blocking: An R Package for Blocking of Records for Record Linkage and Deduplication

by Maciej Beręsewicz and Adam Struzik

Abstract Entity resolution (probabilistic record linkage, deduplication) is essential for estimation based on multiple sources. It aims to link records without common identifiers that refer to the same entity (e.g., person, company). Without identifiers, researchers must specify which records to compare to calculate matching probability and reduce computational complexity. Traditional deterministic blocking uses common variables like names or dates of birth, but assumes error-free, complete data. To address this limitation, we developed the R package **blocking**, which uses approximate nearest neighbour search and graph algorithms to reduce number of comparisons. This paper presents the package design, functionalities, and two case studies.

1 Introduction

1.1 Blocking for record linkage

Entity resolution (probabilistic record linkage, deduplication) is essential for estimation based on multiple sources (for recent review see Binette and Steorts (2022)). The goal is to link records without common identifiers that refer to the same entity (e.g., person, company). This situation is often observed in administrative records, in particular for foreign-born populations. For instance, the Social Insurance Institution register in Poland at the end of 2023 included 1.206 million records which referred to possibly 1.105 million individuals, out of which about 10% had missing information in the personal identifier (PESEL) and about 50% of cases had missing address details. Please note that the exact number of individuals will be certainly lower than 1.105 million as the 10% may include duplicates.

This drives a need to link records without identifiers but often requires certain assumptions such as how to reduce the large number of possible comparisons as it is not possible to compare all pairs of records in a large dataset (e.g., for the mentioned example this would lead to over 600 billion comparisons). That is why *blocking* methods are applied to reduce the number of comparisons prior to the final record linkage/deduplication stage not only because of computational reasons but also due to clerical review workload.

Blocking is a method of reducing the number of possible comparisons by assuming that certain variables should be exactly matched. For instance, a standard method is based on assuming that sex or age (or some other combination) should match exactly while other characteristics of the records could be varying. Another standard method is to use phonetic algorithms such as SOUNDEX or its improvements for non-English languages. Furthermore, due to the use of large language models one may also consider using embeddings to search for the closest neighbor and treat this as a possible pair. For a review of blocking methods see Steorts et al. (2014) or Papadakis et al. (2020) and in Section 2.1.2 we will discuss R packages that implement blocking methods.

Reducing the number of pairs has its costs: missing comparisons which lead to an increased false positive rate (FPR) and false negative rate (FNR) of the linkage study. In order to assess this error, a subset of pairs or simulation studies should be applied. Alternatively, one may consider approaches proposed by Dasylva and Goussanou (2021) and Dasylva and Goussanou (2022) who proposed methods to estimate FPR and FNR without access to an audit sample.

1.2 Existing software and our contribution

The R system offers several packages that implements various blocking techniques which we grouped by the following classification:

- deterministic blocking:
  - **reclin2** (van der Laan, 2024, van der Laan (2022)) which allows to pair records using the `pair_blocking()` with a prespecified list of columns in a `data.frame`, and the `pair_minsim()` function that allows to specify the minimal similarity score (e.g. 1 out of 3 variables should match exactly).
  - **RecordLinkage** (Sariyar and Borg, 2025, Sariyar and Borg (2010)) which allows to specify blocking variable in the `blockfld` in either in `compare.dedup()` or `compare.linkage()` functions in a form of a vector (either character or numeric).
  - **fastLink** (Enamorado et al., 2023, Enamorado et al. (2019)) which implements various blocking methods via the `blockData()` function such as exact matching, window matching (e.g., no more than 2 years difference between birth year) or k-means clustering algorithm. It should be noted that the `fastLink` returns splits dataset(s) into a separate lists while `reclin2` and `RecordLinkage` package create a single dataset.
- phonetic blocking:
  - **RecordLinkage** allows to directly specify the phonetic comparison via the `phonetic` argument of the `compare.dedup()` or `compare.linkage()` function via the `soundex()` function. However, this is not used for blocking but for comparison of strings
  - It should be noted that **stringdist** (van der Loo, 2014) also implements SOUNDEX algorithm while the **phonics** (Howard, II, 2021, Howard, II (2020)) implements various phonetic algorithms that could be applied prior the blocking procedure (e.g., create a new column).
- probabilistic blocking:
  - **klsh** (Steorts, 2020) is the only R package that implements probabilistic blocking using the k-means variant of locality sensitive hashing. The main `klsh()` function implements this approach and a resulting object is a list with row identifiers along for the pre specified number of blocks (via the `num.blocks` argument of the `klsh()` function).

