

# Efficient and Scalable Bipartite Matching with Fast Beta Linkage (fabl)

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**Abstract.** Recently, researchers have developed Bayesian versions of the Fellegi Sunter model for record linkage. These have the crucial advantage of quantifying uncertainty from imperfect linkages. However, current implementations of Bayesian Fellegi Sunter models are computationally intensive, making them challenging to use on larger-scale record linkage tasks. We propose and investigate a variation on Bayesian Fellegi Sunter models that we call fast beta linkage, or **fabl**. Specifically, in **fabl** we propose independent prior distributions over the matching space, allowing us to use hashing techniques that reduce computational overhead. This also allows us to complete pairwise record comparisons over large datasets through parallel computing and reduce memory costs through a new technique called storage efficient indexing. Through simulations and two case studies, we show that **fabl** has markedly increased speed with minimal loss of accuracy.

**Keywords:** entity resolution, data fusion, hashing, record linkage, Bayesian, distributed computing.

## 1 Introduction

In many data analysis tasks, analysts seek to identify duplicate records across two databases. This is an increasingly important task in “data cleaning,” and is used for inferential and predictive analyses in fields such as statistics, computer science, machine learning, political science, economics, precision medicine, official statistics, and others (Christen, 2012; Gutman et al., 2013; Dalzell and Reiter, 2018; Tang et al., 2020). In this article, we consider bipartite record linkage, which merges two databases together that contain duplications across but not within the respective databases.

Many statistical record linkage methods are extensions of the seminal work of Fellegi and Sunter (1969) and Newcombe et al. (1959). Specifically, Fellegi and Sunter (1969) created comparison vectors for each pair of records in the data and independently classified each pair as a match or a non-match using a likelihood ratio test. Recent work in the statistical literature has extended this approach for a wide variety of applications (William E Winkler and Thibaudeau, 1990; Fair, 2004; Wagner et al., 2014; Gill and Goldacre, 2003; Enamorado et al., 2019; Aleshin-Guendel and Sadinle, ming). Additionally, some methods model records directly (Steorts et al., 2016; Marchant et al., 2019; Betancourt et al., 2021), but in this paper, we build on the contributions to the comparison vector approach.

The independent pairwise matching assumption from Fellegi and Sunter (1969) is popular mainly for its mathematical simplicity, but can be unreasonable in practice. In many situations, we know that there are no duplications within a database, meaning that

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each record should be linked with at most one other record. Thus, when the procedure results in many to one matches, some of these links must be false. Many extensions to Fellegi and Sunter (1969) resolve these false matches as a post-processing step (Jaro, 1989), but this model misspecification can still lead to poor results (Sadinle, 2017).

Alternatively, one can embed one-to-one matching requirements into the model specification itself (Gutman et al., 2013; Tancredi and Liseo, 2011), at an additional computational cost. Larsen (2005) employed a Metropolis-Hastings algorithm to only allow sampling matches that respected one-to-one assumptions, but such algorithms exhibit slow mixing due to the combinatorial nature of the constrained matching space. Fortunato (2010) used simulated annealing to target the space of matches permitted under the one-to-one constraint, but the method is quite computationally intensive and, to our knowledge, has not been applied on databases with more than 100 records. Sadinle (2017) proposed the Beta Record Linkage model (BRL), using a prior over the space of bipartite matchings to strictly enforce one-to-one requirements throughout a Gibbs sampler. Additionally, he introduced a class of loss functions that allows for a flexible estimation of the linkage structure, such that the modeller can weight the relative importance of false positives and false negatives, and identify records pairings to be decided through clerical review. BRL was shown to work on larger tasks than previous one-to-one methods, but in our experience, it becomes slow when applied to files with more than a few thousand records.

In this paper, we propose fast beta linkage (**fabl**), which extends the BRL model for increased efficiency and scalability. Following the suggestion in Wortman (2019), we relax the one-to-one matching requirement of BRL and propose independent priors over the matching space, creating a “many-to-one” model for record linkage. This allows us to (1) employ hashing techniques that speed up calculations and reduce computational costs, (2) compute the pairwise record comparisons over large datasets via parallel computing, and (3) reduce memory costs through what we call storage efficient indexing. We demonstrate that even in cases where a bipartite matching is desired, **fabl** (with a simple post-processing procedure) provides accurate estimation of the linkage structure and other parameters, more information through which to assess model misspecification, and greatly enhanced speed. Open source software to use **fabl** in R is available through Github.

In what follows, Section 2 reviews the work of Fellegi and Sunter (1969) and Sadinle (2017). Section 3, proposes the **fabl** model, derives the Gibbs sampler for posterior inference, and provides the loss function used to calculate the Bayes estimate for the bipartite matching. Section 4 introduces the hashing technique and storage efficient indexing used to increase the speed of calculations and the scale of linkage tasks amenable to **fabl**. Sections 5 and 6 demonstrate the speed and accuracy of **fabl** through simulation studies and case studies of homicides from the El Salvadoran Civil War and the National Long Term Care Study.

## 2 Review of Prior Work

Consider two databases  $\mathbf{X}_1$  and  $\mathbf{X}_2$  containing records  $\{x_{1i}\}_{i=1}^{n_1}$  and  $\{x_{2j}\}_{j=1}^{n_2}$  respectively. Without loss of generality, denote files such that  $n_1 \geq n_2$ . We follow the convention established by Sadinle (2017) and say “record  $i \in \mathbf{X}_1$ ” rather than the more compact  $x_{1i}$  in order to avoid double subscripts. In the context of bipartite matching, we assume that there are duplications across, but not within, each database. Under this framework, the set of matches across databases can be represented in two equivalent ways. First, we may use a matrix  $\Delta \in \{0, 1\}^{n_1 \times n_2}$ , where

$$\Delta_{ij} = \begin{cases} 1 & \text{if records } i \in \mathbf{X}_1 \text{ and } j \in \mathbf{X}_2 \text{ refer to the same entity;} \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

Though intuitive, this sparse matrix representation can become cumbersome for large linkage tasks. More compactly, bipartite matching also can be viewed as a labeling  $\mathbf{Z} = (Z_1, \dots, Z_{n_2})$  for the records in database  $\mathbf{X}_2$  such that

$$Z_j = \begin{cases} i & \text{if records } i \in \mathbf{X}_1 \text{ and } j \in \mathbf{X}_2 \text{ refer to the same entity;} \\ n_1 + j & \text{if records } j \in \mathbf{X}_2 \text{ does not have a match in database } \mathbf{X}_1. \end{cases} \quad (2)$$

We can go back and forth between the two using  $\Delta_{ij} = I(Z_j = i)$ , where  $I(\cdot) = 1$  when the expression inside the parentheses is true, and  $I(\cdot) = 0$  otherwise.

Denote the set of matches by  $\mathbf{M} = \{(i, j) : i \in \mathbf{X}_1, j \in \mathbf{X}_2, \Delta_{ij} = 1\}$ , and the set of non-matches by  $\mathbf{U} = \{(i, j) : i \in \mathbf{X}_1, j \in \mathbf{X}_2, \Delta_{ij} = 0\}$ . The record linkage task can be viewed as identifying the sets of  $\mathbf{M}$  and  $\mathbf{U}$ . We refer to record pairs that are estimated as matches as “links”, and record pairs that are estimated as non-matches as “non-links”.

Intuitively, co-referent records (those that refer to the same entity) should be similar; records that are not co-referent should not be similar. Fellegi and Sunter (1969) proposed encoding this is using a comparison vector  $\gamma_{ij}$  computed for each record pair  $(i, j)$  in  $\mathbf{X}_1 \times \mathbf{X}_2$ . Denote the number of criteria for comparing records by  $F$ , such that  $\gamma_{ij} = (\gamma_{ij}^1, \gamma_{ij}^2, \dots, \gamma_{ij}^F, \dots, \gamma_{ij}^F)$ . In most cases,  $\gamma_{ij}$  consists of one comparison for each feature shared between the two datasets.

The simplest way to compare two records is to check for agreement or disagreement, and this is commonly used for categorical variables. For more complex measurements, we can take into account partial agreement to more richly characterize the comparison; for numerical data, we can use absolute difference, and for text data, we can use string distance metrics such as Levenstein or Jaro-Winkler distance (Cohen et al., 2003). We then can set thresholds that allow us to represent comparisons through discrete levels of disagreement (Bilenko and Mooney, 2006; Elmagarmid et al., 2007). Let  $\mathcal{S}_f(i, j)$  denote a general similarity measure for feature  $f$  of records  $i$  and  $j$ , where the range of  $\mathcal{S}_f$  can be divided into  $L_f + 1$  intervals denoted by  $I_{f0}, I_{f1}, \dots, I_{fL_f}$ . Following convention,  $I_{f0}$  represents the highest level of agreement (inclusive of complete agreement) and  $I_{fL_f}$  represents the highest level of disagreement (including complete disagreement). Thus, we can construct comparison vectors in the following way:  $\gamma_{ij}^f = \ell$  if  $\mathcal{S}_f(i, j) \in I_{f\ell}$ . The choice of  $I_{f\ell}$  are application specific, which we discuss in our simulation and case studies.

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In practice, it is not feasible to make all-to-all record comparisons as the computational complexity is of order  $O(n_1 \times n_2)$ . The most common solution is to utilize blocking, which places similar records into partitions, or “blocks,” to reduce this computational burden (Steorts et al., 2014; Murray, 2016). In deterministic blocking, the modeller chooses a field thought to be highly reliable, and only compares records that agree on that field. The record linkage method is then applied independently across all blocks, which can be done in parallel for additional speed gains. However, blocking on an unreliable field can lead to missed matches, making this form of blocking undesirable in some situations (Steorts et al., 2014).

In this paper, we use hashing and a new technique called storage efficient indexing to increase the scale of the linkage tasks we can undertake without blocking. This is useful when there is no reliable blocking field available, or one desires estimates of model parameters for the entire sample in question. In practice, **fabl** can be combined with blocking, but all derivations, simulations, and case studies are presented here without blocking.

### 2.1 Fellegi-Sunter Model

The comparison data  $\gamma_{ij}$  are not sufficient to determine whether a record is a match or non-match because of errors that naturally occur in the data. This motivated Fellegi and Sunter (1969) to consider the likelihood ratio

$$w_{ij} = \frac{P(\gamma_{ij} \mid \Delta_{ij} = 1)}{P(\gamma_{ij} \mid \Delta_{ij} = 0)} \quad (3)$$

as a weight to estimate if record pairs are a match or non-match. This ratio will be large when there is strong evidence of the pair being a match, and small otherwise.

