Robust Entity Resolution Using a CrowdOracle

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Abstract

Entity resolution (ER) seeks to identify which records in a data set refer to the same real-world entity. Given the diversity of ways in which entities can be represented, ER is a challenging task for automated strategies, but relatively easier for expert humans. We abstract the knowledge of experts with the notion of a boolean oracle, that can answer questions of the form "do records u and v refer to the same entity?", and formally address the problem of maximizing progressive recall and F-measure in an online setting.

1 Introduction

Humans naturally represent information about real-world entities in very diverse ways. Entity resolution (ER) seeks to identify which records in a data set refer to the same underlying real-world entity [4, 8]. ER is an intricate problem. For example, collecting profiles of people and businesses, or specifications of products and services from websites and social media sites can result in billions of records that need to be resolved. Furthermore, these entities are represented in a wide variety of ways that humans can match and distinguish based on domain knowledge, but would be challenging for automated strategies. For these reasons, many frameworks have been developed to leverage humans for performing entity resolution tasks [17, 9].

The problem of designing human-machine ER strategies in a formal framework was studied by [18, 16, 6]. These works introduce the notion of an *Oracle* that *correctly* answers questions of the form "do records u and v refer to the same entity?", showing how different ER logics can achieve different performance having access to such a "virtual" tool and a set of machine-generated pairwise matching probabilities. In this setting, the knowledge of experts is abstracted with the notion of a boolean oracle. However, certain questions can be difficult to answer correctly even for humans experts. To this end, the work in [7] formalizes a *robust* version of the above ER problem, based on a "Noisy oracle" that can *incorrectly* label some queried matching and non-matching pairs. The same paper describes a general error correction tool, based on a formal way for selecting indirect "control queries", that can be plugged into any correction-less oracle strategy while preserving the orignal ER logic. We refer to both the perfect and the noisy boolean oracle models as *CrowdOracle*.

Earlier CrowdOracle strategies, such as [18], consider ER to be an *off-line* task that needs to be completed before results can be used. Since it can be extremely expensive in resolving billions of records, more recent strategies [6, 7] focus on an *on-line* view of ER, which enables more complete results in the event of early

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termination or if there is limited resolution time available. On-line strategies consider *progressive* recall and F-measure as the metrics to be maximized in this setting. If one plots a curve of recall (or, analogously, F-measure) as a function of the number of oracle queries, progressive recall is quantified as the area under this curve.

Contributions and outline We describe the CrowdOracle pipelines introduced by [6, 7, 16, 18] by using a common framework. The building blocks of the framework enable the definition of *new* strategies, which can perform even better than those in the most recent works in certain applications. Problem formulation, error correction and some examples are taken from [6, 7]. However, framework formulation, strategy categorization, and an illustrative experiment are original contributions of this paper. This paper is organized as follows.

- In Section 2, we describe our ER problem leveraging the formal notion of a CrowdOracle that can (possibly incorrectly) label some queried matching and non-matching pairs.
- In Section 3, we discuss the components of our descriptive framework for CrowdOracle strategies. Key techniques and theoretical results of [7] are also given in this section.
- In Section 4, we describe previous CrowdOracle strategies leveraging our framework, and show how combining its building blocks in new ways can lead to more efficient algorithms for specific applications.
- Finally, related work is discussed in Section 5.

2 Preliminaries

Let $V = \{v_1, \ldots, v_n\}$ be a set of n records. Given $u, v \in V$, we say that u *matches* v when they refer to the same real-world entity. Let $H = (V, A, p_m)$, $A \subseteq V \times V$, be a graph with pairwise machine-generated matching probabilities $p_m : A \to [0, 1]$. We may not have probabilities of all record pairs, and we may have $|A| << \binom{n}{2}$. Consider a graph $C = (V, E^+)$, where E^+ is a subset of $V \times V$ and $(u, v) \in E^+$ represents that u matches with v. C is transitively closed, that is, it partitions V into cliques representing distinct entities. We call the nodes in each clique a *cluster* of V, and we refer to the clustering C as the *ground truth* for the ER problem. We refer to the cluster including a given node u, as $c(u) \in C$. Consider a black box which can answer questions of the form "are u and v matching?". Edges in C can be either asked to the black box or inferred leveraging previous answers. If the black box always tells the truth, a user can reconstruct C exactly with a reasonable number of queries [18, 16]. In real crowdsourcing applications, however, some answers can be erroneous and we can only build a noisy version of C, which we refer to as C'. $c'(u)$ refers to the cluster in C' including a given node u.

Definition 1: A **CrowdOracle** for C is a function $q : V \times V \to \{YES, NO\} \times [0, 0.5]$. If $q(u, v) = (a, e)$, with $a \in \{YES, NO\}$ and $e \in [0, 0.5]$, then $Pr[(u, v) \in E^+] = 1 - e$ if a=YES, and e otherwise. In the ideal case, when $e = 0$ for any pair (u, v), we refer to the CrowdOracle as **perfect oracle**.

