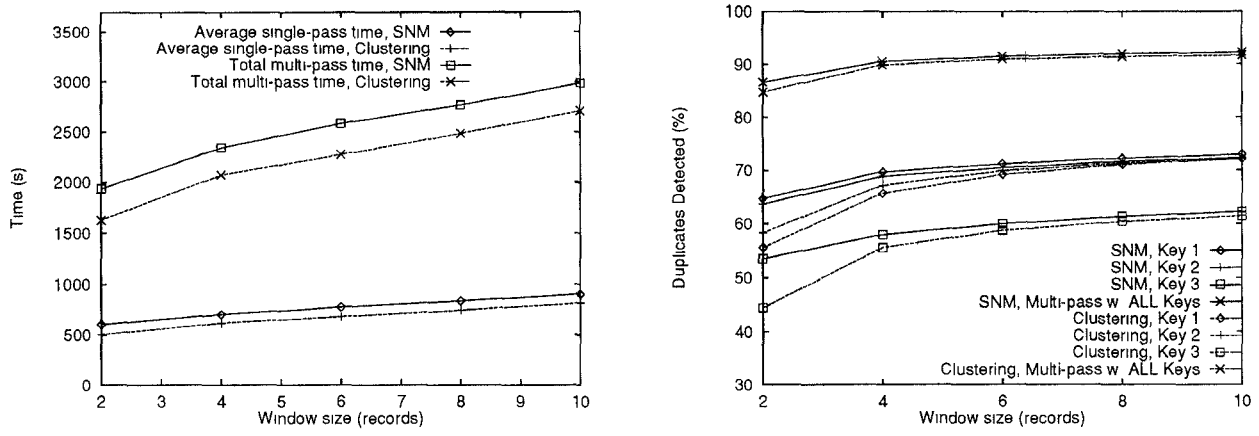
The number of independent runs needed to obtain good results with the computation of the transitive closure depends on how corrupt the data is and the keys selected. The more corrupted the data, more runs might be needed to capture the matching records. The transitive closure, however, is executed on pairs of tuple id's, each at most 30 bits, and fast solutions to compute transitive closure exist [1]. From observing real world scenarios, the size of the data set over which the closure is computed is at least one order of magnitude smaller than the corresponding database of records, and thus does not contribute a large cost. But note we pay a heavy price due to the number of sorts or clusterings of the original large data set. We address this issue in section 4.

3.4 The Clustering Method

To test the clustering method, we created a database with 250,000 records of which 35% of the records were selected to add a maximum of 5 duplicates per selected record. The resulting 468,730 records database was analyzed using the sorted-neighborhood method and the clustering method. We used the same three keys used before for the sorted-neighborhood method and ran three independent runs, one for each key. Then the transitive closure over the results of all independent runs was computed. Each run of the clustering method initially divided the data into 32 clusters. This number of clusters was chosen to match the "fan-out" of the merge-sort algorithm. This way we guarantee each cluster fits in memory. The results presented in this section were obtained on a Sun's Sparc 5's, running SunOS 5.3.

Figure 3(a) compares the average time of all single-pass runs of the sorted neighborhood and clustering method. As expected, the time to execute an independent run (and, thus, the *multi-pass* approach), is lower when we partitioned the data first into independent clusters.

The graph in figure 3(b) shows the accuracy results of both methods for this experiment. In all cases the accuracy of the sorted-neighborhood edged higher than the accuracy of the clustering method. The principal reason for this is the size of the key used on each run. Even though the field used to produce the key for each independent run was the same under each method, the size of the key was not. As explained



(a) Average Total Times

(b) Accuracy of Results

Figure 3: Clustering Method vs. Sorted Neighborhood Method on 1 processor

in section 2.2.1, the clustering method uses the fixed-sized key extracted during its clustering phase to later sort each cluster independently. On the other hand, the sorted-neighborhood method used the complete length of the strings in the key field, making the size of the key used variable. Records that should be merged are expected to end closer together in a sorted list the larger the size of the key used. Since, for the case of this experiment, the average size of the key used by the sorted-neighborhood method is larger that the one used by the clustering method, we must expect the sorted-neighborhood method to produce more accurate results. Figure 3(b) also shows how the accuracy improves after the *multi-pass* approach is applied to the independent runs. As we saw in the previous section, when we applied the closure to all pairs found to be similar with the three independent runs, the accuracy jumped to over 90% for $w > 4$.