Unfortunately, practice is more complicated as missing data can be present in important variables (such as birth date) or typos in the names and surnames. That is why we decided to develop **blocking** that leverage approximate nearest neighbours (ANN) algorithms and graphs to create a large number of small blocks that can be further used in the analysis. The basic idea behind the package can be expressed in the following steps:

1. create shingles via the **tokenizers** (Mullen et al., 2018) and **text2vec** (Selivanov et al., 2023) packages or a matrix of vectors (e.g. embeddings via the **ragnar** (Kalinowski and Falbel, 2025) package).
2. search for nearest neighbours using approximate algorithms implemented in the **rnndescent** (Melville, 2024b), **RcppHNSW** (Melville, 2024a), **mlpack** (Curtin et al., 2023, Singh Parihar et al. (2025)), and **RcppAnnoy** (Eddelbuettel, 2024).
3. create blocks using **igraph** (Csárdi et al., 2025, Csardi and Nepusz (2006)).

This is the solely package in the R ecosystem that allows to easily apply modern ANN algorithms and significantly speed-up the record linkage / deduplication problems. In addition, we have developed the `pair_ann()` function to seamless integrate with the **reclin2** package.

1.3 Outline of article

The paper has the following structure. In the Section 2.2 we provide description of the main functionalities of the `blocking` package and how we can assess the result. In the Section 2.3 we provide two case studies: probabilistic record linkage and deduplication. These examples show how our package can improve pipeline of entity resolution and work with existing R packages.

2 Blocking of records using `blocking` function

2.1 The main function

The main functionality is available via the `blocking()` function which contains the following main arguments:

- `x, y` – reference datasets, where `y = NULL` which indicate that the deduplication is applied,
- `representation` – whether `x` and `y` should be represented as shingles or vectors (provided by the user in the `model` argument),
- `ann` – what ANN algorithm should be applied, by default we use the **rnndescent** package as it allows supports sparse matrices,
- `distance` – what should be applied (default is `cosine` distance),
- `graph` – whether the plot of the graph of connected records should be returned (default `FALSE`),
- `true_blocks` – if a subset of true blocks is available it can be provided here so we measures of quality presented in Section 2.2.2 are returned,
- `n_threads` – how many threads are applied for computation,
- `control_txt` – controls provided in the `controls_txt()` on how the `x, y` are processed,
- `control_ann` – controls provided in the `controls_ann()` allows user to fine-tune ANN algorithm (see documentation of the `controls_ann()` function and `control_*` functions with the names referring to a specific algorithm, e.g., `control_nnd()` for the NND algorithm).

This function return an object of `blocking` class with the following elements:

- `result` – data.table with indices (rows) of x, y, block and distance between points
- `method` – name of the ANN algorithm used,
- `deduplication` – information whether deduplication was applied,
- `representation` – information whether shingles or vectors were used,
- `metrics` – metrics for quality assessment, if true_blocks is provided,
- `confusion` – confusion matrix, if `true_blocks` is provided,
- `colnames` – variable names (`colnames`) used for search,
- `graph` – igraph class object.

2.2 Assessment of results

In the package we have implemented several measures that can be used to assess the results

Reduction Ratio: Provides necessary details about the reduction in comparison pairs if the given blocks are applied to a further record linkage or deduplication procedure. For deduplication:

$$\text{RR}_{\text{deduplication}} = 1 - \frac{\sum_{i=1}^{k} \binom{|B_i|}{2}}{\binom{n}{2}},$$

where k is the total number of blocks, n is the total number of records in the dataset, and $|B_i|$ is the number of records in the i-th block. $\sum_{i=1}^{k} \binom{|B_i|}{2}$ is the number of comparisons after blocking, while $\binom{n}{2}$ is the total number of possible comparisons without blocking. For record linkage the reduction ratio is defined as follows

$$\text{RR}_{\text{record\_linkage}} = 1 - \frac{\sum_{i=1}^{k} |B_{i,x}| \cdot |B_{i,y}|}{(m \cdot n)},$$

where m and n are the sizes of datasets X and Y, and k is the total number of blocks. The term $|B_{i,x}|$ is the number of unique records from dataset X in the i-th block, while $|B_{i,y}|$ is the number of unique records from dataset Y in the i-th block. The expression $\sum_{i=1}^{k} |B_{i,x}| \cdot |B_{i,y}|$ is the number of comparisons after blocking.

Confusion matrix presents results in comparison to ground-truth `blocks` in a pairwise manner (e.g., one true positive pair occurs when both records from the comparison pair belong to the same predicted `block` and to the same ground-truth `block` in the evaluation data frame).

