Record linkage

Record linkage (also known as data linkage)

- □ **for organising ONE dataset**
  - data cleaning
  - removing duplicates

- □ **for merging TWO OR MORE datasets**
  - merging individual-level datasets
  - adding census data to survey data

Identification of Duplicates Given Name, Address, Age

Matching Information

Name	Address	Age
John A Smith	16 Main Street	16
J H Smith	16 Main St	17
Javier Martinez	49 E Applecross Road	33
Haveir Marteenez	49 Aplecross Raod	36
Gillian Jones	645 Reading Aev	22
Jilliam Brown	123 Norcross Blvd	43

Record linkage . . .

“[is] a solution to the problem of recognizing those records in two files which represent identical persons, objects, or events (said to be matched).”

Fellegi IP & Sunter AB (1969) A theory for record linkage. Journal of the American Statistical Association 64, 1183-1210

Problem of record linkage

problem - **quickly and accurately** determining if pairs of records describe the same entity, but unique IDs to bring together the matching records are lacking

records must contain some common identifying information (**keys or matching variables**)

- □ unique identifier (ideal in theory)
- □ name and/or address
- □ age (DOB) and sex

Files A & B, record a in A & record b in B

	File A				File B				
	matching variables					matching variables			
	v_1	$\ldots$	v_K	X	Y	w_1	$\ldots$	w_K	
a									
									b

Methodology of record linkage

- **two distinct methodologies for data linkage**
- **deterministic linkage** methods involve exact one-to-one character matching of linkage variable(s)
- **probabilistic linkage** methods involve the calculation of linkage weights estimated given all the observed agreements and disagreements of the data values of the matching variable(s)
- **probabilistic linkage methods can lead to much better linkage than simple deterministic linkage methods**

Deterministic linkage

- **simplest method of matching** - sort/merge
- exact matching ONLY works well if the linking data are perfect and present in all the databases you want to link
- works best when there is a single unique identifier (key)
- otherwise, matching based on sets of identifiers predetermined by the researcher
- identifiers have equal weight
- identifiers chosen by researcher or by availability
- **works best with high quality data, but yields less success than probabilistic linkage**

Deterministic linkage ...

- **deterministic matching links records**
  - using a fixed set of matching variables
  - **exact 1-to-1 character matching**

- **problems**
  - **often no unique, known and accurate ID**
  - **missing values & partial agreements common**

- sometimes only the first few characters of a field are used with a wildcard substituted for later characters
  - Anders*, for Anderson and Andersen
  - Martin*, but Martin and Martinez also match

Data linkage . . .

Data linkage is a challenging problem because of

- errors, variations and missing data on the information used to link records
- differences in data captured and maintained by different databases, e.g. age versus DOB
- data dynamics and database (DB) dynamics as data regularly and routinely change over time
  - name changes due to marriage & divorce
  - address changes

