A Probabilistic Geocoding System Utilising a Parcel Based Address File

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Abstract. It is estimated that between 80% and 90% of governmental address collections contain address information. Geocoding – the process of assigning geographic coordinates to addresses – is becoming increasingly important in application areas that involve the analysis and mining of address data. In many cases, address records are captured and/or stored in a free-form or inconsistent manner. This fact complicates the task of accurately matching such addresses to spatially-annotated reference data. In this paper we describe a geocoding system that is based on a comprehensive high-quality geocoded national address database. It uses a learning address parser based on hidden Markov models to segment free-form addresses into components, and a rule-based matching engine to determine the best matches to the reference database.

Introduction

Many businesses, government organisations and research projects collect large amounts of data, the techniques collectively known as *data mining* have recently attracted interest both from academia and industry. While there is ongoing research in data mining algorithms (to extract new and unexpected information from data, build predictive models, or detect outliers and anomalies), a large proportion of the time and effort in real world data mining projects is spent understanding the data and in data preparation processes (which may dominate the actual data mining activity) [14]. It is generally accepted that about 20% to 30% of the time and effort in a data mining project is spent on data understanding, and about 50% to 70% for data preparation.

In this paper we discuss one issue of data preparation, namely the matching of user data with geocoded reference data (which comprises cleaned and standardised records containing address information plus their geographical loca-

projects. The US Federal Geographic Data Committee estimates that geographic location is a key feature in 80% to 90% of governmental data collections. In many cases, addresses are the key to spatially enable data (i.e. to convert data with locations). The aim of geocoding is to generate a geographic location (latitude and longitude) from street address information in the user data set. Once geocoded, the data can be used for further processing, for spatial analysis [7], and it can be visualised and combined with other data using Geographical Information Systems (GIS).

Applications of spatial data analysis and mining are widespread. In the health sector, for example, geocoded data can be used to find local clusters of disease. Environmental health studies often rely on GIS and geocoding software to identify areas of potential exposure and to locate where people live in relation to these areas. Geocoded data can also help in the planning of new health resources, so that additional health care providers can be allocated close to where there is an unmet need for such services. An overview of geographical health issues can be found in [1]. Geocoded client data, combined with additional demographic information, can help businesses to better plan marketing and future expansion, and analysis of historical geocoded data, for example, can show changes in their geographic distribution. For national censuses, geocoding can be used to assign people or households to small area units, for example census collection districts, which are the basis of further statistical analysis.

Geocoding can be seen as a special case of data (or record) linkage, the task of linking records from one or more data sets belonging to the same entity. Most of the time, the linkage (or matching) process is challenged by the lack of common entity identifiers, and thus becomes non-trivial [3, 8, 18]. In such cases, available partially identifying information – like names, addresses, and dates – is used to decide if two (or more) records correspond to the same entity. This process is computationally intensive, and linking today's large data sets becomes increasingly difficult using traditional linkage techniques. In many data mining and data analysis projects, data linkage is needed to merge, match, or combine information from multiple sources in order to use all available data and to allow more detailed analysis.

In the following section we discuss geocoding techniques in more detail, and in Section 3 we present an overview of our geocoding system. The two central issues in geocoding are (1) the accurate and efficient matching of user addresses with the address information stored in the geocoded reference data and (2) the efficient retrieval of the address location (latitude and longitude) of the matched geocoded records. In order to achieve accurate matching, addresses both in the user data set and the geocoded reference data must be cleaned and standardised in the same way. We cover this issue in detail in Section 3.1. Address locations can efficiently be retrieved from the geocoded reference data by converting the traditional database tables (or

Geocoding

There are two basic scenarios for geocoding user data. In the first, a user wants to automatically geocode a (large) data set. The geocoding system should find a *possible* match for each record in the user data set without human intervention. Each record needs to be attributed with the corresponding location *match status* which indicates the accuracy of the match obtained (for example, an exact address match, or a street level match, or a locality level match). This scenario might become problematic if the user data is not of high quality and contains records with missing, incorrect, or out-of-date address information. Typographical errors are common with addresses, especially when they are recorded over the telephone, scanned, or manually typed from handwritten forms. As reported in [13], a match rate of 70% successfully geocoded records is often considered an acceptable result.