- True Positive (TP): Record pairs correctly matched in the same block.
- False Positive (FP): Records pairs identified as matches that are not true matches in the same block.
- True Negative (TN): Record pairs correctly identified as non-matches (different blocks)
- False Negative (FN): Records identified as non-matches that are true matches in the same block.

Metric	**Formula**	**Metric**	**Formula**
Recall	$\frac{TP}{TP+FN}$	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$	Specificity	$\frac{TN}{TN+FP}$
F1 Score	$2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision}+\text{Recall}}$	False Positive Rate	$\frac{FP}{FP+TN}$
False Negative Rate	$\frac{FN}{FN+TP}$		

Table: Evaluation Metrics

3 Case studies

3.1 Record linkage example

Let us first load the required packages.

```
library("blocking")
library("data.table")
```

We demonstrate the use of `blocking` function for record linkage on the `foreigners` dataset included in the package. This fictional representation of the foreign population in Poland was generated based on publicly available information, preserving the distributions from administrative registers. It contains 110,000 rows with 100,000 entities. Each row represents one record, with the following columns:

- `fname` – first name,
- `sname` – second name,
- `surname` – surname,

- `date` – date of birth,
- `region` – region (county),
- `country` – country,
- `true_id` – person ID.

Next, we load the data

```
data("foreigners")
head(foreigners)
```

```
#>     fname  sname    surname       date region country true_id
#>    <char> <char>     <char>     <char> <char>  <char>   <num>
#> 1:   emin             imanov 1998/02/05            031       0
#> 2: nurlan        suleymanli 2000/08/01            031       1
#> 3:   amio        maharrsmov 1939/03/08            031       2
#> 4:   amik        maharramof 1939/03/08            031       2
#> 5:   amil        maharramov 1993/03/08            031       2
#> 6:  gadir        jahangirov 1991/08/29            031       3
```

We split the dataset into two separate files: one containing the first appearance of each entity in the `foreigners` dataset, and the other containing its subsequent appearances.

```
foreigners_1 <- foreigners[!duplicated(foreigners$true_id), ]
foreigners_2 <- foreigners[duplicated(foreigners$true_id), ]
```

Now in both datasets we remove separators in the `date` column and create a new character column that concatenates the information from all columns (excluding `true_id`) in each row.

```
foreigners_1[, date := gsub("/", "", date)]
foreigners_1[, txt := paste0(fname, sname, surname, date, region, country)]
foreigners_2[, date := gsub("/", "", date)]
foreigners_2[, txt := paste0(fname, sname, surname, date, region, country)]
head(foreigners_1)
```

```
#>     fname  sname    surname     date region country true_id
#>    <char> <char>     <char>   <char> <char>  <char>   <num>
#> 1:   emin             imanov 19980205            031       0
#> 2: nurlan        suleymanli 20000801            031       1
#> 3:   amio        maharrsmov 19390308            031       2
#> 4:  gadir        jahangirov 19910829            031       3
#> 5:   zaur         bayramova 19961006  01261     031       4
#> 6:   asif          mammadov 19970726            031       5
#>                             txt
#>                          <char>
#> 1:         eminimanov19980205031
#> 2:   nurlansuleymanli20000801031
#> 3:     amiomaharrsmov19390308031
#> 4:    gadirjahangirov19910829031
#> 5: zaurbayramova199610060126103l
#> 6:       asifmammadov19970726031
```

General use

We use the newly created columns in the `blocking` function, which relies on the default **rnndescent** algorithm based on the cosine distance. Additionally, we set `verbose = 1` to monitor progress. Note that a default parameter of the `blocking` function is `seed = 2023`, which sets the random seed.

```
result_reclin <- blocking(x = foreigners_1$txt,
                          y = foreigners_2$txt,
                          verbose = 1)
```

```
#> ===== creating tokens =====
#> ===== starting search (nnd, x, y: 100000, 10000, t: 1232) =====
#> ===== creating graph =====
```

```
blocks_tab <- table(result_reclin$result$block)
block_ids <- rep(as.numeric(names(blocks_tab)), blocks_tab+1)
block_size <- as.numeric(names(table(table(block_ids))))
block_count <- as.vector(table(table(block_ids)))
```

Now we examine the results of record linkage by printing the `result_reclin` object. We have created 6,470 blocks based on 1,232 columns (2 character shingles). Blocks are small as we e have 3,920 blocks of 2 elements, 1,599 blocks of 3 elements,. . . , 2 blocks of 7 elements.

```
result_reclin
```

```
#> ========================================================
#> Blocking based on the nnd method.
#> Number of blocks: 6470.
#> Number of columns used for blocking: 1232.
#> Reduction ratio: 0.9999.
#> ========================================================
#> Distribution of the size of the blocks:
#>    2    3    4    5    6    7
#> 3920 1599  928   19    2    2
```

