Some of Entity Resolution

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Whether the goal is to estimate the number of people that live in a congressional district, to estimate the number of individuals that have died in an armed conflict, or to disambiguate individual authors using bibliographic data, all these applications have a common theme — integrating information from multiple sources. Before such questions can be answered, databases must be cleaned and integrated in a systematic and accurate way, commonly known as structured entity resolution (record linkage or de-duplication). In this article, we review motivational applications and seminal papers that have led to the growth of this area. We review modern probabilistic and Bayesian methods in statistics, computer science, machine learning, database management, economics, political science, and other disciplines that are used throughout industry and academia in applications such as human rights, official statistics, medicine, citation networks, among others. Finally, we discuss current research topics of practical importance.
1 Introduction

As commonly known in computer science and statistics, entity resolution is the process of taking large, noising databases and removing duplicate entities (often in the absence of a unique identifier)\[1, 2, 3, 4, 5, 6, 7, 8\]. This task has become increasingly important in science given that the entity resolution task is critical in order to have more reliable analyses. Since then, entity resolution has been widely studied in many research fields such as statistics, computer science, machine learning \[9, 5, 10, 11, 6, 12, 8\], political and social science \[13, 14\], medicine and epidemiology \[15, 16, 17, 18, 19, 20\], official statistics \[21, 22, 23, 24, 25, 26\], human rights statistics \[27, 28, 29, 30, 31, 32\], author name disambiguation \[33, 34, 35, 36, 37\], and forensic science \[38, 39\], among many other disciplines.

This review is motivated by the long history of entity resolution, its active development in the scientific literature over the years, and its growing relevance throughout many scientific domains. We aim to enable the broader community to understand entity resolution methodology, from its foundation to recent modern developments. Specifically, we focus on social science and official statistics applications of entity resolution such as the United States (U.S.) decennial census, casualty estimation in armed conflicts, voter registration data, and the analysis of co-authorship networks. These applications often require uncertainty quantification – rigorous statements of confidence regarding results – as well as principled and interpretable methods which can be subjected to scientific scrutiny. In contrast with other recent reviews of entity resolution, we therefore emphasize probabilistic record linkage as well as recent progress with Bayesian approaches, graphical modeling, and microclustering. Furthermore, given the breadth of the field, we attempt to explain differences between these communities in a meaningful way as to bridge this gap. There has been an abundance of contributions due to the database, machine learning, and computer science communities (see surveys \[1, 2, 3, 4, 5, 6, 7, 8\]). In contrast to statistical
approaches, their focus has typically been on rule-based approaches [40, 41], supervised learning approaches [42], hybrid human-machine approaches [43, 44], and scalability [45].

Our review is structured as follows. Section 2 provides an overview of entity resolution, including impactful applications, terminology and definitions, challenges, and differences among entity resolution disciplines. Section 3 discusses rule-based and similarity-based approaches, which are popular due to their interpretability and scalability. Section 4 introduces probabilistic record linkage methods that have led to many advancements and extensions. Section 5 reviews advancements of modern probabilistic record linkage, which include extensions to the Fellegi and Sunter framework, Bayesian extensions, and semi-supervised and fully supervised record linkage methods. Moreover, this is where the most contributions from the machine learning and computer science communities have recently evolved, which contrasts that of the statistical literature. Section 6 reviews clustering-based approaches to entity resolution. We cover clustering tasks that are specifically post-processing steps, graphical entity resolution methods, and microclustering models. Section 7 discusses open research problems, and Appendix A provides references to open source software and datasets.

Finally, while we attempt to cover almost all of the entity resolution literature, its breadth makes it impossible to cover all of it. Our focus is solely on structured entity resolution, and our focus is not the other subtasks of the data cleaning pipeline [5, 6, 8]. In addition, we seek to strike a balance between many diverse communities working on the same problem that approach the entity resolution task differently. We hope this article will help build further understanding between the communities and bring them closer together.

2 Overview of Entity Resolution

One of the earliest references to record linkage (here considered synonymous to entity resolution) is from Dunn [46], who defined record linkage as the process of assembling pieces of information
that refer to the same individual. In 1946, Dunn wrote:

“Each person in the world creates a Book of Life. This Book starts with birth and
ends with death. Its pages are made up of the records of the principal events in life.
Record linkage is the name given to the process of assembling the pages of this
Book into a volume.”

In short, record linkage (or entity resolution) seeks to bring together all relevant information
about a person, business, or entity. This problem has gathered significant interest from the
scientific community, including in statistics, computer science, machine learning, database
management, finance, fraud detection, political science, official statistics, and medicine, among
many others. In this section, we provide an overview of some of the most important applications
of entity resolution that have been used throughout science in recent years for structured data
(section 2.1). In addition, we review terminology in entity resolution and the data cleaning
pipeline (section 2.2), and challenges in the entity resolution task (section 2.3). Finally, we
review critical differences between disciplines regarding how researchers approach the entity
resolution task.

2.1 Impactful Entity Resolution Applications

We now review applications across science that have motivated major developments in entity
resolution.

2.1.1 Decennial Census.

One important and timely topic is one that faces the United States Census Bureau each decade
when they attempt to count all the individuals in the population. This enumeration is used
to allocate resources for roads, schools, projects, and apportion representation of legislators.
Unfortunately, it has been shown difficult to accurate enumerate such a population using an
optional census, and response rates are often quite low. Furthermore, some individual may be
counted multiple times. For example, an individual that owns three houses might accidentally fill
out three census forms. As another example, individuals in group quarters (such as universities,
prisons, etc) are often double counted by their “group” and a family member/parent/guardian
[47]. De-duplication is thus needed to obtain an accurate enumeration, with new methodology
from the machine learning and statistical literature being recently proposed to this end [48]. This
methodology is scalable, while providing exact error propagation throughout the blocking and
the entity resolution task [48].

2.1.2 Human Rights Statistics

In this section, we review two case studies in human rights statistics.

**Documented Identifiable Deaths in El Salvador**  Between 1980 and 1991, the Republic of
El Salvador witnessed a civil war. There are three databases available for this conflict, where
duplications occur within and across each of the databases. The first two databases were collected
during the conflict, whereas the third database was collected after the conflict. The first two
databases contain reports on documented identifiable victims. The first source, El Rescate (ER-
TL), a nongovernmental organization (based out of Los Angelos, CA), collected electronic data
from published reports during the civil war [49]. The second source, Comission de Derechos
Humanos de El Salvador (CDHES), collected testimonials on violations from 1979 — 1991
[50]. The third source contains reports on documented identifiable victims after the civil war.
After the peace agreement in 1992, the United Nations created a Commission on the Truth
(UNTC), which invited citizens to report war-related human rights violations. As such, victims
can be duplicated in these data sets.

**Syrian Conflict**  One case study that has been of interest is the ongoing Syrian conflict. To
our knowledge, the Human Rights Data Analysis Group (HRDAG) provided the first published work in this domain \cite{51} \cite{28} \cite{52}. There are four sources that collected data during the same time period — Syrian Center for Statistics and Research (CSR-SY), Syrian Network for Human Rights (SNHR), Syria Shuhada website (SS), and the the Violation Documentation Centre (VDC). Each source provides documented identifiable deaths in the conflict. Attributes available are full full Arabic name, gender, death location, and date of death. HRDAG has labelled the data set, as outlined in their paper \cite{51}.

Both applications have proven to be extremely important to the development of the entity resolution literature. The El Salvadoran application is important as it is an application to small scale human rights data, where some attributes contain a great deal of noise due to the way the information was collected. Given uncertainty in the data, it is natural in this application to utilize fully unsupervised approaches. Furthermore, uncertainty propagation of the entity resolution process has been demonstrated to be important in recently published case studies \cite{53} \cite{50} \cite{30} \cite{31} \cite{32}. In addition, the Syrian data set is also important given that researchers have proposed a near-linear time algorithm for unique entity estimation that provides uncertainty quantification of the number of documented identifiable deaths \cite{54}.

2.1.3 Estimation of Voters in North Carolina.

Another application that has been recently utilized in science has been voter registration databases, which are publicly available (and often online) in the United States. For example, the North Carolina State Board of Elections publicly posts is voter registration database (NCSBE, http://www.ncsbe.gov/). This dataset contains rich information, such as first and last name, year of birth, phone number, and address. However, the voter registration number is often duplicated due to people moving, getting married, and various other reasons. See Table 1 for examples of public records from this dataset. The process through which voter registration
Table 1: Example of public NCSBE records retrieved from [http://www.ncsbe.gov](http://www.ncsbe.gov) for the county of Durham in North Carolina and corresponding to unique voter registration numbers. Some fields have been omitted for brevity, including ZIP code, phone number and voter registration number. Street addresses have been permuted with other individuals as to preserve some anonymity.

| Name                      | Street Address       | Age | Sex | Race | Birth | Party |
|---------------------------|----------------------|-----|-----|------|-------|-------|
| Domineck Q. AAshad Jr     | 914 Monmouth Ave #3  | 26  | M   | B    | –     | LIB   |
| Domineck Q. AAshad Sr     | 1408 Auburndale Dr   | 55  | M   | B    | NY    | DEM   |
| Xiomara A. Martinez       | 1715 Cole Mill Rd    | 31  | F   | O    | HL    | REP   |
| Xiomara A. Martinez       | 2923 Forrestal Dr    | 31  | F   | O    | HL    | –     |
| Virginia, L. Mullinix     | 749 Ninth St #480    | 101 | F   | W    | PA    | REP   |
| Jacqueline D. Fuller      | 141 Bagby LN         | 54  | –   | –    | –     | DEM   |
| Jacqueline Fuller         | 905 Cook Rd          | 56  | F   | B    | NC    | DEM   |

records are matched with other official records can have a profound influence on one’s ability to vote. Georgia’s controversial “exact match” law [55], which was slightly changed in 2019, required an exact match between voter registration records and records from the Department of Driver Services or the Social Security Administration in order to validate voter registrations. For instance, typographical errors, different spellings of the same name, or outdated records could place a voter registration on hold. In 2017, about 670,000 registrations were canceled as a result [56]. Enamorado [57] showed how this law could predominantly affect non-white voters (see also [58]). This application illustrates the need for uncertainty quantification and fairness analyses.

2.1.4 Inventor and Author Disambiguation.

Author disambiguation data sets have been utilized broadly throughout statistics, computer science, and machine learning. These are either fully labelled (or partially labelled) benchmark data sets that tend to illustrate success on new methods. On the other hand, there are research questions of interest that can be posed from fully unsupervised author disambiguation using such
data sets that do not contain any training labels, where the labels would also need to be provided in a principled manner that would not be biased toward any proposed algorithm.

Appendix A.3 reviews recent benchmark data sets, where one can find a more comprehensive review of author disambiguation data sets and methodology in [59]. Appendix A.3 reviews research data sets, which typically do not have unique identifiers or went through an intensive and well-documented manual labelling process. In general, there does not appear to be a strong consensus within the author disambiguation community regarding a standard on benchmark data sets, which holds true for the rest of the entity resolution literature. In addition, most of the entity resolution data sets (including the hand labelled pairs) are not easily reproducible by authors, which presents a strong need for communities to set forth more clear standards regarding how such data sets should be created such that data sets do not favor one proposed method over another.

These applications have proven to be impactful as researchers and industry leaders have been able to consider many types of methods, such as deep learning models, semi-supervised and fully-supervised methods, among others, illustrating the strength of these approaches for this particular application.

2.2 Terminology and Definitions

In this section, we introduce terminology that will be used throughout the article that is commonly known and used in the existing literature [5, 60, 6]. In addition, we formally define the entity resolution problem.

A database (file) is a collection of records. A record in a database contains attributes (fields or features), such as given name, family name, date of death and municipality. In this article, we assume each record refers to an entity (person, object or event) with respect to which we want to aggregate relevant information. Entity resolution is the problem of identifying records which
refer to the same entity, such as identifying individual victims among recorded deaths which contain duplication. Two records which refer to the same entity are said to be co-referent (a link) or to be non co-referent otherwise (non-link). Entity resolution can be framed as clustering records according to the entity to which they refer or, equivalently, of identifying co-referent record pairs. This is also referred to as record linkage, de-duplication, data matching, instance matching, and data linkage.

**Remark.** Performing entity resolution on a single database which contains coreferent records (duplicates) is often referred to as de-duplication (or duplicate detection). This is the simplest case, where any structure corresponding to the source of each record is ignored. When the data is part of two databases, with duplication across but not within databases, the problem is referred to as bipartite record linkage.

