

## DETECTING DUPLICATES IN A HOMICIDE REGISTRY USING A BAYESIAN PARTITIONING APPROACH<sup>1</sup>

BY MAURICIO SADINLE

*Carnegie Mellon University*

Finding duplicates in homicide registries is an important step in keeping an accurate account of lethal violence. This task is not trivial when unique identifiers of the individuals are not available, and it is especially challenging when records are subject to errors and missing values. Traditional approaches to duplicate detection output independent decisions on the coreference status of each pair of records, which often leads to nontransitive decisions that have to be reconciled in some ad-hoc fashion. The task of finding duplicate records in a data file can be alternatively posed as partitioning the data file into groups of coreferent records. We present an approach that targets this partition of the file as the parameter of interest, thereby ensuring transitive decisions. Our Bayesian implementation allows us to incorporate prior information on the reliability of the fields in the data file, which is especially useful when no training data are available, and it also provides a proper account of the uncertainty in the duplicate detection decisions. We present a study to detect killings that were reported multiple times to the United Nations Truth Commission for El Salvador.

**1. Introduction.** Duplicate detection is the task of finding sets of records that refer to the same entities within a data file. This task is not trivial when unique identifiers of the entities are not recorded in the file, and it is especially difficult when the records are subject to errors and missing values. The existence of duplicates in a data file may compromise the validity of any analysis that uses those data, and therefore duplicate detection is needed in a wide variety of contexts, including public health and biomedical research [e.g., Hsu et al. (2000), Miller, Frawley and Sayward (2000), Sariyar, Borg and Pommerening (2012)], and census quality improvement [e.g., Fay (2004), Marshall (2008)].

In the context of an armed conflict, it is common for an institution recording civilian casualties to receive multiple reports on the same victims. These reports may come from witnesses who provide different degrees of detail, therefore leading to nontrivial duplicates in the institution's data file. Finding duplicates in those homicide registries is an important step toward keeping an accurate account of

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lethal violence. In this article we study a case from El Salvador, where a Truth Commission formed by the United Nations in 1992 collected data on killings that occurred during the Salvadoran civil war (1980–1991). Due to the way in which those data were collected, a victim could have been reported by different relatives and friends, and therefore it is important to detect those multiply reported casualties.

1.1. *The United Nations Truth Commission for El Salvador.* From 1980 to 1991, the Republic of El Salvador, in Central America, underwent a civil war between the Salvadoran Government and the left-wing guerrilla Farabundo Martí National Liberation Front (FMLN, after its name in Spanish). The parties signed a peace agreement in 1992 which later led to the creation of the Commission on the Truth for El Salvador by the United Nations [Buergenthal (1994, 1996)], henceforth abbreviated as UNTC.

Between 1992 and 1993, the UNTC summoned the Salvadoran society to report violations that occurred during the war, mainly focusing on homicides and disappearances of noncombatants. The UNTC ran announcements on the radio, television, and in newspapers inviting individuals to testify, and opened offices in different regions of the country where information from witnesses was collected [Commission on the Truth for El Salvador (1993)]. Finally, in 1993 the UNTC published a report with the results of their investigations, including a list of homicides directly obtained from testimonials, which were mainly provided by the victims' family members, but also by close friends. In addition to the names of the victims, this list contains the reported locations and dates of the killings.

Most of the killings reported to the UNTC occurred several years before 1992, and therefore it was expected that friends and relatives of the victims would not recall some details of the killings or would provide testimonials that conflict with each other. These characteristics of the data collection naturally led to missing information and nontrivial duplicate records in the UNTC data file. The variability among records that refer to the same victim and the presence of missing data make finding duplicates specially challenging. Furthermore, it is difficult to construct a reliable training data set for duplicate detection, that is, a set of record pairs with known coreference statuses, which supervised duplicate detection methods require. In this document we develop a new approach to duplicate detection inspired by these type of situations. Our approach handles missing data and allows the duplicate detection process to be assisted with prior information on the reliability of each field in the file, which helps to compensate for the absence of training data.

1.2. *Current approaches to duplicate detection.* Duplicate detection differs from the closely related task of *record linkage* in the sense that the goal of the latter is to link multiple files usually obtained from different data collection processes, and it is assumed that these files do not contain duplicates within them [Fellegi

and Sunter (1969), Herzog, Scheuren and Winkler (2007), Jaro (1989), Larsen and Rubin (2001), Winkler (1988)]. Despite this difference, the same principles and techniques can usually be adapted to solve both tasks.

In this article two or more records referring to the same entity are called *coreferent*. Traditional approaches to unsupervised duplicate detection and record linkage fit mixture models on pairwise comparisons of records with the goal of separating coreferent from noncoreferent pairs [Elmagarmid, Ipeirotis and Verykios (2007), Herzog, Scheuren and Winkler (2007)]. Traditional supervised approaches train classifiers on a sample of record pairs with known coreference statuses, and then predict the coreference statuses of the remaining record pairs [Christen (2012a), Elmagarmid, Ipeirotis and Verykios (2007)]. Both of these type of approaches output independent decisions on the coreference status of each record pair, and therefore neither of them guarantee transitivity of the coreference decisions. For example, it is possible that records  $i$  and  $j$  are declared as being coreferent, as well as records  $j$  and  $k$ , but records  $i$  and  $k$  may be declared as noncoreferent. If  $i$ ,  $j$  and  $k$  truly correspond to the same entity, the nontransitivity could occur due to measurement error and incomplete record information. It may be the case, however, that only two or none of those records are coreferent, but these methodologies do not offer any representation of uncertainty in these situations, and so they require resolving discrepancies in an ad-hoc post-processing step.

Most recently, Bayesian approaches to both duplicate detection and record linkage have been proposed, which provide a natural account of the coreference decisions' uncertainty in the form of posterior distributions. Most of these approaches directly model the information contained in the data files [Fortini et al. (2002), Gutman, Afendulis and Zaslavsky (2013), Matsakis (2010), Steorts, Hall and Fienberg (2013), Tancredi and Liseo (2011)], which require crafting specific models for each type of field in the file, and are therefore currently limited to handle nominal categorical fields or continuous variables modeled under normality. In practice, however, fields that are complicated to model, such as names, addresses, phone numbers or dates, are important to detect coreferent records. These type of fields are often subject to typographical and other types of errors, which make it important to take into account partial agreements between their values. This is certainly an advantage of traditional methodologies, as they base their decisions on pairwise comparisons of records and therefore can use any type of field, as long as these can be compared in a meaningful way. The approaches of Fortini et al. (2001) and Larsen (2002, 2005, 2012) are Bayesian implementations of the traditional unsupervised approach to record linkage [Fellegi and Sunter (1969), Herzog, Scheuren and Winkler (2007), Larsen and Rubin (2001), Winkler (1988)], which bases its coreference decisions on pairwise comparison data. These latter approaches, however, do not currently handle missing data, do not take into account multiple levels of partial agreement, and they would lead to nontransitive decisions if they were applied without modification to a duplicate detection problem.

1.3. *Overview of the article.* The approach that we propose in this article builds upon the previous literature by combining a number of desirable characteristics for a duplicate detection technique. Our approach to duplicate detection guarantees transitivity of the coreference decisions by defining our parameter of interest as the partition of the data file that groups coreferent records together, as in Matsakis (2010). Our approach is closely related to those of Fellegi and Sunter (1969), Winkler (1988), Jaro (1989), Larsen and Rubin (2001), Fortini et al. (2001) and Larsen (2002, 2005, 2012) for record linkage in the sense that our coreference decisions are based on comparison data, but we also extend some ideas of Winkler (1990) to take into account levels of disagreement among the fields' values. In practice, it is also common to have missing values in the data file, and so we show how our method can be adapted to those situations. By taking a Bayesian approach we can incorporate prior knowledge on the reliability of the fields, which is useful in situations where no training data are available. The introduction of prior information to solve this type of problem has been advocated by Fortini et al. (2001), Larsen (2002, 2005, 2012) and others. Our Bayesian approach provides us with a posterior distribution on the possible partitions of the file, which is a natural way to account for the uncertainty in the coreference decisions, similarly as in Matsakis (2010) and Steorts, Hall and Fienberg (2013).

The remainder of the article is organized as follows: Section 2 presents a general description of the proposed methodology; Section 3 presents a conditional independence model that leads to a simple way of dealing with missing values, an illustrative example and a simulation study; Section 4 addresses the problem of detecting killings reported multiple times to the United Nations Truth Commission for El Salvador; and Section 5 concludes.

**2. Methodology.** Assume we have a data file containing  $r$  records labeled  $\{1, \dots, r\}$ , where more than one record may refer to the same underlying entity. Finding duplicates in such a data file is equivalent to grouping records according to the underlying entities that they refer to. If there are  $n \leq r$  entities represented in the data file, we can safely think of partitioning the data file into  $n$  groups of coreferent records. This partition of the file, called *coreference partition* [Matsakis (2010)], is our parameter of interest, and it can be represented in different ways. We use different representations throughout the article depending on which one is more convenient.

2.1. *Representations of partitions.* A partition of a set is a collection of nonempty and nonoverlapping subsets whose union is the original set. In this article those subsets are called *groups* or *cells*. Given a data file with, say, five records  $\{1, 2, 3, 4, 5\}$ , a partition with cells  $\{1, 3\}$ ,  $\{2\}$  and  $\{4, 5\}$  is denoted as  $1, 3/2/4, 5$ . In a coreference partition, each of its cells represents an underlying entity, therefore, in this example records 1 and 3 are coreferent, as well as records 4 and 5. This representation, however, is not useful for computations.

A partition can also be represented by a matrix. Let us consider the matrix  $\mathbf{\Delta}$  of size  $r \times r$ , whose  $(i, j)$ th entry is defined as

$$\Delta_{ij} = \begin{cases} 1, & \text{if records } i \text{ and } j \text{ refer to the same entity;} \\ 0, & \text{otherwise.} \end{cases}$$

In the context of duplicate detection we will refer to  $\mathbf{\Delta}$  as a *coreference matrix*. Notice that  $\mathbf{\Delta}$  is symmetric with only ones in the diagonal, and it would be block-diagonal if coreferent records were contiguous in the data file, with each block representing a group of coreferent records.

