Module 3: Pipeline Approaches and Deterministic ER

Rebecca C. Steorts

Reading

- Binette and Steorts (2020)
- Christen (2012)

Agenda

- Pipeline Approach
- Deterministic Record Linkage
- Exact Matching
- Scoring Functions
- Application to El Salvador

Load R packages

```r
library(RecordLinkage)
```

Data Cleaning Pipeline

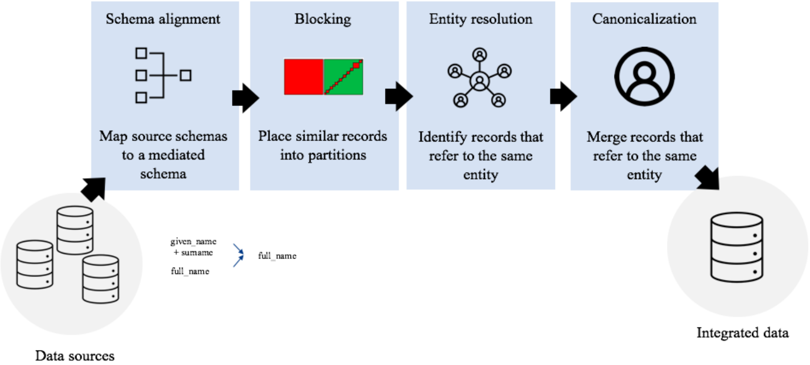


Figure 1: Data cleaning pipeline.

Deterministic Record Linkage

The most commonly used record linkage methods are based on a series of deterministic rules involving the comparison of record attributes.

Exact Matching and off by *k* matching

- Exact matching is where two record pairs are linked if they agree on all common attributes.

Exact Matching and off by *k* matching

- Exact matching is where two record pairs are linked if they agree on all common attributes.
- Off by one matching links records pairs if they link on all common attributes (except for one).

Exact Matching and off by k matching

- Exact matching is where two record pairs are linked if they agree on all common attributes.
- Off by one matching links records pairs if they link on all common attributes (except for one).
- Off by two matching links record pairs if they link on all common attributes (except for two).

Exact Matching and off by k matching

- Exact matching is where two record pairs are linked if they agree on all common attributes.
- Off by one matching links records pairs if they link on all common attributes (except for one).
- Off by two matching links record pairs if they link on all common attributes (except for two).

Exact Matching and off by k matching

- An extension, off by k-matching, states that two record pairs are a match if they match on all common attributes except at most k, where k is an integer larger than 0.

Exact Matching and off by *k* matching

- An extension, off by k-matching, states that two record pairs are a match if they match on all common attributes except at most k, where k is an integer larger than 0.
- Exact matching (or extensions) are used when all the attributes are categorical as it tends to perform well, as opposed to when textual variables are introduced.

RLdata500

Recall the RLdata500 data set, removing any columns that contain missing values.

```
#load RLdata500
library(blink)
data(RLdata500)
data <- RLdata500[-c(2,4)] # Remove
head(data)
```

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

All pairs of records

Now let's consider all possible pairs of records.

```
# create all pairs of records
pairs <- t(combn(1:nrow(RLdata500), 2))
head(pairs)
```

```
##      [,1] [,2]
## [1,]    1    2
## [2,]    1    3
## [3,]    1    4
## [4,]    1    5
## [5,]    1    6
## [6,]    1    7
```

Pairwise features that disagree

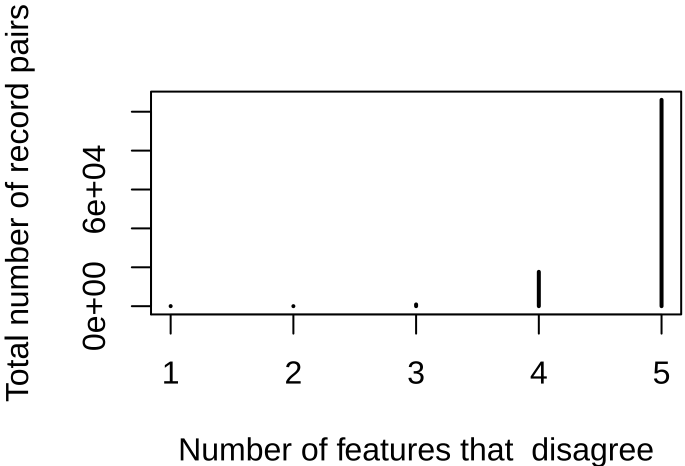
For each pair of records, compute the number of features that disagree. This takes a few minute to compute in R. (There are more efficient ways to do this).

```
n_disagree = sapply(1:nrow(pairs), function(i) {
  recordA = data[pairs[i,1],]
  recordB = data[pairs[i,2],]
  sum(recordA != recordB)
})
```