In practice,  $P(\cdot \mid \Delta_{ij} = 1)$  and  $P(\cdot \mid \Delta_{ij} = 0)$  are unknown to the modeler, and thus must be estimated. Under the Fellegi Sunter model, we assume both that comparison vectors are independent given their matching status, and that the match status of the record pairs are independent. This allows us to model the comparison data using mixture models in the following way:

$$\begin{aligned} \Gamma_{ij} &= \gamma_{ij} \mid \Delta_{ij} = 1 \stackrel{iid}{\sim} \mathcal{M}(\mathbf{m}), \\ \Gamma_{ij} &= \gamma_{ij} \mid \Delta_{ij} = 0 \stackrel{iid}{\sim} \mathcal{U}(\mathbf{u}), \\ \Delta_{ij} &\stackrel{iid}{\sim} \text{Bernoulli}(p), \end{aligned} \quad (4)$$

where  $p$  is the proportion of records that match, and  $\mathbf{m}$  is the set of parameters for the matching record pairs  $m_{fl} = P(\gamma_{ij}^f = l \mid Z_j = i)$  for all fields  $f$  and agreement levels  $\ell_f$ , and  $\mathbf{u}$  is defined similarly for non-matching pairs. These unknown parameters are often estimated using the EM algorithm (Winkler, 1988).

After estimating  $\mathbf{m}$  and  $\mathbf{u}$ , the Fellegi Sunter method uses thresholds  $T_m$  and  $T_u$  such that all record pairs with  $w_{ij} > T_m$  are declared as links, and all those with  $w_{ij} < T_u$

are declared as non-links (with those such that  $T_u < w_{ij} < T_m$  left undetermined and subject to clerical review). This is a problem in practice as transitive closures can be violated. Since each  $w_{ij}$  is calculated independently, there can be situations in which both  $w_{ij} > T_m$  and  $w_{i'j} > T_m$ , so both  $(i, j)$  and  $(i, j')$  are declared as links, even though such a matching is not allowed by assumption.

To address this issue, Jaro (1989) proposed solving the following linear sum assignment problem:

$$\begin{aligned} \max_{\Delta} \quad & \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} w_{ij} \Delta_{ij} \quad \text{subject to} \quad \Delta_{ij} \in \{0, 1\}; \\ & \sum_{i=1}^{n_1} \Delta_{ij} \leq 1, j = 1, 2, \dots, n_2; \text{ and} \\ & \sum_{j=1}^{n_2} \Delta_{ij} \leq 1, i = 1, 2, \dots, n_1. \end{aligned} \quad (5)$$

The solution to this problem, for which several simple algorithms exist, is a bipartite matching that maximizes the sum of the Fellegi Sunter weights among matched pairs. Jaro provided no theoretical justification for using this approach; however Sadinle (2017) recently showed that under certain conditions, (5) is the maximum likelihood estimate for bipartite matching.

## 2.2 Beta Record Linkage Model

One criticism of the independent matching assumption is that the decision rule leads to “many-to-many assignments,” breaking one-to-one matching assumptions. One way of resolving this issue to incorporate the constraint directly into the model as follows:

$$\begin{aligned} \Gamma_{ij} \mid Z_j = i &\stackrel{iid}{\sim} \mathcal{M}(\mathbf{m}) \\ \Gamma_{ij} \mid Z_j \neq i &\stackrel{iid}{\sim} \mathcal{U}(\mathbf{u}) \\ \mathbf{Z} &\sim \mathcal{B}, \end{aligned} \quad (6)$$

where  $\mathcal{B}$  represents a prior on the space of bipartite matchings, and  $\mathcal{M}(\mathbf{m})$  and  $\mathcal{U}(\mathbf{u})$  are models for the comparison vectors of matches and non-matches. For BRL, Sadinle (2017) proposed the beta distribution for bipartite matching, given by

$$P(\mathbf{Z} \mid \alpha_\pi, \beta_\pi) = \frac{(n_1 - n_{12}(\mathbf{Z}))!}{n_1!} \frac{B(n_{12}(\mathbf{Z}) + \alpha_\pi, n_2 - n_{12}(\mathbf{Z}) - \beta_\pi)}{B(\alpha_\pi, \beta_\pi)}$$

where  $B(\cdot, \cdot)$  represents the Beta function, hyperparameters  $\alpha_\pi$  and  $\beta_\pi$  encode prior beliefs about the proportion of records in  $\mathbf{X}_2$  that have matches in  $\mathbf{X}_1$ , and  $n_{12}(\mathbf{Z}) = \sum_{j=1}^{n_2} I(Z_j \leq n_1 + j)$  is the records in  $\mathbf{X}_2$  that have a match in  $\mathbf{X}_1$ . This prior induces a Gibbs sampler that strictly enforces one-to-one matching, removing previously matched records from the set of candidate records when sampling  $Z_j$ . This creates a dependency that makes the sampler inherently serial, which can slow down the sampler when working on large linkage tasks.

### 3 Fast Beta Linkage

Recall the compact representation of the matching structure  $\mathbf{Z} = (Z_1, Z_2, \dots, Z_{n_2})$  with  $Z_j \in \{1, 2, \dots, n_1, n_1 + j\}$ , where  $Z_j < n_1$  indicates a link and  $Z_j = n_1 + j$  indicates a nonlink. In contrast to the prior over the vector  $\mathbf{Z}$  from [Sadinle \(2017\)](#), we follow [Wortman \(2019\)](#) and use independent priors for each component  $Z_j$ . However, unlike [Wortman \(2019\)](#) who proposes a flat prior for  $Z_j$ , we propose a proper and flexible prior. We denote the fast beta prior as follows:

$$Z_j | \pi = \begin{cases} \frac{1}{n_1} \pi & z_j \leq n_1; \\ 1 - \pi & z_j = n_1 + j \end{cases}$$

$$\pi \sim \text{Beta}(\alpha_\pi, \beta_\pi).$$

Intuitively, this set of priors says that record  $j \in \mathbf{X}_2$  has some match in  $\mathbf{X}_1$  with probability  $\pi$ , and that each record  $i \in \mathbf{X}_1$  is equally likely to be that match.  $\pi$  itself is given a prior distribution with hyperparameters  $\alpha_\pi$  and  $\beta_\pi$  to encode prior beliefs about the proportion of records in  $\mathbf{X}_2$  that have matches in  $\mathbf{X}_1$ . One choice might be  $\pi \sim \text{Beta}(1, 1)$ , which corresponds to a prior belief that non-matches and matches are equally likely, and another might be  $\pi \sim \text{Beta}\left(1, \frac{1}{n_1}\right)$ , which corresponds to a uniform prior on the labeling of  $\mathbf{Z}$ . We note here that prior from [Wortman \(2019\)](#) can be viewed as a special case of the fast beta prior, with  $\pi$  fixed at the mean of a  $\text{Beta}\left(1, \frac{1}{n_1}\right)$  random variable.

Note that linkage in this setting is conducted at the record level, rather than at the record pair level as in the Fellegi Sunter model. That is,  $\pi$  under **fabl** estimates the proportion of records in  $\mathbf{X}_2$  that have matches, while  $\lambda$  in the Fellegi Sunter model estimates the proportion of record pairs that are matches. We find  $\pi$  to be more interpretable parameter than  $\lambda$  in the bipartite case. There are at most  $n_2$  matching pairs out of  $n_1 n_2$  total pairs, meaning that  $\lambda$  is bounded above by  $\frac{1}{n_1}$  and tends towards 0 as the size of the linkage task grows. Additionally, while the Fellegi Sunter model makes  $n_1 \times n_2$  independent matching decisions and BRL makes  $n_2$  dependent matching decisions, **fabl** strikes a middle ground between the two, making  $n_2$  independent matching decisions. As shown in Sections 5 and 6, this allows **fabl** to achieve the benefits from BRL while making efficiency gains possible by exploiting independence.

Importantly, this independence relaxes the one-to-one requirement from BRL; the Gibbs sampler under **fabl** does ensure that each record in  $\mathbf{X}_2$  can be matched to at most one record in  $\mathbf{X}_1$ , but allows for the possibility that multiple records in  $\mathbf{X}_2$  match to the same record in  $\mathbf{X}_1$ . To resolve many-to-one matchings and obtain a one-to-one estimate, we use the post processing procedure shown in section 3.2.

Lastly, we note that it is common to encounter missing information in datasets used for record linkage. Whether information is missing in record  $i \in \mathbf{X}_1$  or  $j \in \mathbf{X}_2$ , the comparison vector  $\gamma_{ij}$  will have missing values. We handle this issue by assuming that this missingness occurs at random (MAR, by [Little and Rubin \(2002\)](#)). With this

assumption, we can marginalize over the missing data, and do all computation simply using the observed data. To notate this, we use the indicator  $I_{obs}(\cdot)$ , which takes on the value 1 when the argument inside the parentheses is observed, and 0 otherwise.

With the **fabl** prior defined and our missingness assumptions addressed, we present the full model as follows:

$$\begin{aligned}\mathcal{L}(\mathbf{Z}, \Phi \mid \Gamma) &= \prod_{j=1}^{n_1} \prod_{i=1}^{n_2} \prod_{f=1}^F \prod_{l=1}^{L_f} \left[ m_{fl}^{I(Z_j=i)} u_{fl}^{I(Z_j \neq i)} \right]^{I(\gamma_{ij}^f=l)I_{obs}(\gamma_{ij}^f)} \\ \mathbf{m}_f &\sim \text{Dirichlet}(\alpha_{f0}, \dots, \alpha_{fL_f}) \\ \mathbf{u}_f &\sim \text{Dirichlet}(\beta_{f0}, \dots, \beta_{fL_f}) \\ Z_j \mid \pi &= \begin{cases} \frac{1}{n_1} \pi & z_j \leq n_1; \\ 1 - \pi & z_j = n_1 + j \end{cases} \\ \pi &\sim \text{Beta}(\alpha_\pi, \beta_\pi),\end{aligned}$$

where we have used the condensed notation  $\Phi = \{\mathbf{m}, \mathbf{u}\}$  to denote the set of parameters governing the probabilities of agreement levels for matching and non-matching record pairs.

### 3.1 Gibbs Sampler

We initialize  $\Phi$  from random draws from the prior distributions of  $\mathbf{m}$  and  $\mathbf{u}$ , and initialize  $\mathbf{Z}$  to reflect no matches across datasets, that is  $\mathbf{Z} = (n_1 + 1, \dots, n_1 + n_2)$ . We then iteratively sample  $\Phi$  and  $\mathbf{Z}$  from their respective full conditionals:

$$\begin{aligned}\mathbf{m}_f \mid \mathbf{Z}, \Gamma &\sim \text{Dirichlet}(\alpha_{f1}(\mathbf{Z}), \dots, \alpha_{fL_f}(\mathbf{Z})) \\ \mathbf{u}_f \mid \mathbf{Z}, \Gamma &\sim \text{Dirichlet}(\beta_{f1}(\mathbf{Z}), \dots, \beta_{fL_f}(\mathbf{Z})) \\ p\left(Z_j^{(s+1)} = i \mid \Phi, \mathbf{Z}^{(s)}\right) &\propto \begin{cases} w_{z_j, j} & z_j \leq n_1; \\ n_1 \frac{n_2 - n_{12}(\mathbf{Z}) + \beta_\pi}{n_{12}(\mathbf{Z}) + \alpha_\pi} & z_j = n_1 + j. \end{cases},\end{aligned}$$

where

$$w_{ij} = \prod_{f=1}^F \prod_{l=1}^{L_f} \left( \frac{m_{fl}}{u_{fl}} \right)^{I(\gamma_{ij}^f=l)I_{obs}(\gamma_{ij}^f)}.$$

Derivations for these full conditionals can be found in Section 7.1.

