Introduction to Bayesian record linkage

Brenda Betancourt and Andee Kaplan

Duke University
Department of Statistical Science

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What is “Bayesian”?

1. Setting up a *full probability model* – a joint probability distribution for all observable and unobservable quantities

$$\begin{aligned} p(\boldsymbol{x}|\boldsymbol{\theta}) &- \text{ likelihood} \\ p(\boldsymbol{\theta}) &- \text{ prior} \end{aligned}$$

2. Conditioning on observed data – calculating and interpreting the appropriate *posterior distribution*

$$p(\boldsymbol{\theta}|\boldsymbol{x}) = \frac{p(\boldsymbol{x},\boldsymbol{\theta})}{p(\boldsymbol{x})} = \frac{p(\boldsymbol{x}|\boldsymbol{\theta})p(\boldsymbol{\theta})}{p(\boldsymbol{x})} \propto p(\boldsymbol{x}|\boldsymbol{\theta})p(\boldsymbol{\theta})$$

Why Bayesian Record Linkage?

A Bayesian framework is suitable to solve the following problems:

- Exact computation of the probability that each pair of records is a match, conditional on the observed data.
    - Posterior distribution of linkage structure.
- Propagating linkage error as an added component of uncertainty in the estimation process.
    - Relevant for subsequent modeling.

Clustering Approaches

- Note: Reliable and accurate linkage depends greatly on the quantity and quality of the identifying information.

- Record linkage can be naturally seen as a clustering problem.
  - Supervised and unsupervised approches.

- Records representing the same individual are clustered to a latent entity producing a partition of the data.

Record Linkage and Clustering

Which records correspond to the same person?

Record Linkage and Clustering

Each entity is associated with one or more records and the goal is to recover the latent entities (clusters).

Record Linkage and Clustering

Eight latent entities: One cluster of size 4, one of size 2, six of size 1

Partition-based Bayesian clustering models

Goal: cluster N data points into K clusters.

- Let C_N be a random partition of $[N] = \{1, \ldots, N\}$
- Place a prior distribution over the random partitions $\{C_N\}$
- A partition C_N is represented by a set of cluster assignments i.e linkage structure.
- The number of clusters K does not need to be specified a priori $\rightarrow$ Non-parametric latent variable approach.

Notation

- $X_{ij\ell}$: observed value of the lth field for the jth record in the ith data set, $1 \leq i \leq k$ and $1 \leq j \leq n_i$.

- $Y_{j'\ell}$: true value of the lth field for the j'th latent individual.

- λ_{ij}: latent individual to which the jth record in the ith list corresponds. $\mathbf{\Lambda}$ is the collection of these values..
  - e.g. Five records in one list $\mathbf{\Lambda} = \{1, 1, 2, 3, 3\} \rightarrow$ 3 latent entities or clusters.

- $z_{ij\ell}$: indicator of whether a distortion has occurred for record field value $X_{ij\ell}$

Graphical Record Linkage

Graphical model representation of Steorts et al. (2016):

- Λ_{ij} represents the linkage structure → uniform prior.
- Requires information about the number of latent entities a priori and it is very informative.

Record Linkage and Microclustering

- Enumeration of victims of killings in Syria merging four databases.

- The number of data points in each cluster should remain small even for large data sets → Large number of singletons and small clusters.

Dirichlet Process Mixture Models

Other clustering tasks require models that assume cluster sizes grow linearly with the size of the data set.

- $\mathbf{\Lambda} \sim \text{DP}(\alpha)$, Dirichlet Process prior with concentration parameter α
- Chinese Restaurant Process (CRP)

- Carmona C., Nieto-Barajas L., Canale A. (2017), Model-based approach for household clustering with mixed scale variables `https://arxiv.org/abs/1612.00083` .

Microclustering models

- Prior distributions on partitions that are suitable for the microclustering problem
  - Miller et al, 2015 and Zanella et al, 2016

- Scalable sampling algorithm in combination with blocking techniques.

- NBNB model: Prior distribution on partitions that exhibits the microclustering property:
  - K represents the number of latent entities or clusters
  - N_k represents the size of cluster k i.e. $N = \sum_{k=1}^{K} N_k$

$$K \sim \text{Neg-Bin(a,q)} \quad \text{and} \quad N_1, \ldots, N_k \mid K \sim \text{Neg-Bin}(r, p)$$

Empirically Motivated Priors

- The prior for the latent entities is the empirical distribution of the data (Steorts R., 2015).
  - Avoids the problem of specifying a prior but requires specification of K in advance.

