Febrl – A parallel open source data linkage and geocoding system

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Project web page: **http://datamining.anu.edu.au/linkage.html**

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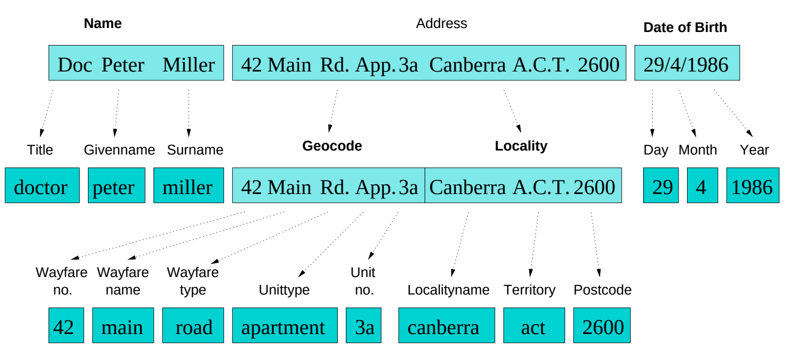
Outline

- Data cleaning and standardisation
- Data linkage and data integration
- *Febrl* overview
- Probabilistic data cleaning and standardisation
- Blocking / indexing
- Record pair classification
- Parallelisation in *Febrl*
- Data set generation
- Geocoding
- Outlook

Data cleaning and standardisation (1)

- Real world data is often *dirty*
  - Missing values, inconsistencies
  - Typographical and other errors
  - Different coding schemes / formats
  - Out-of-date data
- Names and addresses are especially prone to data entry errors
- Cleaned and standardised data is needed for
  - Loading into databases and data warehouses
  - Data mining and other data analysis studies
  - Data linkage and data integration

Data cleaning and standardisation (2)



- Remove unwanted characters and words
- Expand abbreviations and correct misspellings
- Segment data into well defined *output fields*

Data linkage and data integration

- The task of linking together records representing the same entity from one or more data sources
- If no *unique identifier* is available, *probabilistic linkage techniques* have to be applied
- Applications of data linkage
  - Remove duplicates in a data set (internal linkage)
  - Merge new records into a larger master data set
  - Create customer or patient oriented statistics
  - Compile data for longitudinal studies

Data cleaning and standardisation are important first steps for successful data linkage

Data linkage techniques

- Deterministic or exact linkage
  - A *unique identifier* is needed, which is of high quality (precise, robust, stable over time, highly available)
  - For example *Medicare* number (?)
- Probabilistic linkage (*Fellegi & Sunter*, 1969)
  - Apply linkage using available (personal) information
  - Examples: *names*, *addresses*, *dates of birth*
- Other techniques (rule-based, fuzzy approach, information retrieval)

Febrl – Freely extensible biomedical record linkage

- An experimental platform for new and improved linkage algorithms
- Modules for data cleaning and standardisation, data linkage, deduplication and geocoding
- Open source **https://sourceforge.net/projects/febrl/**
- Implemented in *Python* **http://www.python.org**
  - Easy and rapid prototype software development
  - Object-oriented and cross-platform *(Unix, Win, Mac)*
  - Can handle large data sets stable and efficiently
  - Many external modules, easy to extend

Probabilistic data cleaning and standardisation

- Three step approach
  1. Cleaning
     – Based on look-up tables and correction lists
     – Remove unwanted characters and words
     – Correct various misspellings and abbreviations
  2. Tagging
     – Split input into a list of words, numbers and separators
     – Assign one or more tags to each element of this list (using look-up tables and some hard-coded rules)
  3. Segmenting
     – Use either rules or a *hidden Markov model (HMM)* to assign list elements to *output fields*

Cleaning

- Assume the input *component* is one string
  (either name or address – dates are processed differently)
- Convert all letters into lower case
- Use *correction lists* which contain pairs of `original:replacement` strings
- An empty `replacement` string results in removing the original string
- Correction lists are stored in text files and can be modified by the user
- Different correction lists for names and addresses

Tagging

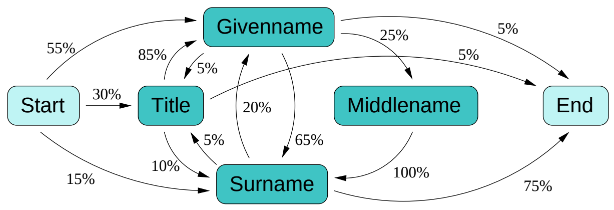
- Cleaned strings are split at whitespace boundaries into lists of words, numbers, characters, etc.
- Using *look-up tables* and some hard-coded rules, each element is tagged with one or more *tags*
- Example:
  - Uncleaned input string: *“Doc. peter Paul MILLER”*
  - Cleaned string: *“dr peter paul miller”*
  - Word and tag lists:

```
[‘dr’, ‘peter’, ‘paul’, ‘miller’]
[‘TI’, ‘GM/SN’,  ‘GM’,    ‘SN’  ]
```


