Non-Deterministic Linkage Overview

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Matching of Fields

…or, should we consider Zbignew and Zbigneu the same first name?

Phonetic Transformation

Textual Similarity/Distance Measures

Phonetic Transformations

- Recode string variables in a manner that makes it possible to identify similarly sounding words
- Carl and Karl won't match in straight deterministic comparison, but phonetically they are identical
- Can be an effective tool for matching records that do not agree due to minor data entry errors arising from multiple variations of some words or names

Soundex

- Soundex
  - 4 character phonetic representations of fields
  - First letter is first character of Soundex code
  - Otherwise, ignores vowels
  - Straightforward rules
- Example
  - “Christine” and “Christina” are both C623
  - “Christopher” is also C623
  - But “Chris” is C620

Soundex and NYSIIS

- Fast, easy, well understood
- Widely available in most software
- NYSIIS
  - New York State Identification and Intelligence System
  - Modest improvement over Soundex

Soundex and NYSIIS

- Issues
  - Problems w/non-traditional, non-English
    - Ethnic variations of Soundex exist
  - Best when one can have many false positives (say records match when they don’t) **OR** false negatives (say records not match when they do)
    - Preferable in combination w/other tools, multiple iterations, or non-exact (probabilistic) techniques

Metaphone and Double Metaphone

- Metaphone
  - Reduces text to 16 consonants
  - Variable length
  - Address additional limitations of Soundex
  - More complex rules, but widely available

Metaphone and Double Metaphone

- Double Metaphone
  - Reduces text to 12 consonants
  - Returns two results for lang/ethnic variations
  - ***Very*** complex
  - Slower than Soundex/NYSIIS

Simple Relative Comparisons

- Allow for ***range*** of differences in original data
- Many approaches, including probabilistic
- **Relative comparisons**: If criteria are met, pairing is considered a match
  - Birthweight +/- 100g
  - Birthweight < 1500g
  - Approximate dates ("June 2008", or +/- 1 day)
  - Note that this is different from moving window approach to blocking

Textual Similarities

- Leading Characters
  - Simplest approach
  - Do two strings agree on the first n characters
  - Can be a quick and efficient tool for long strings
    - Particularly if used with other strategies
  - Example based on first 5 leading characters
    - **Johns**on and **Johns**en match
    - **Johns**on and **Johan**sen do not

Similarities Indices

- A variety of similarity indices reflecting how ***similar*** two strings are
- Not making the comparison of two strings a dichotomous “match” vs. “not match”
- Some numeric value that reflects the degree to which the two fields are similar
  - Ranging from completely unrelated to very similar to identical
  - Often scaled 0 (no similarity) to 1 (identical)

Edit Distance

- **Available in FRIL**
- A variety of similarity indices reflecting how similar two strings are
- Edit Distance
  - How many changes are required to make two strings identical
  - Johnson to Johansen
    - Johansen → Johnsen → Johnson
    - Edit distance of 2
  - If this sounds familiar…

Jaro Distance

- Jaro and others have proposed similarity indices based on string length, number of common characters, and transpositions
- ***Jaro Distance***…

$$d_J = \frac{1}{3}\left[\frac{m}{|s_1|} + \frac{m}{|s_2|} + \frac{m-t}{m}\right]$$

…where m is the number of matches within a window of $\frac{\max(|s_1|,|s_2|)}{2} - 1$ characters of each other

Jaro-Winkler Distance

- Jaro and Winkler Distance
  - **Available in FRIL**
  - Further modifies the Jaro Distance
  - Gives extra weight to agreement in the leading characters of a string
    - *l* is the length of the leading string (max 4?)
    - *p* is the additional weighting factor that one wants to give to this adjustments

- $d_{jw} = \max(1, d_j + lp(1 - d_j))$

Dice Scores

Birth Certificate				Medicaid Enrollment			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsky	534	Zbignew	J	Brezinski

- Create bigrams for each string
- Birth certificate record
  - "br", "re", "ez", "zi", "in", "ns", "sk", "ky"
- Medicaid enrollment record
  - "br", "re", "ez", "zi", "in", "ns", "sk", "ki"
- Agree on 7 of the 8 bi-grams

