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New Directions in Record Linkage

Yves Thibaudeau
Center for Statistical Research and Methodology
Research and Methodology Directorate
U.S. Census Bureau
Plan of Talk

- Historical Context
- Modern Record Linkage
- Advanced Methods
- Some Census Bureau Projects
Historical Context

Early Record-Linkage Applications

Canada Vital Statistics Index (1943)

The operation of the index is completely decentralized, the indexes being forwarded in all cases to the province of birth. Activities of the Dominion Bureau

Functional Organization Chart

- National index and vital statistics
- Registration
- Statistical coding
- Death coding
- Vital statistics
- Mechanical tabulation
  - Key-punching
  - Verifying
  - Sorting
  - Listing
  - Summary tabulation
- National index of vital records
- National vital statistics tabulation and publication

Fig. 1. Functional organization chart.

Fig. 2. National index punch card.

of Statistics are limited to the continuous preparation of indexes to keep the system going. The Bureau maintains no central identification or posting system, but a duplicate index is retained in the form of the basic Hollerith cards in numeric
Medical Applications

Oxford Record Linkage Study (1962-1968)

"Computerized Linkage"

MEDICINE AND THE COMPUTER

III—Record Linkage*

[From a Seminar, Computer Science Department, University of California, Irvine]

Many epidemiological studies of the causes of chronic diseases involve the assessment of the role of heredity, occupation, and previous illnesses. But at present this is difficult, because this information is scattered in the records of many different departments and authorities. One of the ways of solving this problem is to produce a complete medical history of the population of a city or town as a system of linked records, containing only details about a person's medical and occupational history from birth to death, but also about his parents and family as well.

In 1962 the Oxford Record Linkage Study was started as a pilot scheme, and this now covers a large part of the Oxford region, with a total population of about 1 million. A year later the decision was taken to try to replace the conventional method of processing the data—which was rapidly becoming overwhelmed by the sheer mass of facts—by computer processing. Work continues on the development of this system, but a successful operation of record matching has been started and certain analysis for medical research and administration carried out.

Collecting the Data

One of the most important decisions was which medical events should be recorded about each person. To get the system working properly it was decided to start with just a few key facts—birth, discharge from hospital, confinement, and death. Data about these events are abstracted from the study's records. From various sources—birth and death certificates, discharge summaries in hospital case notes, and from domiciliary chronic records. For, even to get just these data readout into a form suitable for the computer has proved to be one of the more time-consuming, difficult, and expensive operations in the whole study.

Data obtained in this way were condensed and punched into cards by the headquarters of the Linkage Study in Oxford. Two cards are punched for each event—a identification or name card, and a statistics card containing diagnostic and administrative information. It is the first card—the name card—which provides the link enabling any details to be added to the file of a person's record. Successful linkage of this kind must amount to an almost unmatched ability to differentiate that person's records from those of all the other people in the city. Obviously this is a population that cannot be identified directly in any other way. The H.B. number has been decided on, but is still too long and of birth place. The H.B. number is also recorded when available, but unfortunately at present this is known only to a minority of the population.

Computer Linkage

A big problem in record linkage is caused by changes, omission, and discrepancies in the identification data. People change their names and addresses, and tend to give different personal details on successive occasions. Using a manual index system a clerk will use his own judgment whether a given name record refers to the same person as a given card despite these discrepancies. To be successful any linkage system must also aim to do the same, and this can be done by programming the computer to make successful matching judgments.

The medical records are kept on a master magnetic tape file, and they are arranged in surname order, according to Soundex code—a phonetic version of the Alphabet. By this system similar sounding surnames are grouped into Soundex blocks to allow the matching of records in which the surnames have been misspelled. One such block, for example, contains the names Addicks, Adams, Adkins, and others. Within the Soundex block the records are further sorted by sex and date of birth.