3.5 Analysis

The natural question to pose is when is the *multi-pass* approach superior to the single-pass case? The answer to this question lies in the complexity of the two approaches for a *fixed accuracy rate* (for the moment we consider the percentage of correctly found matches).

Here we consider this question in the context of a main-memory based sequential process. The reason being that, as we shall see, clustering provides the opportunity to reduce the problem of sorting the entire disk-resident database to a sequence of smaller, main-memory based analysis tasks. The serial time complexity of the *multi-pass* (mp) approach (with r passes) is given by the time to create the keys, the time to sort r times, the time to window scan r times (of window size w) plus the time to compute the transitive closure. In our experiments, the creation of the keys was integrated into the sorting phase. Therefore, we treat both phases as one in this analysis. Under the simplifying assumption that all data is memory resident (i.e., we are not I/O bound),

$$T_{mp} = c_{sort} r N \log N + c_{wscan} r w N + T_{cl_{mp}}$$

where r is the number of passes and $T_{cl_{mp}}$ is the time for the transitive closure. The constants depict the costs for comparison only and are related as $c_{wscan} = \alpha c_{sort}$, where $\alpha > 1$. From analyzing our experimental program, the window scanning phase contributes a constant, c_{wscan}, which is at least $\alpha = 6$ times as large as the comparisons performed in sorting. We replace the constants in terms of the single constant c. The complexity of the closure is directly related to the accuracy rate of each pass and depends upon the duplication in the database. However, we assume the time to compute the transitive closure on a database that is orders of magnitude smaller than the input database to be less than the time to scan the input database once (i.e. it contributes a factor of $c_{cl} N < N$). Therefore,

$$T_{mp} = crN \log N + \alpha crwN + T_{cl_{mp}}$$

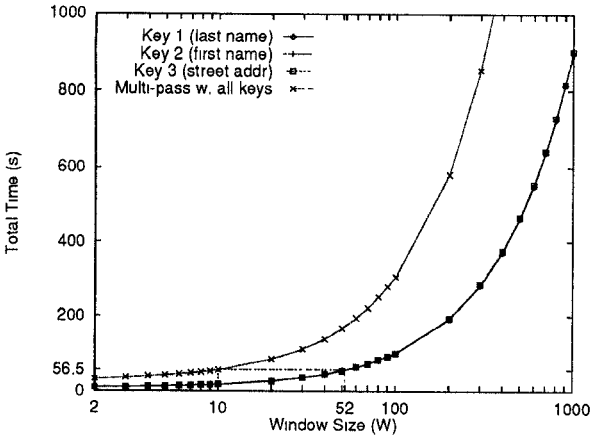
for a window size of w. The complexity of the single pass (sp) sorted-neighborhood approach is similarly given by:

$$T_{sp} = cN \log N + \alpha cWN + T_{cl_{sp}}$$

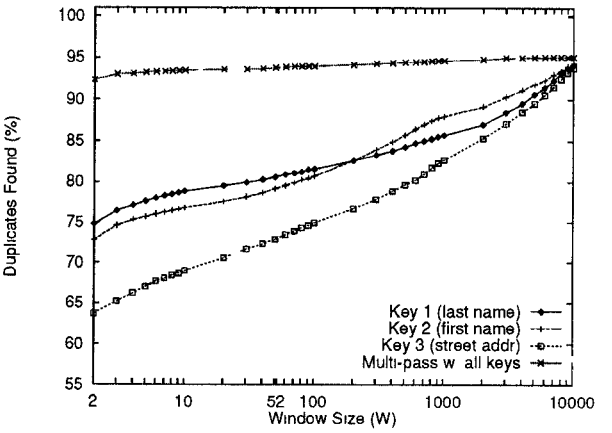
for a window size of W.

