Module 4: Deterministic Blocking

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Reading

- Binette and Steorts (2020)
- Steorts, Ventura, Sadinle, Fienberg (2014)
- Murray (2016)
- Christen (2012), Chapter 4

Agenda

- Data Cleaning Pipeline
- Blocking
- Traditional Blocking
- Probabilistic Blocking
- Evaluation Metrics
- Examples

Load R packages and data

```
knitr::opts_chunk$set(echo = TRUE,
                      fig.width=4,
                      fig.height=3,
                      fig.align="center")
library(RecordLinkage)
library(blink)
library(italy)
library(tidyverse)
library(assert)
data(italy08)
data(italy10)
data(RLdata500)
```

Data Cleaning Pipeline

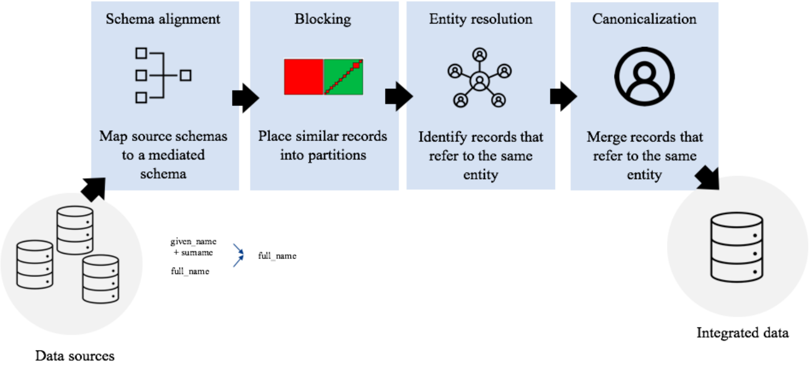


Figure 1: Data cleaning pipeline.

Blocking

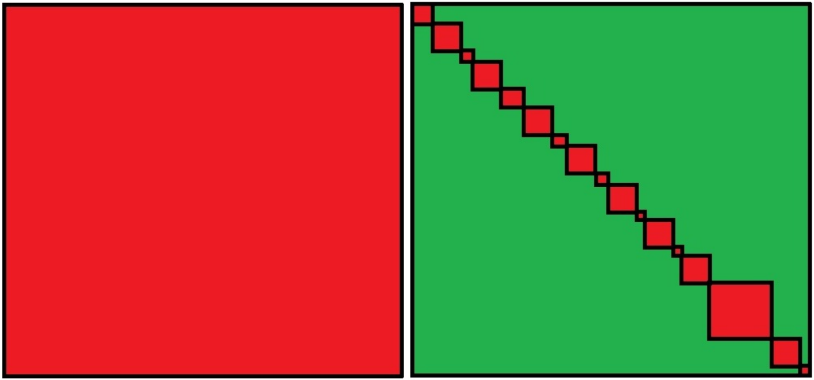


Figure 2: Left: All to all record comparison. Right: Example of resulting blocking partitions.

Blocking

- Blocking places similar records into partitions/blocks.
- ER (typically) is only performed within each block.

Traditional Blocking

- A deterministic (fixed) 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: Blocking on date of birth year.

Traditional Blocking

- Benefits: simple, easy to understand, and fast to implement.
- Downsides: the blocks are treated as error free, which is not usually accurate and can lead to errors in the ER task that cannot be accounted for.

Probabilistic Blocking

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

Example: Fellegi-Sunter (1969), or Locality Sensitive Hashing

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

Evaluation Metrics

Evaluation metrics are important for ER as they help us evaluate our proposed methodology (as long as some notion of ground truth exists).

The three that we will focus on in this module are:

- reduction ratio
- precision
- recall
- f-measure

Reduction Ratio

The reduction ratio (RR) measures the relative reduction of the comparison space from the de-duplication or hashing technique.

See Christen (2012), Steorts, Ventura, Sadinle, Fienberg (2014) for a formal definition.

Pairwise Precision and Recall

Let's now turn to formally defining the pairwise precision and recall.

The confusion matrix

1. Pairs of data can be linked in both the handmatched training data (which we refer to as “truth") and under the estimated linked data. We refer to this situation as true positives (TP).
2. Pairs of data can be linked under the truth but not linked under the estimate, which are called false negatives (FN).
3. Pairs of data can be not linked under the truth but linked under the estimate, which are called false positives (FP).
4. Pairs of data can be not linked under the truth and also not linked under the estimate, which we refer to as true negatives (TN).