Dice Scores

Birth Certificate				Medicaid Enrollment			
ID	First	Mid	Last	ID	First	Mid	Last
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- Agree on 7 of the 8 bi-grams

$$\text{DiceCoef} \quad = \quad 2\left[\frac{A_{bigrams} \cap B_{bigrams}}{A_{bigrams} + B_{bigrams}}\right]$$

$$\text{DiceCoef} \quad = \quad 2\left[\frac{7}{8+8}\right] \quad = \quad .875$$

Q-Grams in FRIL

- Dice Scores ***with a twist***
- Includes a minimal level of agreement, below which the score is automatically “0”
- Includes a ceiling level of agreement, above which the score is automatically “1”
- Can include a linearly extrapolated score for levels of agreement that fall between these values

Numeric and Date Distance

- Accept as match values falling within a given range (as raw score or percentage) of each other
- Matches – without linear approximation
  - 0: Outside the range
  - 1: Any value within the range
- Matches – with linear approximation
  - 0: Outside the range
  - 1: A “true” exact match
  - A linear approximation between 0 and 1 proportion to how close the match is within the range

Summary of Similarity Indices

- Many of these can be relatively computationally demanding
  - Both in programming and tech resources
  - Similar to probabilistic computational demands?
- A variety of situations where valuable
  - A field is necessary but susceptible to typos
  - Adds depth to comparisons of individual fields beyond weights reflecting match/not match dichotomy

Non-Deterministic Matching of Records

…or, should we consider Zbignew Brezinski and Zbignew Brezinsky the same person?

Non-Deterministic Linkage Methodology

Weighted Matches

Probabilistic

Machine Learning

Non-Deterministic Methods

- Two records do not have to agree across all fields in order to be matched
- A record in one file is compared to multiple records in another file
- Various methods then employed to determine whether each comparison reflects a true match

Background

Record Set-A
Birth Certificates

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_{n_A} \end{bmatrix}$$

Record Set-B
Enrollments

$$\begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_{n_A} \end{bmatrix}$$

- Consider linking two data sets
  - A: Birth Certificates
  - B: Medicaid Enrollments

Background

Record Set-A Birth Certificates

Record Set-B Enrollments

Possible Matches

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_{n_A} \end{bmatrix} \times \begin{bmatrix} b_1 & b_2 & b_3 & \cdots & b_{n_B} \end{bmatrix} \Rightarrow \begin{bmatrix} a_1b_1 & a_1b_2 & a_1b_3 & \cdots & a_1b_{n_B} \\ a_2b_1 & a_2b_2 & a_2b_3 & \cdots & a_2b_{n_B} \\ a_3b_1 & a_3b_2 & a_3b_3 & \cdots & a_3b_{n_B} \\ \vdots & \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ a_{n_A}b_1 & a_{n_A}b_2 & a_{n_A}b_3 & \cdots & a_{n_A}b_{n_B} \end{bmatrix}$$

- Many possible matches

Background

Record Set-A	Record Set-B		Possible Matches
Birth Certificates	Enrollments		

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_{n_A} \end{bmatrix} \times \begin{bmatrix} b_1 & b_2 & b_3 & \cdots & b_{n_B} \end{bmatrix} \Rightarrow \begin{bmatrix} a_1b_1 & a_1b_2 & a_1b_3 & \cdots & a_1b_{n_B} \\ a_2b_1 & a_2b_2 & a_2b_3 & \cdots & a_2b_{n_B} \\ a_3b_1 & a_3b_2 & a_3b_3 & \cdots & a_3b_{n_B} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n_A}b_1 & a_{n_A}b_2 & a_{n_A}b_3 & \cdots & a_{n_A}b_{n_B} \end{bmatrix}$$

- The truth is out there…

General Principles

Possible Matches	Set M: “True” Correct Matches	Set U: “True” Incorrect Matches
Matrix of Possible Matches from previous slide, described below.	a_1b_3 $a_2b_{n\ B}$ a_3b_1 $\vdots$ $a_{nA}b_2$	a_1b_1, a_1b_2, …, a_1b_1, a_2b_2, a_2b_3, a_3b_2, a_3b_3, …$a_{nA}b_{nB}$,

$$\begin{bmatrix} a_1b_1 & a_1b_2 & a_1b_3 & \cdots & a_1b_{n_B} \\ a_2b_1 & a_2b_2 & a_2b_3 & \cdots & a_2b_{n_B} \\ a_3b_1 & a_3b_2 & a_3b_3 & \cdots & a_3b_{n_B} \\ \vdots & \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ a_{n_A}b_1 & a_{n_A}b_2 & a_{n_A}b_3 & \cdots & a_{n_A}b_{n_B} \end{bmatrix}$$