For a fixed accuracy rate, the question is then for what value of W of the single pass sorted-neighborhood method does the *multi-pass* approach perform better in time, i.e., when is $T_{sp} > T_{mp}$. Solving this inequality, we have:

$$W > \frac{r-1}{\alpha} \log N + rw + \frac{1}{\alpha cN} \left(T_{cl_{mp}} - T_{cl_{sp}} \right)$$



(a) Time for each single-pass runs and the multi-pass run



(b) Accuracy of each single-pass runs and the multi-pass run

Figure 4: Time and Accuracy for a Memory-based Database (13751 records)

$$W > \frac{r-1}{\alpha} \log N + rw + \frac{r-1}{\alpha cN} T_{cl_{sp}} + \frac{1}{\alpha cN} T_{cl_{mp}}$$

To validate this model, we generated a small database of 13,751 records (7,500 original records, 50% selected for duplications, and 5 maximum duplicates per selected record. The total size of the database in bytes was approximately 1 MByte). Once read, the database stayed in core during all phases. We ran three independent single-pass runs using different keys and a multi-pass run using the results of the three single-pass runs. The parameters for this experiment were $N = 13751$ records and $r = 3$. For the particular case were $w = 10$, we have $\alpha \simeq 6$, $c \simeq 1.2 \times 10^{-5}$, $T_{cl_{sp}} = 1.2s$, and $T_{cl_{mp}} = 7$. Thus, the *multi-pass* approach dominates the single sort approach for these datasets when $W > 41$.

Figure 4(a) shows the time required to run each independent run of the sorted-neighborhood method on one processor, and the total time required for the *multi-pass* approach while figure 4(b) shows the accuracy of each independent run as well as the accuracy of the *multi-pass* approach (please note the logarithm scale). For $w = 10$, figure 4(a) shows that the *multi-pass* approach needed 56.5s to produce an accuracy rate of 93.4% (figure 4(b)). Looking now at the times for each single-pass run, their total time is close to $56s$ for $W = 52$, slightly higher than estimated with the above model. But the accuracy of all single-pass runs in figure 4(b) at $W = 52$ goes from 73% to 80%, well below the 93.4% accuracy level of the *multi-pass* approach. Moreover, no single-pass run reaches an accuracy of more than 93% until $W > 7000$, at which point (not shown in figure 4(a)) their execution time are over 4,800 seconds (80 minutes).

Let us now consider the issue when the process is I/O bound rather than a compute-bound main-memory process. We consider three cases. In the first case, the sorted-neighborhood method, one pass is needed to create keys, $logN$ passes[3] to globally sort the entire database, and one final pass for the window scanning phase. Thus, approximately $2 + logN$ passes are necessary. In the second case, the clustering method, one pass is needed to assign the records to clusters followed by another pass where each individual cluster is independently processed by a main-memory sort and a window scanning phase. The clustering method, with approximately only 2 passes, would dominate the global sorted-neighborhood method. Nevertheless, notice that the actual difference in time, shown in figure 3(b), is small for the case we considered. This is mainly due to the fact that the window-scanning phase is, for the case of our equational-theory, much more expensive than the sorting or clustering phase and thus any time advantage gained by first clustering and then sorting becomes small with respect to the overall time.

The third case, the *multi-pass* approach, would seem to be the worse of the lot. The total number of passes will be a multiple of the number of passes required for the method we chose to do each pass. For instance, if we use the clustering method for 3 passes, we should expect at least 6 passes over the dataset (for each key, one pass to cluster and another pass to window scan each cluster), while if we use the sorted-neighborhood method, we should expect $6 + 3logN$ passes (3 separate

[3] In our experiments we used merge sort, as well as its parallel variant, which used a 16-way merge algorithm to merge the sorted runs.

sorts). Clearly then the *multi-pass* approach would be the worst performer in time over the less expensive clustering method. Figure 3 shows this increase in time. However, notice the large difference in accuracy between the multi-pass and single-pass approaches in figure 3(a). Clearly the *multi-pass* approach has a larger accuracy than any of the two single-pass approaches. Thus, in a serial environment, the user must weigh this trade-off between execution time and accuracy.

In the next section we explore parallel variants of the three basic techniques discussed here to show that with suitable parallel hardware, we can speed-up the *multi-pass* approach to a level comparable to the time to do a single-pass approach, but with a very high accuracy, i.e. a few small windows ultimately wins.

4 Parallel implementation

With the use of a centralized parallel or distributed shared-nothing multiprocessor computer we seek to achieve a linear speedup over a serial computer. Here we briefly sketch the means to achieve this goal.

4.1 Single and Multi-pass sorted neighborhood method

The parallel implementation of the sorted-neighborhood method is as follows. Let N be the number of records in the database, P be the number of processors in our multiprocessor environment, and w be the size (in number of records) of the merge phase window.

For the sort phase, a coordinator processor (CP) fragments the input database in a round-robin fashion among all P sites. Each site then sorts its local fragment in parallel. Then the CP does a P-way join, reading a block at a time (as needed) from each of the P sites.