For instance, if $q(u, v) =$ (YES, 0.15), then $(u, v) \in E^+$ with probability 0.85, and if $q(u, v) =$ (NO, 0.21), then probability of $(u, v) \in E^+$ is 0.21. We refer to the probability of a specific answer for the pair (u, v) being erroneous, conditioned on the answer being YES or NO, as its *error probability* $p_e(u, v)$. Let $Q = Q_+ \cup Q_-$ be a graph containing all the edges that have been queried until a given moment, along with the oracle answers, we state $p_e : Q \to [0, 0.5]$. An ER strategy s takes as input matching probability graph H and grows a clustering C' by asking edges as queries to the noisy oracle. We call *inference* the process of building a clustering C' from Q. C' initially consists of singleton clusters: s can either merge existing clusters into larger clusters, or split an already established cluster. Note that the sub-graph of Q_- induced by $c'(u)$ (that is, $Q_- \cap c'(u)$) can be non-empty, because of wrong answers. We refer to such a sub-graph as $Q_-[c'(u)]$.

Input data There are many ways of estimating the *matching* probability function p_m. For instance, automated classifier methods can provide pairwise similarities, which can be mapped to matching probabilities, as in Section 3.1 of [20]. Analogously, there are many ways of accessing *error* probabilities. For instance, the crowd platform could return a confidence score associated with each answer. Another option is to learn a function mapping similarity scores to error probabilities, akin to matching probabilities [20]. However, computing all the $\binom{n}{2}$ pairwise matching probabilities may not be feasible when the number of records n is large, and adopting a crowd-only approach may be prohibitively expensive. To this end, people often remove obvious non-matching pairs during a pre-processing phase. Then, they ask the crowd to examine the remaining pairs, which lead to a relatively sparse graph. One approach is to put obviously non-matching nodes (e.g., watches and dishwashers in an e-commerce dataset) in separate "domains" and consistently remove cross-domain edges. The result, similarly to what is done in [15], is a collection of disconnected complete sub-graphs that can be resolved independently. Another approach, exploited for instance in [3, 14], is to remove obviously non-matching edges either by a matching probability threshold or other cheap procedures such as (overlapping) *blocking*. The result is a sparse graph, possibly consisting of several connected components (not necessarily cliques). In the traditional (non-crowdsourcing) setting, there is an extensive literature about blocking (see for instance [22]).

3 CrowdOracle Framework

We now define a conceptual framework for describing recent CrowdOracle strategies in terms of basic operations. The input of each CrowdOracle strategy includes the CrowdOracle answers Q, the matching probability function p_m, and the error probabilities p_e, as in definition of Problem 1. In our framework, a *strategy* is a mechanism for selecting non-exhaustive *sequence* of CrowdOracle queries (i.e., less than $\binom{n}{2}$ queries) and inferring clusters according to answers. An oracle strategy also uses the following shared data and methods.

- The partition C', which can be updated upon the arrival of new answers.
- The method `query_pair`(u, v), which returns a $\{YES, NO\}$ oracle answer for the pair (u, v). Every invocation of such method contributes to the cost of the ER process and each strategy can be thought of determining a different sequence of `query_pair()` invocations. We note that given two partially grown clusters $c_1, c_2 \in C'$ in the perfect oracle setting, the result of `query_pair`(u, v) is consistently the same for any $(u, v) \in c_1 \times c_2$. For sake of simplicity, then, we sometimes use notations such as `query_pair`(u, c_2) or `query_pair`(c_1, c_2) for referring to an arbitrary inter-cluster pair-wise query.

Our framework consists of three aspects, useful for describing a variety of CrowdOracle strategies:

- the cost model of the ER task, which can represent off-line or on-line ER;
- the CrowdOracle model and the selection criteria for issued queries;
- the algorithms for updating the partition C', which we refer to as "building blocks".

We discuss each of the above components in the following sub-sections.

3.1 Cost model

Recall and F-measure denote, respectively, the fraction of positive edges found among those of the unknown clustering C, and the harmonic mean of this value and *precision*, which is the fraction of positive edges found that truly belong to C. Specifically, F-measure is defined as $\frac{2 \cdot \text{recall} \cdot \text{precision}}{\text{recall} + \text{precision}}$. Recall and F-measure naturally represent the "amount" of the information that is available to the user at a given point. However, they cannot distinguish the *dynamic* behaviour of different strategies. In other words, they cannot represent whether a strategy achieves high F-measure only *at the end* of the ER process or *earlier on*, thus enabling early usage by the user. Consider the following example with perfect oracle access. In this ideal setting, we can leverage transitivity: if u matches with v, and v matches with w, then we can deduce that u matches with w without needing to ask the oracle. Similarly, if u matches with v, and v is non-matching with w, then u is non-matching with w.