Segmenting

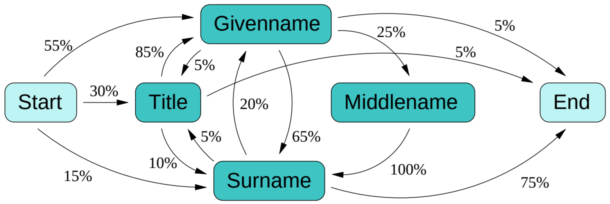
- Using the tag list, assign elements in the word list to the appropriate *output fields*
- Rules based approach (e.g. *AutoStan*)
  - Example: *“if an element has tag ‘TI’ then assign the corresponding word to the ‘Title’ output field”*
  - Hard to develop and maintain rules
  - Different sets of rules needed for different data sets
- Hidden Markov model (HMM) approach
  - A machine learning technique (supervised learning)
  - Training data is needed to build HMMs

Hidden Markov model (HMM)



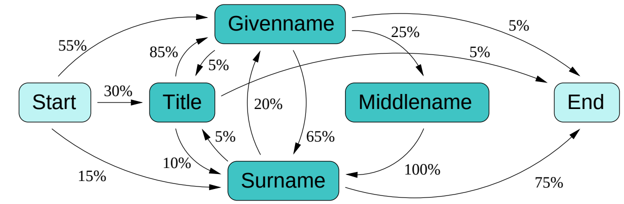
- A HMM is a *probabilistic* finite state machine
  - Made of a set of *states* and *transition probabilities* between these states
  - In each state an *observation* symbol is emitted with a certain probability distribution
  - In our approach, the observation symbols are *tags* and the states correspond to the *output fields*

HMM probability matrices



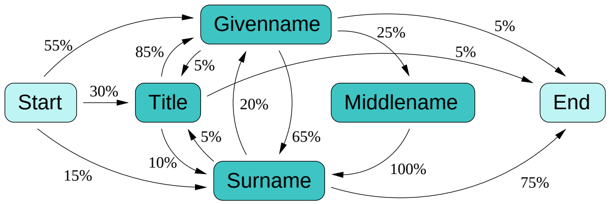
	State					
Observation	*Start*	Title	Givenname	Middlename	Surname	*End*
TI	–	96%	1%	1%	1%	–
GM	–	1%	35%	33%	15%	–
GF	–	1%	35%	27%	14%	–
SN	–	1%	9%	14%	45%	–
UN	–	1%	20%	25%	25%	–

HMM data segmentation



- For an observation sequence we are interested in the most likely path through a given HMM
  (in our case an observation sequence is a *tag list*)
- The *Viterbi* algorithm is used for this task
  (a dynamic programming approach)
- *Smoothing* is applied to account for unseen data
  (assign small probabilities for unseen observation symbols)

HMM segmentation example



- Input word and tag list

```
['dr',  'peter',  'paul',  'miller']
['TI',  'GM/SN',  'GM',     'SN'   ]
```

- Two example paths through the HMM

1: `Start -> Title (TI) -> Givenname (GM) -> Middlename (GM) -> Surname (SN) -> End`

2: `Start -> Title (TI) -> Surname (SN) -> Givenname (GM) -> Surname (SN) -> End`

HMM training (1)

- Both transition and observation probabilities need to be trained using *training data*
  (maximum likelihood estimates (MLE) are derived by accumulating frequency counts for transitions and observations)
- Training data consists of records, each being a sequence of `tag:hmm_state` pairs
- Example (2 training records):

```
# '42 / 131 miller place manly 2095 new_south_wales'
NU:unnu,SL:sla,NU:wfnu,UN:wfna1,WT:wfty,LN:loc1,PC:pc,TR:ter1

# '2 richard street lewisham 2049 new_south_wales'
NU:wfnu,UN:wfna1,WT:wfty,LN:loc1,PC:pc,TR:ter1
```

HMM training (2)

- A *bootstrapping* approach is applied for semi-automatic training
  1. Manually edit a small number of training records and train a first rough HMM
  2. Use this first HMM to segment and tag a larger number of training records
  3. Manually check a second set of training records, then train an improved HMM
- Only a few person days are needed to get a HMM that results in an accurate standardisation (instead of weeks or even months to develop rules)