In the second scenario a user interactively wants to geocode a single address (or a small number of addresses) that may be incomplete, erroneous or uncertain. The system should return the location if an exact match can be found, or alternatively a list of possible matches, together with a matching status and a likelihood rating. This geocoding of a single record should be done in (near) real time (i.e. less than a couple of seconds response time) and be available via a graphical user interface (for example a Web site).

Record linkage techniques [3, 8, 18], where the aim is to link together all records belonging to the same entity, normally classify matched record pairs into one of the three classes *matches*, *non-matches* or *possible matches*, with the latter class containing those record pairs for which a human oversight, also known as *clerical review*, is needed to decide their final status. This is similar to the second geocoding scenario described above, where the user is presented with a selection of possible matches (sorted according to matching status and likelihood rating).

Modern GIS software packages provide for street level geocoding. As a recent study shows [2], substantial differences in positional error exist between addresses geocoded using street reference files (containing geographic centreline coordinates, street numbers and names, and postcodes) and the corresponding cadastral coordinates. The use of point property parcel coordinates (i.e. the centres or centroids of properties), derived from cadastral data, is expected to significantly reduce these positional errors. Figure 1 gives an illustrative example. Even small inaccuracies in geocoding can result in addresses being assigned to, for example, different census collection districts, which can have significant implications for small area analysis. A comprehensive property based database is available for Australia: the Geocoded National Address File (G-NAF). It is discussed in details in the following section.

Figure 2: Sample geocoding using property parcel centres (numbers 1 to 7) and street file centreline (dashed line and numbers 8 to 13, with the dotted lines corresponding to a global street offset)

Figure 3: Simplified G-NAF data model (10 main tables only). Links 1-n denote one-to-many relationships, links 1-1 denote one-to-one relationships.

that collects data to be used for land planning, as well as property, infrastructure or resource management. Additionally, national organisations like telecommunications, electoral rolls and statistics or census bureaus collect their own data. All these data sets are collected for specific purposes, serving different content and might be stored in different formats.

In 2004, the Australian Bureau of Statistics (ABS) released a nation-wide, standardised and high-quality geocoded data set known as the Geocoded National Address File (G-NAF), which is now recognised in Australia since 1990 [13], and after years of planning, development and refinement the G-NAF was first released in March 2004. Currently 32 million address records from 13 organisations were used in a large-scale cleaning and integration process, resulting in a database consisting of 10 tables (or files). Figure 2 shows the simplified data model of the 10 G-NAF tables. For our project we only used the G-NAF records covering the Australian state of New South Wales (NSW), containing around 4.5 million records.

Table 1. Characteristics of the 10 main G-NAF tables (NSW data only)

table	Numbers of records and attributes	Keys (persistent identifiers)
ADDRESS_ALIAS	333,729 / 7	PRINCIPAL_PID ALIAS_PID
ADDRESS_DETAIL	4,585,707 / 34	GNAF_PID LOCALITY_PID STREET_PID ADDRESS_SITE_PID
ADDRESS_SITE	4,499,157 / 7	ADDRESS_SITE_PID
ADDRESS_SITE_GEOCODE	3,872,217 / 15	ADDRESS_SITE_PID
CITY	5,357 / 9	LOCALITY_PID
CITY_ALIAS	575 / 9	LOCALITY_PID ALIAS_PID
CITY_GEOCODE	5,318 / 14	LOCALITY_PID
STREET	60,586 / 6	STREET_PID
STREET_LOCALITY_ALIAS	2,940 / 10	STREET_PID LOCALITY_PID
STREET_LOCALITY_GEOCODE	130,262 / 16	STREET_PID LOCALITY_PID