### 2.2.1 The Data Cleaning Pipeline

Entity resolution is usually thought of one stage in the data cleaning pipeline [2,60,5] represented below:

\[
\text{attribute alignment} \rightarrow \text{blocking} \rightarrow \text{entity resolution} \rightarrow \text{canonicalization.} \quad (1)
\]

In the first stage, attribute or schema alignment, records are parsed as to identify a set of common attributes among the datasets. In the second stage, blocking, similar records are grouped into blocks. Only records appearing in the same block will then be compared; records that do not appear in the same block are automatically determined to be non-matches. In the entity resolution stage, coreferent records are identified. Finally, in the fourth stage, merging, data fusion, or canonicalization, entities resolved as matches in the third stage are merged to produce a single representative record. **The focus of this review article is on structured entity resolution and not on the other stages of the pipeline.** For surveys of the entire pipeline, we refer to [5, 6, 8].
2.3 Challenges of Entity Resolution

Entity resolution tasks face a tradeoff between (1) scaling to large databases, (2) providing uncertainty propagation of the entity resolution task through all stages of the data cleaning pipeline, and (3) proposing methods that account for the distortions and errors found in the databases. For databases with a combined total of \( N \) records, there are \( \frac{N(N - 1)}{2} \) pairs of records which must be considered as being possibly co-referent. Evaluating each pair is therefore not scalable as the number of records grows. Most entity resolution methods avoid comparing all pairs by *blocking*. While this increases the computational speed, uncertainty cannot be propagated exactly from the blocking stage to the entity resolution stage as shown in diagram [1]. Specifically, the entity resolution task will inherit any errors from the blocking task, some of which cannot be resolved. On the other hand, one can achieve exact uncertainty propagation by building a joint blocking and entity resolution model, however, this typically results in slower computational run times. Finally, when dealing with data that contains distortions, typographical errors, and noise, generative methods have seen success. Such models are typically more complex, and thus, are typically may not scale to large databases. The tradeoff between (1)–(3) must be evaluated by the user based upon each motivating application so that the most appropriate method can be chosen.

2.4 Differences in Entity Resolution Disciplines

As previously stated, entity resolution is a broad interdisciplinary field of research. Given our motivating applications, our review paper is specifically concerned with *structured* entity resolution problems, where records are composed of clear attributes such as names, phone numbers, etc. This can be contrasted with *unstructured* entity resolution, where entity instances may contain textual descriptions or images. Additionally, we focus on entity resolution approaches which provide uncertainty quantification, such as probabilistic record linkage, Bayesian approaches, graphical modeling approaches, microclustering models, and semi and fully supervised
approaches, among others. These methods are needed in scientific applications where all sources of uncertainty which may affect the validity of results must be accounted for. The main challenge, in this case, is to properly quantify this uncertainty and to account for it in downstream analyses. This is a very different focus than what is found in most of the computer science, machine learning, and database management literature, where the main goal is to address big data challenges such as large amounts of data, continuously evolving databases, and streaming data. Without losing sight of our motivating applications, we have attempted to highlight approaches from both disciplines in order to bring these communities (and others) closer together.

3 Deterministic Record Linkage

In practice, the most commonly used record linkage methods are based on a series of deterministic rules involving the comparison of record attributes. These are called deterministic, rule-based, and similarity-based approaches. A simple example is exact matching, where two record pairs are linked if they agree on all common attributes. This strict matching condition can be relaxed by allowing mismatch on a fixed number of attributes, by using disjunctions of exact matching rules, and by using similarity functions. These rules can also be learned from data, bringing us closer to the topic of probabilistic record linkage discussed in sections 4.2 and 5. However, the differentiating characteristic of deterministic approaches is that they do not account for uncertainty in the matching process. No probability model is used and no level of confidence is provided for the matching status of record pairs.

Record attributes are often distorted by noise (due to data entry errors, variant spellings, outdated records, etc.). Naturally, linkage rules should account for slight differences between attributes. One simple way to quantify such differences for names, addresses, and other textual attributes is via string distance functions. For westernized words, edit distances such as the Levenshtein distance \([61, 62]\) are used to account for deletions, insertions, and substitutions. The
Jaro-Winkler distance \([21, 63]\) works well for the comparison of short strings such as name. In addition to edit distances and their variants, token-based similarity measures such as the Jaccard similarity and the cosine similarity are often used when dealing with unstructured text and longer strings. We refer the reader to \([64, 65]\) for more information regarding simple string distance functions.

In practice, rule-based systems are carefully crafted for the application at hand. As noted in \([66, 67]\), a large body of work in the computer science and database communities is devoted to rule-based methods. This includes the specification and learning of linkage rules (including learning string similarity functions) \([68, 69, 70, 40, 71, 72, 73]\), the use and efficient computation of similarity functions \([74, 75, 76]\), the use of indexing structures and algorithms for efficient execution of record linkage in large databases (including blocking and filtering) \([77, 78, 79, 80]\), the use of clustering techniques to resolve linkage transitivity (see section \([6.1]\) \([81, 82, 83]\), and the integration of matching records (data fusion) \([60, 84]\). Notably, \([85]\) provides algorithms to minimize the number of pairwise comparisons when matching and merging records. This literature is thoroughly reviewed as part of \([1, 6, 7, 8]\). These methods allow the use of entity resolution at much larger scales than what is possible using probabilistic approaches of the kind discussed in the following sections. Additionally, they can be used as part of a blocking stage to scale up other entity resolution methods which account for uncertainty.

While deterministic approaches are appealing for their simplicity, interpretability, and computational scalability, empirical studies comparing deterministic and probabilistic record linkage techniques used for epidemiological research have shown consistent improvements of probabilistic methods over deterministic approaches \([86, 87, 88, 89, 90]\). Other literature has surveyed probabilistic versus deterministic methods more broadly in terms of comparisons, also finding improved performance with probabilistic methods \([91, 92]\). While being application-specific, these evaluations showcase the potential of probabilistic approaches when linking noisy data,
both accounting for uncertainty and providing good performance.

4 Probabilistic Record Linkage

We now take a step back and turn to the earliest published works on probabilistic record linkage. These works have laid down foundations for the field which we use as the basis of our discussion of modern methodology. First, we discuss the work of Halbert Dunn who defined record linkage, leading to the first algorithm solution by Newcombe et al. [93] (section 4.1). Next, we discuss in depth the Fellegi-Sunter record linkage framework [94] (section 4.2). This framework provides a principled statistical model for record linkage which is still widely used today. It has the notable property of requiring no training data for record linkage — it is entirely unsupervised. Since its introduction in 1969, the Fellegi-Sunter has been widely studied, extended, and even recently reinvented [95]. These extensions, such as more flexible modelling, Bayesian propagation of uncertainty, and semi-supervised learning, are discussed afterwards in section 5.

4.1 Dunn’s “Book of Life” and Early References

As previously mentioned, the concept of record linkage first appeared in a paper by Dunn [46] in 1946. In the context of administering governmental programs and services, he defined record linkage as the process of assembling pieces of information which refer to the same individual.

Interestingly, Dunn framed record linkage as an entirely logistical problem: if birth certificate numbers were widely used, then any centralized index would effectively bind individual records into this “book of life.” However, the reality is that birth certificate numbers, or other unique identifiers for that matter, are not widely used. Records collected from different organizations, at different times, and for different purposes, usually cannot be trivially matched together. Record linkage thus becomes an algorithmic problem — what can best be used to identify records which refer to the same individual, given noisy, uncertain information?
This is a problem which Newcombe et al. [93] faced in 1959 when trying to match birth and marriage records for demographic studies [96, 97, 98, 99]. The authors proposed, to our knowledge, the first automated record linkage method, which did not require a unique identifier. Specifically, they used domain knowledge of last names, first initials, birth places, ages (of some records), and location of child birth/marriage events. While no single one of these pieces of information was entirely reliable, together they were used for accurate record linkage. The idea of their method was quite simple and had two steps. In the first step, the authors utilized blocking. Specifically, to account for variations in spelling, records were blocked (indexed) based on the Soundex coding of the names. Note that the Soundex coding scheme was introduced by Margaret K. Odell and Robert C. Russell (see U.S. patents 1261167 (1918) and 1435663 (1922)). It codifies names by the first letter and by a string of three numbers, with the property that phonetically similar names often share the same code. Table 2 provides an example of attribute information from compared marriage and birth records from the original [93]. Second, when Soundex coding agreed between two records, they computed a likelihood ratio comparing the hypothesis that the record pair were a match to the hypothesis that they were not. If this likelihood ratio exceeded a threshold, then the two records were linked (declared co-referent); otherwise, they were not linked (declared non co-referent). Studies of the accuracy of the linkage showed about 98.3% of the true matches were detected, and about 0.7% of the linked records were not actual matches. In terms of computational speed, 10 records could be linked every minute on the Datatron 205 computer.

In short, the work of [93] introduced key ideas for record linkage in an application to demographic data, where blocking (indexing) was used to make the problem computationally tractable. They proposed an informal statistical approach based on a likelihood ratio test, where the pipeline was fully automated and required no training data.
Table 2: Example of attribute information from marriage and birth records. This table is adapted from Table I of [99] and translated from French to English. AB and PE represent the Canadian provinces of Alberta and Prince Edward Island. Only the initials of the first and middle names are provided in this data.

### 4.2 A Theory of Record Linkage

We now turn to the Fellegi-Sunter framework [94] introduced in 1969 and which formalizes the approach of Newcombe et al. [93] in a decision-theoretic framework. We will define the likelihood ratio of the type used by Newcombe et al. and we will see how records can be linked while controlling fixed error rates. Furthermore, we will review the Fellegi-Sunter probability model, its interpretation, and its underlying assumptions.

The decision model of the Fellegi-Sunter framework considers records in independent pairs. For a given pair of records, three possible actions are considered: to link, to possibly link, or to not link. The goal is to minimize the number of possible links, while controlling for type I and type II error rates (false match rate and false non-match rate). In the Fellegi-Sunter framework, an optimal linkage procedure attains the specified error rates while minimizing the number of possible link assignments. A “fundamental theorem for record linkage” demonstrated by the authors shows that the optimal linkage procedure corresponds to thresholding a likelihood ratio.

The likelihood ratio is defined as follows. Let $\gamma$ be the comparison vector used to represent the level of agreement/disagreement between two specified records. In practice, $\gamma$ is usually
decomposed as \( \gamma = (\gamma_1, \gamma_2, \ldots, \gamma_k) \), where each \( \gamma_i \) corresponds to a comparison between a particular attribute (name, age, etc.) of the record pair. One can consider binary comparisons, where \( \gamma_i \in \{0, 1\} \) represents agreement or disagreement between record attributes, as well as more detailed comparisons involving the specific value for which there is an agreement (such as \( \gamma_i = \text{"initials agree and are J&M"} \)). Now let \( m(\gamma) \) be the probability of observing the comparison vector \( \gamma \) for two records that are an actual match, let \( u(\gamma) \) be the probability of observing the comparison vector \( \gamma \) for two records that are not a match. The likelihood ratio is then defined as \( m(\gamma)/u(\gamma) \) and its logarithm \( W(\gamma) = \log(m(\gamma)) - \log(u(\gamma)) \) is called the matching weight.

Two unsupervised methods are proposed by Fellegi and Sunter to estimate the \( m \) and \( u \) probabilities. In both methods presented below, the authors assumed conditional independence between the attribute comparisons \( \{\gamma_i\}_{i=1}^k \) given the true underlying match/non-match status of the record pairs.

First, the authors considered detailed comparison vectors, which provide both an indication of agreement or disagreement for each attribute and a precise shared value in the case of an agreement. This allows one to exploit specific information about the record’s attributes. For instance, two records agreeing on the less common name “Xander” are more likely to be a match than two records which only agree on the first name “John.” In applications, it is often helpful to exploit such frequency information. Under this assumption, the authors used the frequency distribution of the record’s attributes, together with prior information about error rates, to obtain estimates of the \( m \) and \( u \) probability distributions.

Second, the authors considered binary comparisons, where each \( \gamma_i \) is a binary variable indicating agreement or disagreement the records’ \( i \)th attribute. The distributions \( m \) and \( u \) can then be estimated from the observed frequencies of agreement or disagreement between these fields. In particular, they derived analytical formulas to estimate \( m \) and \( u \) when only three fields
are under comparison.

Winkler [100] extended the above estimation methods by proposing the use of the EM algorithm to estimate the $m$ and $u$ distributions both in the context of detailed comparisons between fields (where particular agreement values are also taken into consideration) and binary comparisons. Independently, Jaro [21] proposed the EM algorithm for binary comparisons and considered its application for matching the 1985 test census (dress rehearsal) of Tampa, Florida, to an independent post-enumeration survey as to evaluate the census coverage.

