Introduction to Blocking and Classical Record Linkage

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Blocking and Classical Record Linkage

1. Blocking

- Focus will be on deterministic blocking

2. Classical Record Linkage Methods

- Exact Matching
- String Matching
- Fellegi and Sunter (1969); Newcombe (1959).

3. Demos

- There are demos illustrating each proposed method

Computational challenge of entity resolution

- Assume M total records in two databases.
- Naive record linkage requires M^2 record comparisons.

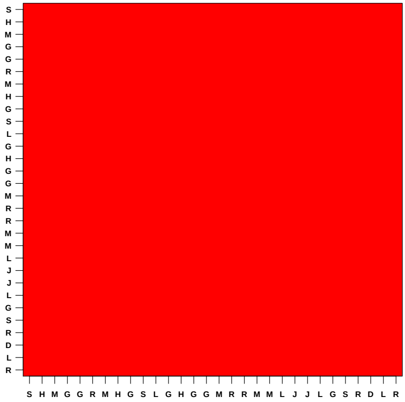


Figure: Must perform all-to-all record comparisons.

Blocking

- Blocking partitions similar records into bins or blocks.
- Record linkage is only performed within the blocks.

Blocking

1. Traditional blocking

- A deterministic partition is formed based upon the data.
- A partition is created by treating certain fields that are thought to be nearly error-free as fixed.

Example: Partition of date of birth year.

2. Probabilistic blocking

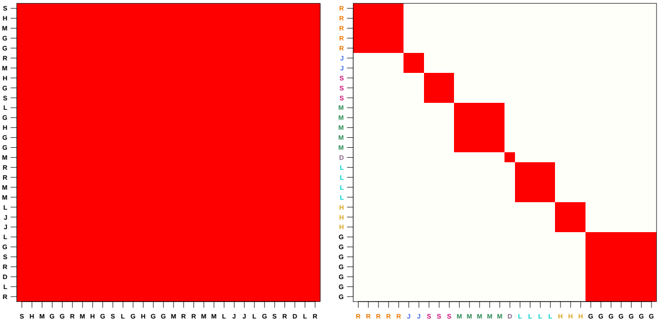
- A probability model is used to cluster the data into blocks/partitions.

Example: Locality Sensitive Hashing.

Under both blocking approaches, record pairs that do not meet the blocking criteria are automatically classified as non-matches.

Example: Traditional blocking

All-to-all record comparisons (left) versus partitioning records into blocks by lastname initial and comparing records only within each partition (right).



Example: RLdata500

```
library(RecordLinkage)
data(RLdata500)
head(RLdata500)
```

```
##   fname_c1 fname_c2 lname_c1 lname_c2   by bm bd
## 1  CARSTEN     <NA>    MEIER     <NA> 1949  7 22
## 2     GERD     <NA>    BAUER     <NA> 1968  7 27
## 3   ROBERT     <NA> HARTMANN     <NA> 1930  4 30
## 4   STEFAN     <NA>    WOLFF     <NA> 1957  9  2
## 5     RALF     <NA>  KRUEGER     <NA> 1966  1 13
## 6  JUERGEN     <NA>   FRANKE     <NA> 1929  7  4
```

Continuation: RLdata500

```r
# Record pairs for comparison
choose(500,2)
```

```
## [1] 124750
```

```r
# Blocking by last name initial
last_init <- substr(RLdata500[,"lname_c1"], 1, 1)
head(last_init)
```

```
## [1] "M" "B" "H" "W" "K" "F"
```

```r
# Number of blocks
length(unique(last_init))
```

```
## [1] 20
```

Continuation: RLdata500

```r
# Number of records per block
tbl <- table(last_init)
head(tbl)
```

```
## last_init
##  A  B  D  E  F  G
##  5 56  2  6 38 12
```

```r
# Block sizes can vary a lot
summary(as.numeric(tbl))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    2.00    5.75    8.00   25.00   40.00  115.00
```

Continuation: RLdata500

```
# Number of records pairs per block
sapply(tbl, choose, k=2)
```

```
##    A    B    D    E    F    G    H    J    K    L    M
##   10 1540    1   15  703   66  496   28 1035   78 2850
##    S    T    V    W    Z
## 6555    1   21 1326   10
```

```
# Reduction on comparison space
sum(sapply(tbl, choose, k=2))
```

```
## [1] 14805
```

Continuation: RLdata500

What is the reduction from the overall space to the reduced space?