Estimating M and U

Predicted Matches **a_1b_3 , a_2b_{nB}, a_3b_3, …**	→	Set M: "True" Correct Matches a_1b_3 $a_2b_{n\ B}$ a_3b_1 ⋮ $a_{nA}b_2$
Predicted Non-Matches **a_1b_1, a_1b_2, a_2b_1, a_3b_1, a_2b_3, a_3b_2, …**	→	Set U: "True" Incorrect Matches a_1b_1, a_1b_2, …, a_1b_1, a_2b_2, a_2b_3, a_3b_2, a_3b_3, …$a_{nA}b_{nB}$,
Uncertain Matches **a_2b_2, $a_{nA}b_2$, …**	→	?

False Matches

Predicted Matches **a_1b_3 , a_2b_{nB}, a_3b_3,** …	→	Set M: “True” Correct Matches a_1b_3 $a_2b_{n\ B}$ a_3b_1 ⋮ $a_{nA}b_2$
Predicted Non-Matches **a_1b_1, a_1b_2, a_2b_1, a_3b_1, a_2b_3, a_3b_2, …**	→	Set U: “True” Incorrect Matches a_1b_1, a_1b_2, …, a_1b_1, a_2b_2, a_2b_3, a_3b_2, a_3b_3, …$a_{nA}b_{nB}$,
Uncertain Matches **a_2b_2, $a_{nA}b_2$, …**	→	?

False Non-Matches

Predicted Matches **a_1b_3 , a_2b_{nB}, a_3b_3, …**	→	Set M: "True" Correct Matches a_1b_3 $a_2b_{n\ B}$ a_3b_1 ⋮ $a_{nA}b_2$
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Uncertain Matches **a_2b_2, $a_{nA}b_2$, …**	→	?

Optimization Problem

Uncertain Matches a_2b_2, $a_{nA}b_2$, …	→	**?**

- For a given level of false matches and non-matches, how do you obtain the smallest number of uncertain matches?

Optimization Problem

- For a given level of false matches and non-matches, how do you obtain the smallest number of uncertain matches?
- In practice…
  - Minimize the false matches
  - Minimize the false nonmatches
  - Minimize the uncertain matches
- *May not be possible to do all at the same time*

Correct Solution…

Record Set-A Birth Certificates

Record Set-B Enrollments

Possible Matches

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_{n_A} \end{bmatrix} \times \begin{bmatrix} b_1 & b_2 & b_3 & \cdots & b_{n_B} \end{bmatrix} \Rightarrow \begin{bmatrix} a_1 b_1 & a_1 b_2 & a_1 b_3 & \cdots & a_1 b_{n_B} \\ a_2 b_1 & a_2 b_2 & a_2 b_3 & \cdots & a_2 b_{n_B} \\ a_3 b_1 & a_3 b_2 & a_3 b_3 & \cdots & a_3 b_{n_B} \\ \vdots & \vdots & \vdots & \vdots\vdots & \vdots \\ a_{n_A} b_1 & a_{n_A} b_2 & a_{n_A} b_3 & \cdots & a_{n_A} b_{n_B} \end{bmatrix}$$

- But life is rarely perfect…

Solution Challenges

Record Set-A Birth Certificates

Record Set-B Enrollments

Possible Matches

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_{n_A} \end{bmatrix} \times \begin{bmatrix} b_1 & b_2 & b_3 & \cdots & b_{n_B} \end{bmatrix} \Rightarrow \begin{bmatrix} a_1b_1 & a_1b_2 & a_1b_3 & \cdots & a_1b_{n_B} \\ a_2b_1 & a_2b_2 & a_2b_3 & \cdots & a_2b_{n_B} \\ a_3b_1 & a_3b_2 & a_3b_3 & \cdots & a_3b_{n_B} \\ \vdots & \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ a_{n_A}b_1 & a_{n_A}b_2 & a_{n_A}b_3 & \cdots & a_{n_A}b_{n_B} \end{bmatrix}$$