In order to access the result one should use `result_reclin$result`. The resulting `data.table` has four columns (as presented below):

- `x` – reference dataset (i.e. `foreigners_1`) – this may not contain all units of `foreigners_1`,
- `y` – query (each row of `foreigners_2`) – this will contain all units of `foreigners_2`,
- `block` – the block ID,
- `dist` – distance between objects.

```
head(result_reclin$result)
```

```
#>         x     y block      dist
#>     <int> <int> <num>     <num>
#> 1:      3     1     1 0.2216882
#> 2:      3     2     1 0.2122737
#> 3:     21     3     2 0.1172652
#> 4:     57     4     3 0.1863238
#> 5:     57     5     3 0.1379310
#> 6:     61     6     4 0.2307692
```

Let's examine the first pair. Obviously, there are typos in the `fname` and `surname`. Nevertheless, the pair is a match.

```
cbind(t(foreigners_1[3, 1:6]), t(foreigners_2[1, 1:6]))
```

```
#>          [,1]         [,2]
#> fname    "amio"       "amik"
#> sname    ""           ""
```

```
#> surname "maharrsmov" "maharramof"
#> date    "19390308"   "19390308"
#> region  ""           ""
#> country "031"        "031"
```

Now we use the `true_id` values to evaluate our approach.

```
matches <- merge(x = foreigners_1[, .(x = 1:.N, true_id)],
                 y = foreigners_2[, .(y = 1:.N, true_id)],
                 by = "true_id")
matches[, block := rleid(x)]
head(matches)
```

```
#> Key: <true_id>
#>    true_id     x     y block
#>      <num> <int> <int> <int>
#> 1:       2     3     1     1
#> 2:       2     3     2     1
#> 3:      20    21     3     2
#> 4:      56    57     4     3
#> 5:      56    57     5     3
#> 6:      60    61     6     4
```

We have 10,000 matched pairs which can be used in the `true_blocks` argument in the `blocking()` function to specify the true block assignments. We obtain the quality metrics for the assessment of record linkage.

```
result_2_reclin <- blocking(x = foreigners_1$txt,
                            y = foreigners_2$txt,
                            verbose = 1,
                            true_blocks = matches[, .(x, y, block)])
```

```
#> ===== creating tokens =====
#> ===== starting search (nnd, x, y: 100000, 10000, t: 1232) =====
#> ===== creating graph =====
```

```
result_2_reclin
```

```
#> ========================================================
#> Blocking based on the nnd method.
#> Number of blocks: 6470.
#> Number of columns used for blocking: 1232.
#> Reduction ratio: 0.9999.
#> ========================================================
#> Distribution of the size of the blocks:
#>    2    3    4    5    6    7
#> 3920 1599  928   19    2    2
#> ========================================================
#> Evaluation metrics (standard):
#>      recall   precision         fpr         fnr    accuracy specificity
#>     96.7532     78.6700      0.0038      3.2468     99.9957     99.9962
#>    f1_score
#>     86.7795
```

For example, our approach results in a 3.25% false negative rate (FNR). To improve this, we can increase the `epsilon` parameter of the NND method from 0.1 to 0.5. To do so, we configure the `control_ann` parameter in the `blocking` function using the `controls_ann` and `control_nnd` functions.

```
result_3_reclin <- blocking(x = foreigners_1$txt,
                            y = foreigners_2$txt,
                            verbose = 1,
                            true_blocks = matches[, .(x, y, block)],
                   control_ann = controls_ann(nnd = control_nnd(epsilon = 0.5)))

#> ===== creating tokens =====
#> ===== starting search (nnd, x, y: 100000, 10000, t: 1232) =====
#> ===== creating graph =====

result_3_reclin

#> ========================================================
#> Blocking based on the nnd method.
#> Number of blocks: 6394.
#> Number of columns used for blocking: 1232.
#> Reduction ratio: 0.9999.
#> ========================================================
#> Distribution of the size of the blocks:
#>    2    3    4    5    7
#> 3800 1615  954   21    4
#> ========================================================
#> Evaluation metrics (standard):
#>      recall   precision         fpr         fnr    accuracy specificity
#>     96.8776     80.0500      0.0036      3.1224     99.9960     99.9964
#>    f1_score
#>     87.6636
```

That decreases the FNR to 3.12%.