The confusion matrix

Model

Ground Truth	M	N
M	TP (true match)	FN match under GT but not under the model
N	FP match under the model but not under ground truth	TN (a true non match)

Pairwise evaluation metrics

$$\text{Recall} = \frac{TP}{TP + FN} = 1 - \text{FNR}.$$

$$\text{Precision} = \frac{TP}{TP + FP} = 1 - \text{FDR}.$$

$$\text{F-measure} = 2 \times \frac{(precision \times recall)}{(precision + recall)}.$$

Recall

- For blocking, it is critical the recall be as close a possible to 1.
- To think about why, what does it mean if we have a blocking criterion where our recall is 0.5?

See Shrivastava and Steorts (2018) and Chen, Shrivastava, Steorts (2018) for further regarding about blocking criterion using human rights data.

Example: RLdata500

Let's return to the RLdata500 data set, where we will block by last name initial.

Our goal are the following:

- visualize the blocks
- compute the evaluation metrics introduced

Example: RLdata500

```r
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
```

Example: Traditional blocking

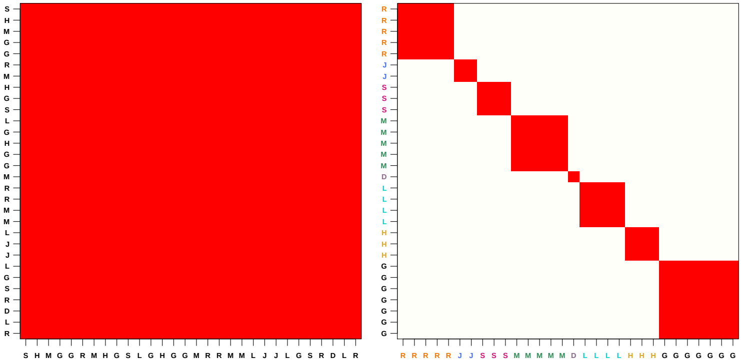


Figure 4: All-to-all record comparisons (left) versus partitioning records into blocks by lastname initial and comparing records only within each partition (right).

RLdata500 (Continued)

```r
# Total number of all to all record comparisons
choose(500,2)
```

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

RLdata500 (Continued)

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

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

```
# Total number of blocks
length(unique(last_init))
```

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

RLdata500 (Continued)

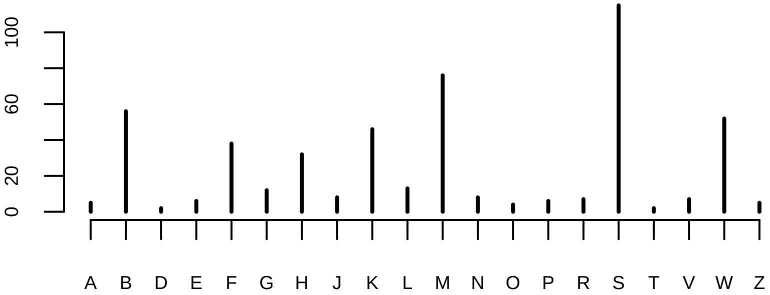
```
# Total number of records per block
recordsPerBlock <- table(last_init)
head(recordsPerBlock)
```

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

RLdata500 (Continued)

Observe that the block sizes vary.

```
# Block sizes can vary
plot(recordsPerBlock,
     cex.axis=0.6, xlab="", ylab="")
```



RLdata500 (Continued)

What is the overall dimension reduction form the original space to the reduced space induced by blocking?

RLdata500 (Continued)

Recall the total number of all-to-all record comparisons made was:

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

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

Using blocking, we have reduced the compison space to the following:

```
sum(choose(recordsPerBlock, 2))
```

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

How do we calculate the reduction ratio (RR)?

The reduction ratio is

$$\text{RR} = \% \text{ comparisons eliminated by blocking.}$$

```
(choose(500, 2) - sum(choose(recordsPerBlock, 2))) /
choose(500, 2)
```

```
## [1] 0.8813226
```

How do we calculate the RR (via a function)?

```
reduction.ratio <- function(block.labels) {
  n_all_comp = choose(length(block.labels), 2)
  n_block_comp = sum(choose(table(block.labels), 2))

  (n_all_comp - n_block_comp) / n_all_comp
}

reduction.ratio(last_init)
```

```
## [1] 0.8813226
```

Reduction Ratio

In summary, we have reduced the comparison space by roughly 88 percent.