Representing partitions using matrices is computationally inefficient, especially when the number of records is large. An alternative is to use arbitrary labelings of the partition's cells. Since  $r$  is the number of records in the data file, it is safe to assume that  $r$  is the maximum number of entities possibly represented in the data file, and therefore it is the maximum number of labels that we need. By assigning an arbitrary labeling to these  $r$  potential entities, we can introduce the variables  $Z_i$ ,  $i = 1, \dots, r$ , where  $Z_i = q$  if record  $i$  represents entity  $q$ , with  $1 \leq q \leq r$ , and the vector  $\mathbf{Z} = (Z_1, \dots, Z_r)$  contains all the records' labels. Notice that although the labeling of the  $r$  potentially existing entities is arbitrary, any relabeling leads to the same partition of the records. In fact,  $\Delta_{ij} = I(Z_i = Z_j)$ , where  $I(\cdot)$  is the indicator function, and this relationship does not depend on the labeling that we use. This relationship is important since a prior distribution on the space of partitions can be obtained by specifying a distribution for the records' labels  $\mathbf{Z}$ . Notice that if the number of entities  $n$  is lower than  $r$ , then there will be  $r - n$  labels not in use for each particular labeling. According to this labeling scheme, a partition of  $r$  elements into  $n$  cells has  $r!/(r - n)!$  possible labelings. Finally, to fix ideas, the vectors  $\mathbf{Z} = (1, 2, 1, 3, 3)$  and  $\mathbf{Z} = (4, 1, 4, 2, 2)$  are instances of arbitrary labelings of the partition  $1, 3/2/4, 5$ , since in both  $Z_1 = Z_3 \neq Z_4 = Z_5$ , and  $Z_2$  gets its own unique value.

The number of ways in which a data file with  $r$  records can be partitioned is given by the  $r$ th Bell number [see, e.g., Rota (1964)], which grows rapidly with  $r$ . For example, the number of possible partitions of a file with 10 records is 115,975, and if the file contains 15 records, the Bell number grows to 1,382,958,545. In practice, most files are much larger, but fortunately most partitions can be ruled out at an early stage, as we describe in Section 2.3. To make inferences on the file's coreference partition, we find how similar each pair of records is.

*2.2. Levels of disagreement as comparison data.* Comparison data are obtained by comparing pairs of records, with the goal of finding evidence of whether two records refer to the same entity. Intuitively, two records referring to the same entity should be very similar. The way of constructing the comparisons depends on the information contained by the records. The most straightforward way of comparing the same field of two records is by checking whether their information agrees or not. Although this comparison method is extensively used, and it is

appropriate for comparing unordered categorical fields (e.g., sex or race), it completely ignores partial agreement.

Winkler (1990) proposes to take into account partial agreement among fields that contain strings (e.g., given names) by computing a string metric, such as the normalized Levenshtein edit distance or any other [see Bilenko et al. (2003), Elmagarmid, Ipeirotis and Verykios (2007)], and then dividing the resulting set of similarity values into different *levels of disagreement*. Winkler's approach can be extended to compute levels of disagreement for fields that are not appropriately compared in a dichotomous fashion.

We compare the field  $f$  of records  $i$  and  $j$  by computing some similarity measure  $\mathcal{S}_f(i, j)$ . The range of this similarity measure is then divided into  $L_f + 1$  intervals  $I_{f0}, I_{f1}, \dots, I_{fL_f}$ , that represent different levels of disagreement. By convention, the interval  $I_{f0}$  represents the highest level of agreement, which includes no disagreement, and the last interval,  $I_{fL_f}$ , represents the highest level of disagreement, which depending on the field represents complete or strong disagreement. We can then build ordinal variables from these intervals. For records  $i$  and  $j$ , and field  $f$ , we define

$$\gamma_{ij}^f = l \quad \text{if } \mathcal{S}_f(i, j) \in I_{fl}.$$

The larger the value of  $\gamma_{ij}^f$ , the larger the disagreement between records  $i$  and  $j$  with respect to field  $f$ . These different field comparisons are collected in a vector for each record pair, as in the record linkage literature [e.g., Fellegi and Sunter (1969)].  $\boldsymbol{\gamma}_{ij} = (\gamma_{ij}^1, \dots, \gamma_{ij}^f, \dots, \gamma_{ij}^F)$  denotes the comparison vector for records  $i$  and  $j$ , where  $F$  is the number of fields being compared.

Notice that, in principle, we could construct  $\boldsymbol{\gamma}_{ij}$  using the original similarity values  $\mathcal{S}_f(i, j)$ . In our approach, however, we model these comparison vectors as a way to make inference on the coreference partition. Modeling directly the original  $\mathcal{S}_f(i, j)$ 's requires a customized model per type of comparison, since these similarity measures output values in different ranges, depending on their functional form and the field being compared. By building levels of disagreement as ordinal categorical variables, we can use a generic model for any type of comparison, as long as its values are categorized.

This approach also raises the question of how to choose the thresholds to build the intervals  $I_{fl}$ . The selection of the thresholds should correspond to what the researcher genuinely considers as levels of disagreement. This depends on the specific application at hand and the type of field being compared. For example, in Sections 3 and 4 we build levels of disagreement according to what we consider to be no disagreement, mild disagreement, moderate disagreement and extreme disagreement.

Although in principle the number of record comparisons is  $\binom{r}{2} = r(r-1)/2$ , in practice, most record pairs are noncoreferent, and most of them can be trivially detected using some simple criteria, thereby avoiding the computation of the complete set of comparisons, as we show next.

2.3. *Reducing the inferential and computational complexity.* In most applications there are simple ways to detect large numbers of obvious noncoreferent pairs at some early stage of the duplicate detection process. Detecting those pairs reduces tremendously the inferential and computational complexity of the problem, given that whenever records  $i$  and  $j$  are declared as noncoreferent, this translates to fixing  $\Delta_{ij} = 0$  in the coreference matrix, which in turn assigns probability zero to all the partitions where records  $i$  and  $j$  are grouped together.

There are different techniques to detect sets of noncoreferent pairs, and here we refer to a few of them [see Christen (2012b) for an extensive survey]. The most popular approach is called *blocking*, and it consists of dividing the data file into different blocks (sets of records) according to one or more reliable categorical fields, such that records in different blocks are considered to be noncoreferent. The idea is that if a field is reliable enough, then it would be unlikely to find a coreferent pair among pairs of records disagreeing in that field. For example, if we believe a field like gender or postal code (zip code) to be free of error, we can declare records disagreeing on that field to be noncoreferent. This approach is appealing since it does not even require us to compute comparisons, as the file can be simply divided according to the categories of the fields being used for blocking.

In many cases no field may be completely trusted, and therefore blocking may lead to miss truly coreferent pairs. We can, however, exploit prior knowledge on the types of errors expected for the different fields. By understanding what kind of errors would be unlikely for a certain field, we can declare as noncoreferent any pair of records that disagrees by more than a predefined threshold with respect to the field in consideration. Ideally, this comparison should be cheap to compute, since it will be checked for all record pairs. For example, information on time events for individuals, such as date of birth or date of death, is misreported in certain contexts, but it is common that whenever the correct date is not recorded, the date that appears in the record is somehow close to the true one. In this example, two records containing dates that are very different could be declared as noncoreferent. Other fields that can be used in this fashion include age or geographic information, given that in many contexts it is unlikely to find coreferent pairs among records that report very different ages or distant locations. Naturally, the validity of any of these approaches has to be assessed on a case-by-case basis.

Ideally after applying one of the previous steps, or a combination of them, the set of pairs is reduced to a manageable size for which complete comparisons can be computed, as explained in Section 2.2. Computationally expensive comparisons, such as those involving string metrics, should be reserved for this stage. We call  $\mathcal{P}$  the set of pairs for which complete comparisons are computed. The comparison data for the pairs in  $\mathcal{P}$  comprises the information that we will use to estimate the partition of the file. Within  $\mathcal{P}$ , however, many pairs may still be obvious noncoreferent pairs that can be detected using combinations of the different levels of disagreement. Therefore, we can further reduce the complexity of the inferential

task by declaring record pairs as noncoreferent whenever they strongly disagree according to some user-defined criteria built using the computed levels of disagreement. For instance, criteria for declaring a pair as noncoreferent could be having strong disagreements in given and family names, or having strong disagreements in a combination of fields such as age, race and occupation, if they were available. Finally, if a pair of records meet any of the established criteria, then it is declared as noncoreferent. The reasoning behind this approach is that, although no single field may be enough to distinguish further noncoreferent records, strong disagreements in a combination of fields are probably a good indication of the records being noncoreferent, and therefore we would expect this approach to be robust to errors. The set of remaining pairs whose coreference statuses are still unknown is denoted by  $\mathcal{C}$ , and we refer to it as the set of candidate pairs. Although we fix the pairs in  $\mathcal{P} - \mathcal{C}$  as noncoreferent, we use their comparison data in the model presented in the next section, since those pairs provide examples of noncoreferent records.

The possible coreference partition of the file is now constrained to the set  $\mathcal{D} = \{\mathbf{\Delta} : \Delta_{ij} = 0, \forall (i, j) \notin \mathcal{C}\}$ , that is, the set of partitions that do not group together the record pairs that have already been declared as noncoreferent. In practice,  $\mathcal{D}$  is much smaller than the set of all possible partitions of the file, which is why we heavily rely on being able to have a small set of candidate pairs  $\mathcal{C}$  to apply our method to medium or large size data files.

*2.4. Model description.* We now present a model for the comparison data  $\boldsymbol{\gamma} = \{\boldsymbol{\gamma}_{ij}\}_{(i,j) \in \mathcal{P}}$  such that the distribution of the comparison vectors depends on whether the pairs are coreferent or not, which will allow us to estimate the coreference partition. Notice that we model all the pairs in  $\mathcal{P}$  even though those in  $\mathcal{P} - \mathcal{C}$  are fixed as noncoreferent.

We assume that the comparison vector  $\boldsymbol{\gamma}_{ij}$  is a realization of a random vector  $\mathbf{\Gamma}_{ij}$ , and the comparison data  $\boldsymbol{\gamma}$  are a realization of a random array  $\mathbf{\Gamma}$ . It is clear that the set of record pairs is composed of two types: coreferent and noncoreferent pairs. Furthermore, we expect the distribution of the comparison vectors  $\mathbf{\Gamma}_{ij}$  to be very different among those two types. For example, we expect to observe more agreements among coreferent pairs than among noncoreferent pairs and, similarly, we expect many more disagreements among noncoreferent pairs than among coreferent pairs. This intuition can be formalized by assuming that the distribution of  $\mathbf{\Gamma}_{ij}$  is the same for all record pairs that refer to the *same* entity (regardless of the entity), and that the distribution of  $\mathbf{\Gamma}_{ij}$  is the same for all record pairs that refer to *different* entities (regardless of the pair of entities). These assumptions have been widely employed for linking different data files under the Fellegi–Sunter framework for record linkage [Fellegi and Sunter (1969), Herzog, Scheuren and Winkler (2007), Larsen and Rubin (2001), Winkler (1988)].