3.2 Deduplication example

Next, we demonstrate deduplication using the `blocking` function on the `RLdata500` dataset from the **RecordLinkage** package. Note that the dataset is included in the `blocking` package. It contains artificial personal data and fifty records have been duplicated with randomly generated errors. Each row represents one record, with the following columns:

- `fname_c1` – first name, first component,
- `fname_c2` – first name, second component,
- `lname_c1` – last name, first component,
- `lname_c2` – last name, second component,
- by, bm, bd – year, month and day of birth,
- `rec_id` – record id,
- `ent_id` – entity id.

```
data("RLdata500")
head(RLdata500)

#>    fname_c1 fname_c2 lname_c1 lname_c2    by    bm    bd rec_id ent_id
#>      <char>   <char>   <char>   <char> <int> <int> <int>  <int>  <int>
#> 1:  CARSTEN              MEIER           1949     7    22      1     34
#> 2:     GERD              BAUER           1968     7    27      2     51
#> 3:   ROBERT           HARTMANN           1930     4    30      3    115
#> 4:   STEFAN              WOLFF           1957     9     2      4    189
#> 5:     RALF            KRUEGER           1966     1    13      5     72
#> 6:  JUERGEN             FRANKE           1929     7     4      6    142
```

We create a new column (`id_count`) that indicates how many times a given unit occurs and then add leading zeros to the `bm` and `bd` columns. Finally, we create a new string column that concatenates the information from all columns (excluding `rec_id`, `ent_id` and `id_count`) in each row.

```
RLdata500[, id_count :=.N, ent_id]
RLdata500[, bm:=sprintf("%02d", bm)]
RLdata500[, bd:=sprintf("%02d", bd)]
RLdata500[, txt:=tolower(paste0(fname_c1,fname_c2,lname_c1,lname_c2,by,bm,bd))]
head(RLdata500)
```

```
#>    fname_c1 fname_c2 lname_c1 lname_c2    by     bm     bd rec_id ent_id
#>      <char>   <char>   <char>   <char> <int> <char> <char>  <int>  <int>
#> 1:  CARSTEN              MEIER            1949     07     22      1     34
#> 2:     GERD              BAUER            1968     07     27      2     51
#> 3:   ROBERT           HARTMANN            1930     04     30      3    115
#> 4:   STEFAN              WOLFF            1957     09     02      4    189
#> 5:     RALF            KRUEGER            1966     01     13      5     72
#> 6:  JUERGEN             FRANKE            1929     07     04      6    142
#>    id_count                    txt
#>       <int>                 <char>
#> 1:        1   carstenmeier19490722
#> 2:        2      gerdbauer19680727
#> 3:        1 roberthartmann19300430
#> 4:        1    stefanwolff19570902
#> 5:        1    ralfkrueger19660113
#> 6:        1  juergenfranke19290704
```

As in the previous example, we use the `txt` column in the `blocking` function. This time, we set `ann = hnsw` to use the Hierarchical Navigable Small World (HNSW) algorithm from the **RcppHNSW** package and `graph = TRUE` to obtain an **igraph** object for visualization.

```
result_dedup_hnsw <- blocking(x = RLdata500$txt,
                              ann = "hnsw",
                              graph = TRUE,
                              verbose = 1)
```

```
#> ===== creating tokens =====
#> ===== starting search (hnsw, x, y: 500, 500, t: 429) =====
#> ===== creating graph =====
```

The results are as follows.

```
result_dedup_hnsw
```

```
#> ========================================================
#> Blocking based on the hnsw method.
#> Number of blocks: 133.
#> Number of columns used for blocking: 429.
#> Reduction ratio: 0.9916.
#> ========================================================
#> Distribution of the size of the blocks:
#>  2  3  4  5  6  7  8  9 10 11 12 17
#> 46 35 23  8  6  6  2  3  1  1  1  1
```

We create a long `data.table` with information on blocks and units from the original dataset. We add the block information to the final dataset. We can check in how many blocks the same entities (`ent_id`) are observed. In our example, all the same entities are in the same blocks.

```
df_block_melted <- melt(result_dedup_hnsw$result, id.vars = c("block", "dist"))
df_block_melted_rec_block <- unique(df_block_melted[, .(rec_id=value, block)])
RLdata500[df_block_melted_rec_block, on = "rec_id", block_id := i.block]
RLdata500[, .(uniq_blocks = uniqueN(block_id)), .(ent_id)][, .N, uniq_blocks]

#>    uniq_blocks     N
#>          <int> <int>
#> 1:           1   450
```