Data problems

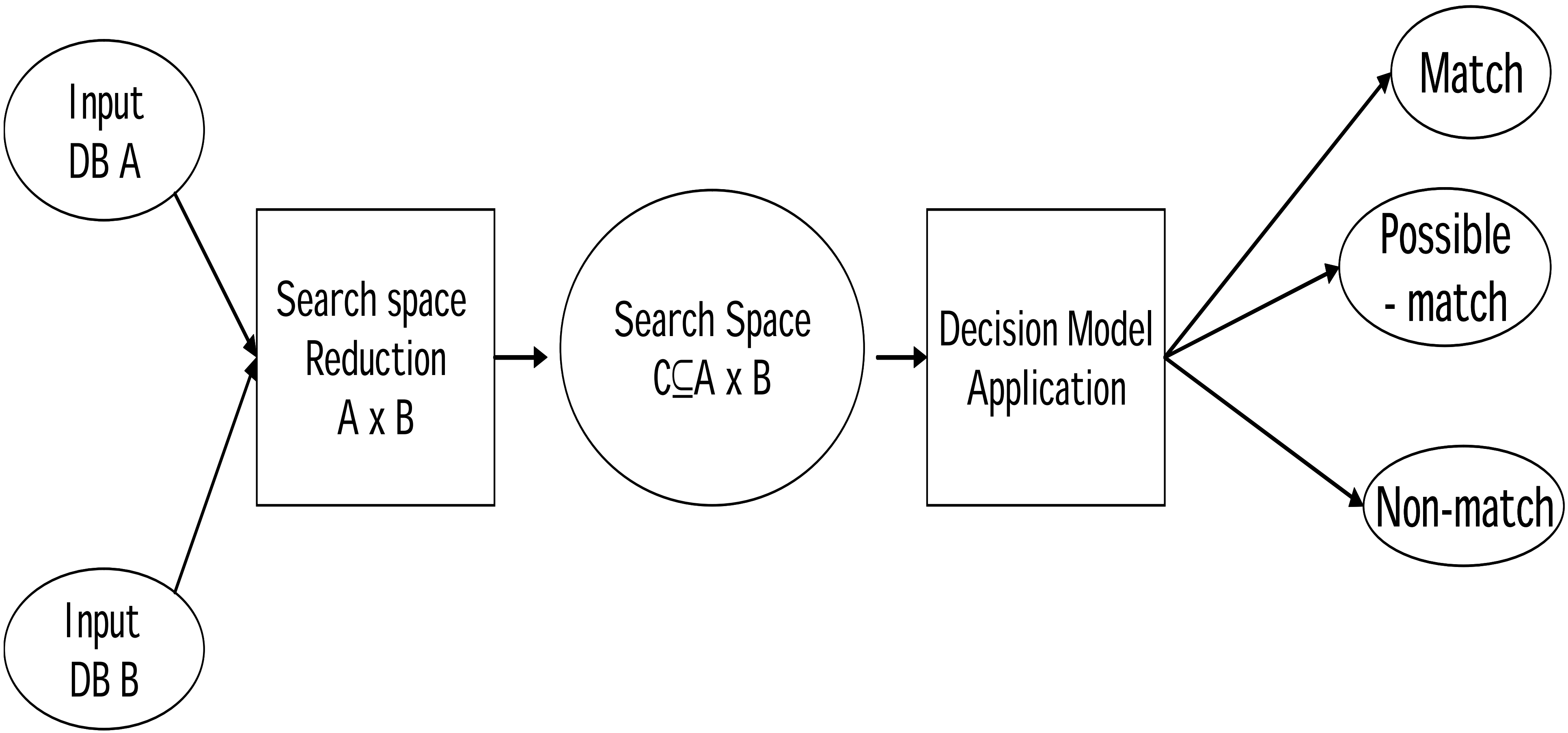
- typos/mispelling
- letters or words out of order
- fused or split words
- missing or extra letters
- incomplete words
- extraneous information
- incorrect or missing punctuation
- abbreviations
- multiple errors

Surname	Name	Day of B	Year of B	freq
0	0	0	0	414138
0	0	0	1	5321
0	0	1	0	14004
0	0	1	1	168
0	1	0	0	3090
0	1	0	1	43
0	1	1	0	102
0	1	1	1	9
1	0	0	0	969
1	0	0	1	17
1	0	1	0	22
1	0	1	1	19
1	1	0	0	14
1	1	0	1	9
1	1	1	0	6
1	1	1	1	513

Linkage projects typically have three phases

- **pre-linkage**
  - data cleaning
  - processing data fields to recognize similarity
- **linkage phase: deciding whether two records are a**
  - **duplicate**
  - **match (link)**
- **post-linkage**
  - manual/clerical review of unlinked records
  - research using the linked data