locations for a single address, and vice versa, and aliases are available at multiple levels. Three geocode tables contain location (latitude and longitude) information for different levels. If an exact address match can be found, its location is retrieved from the ADDRESS_SITE_GEOCODE table. If there is only a match at the street level (but not street number), then the STREET_LOCALITY_GEOCODE table provides an overall street geocode. Finally, if no street level match can be found, the LOCALITY_GEOCODE table contains geocode information for cities, suburbs, and localities. The street and locality level geocode tables also contain information about the extent of streets and localities, respectively.

System Overview

The geocoding system presented in this paper is part of the *Febri* (Freely Extended Record Linkage) data linkage system [3], that contains modules to clean and standardise data sets which can contain names, addresses and dates; deduplicate such cleaned data. An overview of the *Febri* geocoding system is shown in Figure 3. The geocoding process can be split into the preprocessing of the G-NAF tables (which is described in detail in Sections 3.1 and 3.2), matching with user-supplied addresses as presented in Section 4.

The preprocessing step takes the G-NAF tables and uses the *Febri* address cleaning and deduplication modules to clean and deduplicate the data.

Fig. 3. Overview of the *Febri* geocoding system

already come in a highly standardised form, but the finer details, for example how whitespaces within locality names are treated, make the difference between successful or failed matching. The cleaned and standardised reference addresses are then inserted into a number of inverted index data structures.

In order to be able to find matches with typographical errors (like in street names or locality names), indices based on q -grams (substrings of length q) are built for the main address name fields. If no exact match can be found, for example for a street name or suburb name, these approximate indices will return the most similar matches available in the G-NAF.

Additional data used in the preprocessing step are a postcode-suburb look-up table derived from a publicly-available file made available by the Australian postal authority (Australia Post), and which can be used to impute missing postcodes for missing values in the G-NAF locality table; and a look-up table of adjacent localities and suburbs, derived from boundary information, which is used to build *neighbouring region* look-up tables.

The geocode matching engine takes as input the inverted indices and the raw user data, which is cleaned and standardised before geocoding is attempted. As shown in Figure 3, the user data can either be loaded from a data file, geocoded directly, saved into a new data file, or it can be passed as one or more addresses to the geocoding system via a Web interface. An extension module has been developed by the New South Wales Department of Health which allows geocoded addresses derived from such addresses to be immediately visualised as a layer in a web-based GIS (geographic information system) facility.

The complete *Febri* system, including the geocoding and Web server modules, is implemented in the object-oriented open source language *Python*¹, which allowed rapid prototype development and testing.

ding. It is commonly accepted that real world data collections contain, incomplete and incorrectly formatted information. Data cleaning and standardisation are important preprocessing steps for successful data linkage and matching, and must also be carried out before including such data in a database for further analysis [16]. Data may be recorded or captured in various, inconsistent, formats and data items may be missing, out-of-date, or contain errors. The cleaning and standardisation of addresses is especially important for data linkage and geocoding so that accurate matching results can be achieved. A major task in the cleaning and standardisation of addresses is the conversion of the raw input data into well defined, consistent forms and the resolution of ambiguities in the manner in which address values are represented or encoded. Rule-based data cleaning and standardisation, as currently used by many commercial systems, can be cumbersome to set up and maintain, and often needs adjustment for new data sets. We have recently developed (and implemented within our system) probabilistic techniques [4] based on hidden Markov models (HMMs) [15] which achieved better address standardisation accuracy and which seem to be easier to set up and maintain than rule-based address processing software.

An HMM is a probabilistic finite-state machine consisting of a set of observation symbols, a finite set of discrete, hidden (unobserved) states, a matrix of transition probabilities between those hidden states, and a matrix of probabilities for each hidden state emits an observation symbol [15] (this *emission matrix* is also sometimes referred to as an *observation matrix*). In our case, the hidden states of the HMM correspond to the output fields of the standardised address.