The intuitive description above can be formalized into a model for the comparison data as

$$(2.1) \quad \begin{aligned} \Gamma_{ij} | \Delta_{ij} = 1 &\stackrel{\text{i.i.d.}}{\sim} G_1, \\ \Gamma_{ij} | \Delta_{ij} = 0 &\stackrel{\text{i.i.d.}}{\sim} G_0, \end{aligned}$$

for all  $(i, j) \in \mathcal{P}$ , where  $G_1$  and  $G_0$  represent the models of the comparison vectors for pairs that are coreferent and noncoreferent, respectively. These models have to be specified according to the comparison data at hand. Leaving  $G_1$  and  $G_0$  unspecified by now, we can see that for a configuration of the coreference matrix  $\Delta$ , the joint probability of observing the comparison data  $\boldsymbol{\gamma}$  can be written as

$$(2.2) \quad \begin{aligned} &\mathbb{P}(\boldsymbol{\Gamma} = \boldsymbol{\gamma} | \Delta, \Phi) \\ &= \prod_{(i,j) \in \mathcal{C}} \mathbb{P}_1(\boldsymbol{\gamma}_{ij} | \Phi_1)^{\Delta_{ij}} \mathbb{P}_0(\boldsymbol{\gamma}_{ij} | \Phi_0)^{1-\Delta_{ij}} \prod_{(i,j) \in \mathcal{P}-\mathcal{C}} \mathbb{P}_0(\boldsymbol{\gamma}_{ij} | \Phi_0), \end{aligned}$$

where  $\mathbb{P}_1(\boldsymbol{\gamma}_{ij} | \Phi_1) := \mathbb{P}(\boldsymbol{\Gamma}_{ij} = \boldsymbol{\gamma}_{ij} | \Delta_{ij} = 1, \Phi_1)$  and, similarly,  $\mathbb{P}_0(\boldsymbol{\gamma}_{ij} | \Phi_0) := \mathbb{P}(\boldsymbol{\Gamma}_{ij} = \boldsymbol{\gamma}_{ij} | \Delta_{ij} = 0, \Phi_0)$ , with  $\Phi = (\Phi_1, \Phi_0)$  representing a parameter vector of the models  $G_1$  and  $G_0$ . Notice that equation (2.2) is obtained given that we fix  $\Delta_{ij} = 0$  for those pairs in  $\mathcal{P} - \mathcal{C}$ . Also, although the posterior on  $\Delta$  does not depend directly on the comparison data for pairs in  $\mathcal{P} - \mathcal{C}$ , it does depend on  $\Phi_0$ , which in turn depends on those pairs in  $\mathcal{P} - \mathcal{C}$ . In fact, the previous formulation is equivalent to a model for only the candidate pairs  $\mathcal{C}$ , as long as the factor  $\prod_{(i,j) \in \mathcal{P}-\mathcal{C}} \mathbb{P}_0(\boldsymbol{\gamma}_{ij} | \Phi_0)$  gets incorporated in the prior for  $\Phi_0$ .

*2.5. Prior distribution on the coreference partition.* Since the coreference matrix  $\Delta$  represents a partition, the entries of  $\Delta$  are not independent, for example, if  $\Delta_{ij} = 1$  and  $\Delta_{jk} = 1$ , then  $\Delta_{ik} = 1$ . In a mixture model implementation of the model presented in equations (2.1) and (2.2), the  $\Delta_{ij}$ 's ( $i < j$ ) are taken as i.i.d. Bernoulli( $p$ ), where  $p$  represents the proportion of coreferent pairs [Christen (2012a), Elmagarmid, Ipeirotis and Verykios (2007), Sariyar and Borg (2010), Sariyar, Borg and Pommerening (2009)]. The independence assumption of the  $\Delta_{ij}$ 's in a mixture model approach to duplicate detection leads to nontransitive decisions on the coreference statuses of record pairs. To avoid these undesirable results, we treat  $\Delta$  as a partition and put a prior distribution on it accordingly.

As we showed before,  $\mathcal{D}$  denotes the set of possible coreference partitions. In this article we use the prior that assigns equal probability to each partition in  $\mathcal{D}$ . This flat prior is such that  $\pi(\Delta) \propto I(\Delta \in \mathcal{D})$ . We can also obtain this prior in terms of the partition labelings introduced in Section 2.1. The set  $\mathcal{D}$  is equivalent to the set of labelings  $\mathcal{Z} = \{\mathbf{Z} : Z_i \neq Z_j, \forall (i, j) \notin \mathcal{C}\}$ . A simple way to obtain the flat prior for  $\Delta$  from a prior for  $\mathbf{Z}$  is by assigning equal probability to each of the  $r!/(r - n)!$  labelings of a partition with  $n$  cells, which leads to the prior on

labelings  $\pi(\mathbf{Z}) \propto [(r - n(\mathbf{Z}))! / r!] I(\mathbf{Z} \in \mathcal{Z})$ , where  $n(\mathbf{Z})$  measures the number of different labels in labeling  $\mathbf{Z}$ .

Notice that in some situations it may be desired to use a more structured prior on partitions, for example, if the researcher has a prior idea about the percentage of duplicates. How to appropriately incorporate this information requires further investigation, since commonly used distributions on partitions encourage the formation of large cells as they are designed for traditional clustering problems [see, e.g., the Dirichlet-Multinomial model for partitions in Keener, Rothman and Starr (1987), McCullagh (2011)], but in duplicate detection we rather expect the coreference partition to be composed by small cells.

2.6. *Missing comparisons.* The model presented in Section 2.4 was described assuming that the  $F$  different comparison criteria were available for each pair of records. In practice, however, it is rather common to find records with missing fields of information, which lead to missing comparisons for the corresponding record pairs. If a certain field is missing for record  $i$ , and this field is being used to compute comparison data, then the vector  $\boldsymbol{y}_{ij}$ ,  $j \neq i$ , will be incomplete, regardless of whether the field is missing for record  $j$ .

In order to deal with this common situation, we assume that the missing comparisons occur at random [MAR assumption in Little and Rubin (2002)], and therefore we can base our inferences on the marginal distribution of the observed comparisons [Little and Rubin (2002), page 90]. The complete array of comparisons  $\boldsymbol{\Gamma}$  can be decomposed into observed  $\boldsymbol{\Gamma}^{\text{obs}}$  and missing  $\boldsymbol{\Gamma}^{\text{mis}}$  comparisons; similarly, for each record pair  $\boldsymbol{\Gamma}_{ij} = (\boldsymbol{\Gamma}_{ij}^{\text{obs}}, \boldsymbol{\Gamma}_{ij}^{\text{mis}})$ . From equation (2.2), summing over the possible missing comparison patterns, it is easy to see that the probabilities involving  $\boldsymbol{\Gamma}^{\text{obs}}$  can be computed as

$$\begin{aligned}
 (2.3) \quad & \mathbb{P}(\boldsymbol{\Gamma}^{\text{obs}} = \boldsymbol{y}^{\text{obs}} | \boldsymbol{\Delta}, \Phi) \\
 &= \prod_{(i,j) \in \mathcal{C}} \mathbb{P}_1(\boldsymbol{y}_{ij}^{\text{obs}} | \Phi_1)^{\Delta_{ij}} \mathbb{P}_0(\boldsymbol{y}_{ij}^{\text{obs}} | \Phi_0)^{1 - \Delta_{ij}} \prod_{(i,j) \in \mathcal{P} - \mathcal{C}} \mathbb{P}_0(\boldsymbol{y}_{ij}^{\text{obs}} | \Phi_0),
 \end{aligned}$$

where

$$(2.4) \quad \mathbb{P}_1(\boldsymbol{y}_{ij}^{\text{obs}} | \Phi_1) = \sum_{\boldsymbol{y}_{ij}^{\text{mis}}} \mathbb{P}_1(\boldsymbol{y}_{ij}^{\text{obs}}, \boldsymbol{y}_{ij}^{\text{mis}} | \Phi_1),$$

and we obtain an analogous expression for  $\mathbb{P}_0(\boldsymbol{y}_{ij}^{\text{obs}} | \Phi_0)$ . Notice that equation (2.2) is a particular case of equation (2.3) arising when all the comparisons are complete for each record pair. In Section 3 we present a simple model under which this approach leads to a straightforward treatment of missing comparisons. Finally, we notice that equation (2.3) can be rewritten in terms of partition labelings

as

$$\begin{aligned}
 & \mathbb{P}(\mathbf{y}^{\text{obs}} | \mathbf{Z}, \Phi) \\
 (2.5) \quad &= \prod_{(i,j) \in \mathcal{C}} \mathbb{P}_1(\mathbf{y}_{ij}^{\text{obs}} | \Phi_1)^{I(Z_i=Z_j)} \mathbb{P}_0(\mathbf{y}_{ij}^{\text{obs}} | \Phi_0)^{I(Z_i \neq Z_j)} \\
 & \quad \times \prod_{(i,j) \in \mathcal{P}-\mathcal{C}} \mathbb{P}_0(\mathbf{y}_{ij}^{\text{obs}} | \Phi_0).
 \end{aligned}$$

2.7. *Conditional interpretation of the model.* Let us think about the hypothetical scenario where we know the coreference partition for all the records except for the  $i$ th one. In this case we are interested in finding the probabilities that record  $i$  refers to the different  $r$  potential entities given the comparison data, the model parameters and the partition memberships of the remaining records, represented by an arbitrary labeling  $\mathbf{Z}^{(-i)}$ . Using the prior for  $\mathbf{Z}$  presented in Section 2.5, regardless of the parametrization used for  $G_1$  and  $G_0$ , one can show that the probability that  $i$  refers to potential entity  $q$  is given by

$$\begin{aligned}
 (2.6) \quad & \mathbb{P}(Z_i = q | \mathbf{Z}^{(-i)}, \mathbf{y}^{\text{obs}}, \Phi) \\
 & \propto \begin{cases} \prod_{j: Z_j=q} I((i,j) \in \mathcal{C}) \left[ \frac{\mathbb{P}_1(\mathbf{y}_{ij}^{\text{obs}} | \Phi_1)}{\mathbb{P}_0(\mathbf{y}_{ij}^{\text{obs}} | \Phi_0)} \right], \\ \text{if } q \text{ labels a partition cell according to } \mathbf{Z}^{(-i)}; \\ (r - n(\mathbf{Z}^{(-i)}))^{-1}, \\ \text{otherwise.} \end{cases}
 \end{aligned}$$