Distribution of Feature Disagreement Among Record Pairs

Let's plot the total number of record pair comparisons versus the number of featurs that disagree.

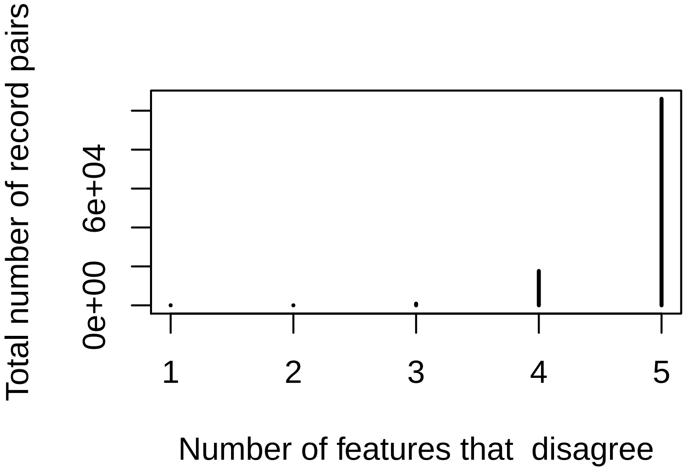
```
plot(table(n_disagree),
     xlab="Number of features that  disagree",
     ylab="Total number of record pairs")
```



Distribution of Feature Disagreement Among Record Pairs

What do you observe?

```
plot(table(n_disagree),
     xlab="Number of features that  disagree",
     ylab="Total number of record pairs")
```



Distribution of Feature Disagreement Among Record Pairs

- Observe that record pairs disagree on four or 5 features. We expect these records to not be matched.

Distribution of Feature Disagreement Among Record Pairs

- Observe that record pairs disagree on four or 5 features. We expect these records to not be matched.
- Pairs disagreeing only on 1, 2 or 3 features *might* be matches.

Distribution of Feature Disagreement Among Record Pairs

- Observe that record pairs disagree on four or 5 features. We expect these records to not be matched.
- Pairs disagreeing only on 1, 2 or 3 features *might* be matches.

Is this intuitive?

Exact Matching

Exact matching: Link record pairs that agree on all features.

```
sum(n_disagree == 0)
```

```
## [1] 0
```

No pairs are exact matches!

Off by one matching

Off by 1 matching: Link record pairs that disagree only in one feature.

```
# Links
links = pairs[n_disagree <= 1, ]

# Number of estimated links
nrow(links)
```

```
## [1] 46
```

```
# Number of correctly estimated links
sum(sapply(1:nrow(links), function(i) {
  identity.RLdata500[links[i,1]] ==
    identity.RLdata500[links[i,2]]
}))
```

```
## [1] 46
```

Off by two matching example

Off by 2 matching: link record pairs that disagree only in two features.

```
# Links
links = pairs[n_disagree <= 2, ]

# Number of estimated links
nrow(links)
```

```
## [1] 69
```

```
# Number of correctly estimated links
sum(sapply(1:nrow(links), function(i) {
  identity.RLdata500[links[i,1]] == identity.RLdata500[links[i,2]]
}))
```

```
## [1] 50
```

Off by three matching example

Off by 3 matching: link record pairs which disagree only in three features.

```
# Links
links = pairs[n_disagree <= 3, ]

# Number of estimated links
nrow(links)
```

```
## [1] 975
```

```
# Number of correctly estimated links
sum(sapply(1:nrow(links), function(i) {
  identity.RLdata500[links[i,1]] == identity.RLdata500[links[i,2]]
}))
```

```
## [1] 50
```

Scoring Rules

- Record attributes are often distorted by noise. Why would this occur?
- Linkage rules should account for such noise, distortions, and errors through scoring rules or functions.
- Examples commonly used for westernized names are the Edit (Levenshtein), Jaro, and Jaro-Winkler distance functions.