The training data are representative samples of the input records which have been converted into sequences of observation symbols as described below (steps 1 and 2) and then tagged with the hidden state which the (human) trainer thought was most likely to have been responsible for emitting each observation symbol. Maximum likelihood estimates (MLEs) are derived for the HMM transition and emission probability matrices by accumulating frequency counts for each type of transition and observation symbol from the training records [4]. The HMMs appear to be quite robust with respect to the training set used and quite flexible with respect to the data sources with which they can be used. As a result, it is quite feasible to add specific training records which are archetypes of particular address patterns, without compromising the performance of the HMMs on typical source records.

The *tebrl* approach to address cleaning and standardisation consists of the following three steps.

1. User input addresses are *cleaned*. This involves converting all letters to upper-case, removing certain characters (such as punctuation), and converting certain sub-strings into their canonical form, for example 'c/-', 'c/o' and 'c/o' into 'c/-', 'c/o' and 'c/o' respectively. This step is necessary to ensure that the data is consistent and that the HMMs can be trained on a consistent set of data.

cleaned input strings are split into a list of words, numbers and characters using whitespace as the delimiter. Look-up tables and some hard-coded rules are then used to assign one or more tags to the elements in this list. The tags will be the observation symbols in the HMM used in the next step. The list of tags is given to the HMM, assuming that each tag (observation symbol) has been emitted by one of the hidden states. The *Viterbi* algorithm [15] is then used to find the most likely path through the HMM, and the corresponding hidden states provide the assignment of the elements from the input list to the output fields.

For example the address '73 Miller St, NORTH SYDNEY 2060', which was cleaned in step 1 ('SYDNEY' corrected to 'sydney'), and split into a list of words and numbers, and tagged in step 2. The resulting lists of words/numbers and tags looks as follows.

```
['73', 'miller', 'street', 'north_sydney', '2060']
['NU', 'UN', 'WT', 'LN', 'PC' ]
```

'NU' being the tag for numbers, 'UN' the tag for unknown words (not found in any look-up table or covered by any rule), 'WT' the tag for a word from the wayfare (street) type look-up table, 'LN' the tag for a word found to be a locality name, and 'PC' the tag for a known postcode. In step 3 the tag list is given to a HMM (like the simple example shown in Figure 4), which has previously been trained using similar address training data. The *Viterbi* algorithm will return the most likely path through the HMM. For the given example will correspond to the following sequence of output

```
'wayfare number': '73'
'wayfare name': 'miller'
'wayfare type': 'street'
'locality name': 'north_sydney'
'postcode': '2060'
```

For details of how to efficiently train the HMMs for address (as well as address standardisation, and the results of trials with real-world data are given in the next chapter. Training of the HMMs is relatively quick compared to the creation of parsing rules and does not require any programming skills. For addresses,

Our approach produced equal or better standardisation accuracies than the previously-used rule-based system *AutoStan* [10], which uses a re-entrant, regular expression-like pattern matching approach.

Processing the G-NAF Files

Processing the G-NAF tables consists of two steps, the first being the cleaning and standardisation as described above, and the second step being the building of inverted indices. An inverted index is a keyed hash-table in which the keys are the values from the cleaned G-NAF tables, and the entries in the hash-tables are sets with the corresponding PIDs (persistent identifiers, see Table 1) of the records. For example, assume there are four records in the `LOCALITY` table with the following content (the first line is a header-line with the attribute

locality_pid,	locality_name,	state_abbrev,	postcode
60310919,	sydney,	nsw,	2000
60709845,	north_sydney,	nsw,	2059
60309156,	north_sydney,	nsw,	2060
61560124,	the_rocks,	nsw,	2000

the inverted indices for the three attributes `locality_name`, `state_abbrev` and `postcode` are then as follows (curly brackets denote keyed hash-tables and round brackets denote sets):

```
locality_name_index = {'north_sydney': (60709845, 60309156),
                      'sydney': (60310919),
                      'the_rocks': (61560124)}

state_abbrev_index = {'nsw': (60310919, 60709845, 60309156, 61560124)}

postcode_index = {'2000': (60310919, 61560124),
                  '2059': (60709845),
                  '2060': (60309156)}
```