Phases of record linkage



Hypothetical example

- Clark DE (2004) Practical introduction to record linkage for injury research, Injury Prevention, 10, 186-191
- $N_A = 10$ **ambulance cases**
- $N_B = 20$ **emergency department cases**
- **aim to match the cases**
- **prior belief - anticipated number of correct matching records is** $N_X = 9$

http://injuryprevention.bmj.com/content/10/3/186.full.pdf

Prior probability of a match

- **prior probability** that a randomly selected record from file A matches a randomly selected record from file B

$$\Pr(\text{match}) = \frac{N_X}{N_A} \times \frac{1}{N_B} = \frac{9}{10} \times \frac{1}{20} = \mathbf{0.045}$$

- generally, this probability will be a very small number, so the prior odds will be similar

- **prior odds: 0.045 / (1 - 0.045) = 0.047**

- usually we will work with log odds of a match, which will be a negative number

File A - Ambulance data

Case	Year	Day	Hosp	Birth Year	Birthday	Sex
A01	01	Jan01	X	1950	Jan21	M
A02	01	Jan01	X	1950	May01	F
A03	01	Jan10	Y	1975	Dec27	
A04	01	Aug13	X	1977	Apr29	F
A05	01	Sep12	Y	1980	Feb16	F
A06	01	Dec31	Z	1919	Sep16	M
A07	02	Feb02	X	1924	Mar26	F
A08	02	Jun10	Y	1951	Mar29	M
A09	02	Aug06	Y	1953	Apr17	
A10	02	Sep21	Z	1956	Jun03	F

File B - Emergency department data

Case	Year	Day	Hosp	Birth Year	Birthday	Sex
E01	01	Jan01	X	1950	Jan21	M
E02	01	Jan10	Z	1987	Jul17	M
E03	01	Feb23	X	1992	Oct19	M
E04	01	Apr22	Y	1979	May09	M
E05	01	May02	X	1929	Nov12	F
E06	01	May23	Y	1964	Dec01	M
E07	01	Jun01	X	1950	May01	F
E08	01	Aug14	X	1977	Apr29	F
E09	01	Sep12	Y	1980	Feb16	F
E10	01	Oct21	Y	1985	Mar12	M

File B - Emergency department data . . .

Case	Year	Day	Hosp	Birth Year	Birthday	Sex
E11	02	Jan01	Z	1919	Sep16	M
E12	02	Jan10	Y	1975	Dec27	F
E13	02	Feb02	X	1924	Mar26	F
E14	02	May16	X	1924	Oct12	M
E15	02	Jun10	Y	1951	Mar29	M
E16	02	Jul04	Z	1982	Jun12	M
E17	02	Aug05	Y	1953	Apr17	M
E18	02	Aug06	Y	2002	Apr17	F
E19	02	Sep21	Z	1956	Jun03	F
E20	02	Nov22	X	1917	May29	M

Comparing record pairs - exact matches

Case	Year	Day	Hosp	Birth Year	Birthday	Sex
A10	02	Sep21	Z	1956	Jun03	F
E19	02	Sep21	Z	1956	Jun03	F
A01	01	Jan01	X	1950	Jan21	M
E01	01	Jan01	X	1950	Jan21	M
A05	01	Sep12	Y	1980	Feb16	F
E09	01	Sep12	Y	1980	Feb16	F
A07	02	Feb02	X	1924	Mar26	F
E13	02	Feb02	X	1924	Mar26	F
A08	02	Jun10	Y	1951	Mar29	M
E15	02	Jun10	Y	1951	Mar29	M

Comparing record pairs - matches?

Case	Year	Day	Hosp	Birth Year	Birthday	Sex
A03	01	Jan10	Y	1975	Dec27	
E12	02	Jan10	Y	1975	Dec27	F
A02	01	Jan01	X	1950	May01	F
E07	01	Jun01	X	1950	May01	F
A04	01	Aug13	X	1977	Apr29	F
E08	01	Aug14	X	1977	Apr29	F
A09	02	Aug06	Y	1953	Apr17	
E17	02	Aug05	Y	1953	Apr17	M
E18	02	Aug06	Y	2002	Apr17	F
A06	01	Dec31	Z	1919	Sep16	M
E11	02	Jan01	Z	1919	Sep16	M

M-probability (Match probability)

- **M-probability: probability that a field agrees given that the pair of records is a true match**
- **for any given field, the same M-probability applies for all records**
- **assume the following:**
  - admission year: .99
  - admission date: .95
  - hospital: .99
  - birth year: .95
  - birthday: .99
  - sex: .95

M-probability (Match probability) ...