Conceptually, for the merge phase, we should start by partitioning the input database into P fragments and assign each fragment to a different processor. The fragment assigned to processor i should replicate the last $w-1$ records from the fragment assigned to site $i-1$, for $1 < i \leq P$. Similarly, for $1 \leq i < P$, the fragment at site i should replicate the first $w-1$ records from the fragment at site $i+1$. These small "bands" of replicated records are needed to make the fragmentation of the database invisible when the window scanning process is applied in parallel to each fragment. This fragmentation strategy is depicted in figure 5.

For concreteness, we divide the database as follows. Let M be the number of records that fit in memory at each of the P sites. The CP reads a block of M records and sends them to site 1 which stores them in memory and starts applying the window scanning procedure. The CP stores the last $w-1$ of the block sent to site 1 and reads $M-(w-1)$ records from disk, for a total of M records which are then sent to site 2. This algorithm is repeated for each site in a round-robin order until there are no more records available from the input database. Notice that the total number of replicated records is larger for this approach than the method described in the previous paragraph. Nevertheless, with this approach the amount of time a processor is idle is reduced, and each site does not need to write the received blocks into disk since its processing is in memory. In fact, as each site receives a block of records, it applies the window scanning procedure to the records, sends the resulting pairs (a pair of tuple id's) back to the CP, discards the current block, and waits for the CP to send another block.

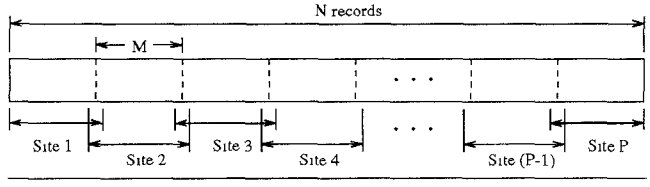
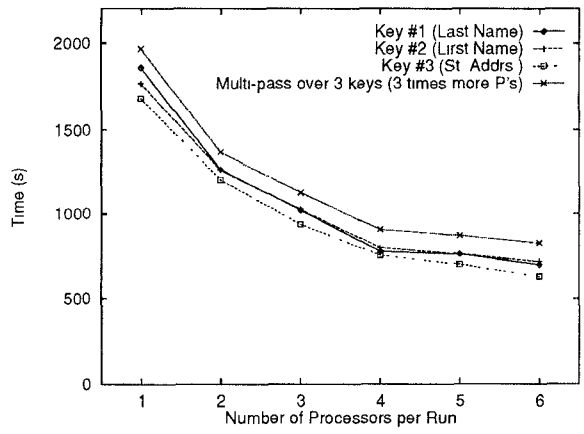


Figure 5: Partition of a sorted database with "bar ds" of replicated tuples.

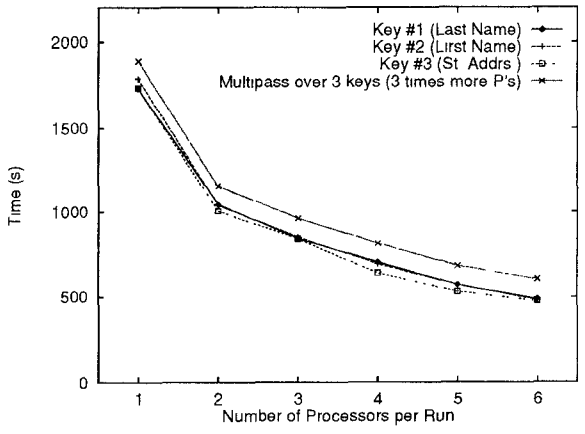
We implemented this method on an HP cluster consisting of 8 HP9000 processors interconnected by a FDDI network. Figure 6(a) shows the total time taken for each of the three independent runs from figure 2 as the number of processors increases. The window size for all these runs was 10 records. The figure also shows the time it will take the sorted-neighborhood method to execute all three independent runs over three times the number of processors and then the computation of the transitive closure of the results. Since we do not have enough processors to actually run all sorted-neighborhood runs concurrently, we must estimate this time using the results of each independent run. We ran all independent runs in turn and stored the results on disk. We then computed the transitive closure over the results stored on disk and measured the time for this operation. The total time, if we run all runs concurrently, is approximately the maximum time taken by any independent run plus the time to compute the closure. Notice that the speed-ups obtained as the number of processors grows are sublinear. The obvious overhead is paid in the process of reading and broadcasting of data to all processors.