### 3.2 Bayes Estimate

We calculate a Bayes estimate  $\hat{\mathbf{Z}}$  for the linkage parameter  $\mathbf{Z}$  by assigning different positive losses to different types of errors, and minimizing posterior expected loss. We

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199 adopt the loss function proposed in [Sadinle \(2017\)](#), in which  $\hat{Z}_j \in \{1, \dots, n_1 + j, R\}$ , with  
 200  $R$  representing the option to leave the matching undetermined by the model. Specifically,  
 201 we have

$$L(\hat{Z}_j, Z_j) = \begin{cases} 0 & \text{if } Z_j = \hat{Z}_j; \\ \theta_R, & \text{if } \hat{Z}_j = R; \\ \theta_{10}, & \text{if } Z_j \leq 1, \hat{Z}_j = n_1 + j; \\ \theta_{01}, & \text{if } Z_j = n_1 + j, \hat{Z}_j \leq n_1; \\ \theta_{11}, & \text{if } Z_j \leq n_1, \hat{Z}_j \leq n_1, Z_j \neq \hat{Z}_j. \end{cases}$$

202 Here,  $\theta_R$  is the loss from not making a decision on the linkage status,  $\theta_{10}$  is the loss  
 203 from a false non-match,  $\theta_{01}$  is the loss from a false match, and  $\theta_{11}$  is the loss from the  
 204 special case of a false match in which the record has a true match other than the one  
 205 estimated by the model.

We seek to minimize the posterior expected loss, given by

$$\mathbb{E}[L(\hat{\mathbf{Z}}, \mathbf{Z}) | \Gamma^{obs}] = \sum_{\mathbf{Z}} L(\hat{\mathbf{Z}}, \mathbf{Z}) P(\mathbf{Z} | \Gamma^{obs}).$$

206 Here, we set  $(\theta_{10}, \theta_{01}, \theta_{11}, \theta_R) = (1, 1, 2, \infty)$  inducing the intuitive decision rule

$$\hat{Z}_j = \begin{cases} i, & \text{if } P(Z_j = i | \Gamma) > \frac{1}{2}; \\ 0, & \text{otherwise.} \end{cases}$$

207 For a more in-depth explanation of this function and the induced Bayes estimate,  
 208 see [Sadinle \(2017\)](#).

209 Since the Gibbs sampler does not strictly enforce one-to-one matching, it is possible  
 210 for this Bayes estimate to link multiple records in  $\mathbf{X}_2$  to one record in  $\mathbf{X}_1$ . To achieve a  
 211 Bayes estimate that fulfills one-to-one matching requirement, we simply minimize the  
 212 expected loss subject to the constraint that  $\hat{Z}_j \neq \hat{Z}_{j'}$  for all  $j \neq j'$ . In the event that we  
 213 have two records  $j$  and  $j'$  such that both  $P(Z_j = i | \Gamma) > \frac{1}{2}$  and  $P(Z_{j'} = i | \Gamma) > \frac{1}{2}$ , we  
 214 accept the match with the highest posterior probability, and declare the other to have  
 215 no match. A similar approach appears in the most probable maximal matching sets used  
 216 by [Steorts et al. \(2016\)](#) to match records to latent entities.

## 217 4 Efficient and Scalable Implementation

218 To increase the speed of the Gibbs sampler and expand the scale of the linkage tasks  
 219 we can undertake, we propose hashing methods similar to those used by [Enamorado  
 220 et al. \(2019\)](#) in the creation of **fastlink**, a fast and scalable implementation of the  
 221 Fellegi Sunter method. The key insight is to recognize that record pairs contribute to  
 222 posterior calculations only through the agreement pattern of the  $\gamma_{ij}$  vector. To make  
 223 this more precise, let  $h_1, \dots, h_P$  denote the unique agreement patterns, and collect these



unique patterns in the set  $\mathcal{P} = \{h_1, \dots, h_P\}$ . Here,  $P = |\mathcal{P}|$  is the total number of unique agreement patterns.  $P$  is bounded above by  $\prod_{f=1}^F L_f$  which does not depend on  $n_1$  or  $n_2$ . In this context, the integers  $\{1, \dots, P\}$  serve as hashed values that encode the same information as the original vectors themselves. Whenever possible, we conduct calculations over these  $P$  agreement patterns, instead of the typical  $n_1 \times n_2$  record pairs. Additionally, we store “one-hot encodings” of these patterns rather than the original Fellegi Sunter comparison vectors, to aid in vectorized computations. See Appendix 7.3 for details.

## 4.1 Data Representation, Hashing, and Storage

First, we hash record pairs of the same agreement pattern to unique integer values. Enamorado et al. (2019) accomplished this efficiently through the hashing function

$$h^*(i, j) = \sum_{f=1}^F I(\gamma_{ij}^f > 0) 2^{\gamma_{ij}^f + I(k>1) \sum_{e=1}^{k-1} (L_e - 1)}.$$

This function maps each agreement pattern to a unique integer, allowing us to store a scalar quantity instead of an entire vector for each record pair. For computational ease, we then map these integers to sequential integers from  $\{1, \dots, P\}$  corresponding to the enumerated patterns in  $\mathcal{P}$ . When the  $(i, j)$  pair exhibits the  $p^{th}$  pattern, we say  $(i, j) \in h_p$ .

With all record pairs converted to hashed values, we can create a more compact nested list

$$\mathcal{R} = \{\{r_{jp}\}_{p=1}^P\}_{j=1}^{n_2}$$

where  $r_{jp} = \{i \in \mathbf{X}_1 | (i, j) \in h_p\}$ . This representation is useful because it allows us to easily compute sufficient statistics

$$H_{j_p} = \sum_i I((i, j) \in h_p) = ||r_{j_p}||$$

and

$$H_p = \sum_{i,j} I((i, j) \in h_p) = \sum_j H_{j_p}.$$

For convenience, denote this set of sufficient statistics  $\mathcal{H} = \{\{H_{j_p}\}, \{H_p\}\}$ . As we will show in Section 4.3, all posterior calculations are conducted with these sufficient statistics. Note that  $\mathcal{P}$ ,  $\mathcal{R}$ , and  $\mathcal{H}$  fully characterize the comparison matrix  $\Gamma$  with no loss of information, so we proceed with  $\tilde{\Gamma} = \{\mathcal{P}, \mathcal{R}, \mathcal{H}\}$  for posterior inference.

## 4.2 Scaling to Large Linkage Tasks

The hashing procedure described above considerably reduces the memory needed to store the comparison information. That is, instead of storing  $n_1 \times n_2$  comparison vectors,

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we only store the  $P$  unique vectors, and then  $n_1 \times n_2$  scalar quantities relating record pairs to those vectors. However, even storing these  $n_1 \times n_2$  scalar labels can become burdensome with large databases. Additionally, the overwhelming majority of these labels relate to record pairs that are clear non-matches.

To address this issue, we propose storage efficient indexing (SEI). In standard indexing, one decides a priori certain criteria that all true matching pairs must satisfy, and labels any record pairs that do not meet that criteria as non-matches. For example, one might only consider pairs with a certain similarity score on a field deemed to be important (like first name), or only pairs that exactly match on a specified number of fields. While generally chosen to be quite loose, establishing these criteria requires knowledge of the problem and invites room for human error.

With SEI, however, we can reduce the comparison space, and its associated storage costs, while avoiding these drawbacks. Observe that all records  $i \in \mathbf{X}_1$  that share the same agreement pattern with  $j \in \mathbf{X}_2$  have the same Fellegi Sunter weight  $w_{ij}$ , and therefore the same probability when sampling  $Z_j$ . Thus, we know that records  $i \in r_{j_p}$  such that  $H_{j_p}$  is large are very unlikely to be sampled consistently enough to be deemed a match through the Bayes estimate. We know this regardless of the form of the agreement pattern itself, or its associated probabilities. Therefore, rather than store all of these unlikely record labels, we choose to store only a small number  $S$  of them in a new nested listed  $\mathcal{R}^{\text{SEI}}$ . Rather than storing  $n_1 \times n_2$  record labels, SEI allows us to store at most  $n_2 \times P \times S$  labels, regardless of how large  $n_1$  might be. **In practice, we recommend  $S = 10$ , as this reduces the number of stored indices for highly unlikely record pairings, but does is not likely to eliminate any of the indices for likely matches. Choosing  $S$  too low can concentrate undue mass on unlikely matches and distort linkage results.** Posterior calculations still attribute the appropriate weight to all records through the summary statistics in  $\mathcal{H}$ , and thus we can proceed with posterior inference through the memory reduced  $\tilde{\Gamma}^{\text{SEI}} = \{\mathcal{P}, \mathcal{R}^{\text{SEI}}, \mathcal{H}\}$ . For simplicity, we suppress “SEI” in future notation, and use  $\tilde{\Gamma}$  without loss of generality.

For large data, we can partition the two datasets  $\mathbf{X}_1$  and  $\mathbf{X}_2$  into smaller blocks  $\{\mathbf{X}_{1m}\}$  and  $\{\mathbf{X}_{2n}\}$  for more manageable computations. On a single machine, we can read-in data sequentially, conduct hashing, compress information through SEI, and delete the original data from memory before continuing with the next chunk of data. With multiple cores or multiple machines, this can be done in parallel. Summary statistics from each pairwise chunk comparison can then be easily synthesized to recover sufficient statistics for the larger linkage task. Thus, the combination of hashing, SEI, and partitioning allows us to conduct linkage tasks over much larger datasets.

### 283 **4.3 Efficient Posterior Inference**

Calculated at the level of the record pairs, updating  $\alpha_{fl}(\mathbf{Z})$  and  $\beta_{fl}(\mathbf{Z})$  for each field and level in the linkage task constitutes  $2 \times \sum L_f$  many summations over  $n_1 \times n_2$  quantities. These are simple calculations, but become computationally burdensome when working on large linkage tasks.