- This approach allows us to include both categorical and string-valued variables.

- The clustering approaches in Steorts et al. (2016) and Zanella et al. (2016) only handle categorical data.
  - Prior specification involving string data is very difficult!

Model Specification: String model

- The distortion of string-valued variables is modeled using a probabilistic mechanism based on some measure of distance between the true and distorted strings.

$$P(X_{ij\ell} = w | \lambda_{ij}, Y_{\lambda_{ij}\ell}, z_{ij\ell}) = \frac{\alpha_\ell \exp[-cd(w, Y_{\lambda_{ij}\ell})]}{\sum_{w \in S_l} \alpha_\ell \exp[-cd(w, Y_{\lambda_{ij}\ell})]}$$

where c is a parameter that needs to be specified and d represents a string metric distance e.g. Levenshtein or Jaro-Winkler.

Model Specification: Likelihood Function

$$X_{ij\ell} = w | \lambda_{ij}, Y_{\lambda_{ij}\ell}, z_{ij\ell} \overset{iid}{\sim} \begin{cases} \delta(Y_{\lambda_{ij}\ell}), & \text{if } z_{ij\ell} = 0 \\ F_\ell(Y_{\lambda_{ij}\ell}), & \text{if } z_{ij\ell} = 1 \text{ and } \ell \le p_s \\ G_\ell, & \text{if } z_{ij\ell} = 1 \text{ and } \ell > p_s \end{cases}$$

- $z_{ij\ell} = 0$, then $X_{ij\ell} = Y_{\lambda_{ij\ell}}$
- F_ℓ is the string model in the last slide.
- G_ℓ is the empirical distribution function of the categorical data.

Model Specification: Hierarchical Model

$$
\begin{aligned}
&Y_{\lambda_{ij}\ell} \overset{iid}{\sim} G_\ell \\
&z_{ij\ell} | \beta i \ell \overset{iid}{\sim} \text{Bernoulli}(\beta i \ell) \\
&\beta i \ell \overset{iid}{\sim} \text{Beta}(a, b) \\
&\lambda_{ij} \overset{iid}{\sim} \text{DiscreteUniform}(1, \ldots, \text{N})
\end{aligned}
$$

- $\beta_{i\ell}$ represent the distortion probabilities of the fields.
- The parameters a and b for the Beta prior need to be specified.
- The number of latent entities or clusters needs to be specified in advance.

`blink` package

`R` package that removes duplicate entries from multiple databses using the empirical Bayes graphical method:

```r
install.packages("blink")
```

- Formatting data for use with `blink`
- Tuning parameters
- Running the Gibbs sampler (estimate model parameters)
- Output

RLdata500 data

We will continue with the RLdata500 dataset in the RecordLinkage package consisting of 500 records with 10% duplication.

```r
library(blink) # load blink library
library(RecordLinkage) # load data library
data("RLdata500") # load data
head(RLdata500) # take a look
```

```
##   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
```

Formatting the data

```r
# categorical variables
X.c <- as.matrix(RLdata500[, c("by","bm","bd")])

# string variables
X.s <- as.matrix(RLdata500[, c("fname_c1", "lname_c1")])
```

`X.c` and `X.s` include all files stacked on top of each other, for categorical and string variables respectively

```r
# keep track of which rows of are in which files
file.num <- rep(c(1, 2, 3), c(200, 150, 150))
```

Tuning parameters

Hyperparameters

```r
# Subjective choices for distortion probability prior
# parameters of a Beta(a,b)
a <- 1
b <- 999
```