Example 1 (Running Example): There are many colleges and universities around the Italian city of Rome, each with its own *aliases* or abbreviated names and acronyms[1] which humans can distinguish using domain knowledge. Given the six institutions (r_a) Università di Roma, (r_b) La Sapienza, (r_c) Uniroma 1, (r_d) Roma Tre, (r_e) Università degli Studi Roma Tre, (r_f) American University of Rome, humans can determine that these correspond to three entities: r_a, r_b, and r_c refer to one entity, r_d and r_e refer to a second entity, and r_f refers to a third entity. Let us assume that we have the following probability estimates for record pairs. Matching pairs: $p(r_d, r_e) = 0.80$, $p(r_b, r_c) = 0.60$, $p(r_a, r_c) = 0.54$, $p(r_a, r_b) = 0.46$. Non-matching pairs: $p(r_a, r_d) = 0.84$, $p(r_d, r_f) = 0.81$, $p(r_c, r_e) = 0.72$, $p(r_a, r_e) = 0.65$, $p(r_c, r_d) = 0.59$, $p(r_e, r_f) = 0.59$, $p(r_a, r_f) = 0.55$, $p(r_b, r_d) = 0.51$, $p(r_b, r_e) = 0.46$, $p(r_c, r_f) = 0.45$, $p(r_b, r_f) = 0.29$. We let some non-matching pairs have higher probability than matching pairs. Some observers, for instance, may consider r_a and r_e more likely to be the same entity, than r_a and r_b. Consider two strategies S_1 and S_2. Let S_1 ask subsequently (r_a, r_b), (r_a, r_c), (r_d, r_e), (r_a, r_d), (r_a, r_f), and (r_d, r_f). Let S_2 ask instead (r_a, r_d), (r_a, r_f), (r_d, r_f), (r_d, r_e), (r_a, r_b), and (r_a, r_c). Both strategies issue to the oracle the same 6 pair-wise queries and can get recall 1 by leveraging transitivity. However, the recall of S_1 would be 0.75 after labeling the first two record pairs and 1.0 after the third, while the recall of S_2 would be still 0.0 after the first three record pairs, 0.25 after labeling the fourth pair, 0.5 after labeling the fifth record pair, and 1.0 only after labeling the sixth record pair.

In response to the above concerns, we introduce two variants of recall and F-measure, dubbed *progressive recall* and *progressive F-measure*. If one plots a curve of recall as a function of the number of oracle queries, progressive recall denotes the *area* under the curve. Progressive F-measure is defined analogously.

CrowdOracle problems We are now ready to define our progressive CrowdOracle problems, where we aim for high F-measure early on, which we refer to as *on-line* ER, and its traditional *off-line* version. In the perfect oracle setting, optimizing F-measure is the same as optimizing recall.[2]

Problem 1 (On-line): Given a set of records V, a CrowdOracle access to C, and a matching probability function p_m (possibly defined on a subset of $V \times V$), find the strategy that maximizes progressive F-measure.

Problem 2 (Off-line): Given a set of records V, a CrowdOracle access to C, and a matching probability function p_m (possibly defined on a subset of $V \times V$), find the strategy that maximizes F-measure and minimizes queries.

An optimal strategy for Problem 1 is also optimal for Problem 2, making Problem 1 more general.[3] For instance, strategy S_1 in Example 1 is optimal for both problems, whereas S_2 is optimal only for Problem 2.[4] The theory in [18] yields that both problems require at least $n - k$ questions for growing all k clusters (i.e., the size of a spanning forest of C^+) and at least $\binom{k}{2}$ extra questions for proving that clusters represent different entities. Intuitively, a strategy for Problem 2 tries to ask positive queries before negative ones, whereas a strategy for Problem 1 also does this in a connected fashion, growing larger clusters first. We call `ideal()` the optimal

[1] https://en.wikipedia.org/wiki/Category:Universities_and_colleges_in_Rome

[2] In the perfect oracle setting, precision is 1 and F-measure is equal to $\frac{2\cdot\text{recall}}{\text{recall}+1}$

[3] In practice, some strategy can have great performance in the on-line setting at the cost of slightly worse final recall-queries ratio.

[4] For sake of completeness, we also give an example of sub-optimal strategy for Problem 2 and Example 1. Consider S_3 as (r_a, r_d), (r_b, r_d), (r_a, r_f), (r_d, r_f), (r_d, r_e), (r_a, r_b), (r_a, r_c). The second query (r_b, r_d) is somewhat "wasted" in the perfect oracle setting as the corresponding negative edge would have been inferred after (r_a, r_b) by leveraging transitivity.

strategy for the on-line problem. Consider Example 1, `ideal`() first grows the largest cluster $c_1 = \{r_a, r_b, r_c\}$ by asking adjacent edges belonging to a spanning tree of c_1 (that is, every asked edge shares one of its endpoints with previously asked edges). After c_1 is grown, `ideal`() grows $c_2 = \{r_d, r_e\}$ in a similar fashion. Finally, `ideal`() asks negative edges in any order, until all the labels are known, and also $c_3 = \{r_f\}$ can be identified[5].