- **data quality is quantified by the M-probabilities**
- M-probability of 0.95 for surname means that the probability two records belonging to the same person will agree on last name is 0.95
- why will surname on two records belonging to the same person disagree 5% of the time
  - data entry errors
  - missing data
  - instability of value, e.g. surname change
  - misspelling, e.g. Anderson versus Andersen

U-probability (Unmatch probability)

- **U-probability: probability that a field agrees given that the pair of records is NOT a true match**

- **often simplified as the chance that 2 records will randomly match**, i.e. proportion of records with a specific value on the larger file

- **the U-probability is defined as value specific and will often have multiple values for each field**

- assume:
  - admission year: .5; admission date: .0027 (1/365)
  - **hospital X or Y: .4 hospital Z: .2**
  - birth year: .01 (1/100); birth date: .0027 (1/365)
  - **males: .6; females: .4**

U-probability (Unmatch probability) . . .

- **probability of random matches is context specific**
- **generally, gender is of limited value for linkage**
- randomly agrees 50% of the time in most contexts, but
  - males: .6; females: .4 for ambulance data
  - males: .0; females: 1.0 in an all female school
- **gender in an all female school is useless for linkage as one would obtain a match on that field in any random pairing**

U-probability (Unmatch probability) . . .

- **consider a field with a unique value for every person in the dataset**, e.g. unique ID number
  - **this field can be very useful for linkage if it is in both files**
  - one would not expect to obtain a match randomly
  - only limiting factor on correct matches would be the data quality, the value of the M-probability

Jenkins S et al (2006) **The feasibility of linking household survey and administrative record data**: New evidence for Britain. International Journal of Social Research Methodology 11, 29-43

U-probability (Unmatch probability) . . .

- **consider the field surname**
- **different people will have different U-probabilities**, depending on their own specific surname (and context, e.g. country/region)
- **how are U-probabilities estimated?**
- typically estimated as the proportion of records with a specific value, based on the frequencies in the primary or more comprehensive and accurate data source

U-probability (Unmatch probability) . . .

- **how are U-probabilities estimated for surnames?**
- 300 000 birth certificates
- 600 Andersons
- 30 Rumplestilskins
- estimated U-probability
  - $600 \,/\, 300\,000 = .0020$ for Anderson
  - $30 \,/\, 300\,000 = .0001$ for Rumplestilskin

Estimating match (probabilistic) weights

- **for a given field with match probability M and unmatch probability U**

- **for an agreement, we calculate the weight**

$$\log(\frac{M}{U})$$

- **for a disagreement, we calculate the weight**

$$\log(\frac{1-M}{1-U})$$

- assuming independence of information across the fields, **we sum the weights across all the fields** to obtain the total weight for the record pair