288 Instead, we use one-hot encodings of the agreement patterns  $\mathcal{P}$  for more efficient  
 289 calculations. Denote  $H_p^m = \sum_{j=1}^{n_2} \mathbf{1}_{(Z_j, j) \in h_p}$  to be the number of matching record pairs  
 290 with agreement pattern  $p$ . The number of non-matching record pairs with agreement  
 291 pattern  $p$  is  $H_p^u = H_p - H_p^m$ . Then, if  $\alpha_0$  and  $\beta_0$  are vectors of prior parameters for the  
 292  $\mathbf{m}$  and  $\mathbf{u}$  distributions respectively, the posterior update becomes

$$\alpha(\mathbf{Z}) = \alpha_0 + \sum_{p=1}^P H_p^m \times h_p$$

$$\beta(\mathbf{Z}) = \beta_0 + \sum_{p=1}^P H_p^u \times h_p.$$

293 These constitute  $\tilde{L}$  summations over  $P$  quantities, where  $\tilde{L} = \sum_{f=1}^F L_f$  is the total  
 294 number of levels used across all features in the linkage task.

295 Although sampling  $Z_j$  from a the full conditional provided in Section 3.1 is con-  
 296 ceptually straightforward, it becomes computationally burdensome when  $n_1$  is large.  
 297 This is because sampling a value from  $n_1$  many options with unequal weights requires  
 298 normalizing the weights to probabilities, which has a computational cost that scales  
 299 with  $n_1$ . To speed up computation, we break this sampling step into two. First, we  
 300 calculate the Fellegi Sunter weight  $w_p$  associated with each unique pattern and sample  
 301 the agreement pattern between  $j$  and its potential link. Second, we sample the record  
 302 label uniformly among records associated with that agreement pattern for that particular  
 303  $j \in B$ . More concretely, define  $h(Z_j)$  to be the agreement pattern between  $j$  and its  
 304 potential match, and say  $h(Z_j) = h_{P+1}$  when  $Z_j = n_1 + j$ . Then,

$$P\left(h\left(Z_j^{(s+1)}\right) = p \mid \Phi, \mathbf{Z}^{(s)}\right) \propto \begin{cases} w_p \times H_{j_p} & p \leq P; \\ n_1 \frac{n_2 - n_{12}(\mathbf{Z}) + \beta_\lambda}{n_{12}(\mathbf{Z}) + \alpha_\lambda} & p = P + 1 \end{cases} \quad (7)$$

$$P\left(Z_j^{(s+1)} = i \mid h\left(Z_j^{(s+1)}\right) = p\right) = \begin{cases} \frac{1}{H_{j_p}} & (i, j) \in h_p \\ 0 & \text{otherwise.} \end{cases} \quad (8)$$

305 Lastly, we recognize that all posterior updates are governed by the agreement patterns  
 306 of the record pairs rather than the record labels themselves. Thus we complete the entire  
 307 Gibbs sampler first at the level of the  $P$  agreement patterns with (7) above. After all  
 308 iterations are complete, we can back-fill the records corresponding to the agreement  
 309 patterns through (8).

310 We emphasize the computational gains of this split sampler: the first step is a sample  
 311 from  $P$  options, where  $P$  does not scale with the size of the linkage task; and the second  
 312 step is sampling uniformly at random, which is computationally simple even for large  
 313 sets of candidate records. These changes drastically improve the speed of the sampler,  
 314 and each can be parallelized if desired for additional computational gains. We provide a

summary of the `fabl` method through pseudocode in Appendix 7.2. We note here that this split sampler can be adapted for use with BRL as well, but would require updating  $\{H_j\}$  to account for the previously matched records that no are longer candidate matches for the current record. BRL would see considerable speed up through the procedure, but computation time would still scale with the size of the larger dataset.

## 4.4 Computational Complexity

In this section, we prove the computational complexity of `fabl`.

**Lemma 1.** *Recall that  $n_1$  and  $n_2$  are the number of records in  $\mathbf{X}_1$  and  $\mathbf{X}_2$  respectively,  $F$  is the number of fields used for comparisons across records, and  $P$  is the number of patterns that comparison vectors can exhibit. We assume  $B$  processors available for parallelization. Then, the overall computational complexity of `fabl` is  $O(\frac{F}{B}n_1n_2) + O(n_2P)$ .*

*Proof.* To prove the computational complexity, we consider two steps — constructing the comparison vectors and the Gibbs sampler. The computational complexity of all pairwise comparisons across the two databases  $\mathbf{X}_1$  and  $\mathbf{X}_2$  is  $O(Fn_1n_2)$ . The hashing procedure for all pairwise comparisons is also of complexity  $O(Fn_1n_2)$ . With  $B$  processors available, we can split these computations across  $B$  equally sized partitions and compute these comparisons in parallel, so the complexity becomes  $O(\frac{F}{B}n_1n_2)$ . There are then trivial computational costs associated with synthesizing summary statistics across these partitions.

Without hashing, the computational complexity of updating the  $\mathbf{m}$  and  $\mathbf{u}$  parameters is  $O(Fn_1n_2)$ . However, by doing calculations over the agreement patterns rather than the individual records, hashing reduces the overall complexity to  $O(\tilde{L}P)$ . The complexity of updating  $Z$  sequentially at the record level is  $O(n_1n_2)$ . With hashing, we split this sampling into two steps. First we sample the agreement pattern of the match with complexity  $O(n_2P)$ , and then we sample the record exhibiting that pattern with complexity  $O(n_2)$ . Thus the complexity of sampling  $Z$  is  $O(n_2P)$ . Since  $\tilde{L} \ll n_1$  in all reasonable applications, we have reduced the complexity of the Gibbs sampler from  $O(Fn_1n_2)$  under BRL to  $O(n_2P)$  under `fabl`. In summary, the total computational complexity is  $O(\frac{F}{B}n_1n_2) + O(n_2P)$ .  $\square$

## 5 Simulation Studies

We demonstrate the speed, and accuracy of `fabl` as compared to BRL through several simulation studies.

### 5.1 Speed

In our first simulation, we generate comparison vectors from pre-specified distributions so that we can easily increase the size of the linkage problem. The distributions used (see Table 1) are meant to emulate the rates of agreement across first

	m	u
fname	$\left(\frac{19}{20}, \frac{1}{20}\right)$	$\left(\frac{1}{100}, \frac{99}{100}\right)$
lname	$\left(\frac{19}{20}, \frac{1}{20}\right)$	$\left(\frac{1}{100}, \frac{99}{100}\right)$
day	$\left(\frac{19}{20}, \frac{1}{20}\right)$	$\left(\frac{1}{30}, \frac{29}{30}\right)$
month	$\left(\frac{19}{20}, \frac{1}{20}\right)$	$\left(\frac{1}{12}, \frac{11}{12}\right)$
year	$\left(\frac{19}{20}, \frac{1}{20}\right)$	$\left(\frac{1}{12}, \frac{11}{12}\right)$

Table 1: Distributions used for  $m$  and  $u$  probabilities in simulation studies

name, last name, day of birth, and month of birth. For example,  $u^{\text{month, agree}} = P(\text{Records have same birth-month} \mid \text{Nonmatch}) = \frac{1}{12}$ . The parameters for year would vary largely by context, so we choose them here to adjust the desired difficulty of the linkage task. For simplicity, we consider only exact matching, so a vector  $(1, 0)$  corresponds to agreement and  $(0, 1)$  to disagreement. We simulate these data for different values of  $n_1$  and  $n_2$ , and compare the run-time of **fabl** against **BRL**. Since we have 5 binary comparison fields, the number of unique patterns  $P$  is bounded above by  $2^5 = 32$ , a bound which is consistently attained in simulations with more records.

We note here that the implementation of **BRL** that we use is coded in C (Sadinle, 2017). In contrast, we use non-optimized code written in R for **fabl**. While this complicates comparisons, and indeed disfavors **fabl**, the computational speed gains for **fabl** are still evident, especially for larger sample sizes. Additionally, although **fabl** is amenable to parallelization, this simulation was run on a single core. Implementing **fabl** in C++ with parallelization for the hashing step and sampling the matching status of the record pairs should lead to even more computational gains.

In Figure 1, **BRL** is faster than **fabl** for low sample sizes, but that **fabl** is significantly faster at handling larger data. In particular, run-time for **BRL** seems to grow quadratically (or linearly with the size of both  $\mathbf{X}_1$  and  $\mathbf{X}_2$ ) while run-time for **fabl** seems to grow linearly (in the size of  $\mathbf{X}_2$ ).

The above discussion suggests that for fixed  $n_2$ , computation time for **fabl** should remain mostly constant with growing  $n_1$ . In the simulation results displayed in Figure 2 fixing  $n_2 = 500$ , we see linear growth for the run-time under **BRL** as  $n_1$  increases, with much more static run-time under **fabl**. The slight increases in run-time for **fabl** are due primarily to the hashing step, which again can be run in parallel for large data. To illustrate that these trends are generalizable to other specifications of the comparison vectors, we have included the run-time results for an additional simulation study, under different comparison vector settings, in

## 5.2 Accuracy under Full Estimates

We replicate a simulation study from Sadinle (2017) to compare **fabl** against **BRL** on several synthetic datasets with varying amounts of error and overlap (the number of records in common across files). Following methods proposed by Christen and Pudjijono (2009) and Christen and Vatsalan (2013), clean records are first simulated from frequency tables for first name, last name, age, and occupation in Australia. Fields are then chosen

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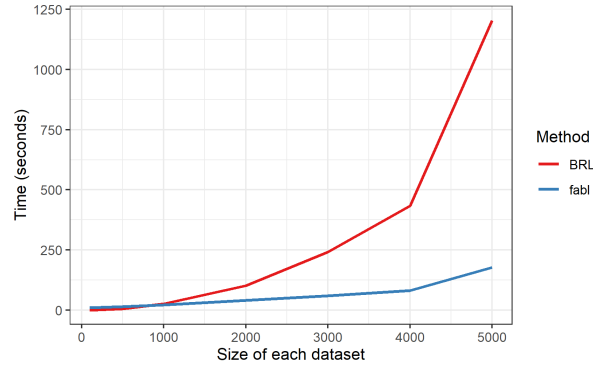


Figure 1: Run-time for BRL and fabl to run 1000 Gibbs iterations, including hashing step for fabl, for increasing values of both  $n_1$  and  $n_2$ . We see near quadratic growth in run-time for BRL, and near linear growth for fabl.

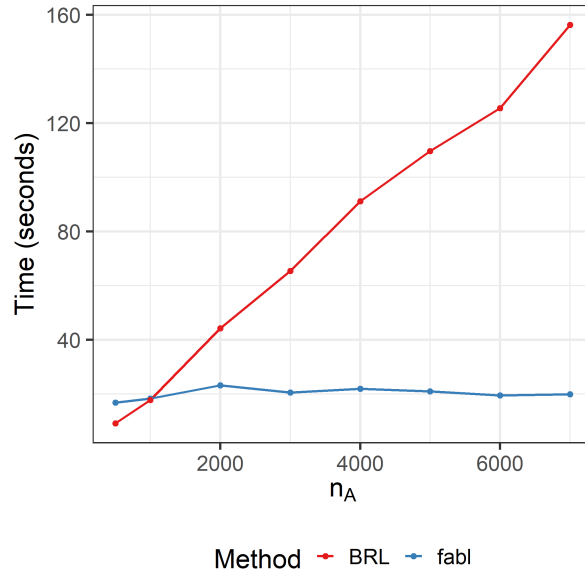


Figure 2: Run-time for BRL and fabl to run 1000 Gibbs iterations, including hashing step for fabl, with increasing  $n_1$ , and  $n_2$  fixed at 500. We see linear growth in run-time for BRL, and near constant run-time for fabl.