3.2 Oracle model and query selection

A strategy S can be thought of as a *sequence*[6] of queries. While in the perfect oracle setting S can leverage transitivity, in real CrowdOracle applications, S can only trade-off queries for F-measure. Let T be the set of positive answers collected by S at a given point of the ER process. We can think of two extreme behaviors.

- S skips all the queries that can be inferred by transitivity, that is, T is a *spanning forest* of V. This is necessary and sufficient to resolve the clusters in the absence of answer error, as shown in Example 1.
- S asks exhaustively all the queries in $V \times V$, that is, T is a noisy collection of cliques, and infers clusters by minimizing disagreements (for instance, via correlation clustering).

In the middle of the spectrum, the work in [7] shows that the error of resolution can be minimized if we strengthen the min-cuts of T with "control queries"[7], exploiting the notion of *expander graphs*. Expander graphs are sparse graphs with strong connectivity properties. We first describe spanning forest approaches for error correction and then we summarize the methods in [7].

Spanning forest As discussed at the end of Section 3.1, the goal of a perfect oracle strategy S is two-fold: promoting positive queries and growing clusters sequentially (only for Problem 1). In order to achieve this goal, the query selection of S can be driven by the *recall gain* of discovering that two specific clusters refer to the same entity. Depending on how S estimates the recall gain of a cluster pair $c_u, c_v \in C'$, we can have *optimistic* and *realistic* query selection. The optimistic approach only considers the maximum inter-cluster matching probability, that is, it estimates the recall gain of c_u and c_v as $\max_{u \in c_u, v \in c_v} p_m(u,v)|c_u|\cdot|c_v|$. Selecting queries optimistically can be computationally efficient, and can give good results if matching probabilities are accurate. However, it can perform badly in presence of non-matching pairs having higher probability than matching pairs [6]. To this end, realistic approach uses a robust estimate, based on the notion of *cluster benefit* $\texttt{cbn}(c_u, c_v) = \sum_{u,v \in c_u \times c_v} p_m(u,v)$. We note that if $|c_u| = |c_v| = 1$ then $\texttt{cbn}(c_u, c_v) = p_m(u,v)$, as in the optimistic approach.[8] Difference between optimistic and realistic is illustrated below.

Example 2 (Optimistic and realistic): Consider clusters grown by S_2 of Example 1 after 4 queries $C' = \{r_a, r_b\}, \{r_c\}, \{r_d, r_e\}, \{r_f\}$. Optimistic estimate of recall gain between non-matching $\{r_a, r_b\}$ and $\{r_f\}$ is $2 \cdot 1 \cdot 0.55 = 1.1$, which is comparable to matching $\{r_a, r_b\}$ and $\{r_c\}$, i.e., $2 \cdot 1 \cdot 0.60 = 1.2$. By switching to realistic, we get $\texttt{cbn}(\{r_a, r_b\}, \{r_f\})$= $0.55 + 0.29 = 0.84$ as opposite to $\texttt{cbn}(\{r_a, r_b\}, \{r_c\})$= $0.60 + 0.54 = 1.14$.

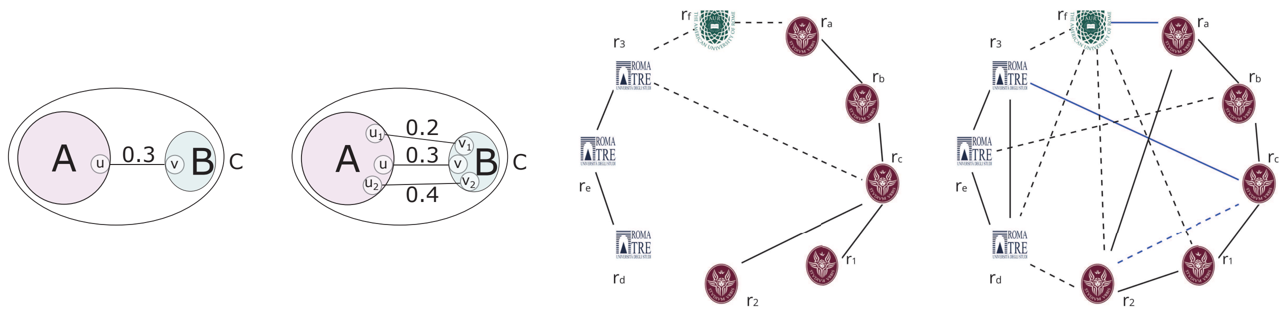
Expander graph Control queries for handling CrowdOracle errors can be selected among those that provide strongest connectivity between records of each cluster, based on the concept of *graph expanders*, which are sparse graphs with formal connectivity properties. Expansion properties of clusters translate into (i) *robustness* since the joint error probability of each cut is small, all the subsets of nodes are likely matching pair-wise;

[5] We note that recall is 1 as soon as c_2 is fully grown.