Estimating match (probabilistic) weights

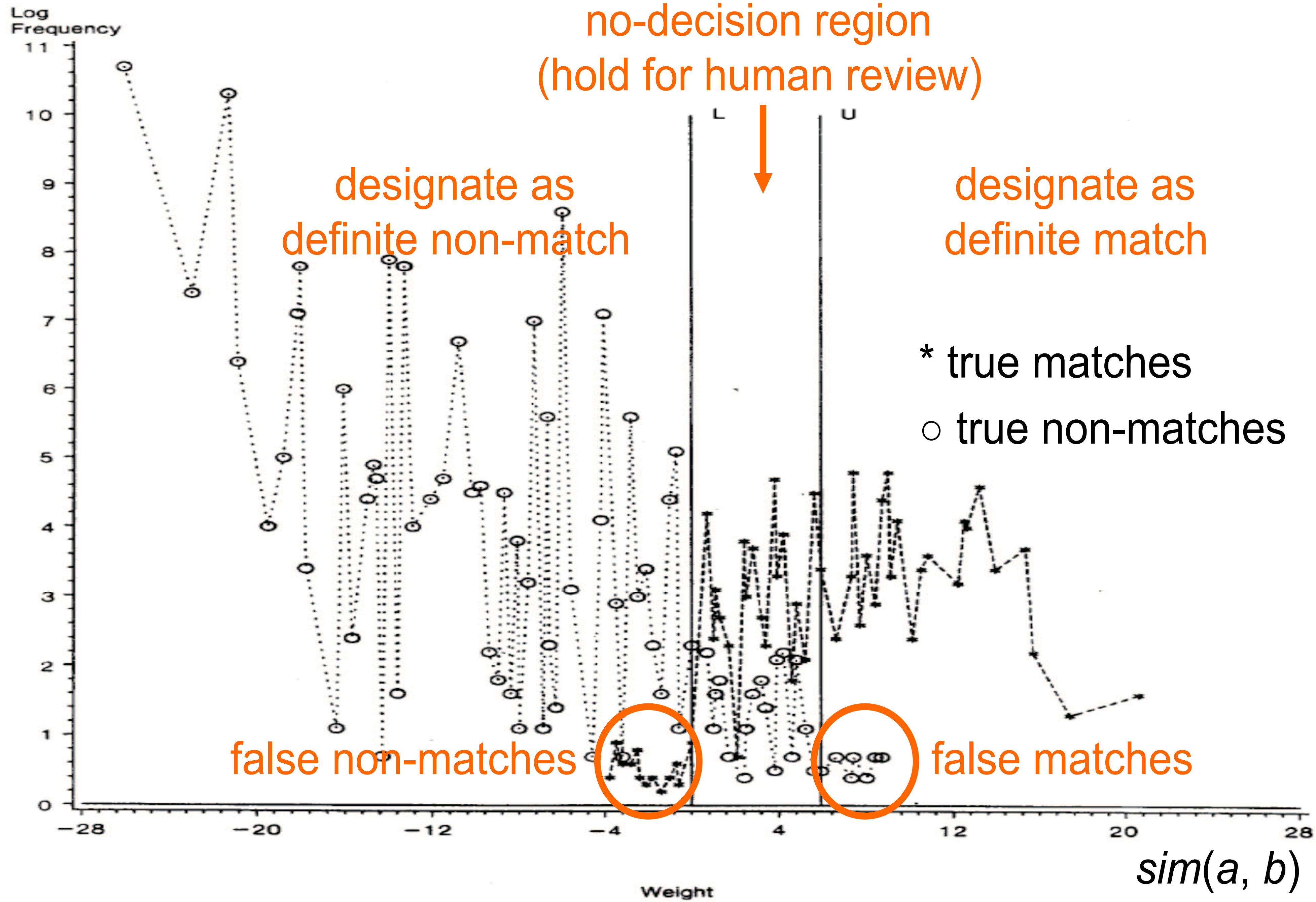
- **highest weight 7.455 is for the pair A10-E19, which agrees across all fields**, as calculated by

$$\log(\frac{.99}{.50})+\log(\frac{.95}{.0027})+\log(\frac{.99}{\mathbf{.20}})+\log(\frac{.95}{.01})+\log(\frac{.99}{.0027})+\log(\frac{.95}{\mathbf{.4}})$$

- **for pair A03-E12, the admission year and sex were different, and the weight is 4.704**, as calculated by

$$\log(\frac{\mathbf{1-.99}}{\mathbf{1-.50}})+\log(\frac{.95}{.0027})+\log(\frac{.99}{.20})+\log(\frac{.95}{.01})+\log(\frac{.99}{.0027})+\log(\frac{\mathbf{1-.95}}{\mathbf{1-.4}})$$