This expression has a simple interpretation. The ratio within square brackets in the right-hand side of equation (2.6) represents the likelihood ratio for testing the hypothesis “records  $i$  and  $j$  are coreferent” versus “records  $i$  and  $j$  are not coreferent,” using the observed comparison vector  $\mathbf{y}_{ij}^{\text{obs}}$ . If  $q$  is a label in  $\mathbf{Z}^{(-i)}$ , then the probability that  $i$  refers to entity  $q$  is the product of the likelihood ratios for all records that refer to entity  $q$  according to  $\mathbf{Z}^{(-i)}$  (all records  $j$  such that  $Z_j = q$ ), which is a measure of how likely record  $i$  is to be coreferent with the group of records in cell  $q$ . However, if there is a record  $j$  such that  $Z_j = q$ , but  $(i, j) \notin \mathcal{C}$ , that is,  $(i, j)$  was fixed as noncoreferent, then  $\mathbb{P}(Z_i = q | \mathbf{Z}^{(-i)}, \mathbf{y}^{\text{obs}}, \Phi) = 0$ . Finally, if  $q$  is a label not in use, then record  $i$  takes this label with probability inversely proportional to the number of unused labels, which is equivalent to saying that record  $i$  gets its own label with probability proportional to one, and the specific label is chosen uniformly at random among the  $r - n(\mathbf{Z}^{(-i)})$  labels not in use. Without being exhaustive, equation (2.6) states that if for all partition cells the products of likelihood ratios are much smaller than one, then record  $i$  will assume its own label with high probability, but if there is a cell partition for which we obtain a product of likelihood ratios much larger than one, then it is likely that record

$i$  gets assigned to that cell. Equation (2.6) is used in the supplementary material [Sadinle (2014)] to derive a Gibbs sampler for the model presented in the next section.

**3. A model for independent comparison fields.** In this section we describe a simple parametrization for  $G_1$  and  $G_0$ , which represent the distributions of the comparison vectors among coreferent and noncoreferent pairs, respectively. Our model assumes that the comparison fields are independent for both coreferent and noncoreferent records.

If comparison  $\Gamma_{ij}^f$  takes  $L_f + 1$  values corresponding to levels of disagreement, its distribution among coreferent records can be modeled according to a multinomial distribution, this is

$$(3.1) \quad \mathbb{P}_1(\Gamma_{ij}^f = \gamma_{ij}^f | \mathbf{m}_f) = \prod_{l=0}^{L_f} (m_{fl}^*)^{I(\gamma_{ij}^f=l)},$$

where  $\gamma_{ij}^f$  represents an observed level of disagreement,  $m_{fl}^* = \mathbb{P}_1(\Gamma_{ij}^f = l)$ , and  $\sum_{l=0}^{L_f} m_{fl}^* = 1$ . It is easy to show that these probabilities can be rewritten as

$$m_{fl}^* = \begin{cases} m_{f0}, & \text{if } l = 0; \\ m_{fl} \prod_{h<l} (1 - m_{fh}), & \text{if } 0 < l < L_f; \\ \prod_{h<L_f} (1 - m_{fh}), & \text{if } l = L_f; \end{cases}$$

where  $m_{f0} = \mathbb{P}_1(\Gamma_{ij}^f = 0)$ , and  $m_{fl} = \mathbb{P}_1(\Gamma_{ij}^f = l | \Gamma_{ij}^f > l - 1)$  for  $0 < l < L_f$ . We choose to parameterize  $G_1$  in terms of the sequential conditional probabilities  $m_{fl}$  since this facilitates prior specification, as we show in Section 3.2. Using this parametrization, equation (3.1) can be reexpressed as

$$\mathbb{P}_1(\mathbf{\Gamma}_{ij}^f = \mathbf{\gamma}_{ij}^f | \mathbf{m}_f) = \prod_{l=0}^{L_f-1} m_{fl}^{I(\gamma_{ij}^f=l)} (1 - m_{fl})^{I(\gamma_{ij}^f>l)},$$

where  $\mathbf{m}_f = (m_{f0}, \dots, m_{f,L_f-1})$ . Following an analogous construction of the distribution of  $\Gamma_{ij}^f$  among noncoreferent pairs, we obtain

$$\mathbb{P}_0(\mathbf{\Gamma}_{ij}^f = \mathbf{\gamma}_{ij}^f | \mathbf{u}_f) = \prod_{l=0}^{L_f-1} u_{fl}^{I(\gamma_{ij}^f=l)} (1 - u_{fl})^{I(\gamma_{ij}^f>l)},$$

where  $u_{f0} = \mathbb{P}_0(\Gamma_{ij}^f = 0)$ ,  $u_{fl} = \mathbb{P}_0(\Gamma_{ij}^f = l | \Gamma_{ij}^f > l - 1)$  for  $0 < l < L_f$ , and  $\mathbf{u}_f = (u_{f0}, \dots, u_{f,L_f-1})$ . Notice that if  $L_f = 1$ , that is, if comparison  $f$  is binary, we obtain the traditional model used in record linkage for binary comparisons [e.g., Jaro (1989), Winkler (1988)].

3.1. *Missing comparisons and conditional independence.* The assumptions of the comparison fields being conditionally independent (CI), along with being missing at random (MAR), make it straightforward to deal with missing comparisons. In fact, under these assumptions, equation (2.4) can be written as

$$(3.2) \quad \mathbb{P}_1(\mathbf{y}_{ij}^{\text{obs}}|\Phi_1) = \prod_{f=1}^F \left[ \prod_{l=0}^{L_f-1} m_{fl}^{I(\gamma_{ij}^f=l)} (1 - m_{fl})^{I(\gamma_{ij}^f>l)} \right]^{I_{\text{obs}}(\gamma_{ij}^f)},$$

where  $I_{\text{obs}}(\cdot)$  is one if its argument is observed, and zero if it is missing, and  $\Phi_1 = (\mathbf{m}_1, \dots, \mathbf{m}_F)$ . Similarly,

$$(3.3) \quad \mathbb{P}_0(\mathbf{y}_{ij}^{\text{obs}}|\Phi_0) = \prod_{f=1}^F \left[ \prod_{l=0}^{L_f-1} u_{fl}^{I(\gamma_{ij}^f=l)} (1 - u_{fl})^{I(\gamma_{ij}^f>l)} \right]^{I_{\text{obs}}(\gamma_{ij}^f)},$$

where  $\Phi_0 = (\mathbf{u}_1, \dots, \mathbf{u}_F)$ . Equations (3.2) and (3.3) indicate that the combination of the CI and MAR assumptions allow us to ignore the comparisons that are not observed and yet model the observed comparisons in a simple fashion.

Under the CI assumption we can write the likelihood for  $\mathbf{Z}$  and  $\Phi$  as

$$\mathcal{L}(\mathbf{Z}, \Phi|\mathbf{y}_{\text{obs}}) = \prod_{f=1}^F \mathcal{L}(\mathbf{Z}, \Phi_f|\mathbf{y}_{\text{obs}}^f),$$

where  $\Phi_f = (\mathbf{m}_f, \mathbf{u}_f)$ , and

$$\mathcal{L}(\mathbf{Z}, \Phi_f|\mathbf{y}_{\text{obs}}^f) = \prod_{l=0}^{L_f-1} m_{fl}^{a_{fl}^1(\mathbf{Z})} (1 - m_{fl})^{\sum_{h>l} a_{fh}^1(\mathbf{Z})} u_{fl}^{a_{fl}^0(\mathbf{Z})} (1 - u_{fl})^{\sum_{h>l} a_{fh}^0(\mathbf{Z})},$$

where

$$a_{fl}^1(\mathbf{Z}) = \sum_{(i,j) \in \mathcal{C}} I_{\text{obs}}(\mathbf{y}_{ij}^f) I(\gamma_{ij}^f = l) I(Z_i = Z_j),$$

$$a_{fl}^0(\mathbf{Z}) = \sum_{(i,j) \in \mathcal{C}} I_{\text{obs}}(\mathbf{y}_{ij}^f) I(\gamma_{ij}^f = l) I(Z_i \neq Z_j) + \sum_{(i,j) \in \mathcal{P}-\mathcal{C}} I_{\text{obs}}(\mathbf{y}_{ij}^f) I(\gamma_{ij}^f = l).$$

For a given matrix of memberships  $\mathbf{Z}$ ,  $a_{fl}^1(\mathbf{Z})$  and  $a_{fl}^0(\mathbf{Z})$  represent the number of coreferent and noncoreferent records disagreeing at level  $l$  for observed comparison  $f$ .

Although our main interest is to make inferences on the coreference matrix  $\Delta$ , a fully Bayesian approach requires the specification of priors for the parameters  $\Phi$  as well.

3.2. *Prior specification for the model parameters.* We now explain our selection of the priors for  $m_{f_l}$  and  $u_{f_l}$ ,  $l = 0, \dots, L_f - 1$ . The first parameter that we focus on is  $m_{f_0} = \mathbb{P}_1(\Gamma_{ij}^f = 0)$ , which represents the probability of observing the level zero of disagreement in the comparison  $f$  among coreferent records. This level represents no disagreement or a high degree of agreement, so if we believe that field  $f$  contains no error,  $m_{f_0}$  should be, a priori, a point mass at one, but as the error in field  $f$  increases, the mass of  $m_{f_0}$ 's prior should move away from one. We therefore take a priori  $m_{f_0}$  to be in some interval  $[\lambda_{f_0}, 1]$  with probability one, for some  $0 < \lambda_{f_0} < 1$ . If we believe that the field used to compute comparison  $f$  is fairly accurate, then we should set the threshold  $\lambda_{f_0}$  to be close to one. On the other hand, the more errors we believe a field contains, the lower the value for  $\lambda_{f_0}$  that we should set. The prior distribution for  $m_{f_0}$  can be taken in general as  $\text{Beta}(\alpha_{f_0}^1, \beta_{f_0}^1)$ , truncated to the interval  $[\lambda_{f_0}, 1]$ , which we denote as  $\text{TBeta}(\alpha_{f_0}^1, \beta_{f_0}^1, \lambda_{f_0}, 1)$ .