Address standardisation results

- Various NSW Health data sets
  - *HMM1* trained on 1,450 Death Certificate records
  - *HMM2* contains *HMM1* plus 1,000 Midwifes Data Collection training records
  - *HMM3* is *HMM2* plus 60 unusual training records
- *AutoStan* rules (for ISC) developed over years

	HMM/Method			
Test Data Set (1,000 records each)	HMM 1	HMM 2	HMM 3	Auto Stan
Death Certificates	95.7%	96.8%	97.6%	91.5%
Inpatient Statistics Collection	95.7%	95.9%	97.4%	95.3%

Name standardisation results

- NSW Midwifes Data Collection (1990 - 2000) (around 963,000 records, no medical information)
- 10-fold cross-validation study with 10,000 random records (9,000 training and 1,000 test records)
- Both *Febrl* rule based and HMM data cleaning and standardisation
  - Rules were better because most names were simple (not much structure to learn for HMM)

	Min	**Max**	**Average**	**StdDev**
HMM	83.1%	97.0%	92.0%	$\pm$4.7%
Rules	97.1%	99.7%	98.2%	$\pm$0.7%

Blocking / indexing

- Number of possible links equals the product of the sizes of the two data sets to be linked
- Performance bottleneck in a data linkage system is usually the (expensive) evaluation of similarity measures between record pairs
- Blocking / indexing techniques are used to reduce the large amount of record comparisons
- *Febrl* contains (currently) three indexing methods
  - Standard blocking
  - Sorted neighbourhood approach
  - Fuzzy blocking using n-grams (e.g. bigrams)

Record pair classification

- For each record pair compared a vector containing *matching weights* is calculated

  Example:

  Record A: ['dr', 'peter', 'paul', 'miller']

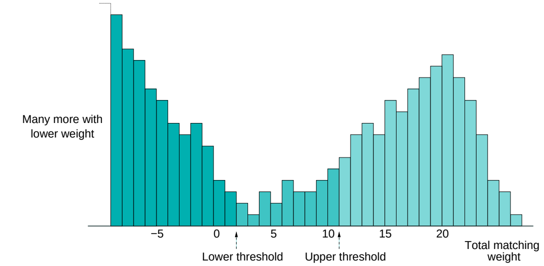
  Record B: ['mr', 'pete', '', 'miller']

  Matching weights: [0.2, 0.8, 0.0, 2.4]
- Matching weights are used to classify record pairs as *links*, *non-links*, or *possible links*
- *Fellegi & Sunter* classifier simply sums all the weights, then uses two thresholds to classify
- Improved classifiers are possible

  (for example using machine learning techniques)

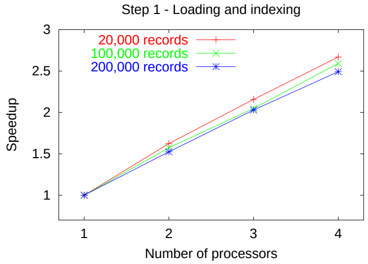
Final linkage decision

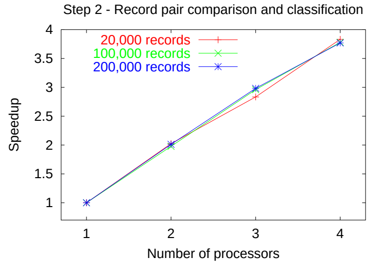
- The final weight is the sum of weights of all fields
  - Record pairs with a weight above an *upper threshold* are designated as a *link*
  - Record pairs with a weight below a *lower threshold* are designated as a *non-link*
  - Record pairs with a weight between are *possible link*



Parallelisation

- Implemented transparently to the user
- Currently using *MPI* via Python module *PyPar*
- Use of supercomputing centres is problematic (privacy) → Alternative: *In-house office clusters*
- Some initial performance results (on *Sun SMP*)





Data set generation

- Difficult to acquire data for testing and evaluation

  (as data linkage deals with names and addresses)
- Also, linkage status is often not known

  (hard to evaluate and test new algorithms)
- *Febrl* contains a data set generator
  - Uses frequency tables for given- and surnames, street names and types, suburbs, postcodes, etc.
  - *Duplicate records* are created via random introduction of modifications (like insert/delete/transpose characters, swap field values, delete values, etc.)