The matching engine then finds intersections of the inverted index sets for the attributes of a given record. For example, a postcode value '2000' would result in the set of PIDs {60310919, 61560124} being returned, and when intersected with the PIDs returned for locality name value 'the_rocks' would result in the intersection set {61560124}, which corresponds to the original record. The geographic location of this PID can then be looked-up in the corresponding G-NAF table. Table 2 shows the 23 attributes for which inverted indices are

For the G-NAF tables containing names, it is possible to create q -gram inverted indices for names of a given length q . This is not done in this

Table 2. G-NAF attributes used for geocode matching

Table	Attributes used
FLAT_DETAIL	flat_number_prefix, flat_number, flat_number_suffix, flat_type, level_number, level_type, building_name, location_description, number_first_prefix, number_first, number_first_suffix, number_last_prefix, number_last, number_last_suffix, lot_number_prefix, lot_number, lot_number_suffix
LOCALITY_ALIAS	locality_name, postcode, state_abbrev
STREET_ALIAS	locality_name, postcode, state_abbrev, street_name, street_type, street_suffix
LOCALITY_ALIAS	street_name, street_type, street_suffix

and then calculating a similarity value (sometimes called the *Dice co-*
[5])

$$sim_value = 2 \times \left(\frac{qgram(x) \cap qgram(y)}{|qgram(x)| + |qgram(y)|} \right)$$

$qgram(s)$ is a function which reduces a string s to its set of q -grams. This measure can have values between 0.0 (no q -grams in common) and 1.0 (all q -grams in common, i.e. the strings are the same). A ranked list of all geocode matches that have a similarity value above a user defined threshold is then used in the matching process for a given user record.

Additional Data Files

Additional information is used in the *Febrl* geocoding system during the preprocessing to verify and correct (if possible) postcode and locality name values, and the matching engine to enable searching for matches in neighbouring postcodes and suburbs) if no exact match can be found.

Australia Post publishes a look-up table containing postcode and suburb information, which is used when processing the G-NAF locality tables to verify incorrect or missing postcodes and suburb names. For example, if a postcode is missing in a record, the Australia Post look-up table can be used to find the official postcode(s) for the suburb in this record, and if this is a unique postcode it can be safely imputed into the record. Similarly, missing suburb names can be imputed if they correspond to a unique postcode.

Neighbourhood look-up tables are used to find *neighbouring* regions for postcodes and suburbs, i.e. for a given region these tables contain all its neighbours. These tables were derived from region boundary data using well-known GIS techniques. Look-up tables of both direct and indirect neighbours (i.e. neigh-

Christen, A. Willmore, and T. Churches

ce has shown that people often record different postcode or suburb val-
neighbouring postcode or suburb has a higher perceived social status, or
re close to the border of such regions.

Postcode Matching Engine

code matching engine in *Febrl* is based on the G-NAF inverted hash
nd takes a deterministic but adaptive approach to find an exact match
atively one or more approximate matches. Its input is one or many
nd standardised user record(s).

atching engine tries to find an exact match first, but if none can be
xtends its search to neighbouring postcode and suburb regions. First
ighbouring regions (level 1) are searched, then direct and indirect neigh-
regions (level 2), until either an exact match or a set of approximate
can be found. In the latter case, either an average location over all
matches is returned, or a ranked (according to a matching weight) list
e matches. The following steps explain in more detail (but still at a
al level) how the matching engine works.

the set of address level matches (using street number and suffix) and
et of street level matches (using street name and type). Street names
st searched using exact string comparison, and if no street name match
e found approximate string matching will be applied (using a q -gram
, allowing to find matches with typographical errors.