The parameter  $m_{f_1} = \mathbb{P}_1(\Gamma_{ij}^f = 1 | \Gamma_{ij}^f > 0)$  represents the probability of observing level one of disagreement in the comparison  $f$ , among coreferent record pairs with disagreement larger than the one captured by the level zero. Depending on the construction of the disagreement levels, and if the number of levels is greater than two, we can think of level one of disagreement as some mild disagreement and, therefore, if we expect the amount of error to be relatively small,  $m_{f_1}$  should be concentrated around values close to one. Following a similar reasoning as for  $m_{f_0}$ , we take the prior of  $m_{f_1}$  as  $\text{TBeta}(\alpha_{f_1}^1, \beta_{f_1}^1, \lambda_{f_1}, 1)$ , where we can set the hyperparameters of this distribution, especially  $\lambda_{f_1}$ , according to the amount of error that we expect field  $f$  to contain.

We can continue the previous reasoning to specify the prior distribution of the remaining parameters  $m_{f_l} = \mathbb{P}_1(\Gamma_{ij}^f = l | \Gamma_{ij}^f > l - 1)$ ,  $l = 2, \dots, L_f - 1$ . In general, we can take the prior of  $m_{f_l}$  as  $\text{TBeta}(\alpha_{f_l}^1, \beta_{f_l}^1, \lambda_{f_l}, 1)$ , where the truncation points  $\lambda_{f_l}$  change according to the way the disagreement levels were constructed and the amount of error expected a priori in each field. Notice, however, that if we believe that a field may be too erroneous, it may be better to exclude it from the duplicate detection process since its inclusion can potentially harm the results [Sadinle and Fienberg (2013) explore this issue in the multiple record linkage context]. For simplicity, in this article we set  $\alpha_{f_l}^1 = \beta_{f_l}^1 = 1$ , for all fields  $f$  and levels  $l$ , that is, we take  $m_{f_l} \sim \text{Uniform}(\lambda_{f_l}, 1)$ , and so we only need to choose the  $\lambda_{f_l}$ 's.

The probabilities  $u_{f_l} = \mathbb{P}_0(\Gamma_{ij}^f = l | \Gamma_{ij}^f > l - 1)$  among noncoreferent records may have quite different distributions depending on the fields used to compute the comparisons. For instance, if a nominal field contains a highly frequent category, then the probability of agreement will be high even for noncoreferent records. On the other hand, if a field is almost a unique identifier of the entities, then the probability of agreement will be small among noncoreferent records. We therefore

simply take  $u_{fl} \sim \text{Uniform}(0, 1)$  for all fields and levels of disagreement, although in general we could take  $u_{fl} \sim \text{Beta}(\alpha_{fl}^0, \beta_{fl}^0)$ , for some hyperparameters  $\alpha_{fl}^0$  and  $\beta_{fl}^0$  if prior information was available.

3.3. *Bayesian inference via Gibbs sampler.* In the supplementary material [Sadinle (2014)] we present a Gibbs sampler to explore the joint posterior of  $\mathbf{Z}$  and  $\Phi$  given the observed comparison data  $\mathbf{y}_{\text{obs}}$ , for the likelihood obtained from equations (2.5), (3.2) and (3.3), and the priors presented in the previous subsection. The supplementary material also contains a brief discussion on point estimation of the coreference partition.

3.4. *An illustrative example.* Table 1 presents a small example to illustrate different situations where different sets of records may be considered as coreferent depending on how reliable we believe the fields are. We explore the results of our duplicate detection method under different scenarios where these data could have arisen, which is why we do not yet specify what the fields year, month, day, and municipality refer to. This example was inspired by the data file that we study in Section 4, where we have to compare Hispanic names. Full Hispanic names are usually composed by four pieces, two corresponding to given name and two to family name. In practice, however, Hispanic people do not always use their full given and family names. For example, someone whose full given name is *JULIAN ANDRES* may be simply known as *JULIAN* or as *ANDRES* in his social circle. This phenomenon makes it particularly challenging to compare Hispanic names, for example, it has been reported to cause problems when tracking citations of Hispanic authors [Fernández and García (2003), Ruiz-Pérez, López-Cózar and Jiménez-Contreras (2002)].

Records 1, 2 and 3 in Table 1 represent an example where pairwise decisions on the coreference statuses of record pairs may not be transitive. In this example, records 1, 2 and 3 agree in all the fields except for month and day. Records 1 and 2 disagree by one month, as well as records 2 and 3, but the comparison for the field day for those two pairs is missing. Notice also that records 1 and 3 disagree by two months and have a strong disagreement in the field day. In this situation, a method taking pairwise decisions, or even a human taking decisions for one pair of records at a time, may decide that records 1 and 2 are coreferent, as well as records 2 and 3, since those pairs are fairly similar, but may decide that records 1 and 3 are not coreferent, since this pair has more disagreements. Table 1 also presents records 4 and 5, which agree in all of their information, except for given and family name. Record 5 could refer to the same person as record 4, since this name is simply missing the second pieces of given and family name, which is common for Hispanic names, and the remaining disagreements could be typographical errors. The decision of whether to declare records 4 and 5 as coreferent will depend on the levels of error that we believe the fields given and family name may contain. Below

TABLE 1

*Illustrative example: Different sets of records may be considered as coreferent in different contexts*

Record	Given name	Family name	Year	Month	Day	Municipality
1.	JOSE	FLORES	1981	1	29	A
2.	JOSE	FLORES	1981	2	NA	A
3.	JOSE	FLORES	1981	3	20	A
4.	JULIAN ANDRES	RAMOS ROJAS	1986	8	5	B
5.	JILIAM	RMAOS	1986	8	5	B

we show how the proposed method deals with the uncertainty of these situations under different scenarios.

Let us think of two different scenarios from where the records in Table 1 could have arisen. In the first scenario, inspired by the application presented in Section 4, each record refers to a person who was killed during a war, and the data were reported by witnesses many years after the events occurred. In this scenario, year, month, day and municipality correspond to the date and location of the killing as reported by the witnesses. Under this scenario we expect to have reporting errors in the names of the victim and in the date and place of the killings, since different witnesses may have different memories of the victims and the events. In the second scenario, the records in Table 1 come from tax forms, and the information was self-reported. In this case, year, month, day and municipality correspond to date and place of birth. In this case we may expect the levels of error in all fields to be much smaller compared to the first scenario, since it is quite unlikely for one person to misreport her information, at least unintentionally.

In Table 2 we show a summary of how we construct disagreement levels in this example. We compare all the record pairs since there are only 10 of them and use a modification of the *Levenshtein edit distance* to compare names. The Levenshtein edit distance between two strings is the minimum number of deletions, insertions

TABLE 2

*Construction of levels of disagreement for the example in Table 1*

Field	Similarity measure	Levels of disagreement			
		0	1	2	3
Given name	Modified Levenshtein	0	(0, 0.25]	(0.25, 0.5]	(0.5, 1]
Family name	Modified Levenshtein	0	(0, 0.25]	(0.25, 0.5]	(0.5, 1]
Year	Absolute difference	0	1	2–3	4+
Month	Absolute difference	0	1	2–3	4+
Day	Absolute difference	0	1–2	3–7	8+
Municipality	Binary comparison	Agree	Disagree		



or replacements that we need to transform one string into the other. The modification that we use simply accounts for the fact that Hispanic names may have missing pieces. Basically, if name  $V$  contains one token and name  $W$  contains two tokens, we take the minimum of the Levenshtein distances between the token of name  $V$  and each token of name  $W$  and, finally, we transform this measure to the 0–1 interval. In this scale, 0 means total agreement (up to missing tokens) and 1 means extreme disagreement. We refer the reader to the supplementary material [Sadinle (2014)] for details on our comparisons of Hispanic names. The intervals that we choose to construct the disagreement levels (except for municipality) correspond to what we consider as no disagreement, mild disagreement, moderate disagreement and extreme disagreement. In this example the field municipality is taken as a nominal variable, and so we compare it in a binary fashion.

To implement the proposed method for duplicate detection, we need to choose the prior truncation points of the parameters  $m_{fl}$ . For the sake of simplicity, we suppose that our prior beliefs about each field of information can be classified in two categories: either the field is nearly accurate or it is inaccurate. If field  $f$  is nearly accurate, we take the prior truncation points for all the parameters related to this field (all  $m_{fl}$ ,  $l = 0, \dots, L_f - 1$ ) as 0.95, whereas if field  $f$  is inaccurate, these prior truncation points are set to 0.85. For simplicity, we fix the prior truncation points for year and municipality parameters at 0.95 for all of the data collection scenarios presented here. For the remaining parameters, in the war scenario we expect the fields to contain considerable amounts of error, and so the prior truncation points for those parameters are set equal to 0.85 (case 1 of Figure 1); for the taxes scenario the prior truncation points are set equal to 0.95 since a priori we expect errors to be rare (case 4 of Figure 1). We also explore two intermediate cases that fall between the previous two extreme scenarios, where we consider day and month to be nearly accurate, but given and family names to be inaccurate (case 2 of Figure 1) and vice versa (case 3 of Figure 1).

For each set of priors we run 10,000 iterations of the Gibbs sampler presented in the supplementary material [Sadinle (2014)], and in each case we discard 1000 iterations as burn-in. Figure 1 presents the posterior frequencies of the eight partitions that appear in the posterior samples. Although a file with five records can be partitioned in 52 ways (the 5th Bell number), the eight partitions presented in Figure 1 concentrate 100% of the posterior frequencies in each case.

