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Panel Discussion

Matching Patient Data

Don Grodecki, President, Browsersoft Inc, Chief Architect, OpenHRE™
Connecting for Health NHIN Team

Dave "Casey" Webster, Chief Architect
IBM Consortium

Matching Patient Data

Data Needs for Matching Patients without Unique Identifiers

- **Information Exchange between disparate healthcare systems depend on ability to match patient identities without benefit of common identifiers**

- **The Problem:**
  - Given sets of identifying information (matching variables) …
    - e.g. Name, Date of Birth, Address, SSN (perhaps), …
  - For a set, or multiple sets, of patient records …
  - Determine which of the records are for the same patient

Matching Patient Data

Theory of Probabilistic Matching

- **A Matching Rule divides the set of all possible record pairs into three sets:**
  - L: (Matched, or Linked)
  - N: (Not matched)
  - C: (not determined, needs Clerical review)
- **The Sensitivity (m) of a rule is the probability that the rule declares a match when there really is a match**
  - 1-m is the probability of a false negative
- **The Specificity (1-u) of a rule is the probability that the rule predicts a non-match when there really is a non-match**
  - u is the probability of a false positive
- **Obviously we want both Sensitivity and Specificity to be high**
- **As an example, using the stated value of "Gender" to decide a match has high Sensitivity (0.99..) but low Specificity (0.5)**

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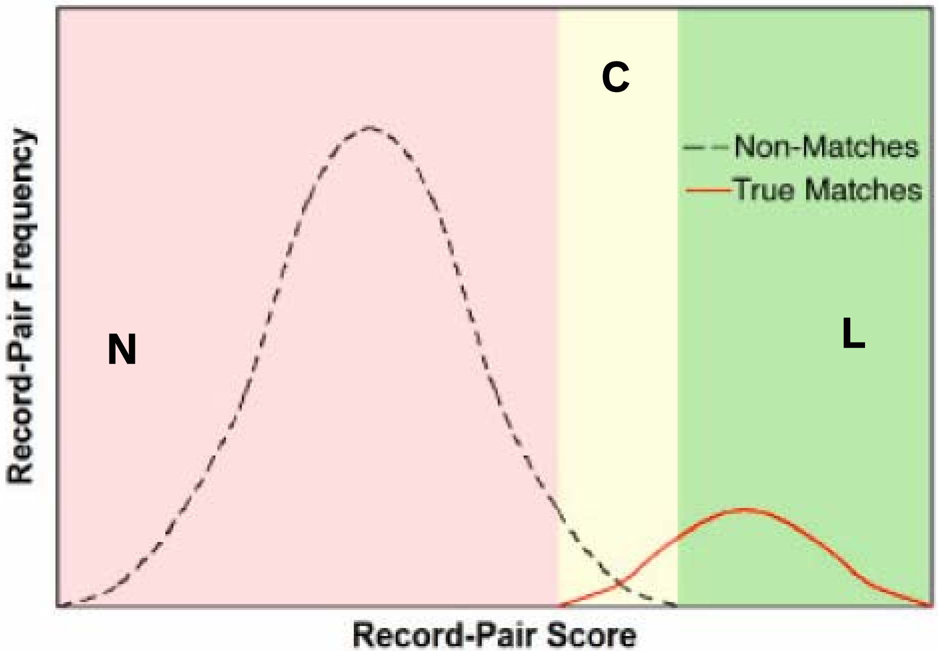
Theory of Probabilistic Matching

- Standard practice is to build a rule using the weighted sum of the values of comparators that each evaluate the match of a single matching variable and assign a value between "0" and "1" to the match.
- The L, C, and N sets are determined from cutoff values applied to the combined score.