[6] Partially ordered if parallel.

[7] In addition to the spanning forest.

[8] One may wonder why not take the average. We note that the recall gain is larger for large clusters. However the average would be a robust estimate of the probability that the two clusters are matching.



(a) Joint error (b) Spanning forest (c) Expander graph

Figure 1: (a) Joint error probability. (b-c) Comparison of spanning forest with no error, and expander graphs. Positive (negative) answers are represented with solid (dashed) edges. Wrong answers are shown in blue.

(ii) *cost-effectiveness*: the total number of queries is small, as edge density of expander is small. Technically, different formalizations of connectivity give rise to different notions of expanders. We focus on *edge* expansion.[9]

Definition 2 (Edge expansion): The edge expansion parameter $h(G)$ of a graph $G = (V, E)$ is defined as the minimum cut size $(V', V \setminus V')$ for every subset of nodes $V' \subseteq V$, $|V'| \leq |V|/2$. Cut size is defined as the number of edges crossing the cut. If $h(G)$ is small, we say that the graph has at least one *weak* cut.

G is a γ-expander if $h(G) \geq \gamma$. Intuitively, every subset of the nodes of G that is not "too large" has a "large" *boundary*. In our ER setting, the boundary of a subset of nodes of the same entity provides evidence of how the subset relates to the rest of the graph. A disconnected graph is not an expander (the boundary of a connected component is empty), and every connected graph is an expander. However, different connected graphs have different edge expansion parameters. Consider an entity C being partitioned in two clusters A and B at some point of the ER process, like in Figure 1(a). Upon a positive answer for the pair (u, v) with error probability 0.3, the two clusters are *connected* but the probability of the whole cluster $C = A \cup B$ of being correct is only 0.7. At this point, whatever answers have been collected inside A, the boundary of A consists indeed of a mere edge. Upon two positive answers for the pairs (u_1, v_1), and (u_2, v_2)[10] with error respective probabilities 0.2 and 0.4, the *connection* between A and B becomes more robust. The probability of the whole cluster $C = A \cup B$ can be quantified with the product of the *cut* error probabilities under the assumption of independent error, that is $1 - 0.3 \cdot 0.2 \cdot 0.4 = 0.976$. At this point, the boundary of A consists indeed of three edges. The larger the boundary the higher the success probability. Suppose at this point the ER algorithm decides to merge A and B. Since C is unknown a priori, in order to trust the result, the large boundary property has to hold for *all* the possible partitions A and B. Therefore, the structure we are looking for is an expander. The weights are introduced because the product value, which is related to the weight of the cut, matters more than the cut cardinality (i.e., number of edges). The complete graph has the best expansion property, but it also has largest possible degree, and it would be prohibitively expensive to build. Informally, a graph is a good expander if it has low degree and high expansion parameters. In the following example and in Figure 1(c) we show the possible result of having an expander ($\gamma = 1$) for data in Example 1, compared with spanning forests of Figure 1(b).

Example 3 (Spanning forest and expander graph): Consider the six places of Example 1, plus three extra names (r_1) Studium Urbis, (r_2) Città Universitaria, (r_3) Uniroma 3. Correct clustering is $\{r_a, r_b, r_c, r_1, r_2\}$, $\{r_d, r_e, r_3\}$, and $\{r_f\}$. Both connected components of Figure 1(b) (i.e., trees in the spanning forest) and expander graphs of Figure 1(c) yield the same, correct, clustering. While connected components only work in absence of errors, expander produces the correct clustering also in presence of plausible human errors such as (r_a, r_f)[11],

[9] Other expansion notions include *node* expanders, and *spectral* expanders. We refer the interested reader to [1] for more discussion.
[10] $u_1, u_2 \in A$, and $v_1, v_2 \in B$
[11] "Università di Roma" means "University of Rome".

(r_c, r_3) (false positives) and (r_c, r_2) (false negative). Even though expansion requires more queries than building a spanning forest, it is far from being exhaustive: in the larger clusters, only 5 queries are asked out of $\binom{5}{2} = 10$.

The method `query_cluster()` in [7] is meant to be called in place of `query_pair()` with the purpose of growing clusters with good expansion properties. Given a query (u, v) selected by a strategy (represented with the two corresponding clusters c_u and c_v), `query_cluster()` provides an intermediate layer between the ER logic and the CrowdOracle. Similarly to `query_pair()`, indeed, `query_cluster()` provides functionalities for deciding when two clusters (or any two sets of nodes) are matching. However, instead of asking the selected query (u, v) as `query_pair`(u, v) would do, `query_cluster`(c_u, c_v, β) selects a bunch of random queries between $c_u = c'(u)$ and $c_v = c'(v)$, and returns a YES answer only if the estimated precision of the cluster $c_u \cup c_v$ is high. The parameter β controls the edge expansion value γ trading-off queries for precision.[12] Smaller values of β correspond to sparser clusters, and therefore to less queries ($\beta = 0$ asks a single positive question, yielding result similar to `query_pair()`). Greater values of β correspond to denser clusters and to higher precision. Formally, expected precision increases exponentially with β. We refer the interested reader to Theorem 3 in [7].