From Figure 1 we can see that for case 1, that is, when given and family names, and day and month are inaccurate, the posterior distribution is mostly concentrated in partition 1, 2, 3/4, 5, that is, records 1, 2 and 3 are assigned to one entity and records 4 and 5 to another; this result is coherent with our priors, which indicated that the fields were potentially inaccurate, and therefore the disagreements between fields are not taken as strong evidence of the records being noncoreferent. In case 2, given and family names are thought to be inaccurate, whereas day and month are considered to be fairly accurate; in this case the strong disagreements

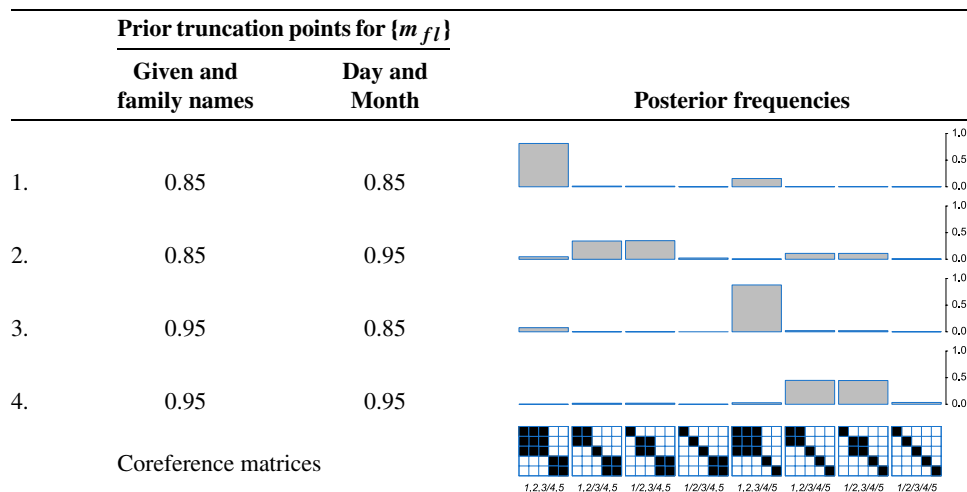


FIG. 1. Posterior distributions of the coreference partition for the records in Table 1, for different sets of priors corresponding to different contexts. Prior truncation points for Year and Municipality parameters are set at 0.95 for all cases. Posterior frequencies are obtained from 9000 iterations of a Gibbs sampler. The eight partitions presented here concentrate 100% of the posterior frequencies in each case. The coreference matrices depicted here have black entries representing ones and white entries representing zeroes.

between records 1 and 3 become important evidence of them not being coreferent, but since record pairs 1 and 2, and 2 and 3 are quite similar, the partitions 1, 2/3/4, 5 and 1/2, 3/4, 5 get equal posterior probability. In case 3, we present a scenario where day and month are thought to be inaccurate, but given and family names are believed to be accurate, and therefore the posterior gets almost completely concentrated in the partition 1, 2, 3/4/5, that is, compared to case 1, disagreements in given and family names become more important for distinguishing noncoreferent records, and therefore records 4 and 5 are probably noncoreferent. Finally, in case 4, all the fields are considered as accurate, and therefore the partitions where records 4 and 5 are coreferent become unlikely a posteriori, as well as the partitions where records 1 and 3 are clustered together. Since records 1 and 2 are quite similar, as well as records 2 and 3, but records 1 and 3 have strong disagreements, the posterior assigns equal probability to the partitions 1, 2/3/4/5 and 1/2, 3/4/5, which accounts properly for the uncertainty of deciding whether records 1 and 2, or records 2 and 3 are coreferent.

Finally, it is important to emphasize that although in this example it seems that the priors of the  $m_{fl}$  parameters completely determine the posterior of  $\Delta$ , both the  $m_{fl}$  and  $u_{fl}$  parameters influence the evolution of the memberships  $\mathbf{Z}$  in the Gibbs sampler (see the supplementary material [Sadinle (2014)]). In particular, if these five records were contained in a larger file, the resolution of their coreference sta-

tuses would depend on the distribution of the comparison data for the complete file, since, for instance, the distributions of the  $u_{fl}$  parameters are heavily influenced by the observed frequencies of the corresponding levels of disagreement.

3.5. *A simulation study.* We now present a simulation study to explore the performance of the proposed methodology under different scenarios of measurement error. Peter Christen and his collaborators [Christen (2005), Christen and Pudjijono (2009), Christen and Vatsalan (2013)] developed a sophisticated data generation and corruption tool to create synthetic data sets containing various types of fields. This tool, written in Python, can include dependencies between fields, permits the generation of different types of errors, and can be easily adapted to generate additional fields that are not included in the default settings.

We now describe the characteristics of the data files used in the simulation. We consider files having either five or seven fields of information. The synthetic files involving five fields include the following: gender, given name, family name, age, and occupation. The files with seven fields additionally include postal code and phone number. The fields gender and given name are sampled jointly from a table that contains frequencies of given names per gender, and therefore popular given names appear with higher probability in the synthetic data sets. Family name and postal codes are generated independently from additional frequency tables. The three tables mentioned so far were compiled by Christen and his collaborators using public sources from Australia. Phone numbers are randomly generated following the Australian format which consists of a two-digit area code and an eight-digit number made of two blocks of four digits. The previously described fields were included in the default configuration of Christen's generator. In addition, age and occupation are jointly sampled from a contingency table that serves as an estimate of the distribution of age and occupation in Australia. This table was obtained from the webpage of the Australian Bureau of Statistics, and it contains eight categories of occupation and eight age intervals.

The generator first creates a number of original records which are later used to create distorted duplicates. The duplicates are allocated by randomly selecting an original record and assigning a random number of duplicates to it. The number of duplicates is generated according to a Poisson(1) truncated to the interval [1, 5]. Each duplicate has a fixed number of erroneous fields which are allocated uniformly at random, and each field contains maximum two errors. The types of errors are selected uniformly at random from a set of possibilities which vary from field to field, as summarized in Table 3. In this table, missing values means that the value of the field becomes missing; edit errors represent random insertions, deletions or substitutions of characters in the string; OCR errors happen typically when a document has been digitized using optical character recognition; keyboard errors use a keyboard layout to simulate typing errors; phonetic errors are simulated using a list of predefined phonetic rules; and finally, misspelling errors are generated by randomly selecting one of possibly many known misspellings of a

TABLE 3  
Types of errors per field in the simulation study of Section 3.5

Field	Type of error					
	Missing values	Edits	OCR	Keyboard	Phonetic	Misspelling
Given name		✓	✓	✓	✓	
Family name		✓	✓	✓	✓	✓
Age interval	✓					
Gender	✓					
Occupation	✓					
Phone number	✓	✓	✓	✓		
Postal code	✓	✓	✓	✓		

family name. For further details on the generation of these types of errors, see Christen and Pudjijono (2009) and Christen and Vatsalan (2013).

In the simulation presented here, each synthetic data set is composed of 450 original records and 50 duplicates. To explore the performance of the method as a function of the amount of error in the data file, we generate 100 five-field and 100 seven-field synthetic data sets for each of three levels of error, which correspond to the number of erroneous fields per duplicate being one, three and five. For each file, comparison data were created as indicated in Table 4. For these files we model all pairs, so  $|\mathcal{P}| = \binom{500}{2}$ , and the record pairs having the level three of disagreement in either given or family name were fixed as noncoreferent, so these pairs constitute the set  $\mathcal{P} - \mathcal{C}$ , as explained in Section 2.3. Our model is then applied under three different sets of priors. For simplicity, each set of priors has the same prior truncation point for all the  $m_{fl}$  parameters, although in practice the priors should be chosen carefully based on knowledge of the potential amounts of error in the file. The prior truncation points are 0.5, 0.8 and 0.95, which correspond to one sce-

TABLE 4  
Construction of levels of disagreement for the simulation study of Section 3.5

Field	Similarity measure	Levels of disagreement			
		0	1	2	3
Given name	Levenshtein	0	(0, 0.25]	(0.25, 0.5]	(0.5, 1]
Family name	Levenshtein	0	(0, 0.25]	(0.25, 0.5]	(0.5, 1]
Age interval	Binary comparison	Agree	Disagree		
Gender	Binary comparison	Agree	Disagree		
Occupation	Binary comparison	Agree	Disagree		
Phone number	Levenshtein	0	(0, 0.25]	(0.25, 0.5]	(0.5, 1]
Postal code	Levenshtein	0	(0, 0.25]	(0.25, 0.5]	(0.5, 1]

nario where we believe the amount of error in the file to be extremely large, one where we believe it to be moderate, and one where we are optimistic and believe the amount of error to be very limited. For each data set, and for each set of priors, we ran 10,000 iterations of the Gibbs sampler and discarded the first 1000 as burn-in. The average runtime using an implementation in R [R Core Team (2013)] with parts written in C language was of 24.5 seconds per file, including the computation of the comparison data, on a laptop with a 2.80 GHz processor. Before starting the complete simulation study, we obtained some longer chains for some data sets and for all priors, and we could check that 9000 iterations provided roughly the same frequencies of partitions as when we ran longer chains.

For each data file, and each set of priors, we obtain a sample of partitions which approximate the posterior distribution of the coreference partition. We can assess how good each partition is in terms of classifying pairs of records as coreferent and noncoreferent. Two records  $i$  and  $j$  are coreferent according to a partition  $\Delta'$  if both belong to the same cell of the partition, that is,  $\Delta'_{ij} = 1$ . Given  $\Delta'$  and the true partition  $\Delta^*$ , let  $b_{11}(\Delta', \Delta^*) = \sum_{i < j} \Delta'_{ij} \Delta^*_{ij}$  be the number of record pairs that are coreferent in both partitions, and  $b_{10}(\Delta', \Delta^*) = \sum_{i < j} \Delta'_{ij} (1 - \Delta^*_{ij})$  and  $b_{01}(\Delta', \Delta^*) = \sum_{i < j} (1 - \Delta'_{ij}) \Delta^*_{ij}$  be the number of record pairs that are coreferent in one partition but not in the other. Given that  $\Delta^*$  is the true partition, the *recall* of  $\Delta'$  is defined as  $b_{11}(\Delta', \Delta^*) / (b_{11}(\Delta', \Delta^*) + b_{01}(\Delta', \Delta^*))$ , whereas the *precision* of  $\Delta'$  is  $b_{11}(\Delta', \Delta^*) / (b_{11}(\Delta', \Delta^*) + b_{10}(\Delta', \Delta^*))$ . The recall of a partition  $\Delta'$  measures the proportion of truly coreferent pairs that are classified correctly by  $\Delta'$ , whereas the precision of  $\Delta'$  measures the proportion of pairs declared as coreferent by  $\Delta'$  that are truly coreferent. These two measures are preferred for evaluating performance in duplicate detection and record linkage problems, where the set of noncoreferent pairs is much bigger than the set of coreferent pairs, and therefore traditional measures of performance in classification, such as the misclassification rate and the true negative rate, are misleading [Christen (2012a), page 165].