Finally, we visualize the result based on the information whether a block contains matches or not.

```
df_for_density <- copy(df_block_melted[block %in% RLdata500$block_id])
df_for_density[, match:= block %in% RLdata500[id_count == 2]$block_id]

plot(density(df_for_density[match==FALSE]$dist),
     col = "blue", xlim = c(0, 0.8), main = "", xlab = "Distance")
lines(density(df_for_density[match==TRUE]$dist),
      col = "red", xlim = c(0, 0.8))
legend("topright",  legend = c("Non-matches", "Matches"),
       col = c("blue", "red"),  lty = 1, lwd = 2)
```

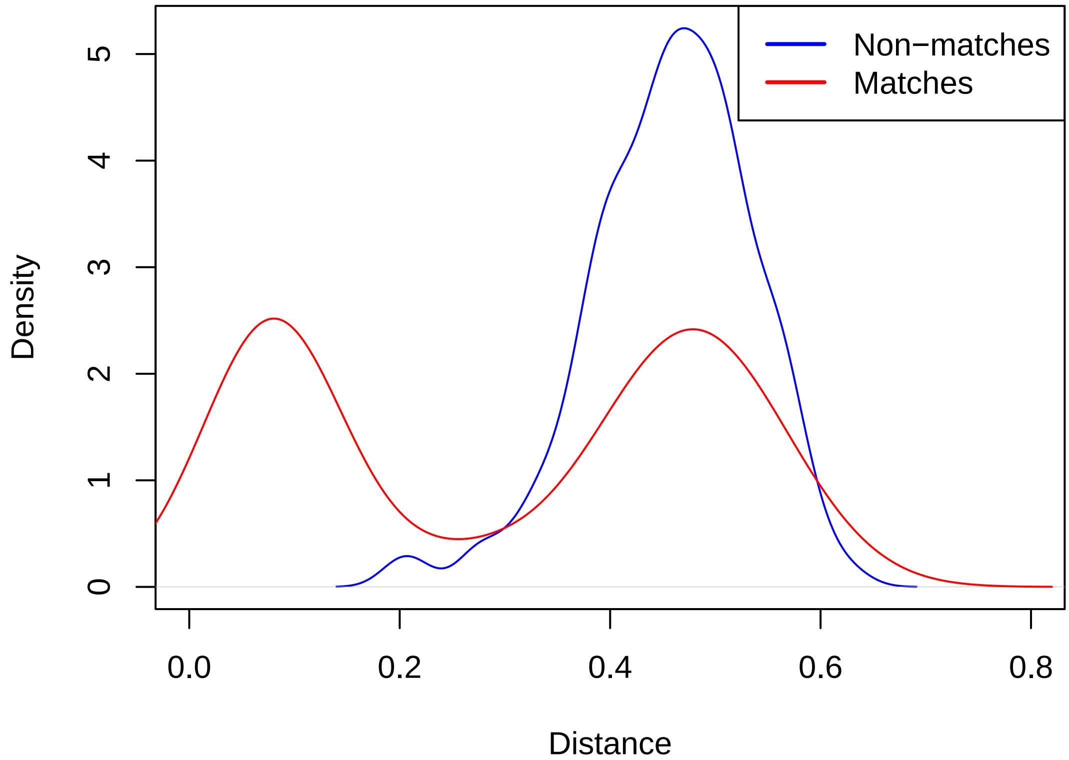

Figure 1: Distribution of distances between clusters type

Now we compare the evaluation metrics across all ANN algorithms supported by the `blocking` function, i.e. NND, HNSW, Approximate Nearest Neighbors Oh Yeah (Annoy, from the **RcppAnnoy** package), Locality-sensitive hashing (LSH, from the **mlpack** package), and k-Nearest Neighbors (kNN – denoted as `"kd"`, from the **mlpack** package). We use the `rec_id` and `ent_id` columns from the `RLdata500` dataset to specify the true blocks and then calculate evaluation metrics for all algorithms. Additionally, we assess blocking using the `klsh()` function from the **klsh** package, configured to create 10 blocks and 100 blocks, respectively. In both settings, we use 20 random projections and 2-character shingles. The results are as follows (klsh_10 and klsh_100 refer to the klsh algorithm with 10 blocks and 100 blocks, respectively).

```
set.seed(2025)
true_blocks <- RLdata500[, c("rec_id", "ent_id"), with = FALSE]
setnames(true_blocks, old = c("rec_id", "ent_id"), c("x", "block"))
eval_metrics <- list()
ann <- c("nnd", "hnsw", "annoy", "lsh","kd")
for (algorithm in ann) {
  eval_metrics[[algorithm]] <- blocking(x = RLdata500$txt,
                               ann = algorithm,
                               true_blocks = true_blocks)$metrics
}

blocks_klsh_10 <- klsh::klsh(
  r.set = RLdata500[, c("fname_c1", "fname_c2", "lname_c1",
                        "lname_c2", "by", "bm", "bd")],
  p = 20,
  num.blocks = 10,
  k = 2)
klsh_10_metrics <- klsh::confusion.from.blocking(
  blocking = blocks_klsh_10,
  true_ids = RLdata500$ent_id)[-1]
klsh_10_metrics$f1_score <- 2 * klsh_10_metrics$precision *
  klsh_10_metrics$recall /
  (klsh_10_metrics$precision + klsh_10_metrics$recall)
eval_metrics$klsh_10 <- unlist(klsh_10_metrics)
blocks_klsh_100 <- klsh::klsh(
  r.set = RLdata500[, c("fname_c1", "fname_c2", "lname_c1",
                        "lname_c2", "by", "bm", "bd")],
  p = 20,
  num.blocks = 100,
  k = 2)
klsh_100_metrics <- klsh::confusion.from.blocking(
  blocking = blocks_klsh_100,
  true_ids = RLdata500$ent_id)[-1]
klsh_100_metrics$f1_score <- 2 * klsh_100_metrics$precision *
  klsh_100_metrics$recall /
  (klsh_100_metrics$precision + klsh_100_metrics$recall)
eval_metrics$klsh_100 <- unlist(klsh_100_metrics)

round(do.call(rbind, eval_metrics) * 100, 2)

#>          recall precision   fpr fnr accuracy specificity f1_score