Fellegi-Sunter model



Posterior odds and posterior probabilities

- **posterior odds = prior odds $\times$ likelihood**

- **for pair A10-E19, the posterior odds are 1 340 000** as calculated from

$$.047 \times \frac{.99}{.50} \times \frac{.95}{.0027} \times \frac{.99}{.20} \times \frac{.95}{.01} \times \frac{.99}{.0027} \times \frac{.95}{.4}$$

- **for pair A03-E12, admission year and sex differed, and the posterior odds are 2 376** as calculated from

$$.047 \times \frac{1-.99}{1-.50} \times \frac{.95}{.0027} \times \frac{.99}{.20} \times \frac{.95}{.01} \times \frac{.99}{.0027} \times \frac{1-.95}{1-.4}$$

Posterior odds and posterior probabilities . . .

- posterior probability $= \dfrac{\text{posterior odds}}{1 + \text{posterior odds}}$
- for pair A10-E19, the posterior probability is .9999
- for pair A03-E12, admission year and sex differed, and the posterior probability is .9996
- A09 is problematic because it might be matched to either E17 or to E18 with posterior probabilities of .9805 or .9921 respectively
- pair A06-E11 is also uncertain with posterior probability of .9507 as pair differs by year and day, but Dec 31, 2001 and Jan 01, 2002!

Probabilistic linkage

- **each matching variable is compared and assigned a score (weight) based on how well it matches**
- frequency analysis of data values is important
- uncommon value agreement stronger evidence for linkage, e.g. Rumplestilskin versus Smith
- **calculates a score for each field that indicates, for any pair of records, how likely it is that they both refer to the same entity**
- **sum the scores over fields**
- sort record pairs in order of their scores (weights)

Probabilistic linkage . . .

- cut off values for scores (weights) are used to distinguish between matches and non-matches
- **above a certain threshold, everything is a match** (link)
- **below a certain threshold, nothing is a match** (nonmatch or nonlink)
- **in between (grey area), possible match needs manual/clerical review**

Probabilistic linkage . . .

- **total score for a link between any two records is the sum of the scores generated from matching individual fields**
- score assigned to a matching of individual fields
  - is based on the probability that a matching variable agrees given that a comparison pair is a match
  - M-probability - similar to “sensitivity”, i.e. the proportion of actual positives which are correctly identified

Probabilistic linkage . . .