384 for distortion uniformly at random. Names are subject to string insertions, deletions  
 385 and substitutions, as well as common keyboard, phonetic, and optical recognition errors.

Fields	Similarity	Level of Disagreement			
		1	2	3	4
First and Last Name	Levenstein	0	(0, .25]	(.25, .5]	(.5, .1]
Age and Occupation	Binary	Agree	Disagree		

Table 2: Construction of comparison vectors for accuracy study with simulated datasets.

386 Age and occupation are distorted through keyboard errors and missingness.

387 We create comparison vectors according to the default settings of the `compareRecords`  
 388 function from the `BRL` package, shown in Table 2. Each simulation identifies matched  
 389 individuals between two datasets, each with 500 records. We conduct linkage when  
 390 matching records exhibit 1, 2, and 3 errors across the four fields, and when there are 50,  
 391 250, and 450 individuals in common across datasets. Under each of these settings, we  
 392 have 100 pairs of simulated datasets in order to obtain uncertainty quantification on  
 393 our performance metrics. We use flat priors for all  $m$  and  $u$  parameters, run the Gibbs  
 394 Sampler for 1000 iterations, and discard the first 100 as burn-in. We calculate Bayes  
 395 estimates of the linkage structure using the losses  $\theta_R = \infty, \theta_{10} = 1, \theta_{01} = 1, \theta_{11} = 2$ .  
 396 Traceplots for parameters of interest for one example simulation are provided in Appendix  
 397 7.4; they show no obvious concern over MCMC convergence.

398 We compare `fabl` to `BRL` in terms of recall, precision and F-measure, as defined in  
 399 Christen (2012). Recall is the proportion of true matches found by the model, that is,  
 400  $\sum_{j=1}^{n_2} I(\hat{Z}_j = Z_j, Z_j \leq n_1) / \sum_{j=1}^{n_2} I(Z_j \leq n_1)$ . Precision is proportion of links found by  
 401 the model that are true matches, that is  $\sum_{j=1}^{n_2} I(\hat{Z}_j = Z_j, Z_j \leq n_1) / \sum_{j=1}^{n_2} I(\hat{Z}_j \leq n_1)$ .  
 402 The F-measure balances the two metrics to provide an overall measure of accuracy, and  
 403 is defined as  $2 \times (\text{Recall} + \text{Precision}) / (\text{Recall} + \text{Precision})$ . In Figure 3, we see that  
 404 the two methods have comparable performance at all levels of error and overlap. In  
 405 the specific case of high error and low overlap, widely regarded as the most difficult  
 406 linkage scenario, we see that `fabl` performs slightly worse on average; however, the  
 407 overall accuracy level remains high.

### 408 5.3 Accuracy under Partial Estimates

409 By leaving  $\theta_{10} = \theta_{01} = 1$  and  $\theta_{11} = 2$ , but setting  $\theta_R = 0.1$ , we allow the model  
 410 to decline to decide a match for certain records, with nonassignment being 10% as  
 411 costly as a false match. In this context, we are no longer focused on finding all true  
 412 matches, but rather protecting against false matches. Thus, instead of recall, we use the  
 413 negative predictive value (NPV), defined as the proportion of non-links that are actual  
 414 non-matches. Mathematically,  $\text{NPV} = \sum_{j=1}^{n_2} I(\hat{Z}_j = Z_j = n_1 + j) / \sum_{j=1}^{n_2} I(\hat{Z}_j = n_1 + j)$ .  
 415 We continue to use the precision, which is renamed the positive predictive value (PPV)  
 416 in this context. Lastly, we also examine the rejection rate (RR), or how often the model  
 417 declines to make a linkage decision, defined as  $\text{RR} = \sum_{j=1}^{n_2} I(\hat{Z}_j = R) / n_2$ . To convey  
 418 this information alongside NPV and PPV, for which values close to 1 indicate strong  
 419 performance, we report the decision rate (DR), defined as  $\text{DR} = 1 - \text{RR}$ .

420 Should I skip defining RR? And just define decision rate  $\text{DR} = \sum_{j=1}^{n_2} I(\hat{Z}_j \neq R) / n_2$ ?

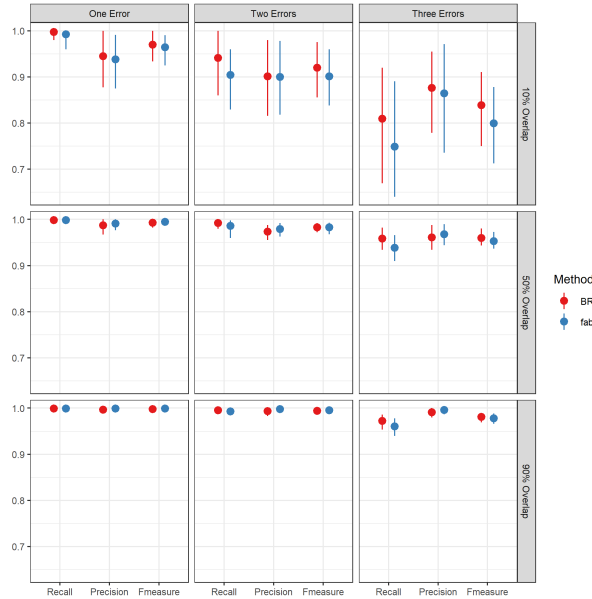


Figure 3: Posterior means and credible intervals for accuracy metrics under the replication of simulation study from [Sadinle \(2017\)](#). For each level of overlap and each level of error, we have 100 paired sets of 500 records. Thus this table represents results for 900 datasets. We see comparable performance for all levels of error and overlap.

421 In Figure 4, we see that **fabl** maintains equivalently strong PPV as **BRL** across all  
 422 linkage settings. However, with high amounts of error, and thus fewer accurate and  
 423 discerning fields of information, the rejection rate under **fabl** rises, leading to a decrease  
 424 in NPV. Since **fabl** does not remove previously matched records from consideration  
 425 for a new record, posterior probabilities of matches at times can be split across more  
 426 records; in contrast, **BRL** is able to maintain higher confidence in matches in this setting.  
 427 If one wishes to use partial estimates, **fabl** will possibly leave more linkages for the  
 428 modeller to match by hand than would be left under **BRL**, but the decisions made by  
 429 each method will have nearly equal accuracy.

## 430 6 Case Studies

431 In our first case study, we revisit data from the El Salvadoran Civil War analyzed by  
 432 [Sadinle \(2017\)](#). Though the data files used in this case study are small, it shows how  
 433 the computational complexity of **fabl** depends on the number of unique agreement  
 434 patterns found in the data, and how significant computational gains can be achieved  
 435 by simplifying the construction of the comparison vectors. In the second case study, we  
 436 apply **fabl** to link records from the National Long Term Care Study (NLTCs), a larger



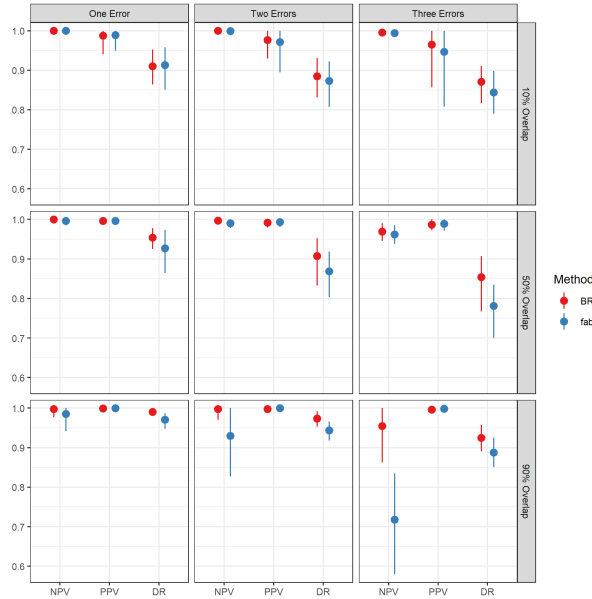


Figure 4: Negative predictive value (NPV), positive predictive value (PPV), and decision rate (DR) on simulated datasets. We see poorer performance for `fabl` only in situations with high overlap.

linkage task that is not feasible in reasonable time under BRL with typical computing setups.

## 6.1 Civilian Casualties from the El Salvadoran Civil War

The country of El Salvador was immersed in civil war from 1980 to 1991. Throughout the time, several organizations attempted to document casualties of the conflict. When estimating the total number of casualties, one cannot simply sum the numbers recorded by each organization, as it is likely that the same individuals are recorded in multiple casualty lists. This is an important step in estimating the total number of deaths from a conflict using multiple systems estimation (Lum et al., 2013). We utilize lists of casualties from the war, one collected by El Rescate - Tutela Regal (ERTL) and another from the Salvadoran Human Rights Commission (CDHES, by its acronym in Spanish).<sup>1</sup> The ERTL dataset consists of digitized denunciations that had been published throughout the conflict, and the CDHES dataset consists of casualties that had been reported directly to the organization (Howland, 2008; Ball, 2000). The ERTL required additional investigation before recording denunciations as human rights abuses, and reports to the CDHES were made shortly after the events occurred; thus, both datasets are thought to

<sup>1</sup>We thank the Human Rights Data Analysis Group (HRDAG) for granting access to this data.

Fields	Similarity	Level of Disagreement			
		1	2	3	4
First and Last Name	Modified Levenstein	0	(0, .25]	(.25, .5]	(.5, 1]
Year of Death	Absolute Difference	0	1	2	3+
Month of Death	Absolute Difference	0	1	2-3	4+
Day of Death	Absolute Difference	0	1-2	3-7	8+
Municipality	Binary	Agree	Disagree		

Table 3: Construction of comparison vectors for El Salvador data resembling original implementation from (Sadinle, 2018). This set up leads to 2048 possible agreement patterns in total.

be fairly reliable.

There are several challenges with these data. First, both datasets have been automatically digitized, which inherently leads to some degree of typographical error. Second, the only fields recorded are given name, last name, date of death, and place of death. It is relatively common for a parent and child to share the same given name, resulting in indistinguishable records for two different individuals.