Data from the incoming new event cards are transferred by the computer to magnetic tape, and are then sorted into the
A MODEL FOR OPTIMUM LINKAGE OF RECORDS

Benjamin J. Tepping

Bureau of the Census

The problem of record linkage arises in many contexts. A typical example is that of file maintenance. In this example there is a file, which we shall call the master file, whose constitution is to be changed from time to time, by adding or deleting records or by altering specific records. Notice of these required changes is given by means of another file of records, which we shall call the transaction file. Presumably, each transaction record specifies the addition of a new master file record, or the deletion of an existing master file record, or the alteration of an existing master file record. It may not be known whether there exists a master file record that corresponds to a given transaction record so that the determination of whether a master file record is to be changed or a new master file record added must wait until it is found whether a corresponding master file record exists. Thus, the fundamental problem is to determine, for each transaction record, which master file record corresponds to it or that no master file record corresponds to it.

If each master file record and each transaction record carried a unique and error-free identification code, the problem would reduce to one of finding an optimum search sequence that would minimize the total number of comparisons. In most cases encountered in practice, the identification of the record is neither unique nor error-free. Thus it becomes necessary to make a decision as to whether or not a given transaction record ought to be treated as though it corresponded to a given master file record. The evidence presented by the identification codes of the two records in question may possibly be quite clear that the records correspond or that they do not correspond. On the other hand, the evidence may not clearly point to one or the other of these two decisions. Thus it may be reasonable to treat the records temporarily as if they corresponded or to treat them temporarily as if they did not correspond, but to seek further information. Or it may be reasonable in a particular case to take no overt action until further information has been obtained. The amount of effort that it is reasonable to expend in resolving a particular problem is also a variable. Thus it is clear that in making the decision on the correspondence between a transaction record and a master file record, there are available at least two and perhaps more possible decisions. If one considers now the costs of the various actions that might be taken and the utilities associated with their pos-
Intuitive Bayesian Approach

Posterior probabilities of a “match” after observing pair pattern $\gamma$.

with taking action $a_i$ on a pair $(\alpha, \beta)$ when in fact that pair is a match, and a loss $C_a$ when in fact the pair is a nonmatch. In this case, the expected value of the loss can easily be seen to be a linear function of the conditional probability that the comparison pair is a match, given $\gamma$, for each action $a_i$.

If the functions $G$ are linear in $P(M | \gamma)$, the interval $(0, 1)$ for the probability of a match is divided into at most $a$ “action intervals” each of which corresponds to one of the possible $a$ actions. The action interval for a given action is the interval in which the cost function $G$ for that action is less than the cost function for any other action.

Figure 1 illustrates a case in which $G(a_i, P(M | \gamma))$ is a linear function of $P(M | \gamma)$ for each $a_i$. In this illustration, the optimum linkage rule specifies:

- Take action $a_1$ if $0 \leq P(M | \gamma) \leq P_1$
- Take action $a_2$ if $P_1 < P(M | \gamma) \leq P_2$
- Take action $a_3$ if $P_2 < P(M | \gamma) \leq 1$

If the functions $G$ are not linear in $P(M | \gamma)$, an “action set” of points of the interval $(0, 1)$ that correspond to one of the possible actions will not be an interval in general. The treatment of the nonlinear case, however, proceeds along the same lines.

The conditional probability that a comparison pair is a match, given that the comparison function $\gamma$ has a stated value depends upon the prior definition of the comparison function $\gamma$ or, equivalently, upon the definition of the corresponding classification of comparison pairs.

As noted above, any comparison function $\gamma$ defines a classification of the pairs $(\alpha, \beta)$. Let $\gamma'$ be any other comparison function, which therefore defines another classification. It is possible to pass from the classification $\gamma'$ to the classification $\gamma$ by a sequence of steps, each of which consists either of splitting a class into two classes or of combining two classes into a single class. Therefore, if we begin with a tentative comparison function $\gamma_i$, we may seek ways of splitting some classes or combining some classes in such a way as to reduce the contribution of the classes involved to the loss function.

Consider the case of splitting a class $\gamma$ into two classes $\gamma_1$ and $\gamma_2$. Without
Fellegi Sunter (1969)

**Classic Statistical Treatment of Record Linkage**

**Neyman-Pearsonian Approach**

Uniformly Most Powerful Decision after observing pair pattern $\gamma$.

the simple alternative that $(a, b) \in M$, the section $A_1$ being the rejection of the null hypothesis and $\mu$ the level of significance. Similarly the section $A_2$ is the rejection at the significance level $\lambda$ of the null hypothesis that $(a, b) \in M$ in favour of the simple alternative that $(a, b) \in U$. The linkage rule $L$ is equivalent to the likelihood ratio test and the theorem above asserts this to be the uniformly most powerful test for either hypothesis.