4.2 Single and Multi-pass clustering method

The parallel implementation of the clustering method works as follows. Let N be the number of records in the database, P the number of processors and C the number of clusters we want to form per processor. Given a frequency distribution histogram, we divide its range into CP subranges as described in section 2.2.1. Each processor is assigned C of those subranges. To cluster the data, a coordinator processor reads the database



(a) Sorted Neighborhood Method



(b) Clustering Method

Figure 6: Time Results for the Sorted-neighborhood and Clustering Methods (1,000,000 records, w=10)

and sends each record to the appropriate processor. Each processor saves the received records in the proper local cluster. (Notice that we may precompute the cluster assignment of each record for the alternative keys on the *multi-pass* approach in only a single pass over the data.) Once the coordinator finishes reading and clustering the data among the processors, all processors sort and apply the window scanning method to their local clusters. Alternatively, to scale the process up, multiple coordinators can be used to cluster the data in parallel, followed by a final "cluster merging phase".

Load balancing of the operation becomes an issue when we use more than one processor and the histogram method does a bad job of partitioning the data. Our program attempts to do an initial static load balancing. The coordinator processor keeps track of how many records it sent to each processor (and cluster) and therefore it knows, at the end of the clustering stage, how balanced the partition is. It then redistributes the clusters among processors using a *longest processing time first*[8] strategy. That is, move the largest job in an overloaded processor to the most underloaded processor, and repeat until a "well" balanced load is obtained. In [4] we detailed the load balancing algorithm in the context of parallel database joins.

The time results for the clustering method are depicted in figure 6(b). These results are for the same database used to obtain the timing results for the sorted neighborhood method, a window size of 10 records, and 100 clusters per processor. Comparing the two graphs in figure 6 we note that the clustering method is, as expected, a faster parallel process than the sorted-neighborhood method.

4.3 Scaling Up

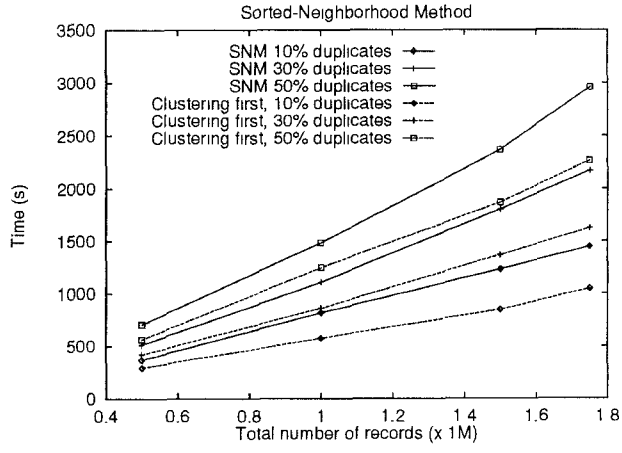


Figure 7: Time performance of the sorted-neighborhood and clustering methods

Finally, we demonstrate that the sorted neighborhood and clustering methods scale well as the size of the database increases. We created 4 databases with no duplicates of different sizes (.5, 1, 1.5, and 2 $\times 10^6$ records) and, for each one of them, we selected 10%, 30%, and 50% of its tuples for duplication[4]. We again ran three concurrent but independent runs of the sorted-neighborhood method (and the clustering method), each with a different key, and then computed the transitive closure of the results. Each independent run used 4 processors. The results are shown in figure 7. As expected, the time increases linearly as the size of the databases increase independent of the duplication factor.

Using the graphs in figure 7 we can estimate how

[4] Thus, we generated 12 databases.

much time it will take to process 1 billion records using both methods. We assume the time will keep growing linearly as the size of the database increases. For the sorted-neighborhood method, let us consider the last point of the 30% graph. Here, a database with 2,639,892 records was processed in 2172 seconds (including all the I/O time). Thus, given a database with 1,000,000,000 records, we will need approximately $1 \times 10^9 \times \frac{2172}{2639892}$ s $= 8.2276 \times 10^5$ s $\simeq$ 10 days. Doing the same analysis with the clustering method, we first notice that a database of size 2,639,892 records was processed in 1621 seconds. Thus, given a database with 1,000,000,000 records, we will need approximately $1 \times 10^9 \times \frac{1621}{2639892}$ s $= 6.1404 \times 10^5$ s $\simeq$ 7 days. Of course, doubling the speed of the workstations and utilizing the various RAID-based striping optimizations to double disk I/O speeds discussed in [13] and elsewhere (which is certainly possible today since the HP processors and disks used here are slow compared to, for example, *Alpha* workstations with modern RAID-disk technology) would produce a total time that is at least half the estimated time, i.e. within 3-4 days.