Matching Patient Data

Theory of Probabilistic Matching

- $u \sim u_1 \times u_2 \times \ldots \times u_k \times \ldots \times u_K$
  - so, we minimize false positives by comparing a sufficient number of independent variables with high specificity

- **Fellegi and Sunter (1969) proved that the "optimal" weight for the comparator for independent variable "k" is:**
  - $\log_2(m_k) / \log_2(u_k)$

- **"Optimal" in the sense that the L and N sets are maximally "distinct"**

Matching Patient Data

Process

- **Data Cleaning**
  - The possibility of matching is greatly enhanced by pre-processing the variables using specific algorithms for each variable
    - Remove most punctuation in names
    - Removing bad values: e.g. "9999...", "0000..."
- **Standardization**
  - Upper/lower case
  - Mapping nicknames to standard names
  - USPS address processing services
- **Pre-processing**
  - Computing phonetically encoded values, e.g. Soundex
- **Blocking**
  - Optimizing database queries by a-priori requiring some exact matches
- **Post-Processing**
  - Using nearness operators on a set of candidate matches
- **Clerical Intervention**
  - Manual processing, a-priori and/or on-the-fly

Patient Matching Errors and their Impacts

- **Bad match ("false positive")**
  - Violation of privacy of wrongly matched individual
  - Data returned could impact diagnosis and/or treatment
  - Clinician and patient faith in the system adversely impacted

- **Missed Match ("false negative")**
  - Missing data could be important to diagnosis or treatment (recurring symptoms, allergies, repeated tests)
  - Clinicians won't trust a system they perceive as delivering partial information

Matching Patient Data

Patient Matching Challenges that Affect Accuracy

- **No universal patient identifier**
  - Nor would one work, reference Great Britain

- **Demographics change**
  - Americans age 18-65 average 1 move every 5-6 years
    - Every year 35% of Americans age 20-30 move
  - Telephone numbers change frequently/Multiple numbers common
  - Name changes due to marriage, divorce, other

- **Cultural Impact**
  - Soundex, Metaphone based on names of European descent
  - Cultural diversity impacts “near-match" algorithms
    - Longest Common Substring, Levenshtein Edit Distance do poorly on names like “Lee”, “Li”, “Leigh”

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Patient Matching Challenges that Affect Accuracy

- **Quality of data**
  - Name suffixes (Jr, Sr, III, etc) are often omitted
  - Compound (hyphenated) last names increasingly common
  - Missing middle name does not imply lack of a middle name
  - Names often have multiple spellings or variants
    - Smith/Smythe, Mac/Mc, Dave/David

- **Special Cases**
  - Single names (“Cher”, “Bono”)
  - George Foreman

Matching Patient Data

Architectural Approaches

Centralized Matching +/- All demographics available, but perhaps not populated + Matches will be consistent across the entire NHIN - Requires centralized database, privacy - Performance may be an issue	**Local (Community) Matching** +Community has personal knowledge of patients, which can aid in matching - Available demographics limited to what each community “knows” - Match success depends on community - Need to link individuals across communities
Homogenous Matching (Single System) + Algorithms and data are consistent + Same input always results in same result - Simplifies administration and validation	**Eclectic Matching (Multiple Systems)** + Leverages existing matching systems that already work and may have large clerical investment + Lowers barrier to entry for some org’s - Tuning and administration require coordinated effort - Same input may result in different results due to differences in underlying matching algorithms
Deterministic Matching + Much smaller chance of false matches - More potential matches will be missed - Without a UPI or similar identifier, requires manual or external confirmation	**Probabilistic (Stochastic) Matching** +/- Tradeoff between potentially missing a match vs returning a mismatch

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Architectural Approaches

Persistent Matching + Once a match is made, it is permanent + Potential for a-prioi clerical review - Requires all systems involved be able to (logically or physically) persist the match	**Transient Matching** - Matches occur "on-the-fly" and could result in different matches over time + Easier to integrate existing systems
All-or-Nothing +/- Returns either a match or nothing + Simplifies use of the results + Better privacy of patient list - Higher rate of false negatives	**List of Candidates** + Returns potential matches with a match probability and allows end user to choose + Fewer false negatives - Potentially more false positives - Potentially exposes another patient's data

Matching Patient Data

Questions for Discussion

- Is there an allowable threshold of "false positives"?
- What is the minimum acceptable threshold for "false negatives"?
  - How does the age of the data affect this threshold?
- Is further matching necessary to tie providers to patients?