Data set generation – Example

- Data set with 4 original and 6 duplicate records

REC_ID,	ADDRESS1,	ADDRESS2,	SUBURB
rec-0-org,	wylly place,	pine ret vill,	taree
rec-0-dup-0,	wyllyplace,	pine ret vill,	taree
rec-0-dup-1,	pine ret vill,	wylly place,	taree
rec-0-dup-2,	wylly place,	pine ret vill,	tared
rec-0-dup-3,	wylly parade,	pine ret vill,	taree
rec-1-org,	stuart street,	hartford,	menton
rec-2-org,	griffiths street,	myross,	kilda
rec-2-dup-0,	griffith sstreet,	myross,	kilda
rec-2-dup-1,	griffith street,	mycross,	kilda
rec-3-org,	ellenborough place,	kalkite homestead,	sydney

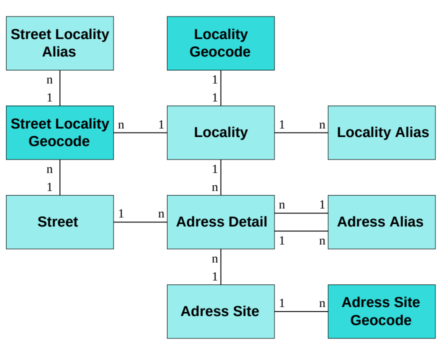
- Each record is given a unique identifier, which allows the evaluation of accuracy and error rates for data linkage

Geocoding

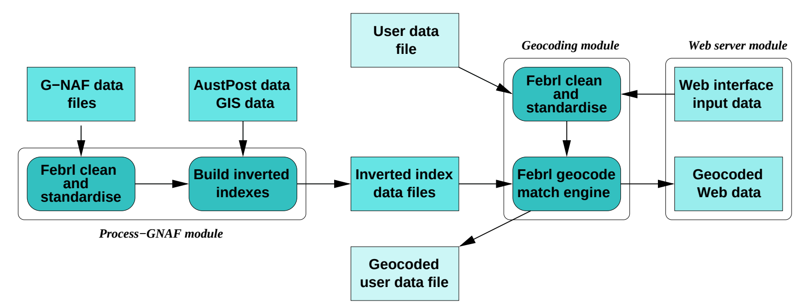
- The process of matching addresses with geographic locations (longitude and latitude)
- Geocoding tasks
  - Preprocess the geocoded reference data (cleaning, standardisation and indexing)
  - Clean and standardise the user addresses
  - (Fuzzy) match of user addresses with the reference data
  - Return location and match status
- Match status: address, street or locality level
- Geocode reference data used: *G-NAF*

Geocoded national address file

- G-NAF: Available since early 2004 (PSMA, `http://www.g-naf.com.au/`)
- Source data from 13 organisations (around 32 million source records)
- Preprocessed into 22 normalised database tables



Febrl geocoding system



- Only NSW G-NAF data available (around 4 million address, 58,000 street and 5,000 locality records)
- Additional Australia Post and GIS data used (for data imputing and to calculate *neighbouring regions*)

Processing G-NAF files

- Clean and standardise
- Build inverted indexes

```
LOCALITY_PID,  LOCALITY_NAME,  STATE_ABBREV,  POSTCODE
    60310919,         sydney,           nsw,      2000
    60709845,   north_sydney,           nsw,      2059
    60309156,   north_sydney,           nsw,      2060
    61560124,      the_rocks,              ,      2000
- - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
locality_name_index = ['north_sydney':(60709845,60309156),
                             'sydney':(60310919),
                          'the_rocks':(61560124)]

state_abbrev_index = ['nsw':(60310919,60709845,60309156)]

postcode_index = ['2000':(60310919,61560124),
                  '2059':(60709845),
                  '2060':(60309156)]
```


Febrl geocoding match engine

- Uses cleaned and standardised user address(es) and G-NAF inverted index data
- Fuzzy rule based approach
  1. Find street match set (street name, type and number)
  2. Find postcode and locality match set (with *no*, then *direct*, then *indirect* neighbour levels)
  3. Intersect postcode and locality sets with street match set (if no match increase neighbour level and go back to 2.)
  4. Refine with unit, property, and building match sets
  5. Retrieve corresponding locality (or localities)
  6. Return locality and match status (address, street or locality level match; none, one or many matches)

Outlook

- Several research areas
  - Improving probabilistic data standardisation
  - New and improved blocking / indexing methods
  - Apply machine learning techniques for record pair classification
  - Improve performances (scalability and parallelism)
- Project web page

  http://datamining.anu.edu.au/linkage.html

Febrl *is an ideal experimental platform to develop, implement and evaluate new data standardisation and data linkage algorithms and techniques*

Contributions / Acknowledgments

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