ne neighbouring search level to 0 (no neighbouring regions are searched).
the locality level matches (using locality name, qualifier and postcode)
ding to the current value of the neighbouring search level. Locality
s are first searched using exact string comparison, and if no locality
match can be found approximate string matching will be applied (using
ram index), allowing to find matches with typographical errors. Post-
are only used in the matching process if they result in the same matches
e locality names (i.e. if they contribute to these matches). If postcodes
in different matches, they are not used in the final match (this is be-
postcodes are not fixed locality regions, but can be – and often are –
ed by Australia Post for the purposes of expediting delivery of mail).
x for matches between street level and locality level, and if they exist
e the set of street level matches using the locality level matches, and
flag *street_locality_match* to true.

x for matches between address level and locality level, and if they exist
e the set of address level matches using the locality level matches, and
flag *address_locality_match* to true.

x for matches between address level and street level, and if they exist
e the set of address level matches using the street level matches, and
flag *address_street_match* to true.

the values of the three matching flags. A match has been found if all match flags are true, or if there was no address level match and the *locality_match* flag is true, or if there was no street level match and *address_locality_match* flag is true, or if there was no locality level match and the *address_street_match* flag is true. If no match has been found then use the neighbouring search level –that is, widen the search to adjacent areas – (up to a maximum of 2) and go back to step 3.

If several matches have been found, try to refine them using unit, flat and building (or property) information (if such information is available in the input record).

Determine the match(es) from the different levels (basically get their set intersections), and set the final *match level* (to either *address*, *street* or *locality*). Retrieve the coordinates of the match(es) from the corresponding G-NAF geocode index (address site, street/locality or locality). If one match has been found, retrieve its coordinates and return them together with the G-NAF persistent identifier). If several matches were found check if they are in a small area (defined by the user). If so, average their coordinates and return the averaged location together with the list of G-NAF PIDs. If the distances between the matches were large, return a '*Many match*' (without coordinates, only a list of G-NAF PIDs).

In some cases a match at a certain level has been found, but no record is available in the corresponding G-NAF geocode index, or a record is available but does not contain coordinates. In this case go to the next higher search level (e.g. from address to street, or from street to locality) and try to retrieve the corresponding coordinates (back to step 10).

If no match was found return a '*No match*' match status.

Geocoding of multiple addresses is an iterative process where each record is first standardised, then geocoded and written into an output data set containing coordinates and a match status added to each record.

Experimental Results

We ran experiments with geocoding various administrative health data sets. The address hidden Markov model (HMM) was trained using 1,300 training records, around half of them randomly selected from the NSW *Midwives Collection* [11] (MDC) containing data from 1990 to 2000, the other half from a NSW *Land and Property Information* (LPI) data set from 2002. Unusual training records (like rural addresses or addresses with property information) were manually added to increase the standardisation for such addresses.

Table 3 presents the results of geocoding 10,000 randomly selected LPI free-

Matching results for geocoding 10,000 free-form LPI address records, with and without ($q = 0$) approximate indices

Match status	Number of records		Percentage	
	$q = 2$	$q = 0$	$q = 2$	$q = 0$
Exact address level match	7,525	7,497	75.27 %	74.97 %
Range address level match	303	303	3.03 %	3.03 %
Fuzzy address level match	178	178	1.78 %	1.78 %
Exact street level match	1,160	1,131	11.60 %	11.31 %
Range street level match	17	17	0.17 %	0.17 %
Fuzzy street level match	65	62	0.65 %	0.62 %
Exact locality level match	653	680	6.53 %	6.80 %
Range locality level match	1	1	0.01 %	0.01 %
Fuzzy locality level match	98	118	0.98 %	1.18 %