Hint: The original space of comparisons was

```
choose(500,2)
```

```
## [1] 124750
```

and we have reduced the number of comparisons to

```
sum(sapply(tbl, choose, k=2))
```

```
## [1] 14805
```

Blocking caveats

- Features often contain errors, noise, etc. and may not be suitable for determistic blocking.
- A noisy feature used for determisitic blocking can miss a large proportion of matches (i.e. increased false negatives rates).
- The frequency distribution of the values of the blocking features will affect the block sizes.
- There is a trade off between the size of the blocks and computational efficency.
    - If the blocks are too big, then the computational speed increases.
    - If the blocks are too small, then true matches may be missed.

How to choose the blocking features (variables or keys)

- Features containing the fewest errors or missing values should be chosen as blocking variables.
- Understand the kind of errors that are unlikely for a certain feature.
- More complex blocking schemes can be constructed using conjunctions.
  - Retain only pairs which agree on last name initial and zip code.

Classical Record Linkage: Exact matching

- Exact matching is a method that says two records are a match if they agree on every feature.
- Performing exact matching is very common in the social and health sciences in practice, however, this is not common in statistics, computer science, or machine learning.
- Other types of matching or merging are used, where records are called to be a match if they agree based upon a similarity comparison or a probabilitistic model.
- Examples include: string matching, Fellegi-Sunter method, semi-supervised methods, and hashing techniques.

Classical Record Linkage: Similarity metrics

- Levenshtein (edit) (1966): minimum number of substitutions required to transform one string into another e.g. Adam vs Alan has a distance $L = 2$, normalized as $1 - \frac{L}{maxLength} = 0.5$ for similarity.

- Jaro-Winkler (1990): The Jaro distance (1989) considers common characters and character transpositions. The JW similarity measure is:

$$JW(A, B) = J(A, B) + 0.1p(1 - J(A, B))$$

where p is the # of the first four characters that agree exactly e.g. Adam vs Alan: p=1, J= 0.67 and JW=0.7.

These work well on English names that are less than 7 characters.

Example: RLdata500

```r
library(RecordLinkage)
data(RLdata500)
```

```
##       fname_c1 lname_c1   by bm bd
## 314     RENATE   SCHUTE 1940 12 29
## 407     RENATE  SCHULTE 1940 12 29
## 289 CHRISTINE   PETERS 1993  2  5
## 399 CHRISTINE   PETERS 1993  2  6
## 402   CHRISTA  SCHWARZ 1965  7 13
## 462  CHRISTAH  SCHWARZ 1965  7 13
```

Example: RLdata500

```r
# Levenshtein similarity
levenshteinSim("SCHUTE", "SCHULTE")
```

```
## [1] 0.8571429
```

```r
levenshteinSim("CHRISTA", "CHRISTAH")
```

```
## [1] 0.875
```

```r
# Jaro-Winkler similarity
jarowinkler(c("SCHUTE","CHRISTA"),
            c("SCHULTE","CHRISTAH"))
```

```
## [1] 0.9714286 0.9750000
```

Similarity metrics (continued)

- The Soundex algorithm generates a code representing the phonetic pronunciation of a word.
- This is typicall more useful on non-English names or longer names.
- The Soundex code for a name consists of a letter followed by three numerical digits:
  - the letter is the first letter of the name,
  - the digits encode the remaining consonants.
- Consonants at a similar place of articulation share the same digit
  - The consonants B, F, P and V are each encoded by a 1.

Example: Soundex algorithm

```
##       fname_c1 lname_c1   by bm bd
## 314     RENATE   SCHUTE 1940 12 29
## 407     RENATE  SCHULTE 1940 12 29
## 289 CHRISTINE   PETERS 1993  2  5
## 399 CHRISTINE   PETERS 1993  2  6
## 402   CHRISTA  SCHWARZ 1965  7 13
## 462  CHRISTAH  SCHWARZ 1965  7 13
```

```r
tail(soundex(dup_set$fname_c1))
```

```
## [1] "R530" "R530" "C623" "C623" "C623" "C623"
```

```r
tail(soundex(dup_set$lname_c1))
```

```
## [1] "S300" "S430" "P362" "P362" "S620" "S620"
```

Example: Soundex algorithm

```
##      fname_c1 lname_c1   by bm bd
## 130  MICHAEL    MEYER 1988  1 31
## 147  MICHAEL     MYER 1988  1 31
## 217    HORST    MEIER 1977  6  6
## 248    HORST    MEIER 1972  6  6
## 34     HEINZ    BOEHM 1938 12 20
## 111    HEINZ   BOEHMR 1938 12 20
```

```r
head(soundex(dup_set$lname_c1))
```

```
## [1] "M600" "M600" "M600" "M600" "B500" "B560"
```

Blocking by disjunctions

- Produces overlapping blocks of the data.
  - Disjunction: records match on field A or field B

- Using multiple keys to consider typographical or measurement errors that would exclude true matches.
  - Blocking by last name initial or zip code

1.	Mary Clain	123 Oak St	90210
2.	Mary Klein	123 Oak Street	90210
3.	Mary Klain	123 Oak St	50210

- Reduction in false negative rates.