Following Sadinle (2017), we utilize records that have non-missing entries for given and last name, which results in  $n_1 = 4420$  records in CHDES and  $n_2 = 1323$  records in ERTL. We standardize names to account for common misspellings and use a modified Levenstein distance when comparing names to account for the fact that second names are often omitted in Spanish. Place of death is recorded by municipality and department within that municipality; however, since department is missing in 95% of records in CHDES and 80% of records in ERTL, we exclude department from our analysis. Thus, we conduct record linkage using given name, last name, municipality, and day, month, and year of death. We again use flat priors for the  $\mathbf{m}$  and  $\mathbf{u}$  parameters.

Sadinle (2017) constructs the comparison vectors using four levels of agreement for each field, according to the thresholds provided in Table 3. This results in  $4^5 \times 2 = 2048$  possible agreement patterns, with 1173 patterns realized in the data. We initially used these comparisons to estimate fabl and BRL. However, after investigating the posterior distributions of the  $\mathbf{m}$  and  $\mathbf{u}$  parameters, we noticed that posterior distributions of several levels of the  $\mathbf{m}$  and  $\mathbf{u}$  parameters are nearly identical, suggesting that these levels are unnecessary for meaningfully modeling the distribution of the comparison vectors.

Therefore we re-ran our analysis with fewer agreement levels for each field according to Table 4. Among the 216 possible agreement patterns, 159 are realized in the data. With this revised comparison specification, fabl ran in 61 seconds, approximately 4 times faster than BRL 239 second run time. The estimates of the  $\mathbf{m}$  parameters under each method are very similar, as shown in Figure 6. Traceplots for parameters of interest are provided in Appendix 7.6.

For completeness, we note that the more detailed comparison vector produced a run time of 240 seconds for BRL, and 261 seconds for fabl. Apparently, the number of patterns was sufficiently many that the computational savings from fabl does not overcome the inherent speed differences of C as opposed to R.

Fields	Similarity	Level of Disagreement		
		1	2	3
First and Last Name	Modified Levenstein	0	(0, .25]	(.25, 1]
Year of Death	Binary	Agree	Disagree	
Month of Death	Binary	Agree	Disagree	
Day of Death	Absolute Difference	0	1	2+
Municipality	Binary	Agree	Disagree	

Table 4: Construction of comparison vectors for El Salvador for increased speed under **fabl**. This set up leads to 216 possible agreement patterns in total.

Through **fabl**, we arrive at a Bayes estimate of 179 individuals recorded in both datasets. We calculate posterior samples of the size of the overlap across files by finding the number of matches found in each iteration of the Gibbs sampler, and subtracting the number of matches that violate one-to-one matching. The posterior 95% credible interval for the overlap across files is (206, 238), indicating that the Bayes estimate identifies fewer matches than the Gibbs sampler identifies on average. This is because a large number of records in ERTL have multiple plausible matches in CDHES; **fabl** recognizes that a match exists among the several options, but is unable to definitely declare a specific pair as a match in the Bayes estimate. We also compute a partial estimate of the linkage structure, using  $\theta_{10} = \theta_{01} = 1$ ,  $\theta_{11} = 2$ , and  $\theta_R = 0.1$  as in the simulation study in Section 5.2. Here, the Bayes estimate provides 136 matches of which the model is quite confident, and 175 records to verify manually. This means that after clerical review, the number of individuals replicated across datasets would fall in the interval (136, 311), encapsulating the posterior credible interval. More or fewer records could be identified for clerical review by decreasing or increasing  $\theta_R$ .

We see similar results under **BRL**, with a Bayes estimate of 181 individuals recorded in both datasets, a posterior 95% credible interval of (211, 244), and a range of (140, 294) after the partial estimate and clerical review. See ‘5 for a visual comparison of the Bayes estimate and posterior credible intervals for the two methods. We note that Bayes estimates falling outside of posterior credible intervals has occurred previously in the record linkage literature (Sadinle, 2017; Steorts et al., 2016), and remains a topic for future research.

## 6.2 National Long Term Care Study

The National Long Term Care Study (NLTCs) is a longitudinal study tracking the health outcomes of Medicare recipients. The initial survey began in 1982, with follow-up surveys taken approximately every five years. For this study, we seek to link records over the  $n_1 = 20485$  records from 1982 to the  $n_2 = 17466$  records from 1989. In each iteration of the study, some participants are added to the lists, and others are lost due to loss of contact or death. The NLTCs data have longitudinal links, so that in reality one does not need to conduct record linkage. However, following the strategy in Guha et al. (2021) we break the longitudinal links and treat the data from 1982 and 1989 as stand-alone files.

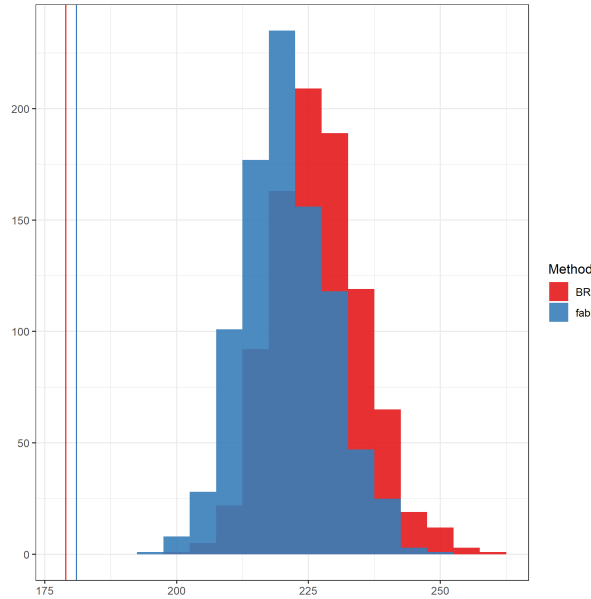


Figure 5: Posterior distribution and Bayes estimate of overlap across the two files. We note they are quite similar under both methods.

517 We link records using sex, date of birth, and location using the thresholds shown  
 518 in Table 5. Storing five comparison scores for each of  $20485 \times 17466 \approx 400,000,000$   
 519 record pairs would require approximately 8GB of memory. Standard settings on a  
 520 16GB personal computer do not allow storage of an object of this size, and thus BRL  
 521 is unable to perform this linkage task on such a machine. However, through the **fabl**  
 522 framework, we compute comparisons over 30 smaller comparison tasks, hash results, and  
 523 compress information through storage efficient indexing; the resulting data object is just  
 524 10 MB, approximately 0.1% of what is required for the raw comparisons. Constructing  
 525 the comparisons sequentially took approximately 40 minutes, which could be reduced  
 526 considerably through parallel computing.

527 We run a Gibbs sampler for 1000 iterations, taking about 235 seconds. As shown  
 528 in 7, the Bayes estimate of the linkage structure consists of 9634 matches, with a 95%  
 529 credible interval of (9581, 9740). Since we have access to the true linkage structure, we  
 530 can calculate recall to be 0.89 and precision to be 0.98, resulting in an F-measure of 0.94.  
 531 Traceplots indicate quick convergence, and are similar to those seen in Appendix 7.4  
 532 and 7.6

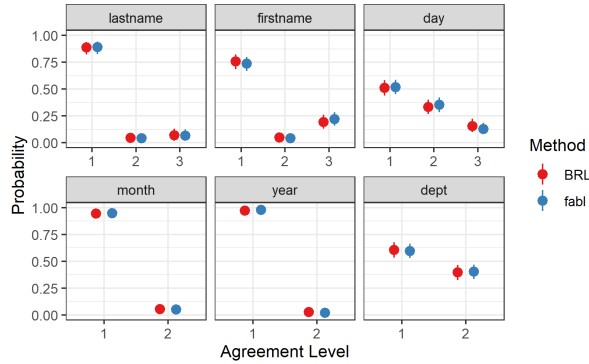


Figure 6: Posterior estimates of  $m$  parameters with 95% credible intervals for El Salvador case study. They are quite similar across the two methods.

Fields	Similarity	Level of Disagreement		
		1	2	3
Sex	Binary	Agree	Disagree	
Year of Birth	Binary	Agree	Disagree	
Month of Birth	Binary	Agree	Disagree	
Day of Birth	Binary	Agree	Disagree	
Location	Custom	Same State and Office	Same State	Otherwise

Table 5: Construction of comparison vectors for NTLCS data

## 7 Conclusion

In this paper, we have proposed **fabl**, a Bayesian record linkage method that scales to large data sets. We have proven that the proposed hashing method and model assumptions allow for a linkage procedure whose computational complexity does not scale with the size of the larger dataset. This makes **fabl** computationally advantageous in many linkage scenarios, particularly when one datafile is substantially smaller than the other. We have demonstrated the speed and accuracy of **fabl** by replicating a simulation study and a case study in [Sadinle \(2017\)](#), and through an additional case study that is computationally infeasible under BRL. Open source software to use **fabl** in R is available through [Github](#).

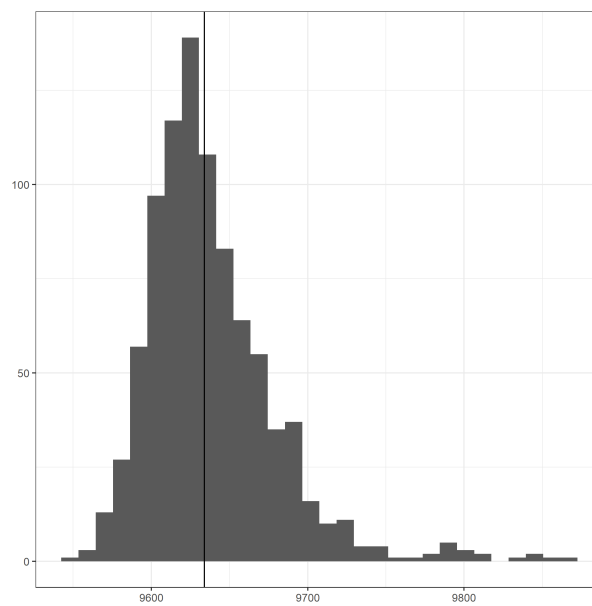


Figure 7: Posterior distribution and Bayes estimate of overlap across years 1982 and 1989 of NLTCs data.