Table 4. Comparative matching results for geocoding 873 MDC addresses

Match status	Number of records		Percentage	
	<i>Febrl</i>	Commercial	<i>Febrl</i>	Commercial
Exact address level match	746	789	85.45 %	90.38 %
Range address level match	23	-	2.63 %	-
Fuzzy address level match	13	-	1.49 %	-
Exact street level match	48	37	5.50 %	4.24 %
Range street level match	3	-	0.34 %	-
Fuzzy street level match	35	46	4.01 %	5.26 %
Exact locality level match	4	-	0.46 %	-
Range locality level match	1	1	0.11 %	0.11 %

Table 5. Comparative matching results for geocoding 607 nursing home addresses

Match status	Number of records		Percentage	
	<i>Febrl</i>	Commercial	<i>Febrl</i>	Commercial
Exact address level match	265	384	43.66 %	63.26 %
Range address level match	30	-	4.94 %	-
Fuzzy address level match	21	-	3.46 %	-
Exact street level match	240	202	39.54 %	33.28 %
Range street level match	1	-	0.16 %	-
Fuzzy street level match	4	-	0.66 %	-
Exact locality level match	38	-	6.26 %	-

tivated, the approximate indices allowed for up to two typographical (i.e. single character insertions, deletions, or substitutions) in street and place names. As the results show, a total of 93.38% (with approximate indices) and 90.1% (without) exact matches were found at different levels. Using approximate indices resulted in only a slightly improved match quality, but geocoding was much longer. Without approximate indices, the average geocoding time per address was 67 milliseconds; using approximate indices it increased to 269 milliseconds per address (around four times slower).

Table 4 the results of a geocoding experiment on 873 randomly selected addresses (1% sample) from the MDC using the *Febrl* geocoder are compared to a commercial (street centreline based) geocoding system (which only returns exact matches). The ‘no match’ address in both cases was for an overseas address. Table 5 shows comparative results on a NSW nursing home data sets containing 1000 addresses. For this data set the commercial system achieves a significantly better geocoding quality. This is because nursing homes are often located at street intersections and have corner addresses. Such addresses are currently not handled properly in our geocoding system, as they correspond to two G-NAF parcel records (with the same address site), and cannot be separated by our address standardiser.

Also note that the comparison results in Tables 4 and 5 only show the match quality, but not the relative accuracy of the coordinates returned. We are planning a more detailed analysis on this issue, comparable to the study presented in [1].

Conclusions and Future Work

In this paper we have described a geocoding system based on a geocoded national address file. We are currently evaluating and improving this system using raw address data and addresses taken from various administrative health related data sets. We are also planning to compare the accuracy of our geocoding system with other commercial geocoders, and similar to [2] we expect to obtain more accurate results. Our geocoding system has been published as part of the *Febrl* data standardisation system [3] under an open source software license. Readers should note that although our geocoding engine is available for free, the G-NAF reference files and address data are not freely available, and must be licensed through PSMA [13] or other partner organisations.

Future efforts will be directed towards the refinement of the geocode matching algorithm to achieve more accurate matching results, as well as improving the performance of the matching engine (i.e. reducing the time needed to match an address). Three other areas of future work include:

1. *Febrl* standardisation routines currently return fields (or attributes) which are different from the ones available in the G-NAF. This makes it necessary to

Christen, A. Willmore, and T. Churches

ntly both the G-NAF preprocessing and indexing, as well as the geocode
ing engine work in a sequential fashion only. Due to the large data files
ed, parallel processing becomes desirable. In the preprocessing step, the G-
tables can be processed independently or in a block-wise fashion, distributed
a number of processors, with only the final inverted indices needing to be
d. Geocoding of a large user data file can easily be done in parallel as the
ng, standardisation and matching of each record is completely independent
all others. An additional advantage of parallelisation is the increased amount
in memory available on many parallel platforms. We are planning to explore
parallelisation techniques and implement them into the *Febri* system to allow
geocoding of larger data sets. Additional performance improvements can be
red by profiling and re-implementing the core computational routines as C
age routines called from the Python code (something which Python makes
o do).