**Interpretation of the Probability Model** While the Fellegi-Sunter approach was introduced in a decision-theoretic framework, it can be interpreted more easily through its underlying probability model, where the comparison vectors $\gamma$ are distributed as the following mixture model:

$$p(\gamma) = \lambda m(\gamma) + (1 - \lambda) u(\gamma),$$

where $\lambda > 0$ is the probability that a randomly chosen comparison vector corresponds to a matching pair of records. The methods proposed by Fellegi-Sunter, as well as the EM algorithm proposed by Jaro and Winkler [21, 100], provide estimates of the parameters $\lambda$, $m$, and $u$.

Denote a true match by $M$. Using Bayes rule, one can express the probability that two records match given their comparison vector $\gamma$, as

$$p(M \mid \gamma) = \frac{\lambda m(\gamma)}{p(\gamma)} = 1 - \left(1 + \frac{m(\gamma)}{u(\gamma)} \frac{\lambda}{1 - \lambda}\right)^{-1}. \quad (2)$$

The left-hand side of equation 2 is the posterior probability of a match, and the right-hand side shows how it can be obtained as a monotonous transformation of the Fellegi-Sunter likelihood ratio $m(\gamma)/u(\gamma)$. Therefore, as noted in [101], thresholding the posterior probability to assign links is equivalent to using a likelihood ratio test and the Fellegi-Sunter optimality result also applies in this context.
Assumptions of Fellegi-Sunter  The Fellegi-Sunter framework relies on crucial simplifying assumptions.

The first assumption is that comparison vectors between the records pairs should be independent from one another. This is usually not satisfied in practice. For example, when Newcombe et al. [93] linked birth and marriage records, it was known that two different marriages could not result in the same birth. This constraint induces dependencies between comparison vectors, and applying the Fellegi-Sunter procedure can lead to impossible linkage configurations when this is not taken into consideration. Generally, any linkage which does not satisfy transitive closure is impossible — knowing that $a$ links to $b$ and that $b$ links to $c$ should entail that $a$ also links to $c$.

The second assumption is that the $m$ and $u$ distributions are known or can be adequately estimated. And to be practically feasible, their estimation relies on simplifying assumptions which usually do not hold. For one thing, the estimation methods discussed so far require conditional independence between the comparison of different record attributes, given the true match/non-match status of the record pairs. [102] first remarked that this conditional independence assumption may not hold in practice. [103] (see also [104, 105, 106]) proposed log-linear models with interaction terms to account for dependencies between field comparisons and showed improved performance in some applications.

Given that the assumptions of Fellegi-Sunter are often not satisfied, this has led to many extensions in the literature, which we review in section 5.

5 Modern Probabilistic Record Linkage

In this section, we review modern probabilistic record linkage, which includes extensions to the Fellegi-Sunter framework, Bayesian variants of Fellegi-Sunter, as well as semi-supervised and fully supervised classification approaches.
5.1 Extensions of Fellegi-Sunter

In many applications, neither the procedures of Fellegi-Sunter nor of Tepping is used to set classification thresholds. According to Belin and Rubin [107], for the matching of the 1990 Census with the post-enumeration survey, thresholds were set “by ‘eyeballing’ lists of pairs of records brought together as candidate matches.” Part of the reason is that the error rates fixed in the Fellegi-Sunter framework, as well as the false-match rates estimated using equation[2] are not attained in practice [105, 108, 104, 107]. This is due to the various simplifying assumptions and estimation errors involved in the application of such models. Therefore, methods using training data (classified record pairs) have been proposed to automate and improve the choice of tuning parameters in probabilistic record linkage.

For instance, Belin and Rubin [107] proposed to calibrate thresholds and error rates by using training data to fit a mixture model to the matching weight distribution. This allowed the authors to quantify uncertainty about the linkage’s error rates and to calibrate the Fellegi-Sunter thresholds. Nigam et al. [109] showed how training data could be combined with unlabeled data as to improve the estimation of the $m$ and $u$ distributions using the EM algorithm for text classification. Building on the same semi-supervised framework, [110, 111] and [101] considered fitting more complex models allowing for dependencies between field comparisons. Finally, Enamorado et al. [14] has scaled the seminal Fellegi-Sunter model to large databases, where they incorporate auxiliary information into the merge and post-merge analyses [112].

5.2 Bayesian Fellegi-Sunter

In the context of entity resolution, Bayesian methods provide a way to quantify and propagate uncertainty for the joint linkage structure of a set of records. Furthermore, Bayesian methods allow the incorporation of prior knowledge, such as linkage transitivity, into analyses. These properties have made them popular in inferential and scientific applications, where uncertainty
must be taken into account in order to reach sound conclusions and where prior knowledge is often available. This section reviews Bayesian record linkage methodology which extends the Fellegi-Sunter framework.

Fortini et al. [23] extended the seminal work of [94] in the special case of bipartite record linkage. The authors assumed a prior on the “matching pairs,” a prior on the “matching configuration matrix,” and a Dirichlet prior on the m and u distributions. Here, the matching configuration matrix, or coreference matrix, indicates the linkage structure between two databases. That is, if we denote by i a record in the first database and j a record in the second database, then this matrix has entries $c_{i,j} \in \{0, 1\}$, with $c_{i,j} = 1$ if records i and j are linked and $c_{i,j} = 0$ otherwise.

More recently, Sadinle [30] proposed the first Bayesian Fellegi Sunter model, where he assumed two databases and a de-deduplication scenario. He assume a likelihood similar to that of [23]. [30] considered a partitioning approach which allows for transitive closures to be satisfied. This allows quantification of uncertainty about the partition of records through a posterior distribution. In later work, Sadinle [31] extended the above framework for bipartite record linkage. In addition, the authors derive Bayes estimates under a general class of loss functions, which provides an alternative to the Fellegi-Sunter decision rule. Both the work of [30] and [31] apply their proposed methodology with deterministic blocking rules to the case study on human rights in El Salvador. In addition to proposing new methodology, [30] performed hand-matching on a small set of the dataset such that pairwise evaluation metrics could be utilized. The work of [30, 31] has been extended in [113], where the author accounts for dependencies between fields and for heterogeneity in the comparison vector distribution.

One difficulty facing Bayesian Fellegi-Sunter is their computational burden. In other recent work, [13] considered this issue by proposing a blocking approach based on simpler probabilistic record linkage techniques. That is, the output of more simple non-Bayesian probabilistic record linkage is used to perform “post-hoc blocking,” after which a Bayesian Fellegi-Sunter method is
used for coherent modeling and uncertainty quantification. This allows the authors to scale their proposed method to voter registration and census datasets with million of entries.

5.3 Semi- and Fully Supervised Classification Approaches

The approaches of [107, 109, 111, 110] and [101] discussed in section 5.1 were semi-supervised [114]. Semi-supervised methods use a relatively small amount of manually classified record pairs, known as labeled pairs, to improve upon unsupervised probabilistic record linkage. In this section, we review semi-supervised methods as well as fully supervised methods which focus on classifying record pairs as a first step to entity resolution.

Note that the use of training data in entity resolution can be a complex problem. In many statistical applications, such as with the El Salvadoran dataset, ground truth is not available. The closest available data for use in training might come from one or more human experts through costly review processes. However, despite best efforts, experts can be subject to errors, biases, and uncertainty. Furthermore, the sampling process from which labeled data is obtained is highly influential and must be accounted for. These issues are the topic of broad research on sampling/querying, crowdsourcing, active learning, and performance evaluation for entity resolution. Here we only briefly touch on these topics, instead focusing on methods which assume a single set of reliable labels.

Semi-Supervised Approaches Following the terminology of [114], we consider three types of semi-supervised approaches. First, generative semi-supervised approaches target the joint likelihood of the labeled and unlabeled data as in Nigam et al. [109] and Larsen and Rubin [101]. Building on this framework, Enamorado [115] proposed an active learning algorithm which iteratively requests labels for specific record pairs. Other active learning approaches are proposed in [116, 117, 118, 119, 120]. Second, change of representation semi-supervised approaches use
unsupervised learning as a first step to summarize the data (such as performing dimensionality reduction), before using a supervised algorithm for further analysis. For instance, Belin and Rubin [107] used the unsupervised Fellegi-Sunter framework to obtain univariate matching weights for all record pairs, before using labeled examples to fit a mixture model to the matching weights. This allows the authors to calibrate the model and potentially select better thresholds.

Third, self-learning algorithms generalize the semi-supervised EM algorithm considered in [109] and [101] to model-free classifiers. In this framework, [121] combined self-learning and boosting of random forests and multi-layer perceptrons as to obtain good performances on entity resolution tasks using only small amounts of labeled pairs.

**Fully Supervised Approaches** Fully supervised methods do not exploit information provided by unlabeled examples; instead they rely on larger numbers of labeled pairs. Given the significant class imbalance when considering record pairs (very few pairs match), vast amounts of reliable training data or carefully selected training data is required for the use of these methods. This training data may come from crowdsourcing [116, 43, 122, 44, 123], from extensive manual record linkage efforts [124, 125, 126], or it may be automatically generated using unsupervised methods as to obtain an approximate training set [127, 128, 129]. In practice, the amount of reliable training data necessary to train sophisticated learning algorithms such as deep neural networks [130, 131, 132, 42, 133, 134] is not always available for entity resolution tasks. For instance, [133] uses over 10 million examples of labeled record pairs (corresponding to more than 3,000 resolved individual records) in an application in order to train deep neural networks.

More recently, [134] considered the issue of training deep neural networks for entity resolution with fewer labels, using active and transfer learning. The use of deep learning techniques in entity resolution is especially promising in application to unstructured or textual problems (see [42, 135, 136]), where, for instance, pre-trained language models can be used [137].
structured entity resolution, simple classifiers (such as logistic regression, decision trees, random forests, Bayesian additive regression trees, others [138]) are often preferred.

To give an example of how such methods are used in practice, consider the work of [139], a case study for inventor disambiguation in the bibliographic database of U.S. Patent and Trademark Office (USPTO) patents. The authors proposed a supervised method based on random forests for deduplication. Their training data was constructed from the curriculum vitae of inventors in the field of optometrics as well as from a previous study on “superstar” academics in the life sciences [140, 125]. This allowed them to evaluate the performance of previous methods used in this application [141, 142] and to train their random forest classifier on labeled comparison vectors of record pairs. Afterwards, applying their entity resolution approach to other records in the USPTO database consisted of a four-stage pipeline. First, they use blocking where, in each block, they calculated comparison vectors for each record pair. Second, the authors calculated the predicted probability of a match using their random forest classifier applied to these comparison vectors. Third, the predicted probability was converted into an estimate of the dissimilarity between each pair of records. Fourth, the authors utilized single linkage hierarchical clustering corresponding to the dissimilarity scores in the previous step to enforce transitive closures among record pairs. Clusters were determined by cutting the dendogram (tree) at a threshold. Finally, all the clustering results were combined across blocks to obtain a final set of de-duplicated records. Such clustering approaches to entity resolution, used either directly or as a follow-up to pairwise classification, are discussed next in section 6.

5.4 Active learning

Active learning models are based on semi-supervised or fully supervised models. Instead of using a pre-determined set of training data, however, they interactively request informative labeled data from an expert labeler. Their goal is to provide a balance between automation and
human interaction, although this balance is difficult to quantify. These models perform well on many entity resolution applications – given the large class imbalance in entity resolution tasks, informative training data may be difficult to choose a priori [143]. The active learning workflow for entity resolution is nicely reviewed in [8], where the authors consider early and modern approaches in the literature.

6 Entity Resolution as a Clustering Problem

The methods discussed so far focused on estimating the probability of a match between pairs of records given their comparison vector. This pairwise match probability provides a measure of uncertainty about specific links, where the corresponding false match and false non-match rates (or precision and recall) are pairwise evaluation metrics of performance. With the exception of Bayesian Fellegi-Sunter, these methods treat record pairs as being independent of one another, without accounting for the consequences of transitivity or other constraints on the linkage structure. This limits their practicality when linking more than two databases (and dealing with applications that have duplication across/within databases). Much of the literature has therefore advocated for a clustering-based approach to entity resolution and deduplication which can integrate multiple databases [81, 144, 145, 30, 146, 147, 148, 149, 150, 31, 48, 151]. In this context, the goals shift. Instead of linking record to record, the goal is to cluster records to their true (unknown, latent) entity.

A large portion of this literature uses clustering as a second step to probabilistic record linkage to enforce transitivity of the output [82, 6]. Other clustering approaches are model-based, and in particular we focus on graphical entity resolution in section [6.2]. By probabilistically modeling the relationship of records to the latent entities to which they refer, these methods naturally provide uncertainty quantification regarding the clustering structure [148, 152]. Finally, entity resolution can be viewed as what we refer to as a microclustering problem, meaning that
the size of the latent clusters grows sub-linearly as the number of records grows. This means that entity resolution does not experience power law (linear) growth as many traditional clustering tasks. We discuss microclustering in sections 6.3.