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## Appendix

### 7.1 Derivations of Full Conditionals

The  $\mathbf{m}$  and  $\mathbf{u}$  parameters are updated through standard multinomial-Dirichlet distributions. For a particular  $m_{fl}$ , we have

$$\begin{aligned} p(m_{fl}|\Gamma, \mathbf{Z}) &\propto \prod_{i=1}^{n_1} \prod_{j=1}^{n_2} m_{fl}^{I(Z_j=i)I(\gamma_{ij}^f=l)I_{obs}(\gamma_{ij}^f)} \times m_{fl}^{\alpha_{fl}-1} \\ &= m_{fl}^{\alpha_{fl}(\mathbf{Z})-1} \end{aligned}$$

where  $\alpha_{fl}(\mathbf{Z}) = \alpha_{fl} + \sum_{i,j} I_{obs}(\gamma_{ij}^f)I(\gamma_{ij}^f = l)I(z_j = i)$ . Analogous procedures lead to the posterior distribution  $p(u_{fl}|\Gamma, \mathbf{Z}) \propto u_{fl}^{\beta_{fl}(\mathbf{Z})-1}$ , where  $\beta_{fl}(\mathbf{Z}) = \beta_{fl} + \sum_{i,j} I_{obs}(\gamma_{ij}^f)I(\gamma_{ij}^f = l)I(z_j \neq i)$ . Thus for the vectors of parameters  $\mathbf{m}_f$  and  $\mathbf{u}_f$ , we have

$$\begin{aligned} \mathbf{m}_f|\mathbf{Z}, \Gamma &\sim \text{Dirichlet}(\alpha_{f1}(\mathbf{Z}), \dots, \alpha_{fL_f}(\mathbf{Z})) \\ \mathbf{u}_f|\mathbf{Z}, \Gamma &\sim \text{Dirichlet}(\beta_{f1}(\mathbf{Z}), \dots, \beta_{fL_f}(\mathbf{Z})). \end{aligned}$$

Since  $\pi$  encodes the rate of matching across the two datasets, the posterior distribution  $p(\pi|\Gamma, \mathbf{Z}, \Phi, \alpha_\pi, \beta_\pi)$  depends only on the number of links  $n_{12}(\mathbf{Z}) = \sum_{i=1}^{n_2} I(z_j < n_1 + j)$  encoded by  $\mathbf{Z}$  (and hyperparameters). Thus we use  $p(\pi|\mathbf{Z}, \alpha_\pi, \beta_\pi)$ , and have

$$\begin{aligned} p(\pi|\mathbf{Z}, \alpha_\pi, \beta_\pi) &\propto p(\mathbf{Z}|\pi)p(\pi) \\ &\propto \pi^{n_{12}(\mathbf{Z})}(1-\pi)^{n_2-n_{12}(\mathbf{Z})}\pi^{\alpha_\pi-1}(1-\pi)^{\beta_\pi-1} \\ &\propto \pi^{n_{12}(\mathbf{Z})+\alpha_\pi-1}(1-\pi)^{n_2-n_{12}(\mathbf{Z})+\beta_\pi-1}. \end{aligned}$$

Thus  $\pi^{(s+1)}|\mathbf{Z}^{(s+1), \alpha_\pi, \beta_\pi}$  has a  $\text{Beta}(n_{12}(\mathbf{Z}) + \alpha_\pi, n_2 - n_{12}(\mathbf{Z}) + \beta_\pi)$  distribution.

Because we sample each  $Z_j$  independently of all other  $Z_{j'}$ , we use only the full conditional for an individual  $Z_j$ . Let  $\Gamma_{\cdot j}$  denote the set of  $n_1$  comparison vectors with  $j \in \mathbf{X}_2$ . We have

$$\begin{aligned} p(\Gamma_{\cdot j}|Z_j = z_j, \Phi) &\propto \prod_{i=1}^{n_1} \left[ \prod_{f=1}^F \prod_{l=1}^{L_f} m_{fl}^{I(Z_j=i)} u_{fl}^{I(Z_j \neq i)} \right]^{I(\gamma_{ij}^f=l)I_{obs}(\gamma_{ij}^f)} \\ &\propto \prod_{i=1}^{n_1} \frac{\left[ \prod_{f=1}^F \prod_{l=1}^{L_f} m_{fl}^{I(Z_j=i)} u_{fl}^{I(Z_j \neq i)} \right]^{I(\gamma_{ij}^f=l)I_{obs}(\gamma_{ij}^f)}}{\prod_{f=1}^F \prod_{l=1}^{L_f} u_{fl}^{I(\gamma_{ij}^f=l)I_{obs}(\gamma_{ij}^f)}} \end{aligned}$$

$$\begin{aligned}
& \propto \prod_{i=1}^{n_1} \left( \prod_{f=1}^F \prod_{l=1}^{L_f} \frac{m_{fl}}{u_{fl}} \right)^{I(z_j=i)I(\gamma_{ij}^f=l)I_{obs}(\gamma_{ij}^f)} \\
& = \begin{cases} w_{z_j,j} & z_j \leq n_1; \\ 1 & z_j = n_1 + j, \end{cases}
\end{aligned}$$

where

$$w_{ij} = \prod_{f=1}^F \prod_{l=1}^{L_f} \left( \frac{m_{fl}}{u_{fl}} \right)^{I(\gamma_{ij}^f=l)I_{obs}(\gamma_{ij}^f)}.$$

With the likelihood in this form, we derive an expression for the posterior distribution of  $Z_j$ :

$$\begin{aligned}
p\left(Z_j^{(s+1)} | \Gamma_{\cdot,j}, \Phi, \mathbf{Z}^{(s)}, \pi\right) & \propto p(\Gamma_{\cdot,j} | Z_j^{(s+1)}, \Phi) P(Z_j^{(s+1)} | \pi) \\
& \propto \left( \sum_{i=1}^{n_1} w_{z_j,j} I(z_j = i) + I(z_j = n_1 + j) \right) \left( \pi \sum_{i=1}^{n_1} \frac{1}{n_1} I(z_j = i) + (1 - \pi) I(z_j = n_1 + j) \right) \\
& = \frac{\pi}{n_1} \sum_{i=1}^{n_1} w_{z_j,j} I(z_j = i) + (1 - \pi) I(z_j = n_1 + j). \\
& = \begin{cases} \frac{\pi}{n_1} w_{z_j,j} & z_j \leq n_1; \\ 1 - \pi & z_j = n_1 + j. \end{cases}
\end{aligned}$$

653 For more direct comparability with the method from [Sadinle \(2018\)](#), we avoid  
654 sampling  $\pi$  directly, and instead integrate over it in the final full conditional for  $Z_j$ .

$$\begin{aligned}
p\left(Z_j^{(s+1)} = i | \Gamma, \Phi, \mathbf{Z}^{(s)}\right) & = \int_{\pi} p(Z_j^{(s+1)} | \Gamma, \Phi, \mathbf{Z}^{(s)}, \pi) d\pi \\
& = \int_{\pi} \left[ \frac{\pi}{n_1} w_{z_j,j} I(z_j \leq n_1) + (1 - \pi) I(z_j = n_1 + j) \right] d\pi \\
& = \frac{\int_{\pi} \pi d\pi}{n_1} w_{z_j,j} I(z_j \leq n_1) + \left( 1 - \int_{\pi} \pi d\pi \right) I(z_j = n_1 + j) \\
& = \frac{n_{12}(\mathbf{Z}) + \alpha_{\pi}}{n_1(n_2 + \alpha_{\pi} + \beta_{\pi})} w_{z_j,j} I(z_j \leq n_1) + \frac{n_2 - n_{12}(\mathbf{Z}) + \beta_{\pi}}{n_2 + \alpha_{\pi} + \beta_{\pi}} I(z_j = n_1 + j) \\
& \propto w_{z_j,j} I(z_j \leq n_1) + n_1 \frac{n_2 - n_{12}(\mathbf{Z}) + \beta_{\pi}}{n_{12}(\mathbf{Z}) + \alpha_{\pi}} I(z_j = n_1 + j) \\
& \propto \begin{cases} w_{z_j,j} & z_j \leq n_1; \\ n_1 \frac{n_2 - n_{12}(\mathbf{Z}) + \beta_{\pi}}{n_{12}(\mathbf{Z}) + \alpha_{\pi}} & z_j = n_1 + j. \end{cases}
\end{aligned}$$

**7.2 Summary of Fast Beta Linkage Method**


---

```

1: procedure HASHING AND PREPROCESSING
2:   Construct and enumerate set of unique patterns  $\mathcal{P}$  from  $F$  and  $\{L_f\}$ .
3:   Partition files  $\mathbf{X}_1$  and  $\mathbf{X}_1$  into chunks  $\{\mathbf{X}_{1n}\}, \{\mathbf{X}_{2m}\}$ .
4:   for each  $n, m$  do
5:     Create comparison vectors between  $\mathbf{X}_{1n}$  and  $\mathbf{X}_{2m}$ .
6:     Hash records to  $\mathcal{R}_{nm}$  and calculate summary statistics  $\mathcal{H}_{nm}$ .
7:     Use SEI to reduce memory usage;  $\mathcal{R}_{nm} \rightarrow \mathcal{R}_{nm}^{\text{SEI}}$ .
8:   end for
9:   Synthesize results across pairings to get  $\tilde{\Gamma} = \{\mathcal{P}, \mathcal{R}, \mathcal{H}\}$ .
10: end procedure
11: procedure GIBBS SAMPLING
12:   Initialize  $\Phi$ , and  $Z$  parameters.
13:   for  $t \in \{1, \dots, T\}$  do
14:     Sample  $\Phi^{t+1} | Z^t, \tilde{\Gamma}$ .
15:     Sample  $h(Z^{t+1}) | \Phi^{t+1}, \tilde{\Gamma}$ . ▷ Sample agreement pattern, not record
16:   end for
17:   Sample  $Z | h(Z), \tilde{\Gamma}$ . ▷ Fills in record label based on agreement pattern
18: end procedure

```

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### 7.3 One Hot Encoding Transformation

`fabl` makes use of one-hot encodings to aid in vectorized computations. For  $\gamma_{ij}^f$  with  $L_f$  levels, define  $e_{ij}^f$  to be an  $L_f \times 1$  vector. When  $\gamma_{ij}^f = \ell$ , we set the  $\ell^{th}$  element of  $e_{ij}^f$  to be 1, and set the other  $L_f - 1$  elements of  $e_{ij}^f$  to be 0. We then concatenate the  $e_{ij}^f$  for all  $f \in \{1, \dots, F\}$ , resulting in the one-hot encoded comparison vector  $e_{ij}$  of length  $\sum_{f=1}^F L_f$ .

For example, consider comparing the toy records shown in Table 6 with  $L = (3, 3, 2, 2)$  levels of agreement for last name, first name, DOB, and city respectively. Since the first name differs by only one letter, a reasonable comparison vector for this pair would be  $\gamma_{ij} = (1, 2, 1, 2)$ . The one hot encoding representation of this vector is  $e_{ij} = (1, 0, 0, 0, 1, 0, 1, 0, 0, 1)$ .

Last Name	First Name	DOB	City
Smith	Taylor	01/01/2000	Durham
Smith	Tayler	01/01/2000	Raleigh

Table 6: Example records for one hot encoding.

### 7.4 Traceplots for Simulation Study

Below are traceplots for one of the 900 linkage tasks that comprise the simulation in Section 5.2. It is set up with one error across the linkage fields and 50 duplicates across files. Traceplots across other settings exhibit similar behavior. Note that traceplots for `u` parameters show very little variation because the overwhelming majority of record pairs are nonmatching.