- One mistake and the dominoes begin to fall…

Solution Challenges

Record Set-A Birth Certificates

Record Set-B Enrollments

Possible Matches

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_{n_A} \end{bmatrix} \times \begin{bmatrix} b_1 & b_2 & b_3 & \cdots & b_{n_B} \end{bmatrix} \Rightarrow \begin{bmatrix} a_1 b_1 & a_1 b_2 & a_1 b_3 & \cdots & a_1 b_{n_B} \\ a_2 b_1 & a_2 b_2 & a_2 b_3 & \cdots & a_2 b_{n_B} \\ a_3 b_1 & a_3 b_2 & a_3 b_3 & \cdots & a_3 b_{n_B} \\ \vdots & \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ a_{n_A} b_1 & a_{n_A} b_2 & a_{n_A} b_3 & \cdots & a_{n_A} b_{n_B} \end{bmatrix}$$

Solution Challenges

Record Set-A
Birth Certificates

Record Set-B
Enrollments

Possible Matches

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Uncertain Matches a_2b_2, $a_{nA}b_2$, …	→	?

- Start by throwing the majority of possible matches into predicted non-matches through blocking

Blocking Techniques

- Typically begin by essentially eliminating the vast majority of possible matches
  - Automatically code as non-matches
- All-to-All Comparison
  - Every record in A compared to every record in B
  - Generally only practical in smaller databases

Blocking

- Possible matches must agree on a subset of specified fields
- Possible matches not agreeing on those fields automatically classified as non-matches
- Can dramatically reduce the number of possible comparisons to make
- Generally some form of blocking is necessary for computational efficiency

Blocking

- Selection of fields used for blocking is key
- The poorer the quality of the fields used in blocking, the more erratic the results
  - If data in blocking fields are random, results are meaningless
  - If data in blocking fields are “perfect”, results will still contain all correct matches
  - Quantify the upfront minimum/base error rate as the product of the corresponding *m* probabilities (more later..)

Moving Window Blocking

- Records are sorted based on some combination of one or more fields
- Records in A are compared to similar records in B that fall within a specified window size
  - Sort by date of birth
  - Select window size of 30
  - If a baby in A was born on August 18, 2007 only consider the 30 records in B around that value

Moving Window Blocking

- Selection of fields for sorting is again key
  - Sorting on different fields may increase the separation of “correct” matches
  - Typos may dramatically impact windows
- Multiple iterations with different sort orders may be valuable
- Powerful tool when one wants to block on quantitative field with expected small errors (dates, birth weight…)

Comparison of Blocking Approaches

- If great confidence in a given field, traditional blocking may make the most sense
- If one wishes to use a quantitative variable (birthweight, date of birth) for blocking, moving window comparison probably makes the most sense
- Note that this is different than a distance measure for an individual field (e.g., a birth within 100g is considered a match)

Non-Deterministic Methods

Weighted matches

Probabilistic methods

Machine learning

Hold on Tight for a Minute…

- Winnie the Pooh Video

Non-Deterministic Methods

- Two records do not have to agree across all fields in order to be matched
  - Weights are used to quantify the likelihood that a pair of records are a true match
- A record in one file is compared to multiple records in another file
  - Using the weights, scores are calculated for possible matches that suggest whether it is correct (i.e., are the same person)

Cutoff Scores

- Cutoff scores
  - Above some value (e.g. “14”) conclude it ***is*** a true match
  - Below some value (“11”), conclude it ***is not*** a true match
  - Any possible match with a score between these two values is a manually reviewed
- Individual choice in cutting off low weights

Weighted Fields

- Match two data files based on SSN, First Name, Last Name, Date of Birth, …
- Agreement in some fields are given more "weight" than agreement in other fields
  - A match on SSN has a weight of 3
  - A match on First Name has a weight of 1
  - A match on Last Name has a weight of 2
- The weight is ***non-specific*** (i.e., does not change based on the values in the field)