6.1 Clustering as a Post-Processing Step

Many clustering approaches to entity resolution are based on pairwise similarities, pairwise match probabilities, or determined links and non-links. Therefore, these can be seen as post-processing the result of other pairwise record linkage procedures. They are used to resolve intransitivities in the linkage method and ensure a coherent output. There is a vast literature on the subject; we only review a selection of the proposed methodology for entity resolution. We refer the reader to [82, 3, 5, 153] and [6] for more exhaustive reviews.

One of the first references in this area is Monge and Elkan [81], who framed entity resolution as a clustering problem. Specifically, they proposed that one should detect the connected components in the undirected graph of pairwise links (see also [154, 155]) using a dynamic connectivity structure. Pairwise links were determined iteratively. At any given step, only records which were not in the same connected component were compared in order to determine the match/non-match status. It allowed the authors to resolve intransitivities in pairwise matching while avoiding superfluous comparisons. The idea of clustering through connected components is computationally efficient and has recently been exploited as part of a blocking stage in McVeigh et al. [13]. A more sophisticated technique, correlation clustering [156], maximizes the number of links within clusters plus the number of non-links across clusters. This approach was originally introduced in the context of document classification. The number of clusters is determined from an objective function, which is one advantage of this method. However, correlation clustering is NP-hard [157, 156] and in practice variants and approximate solutions are used [158, 159, 160, 82]. Another approach is hierarchical agglomerative clustering [161, 138].
which Ventura et al. [146] advocated in conjunction with ensemble classifiers for large scale entity resolution. Ventura et al. [139] also applied this method for inventor disambiguation in the USPTO dataset as discussed in section 5.3.

6.2 Graphical Entity Resolution

We now turn to model-based clustering approaches which allow quantification of uncertainty about the clustering structure. Battacharya and Getoor [162] built on the Latent Dirichlet Allocation (LDA) model to this end, where the goal in their application was to resolve individual authors in bibliographic databases. Their approach leveraged co-authorship groups (analogously to topics in LDA) in order to support the entity resolution process. They probabilistically modeled the unknown set of individual authors, the authors’ group membership, as well as possible distortions in authors’ names. Posterior inference was carried out using Gibbs sampling.

In a similar spirit, Tancredi and Liseo [145] proposed a new model for record linkage which, instead of linking record to record, linked records to latent individuals. The authors used the hit and miss model of [163] as a measurement error model to explain possible distortions in the observed data. This deviates from the Fellegi-Sunter approach as it does not utilize comparison data, instead working with the actual attribute information.

We refer to such approaches, where one recovers a bipartite graph linking records to reconstructed latent entities, as graphical entity resolution. More specifically, in [147] and [152], the authors developed a fully hierarchical-Bayesian approach to entity resolution, using Dirichlet prior distributions over categorical latent attributes and assuming a data distortion model. They derived an efficient hybrid (Metropolis-within-Gibbs) MCMC algorithm for fitting these models. As with other Bayesian approaches, this allows full quantification of uncertainty regarding the number of latent individuals and the clustering structure of records into coreferent groups. In addition, [152] showed that for the proposed work and the work of [30] and [145], the use
of a uniform prior on the set of links or non-links, in practice, leads to one having a biased estimation of the sample. This, in turn, led to the development of subjective priors on the linkage structure which have appeared in [150]. In addition to Bayesian models for categorical data, [148] extended the above work to both categorical and noisy string data using by proposing a string pseudo-likelihood and an empirically motivated prior.

Motivated by the computational limitations of [148] and a case study of the 2010 Census, [48] have proposed a scalable extension to this model. Their approach uses probabilistic blocking at the level of the latent entities, which enables distributed inference through a partially collapsed Gibbs sampler while accounting for blocking uncertainty.

6.3 The Microclustering Property

The work of [148] and [152] led to interesting developments both in clustering and in entity resolution. The first is the formalization of the microclustering property, which describes the sub-linear growth of clusters in entity resolution (and in other clustering tasks such as community detection). That is, one expects the size of the clusters to grow sub-linearly as the total number of records also grows [150]. On the other hand, traditional probabilistic, generative models for clustering, such as finite mixtures [164], Dirichlet processes [165, 166, 167], Pitman-Yor processes [168, 169], and many others assume a power law growth in the total number of records (data points) [170, 171]. Therefore, traditional probabilistic, generative models are misspecified for microclustering tasks, such as entity resolution, given that they have a sub-linear growth rate. Therefore, applying a Bayesian nonparametric (BNP) model which favors large clusters makes little sense in the context where each cluster should correspond to a single true entity. The second development is the proposal of general BNP models which can satisfy the microclustering property. The authors also propose a more scalable algorithm, the chaperones algorithm, which allows for computational speed-ups for entity resolution that are similar in spirit to the Split and
Merge approach as also used by [152].

The aforementioned work has led to considerations regarding the feasibility of entity resolution in the context of microclustering. There are only two papers addressing such implications in the literature to our knowledge. In recent work, [172] provided the first quantitative bounds, to our knowledge, that can be used for entity resolution. Simulations studies offer guidance for when the bounds are tight and loose in practice. [173] showed that unless the number of attributes (or features) grows with the number of records, entity resolution is not possible in certain situations.

7 Discussion

In this article, we have introduced the entity resolution problem as it relates to important social science issues such as the decennial census, human rights violations, voter registration, and inventor and author disambiguation. Applications are more widespread, dealing with medical, housing, and financial databases, among others. We have introduced the main terminology used in the literature, and we have provided the major challenges that researchers face within an entity resolution framework. We have reviewed deterministic methods (section 3) and seminal probabilistic record linkage methods, such as those proposed by Dunn, Newcombe, and Fellegi and Sunter (section 4), which led to many modern day extensions (section 5). These extensions can be viewed as extensions of Fellegi and Sunter (frequentist and Bayesian) or as semi- or fully supervised classification approaches. Section 6 reviewed entity resolution methods that can be viewed as clustering tasks. These include methods where clustering is a post-processing step, graphical entity resolution, and microclustering models.

In the remainder of our discussion, we highlight a few remaining topics which are the subject of active research and which have important practical implications. First, we discuss the need to rigorously evaluate the performance of entity resolution methods in applications. Second, we
discuss potential directions regarding scaling Bayesian entity resolution methods. Finally, we discuss privacy issues surrounding the use of entity resolution.

**Data Fusion, Merging, and Canonicalization** In this paper, our focus has been on the structured entity resolution task. Of course, what happens after this task is equally as important, which is in the fourth stage — data fusion, merging, or canonicalization. Specifically, the entity resolution task provides one with potential records that may match to one another, however, it does not tell us which record is the true underlying entity. Canonicalization, merging, or data fusion is the task of merging groups of records that have been classified as matches into one record that represents the true entity \[174, 5, 175\]. The earliest proposals of canonicalization were deterministic, rule-based methods, which were application specific and fast to implement \[176\]. The existing literature assumes training is available in order to select the canonical record, and authors have proposed optimization and semi-supervised methods to finding the most representative record \[177, 178, 179\]. For a full review of data fusion techniques, we refer to \[174\]. This is an important area of future research as, to our knowledge, it’s often unclear how researchers choose the canonical record or canonical data set and proceed with downstream tasks, such as logistic regression or predictive analysis.

**Evaluating Entity Resolution Performance** Despite methodological advances, evaluating the performance of entity resolution remains a challenge for a number of reasons. Murray \[180\] expressed concerns regarding over-reliance on simple (toy) datasets that may not be representative of real applications, as this could potentially lead methodological research astray. As a starting point, we review in section A.2 of the supplementary materials some public datasets that can be used for comparisons/evaluations. However, given the wide range of fields of application of entity resolution, these datasets are comparatively few in number. We stress that when using “benchmark datasets,” it is crucial that researchers note the number of records under consideration,
the level of noise in the data, its overall quality, and the reliability of the unique identifiers used for performance evaluation. In addition, one should not solely rely on toy datasets, but one should perform carefully thought out simulation studies in order to understand robustness to model misspecification to provide practitioners with a guide for using their method. In addition, extreme care should be taken regarding sensitivity of tuning parameters in proposed methods and sensitivity of the evaluated performance on choices of such parameters. Finally, case studies should be considered if possible as this gives one an idea of how proposed methods work for “data in the wild.”

In addition, many researchers advocate the use of expert-labeled data to help train entity resolution model and to evaluate their performance in applications. However, care should be taken as labeling errors and sampling procedures may introduce bias into estimates. Effectively eliciting expert-labeled data while accounting for such sources of bias is an active area of research, and one that we consider to be its own field given the complexities involved.

**Scaling Entity Resolution**  Bayesian entity resolution algorithms have been successful in scaling to large datasets, as illustrated by [13] and [48]. McVeigh et al. [13] have scaled a Bayesian Fellegi-Sunter approach to roughly 57 millions of records using so-called post-hoc blocks. The approach of Marchant et al. [48] is quite different as blocking and entity resolution are jointly modeled in a Bayesian framework, allowing for uncertainty quantification about both parts of the pipeline. The authors scaled to roughly one million records using distributed computing. Further research is needed in this area to scale to larger datasets, such as census-size data or industrial sized datasets, while accounting for uncertainties encountered at all stages of the entity resolution pipeline.

**Privacy Issues**  Entity resolution is fundamentally antithetic to data privacy – it is about gaining information about social entities through the integration of diverse databases. This raises ethical
and legal questions for users of entity resolution as well as important privacy considerations [181]. In particular, as more data is being collected, stored, analyzed and shared across multiple domains, disclosure risks associated with (even anonymized) data releases become serious. For example, [182] showed how a simple record linkage algorithm could be used to de-anonymize Netflix movie rankings data through the use of public IMDb profiles. [183] used public voter registration data to de-anonymize a health insurance dataset, in order to showcase the need for stronger privacy measures. These are examples of linkage attacks, where an adversary uses background knowledge (such as voter registration files) to de-anonymize data or to gain information about individuals.

Data releases should therefore be managed through statistical disclosure control (SDC) systems, which aim to balance the utility of released data with privacy protections. To address these competing goals, many SDC techniques have been proposed and implemented such as top-coding, data swapping, data perturbation, and synthetic data generation, each potentially having its own measures of utility and risk properties; more details are those methods can be found in [184, 185]. Furthermore, differential privacy [186] has emerged as a key rigorous definition of privacy. It provides a framework that can inform the design of privacy mechanisms with specified disclosure risks, in the presence of arbitrary external information.

As we have discussed, analyses often require or can benefit from the linkage of multiple databases. However, when databases are held by different organizations and contain private information that cannot be shared across them, record linkage should be done as to ensure that: (1) private information such as quasi-identifiers (name, date of birth, etc) are not disclosed across organizations during the linkage process, and (2) only relevant summaries of the resulting linkage (usually a set of pre-determined attributes of the linked records) are reported as to manage disclosure risks. The achievement of these two goals is the subject of privacy-preserving record linkage (PPRL) [187, 188, 189]. This is closely related to the problem of private multi-party
data publishing under a vertical partitioning scheme \cite{190, 191, 192, 193}. While progress has been made on point (1), the privacy implications of post-linkage data releases are difficult to analyze even under mild adversary models \cite{191, 188}. Great care should be taken when using PPRL as to ensure that all disclosure risks are properly assessed.
References

1. A. Doan, A. Halevy, Z. Ives, Principles of Data Integration (Morgan Kaufmann, Waltham, MA, 2012).

2. A. K. Elmagarmid, P. G. Ipeirotis, V. S. Verykios, Duplicate record detection: A survey. IEEE Transactions on Knowledge and Data Engineering 19, 1–16 (2007).

3. F. Naumann, M. Herschel, An Introduction to Duplicate Detection (Morgan & Claypool Publishers, 2010).

4. L. Getoor, A. Machanavajjhala, Entity resolution: Theory, practice & open challenges. Proceedings of the VLDB Endowment 5, 2018–2019 (2012).

5. P. Christen, Data matching: Concepts and techniques for record linkage, entity resolution, and duplicate detection, Data-Centric Systems and Applications (Springer-Verlag, Berlin Heidelberg, 2012).

6. V. Christophides, V. Efthymiou, T. Palpanas, G. Papadakis, K. Stefanidis, An overview of end-to-end entity resolution for big data. ACM Computing Surveys 53 (2021).

7. I. F. Ilyas, X. Chu, Data Cleaning (Association for Computing Machinery, New York, NY, USA, 2019).

8. G. Papadakis, E. Ioannou, E. Thanos, T. Palpanas, The Four Generations of Entity Resolution (Morgan & Claypool Publishers, 2021).