Example: Blocking by disjunctions

```
# Two records must agree in either first name initial
# or bith year to be compared.
# Only 2709 pairs instead of 124750!

# Builds comparison patterns of record pairs
rpairs <- compare.dedup(RLdata500c,
blockfld = list(1, 3), #list with blocking fields
identity = identity.RLdata500)

tail(rpairs$pairs)
```

```
##       id1 id2 fname_c1 lname_c1 by bm bd is_match
## 2704 477 497        1        0  0  0  0        0
## 2705 479 483        0        0  1  1  0        0
## 2706 480 481        1        0  0  0  0        0
## 2707 480 490        1        0  0  0  0        0
## 2708 481 490        1        1  0  1  1        1
## 2709 494 497        0        0  1  1  0        0
```

Example: String comparison and blocking

```r
rpairsfuzzy <- compare.dedup(RLdata500c,
               phonetic = FALSE, blockfld = 3,
               strcmp = TRUE, strcmpfun = jarowinkler)

tail(rpairsfuzzy$pairs)
```

```
##      id1 id2  fname_c1  lname_c1 by  bm  bd is_match
## 1540 460 485 0.0000000 0.5396825  1 0.7 0.0       NA
## 1541 464 466 0.4555556 0.5396825  1 0.7 0.0       NA
## 1542 467 472 1.0000000 0.9333333  1 1.0 1.0       NA
## 1543 468 469 0.5777778 0.4666667  1 0.7 0.7       NA
## 1544 479 483 0.4370370 0.5619048  1 1.0 0.0       NA
## 1545 494 497 0.6111111 0.5026455  1 1.0 0.0       NA
```

Fellegi-Sunter (1969); Newcombe (1959)

- Fellegi-Sunter (1969); Newcombe (1959) proposed the first method for record linkage.
- Records are determined to be a match/non-match using a likelihood ratio test, which can be written as a mixture model.
- String metrics were used for names/numerical data (Levenshtein or Jaro-Winkler).

Fellegi-Sunter (1969); Newcombe (1959)

- There are feature vector for record pairs, which are classfied into matches (M), nonmatches (U), and possible matches.

- Let $P(\gamma|M)$ and $P(\gamma|U)$ be probabilities of observing a feature vector γ for a matched and nonmatched pair, respectively.

Fellegi-Sunter (1969); Newcombe (1959)

- Perform record-pair classification by calculating the ratio

$$w = (P(\gamma|M)/P(\gamma|U))$$

  for each candidate record pair.

- Find two thresholds based on desired error levels to optimally separate the weight values for matches, possible matches, and nonmatches.[1]

- The quality of classification of the Fellegi-Sunter method relies strongly on reasonable estimations of M and U probabilities.

[1] This method is very sensitive to the valueds of the thresholds.

Example: Blocking and Fellegi-Sunter

```r
# tail(rpairs$pairs)
# Using comparison data blocking by first name initial
# and birth year
rpairs1 <- epiWeights(rpairs)

# Weights to compute thresholds for classification
rpairs1$Wdata[1:5]
```

```
## [1] 0.2223402 0.2223402 0.2488181 0.2488181 0.3936336
```

Example: Fellegi-Sunter

```r
summary(rpairs1)
```

Weight distribution:

(0.35,0.4]	(0.4,0.45]	(0.45,0.5]	(0.55,0.6]	(0.6,0.65]
2	10	30	50	8
(0.65,0.7]	(0.7,0.75]	(0.75,0.8]	(0.8,0.85]	(0.85,0.9]
0	0	35	8	3

Example: Fellegi-Sunter

```
result <- epiClassify(rpairs1, 0.7)
summary(result)

alpha error: 0.080000 # False negative rate
beta error: 0.000000  # False positive rate
accuracy: 0.998523

Classification table:

           classification
true status    N    P    L
      FALSE 2659    0    0
      TRUE     4    0   46
```

Summary

- Blocking: reduce comparison space by choosing relatively noise free fields to match records
  - Use conjunctions (and) create a partition of the data or disjunctions (or) to create overlapping blocks.
- Strings: choose a string similarity metric to compare record pairs within blocks.
  - Levenshtein or Jaro-Winkler.
- Record linkage: use Fellegi-Sunter method to classify records as matches, posibble matches or nonmathches.

References

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- Fellegi I.P., Sunter A.B. (1969), A Theory for Record Linkage, Journal of the American Statistical Association 64(328), pp. 1183–1210.
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