Weighted Fields

- Sum the weights for each possible match
  - Agreement in different fields results in different sums
  - Larger sums reflect greater confidence of a match
  - Distribution evaluated and cutoff scores determined
  - Each possible match is compared to these cutoff scores to conclude whether a match, non-match, or review

Weighted Fields

- Determining values for the weights
  - Different fields may be a stronger indicator of a true match (ID number versus name)
  - Can assign "penalty" weights for non-matches
    - High quality field that ***should*** almost always agree
  - Subjective, EM algorithm, machine learning
- With ***non-specific weights***, the same weight applies for regardless of the actual data values being matched
    - "Jones-Jones" gets the same weight as "Szapocznik-Szapocznik"

Probabilistic Matching

Birth Certificate				Enrollment Data			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsk*y*	534	Zbignew	J	Brezinsk*i*

- In contrast, probabilistic matching takes into consideration the specific values in the fields being matched
  - Considers the quality of the data in the field
  - Open to further analysis of matching strength

Probabilistic Matching

Birth Certificates				Birth Defects Registry			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsk*y*	534	Zbignew	J	Brezinsk*i*

- More complicated (and expensive) strategy
- Still need to estimate some weights (m and u probs)

Probabilistic Matching

Birth Certificate				Enrollment Data			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsk*y*	534	Zbignew	J	Brezinsk*i*

w_1 w_2

- Two records are compared on each of the specified fields.
- A weight—w_i—is calculated for each field in a potential match reflecting the strength of the agreement or disagreement

Factors Influencing Likelihood of Match

- Reliability of data fields
  - Good quality data counts more than poor quality
    - High quality data suggests that fields should agree if a correct match
    - Low quality data suggests that even if fields don’t agree, it may still be a correct match
  - If a field is pure noise, correct matches will be random across the databases
  - Reflects the likelihood that fields would agree if it ***is*** a correct link

Factors Influencing Likelihood of Match

- Frequency of field values
  - The more common the value in a field, the greater the odds that records will be erroneously matched
    - A match based on the Zbignew is a good indicator of a match, even if there may be disagreement in other fields
    - A match based on the John is of less value, requiring matches on more fields to conclude its the same person
    - Rare values count more than common values
  - Reflects the likelihood that fields would agree if ***not*** a correct link

Factors Influencing Likelihood of Match

- Number of Matches
  - The greater the number of individuals in one database that also appear in the other database, the greater probability of linkage across databases.
  - If two databases are the same size, and every record in one has a match in the other, it is easier to infer that two records are the same individual
  - If two databases have ***no*** individuals in common, the probability of a linkage across the databases is nil, regardless of how well two records agree

Calculating Match Weights

Birth Certificate				Enrollment Data			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsk*y*	534	Zbignew	J	Brezinsk*i*

- Weight Calculation
  - M-probability
    - Probability that a field agrees if the pair is a correct match
  - U-probability
    - Prob that a field agrees if the pair is an incorrect match
    - Chance that a given field will agree randomly
    - ≈ the proportion of records with a specific value

Probabilistic Matching

Birth Certificate				Enrollment Data			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsk*y*	534	Zbignew	J	Brezinsk*i*

w_1 w_2

- If the field agrees, w_i is equal to ….

$$w_i = \log_2 (m_i/u_i)$$

Probabilistic Matching

Birth Certificate				Enrollment Data			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsk*y*	534	Zbignew	J	Brezinsk*i*

w_1 w_2

– m_i for first name = .98, or 98% of the time, if it's a correct match, the first names will agree

– u_i for Zbignew is .00001 is the probability of randomly getting two first names that are Zbignew

$$w_{i1} = \log_2 (m_i/u_i) = \log_2 (.98/.00001) = 16.58049$$

Probabilistic Matching

Birth Certificate				Enrollment Data			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsk*y*	534	Zbignew	J	Brezinsk*i*

w_1 w_2

- In cases where two records disagree on a specified field, w_i is equal to ….

$$w_i = \log_2 (1 - m_i / 1 - u_i)$$

Probabilistic Matching

Birth Certificate				Enrollment Data			
ID	First	Mid	Last	ID	First	Mid	Last
9	Zbignew		Brezinsk*y*	534	Zbignew	J	Brezinsk*i*

w_1 w_2

- m_i for last name = .96, or 96% of the time, if it's a correct match, the last names will agree
- u_i for Brezinsky is .00003 is the probability of randomly getting two last names that are Brezinsky