Edit (Levenshtein) distance (1966)

The Edit distance calculates the minimum number of substitutions required to transform a string s_1 into a string s_2.

Formally,

$$\text{Edit} = 1 - \frac{L}{maxLength(s_1, s_2)}.$$

Example

Consider the number of substitutions required to transform from **Adam** to **Alan.** Use the Edit distance formulate to find the similarity score that is between $[0, 1]$.

Solution

The number of substitutions required is $L = 2$.

This is normalized into a similarity function using the following:

$$\text{Edit} = 1 - \frac{L}{maxLength(s_1, s_2)} = 1 - 2/4 = 1 - 0.5 = 0.5$$

Solution

Let's verify this in R.

```
s1 <- "Adam"
s2 <- "Alan"
levenshteinSim("s1", "s2")
```

```
## [1] 0.5
```

Jaro-Winkler

- The Jaro distance (1989), called J, considered common characters and character transpositions.
- The Jaro-Winkler (1990) similarity measure, denoted JW 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.

Example

Let's return to the example of comparing Adam and Alan.

- Here, $p = 1$.
- Given the complexity, we will calculate J and JW using `R`.

Example

```r
## It seems Jaro is not supported in R
jarowinkler(s1,s2)
```

```
## [1] 0.7
```

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.

Other distance functions

There are many other distance functions, such as the Jaccard, Hamming, and Cosine distances just to name a few.

Case study on El Salvador.

Let's consider a case study from El Salvador that we will return to throughout the course.

Civil War in the Republic of El Salvador

Between 1980 and 1991, the Republic of El Salvador witnessed a civil war between the central government, the left-wing guerrilla Farabundo Marti National Liberation Front (FMLN), and right-wing paramilitary death squads.

After the peace agreement in 1992, the United Nations created a Commission on the Truth (UNTC) for El Salvador, which invited members of Salvadoran society to report war-related human rights violations, which mainly focused on killings and disappearances.

Civil War in the Republic of El Salvador

In order to collect such information the UNTC invited individuals through newspapers, radio, and television advertisements to come forward and testify.

The UNTC opened offices through El Salvador where witnesses could provide their testimonials, and this resulted in a list of potential victims with names, date of death, and reported location.

Data analysis

Let's read in the data and inspect it.

```r
# read in data
df <- read.csv("./sv-mauricio/sv-mauricio.csv")
head(df)
```

```
##     X  ID         lastname firstname day month year geocode HandID dept muni
## 1  26  32 ASENSIO ERNANDES   ALBERTO  NA     2 1981  150000     NA   15   NA
## 2  84  95   PALASIOS AYALA    OBIDIO  NA    10 1985  150000     NA   15   NA
## 3 100 117            PALMA SEBASTIAN  13     5 1980   40000     NA    4   NA
## 4 143 173            PERES   ARCADIO  NA     8 1984   40000     NA    4   NA
## 5 170 205     MAYA QUESADA   ANTONIO  22     9 1984       0     NA    0   NA
## 6 189 227            MEJIA   ALFONSO  13     5 1980   40000     NA    4   NA
```

First steps

What steps do we need to take before running any algorithms or methods on this data?

Meet with your group and discuss. Be prepared to discuss ideas and any observations.

Task 1

What types of string distance metrics are appropriate and which are not appropriate?

Task 2

How does exact matching perform on this data set? What about off-by-one matching?

Task 3

How would you build a decision rule for matches/non-matches based upon scoring rules. What would your scoring rule be? Write this up.

Task 4

Implement you scoring rule from Task 4 and compare it to exact and off-by-one matching. What are you findings?

Task 5

Give insights into how you might be able to improve deterministic approaches moving forward if you re-did your analysis.