#> nnd         100      5.17  0.74   0    99.26       99.26     9.83
#> hnsw        100      4.76  0.80   0    99.20       99.20     9.08
#> annoy       100      4.80  0.79   0    99.21       99.21     9.17
#> lsh          98      1.04  3.74   2    96.26       96.26     2.06
#> kd          100      5.19  0.73   0    99.27       99.27     9.87
#> klsh_10      80      0.32 10.14  20    89.86       89.86     0.63
#> klsh_100     82      3.38  0.94  18    99.05       99.06     6.49
```

4 Summary

In this paper we have demonstrated the basic use cases of the **blocking** package. We believe that the software will be useful for researchers working in various fields where integration of multiple sources is an important aspect.

Users interested in integration with the **reclin2** package we refer to the documentation of the `pair_ann()` function and the vignette entitled `"Integration with existing packages"`

5 Acknowledgements

Work on this package is supported by the National Science Centre, OPUS 20 grant no. 2020/39/B/HS4/00941. We also thank participants of the uRos 2024 conference for valuable comments and discussion.

We also have developed a python version of the package {BlockingPy} that is available through the PyPi It has the similar structure but offers more ANN algorithms (e.g. FAISS) or usage of embeddings. For more details see: Strojny, T., & Beręsewicz, M. (2025). BlockingPy: approximate nearest neighbours for blocking of records for entity resolution. arXiv preprint arXiv:2504.04266.

References

O. Binette and R. C. Steorts. (almost) all of entity resolution. *Science Advances*, 8(12):eabi8021, 2022. doi: 10.1126/sciadv.abi8021. URL `https://www.science.org/doi/abs/10.1126/sciadv.abi8021`. [p1]

G. Csardi and T. Nepusz. The igraph software package for complex network research. *InterJournal*, Complex Systems:1695, 2006. URL `https://igraph.org`. [p2]

G. Csárdi, T. Nepusz, V. Traag, S. Horvát, F. Zanini, D. Noom, and K. Müller. *igraph: Network Analysis and Visualization in R*, 2025. URL `https://CRAN.R-project.org/package=igraph`. R package version 2.1.4. [p2]

R. R. Curtin, M. Edel, O. Shrit, S. Agrawal, S. Basak, J. J. Balamuta, R. Birmingham, K. Dutt, D. Eddelbuettel, R. Garg, S. Jaiswal, A. Kaushik, S. Kim, A. Mukherjee, N. G. Sai, N. Sharma, Y. S. Parihar, R. Swain, and C. Sanderson. mlpack 4: a fast, header-only c++ machine learning library. *Journal of Open Source Software*, 8(82), 2023. doi: 10.21105/joss.05026. [p2]

A. Dasylva and A. Goussanou. Estimating the false negatives due to blocking in record linkage. *Survey Methodology*, 47(2):299–312, 2021. [p1]

A. Dasylva and A. Goussanou. On the consistent estimation of linkage errors without training data. *Japanese Journal of Statistics and Data Science*, 5(1):181–216, 2022. [p1]

D. Eddelbuettel. *RcppAnnoy: 'Rcpp' Bindings for 'Annoy', a Library for Approximate Nearest Neighbors*, 2024. URL `https://CRAN.R-project.org/package=RcppAnnoy`. R package version 0.0.22. [p2]