$w_{i2} = \log_2((1 - m_i)/(1 - u_i)) = \log_2((1 - .96)/(1 - .00003)) = -4.64381$

Calculating Match Weights

- A composite weight, w_t calculated for each pair of records
  - The sum of weights across all fields used in linkage

$$w_t = \sum_{i=1}^{k} w_i$$

w_{it} = 16.58049 – 4.64381 = 11.93668

- Larger w_t suggest a correct match,
- Smaller or negative w_t suggest an incorrect match.

Probabilistic Matching

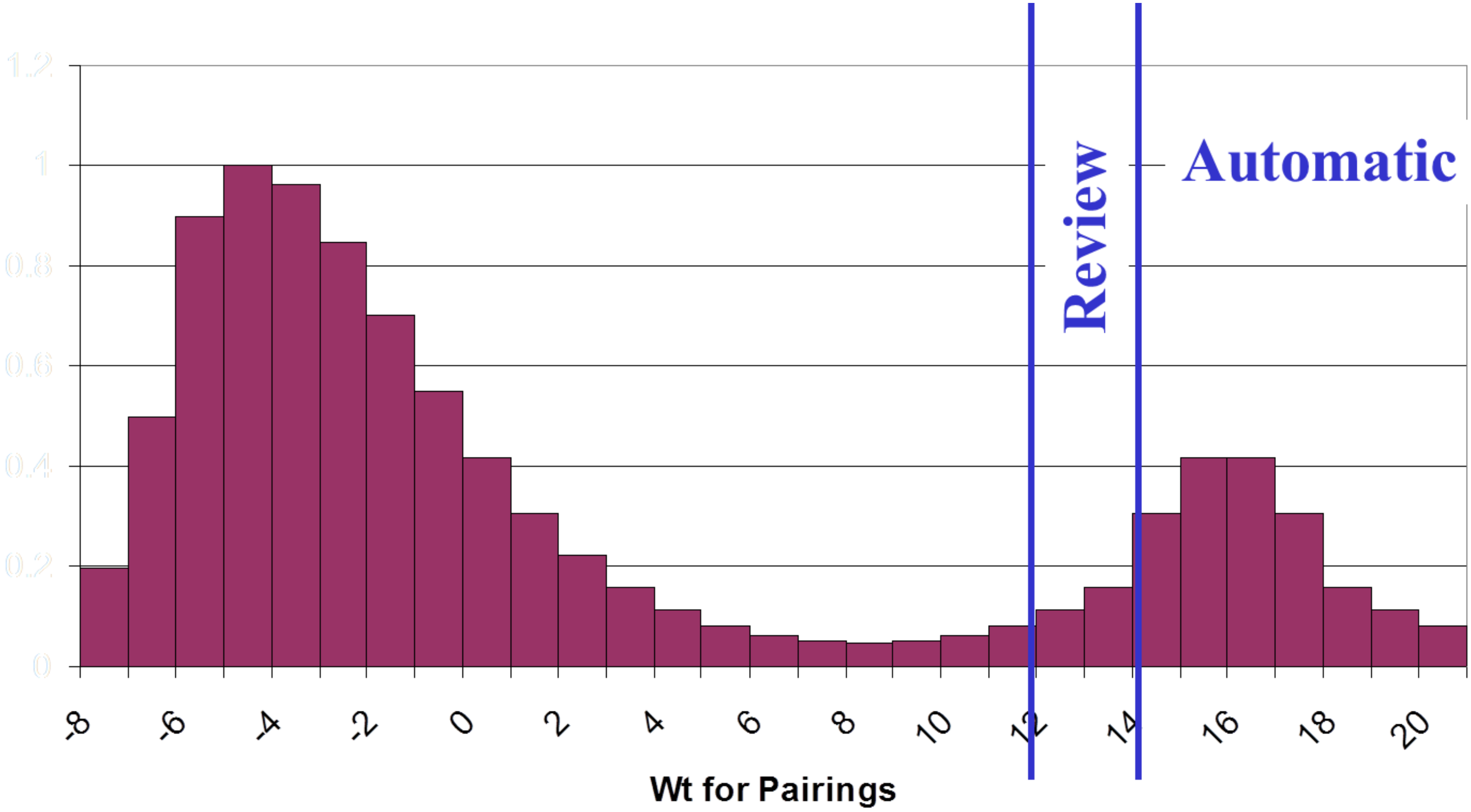
- Two fields disagree
  – m-probabilities generally come into play
  – How big of a hit do you take when last name doesn't agree across a possible match?
- Two fields agree
  – Differences in the u-probabilities that typically matter most
  – (e.g., last name of Smith versus Brezinski).