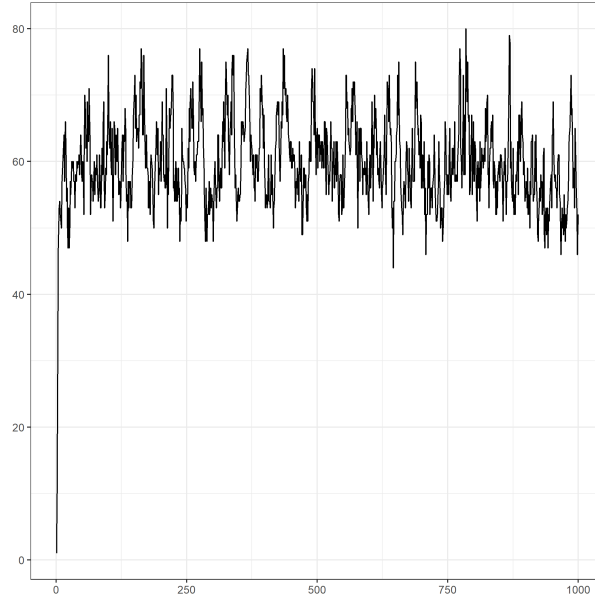


Figure 8: Representative traceplot of overlap between files from simulation study in Section 5.2

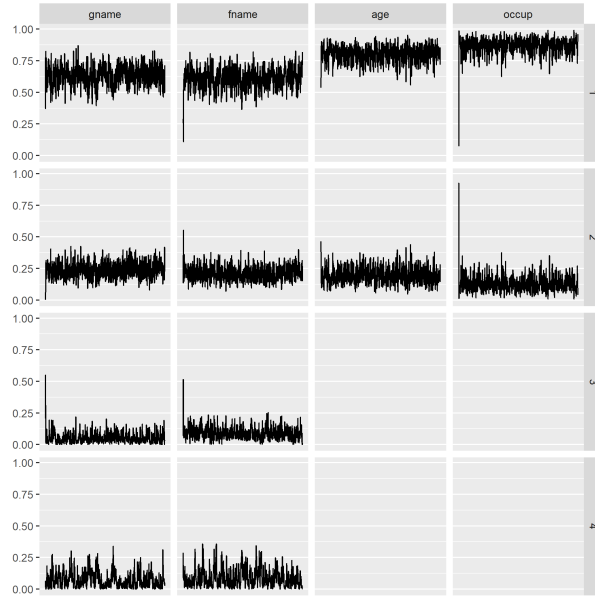


Figure 9: Representative traceplot of  $m$  parameter from simulation study in Section 5.2

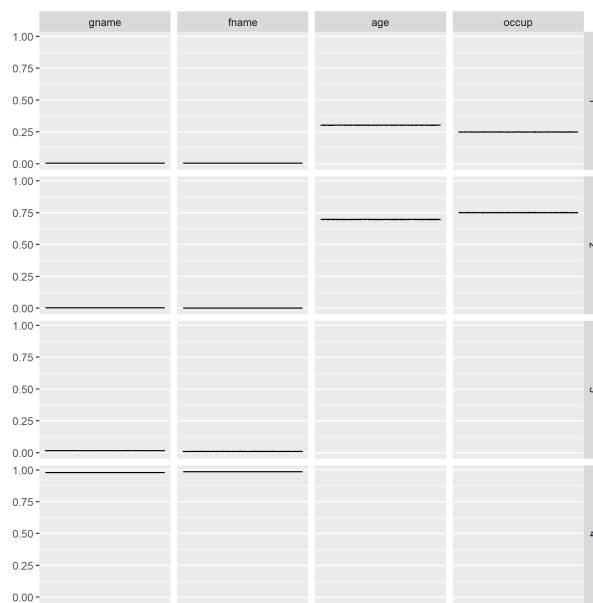


Figure 10: Representative traceplot of  $u$  parameters from simulation study in Section 5.2

## 7.5 Additional Speed Simulation Study

To illustrate that different constructions of the comparison vectors lead to similar speed gains, we replicate the speed study of Section 5.1 under different settings. Here, we use four fields of comparison, each with three possible levels of agreement, resulting in  $3^4 = 81$  possible patterns.

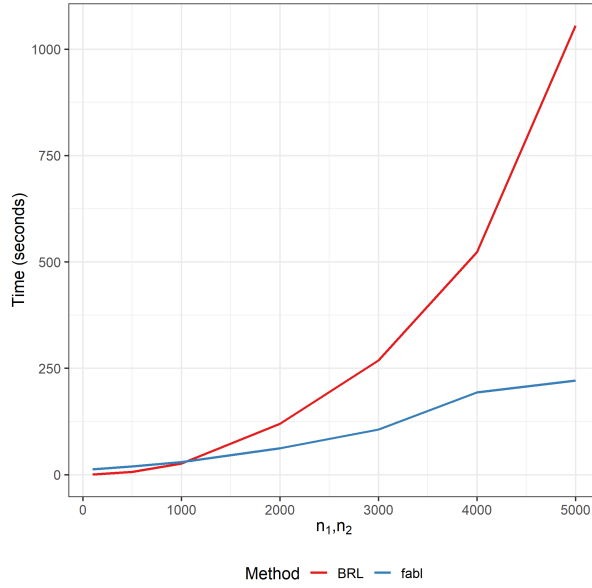


Figure 11: Run-time for BRL and fabl to run 1000 Gibbs iterations, including hashing step for fabl, for increasing values of both  $n_1$  and  $n_2$ . We see near quadratic growth in run-time for BRL, and near linear growth for fabl.



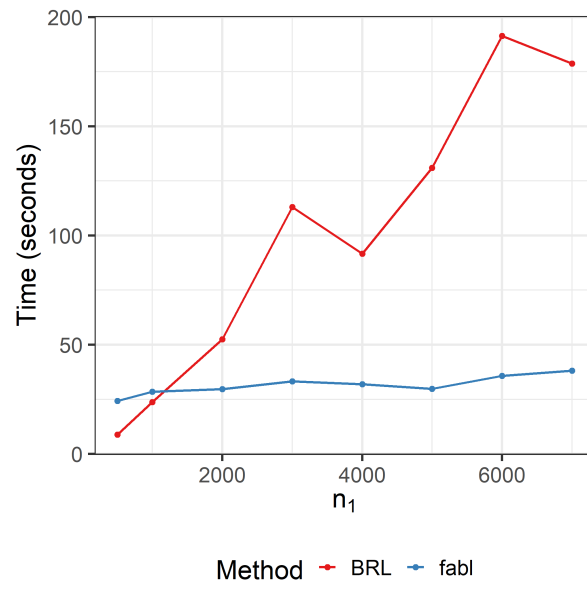


Figure 12: Run-time for BRL and fabl to run 1000 Gibbs iterations, including hashing step for fabl, with increasing  $n_1$ , and  $n_2$  fixed at 500. We see linear growth in run-time for BRL, and near constant run-time for fabl.

678 **7.6 Traceplots for El Salvador Case Study**

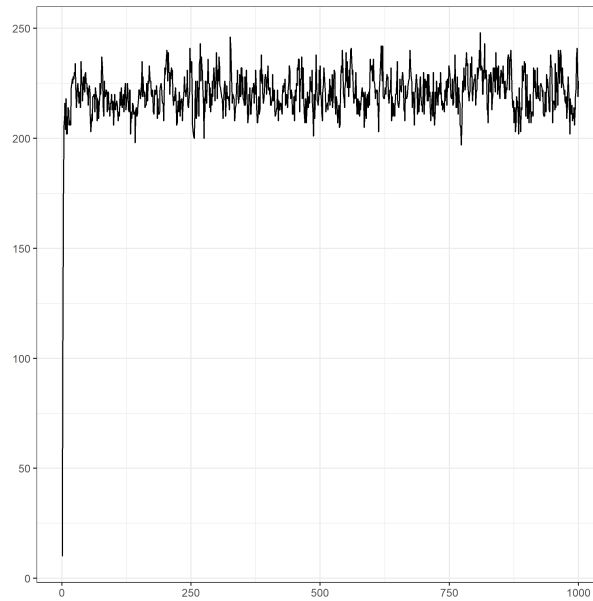
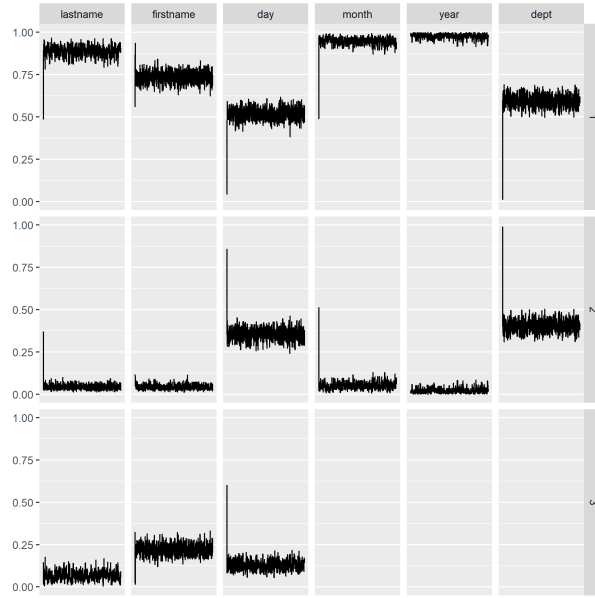
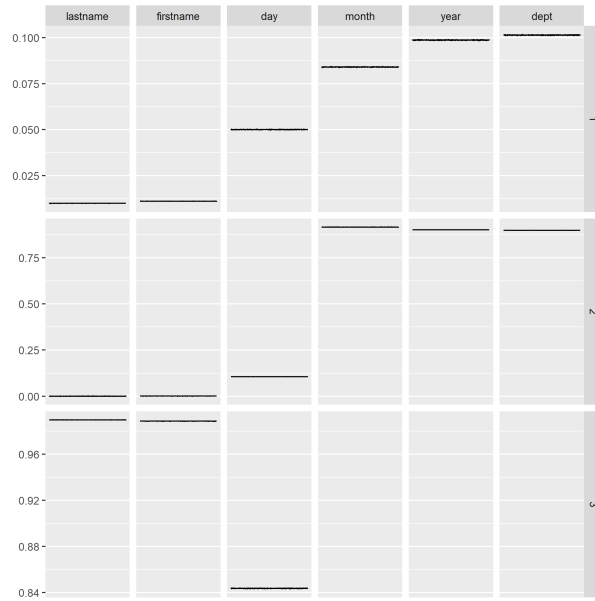


Figure 13: Traceplot for number of matches found across datasets in El Salvador case study

Figure 14: Traceplot for  $m$  parameter in El Salvador case studyFigure 15: Traceplot for  $u$  parameter in El Salvador case study