9. T. Herzog, F. Scheuren, W. Winkler, Data Quality and Record Linkage Techniques (Springer, New York, NY, 2007).
10. W. E. Winkler, Matching and record linkage. *Wiley Interdisciplinary Reviews: Computational Statistics* **6**, 313–325 (2014).

11. A. Jurek-Loughrey, P. Deepak, *Semi-supervised and unsupervised approaches to record pairs classification in multi-source data linkage* (Springer, 2019), pp. 55–78.

12. J. Asher, D. Resnick, J. Brite, R. Brackbill, J. Cone, An introduction to probabilistic record linkage with a focus on linkage processing for wtc registries. *International journal of environmental research and public health* **17**, 6937 (2020).

13. B. S. McVeigh, B. T. Spahn, J. S. Murray, Scaling Bayesian probabilistic record linkage with post-hoc blocking: an application to the california great registers. *arXiv e-prints* (2019). arxiv:1905.05337.

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

15. E. Rogot, P. Sorlie, N. J. Johnson, Probabilistic methods in matching census. *Journal of Chronic Diseases* **39**, 719–734 (1986).

16. N. M´eray, J. B. Reitsma, A. C. Ravelli, G. J. Bonsel, Probabilistic record linkage is a valid and transparent tool to combine databases without a patient identification number. *Journal of Clinical Epidemiology* **60**, 883 - 891 (2007).

17. M. A. Jaro, Probabilistic linkage of large public health data files. *Statistics in Medicine* **14**, 491–498 (1995).

18. R. Gutman, C. C. Afendulis, A. M. Zaslavsky, A Bayesian procedure for file linking to analyze end-of-life medical costs. *Journal of the American Statistical Association* **108**, 34–47 (2013).
19. M. Shan, K. Thomas, R. Gutman, A Bayesian multi-layered record linkage procedure to analyze functional status of medicare patients with traumatic brain injury. *arXiv e-prints* (2020). arxiv:2005.08549.

20. E. Farley, R. Gutman, A Bayesian approach to linking data without unique identifiers. *arXiv e-prints* (2020). arxiv:2012.00601.

21. M. A. Jaro, Advances in record-linkage methodology as applied to matching the 1985 census of Tampa, Florida. *Journal of the American Statistical Association* **84**, 414–420 (1989).

22. William E Winkler, Y. Thibaudeau, An application of the Fellegi-Sunter model of record linkage to the 1990 US decennial census. *Research Report* pp. 1–22 (1990).

23. M. Fortini, B. Liseo, A. Nuccitelli, M. Scanu, On Bayesian record linkage. *Research in Official Statistics* **4**, 185–198 (2001).

24. A. Chevrette, G-link : A probabilistic record linkage system, *Tech. rep.*, Statistics Canada (2011).

25. A. Dasylva, R.-C. Titus, C. Thibault, Overcoverage in the 2011 Canadian census. *Proceedings of Statistics Canada Symposium* (2014).

26. A. Dasylva, Pairwise estimating equations for the primary analysis of linked data. *Proceedings of Statistics Canada Symposium* (2018).

27. K. Lum, M. E. Price, D. Banks, Applications of multiple systems estimation in human rights research. *The American Statistician* **67**, 191–200 (2013).

28. M. Price, A. Gohdes, P. Ball, Documents of war: Understanding the Syrian conflict. *Significance* **12**, 14–19 (2015).
29. P. Sadosky, A. Shrivastava, M. Price, R. C. Steorts, Blocking methods applied to casualty records from the Syrian conflict. *arXiv e-prints* pp. 1–25 (2015). arxiv:1510.07714.

30. M. Sadinle, Detecting duplicates in a homicide registry using a Bayesian partitioning approach. *The Annals of Applied Statistics* **8**, 2404–2434 (2014).

31. M. Sadinle, Bayesian estimation of bipartite matchings for record linkage. *Journal of the American Statistical Association* **112**, 600–612 (2017).

32. M. Sadinle, Bayesian propagation of record linkage uncertainty into population size estimation of human rights violations. *The Annals of Applied Statistics* **12**, 1013–1038 (2018).

33. R. Lai, A. D’Amour, A. Yu, Y. Sun, V. Torvik, L. Fleming, Disambiguation and co-authorship networks of the US patent inventor database. *Harvard Institute for Quantitative Social Science, Cambridge, MA* 2138 (2011).

34. G. Louppe, H. T. Al-Natsheh, M. Susik, E. J. Maguire, Ethnicity sensitive author disambiguation using semi-supervised learning. *international conference on knowledge engineering and the semantic web* pp. 272–287 (2016).

35. Y. Zhang, F. Zhang, P. Yao, J. Tang, Name disambiguation in aminer: Clustering, maintenance, and human in the loop. *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* pp. 1002–1011 (2018).

36. S. Subramanian, D. King, D. Downey, S. Feldman, S2and: A benchmark and evaluation system for author name disambiguation. *arXiv e-prints* (2021). arXiv:2103.07534.

37. X. Liu, D. Yin, X. Zhang, K. Su, K. Wu, H. Yang, J. Tang, OAG-BERT: Pre-train
heterogeneous entity-augmented academic language models. *arXiv e-prints* (2021). arXiv:2103.02410.

38. X. H. Tai, Record linkage and matching problems in forensics. *IEEE International Conference on Data Mining Workshops* pp. 510–517 (2018).

39. X. H. Tai, W. F. Eddy, Automatically matching topographical measurements of cartridge cases using a record linkage framework. *arXiv e-prints* (2020). arXiv:2003.00060.

40. W. Fan, X. Jia, J. Li, S. Ma, Reasoning about record matching rules. *Proceedings of the VLDB Endowment* 2, 407–418 (2009).

41. R. Singh, V. Meduri, A. Elmagarmid, S. Madden, P. Papotti, J.-A. Quiané-Ruiz, A. Solar-Lezama, N. Tang, Generating concise entity matching rules. *Proceedings of the 2017 ACM International Conference on Management of Data* pp. 1635–1638 (2017).

42. S. Mudgal, H. Li, T. Rekatsinas, A. Doan, Y. Park, G. Krishnan, R. Deep, E. Arcaute, V. Raghavendra, Deep Learning for Entity Matching: A Design Space Exploration. *Proceedings of the 2018 International Conference on Management of Data* pp. 19–34 (2018).

43. J. Wang, T. Kraska, M. J. Franklin, J. Feng, Crowder: Crowdsourcing entity resolution. *Proceedings of the VLDB Endowment* 5, 1483–1494 (2012).

44. C. Gokhale, S. Das, A. Doan, J. F. Naughton, N. Rampalli, J. Shavlik, X. Zhu, *Corleone: Hands-off crowdsourcing for entity matching* (2014), pp. 601–612.

45. G. Papadakis, J. Svirsky, A. Gal, T. Palpanas, Comparative analysis of approximate blocking techniques for entity resolution. *Proceedings of the VLDB Endowment* 9, 684–695 (2016).

46. H. L. Dunn, Record linkage. *American Journal of Public Health and the Nation’s Health* 36, 1412–1416 (1946).
47. H. Hogan, P. J. Cantwell, J. Devine, V. T. Mule, V. Velkoff, Quality and the 2010 census. *Population Research and Policy Review* **32**, 637–662 (2013).

48. N. G. Marchant, R. C. Steorts, A. Kaplan, B. I. P. Rubinstein, D. N. Elazar, d-blink: Distributed end-to-end Bayesian entity resolution. *arXiv e-prints* (2019). arxiv:1909.06039.

49. T. Howland, How El Rescate, a small nongovernmental organization, contributed to the transformation of the human rights situation in El Salvador. *Human Rights Quarterly* **30**, 703–757 (2008).

50. P. Ball, The Salvadoran human rights commission: Data processing, data representation, and generating analytical reports. *Making the Case: Investigating Large Scale Human Rights Violations Using Information Systems and Data Analysis*, P. Ball, H. F. Spirer, L. Spirer, eds. (American Association for the Advancement of Science, 2000), pp. 15–24.

51. M. Price, J. Klingner, A. Qtiesh, P. Ball, Full updated statistical analysis of documentation of killing in the Syrian Arab Republic. *Report by the Human Rights Data Analysis Group to the United Nations Office of the High Commissioner for Human Rights (OHCHR)* (2013).

52. M. Price, P. Ball, Big data, selection bias, and the statistical patterns of mortality in conflict. *SAIS Review of International Affairs* **34**, 9–20 (2014).

53. A. H. Green, P. Ball, Civilian killings and disappearances during civil war in El Salvador (1980–1992). *Demographic Research* **41**, 781–814 (2019).

54. B. Chen, A. Shrivastava, R. C. Steorts, Unique entity estimation with application to the Syrian conflict. *The Annals of Applied Statistics* **12**, 1039–1067 (2018).

55. J. Ax, Georgia lawsuit is latest blow in U.S. fight over voting rights (2018). Online; posted October 12, 2018; retrieved July 17, 2020.
56. B. Nadler, Voting rights become a flashpoint in georgia governor’s race (2018). Online; posted October 9, 2018; retrieved July 17, 2020.

57. T. Enamorado, Georgia’s ‘exact match’ law could potentially harm many eligible voters (2018). Online; posted October 20, 2018; retrieved July 17, 2020.

58. Georgia Coalition For the Peoples’ Agenda, Inc. et al v. Kemp, Complaint for injunctive and declaratory relief (2018).

59. M.-C. Müller, F. Reitz, N. Roy, Data sets for author name disambiguation: an empirical analysis and a new resource. *Scientometrics* **111**, 1467–1500 (2017).

60. X. L. Dong, D. Srivastava, *Big Data Integration* (Morgan and Claypool Publishers, 2015).

61. V. I. Levenshtein, Binary codes capable of correcting deletions, insertions, and reversals. *Soviet physics doklady* **10**, 707–710 (1966).

62. L. Yujian, L. Bo, A normalized levenshtein distance metric. *IEEE transactions on pattern analysis and machine intelligence* **29**, 1091–1095 (2007).

63. W. E. Winkler, String comparator metrics and enhanced decision rules in the Fellegi-Sunter model of record linkage. *Proceedings of the Section on Survey Research, American Statistical Association* pp. 354–359 (1990).

64. G. Navarro, A guided tour to approximate string matching. *ACM computing surveys* **33**, 31–88 (2001).

65. W. W. Cohen, P. Ravikumar, S. E. Fienberg, A comparison of string distance metrics for name-matching tasks. *Proceedings of the 2003 International Conference on Information Integration on the Web* p. 73–78 (2003).
66. J. Wang, G. Li, J. X. Yu, J. Feng, Entity matching: How similar is similar. *Proceedings of the VLDB Endowment* **4**, 622–633 (2011).

67. C. R. Rivero, D. Ruiz, Selecting suitable configurations for automated link discovery. *Proceedings of the ACM Symposium on Applied Computing* pp. 907–914 (2020).

68. E. Ristad, P. Yianilos, Learning string-edit distance. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **20**, 522-532 (1998).

69. H. Galhardas, D. Florescu, D. Shasha, E. Simon, C. Saita, Declarative data cleaning: Language, model, and algorithms, Ph.D. thesis, INRIA (2001).

70. M. Bilenko, R. J. Mooney, Adaptive duplicate detection using learnable string similarity measures. *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining* pp. 39–48 (2003).

71. A. McCallum, K. Bellare, F. Pereira, A conditional random field for discriminatively-trained finite-state string edit distance. *arXiv e-prints* (2012). arXiv:1207.1406.

72. M. Nentwig, M. Hartung, A. C. Ngonga Ngomo, E. Rahm, A survey of current link discovery frameworks. *Semantic Web* **8**, 419–436 (2017).

73. N. Andrews, J. Eisner, M. Dredze, Name phylogeny: A generative model of string variation. *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning* pp. 344–355 (2012).

74. W. W. Cohen, Data integration using similarity joins and a word-based information representation language. *ACM Transactions on Information Systems* **18**, 288–321 (2000).

75. T. Soru, A. C. N. Ngomo, Rapid execution of weighted edit distances. *Proceedings of the Ontology Matching Workshop* (2013).
76. H. Zhang, Q. Zhang, Embedjoin: Efficient edit similarity joins via embeddings. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* pp. 585–594 (2017).

77. J. Wang, J. Feng, G. Li, Trie-join: Efficient trie-based string similarity joins with edit distance constraints. *Proceedings of the VLDB Endowment* 3, 1219–1230 (2010).

78. M. Yu, J. Wang, G. Li, Y. Zhang, D. Deng, J. Feng, A unified framework for string similarity search with edit-distance constraint. *VLDB Journal* 26, 249–274 (2017).

79. H. Wei, J. X. Yu, C. Lu, String similarity search: A hash-based approach. *IEEE Transactions on Knowledge and Data Engineering* 30, 170–184 (2018).