We state, without proof, two corollaries to the theorem. These corollaries, although mathematically trivial, are important in practice.

**Corollary 1:** If

$$\mu = \sum_{i=1}^{n} u_i, \quad \lambda = \sum_{i=n+1}^{n'} m_i, \quad n < n',$$

the $L(a, \lambda, \Gamma)$, the best linkage rule at the levels $(\mu, \lambda)$ becomes

$$d(\gamma) = \begin{cases} (1, 0, 0) & \text{if } 1 \leq i \leq n \\ (0, 1, 0) & \text{if } n < i < n' \\ (0, 0, 1) & \text{if } n' \leq i \leq N. \end{cases}$$

(18)

If we define

$$T_a = \frac{m(\gamma)}{n(\gamma)}$$
$$T_b = \frac{u(\gamma)}{u(\gamma)}$$

then the linkage rule (18) can be written equivalently as

$$d(\gamma) = \begin{cases} (1, 0, 0) & \text{if } T_a \leq m(\gamma)/u(\gamma) \\ (0, 1, 0) & \text{if } T_a < m(\gamma)/u(\gamma) < T_b \\ (0, 0, 1) & \text{if } m(\gamma)/u(\gamma) \leq T_b. \end{cases}$$

(19)

**Corollary 2:** Let $T_a$ and $T_b$ be any two positive numbers such that

$$T_a > T_b.$$

Then there exist an admissible pair of error levels $(\mu, \lambda)$ corresponding to $T_a$ and $T_b$, such that the linkage rule (19) is best at those levels. The levels $(\mu, \lambda)$ are given by

$$\mu = \sum_{\gamma \in T_a} w(\gamma)$$
$$\lambda = \sum_{\gamma \in T_b} w(\gamma)$$

(20)

(21)

where

$$\Gamma_a = \left\{ \gamma : T_a \leq m(\gamma)/u(\gamma) \right\}$$
$$\Gamma_b = \left\{ \gamma : m(\gamma)/u(\gamma) \leq T_b \right\}.$$

(22)

(23)

*We are grateful to the referee for pointing out that (19) and (18) are exactly equivalent only if $w_a(w) < w_a(w_a(w))$ and $w_b(w) > w_b(w_b(w))$.*
For a given prior probability $P(M)$, the posterior probability $P(M|\gamma)$ is strictly increasing in the likelihood ratio $P(\gamma|M)/P(\gamma|U)$:

$$P(M|\gamma) = \frac{P(\gamma|M)P(M)}{P(\gamma|M)P(M) + P(\gamma|U)(1 - P(M))}$$

$$= \frac{1}{1 + \left(\frac{P(\gamma|U)}{P(\gamma|M)}\right)\left(\frac{1 - P(M)}{P(M)}\right)}$$
Modern Record Linkage

Learning

Matching/Sorting  Scoring
Matching/Sorting (Pairs)

- Statistics Canada (Lalonde, Fair, Armstrong,...) 1970’s –


Learning

Supervised
- Previous record linkage, simulations. Contemporary Python Tools.

Unsupervised
- Latent Class Models
- EM Algorithm

Hybrid
- Larsen/Rubin (2001), Neural Network (Python, Bouch, 2019).
Basic Scoring

- Use basic Learning methods to score Pairs (more on this).
- Various levels of integration.
- Least integrated: unsupervised learning. EM algorithm is ran once after sorting. Pairs are scored only once.
- Decision rules are based on pairs. Can involve multiple records/file.
Advanced Methods (Selected)

- Sorting/Matching/Scoring \textit{n-tuples}: Generalizing Fellegi-Sunter Theory, \textit{Sadinle/Fienberg (2013)}:
- Conditional probabilities: A-C \textit{given A-B and B-C}.
- Sorting/Matching grows exponentially with \textit{“n”}. 
Advanced Methods (Selected)

- Bayesian matching integrating capture-recapture Models – *Tancredi/Liseo (2011)* (Hierarchical conditional Scoring)
- Bayesian Clustering (Hierarchical Model) – *Steorts (2015)* – Estimation methods based on very large lists.
Some Census Bureau Record-Linkage Projects

- Post Enumeration Matching Studies (*Mulry/Spencer 1991*): Linking a Post Enumeration Survey to the Decennial Census to evaluate coverage.