Evaluation metrics

Let's now code up the evaluation metrics for pairwise precision and recall.

Pairwise Precision

```r
clusters = split(1:length(last_init), identity.RLdata500)

# Number of matching pairs among blocks
n_matches = sapply(clusters, function(records) {
  # Number of matches in that block
  sum(choose(table(identity.RLdata500[records]), 2))
})

# Total number of pairs
n_pairs = sum(choose(table(last_init), 2))

sum(n_matches) / n_pairs
```

```
## [1] 0.003377237
```

Pairwise Precision

```r
precision <- function(block.labels, IDs) {
  assert(length(block.labels) == length(IDs))

  clusters = split(1:length(block.labels), block.labels)

  # Number of matching pairs among blocks
  n_matches = sapply(clusters, function(records) {
    sum(choose(table(IDs[records]), 2))
  })

  # Total number of pairs
  n_pairs = sum(choose(table(block.labels), 2))

  sum(n_matches) / n_pairs
}
```

Pairwise Recall

```
recall <- function(block.labels, IDs) {
  assert(length(block.labels) == length(IDs))

  precision(IDs, block.labels)
}
```

Pairwise Precision and Recall

```r
precision(last_init, identity.RLdata500)
```

```
## [1] 0.003377237
```

```r
recall(last_init, identity.RLdata500)
```

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

Italian Survey on Household and Wealth (SHIW)

- We will now explore a case study to the Italian Survey on Household and Wealth (SHIW)
- The SHiW is a sample survey 383 households conducted by the Bank of Italy every two years (2008 and 2010).
- The data set is anonymized to remove first and last name (and other sensitive information).

SHIW

The following attribute information is available:

- PARENT (parental status)
- GENDER
- ANASC (year of birth)
- NASCREG (working status)
- CIT (employment status)
- ACOM4C (branch of activity)
- STUDIO (town size)
- Q (quality of life status)
- QUAL (whether or not Italian national)
- SETT (highest educational level obtained)
- IREG (region of italy)

Explore Data

```r
head(italy08) # first year of SHIW
```

```
##        id PARENT SEX ANASC NASCREG CIT ACOM4C STUDIO Q QUAL SETT IREG
## 1 1040021      1   2  1948      16   1      0      5 1    2    3   16
## 2 1040022     10   2  1952      16   1      0      7 1    2    3   16
## 3 1110521      1   1  1972      20   1      2      5 1    1    4   20
## 4 1110522      3   1  1935      20   1      2      2 3    6    5   20
## 5 1110523      3   2  1941      20   1      2      3 3    6    5   20
## 6  119401      1   1  1941       7   1      0      4 3    6    5    7
```

Explore Data

```r
head(italy08) # second year of SHIW
```

```
##        id PARENT SEX ANASC NASCREG CIT ACOM4C STUDIO Q QUAL SETT IREG
## 1 1040021      1   2  1948      16   1      0      5 1    2    3   16
## 2 1040022     10   2  1952      16   1      0      7 1    2    3   16
## 3 1110521      1   1  1972      20   1      2      5 1    1    4   20
## 4 1110522      3   1  1935      20   1      2      2 3    6    5   20
## 5 1110523      3   2  1941      20   1      2      3 3    6    5   20
## 6  119401      1   1  1941       7   1      0      4 3    6    5    7
```

Reformat Data

```r
id08 <- italy08$id
id10 <- italy10$id
id <- c(italy08$id, italy10$id) # combine the id
italy08 <- italy08[-c(1)] # remove the id
italy10 <- italy10[-c(1)] # remove the id
italy <- rbind(italy08, italy10)
head(italy)
```

```
##   PARENT SEX ANASC NASCREG CIT ACOM4C STUDIO Q QUAL SETT IREG
## 1      1   2  1948      16   1      0      5 1    2    3   16
## 2     10   2  1952      16   1      0      7 1    2    3   16
## 3      1   1  1972      20   1      2      5 1    1    4   20
## 4      3   1  1935      20   1      2      2 3    6    5   20
## 5      3   2  1941      20   1      2      3 3    6    5   20
## 6      1   1  1941       7   1      0      4 3    6    5    7
```

Your turn

- Construct a blocking criterion for the SHIW data set
- Provide code to construct the blocks
- Are your blocks well balanced?
- What is the reduction ratio?
- What is the pairwise recall and precision?
- Would you recommend your blocking criterion for an ER task? Why or why not.