Discussion By analogy with the optimistic and realistic spanning forest approaches, we refer to graph expanders as *pessimistic* approach. We note that a CrowdOracle strategy S can leverage multiple approaches together, as discussed later in Section 4. For instance, S can select a cluster pair to compare by using the realistic cluster benefit but then use `query_cluster()` as a substitute of plain connectivity, and so on. Finally, experiments in [7] show that $\beta = 1$ achieves the best progressive F-measure, and we set this as default value.

3.3 Building block algorithms

We now describe the basic operations of our framework. The operations can be implemented either with the simple `query_pair()` oracle interface, or can be modified to apply random expansion with `query_cluster()`.

- **Insert node** This operation grows already established clusters by adding a new node u. Possible outcomes are success, when u is recognized as part of one of the clusters, or fail, in which case $\{u\}$ is established as a new singleton cluster. Specifically, `insert-node`(u) compares u to cluster c_i, $i = 1, 2, \ldots$ until `query_pair`(u, c_i) (or `query_cluster`$(\{u\}, c_i)$, when using the error-correction layer) returns a positive answer. The main lemma in [16] proves that an insert-node-only strategy in the perfect oracle setting requires at most $n - k + \binom{k}{2}$ queries. We can do better by introducing an "early termination" condition (e.g., at most τ comparisons before establishing a new cluster) at the price of possible loss in recall.

- **Merge clusters** Recall of an insert-node-only algorithm can be smaller than 1 for two reasons: (i) positive-to-negative errors of CrowdOracle, and (ii) positive questions "deferred" for early termination. This operation can boost recall by merging pairs of partially grown clusters that represent the same entity. To this end, `merge-clusters`(c_i, c_j) can rely upon a single intra-cluster query `query_pair`(u, v) with arbitrary $u, v \in c_i \times c_j$, or leverage `query_cluster`(c_i, c_j) for expander-like control queries.

In real CrowdOracle applications, the above methods can make mistakes – even when equipped with the pessimistic random expansion toolkit – by adding a node to the wrong cluster or by putting together clusters referring to different entities. Specifically, false negatives can separate in different clusters nodes referring to the same entity, while false positives can include in the same cluster nodes referring to different entities. This is more likely to happen early in the ER process, when we have collected few CrowdOracle answers. Luckily, mistakes can become evident later on, upon the arrival of new answers. The methods below are useful for identifying and correcting `insert-node()` and `merge-clusters()` mistakes.

[12]Technically, β controls the ratio between the edge expansion parameter and the log of the given cluster size.

STRATEGY	COST MODEL	QUERIES	`insert-node()`	`delete-node()`	`merge-clusters()`
`wang()`	off-line	spanning forest			optimistic
`vesd()`	on-line		optimistic		
`hybrid()`	on-line		realistic		optimistic
`mixed()`	on-line		realistic		realistic
`lazy()`	off-line	edge expansion	realistic	pessimistic	realistic phase + pessimistic phase
`eager()`	on-line		realistic/pessimistic	pessimistic	realistic/pessimistic
`adaptive()`	on-line	both	realistic/pessimistic	pessimistic	realistic/pessimistic

Table 1: Recent strategies categorization. We note that *spanning forest* strategies do not use `delete-node()`, and that *edge expansion* strategies can leverage optimistic and realistic approaches in some of their phases.

- **Delete node** This operation removes erroneous nodes from the clusters. Specifically, `delete-node`(u) triggers `query_cluster`$(u, c'(u))$ and whenever it returns NO, it pulls out the node and sets up a new singleton cluster $\{u\}$. We note that `delete-node()` can successfully fix both single-node errors due to `insert-node()` failure and larger `merge-clusters()` errors if one of the clusters c is sufficiently small. In the latter case, we can indeed repeatedly apply `delete-node()` to remove the smaller cluster, and then put it back together with `insert-node()` and `merge-clusters()` operations.
- **Split cluster** In case of severe `merge-clusters()` errors, we can try to recover by identifying "weak cuts" (see Definition 2) and splitting low confidence clusters into high confidence sub-graphs. To this end, `split-cluster`(c) selects the minimum cut (c_u, c_v) of a given cluster c (which corresponds to maximum joint error probability) and tries to expand it with `query_cluster`(c_u, c_v). If it succeeds, no changes to c need do be done. Otherwise, the cluster is split into the two sides of the cut.

In the next section, we will illustrate how combining the above operations leads to various strategies.

4 CrowdOracle Strategies

We now describe prior CrowdOracle strategies using the framework in Section 3, as summarized in Table 1. Then, we summarize the experimental results of the original papers [6, 7] and provide intuitions and illustrative experiments for a new strategy – `mixed()` – that can outperform `hybrid()` in specific application scenarios.