The results of the simulation are presented in Figure 2, where the rows of panels correspond to different number of fields and the columns to different priors. Notice that for each data set and each set of priors we obtain a distribution of recall and precision measures, since both of these measures are computed for each partition in the posterior sample. Therefore, we compute the median, the first and 99th percentile of each measure for each data set and each set of priors, and average over all the 100 results corresponding to each level of error, each number of fields and each prior. In each panel of Figure 2 black lines refer to recall, gray lines to precision, solid lines show average medians, and dashed lines show average first and 99th percentiles.

We can see that the performance of the method depends greatly on the amount of identifying information contained in the files (number and type of fields) and the interplay between our prior beliefs and the real amount of error. As we would naturally expect, our ability to obtain results with high precision will depend on the amount of identifying information contained in the files, that is, in general we

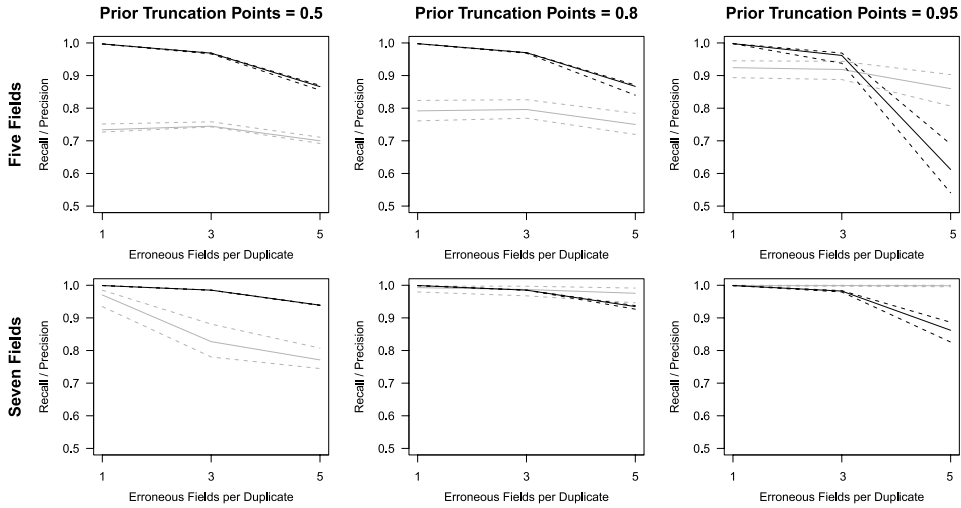


FIG. 2. Performance of the proposed methodology in the simulation of Section 3.5. Black lines refer to recall, gray lines to precision, solid lines show average medians, and dashed lines show average first and 99th percentiles.

will tend to obtain large proportions of false coreferent pairs whenever we have a small number of fields (see first row of Figure 2). For the five-field data files the precision of the method is generally sensitive to prior specification, whereas the recall is somewhat insensitive except for when the amount of error is large but we believe it to be small (see upper right panel), in which case we obtain a very poor recall, which means that a large proportion of truly coreferent pairs will not be detected. For files with seven fields, if the amount of error is small, then both recall and precision are somewhat insensitive to the choice of the prior truncation points, as long as the prior is not overly pessimistic in terms of the expected amount of error, in which case the precision deteriorates (see bottom left panel). This indicates that when there are not many errors, it is easy to identify most truly coreferent pairs, but if our priors are overly pessimistic, indicating that the amount of error is potentially much larger than what it really is, then we will end up obtaining many false coreferent pairs.

Although for some scenarios it is possible to obtain results that are both good and not too sensitive to prior specification, the general performance of the method can be seen in terms of a trade-off between recall and precision: if the priors indicate that the amount of error may be too small when it is actually large, then we may wind up missing too many true coreferent pairs; if the priors indicate that the amount of error may be too large when it is actually small, then we may end up having too many false coreferent pairs.

The results of this simulation study provide us with some guidance for the application presented in the next section, where the data file we work with contains a small number of fields, and we believe its levels of error to be intermediate.

**4. Detecting killings multiply reported to the U.N. Truth Commission for El Salvador.** Unfortunately, the list of homicides obtained by the UNTC was never made available in electronic form and was publicly available only as photocopies as of 2007 [Hoover Green (2011)]. As part of her Ph.D. thesis, Amelia Hoover Green utilized Optical Character Recognition (OCR) technology, along with data cleaning and standardization, to transfer those scanned lists into spreadsheet format. The digitized lists therefore contained OCR errors that were corrected by hand as part of the current project.

We now describe how we use the proposed methodology to find duplicated homicide records in the UNTC database. The fields that we use are given name, family name, date of death (year, month and day) and municipality of death, similarly as in the example of Section 3.4. In this article, a valid homicide report is defined as a record in the data file that specifies given and family name of the victim, which leads to a data file containing 5395 records. We believe that no single field in this file is free of error, and therefore we do not use traditional blocking, as it may lead to miss many truly coreferent pairs. There are, however, some disagreements between pairs of records that make us confident about their noncoreference statuses.

4.1. *Filtering trivial noncoreferent record pairs, and comparison data.* We consider it reasonable to assume that two reports correspond to different homicides whenever their recorded municipalities have names with no overlap and are not geographical neighbors. This approach takes into account the fact that some homicides occurring near the boundary of two municipalities may get reported in the wrong, although neighboring, municipality. Another source of error occurs when a municipality gets wrongly coded due to multiple municipalities having similar names. Although the testimonies were collected in different regions of El Salvador, they were digitized in a central location and, therefore, if, for example, a report indicated simply *San Francisco* as the municipality where a killing occurred, the clerks who entered the data could have potentially assigned the wrong municipality code to this report, given that there are six different municipalities in El Salvador that include those two tokens, for example, *San Francisco Morazán*, *San Francisco Lempa*, among others. We therefore only fully compare record pairs that either have the same municipality, neighboring municipalities, municipalities with names that overlap by at least one token (ignoring the common tokens *San*, *Santa*, *Santo*, *La*, *El*, *Las*, *Los*, *Del*, *De*), or for which the municipality is missing. The set of pairs that meet any of the previous criteria constitute the set  $\mathcal{P}$  introduced in Section 2.3, and the remaining pairs are fixed as noncoreferent. By using this approach we only need to fully compare around 12% of the  $\binom{5395}{2} = 14,550,315$  possible record pairs.

We construct the comparison data in the same way as in the illustrative example of Section 3.4, as summarized in Table 2. Given and family names were standardized and compared as described in the supplementary material [Sadinle (2014)].

TABLE 5

Prior truncation points  $\lambda_{fl}$  for the  $m_{fl}$  parameters in the detection of duplicate homicide records in the UNTC data file

$l$	Field ( $f$ )					
	Given name	Family name	Year	Month	Day	Municipality
0	0.85	0.85	0.85	0.85	0.70	0.85
1	0.90	0.90	0.90	0.90	0.70	–
2	0.99	0.99	0.99	0.99	0.70	–

The record pairs having the level three of disagreement in either given or family name, or in year and month, were fixed as noncoreferent (these are the pairs in the set  $\mathcal{P} - \mathcal{C}$  introduced in Section 2.3). After this step, the number of pairs on which we still need to take decisions reduces to only  $|\mathcal{C}| = 759$ , which involve only 1035 records.

**4.2. Prior specification.** Following the general guidelines presented in Section 3.2, we use uniform priors on  $[0, 1]$  for all the  $u_{fl}$  parameters,  $f \in \{\text{Given name, Family name, Year, Month, Day, Municipality}\}$ ,  $l = 0, \dots, L_f - 1$ . For the  $m_{fl}$  parameters, we use flat priors in the intervals  $[\lambda_{fl}, 1]$  for the truncation points  $\lambda_{fl}$  given in Table 5. These priors indicate our belief that coreferent pairs are very likely to have exact agreements, although we still expect a considerable amount of error in the fields. For example, the probability of exact agreement in the field year of death for coreferent pairs [ $m_{\text{Year},0} = \mathbb{P}_1(\Gamma_{ij}^{\text{Year}} = 0)$ ] is set to be at least 0.85 (i.e.,  $\lambda_{\text{Year},0} = 0.85$ ), which indicates that we expect a pair of coreferent records to agree exactly on year of death with high probability, but we still think that the amount of error could go up to 15%. The remaining  $\lambda_{f0}$  truncation points have similar interpretations.

The truncation points for the remaining parameters reflect our belief on the fields' error structure. We believe that although the fields are erroneous, the error distribution has to be such that errors become more unlikely as their magnitude increases. For example, the family name *RODRIGEZ* is more likely to be a misrecording of *RODRIGUEZ* than of *RAMIREZ*. Therefore, these truncation points  $\lambda_{fl}, l > 0$ , indicate that the probability of observing a level of disagreement among coreferent pairs decreases as the disagreement increases. For example, the probability  $m_{\text{Year},1} = \mathbb{P}_1(\Gamma_{ij}^{\text{Year}} = 1 | \Gamma_{ij}^{\text{Year}} > 0)$  is set to be minimum 0.9 a priori, that is, the probability that a coreferent pair disagrees by one year (level one of disagreement, see Table 2) given that it disagrees in year of death (i.e.,  $\Gamma_{ij}^{\text{Year}} > 0$ ) should be at least 0.9. This indicates that among all coreferent pairs that have disagreements in year of death, we expect the majority to have the minimum disagreement, which is one year ( $\Gamma_{ij}^{\text{Year}} = 1$ ). Similarly,  $m_{\text{Year},2}$  is set to be minimum 0.99 a priori, that is, the probability that a coreferent pair disagrees by two or three years



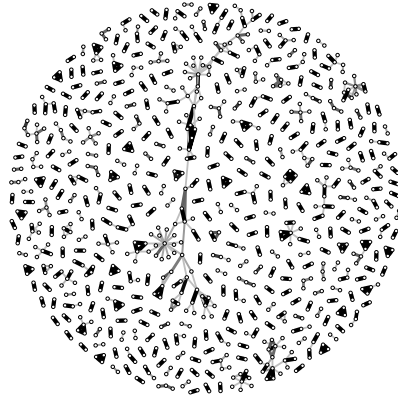


FIG. 3. *The set  $\mathcal{C}$  of candidate pairs for duplicate detection. Each node represents a record, and two nodes appear connected if their corresponding records are candidates to be coreferent (i.e., not fixed as noncoreferent in the preprocessing step). The color and width of the edges convey the same information: The darker and thicker the edge, the larger the proportion of partitions in the posterior sample that group the pair together. Therefore, the lightest and thinnest edges indicate that those pairs never appeared together, and the black and thickest edges indicate those pairs were grouped together across all partitions in the posterior sample.*

(level two of disagreement, see Table 2) given that it disagrees by more than one year (i.e.,  $\Gamma_{ij}^{\text{Year}} > 1$ ) should be at least 0.99. This prior specification constrains the prior probability of the level three of disagreement (difference of four or more years, see Table 2) to be very small among coreferent pairs.