Distortion

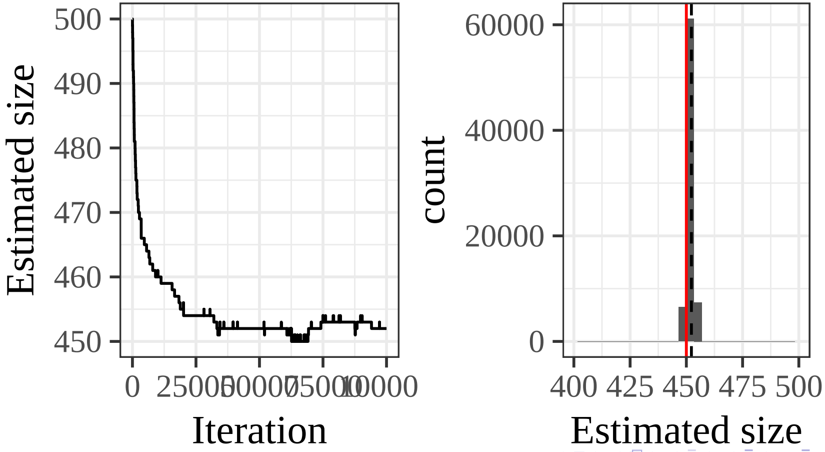
```r
# string distance function example
d <- function(s1, s2) {
  adist(s1, s2) # approximate string distance
}

# steepness parameter
c <- 1
```

Running the Gibbs sampler

```
lam.gs <- rl.gibbs(file.num = file.num, # file
                   X.s = X.s, X.c = X.c, # data
                   num.gs = 100000, # iterations
                   a = a, b = b, # prior params
                   c = c, d = d, # distortion
                   M = 500) # max # latents
```

Output

```
# count how many unique latent individuals
size_est <- apply(lam.gs, 1, function(x) {
  length(unique(x))
  })
```



Evaluation

```r
# estimated pairwise links
est_links_pair <- pairwise(links(lam.gs[-(1:25000), ]))

# true pairwise links
true_links_pair <- pairwise(links(matrix(identity.RLdata500, nrow = 1)))

#comparison
comparison <- links.compare(est_links_pair, true_links_pair, counts.only = TRUE

# precision
precision <- comparison$correct/(comparison$incorrect + comparison$correct)

# recall
recall <- comparison$correct/(comparison$correct + comparison$missing)


# results
c(precision, recall)
```

```
## [1] 1.00 0.96
```

Your turn

Using the `title`, `authors`, `year`, and `journal` columns in the `cora` dataset from the `RLdata` package,

1. Let's only use data with **complete cases** (for simplicity):
2. Format the data to use with `blink`
    - Which columns are string vs. categorical?
    - Of the remaining data, assume that the rows 1-200 are from database 1, 201-400 are from database 2, and 401-560 are from database 3
3. Create tuning parameters for your model
    - Think about prior hyperparameters as well as the string distortion function
4. Run the Gibbs sampler 50 times to update the linkage structure
5. Evaluate your estimated linkage structure using precision and recall

Your turn (solution)

```r
# 1. formatting data
# load data
library(RLdata)
data("cora")

not_missing <- complete.cases(cora[, c("year", "journal", "title", "authors")])

# categorical variables
X.c <- as.matrix(cora[not_missing, c("year","journal")])

# string variables
X.s <- as.matrix(cora[not_missing, c("title", "authors")])

# keep track of which rows of are in which files
file.num <- rep(c(1, 2, 3), c(200, 200, 160))

# 2. hyperparameters

# Subjective choices for distortion probability prior
# parameters of a Beta(a,b)
a <- 1
b <- 999

# string distance function example
d <- function(s1, s2) {
  adist(s1, s2) # approximate string distance
}

# steepness parameter
c <- 1

# 3. run the gibbs sampler
lam.gs <- rl.gibbs(file.num = file.num, # file
                   X.s = X.s, X.c = X.c, # data
                   num.gs = 10, # iterations
                   a = a, b = b, # prior params
```

References

- Steorts, R. (2015), Entity Resolution with Empirically Motivated Priors, Bayesian Analysis 10(4), pp. 849–875.
- Steorts et al. (2016). A Bayesian Approach to Graphical Record Linkage and De-duplication, Journal of the American Statistical Association, 111:516, pp.1660-1672.
- Sadinle, M. (2014). Detecting duplicates in a homicide registry using a bayesian partitioning approach. The Annals of Applied Statistics 8(4), pp. 2404–2434
- Zanella et al. (2016). Flexible Models for Microclustering with Applications to Entity Resolution, Advances in Neural Information Processing Systems (NIPS) 29, pp. 1417-1425.
- Miller et al. (2015). The Microclustering Problem: When the Cluster Sizes Don't Grow with the Number of Data Points. NIPS Bayesian Nonparametrics: The Next Generation Workshop Series.