5 Conclusion

The sorted neighborhood method described in this paper is expensive due to the sorting phase, as well as the need to search in large windows for high accuracy. An alternative method based on data clustering modestly improves the process in time. However, neither achieves high accuracy without inspecting large neighborhoods of records. Of particular interest is that performing the merge/purge process multiple times over small windows, followed by the computation of the transitive closure, dominates in accuracy for either method. While multiple passes with small windows increases the number of successful matches, small windows also favor decreases in false positives, leading to high overall accuracy of the merge phase! An alternative view is that a single pass approach would be far slower to achieve a comparable accuracy as a multi-pass approach.

In this paper we have only addressed the most time consuming and important part of the merge/purge problem, namely, the merge phase. We have not addressed the *purge* phase. In many applications the purge phase requires complex functions to extract or "deduce" relevant information from merged records, including various statistical measures. The rule base comes in handy here as well. The consequent of the rules can be programmed to specify selective extraction, purging, and even deduction of information, i.e. "data-directed" projections, selections and deductions can be specified in the rule sets when matching records are found.

6 Acknowledgments

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References

[1] R. Agrawal and H. V. Jagadish. Multiprocessor Transitive Closure Algorithms. In *Proc. Int'l Symp. on Databases in Parallel and Distributed Systems*, pages 56–66, December 1988.

[2] M. A. Bickel. Automatic Correction to Misspelled Names: a Fourth-generation Language Approach. *Communications of the ACM*, 30(3):224–228, 1987.

[3] D. Bitton and D. J. DeWitt. Duplicate Record Elimination in Large Data Files. *ACM Transactions on Database Systems*, 8(2):255–265, June 1983.

[4] H. M. Dewan, M. A. Hernández, K. Mok, and S. Stolfo. Predictive Load Balancing of Parallel Hash-Joins over Heterogeneous Processors in the Presence of Data Skew. In *Proc. 3rd Int'l Conf. on Parallel and Distributed Information Systems*, pages 40–49, September 1994.

[5] D. J. DeWitt, J. F. Naughton, and D. A. Schneider. An Evaluation of Non-Equijoin Algorithms. In *Proc. 17th Int'l. Conf. on Very Large Databases*, pages 443–452, Barcelona, Spain, 1991.

[6] C. L. Forgy. OPS5 User's Manual. Technical Report CMU-CS-81-135, Carnegie Mellon University, July 1981.

[7] S. Ghandeharizadeh. *Physical Database Design in Multiprocessor Database Systems.* PhD thesis, Department of Computer Science, University of Wisconsin - Madison, 1990.

[8] R. Graham. Bounds on multiprocessing timing anomalies. *SIAM Journal of Computing*, 17:416–429, 1969.

[9] M. A. Hernández. A Generalization of Band-Joins and the Merge/Purge Problem. Technical Report CUCS-005-1995, Department of Computer Science, Columbia University, February 1995.

[10] W. Kent. The Breakdown of the Information Model in Multi-Database Systems. *SIGMOD Record*, 20(4):10–15, December 1991.

[11] K. Kukich. Techniques for Automatically Correcting Words in Text. *ACM Computing Surveys*, 24(4):377–439, 1992.

[12] D. P. Miranker, B. Lofaso, G. Farmer, A. Chandra, and D. Brant. On a TREAT-based Production System Compiler. In *Proc. 10th Int'l Conf. on Expert Systems*, pages 617–630, 1990.

[13] C. Nyberg, T. Barclay, Z. Cvetanovic, J. Gray, and D. Lomet. AlphaSort: A RISC Machine Sort. In *Proceedings of the 1994 ACM-SIGMOD Conference*, pages 233–242, 1994.

[14] Y. R. Wang and S. E. Madnick. The Inter-Database Instance Identification Problem in Integrating Autonomous Systems. In *Proceedings of the Sixth International Conference on Data Engineering*, February 1989.