80. G. Papadakis, D. Skoutas, E. Thanos, T. Palpanas, Blocking and filtering techniques for entity resolution: A survey. *ACM Computing Surveys* 53 (2020).

81. A. E. Monge, C. P. Elkan, An efficient domain-independent algorithm for detecting approximately duplicate database records. *Proceedings of the SIGMOD 1997 Workshop on Research Issues on Data Mining and Knowledge Discovery* pp. 23–29 (1997).

82. O. Hassanzadeh, F. Chiang, H. C. Lee, R. J. Miller, Framework for evaluating clustering algorithms in duplicate detection. *Proceedings of the VLDB Endowment* 2, 1282–1293 (2009).

83. A. Saeedi, E. Peukert, E. Rahm, *Comparative Evaluation of Distributed Clustering Schemes for Multi-source Entity Resolution* (Springer International Publishing, Cham, 2017), pp. 278–293.

84. A. Heidari, G. Michalopoulos, S. Kushagra, I. F. Ilyas, T. Rekatsinas, Record fusion: A learning approach. *arXiv e-prints* (2020). arxiv:2006.10208.
85. O. Benjelloun, H. Garcia-Molina, D. Menestrina, Q. Su, S. E. Whang, J. Widom, Swoosh: A generic approach to entity resolution. *VLDB Journal* **18**, 255–276 (2009).

86. S. B. Dusetzina, S. Tyree, A.-M. Meyer, A. Meyer, L. Green, W. R. Carpenter, *Linking Data for Health Services Research: A Framework and Instructional Guide* (Agency for Healthcare Research and Quality, Rockville, MD, 2014).

87. S. Gomatam, R. Carter, M. Ariet, G. Mitchell, An empirical comparison of record linkage procedures. *Statistics in Medicine* **21**, 1485–1496 (2002).

88. K. M. Campbell, D. Deck, A. Krupski, Record linkage software in the public domain: A comparison of Link plus, the Link King, and a ‘basic’ deterministic algorithm. *Health Informatics Journal* **14**, 5–15 (2008).

89. M. Tromp, A. C. Ravelli, G. J. Bonsel, A. Hasman, J. B. Reitsma, Results from simulated data sets: Probabilistic record linkage outperforms deterministic record linkage. *Journal of Clinical Epidemiology* **64**, 565–572 (2011).

90. T. Avoundjian, J. C. Dombrowski, M. R. Golden, J. P. Hughes, B. L. Guthrie, J. Baseman, M. Sadinle, Comparing methods for record linkage for public health action: Matching algorithm validation study. *JMIR Public Health and Surveillance* **6**, e15917 (2020).

91. R. C. Steorts, S. L. Ventura, M. Sadinle, S. E. Fienberg, A comparison of blocking methods for record linkage. *Privacy in Statistical Databases* pp. 253–268 (2014).

92. J. S. Murray, Probabilistic record linkage and deduplication after indexing, blocking, and filtering. *Journal of Privacy and Confidentiality* **7**, 3–24 (2016).

93. H. B. Newcombe, J. M. Kennedy, S. J. Axford, A. P. James, Automatic linkage of vital records. *Science* **130**, 954–959 (1959).
94. I. P. Fellegi, A. B. Sunter, A theory for record linkage. *Journal of the American Statistical Association* **64**, 1183–1210 (1969).

95. R. Wu, S. Chaba, S. Sawlani, X. Chu, S. Thirumuruganathan, ZeroER: Entity resolution using zero labeled examples. *Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data* pp. 1149–1164 (2020).

96. H. B. Newcombe, P. O. W. Rhynas, Child spacing following stillbirth and infant death. *Eugenics Quarterly* **9**, 25–35 (1962).

97. H. B. Newcombe, The study of mutation and selection in human populations. *The Eugenics Review* **57**, 109–125 (1965).

98. H. B. Newcombe, O. G. Tavendale, Effects of father’s age on the risk of child handicap or death. *Obstetrical and Gynecological Survey* **20**, 655–656 (1965).

99. H. B. Newcombe, Couplage de données pour les études démographiques. *Population (French Edition)* **24**, 653 (1969).

100. W. E. Winkler, Using the em algorithm for weight computation in the Fellegi-Sunter model of record linkage. *Proceedings of the Section on Survey Research Methods* pp. 667–671 (1988).

101. M. D. Larsen, D. B. Rubin, Iterative Automated Record Linkage Using Mixture Models. *Journal of the American Statistical Association* **96**, 32–41 (2001).

102. M. E. Smith, H. B. Newcombe, Methods for computer linkage of hospital admission separation records into cumulative health histories. *Methods of Information in Medicine* **14**, 118–125 (1975).
103. Y. Thibaudeau, The discrimination power of dependency structures in record linkage. *Survey Methodology* **19** (1993).

104. J. Armstrong, J. Mayda, Estimation of record linkage models using dependent data. *Proceedings of the Section on Survey Research Methodology* pp. 853 – 858 (1992).

105. W. E. Winkler, Comparative analysis of record linkage decision rules. *Proceedings of the Section on Survey Research Methods* pp. 829–834 (1992).

106. W. E. Winkler, Improved decision rules in the Fellegi-Sunter model of record linkage. *Proceedings of the Section on Survey Research Methods* pp. 274–279 (1993).

107. T. R. Belin, D. B. Rubin, A method for calibrating false-match rates in record linkage. *Journal of the American Statistical Association* **90**, 694–707 (1995).

108. T. R. Belin, A proposed improvement in computer matching techniques. *Statistics of Income and Related Administrative Record Research* (International Revenue Service, Washington, DC, 1990), pp. 167–172.

109. K. Nigam, A. K. McCallum, S. Thrun, T. Mitchell, Text classification from labeled and unlabeled documents using EM. *Machine Learning* (2000).

110. W. E. Winkler, Machine learning, information retrieval, and record linkage. *Proceedings of the Section on Survey Research Methods* pp. 20–29 (2000).

111. W. E. Winkler, Methods for record linkage and Bayesian networks, *Tech. rep.*, Statistical Research Division, US Census Bureau, Washington, DC (2002).

112. P. Lahiri, M. Larsen, Regression analysis with linked data. *Journal of the American Statistical Association* **100**, 222-230 (2005).
113. J. P. H. Wortman, Record linkage methods with applications to causal inference and election voting data, Ph.D. thesis, Duke University (2019).

114. O. Chapelle, S. Bernhard, A. Zien, *Semi-Supervised Learning* (The MIT Press, Cambridge, Massachusetts, 2006).

115. T. Enamorado, Active learning for probabilistic record linkage (2019). Available at SSRN: [https://ssrn.com/abstract=3257638](https://ssrn.com/abstract=3257638).

116. S. Sarawagi, A. Bhamidipaty, Interactive deduplication using active learning. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* pp. 269–278 (2002).

117. K. Bellare, S. Iyengar, A. G. Parameswaran, V. Rastogi, Active sampling for entity matching. *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* p. 1131–1139 (2012).

118. Q. Wang, D. Vatsalan, P. Christen, Efficient interactive training selection for large-scale entity resolution. *Advances in Knowledge Discovery and Data Mining* pp. 562–573 (2015).

119. P. Christen, D. Vatsalan, Q. Wang, Efficient entity resolution with adaptive and interactive training data selection. *IEEE International Conference on Data Mining* pp. 727–732 (2015).

120. D. Firmani, B. Saha, D. Srivastava, Online entity resolution using an oracle. *Proceedings of the VLDB Endowment* 9, 384–395 (2016).

121. M. Kejriwal, D. P. Miranker, Semi-supervised instance matching using boosted classifiers. *European semantic web conference* pp. 388–402 (2015).
122. N. Vesdapunt, K. Bellare, N. Dalvi, Crowdsourcing algorithms for entity resolution. *Proceedings of the VLDB Endowment* **7**, 1071–1082 (2014).

123. K. Frisoli, B. LeRoy, R. Nugent, A novel record linkage interface that incorporates group structure to rapidly collect richer labels. *IEEE International Conference on Data Science and Advanced Analytics* pp. 580–589 (2019).

124. M. Trajtenberg, G. Shiff, Identification and mobility of Israeli patenting inventors, *Tech. rep.*, Pinhas Sapir Center for Development (2008).

125. P. Azoulay, J. S. G. Zivin, B. N. Sampat, The diffusion of scientific knowledge across time and space: Evidence from professional transitions for the superstars of medicine. *The Rate and Direction of Inventive Activity Revisited*, J. Lerner, S. Stern, eds. (University of Chicago Press, 2012).

126. M. J. Bailey, C. Cole, M. Henderson, C. Massey, How well do automated linking methods perform? lessons from US historical data. *Journal of Economic Literature* **58**, 997–1044 (2020).

127. V. I. Torvik, M. Weeber, D. R. Swanson, N. R. Smalheiser, A probabilistic similarity metric for medline records: A model for author name disambiguation. *Journal of the American Society for Information Science and Technology* **56**, 140–158 (2005).

128. P. Christen, A two-step classification approach to unsupervised record linkage. *Proceedings of the Sixth Australasian Conference on Data Mining and Analytics* p. 111–119 (2007).

129. P. Christen, Automatic record linkage using seeded nearest neighbour and support vector machine classification. *Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* p. 151–159 (2008).
130. R. D. Gottapu, C. Dagli, B. Ali, Entity resolution using convolutional neural network. *Procedia Computer Science* **95**, 153–158 (2016).

131. M. Ebraheem, S. Thirumuruganathan, S. Joty, M. Ouzzani, N. Tang, DeepER – Deep entity resolution. *arXiv e-prints* (2017). arxiv:1710.00597.

132. M. Ebraheem, S. Thirumuruganathan, S. Joty, M. Ouzzani, N. Tang, Distributed representations of tuples for entity resolution. *Proceedings of the VLDB Endowment* **11**, 1454–1467 (2018).

133. N. Kooli, R. Allesiardo, E. Pigneul, Deep learning based approach for entity resolution in databases. *Intelligent Information and Database Systems* pp. 3–12 (2018).

134. J. Kasai, K. Qian, S. Gurajada, Y. Li, L. Popa, Low-resource deep entity resolution with transfer and active learning. *57th Annual Meeting of the Association for Computational Linguistics* pp. 5851–5861 (2020).

135. B. Li, W. Wang, Y. Sun, L. Zhang, M. A. Ali, Y. Wang, GraphER: Token-centric entity resolution with graph convolutional neural networks. *34th AAAI Conference on Artificial Intelligence* pp. 8172–8179 (2020).

136. Y. Li, J. Li, Y. Suhara, J. Wang, W. Hirota, W. C. Tan, Deep Entity Matching: Challenges and Opportunities. *Journal of Data and Information Quality* **13**, 1–17 (2021).

137. Y. Li, J. Li, Y. Suhara, A. Doan, W. C. Tan, Deep entity matching with pre-trained language models. *Proceedings of the VLDB Endowment* **14**, 50–60 (2020).

138. T. Hastie, R. Tibshirani, J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (Springer, New York, 2001).
139. S. L. Ventura, R. Nugent, E. R. Fuchs, Seeing the non-stars: (Some) sources of bias in past disambiguation approaches and a new public tool leveraging labeled records. *Research Policy* **44**, 1672–1701 (2015).

140. P. Azoulay, R. Michigan, B. N. Sampat, The anatomy of medical school patenting. *New England Journal of Medicine* **357**, 2049-2056 (2007).

141. G. C. Li, R. Lai, A. D’Amour, D. M. Doolin, Y. Sun, V. I. Torvik, A. Z. Yu, F. Lee, Disambiguation and co-authorship networks of the U.S. patent inventor database (1975-2010). *Research Policy* **43**, 941–955 (2014).

142. L. Fleming, C. King III, A. I. Juda, Small worlds and regional innovation. *Organization Science* **18**, 938–954 (2007).

143. A. Arasu, M. Götz, R. Kaushik, On active learning of record matching packages. *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data* pp. 783–794 (2010).

144. W. W. Cohen, J. Richman, Learning to match and cluster large high-dimensional data sets for data integration. *Proceedings of the Eighth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* p. 475–480 (2002).

145. A. Tancredi, B. Liseo, et al., A hierarchical Bayesian approach to record linkage and population size problems. *The Annals of Applied Statistics* **5**, 1553–1585 (2011).

146. S. L. Ventura, R. Nugent, E. R. Fuchs, Hierarchical linkage clustering with distributions of distances for large-scale record linkage. *Privacy in Statistical Databases* pp. 283–298 (2014).
147. R. C. Steorts, R. Hall, S. E. Fienberg, SMERED: A Bayesian approach to graphical record linkage and de-duplication. *Journal of Machine Learning Research* 33, 922–930 (2014).