Finally, the prior for the field day of death has lower truncation points since we believe this field to be more unreliable than the rest, given that we do not expect witnesses to have been very accurate reporting the exact date of the killings.

4.3. *Exploring the posterior sample of coreference partitions.* We obtained a posterior sample of partitions of size 19,800 using the Gibbs sampler and the implementation presented in the supplementary material [Sadinle (2014)]. For the sake of illustration, in Figure 3 we present a graph where each node represents one record, and the existence of an edge indicates that the pair was not fixed as noncoreferent in the preprocessing step, that is, there is one edge per pair in  $\mathcal{C}$ . This graph was obtained using the R package “igraph” [Csardi and Nepusz (2006)]. Our target coreference partition can be thought of as a subgraph of this graph composed by cliques. The sparsity of the graph in Figure 3 illustrates the impact of fixing trivially noncoreferent pairs in the preprocessing step: the number of pairs that have to be resolved is small, and the possible set of partitions of the file gets greatly constrained. In Figure 3 the color and the width of an edge are both proportional to the number of times that the pair appears grouped together across the chain of partitions. The thinnest and lightest edges indicate that the pair never appeared together in the partitions of the chain, whereas the thickest and black

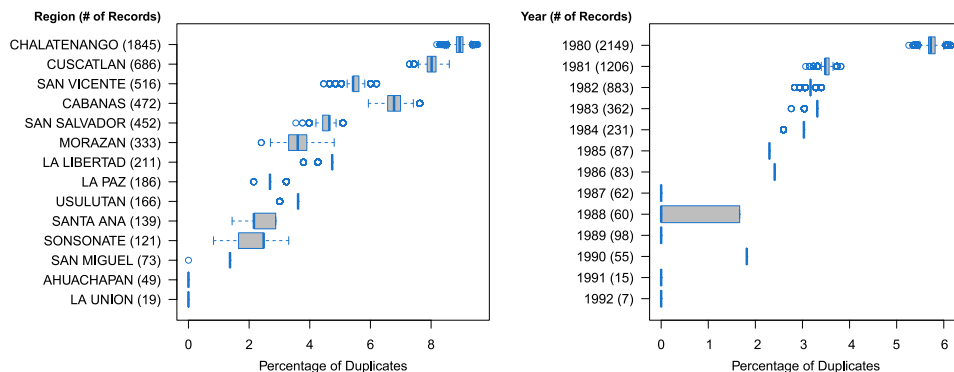


FIG. 4. *Left panel: Percentage of duplicates per reported region of death. The regions are ordered by the number of records. Right panel: Percentage of duplicates per reported year of death, in chronological order. In both cases the corresponding numbers of records appear in parenthesis.*

edges indicate that the pair appeared grouped together in all the partitions of the chain. The black edges in Figure 3 illustrate the property of the method of ensuring transitive coreference decisions.

The output of our method is a posterior sample of possible coreference partitions. Each of those partitions has a number of cells, which represent unique entities, or, in this case, unique homicides. The number of records minus the number of cells of a partition represents the number of duplicates according to that partition. We can therefore obtain a posterior distribution on this number. For the complete file, which contained 5395 records, the posterior distribution on the number of unique homicides has a mean and median of 5008, with a minimum of 4991, and a maximum of 5026 unique homicides, and a posterior 90% probability interval of [5001, 5015], which corresponds to a posterior interval on the percentage of duplicates of [7.04, 7.30]. The rate of duplication greatly varies across different subsets of the file. In Figure 4 we summarize the posterior distribution of the percentage of duplicates for subsets of the data file corresponding to the different reported years and regions. The left panel of Figure 4 presents the regions of El Salvador ordered by the number of records in the data file. We can observe that the percentage of duplicates is correlated with the number of homicides reported in that region: the more homicides reported, the larger the proportion of duplicates. A similar relation can be observed from the right panel of Figure 4, which shows the percentage of duplicates per year.

4.4. *Evaluation of results and sensitivity analysis.* Although there is no ground truth for the UNTC data file, it is important to have an idea of whether the results that we obtained are reasonable at all. To this end, we took the UNTC records that reported Cuscatlán and Ahuachapán as the regions of death (735 records), and identified possible duplicates among them by hand. At this point,

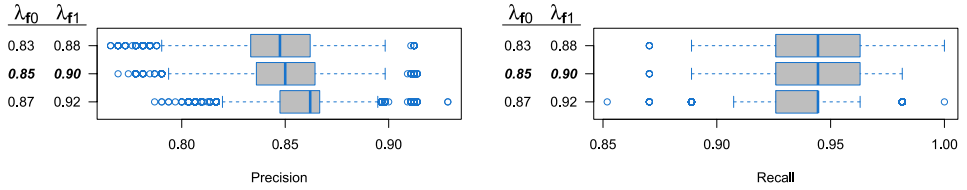


FIG. 5. Posterior distribution of precision (left panel) and recall (right panel) computed with respect to hand-labeled records for two regions of El Salvador. Results obtained under three different sets of prior truncation points  $\lambda_{f1}$  of the  $m_{f1}$  parameters. The  $\lambda_{f2}$ 's are fixed as in Table 5. The prior truncation points used in the application to the UNTC data set are indicated in bold italics.

it is important to clarify that we do not intend to treat these hand-labeled records as ground truth, since they are also the product of our subjective decisions, but rather we use them as a way to create a sanity check for our results. The idea is to compare each partition in the posterior sample with the hand-partitioned file subset in terms of precision and recall.

We also would like to explore how sensitive our results are to small changes in the prior truncation points that we chose. For this purpose, we obtained two new posterior samples of partitions using two alternative priors. We consider one prior more pessimistic and one more optimistic than the one used in our application, in the sense that the maximum amounts of error in the fields could be larger or smaller than the ones implied by the prior truncation points set in Table 5. These priors are obtained from subtracting/adding 0.02 to the prior truncation points of the  $m_{f1}$  parameters in Table 5, for  $l = 0, 1$ , and for all fields. For these two additional priors we keep the same truncations of the  $m_{f2}$  parameters.

In Figure 5 we summarize the posterior distributions of precision and recall under the different priors considered here. We can see that the precision of the method is somewhat sensitive to changes in the prior truncation points and, although the recall is somewhat robust, it starts to decay in the more optimistic scenario. These results agree with the findings presented in Section 3.5 for data files with a small number of fields. We conclude that the prior employed in the application to the UNTC data file achieves a good balance between precision and recall, since a more optimistic prior would lead to less recall, and a more pessimistic prior would lead to less precision.

Finally, we want to illustrate the issues that we would encounter if we were using a model that outputs pairwise coreference decisions for the UNTC data set. We implemented a two-components mixture model version of the model presented in Section 3 to classify the pairs in  $\mathcal{C}$  into coreferent and noncoreferent pairs. The mixture model is obtained by simply taking  $\Delta_{ij}|p \stackrel{\text{i.i.d.}}{\sim} \text{Bernoulli}(p), i < j$ , instead of treating  $\mathbf{\Delta}$  as the representation of a partition. We used Bayesian estimation of this mixture model employing the same priors for the  $m_{f1}$  and  $u_{f1}$  parameters as in the application to the UNTC data set, and  $p \sim \text{Uniform}(0, 1)$ . From running

a Gibbs sampler for 100,000 iterations, we obtained a posterior sample of  $\Delta_{ij}$ 's. The number of nontransitive triplets varies between 69 and 564 across the Gibbs iterations, which is not surprising given that this model treats the  $\Delta_{ij}$ 's as independent. As we mentioned in the [Introduction](#) of this article, if we wanted to use this mixture model approach, we would have to implement some ad-hoc strategy to ensure transitivity of the coreference decisions.

**5. Conclusions and future work.** We presented a novel, unsupervised approach to duplicate detection problems. This approach improves over current methodology since it guarantees transitive decisions, it allows us to incorporate prior information on the amount of error in the fields, and it provides a natural account for uncertainty of the coreference decisions in the form of a posterior distribution. We showed that the method provides reasonable results in an illustrative example and in a realistic simulation study. The application of this methodology to detect homicides reported multiple times to the Salvadoran UNTC indicates that, with 90% of probability, between 7.04% and 7.30% of those reports are duplicates.

A number of improvements can be made to this methodology. For example, the usage of field value frequencies would take into account that, for instance, a name that is relatively rare has more distinguishing power than a common one [[Winkler \(1989\)](#)]. Other extensions include modeling dependencies between field comparisons, possibly building on the work of [Larsen and Rubin \(2001\)](#), and point estimation for the coreference partition.

Our approach to duplicate detection is especially promising in the context of multiple systems estimation of population sizes, which plays an important role in human rights research [see [Lum, Price and Banks \(2013\)](#)]. It is important to note that the UNTC data file does not cover all the deaths that occurred during the civil war of El Salvador. Nevertheless, the combination of this source of information with other data files on killings can provide a better account of the lethal violence in El Salvador during the civil war. To pursue this goal, our future work includes the extension of this methodology to link multiple files, at the same time as finding duplicates within them. Our Bayesian approach to this problem will allow us to incorporate the uncertainty from record linkage and duplicate detection into subsequent procedures, such as population size estimation.

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## SUPPLEMENTARY MATERIAL

**Supplement to “Detecting duplicates in a homicide registry using a Bayesian partitioning approach”** (DOI: [10.1214/14-AOAS779SUPP](https://doi.org/10.1214/14-AOAS779SUPP); .pdf). We provide a Gibbs sampler for the model presented in Section 3, a brief discussion on point estimation of the coreference partition, we explain how we standardized and compared Hispanic names and, finally, we present details on the implementation of the Gibbs sampler for the application in Section 4.

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DEPARTMENT OF STATISTICS  
CARNEGIE MELLON UNIVERSITY  
PITTSBURGH, PENNSYLVANIA 15213  
USA  
E-MAIL: [msadinle@stat.cmu.edu](mailto:msadinle@stat.cmu.edu)