Hint: You might consider blocking on gender, regions (in Italy), or combinations of these. What do you find?

Your turn solution

Let's block on gender.

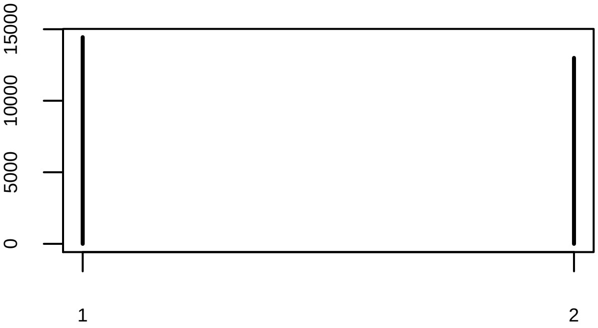
```
# block by gender
blockByGender <- italy$SEX
recordsPerBlock <- table(blockByGender)
head(recordsPerBlock)
```

```
## blockByGender
##     1     2
## 14442 12993
```

Your turn solution

The block sizes are similar. But note, they are still quite large.

```
# Checking block sizes
plot(recordsPerBlock,
cex.axis=0.6, xlab="", ylab="")
```



Your turn solution

```
print(rr <- reduction.ratio(blockByGender))
```

```
## [1] 0.4986234
```

We have reduced the overall space by rougly 50 percent.

Your turn solution

```r
precision(blockByGender, id)
```

```
## [1] 3.599727e-05
```

```r
recall(blockByGender, id)
```

```
## [1] 0.9113109
```

This is not an optimal blocking criterion as ideally, we would want both the precision and recall to be close to 1.

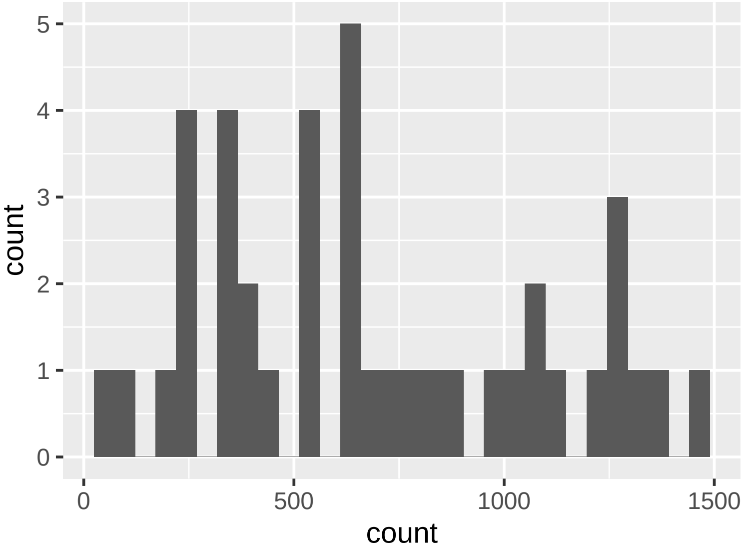
Your turn solution 2

Let's block on a combination of gender and region.

Hint: Use `tidyverse`.

Your turn solution 2

```
italy %>%
 group_by(IREG, SEX) %>%
 summarise(count = n(), .groups="drop") %>%
 ggplot() +
 geom_histogram(aes(count))
```



Your turn solution 2

```
blockIDs = paste(italy$IREG, italy$SEX, sep="_")
table(blockIDs)
```

```
## blockIDs
##  1_1  1_2 10_1 10_2 11_1 11_2 12_1 12_2 13_1 13_2 14_1 14_2 15_1 15_2 16_1 16_2
## 1282 1248  536  534  624  611  772  671  368  339  249  229 1310 1019  846  615
## 17_1 17_2 18_1 18_2 19_1 19_2  2_1  2_2 20_1 20_2  3_1  3_2  4_1  4_2  5_1  5_2
##  246  209  333  262  969  709   91   73  634  659 1489 1386  324  321 1056  882
##  6_1  6_2  7_1  7_2  8_1  8_2  9_1  9_2
##  418  371  517  533 1254 1243 1124 1079
```

```
print(rr <- reduction.ratio(blockIDs))
```

```
## [1] 0.9667954
```

Your turn solution 2

```r
precision(blockIDs, id)
```

```
## [1] 0.0005429847
```

```r
recall(blockIDs, id)
```

```
## [1] 0.9103717
```