4.1 Strategy description

We consider `wang()`, `vesd()` and `hybrid()` from [6] in the perfect oracle setting, and `lazy()`, `eager()` and `adaptive()` from [7] in the general CrowdOracle model. (We refer the interested reader to original papers for more discussion.) For the perfect oracle – or, equivalently, spanning forest – strategies, we also report the key approximation results in [6] for our two problems 1 and 2, under a realistic *edge noise* model for p_m.

Wang The strategy in [18], which we refer to as `wang()`, is purely based on *optimistic merge clusters* operations. Every node starts as a singleton cluster. Then, cluster pairs are possibly merged in non-increasing order of matching probability, leveraging transitivity. Consider Example 1, where (r_a, r_d) is the edge with highest p_m value. The first operation is `merge-clusters`$(\{r_a\}, \{r_d\})$ – which is equivalent to `query_pair`(r_a, r_d) in this setting – yielding a negative outcome. The next edge in non-increasing order of matching probability is (r_d, r_f), thus, the second operation is `merge-clusters`$(\{r_d\}, \{r_f\})$, yielding another negative result. Something different happens upon the third operation, which is `merge-clusters`$(\{r_d\}, \{r_e\})$, because query_cluster(r_d, r_e) yields a positive answer. The singleton clusters r_a and r_d are merged into a "doubleton" cluster $\{r_d, r_e\}$, and – given that the next edge in the ordering is (r_a, r_e) – the fourth operation is merge-clusters($\{r_a\}, \{r_d, r_e\}$) and so on. We note that, being based on spanning forests, the optimistic merge-clusters() variant used by wang() asks only one of the two inter-cluster edges (r_a, r_d) and (r_a, r_e). We can make the strategy *pessimistic* by replacing the query_pair() step with query_cluster().[13]

The wang() strategy has an approximation factor of $\Omega(n)$ for Problem 1 and $O(\log^2 n)$ for Problem 2.

Vesd The strategy in [16], which we refer to as vesd(), leverages *optimistic insert node* operations. Differently from wang(), vesd() starts with a unique singleton cluster, corresponding to the node with highest expected cluster size. In our running example, this is the cluster $\{r_d\}$.[14] Nodes are possibly inserted in current clusters in non-increasing order of expected cluster size: the next node in the ordering is r_e, thus the first operation is insert-node(r_e). This operation triggers query_pair(r_e, r_d) as the first query (differently from wang()) and yields a positive answer, upon which the initial cluster $\{r_d\}$ is "grown" to $\{r_d, r_e\}$. After processing r_a and r_c, the current clusters are $c_1 = \{r_d, r_e\}$ and $c_2\{r_a, r_c\}$. When we consider r_f (which represents a different entity) we have two candidate clusters for insertion, and four intra-cluster edges connecting r_f to nodes in c_1 and c_2. Since optimistic insert node is driven by the highest matching probability edge among those (i.e., (r_a, r_f)) the first cluster selected for comparison – with no success – is $c = \{r_a, r_c\}$. Similarly to wang(), vesd() requires one query for comparing r_f and c, which can be arbitrarily chosen between query_pair(r_a, r_f) and query_pair(r_c, r_f). Before moving to node r_b, insert-node(r_f) compares r_f to the other clusters (i.e., c_2) until possibly success. Otherwise, a new cluster is created. Analogously to wang(), the strategy can be made pessimistic by replacing query_pair() with query_cluster().

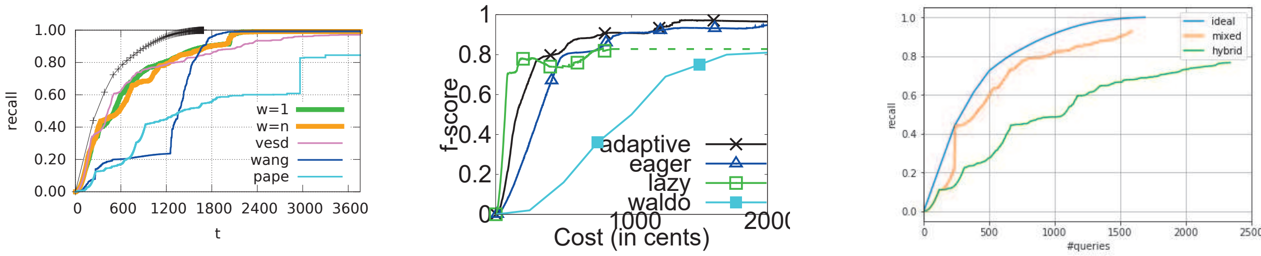
The vesd() strategy has better approximation factor of $\Omega(\sqrt{n})$ than wang() for Problem 1 and same $O(\log^2 n)$ for Problem 2. Without assumptions on matching probabilities, vesd() is shown to be $O(k)$ (which is usually $O(n)$) for the off-line setting[15], while wang() can be arbitrarily bad.