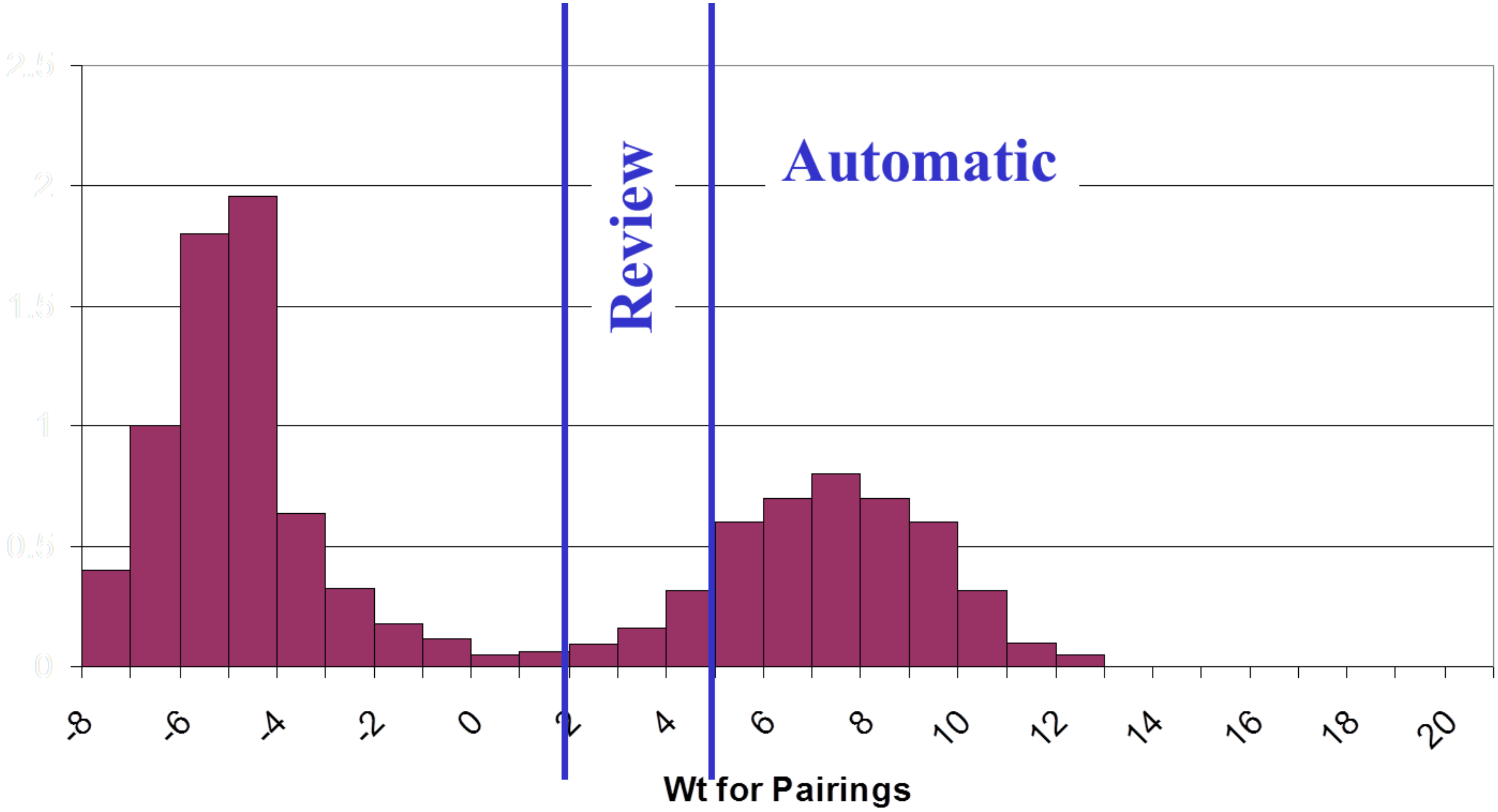
Probabilistic Match Weights

- Cutoff values for w_t are determined and used to classify possible matches
  - Automatic matches
  - Manual review
  - Automatic rejection
- Traditionally, techniques end at this point