r addresses are stored in the G-NAF as two separate addresses with the same
ss site PID, but when processed in a user data set this becomes problematic,
standardisation process is currently not capable of separating the compo-
of a corner address. We aim to work on this issue and add it to a future
n of our geocoding system.

ding uses identifying information (i.e. addresses) which raises privacy and
entiality issues. Organisations that collect sensitive data (e.g. disease reg-
) cannot send their data to a third-party geocoding service as this may result
loss of privacy for individuals involved. It is desirable to develop methods
allow for privacy-preserving geocoding. We aim to develop such methods
on techniques recently described for blindfolded data linkage [5, 9, 12].

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References

s, M.N.K.: Towards evidence-based, GIS-driven national spatial health
ation infrastructure and surveillance services in the United Kingdom.
ational Journal of Health Geographics 2004, 3:1. Available online at:
//www.ij-healthgeographics.com/content/3/1/1
M.R. and Talbot, T.O.: Positional error in automated geocoding of residen-
ddresses. International Journal of Health Geographics 2003, 2:10. Available

- Ches, T., Christen, P., Lim, K. and Zhu, J.X.: Preparation of name and address data for record linkage using hidden Markov models. *BioMed Central Medical Informatics and Decision Making* 2002, 2:9, Dec. 2002. Available online at: <http://www.biomedcentral.com/1472-6947/2/9/>
- Ches, T. and Christen, P.: Some methods for blindfolded record linkage. *BioMed Central Medical Informatics and Decision Making* 2004, 4:9, June 2004. Available online at: <http://www.biomedcentral.com/1472-6947/4/9/>
- Elkan, C.: The CRISP-DM Model: The new blueprint for data mining. *Journal of Data Warehousing*, vol. 5, no. 4, pp. 13–22, Fall 2000.
- Elkan, C., Krieger, H.-P. and Sander, J.: Spatial Data Mining: A Database Approach, Fifth Symposium on Large Spatial Databases (SSD'97). Springer LNCS 1658, pp. 48–66, 1997.
- Elkan, I. and Sunter, A.: A Theory for Record Linkage. *Journal of the American Statistical Society*, 1969.
- Elkan, C.: Development of a Blind Geocoding System. Honours thesis, Department of Computer Science, Australian National University, Canberra, November 2004.
- Elkan, C.: *MatchWare and AutoMatch, User's Manuals*, MatchWare Technologies, Kennebunk, ME, 1998.
- Elkan, C.: Record Linkage for Epidemiology and Research, NSW Department of Health. New South Wales Health Bulletin 2001, 13(S-4).
- Elkan, C.M., Yung, M., Gu, L. and Baxter, R.: Privacy-Preserving Data Linkage Protocols. *Proceedings of the Workshop on Privacy in the Electronic Society (WPES'04)*. Washington, DC, October 2004.
- Elkan, C.: D.L.: A geocoded National Address File for Australia: The G-NAF What, Where and When? PSMA Australia Limited, Griffith, ACT, Australia, 2003. Available online at: <http://www.g-naf.com.au/>
- Elkan, C.: D.L.: Data Preparation for Data Mining. Morgan Kaufmann Publishers, Inc., San Francisco, 2003.
- Elkan, L.R.: A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition. *Proceedings of the IEEE*, vol. 77, no. 2, Feb. 1989.
- Elkan, C. and Do, H.H.: Data Cleaning: Problems and Current Approaches. *IEEE Engineering Bulletin*, 2000.
- Elkan, C.: Federal Geographic Data Committee. Homeland Security and Geographic Information Systems – How GIS and mapping technology can save lives and protect property in post-September 11th America. *Public Health GIS News and Information*, no. 52, pp. 21–23, May 2003.
- Elkan, C.: W.E.: The State of Record Linkage and Current Research Problems. *Proceedings of the 1993 US Bureau of the Census*, 1999.