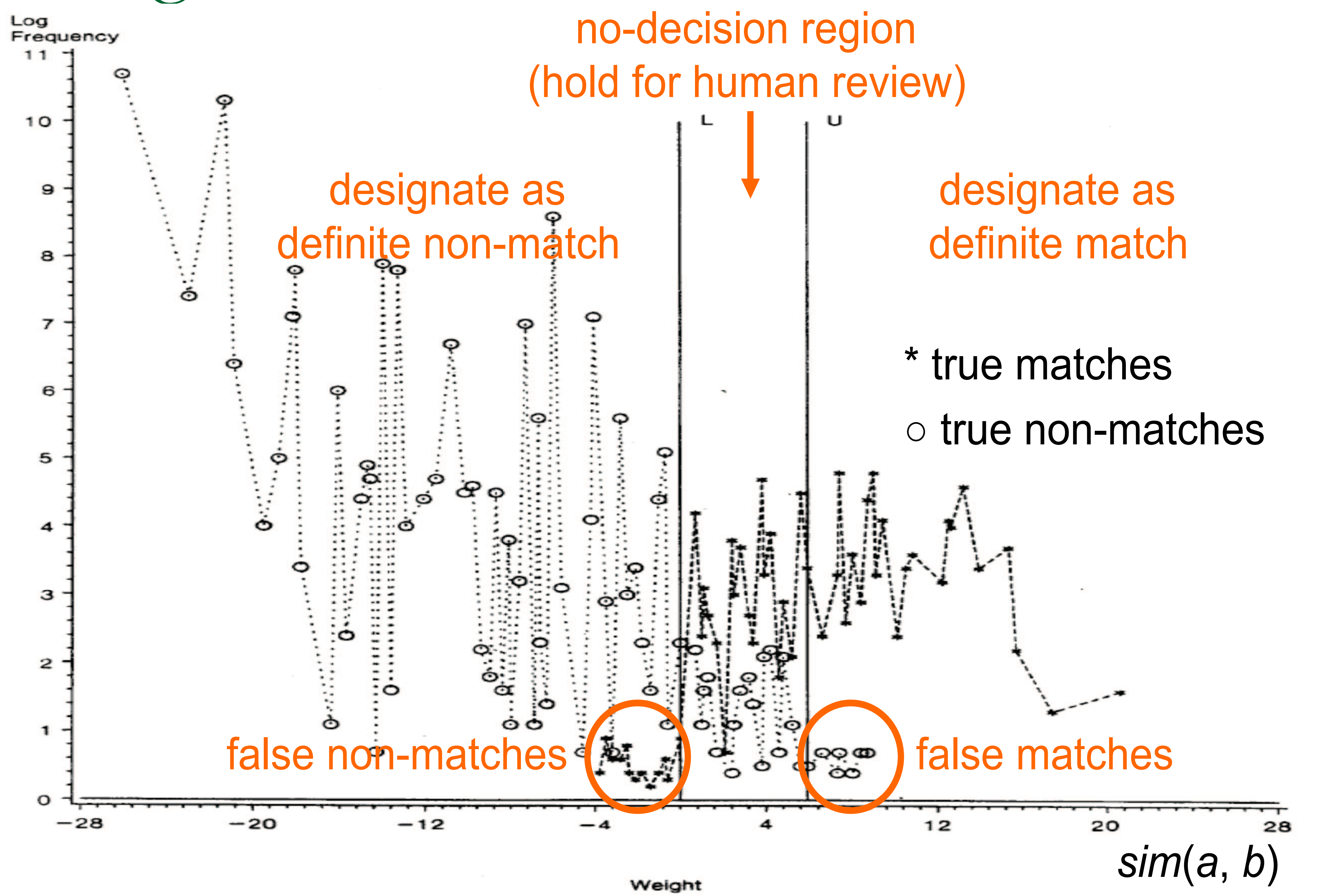
- score assigned to a matching of individual fields
  - reduced by the probability that a matching variable agrees given that a comparison pair is not a match (U = unmatched)
  - U-probability - similar to “specificity”, i.e. the proportion of negatives which are correctly identified
- **agreement argues for linkage**
- **disagreement argues against linkage**
- full agreement stronger evidence for linkage than partial agreement

Probabilistic linkage . . .

- based on the probabilities of agreement or disagreement between the identifiers
- all identifiers do not have equal weight
- **accurate linkage is mainly dependent on the amount of discriminating power inherent in the variables common to the records that need to be matched and 'good' data**

Fellegi IP & Sunter AB (1969) A theory for record linkage. Journal of the American Statistical Association 64, 1183-1210

Fellegi-Sunter model



Deterministic versus probabilistic methods

studies using human review or artificially withheld identifying information as 'gold standard'

Gomatam S et al (2002) An empirical comparison of record linkage procedures, Statistics in Medicine, 21, 1485-1496

http://nisla05.niss.org/dgii/presentations/gomatam-sic-200305.pdf

Roos LL, Walld R, Wajda A, Bond R, Hartford K (1996) Record linkage strategies, outpatient procedures, and administrative data. Medical Care 34, 570–582

Jamieson E, Roberts J, Browne G (1995) The feasibility and accuracy of anonymized record linkage to estimate shared clientele among three health and social service agencies. Methods Inf Med. 34, 371–377

RELAIS

- RELAIS (Record Linkage At IStat) toolkit
- **an open source toolkit for building record linkage workflows**
- JAVA based
- statistical methods implemented in R

http://www.istat.it/strumenti/metodi/software/analisi_dati/relais/

References

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Krewski D, Dewanji A, Wang Y, Bartlett S, Zielinski JM & Mallick R (2005) The effect of record linkage errors on risk estimates in cohort mortality studies. Survey Methodology 31,13–21

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