- Longitudinal Employment Household Dynamics (*Abowd et Al. 2005*): Record linkage to match and follow employer and employee characteristics across time.

- *Research*: CPEX: Matching/unduplicating files to enumerate the U.S. population (*Research and Methodology Directorate*).
CPEX Research Project: Files

- Master Address File (Census Bureau): *Geocoded* Housing Units in U.S.
- Administrative Files: Examples: *Social Security, Medicare.*
- Commercially Available Files
Matcher Evaluation

- BigMatch
- SAS-Based Matcher
- Python BigMatch (Center for Optimization and Data Science)
Evaluation Methodology

- *FEBRL “generate2.py”*: Household/Person File Simulator (Christen 2011)
- Emphasis of the evaluation is on *accuracy*.
- Simulated transcription and phonetic errors.
- “*Truth*” is known
- “*False Positives*” & “*False Negatives*” are identifiable.
- Other measurements can be computed.
generate2.py – FEBRL (Christen et al. 2004)

“python generate2.py dataset1.csv 100000 100000 2 2 2 uniform typ 2 > classificationInfo.dat”

- 100,000 originals 100,000 duplicates, max 2 duplicates per record, max 2 modifications per field, max 2 modifications per record, distribution, modification types, number of family and household records to be generated.
- ./data contains dictionaries and frequency tables for last names, surnames, street names, etc.
- dataset1.csv has approximately 200,000 person/household records and 100,000 duplicated records.
- classificationInfo.dat has complete information on “truth”.
Example: *BigMatch*

- "./BigMatch" compiled "C" object.
- Create file of duplicates and complete audit track
- Parameter file: "parmn.dat" contains name of file to be unduplicated (*dataset1.dat* is a fixed-field format of *dataset1.csv*).
- Parameter file: "parmf.dat" contains information on blocking and matching strategies.
- Similar parameter files for "SAS-Based Matcher".
BigMatch Parameter File

1 1 1 0 1 1 0 400 400
2
5

st 91 15 91 15 1
block 166 15 166 15 1
given 61 15 61 15 0 \, uo \, 0.99 \, 0.01
Surname 76 15 76 15 0 \, uo \, 0.99 \, 0.01
...

...
BigMatch Parameter File

- First line: blocking strategy, sequence fields, duplicate flag, Memory file records, length of record file record, length of memory file record.

- Blocking Run Parameter Lines: flocking field parameters, matching fields parameters...

- Blocking Field Parameters: blocking filed name, start position of field, start position in the memory file.

- Matching Fields Parameters: matching filed name... Field comparison type: *uo* string comparison with typographical variations,
References

Rate today’s session

Cyberconflict: A new era of war, sabotage, and fear

9:55am - 10:10am Wednesday, March 27, 2019
Location: Ballroom
Secondary Topics: Security and Privacy

We’re living in a new era of constant sabotage, misinformation, and fear, in which everyone is a target, and you’re often the collateral damage in a growing conflict among states. From crippling infrastructure to sowing discord and doubt, cyber is now the weapon of choice for democracies, dictators, and terrorists.

David Sanger explains how the rise of cyberweapons has transformed geopolitics like nothing since the invention of the atomic bomb. Moving from the White House Situation Room to the dens of Chinese, Russian, North Korean, and Iranian hackers to the boardrooms of Silicon Valley, David reveals a world coming face-to-face with the perils of technological revolution—a conflict that the United States helped start when it began using cyberweapons against Iranian nuclear plants and North Korean missile launches. But now we find ourselves in a conflict we’re uncertain how to control, as our adversaries exploit vulnerabilities in our hyperconnected nation and we struggle to figure out how to deter these complex, short-of-war attacks.

David Sanger
The New York Times

David E. Sanger is the national security correspondent for The New York Times as well as a national security and political contributor for CNN and a frequent guest on CBS This Morning, Face the Nation, and many PBS shows.

Session page on conference website
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