148. R. C. Steorts, Entity Resolution with Empirically Motivated Priors. *Bayesian Analysis* 10, 849–875 (2015).

149. E. Rahm, The case for holistic data integration. *Advances in Databases and Information Systems* pp. 11–27 (2016).

150. G. Zanella, B. Betancourt, H. Wallach, J. Miller, A. Zaidi, R. C. Steorts, Flexible models for microclustering with application to entity resolution. *Proceedings of the 30th International Conference on Neural Information Processing Systems* pp. 1425–1433 (2016).

151. N. Monath, A. Kobren, A. Krishnamurthy, M. R. Glass, A. McCallum, Scalable hierarchical clustering with tree graging. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* pp. 1438–1448 (2019).

152. R. C. Steorts, R. Hall, S. E. Fienberg, A Bayesian approach to graphical record linkage and deduplication. *Journal of the American Statistical Association* 111, 1660–1672 (2016).

153. J. Han, M. Kamber, J. Pei, *Data Mining: Concepts and Techniques* (Morgan Kaufmann Publishers, Waltham, MA, 2011).

154. M. A. Hernández, S. J. Stolfo, The merge/purge problem for large databases. *Proceedings of the 1995 ACM SIGMOD International Conference on Management of Data* p. 127–138 (1995).

155. M. A. Hernández, S. J. Stolfo, Real-world data is dirty: Data cleansing and the merge/purge problem. *Data Mining and Knowledge Discovery* 2, 9–37 (1998).
156. N. Bansal, A. Blum, S. Chawla, Correlation clustering. *Machine Learning* **56**, 89–113 (2004).

157. V. Filkov, S. Skiena, Integrating microarray data by consensus clustering. *Proceedings of the International Conference on Tools with Artificial Intelligence* pp. 418–426 (2003).

158. M. Charikar, V. Guruswami, A. Wirth, Clustering with qualitative information. *Journal of Computer and System Sciences* **71**, 360 - 383 (2005).

159. N. Ailon, M. Charikar, A. Newman, Aggregating inconsistent information: Ranking and clustering. *Journal of the ACM* **55**, 1–27 (2008).

160. A. Gionis, H. Mannila, P. Tsaparas, Clustering aggregation. *ACM Transactions on Knowledge Discovery from Data* **1**, 4–es (2007).

161. S. C. Johnson, Hierarchical clustering schemes. *Psychometrika* **32**, 241–254 (1967).

162. I. Bhattacharya, L. Getoor, A latent dirichlet model for unsupervised entity resolution. *Proceedings of the Sixth SIAM International Conference on Data Mining* pp. 47–58 (2006).

163. J. B. Copas, F. J. Hilton, Record Linkage: Statistical Models for Matching Computer Records. *Journal of the Royal Statistical Society. Series A (Statistics in Society)* **153**, 287–320 (1990).

164. D. M. Blei, A. Y. Ng, M. I. Jordan, Latent Dirichlet allocation. *Journal of Machine Learning Research* **3**, 993–1022 (2003).

165. C. E. Antoniak, Mixtures of Dirichlet processes with applications to Bayesian nonparametric problems. *The Annals of Statistics* **2**, 1152–1174 (1974).
166. S. N. MacEachern, Estimating normal means with a conjugate style Dirichlet process prior. *Communications in Statistics-Simulation and Computation* 23, 727–741 (1994).

167. S. N. MacEachern, Computational methods for mixture of Dirichlet process models. *Practical nonparametric and semiparametric Bayesian statistics* (Springer, 1998), pp. 23–43.

168. M. Perman, J. Pitman, M. Yor, Size-biased sampling of Poisson point processes and excursions. *Probability Theory and Related Fields* 92, 21–39 (1992).

169. J. Pitman, M. Yor, The two-parameter Poisson-Dirichlet distribution derived from a stable subordinator. *The Annals of Probability* 25, 855–900 (1997).

170. J. F. C. Kingman, The representation of partition structures. *Journal of the London Mathematical Society* 2, 374–380 (1978).

171. T. Broderick, J. Pitman, M. I. Jordan, Feature allocations, probability functions, and paintboxes. *Bayesian Analysis* 8, 801–836 (2013).

172. R. C. Steorts, M. Barnes, W. Neiswanger, Performance bounds for graphical record linkage. *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics* 54, 298–306 (2017).

173. J. E. Johndrow, K. Lum, D. B. Dunson, Theoretical limits of microclustering for record linkage. *Biometrika* 105, 431-446 (2018).

174. J. Bleicher, F. Naumann, Data fusion. *ACM Computing Surveys* 41, 1–41 (2009).

175. A. Kaplan, B. Betancourt, R. C. Steorts, Entity resolution and the downstream task: A case study of north carolina voter registration records. *Submitted* (2020).
176. S. Cohen, Y. Sagiv, An incremental algorithm for computing ranked full disjunctions. *Proceedings of the Twenty-Fourth ACM SIGMOD-SIGACT-SIGART Symposium on Principles of Database Systems* p. 98–107 (2005).

177. L. L. Yan, M. T. Ozsu, Conflict tolerant queries in aurora. *Proceedings Fourth IFCIS International Conference on Cooperative Information Systems* pp. 279–290 (1999).

178. P. Bohannon, W. Fan, M. Flaster, R. Rastogi, A cost-based model and effective heuristic for repairing constraints by value modification. *Proceedings of the 2005 ACM SIGMOD International Conference on Management of Data* pp. 143–154 (2005).

179. A. Culotta, M. Wick, R. Hall, M. Marzilli, A. McCallum, Canonicalization of database records using adaptive similarity measures. *Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* p. 201–209 (2007).

180. J. Murray, A unified framework for de-duplication and population size estimation (invited discussion). *Bayesian Analysis* 15, 664–669 (2020).

181. J. Lane, V. Stodden, S. Bender, H. Nissenbaum, *Privacy, Big Data, and the Public Good: Frameworks for Engagement* (Cambridge University Press, 2014).

182. A. Narayanan, V. Shmatikov, Robust de-anonymization of large sparse datasets. *Proceedings - IEEE Symposium on Security and Privacy* pp. 111–125 (2008).

183. L. Sweeney, K-anonymity: A model for protecting privacy. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 10, 557–570 (2002).

184. S. Fienberg, A. Slavković, *Data Privacy and Confidentiality*, International Encyclopedia of Statistical Science (Springer-Verlag, 2010), pp. 342–345.
185. A. Hundepool, J. Domingo-Ferrer, L. Franconi, S. Giessing, E. S. Nordholt, K. Spicer, P.-P. De Wolf, Statistical Disclosure Control (John Wiley & Sons, 2012).

186. C. Dwork, F. McSherry, K. Nissim, A. Smith, Calibrating noise to sensitivity in private data analysis. Theory of Cryptography Conference pp. 265–284 (2006).

187. R. Hall, S. E. Fienberg, Privacy-preserving record linkage. Privacy in Statistical Databases pp. 269–283 (2010).

188. D. Vatsalan, P. Christen, V. S. Verykios, A taxonomy of privacy-preserving record linkage techniques. Information Systems 38, 946–969 (2013).

189. D. Vatsalan, Z. Sehili, P. Christen, E. Rahm, Privacy-preserving record linkage for big data: Current approaches and research challenges. Handbook of Big Data Technologies, A. Y. Zomaya, S. Sakr, eds. (Springer International Publishing, Cham, 2017), pp. 851–895.

190. W. Jiang, C. Clifton, A secure distributed framework for achieving k-anonymity. VLDB Journal 15, 316–333 (2006).

191. N. Mohammed, B. C. Fung, M. Debbabi, Anonymity meets game theory: Secure data integration with malicious participants. VLDB Journal 20, 567–588 (2011).

192. N. Mohammed, D. Alhadidi, B. C. Fung, M. Debbabi, Secure two-party differentially private data release for vertically partitioned data. IEEE Transactions on Dependable and Secure Computing 11, 59–71 (2014).

193. X. Cheng, P. Tang, S. Su, R. Chen, Z. Wu, B. Zhu, Multi-party high-dimensional data publishing under differential privacy. IEEE Transactions on Knowledge and Data Engineering 32, 1557–1571 (2020).
194. H. Köpcke, E. Rahm, Frameworks for entity matching: A comparison. *Data and Knowledge Engineering* **69**, 197–210 (2010).

195. F. Gregg, D. Eder, Dedupe (2015). Online; retrieved July 29, 2020; [https://github.com/dedupeio/dedupe](https://github.com/dedupeio/dedupe).

196. J. de Bruin, recordlinkage 0.14 (2019). Online; released December 1, 2019; retrieved July 29, 2020; [https://pypi.org/project/recordlinkage/](https://pypi.org/project/recordlinkage/).

197. P. Christen, Febrl – an open source data cleaning, deduplication and record linkage system with a graphical user interface. *In ACM International Conference on Knowledge Discovery and Data Mining* pp. 1065–1068 (2008).

198. Y. Govind, P. Konda, P. Suganthan G.C., P. Martinkus, P. Nagarajan, H. Li, A. Soundararajan, S. Mudgal, J. R. Ballard, H. Zhang, A. Ardalan, S. Das, D. Paulsen, A. Singh Saini, E. Paulson, Y. Park, M. Carter, M. Sun, G. M. Fung, A. Doan, Entity matching meets data science: A progress report from the magellan project. *Proceedings of the 2019 International Conference on Management of Data* p. 389–403 (2019).

199. P. Konda, S. Das, P. Suganthan GC, A. Doan, A. Ardalan, J. R. Ballard, H. Li, F. Panahi, H. Zhang, J. Naughton, *et al.*, Magellan: Toward building entity matching management systems. *Proceedings of the VLDB Endowment* **9**, 1197–1208 (2016).

200. M. Sariyar, A. Borg, The recordlinkage package: Detecting errors in data. *The R Journal* **2**, 61–67 (2010).

201. A. Kaplan, B. Betancourt, R. C. Steorts, Posterior prototyping: Bridging the gap between Bayesian record linkage and regression. *arXiv e-prints* (2018). arxiv:1810.01538.
202. M. Friedrichs, C. Webster, B. Marsh, J. Dice, S. Lee, *fedmatch: Fast, Flexible, and User-Friendly Record Linkage Methods* (2021). R package version 2.0.3.

203. R. Linacre, S. Lindsay, *splink: Probabilistic record linkage and deduplication at scale*, https://github.com/moj-analytical-services/splink (2021).

204. L. Gagliardelli, G. Simonini, D. Beneventano, S. Bergamaschi, *SparkER: Scaling entity resolution in spark* (2019).

205. G. Papadakis, L. Tsekouras, E. Thanos, G. Giannakopoulos, T. Palpanas, M. Koubarakis, The return of JedAI: End-to-end entity resolution for structured and semi-structured data. *Proceedings of the VLDB Endowment, Vol. 11, No. 12* 11, 1950–1953 (2018).

206. K.-N. Tran, D. Vatsalan, P. Christen, Geco: An online personal data generator and corruptor. *Proceedings of the 22nd ACM International Conference on Information & Knowledge Management* p. 2473–2476 (2013).

207. M. Bilenko, R. Mooney, Riddle: Repository of information on duplicate detection, record linkage, and identity uncertainty (2006). Online; retrieved July 29, 2020; http://www.cs.utexas.edu/users/ml/riddle/

208. B. Spahn, Before the american voter pp. 1–38 (2019). Available at SSRN: https://ssrn.com/abstract=3478473

209. J. Tang, A. C. Fong, B. Wang, J. Zhang, A unified probabilistic framework for name disambiguation in digital library. *IEEE Transactions on Knowledge and Data Engineering* 24 (2012).

210. V. I. Torvik, N. R. Smalheiser, Author-ity 2009 - pubmed author name disambiguated dataset (2018).
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Supplementary Materials

Appendix A can be found in the Supplementary Materials.
Supplementary Materials for
Some of Entity Resolution

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This PDF file includes:

Supplementary Text (Appendix A)
A Open Source Software and Datasets

In this supplement, we review open source entity resolution software (Appendix A.1 and entity resolution datasets (Appendix A.2).

A.1 Open Source Software

This section reviews open source entity resolution software. We focus on libraries available in R or Python software packages, however, we cover a few recent packages that are available in Julia, Java, and Apache Spark. Other software is reviewed in [194, 5, 6].