T. Enamorado, B. Fifield, and K. Imai. Using a probabilistic model to assist merging of large-scale administrative records. *American Political Science Review*, 113(2):353–371, 2019. [p2]

T. Enamorado, B. Fifield, and K. Imai. *fastLink: Fast Probabilistic Record Linkage with Missing Data*, 2023. URL `https://CRAN.R-project.org/package=fastLink`. R package version 0.6.1. [p2]

J. P. Howard, II. Phonetic spelling algorithm implementations for R. *Journal of Statistical Software*, 95(8):1–21, 2020. doi: 10.18637/jss.v095.i08. [p2]

J. P. Howard, II. *phonics: Phonetic Spelling Algorithms in R*, 2021. URL `https://jameshoward.us/phonics-in-r/`. R package version 1.3.10. [p2]

T. Kalinowski and D. Falbel. *ragnar: Retrieval-Augmented Generation (RAG) Workflows*, 2025. URL https://CRAN.R-project.org/package=ragnar. R package version 0.2.0. [p2]

J. Melville. *RcppHNSW: 'Rcpp' Bindings for 'hnswlib', a Library for Approximate Nearest Neighbors*, 2024a. URL https://CRAN.R-project.org/package=RcppHNSW. R package version 0.6.0. [p2]

J. Melville. *rnndescent: Nearest Neighbor Descent Method for Approximate Nearest Neighbors*, 2024b. URL https://CRAN.R-project.org/package=rnndescent. R package version 0.1.6. [p2]

L. A. Mullen, K. Benoit, O. Keyes, D. Selivanov, and J. Arnold. Fast, consistent tokenization of natural language text. *Journal of Open Source Software*, 3:655, 2018. doi: 10.21105/joss.00655. URL https://doi.org/10.21105/joss.00655. [p2]

G. Papadakis, D. Skoutas, E. Thanos, and T. Palpanas. Blocking and filtering techniques for entity resolution: A survey. *ACM Comput. Surv.*, 53(2), Mar. 2020. ISSN 0360-0300. doi: 10.1145/3377455. URL https://doi.org/10.1145/3377455. [p1]

M. Sariyar and A. Borg. The RecordLinkage Package: Detecting Errors in Data. *The R Journal*, 2(2):61–67, 2010. doi: 10.32614/RJ-2010-017. URL https://doi.org/10.32614/RJ-2010-017. [p2]

M. Sariyar and A. Borg. *RecordLinkage: Record Linkage Functions for Linking and Deduplicating Data Sets*, 2025. URL https://CRAN.R-project.org/package=RecordLinkage. R package version 0.4-12.5. [p2]

D. Selivanov, M. Bickel, and Q. Wang. *text2vec: Modern Text Mining Framework for R*, 2023. URL https://CRAN.R-project.org/package=text2vec. R package version 0.6.4. [p2]

Y. Singh Parihar, R. Curtin, D. Eddelbuettel, and J. Balamuta. *mlpack: 'Rcpp' Integration for the 'mlpack' Library*, 2025. URL https://CRAN.R-project.org/package=mlpack. R package version 4.6.2. [p2]

R. Steorts. *klsh: Blocking for Record Linkage*, 2020. URL https://CRAN.R-project.org/package=klsh. R package version 0.1.0. [p2]

R. C. Steorts, S. L. Ventura, M. Sadinle, and S. E. Fienberg. A comparison of blocking methods for record linkage. In J. Domingo-Ferrer, editor, *Privacy in Statistical Databases*, pages 253–268, Cham, 2014. Springer International Publishing. ISBN 978-3-319-11257-2. [p1]

D. J. van der Laan. reclin2: a toolkit for record linkage and deduplication. *R Journal*, 14(2), 2022. [p2]

J. van der Laan. *reclin2: Record Linkage Toolkit*, 2024. URL https://CRAN.R-project.org/package=reclin2. R package version 0.5.0. [p2]

M. van der Loo. The stringdist package for approximate string matching. *The R Journal*, 6: 111–122, 2014. URL https://CRAN.R-project.org/package=stringdist. [p2]

Maciej Beręsewicz
University of Economics and BusinessStatisical Office in Poznań
Department of Statistics, Poznań, Poland
Centre for the Methodology of Population Studies
https://maciejberesewicz.com
ORCiD: 0000-0002-8281-4301
maciej.beresewicz@poznan.pl

Adam Struzik
Adam Mickiewicz UniversityStatisical Office in Poznań

Department of Mathematics, Poznań, Poland
Centre for Urban Statistics
adastr5@st.amu.edu.pl