Probabilistic Match Weights

- Issues
  - w_t values have no inherent meaning
    - No set range as to large or small w_ts
  - If multiple iterations are performed, cutoffs must be analyzed and determined for every iteration


Review
Automatic
1.2
1
0.8
0.6
0.4
0.2
0
-8
-6
-4
-2
0
2
4
6
8
10
12
14
16
18
20
Wt for Pairings



2.5
2
1.5
1
0.5
0
Review
Automatic
-8
-6
-4
-2
0
2
4
6
8
10
12
14
16
18
20
Wt for Pairings

Estimating Probabilities

- The total-weight required for two records to have a probability, p, of being a match is equal to…

$$w_t = \log_2(p/(1 - p)) - \log_2 (E/(N_1 N_2 - E))$$

…and…

$\log_2 (E/(N_1 N_2 - E)$) is the base 2 log of the odds of a random match

Estimating Probabilities

From this formula, it is possible to derive an equation for estimating *p*, the probability that any two records are a match, where…

$$p = \frac{\prod_{i=0}^{K} x_i}{\prod_{i=0}^{K} x_i + 1}$$

$x_0 = E/(N_1 N_2 - E)$ odds of a random match,

$x_{i,i>0} = m_i/u_i$ if two fields agree, and…

$x_{i,i>0} = (1 - m_i)/(1 - u_i)$ if two fields do not agree

Sum of Weights (w_t) vs Probabilities

- Sum of Weights (w_t)
  - Requires repeatedly calculating $\log_2$’s
  - No inherent interpretability, must subjectively determine a “large” w_t with each linkage
- Probabilities
  - Does not requires $\log_2$’s, and so improved speed with large linkage projects
  - More readily understood and interpreted criteria for determining whether to classify two records as being a match

Machine Learning

- Through a series of software-driven iterations, software “learns” which weights to use or which combinations of linkage fields are best
- May use any of these approaches
  - Most likely use weighted fields or probabilistic

Machine Learning

- Typically, use training datasets
  - Software fed ***training data*** with known solution regarding “true” matches
  - Algorithms match records based on initial sets of weights
  - Results compared to information regarding “true” matches to see if replicated
  - Modifies weights and re-runs with same or different training data

Machine Learning

- After various trials with training data, final set of weights determined
  - May see minimal modifications made to new trials
- Algorithm should now work with real data
- Issues
  - Identifying a training data set that reflects the nature, qualities, and issues in the data sets you wish to link
  - Complexity
  - Some approaches seek to skip need for training sets

Probabilistic Linkage Methods

- Some SAS programmers write their own code for probabilistic matching
- Software packages
  - Can be very expensive
  - Difficult to use
  - Some applications are available as freeware or shareware

Choosing Probabilistic Software

Program	**OS**	**Initial $**	**Yearly $**	**Link Type**	**Desc**	**Audience**	**Organization**
Automatch (Integrity)	Windows	$100,000	???	Probabilistic	GUI	Marketing	
Generalized Record Linkage System (GRLS)	UNIX	$18,800	10%	Probabilistic	ORACLE	Health care	Stats Canada
LinkPro	Windows/ Server	$1,455 / $1,190	None	Determ & Prob	SAS	Health care	U. of Manitoba

- Links: same as LinkPro but freeware
- FRIL: also freeware, open source

Overall Summary of Linkage Methods

- Many tools and strategies available
- No single approach is perfect for every situation
- Factors to consider
  - Purpose of linkage
  - Nature of the data
    - Quality of fields used for linkage
    - Type of data (string, date, numeric) used for linkage
    - Resources available