Available in Python  The python library dedupe [195], available on PyPI and on GitHub, implements the Fellegi-Sunter framework together with active learning to select threshold weights. Based on this probabilistic record linkage step, it allows clustering records in coreferent groups using hierarchical agglomerative clustering with a centroid linkage. The library recordlinkage [196], available on PyPI and on GitHub, implements the Fellegi-Sunter framework, $k$-means clustering and a number of fully supervised classifiers (logistic regression, support vector machines, etc). The Freely Extensible Biomedical Record Linkage FEBRL library [197], available on SourceForge, provides a graphical user interface and implements the Fellegi-Sunter framework as well as supervised classifiers and clustering algorithms. Also, the library py-entitymatching [198] (part of the Magellan project [199]), available on PyPI and GitHub, provides tools to facilitate the development of entity resolution models. It implements rule-based systems as well as a number of supervised machine learning classifiers. Finally, the package fasthash available on Github implements the work of [54].

Available in R  The RecordLinkage package on CRAN [200] implements the Fellegi-Sunter framework and a number of supervised algorithms (logistic regression, support vector
machines, random forests, and others). It also contains the two datasets RLdata500 and RLdata10000 which have been widely used in the literature as benchmark datasets. \cite{14} extended the work of \cite{94} and provided efficient open source software on CRAN and GitHub known as fastLink. The BRL package on GitHub implements the bipartite record linkage approach of \cite{31}. The blink package on CRAN and GitHub implements the work of \cite{148}. The representr package on GitHub implements the work of \cite{201} for canonicalization. The fedmatch package on CRAN implements exact, fuzzy, and probabilistic matching based on the Fellegi-Sunter framework \cite{202}.

Available in Julia \cite{13} provide a Julia package to perform blocking and Bayesian Fellegi-Sunter called BayesianRecordLinkage.jl on GitHub.

Available in Apache Spark \cite{48} provide a joint blocking and entity resolution package on GitHub, which is provided in Apache Spark with a Java and Scala back-end. The splink library \cite{203} implements the Fellegi-Sunter framework in Spark, using the same model as fastLink. The SparkER library \cite{204} provides an entity resolution framework for Spark.

Available in Java The Serf library implements the R-swoosh algorithm \cite{85} for matching and merging. The JedAI library \cite{205} provides end-to-end entity resolution with an user-friendly gui.

A.2 Entity Resolution Datasets

In this section, we review entity resolution datasets that are publicly available.
A.2.1 Synthetic datasets

First we review synthetic datasets that are publicly available. For all of these datasets, a unique identifier is available to evaluate entity resolution performance.

**RLdata**  This package contains two synthetic data sets — RLdata500 and RLdata10000 from the RecordLinkage package in R. Attribute information available is first name, last name, and full date of birth.

**GeCo Tool**  One is able to create a synthetic dataset using the GeCo Tool [206], where features can consist of first name, last name, and birth date. Distortions can be included as to emulate the effect of optical character recognition, keyboard errors, phonetic errors, and common misspellings.

**FEBRL**  The FEBRL datasets [197] consist of comparison patterns from an epidemiological cancer study in Germany (https://recordlinkage.readthedocs.io/en/latest/ref-datasets.html).

**ABSEmployee**  The ABSEmployee synthetic dataset was constructed to mimic real data from the Australian Bureau of Statistics (ABS), which cannot be released due to privacy reasons. [48] simulated three data sources from the ABS that results in 666,000 total records, with 400,000 unique entities. The three data sources are a supplementary survey of permanent employees (source A), a supplementary survey of all employees (source B), and a census of all employees (source C). The size of source A is 120,000; the size of source B is 180,000; the size of source C is 360,000. Duplication occurs across and within the three data sources.

Feature information available is statistical area level of the employee, mesh block, birth day, birth year, gender (binary), industry, whether employment is on a casual basis (binary), whether
employment is full-time, hours worked per week, payrate, average weekly earnings. In all sources, there are missing variables, which are explained further at [https://github.com/cleanzr/dblink-experiments/tree/master/data](https://github.com/cleanzr/dblink-experiments/tree/master/data).

### A.2.2 Real Datasets (Publicly Available)

In this section, we review datasets from the literature which arise from real applications and which are publicly available. For all of these datasets, except for the 1901 and 1911 Irish Census, unique identifiers are available to evaluate entity resolution performance. However, the reliability of these unique identifiers vary. In some cases, these unique identifiers were obtained as the result of extensive record linkage efforts involving expert clerical review of the data. In other cases, the unique identifiers were obtained using external information which is not provided in these datasets.

**Cora** The cora dataset consists of citations and is hosted on the RIDDLE repository [207]. Features include title, author, and year of publication. This dataset needs some pre-processing steps before a record linkage method can be applied, such as removing punctuation.

**SHIW** The Italian Survey on Household and Wealth (FWIW) is a survey that was conducted in 2008 and 2010. Attributes available are branch of activity, employment status, gender, geographical area of birth, highest educational level obtained, town size, year of birth, whether or not Italian national, and working status. The data set can be obtained at [https://github.com/ngmarchant/shiw](https://github.com/ngmarchant/shiw).

**NLTCS** The National Long Term Care Survey (NLTCS) is a publicly available longitudinal survey conducted at Duke University, consisting of six waves. The goal of the survey is to study the health and well being of those older than sixty-five years old across the six waves of the
survey. Unfortunately, only three waves are appropriate for record linkage due to issues with
the survey design. Thus, only a subset can be utilized, which are waves 1982, 1989 and 1994.
The features available for linking are all categorical and are: gender (SEX), full date of birth
(DOB), location of the patient (STATE) and office location of the physician (REGOFF). The
provided unique identifier is based upon the social security number. The data is available at
https://www.icpsr.umich.edu/web/NACDA/studies/9681.

CD  The CD dataset includes information about 9,763 CDs randomly extracted from freeDB.
This dataset can be found at [https://hpi.de/naumann/projects/repeatability/datasets/cd-datasets.html]
There are a total of 299 duplicate records. Attribute information consists of 106 total features such as artist name, title, genre, among others.

Restaurant  The Restaurant dataset contains duplications of restaurants from Fodor’s and
Zagat’s. Attribute information contains name, address, city, and cuisine.

NCSBE  The North Carolina State Board of Elections (NCSBE) releases an online publication
of North Carolina voter registration snapshot data. Records are updated temporally, resulting
in voters being duplicated within this dataset. While the NCSBE provides each voter with
an identifier in each of the snapshots, they do not provide any public information regarding
how duplicate records are removed. In addition, the reliability of the NCSBE “unique” voter
identifiers has been recently been questioned [113]. Feature information consists of first and
last name, age, gender, race, place of birth, age, political affiliation, telephone number, and full
address.

USPTO  In 2015, PatentsView (see [https://www.patentsview.org/]) organized a com-
petition aiming to develop an inventor disambiguation algorithm for the USPTO patents records.
Five datasets of inventor-disambiguated patent records were provided as training data to help develop proposed algorithms and can be downloaded from [https://patentsview.org/events/workshop-2015](https://patentsview.org/events/workshop-2015).

**SDS** The Social Diagnosis Survey (SDS) is a longitudinal survey regarding households in Poland. The data set is publicly available at [http://www.diagnoza.com/index-en.html](http://www.diagnoza.com/index-en.html). Feature information available is complete date of birth, gender, residence (province), and level of education.

**SIPP** The Survey of Income and Program Participation (SIPP) is a longitudinal survey of local, state, and federal programs in the United States that collects information about individuals every few years. Specifically, individuals are sampled within panels. The data set is publicly available from the Census Bureau website at [https://www.census.gov/programs-surveys/sipp/data/datasets.html](https://www.census.gov/programs-surveys/sipp/data/datasets.html). Feature information available is year of birth, month of birth, gender, and the state where an individual resides.

**1901 and 1911 Irish Census** These are two publicly available censuses from Ireland in 1901 and 1911. The census of 1901 occurred on March 31, where the those residing (full name) in a household were recorded in addition to visitors. Additional information was collected such as age, gender, relationship to head of household, religion, occupation, marital status, county of birth (unless born abroad, in which case only the country was recorded), ability to read or write, ability to speak Irish, English, both, or none. The census of 1911 was slightly different. The head of household completed and signed the form. In addition, disability status information was collected. Full information on both censuses can be found at [http://www.census.nationalarchives.ie/](http://www.census.nationalarchives.ie/) and [https://www.irish-genealogy-toolkit.com/census-forms.html](https://www.irish-genealogy-toolkit.com/census-forms.html).
A.2.3 Real Sata Sets (Private)

In this section, we review datasets that are not available in the public domain, but have an important place in the literature.

**El Salvador** Between 1980 and 1991, the Republic of El Salvador witnessed a civil war between the central government, the left-wing guerrilla Farabundo Marti National Liberation Front (FMLN), and right-wing paramilitary death squads. There are three databases available for this conflict, where duplications occur within and across each of the databases. The first two databases were collected during the conflict, whereas the third database was collected after the conflict. The first two databases contain reports on documented identifiable victims. The first source, *El Rescate* (ER-TL), a nongovernmental organization (based out of Los Angelos, CA), collected electronic data from published reports during the civil war [49]. The second source, *Comission de Derechos Humanos de El Salvador* (CDHES), collected testimonials on violations from 1979 — 1991 [50]. The third source contains reports on documented identifiable victims after the civil war. After the peace agreement in 1992, the United Nations created a Commission on the Truth (UNTC), which invited citizens to report war-related human rights violations. As such, victims can be duplicated in these data sets. Further information regarding these datasets is summarized in [31].

**Syria** One case study that has been of interest is the ongoing Syrian conflict. To our knowledge, the Human Rights Data Analysis Group (HRDAG) provided the first published work in this domain. There are four sources that collected data during the same time period — Syrian Center for Statistics and Research (CSR-SY), Syrian Network for Human Rights (SNHR), Syria Shuhada website (SS), and the the Violation Documentation Centre (VDC). Each source provides documented identifiable deaths in the conflict. Attributes available are full full Arabic name,
gender, death location, and date of death. HRDAG has labelled the data set, as outlined in their paper \cite{51}.

**Decennial Census and Administrative Records** One important and timely topic is one that faces the United States Census Bureau each decade when they attempt to count all the individuals in the population. This enumeration is used to allocate resources for roads, schools, projects, and apportion representation of legislators. Unfortunately, it has been shown difficult to accurately enumerate such a population using an optional census, and response rates are often quite low. Furthermore, some individual may be counted multiple times. For example, an individual that owns three houses might accidentally fill out three census forms. As another example, individuals in group quarters (such as universities, prisons, etc) are often double counted by their “group” and a family member/parent/guardian \cite{47}. De-duplication is thus needed to obtain an accurate enumeration, with new methodology from the machine learning and statistical literature being recently proposed to this end \cite{48}. This methodology is scalable, while providing exact error propagation throughout the blocking and the entity resolution task \cite{48}.

**California Great Registers** Starting in 1900, each country in California (CA) printed and bound voter lists in each election year, which contained the following feature information of each voter: name, address, party registration, and occupation \cite{208,13}. This became known as the California Great Registers dataset, and was used as the county’s form of book keeping on election day. These original voter lists have now been digitized using ancestry.com and optical character recognition, however, this can cause errors in the data. The entire dataset can be viewed as a panel dataset, where it may be possible to track partisan change during certain time periods. This dataset spans 1908 — 1968. It is possible to potentially match voters from this time period with individuals from three decennial censuses from 1920, 1930, and 1940, which are publicly available. To our knowledge, the California registers database is not publicly
available. Together, the three decennial censuses and the California Great Registers dataset combine to form a dataset of 57 million records of Californians.

A.3 Benchmark and Research Data sets for Inventor and Author Disambiguation

In this section, we review some benchmark data sets for author disambiguation that have been recently utilized in the literature.

First we review benchmark data sets that have been used in the literature. AMINER contains many author disambiguation data sets used in [209]. As it pertains to this review, the most relevant data set contains author names and ground truth. This data set is publicly available. Authority 2009 is a Pubmed author data set [210]. DBLP is a computer science bibliography data sets, where the full data is publicly available. Groups within the computer science community have created subsets of the DBLP, which are available at PSU-DBLP and Naumann-DBLP. INSPIRE is an author disambiguation data set from a digital library for scientific literature in high-energy physics [211]. The data set is publicly available. Rexa is a data set on scientific author records derived from bibliographic data, which has been blocked according to unique first initial and last name, which is publicly available. S2AND is a union of eight existing author name disambiguation (AND) datasets, described in [36]. Open source software is available.

Now, we review some research data sets, which typically do not have unique identifiers or went through an intensive and well-documented manual labelling process.

KDD 2013 is a challenge data set created by the Microsoft Corporation for author disambiguation, where there are no unique identifiers to our knowledge that are error free. [139] discusses a private data set of 98,762 labeled USPTO records corresponding to inventors of optoelectronics patents. The authors have released various sample pairwise comparisons datasets that are publicly available. The USPTO provides many publicly available research data sets.
which have been mostly unexplored from a purely research point of view to our knowledge. IJCAI 2021 provides papers with authors that have same names, which is publicly available.