Hybrid The hybrid() strategy in [6] combines wang() and vesd(), and can be modified to apply random expansion similarly. Specifically, it first applies a variant of vesd() where insert-node() is modified with a parametric early termination option.[16] That is, some edges between established clusters may be non-resolved (i.e., non-inferable) at some point. In addition, nodes to add are selected based on their singleton-cluster benefit (i.e., sum of incident matching probabilities) with respect to established clusters, making hybrid() a *realistic insert node* strategy. After this phase, recall can be smaller than 1. To this end, hybrid() applies wang() taking care of "deferred" questions due to early termination. The early termination's parameters can be set such that i) hybrid() becomes a realistic variant of vesd(), by letting insert-node() terminate only in case there are no more clusters to consider (that is, no further merge-clusters() operations are needed); 2) hybrid() works like wang(), by inhibiting insert-node() completely; 3) anything in between.

In the worst case, hybrid() provides an $O(\sqrt{n})$-approximation to the on-line Problem 1. If matching probabilities are such that we can pick two representatives from any cluster A before elements of a smaller cluster B, then (no matter what the matching probability noise is) hybrid() performs like ideal(), because the benefit of a third node in the same cluster is higher than any other node in a different cluster, and so on.

Lazy This pipeline is described in [7] and can be thought of as the simplest edge expansion strategy in the framework. lazy() is indeed focused towards optimizing the progressive F-measure at the cost of lower precision at the start. It does so by following a mix of perfect oracle strategies vesd() and wang() – similarly to what

[13]parameters correspond to the clusters of the edge endpoints
[14]Expected cluster size of r_d is 3.55
[15]In this setting, we only need to minimize the number of queries.
[16]Intuitively, insert-node(u) fails not only if there are no more clusters to examine to, but also if cbn(u, c) drops below a given threshold θ or the number of questions related to node u exceeds a given amount of trials τ.



(a) `hybrid()` (b) `adaptive()` (c) `mixed()`

Figure 2: Experiments on `cora` dataset, featuring $\approx$ 1.9K records and 191 entities. Figure 2(b) considers a subset of 200 records, representing different entities. `pape` and `waldo` strategies are described respectively in [13, 15]

`hybrid()` does – in the beginning to avoid asking extra queries as required to form expanders. However, at the end, `lazy()` runs `merge-clusters()` with `query_cluster()` over all cluster pairs and `delete-node()` over all the nodes, aiming at the correction of recall and precision errors, respectively. We note that the final error correction phase may be challenged by large `merge-clusters()` errors[17], and `delete-node()` could give better results. This was not considered in [7], where `lazy()` is used as a baseline. In the beginning, the only difference with `hybrid()` is `merge-clusters()`, because cluster pairs are possibly merged in non-increasing order of cluster benefit (rather than matching probability), making `lazy()` a *realistic merge cluster* strategy.

Eager The strategy `eager()` in [7] has “orthogonal” behaviour with respect to `lazy()`. Indeed, it maintains high precision at the cost of low progressive F-score. It is a *pessimistic* version of `lazy()` where both `insert-node()` and `merge-clusters()` use `query_cluster()` as a substitute of `query_pair()`. Since expander properties are maintained throughout the execution, large cluster merge errors are unlikely. Therefore, `split-cluster()` is not used and the final error correction phase of `eager()` is the same as `lazy()`.

Adaptive The strategy `adaptive()` in [7] achieves the best of `eager()` and `lazy()` in real CrowdOracle applications. It provides the same final F-measure of `eager()` earlier in the querying procedure, along with the high progressive F-measure of `lazy()`. The intuition is to switch between `query_pair()` and `query_cluster()` depending on the current answer. We compare clusters with `query_pair()` as in `lazy()`, but we use our robust comparison tool `query_cluster()` if the result is in “disagreement” with matching probabilities. Formally, a disagreement can be: (i) a positive answer in case of low average matching probability (< 0.5); (ii) a negative answer in case of high average matching probability (≥ 0.5). `hybrid()` runs two executions of the error correction `merge-clusters()`+`delete-node()` procedure, one at the end (similarly to what `lazy()` and `eager()` do) and another when switching from the insert node phase to the merge cluster phase. Such extra-execution is useful for correcting early errors due to the adaptive nature of the initial `insert-node()` phase.

4.2 Empirical evaluation

Depending on matching and error probabilities (i.e., how accurate machine-based methods and crowd can be on the specific application), the considered strategies may have different performances. `hybrid()` and `adaptive()` are shown to be comparable or better than other strategies in their respective settings. However, when comparable, a user may prefer simpler strategies. Next, we report the main takeaways from [6, 7].

[17]Only removing singleton nodes of one of two erroneously merged clusters, without putting them back together.

1. Suppose there are no erroneous answers, and matching probabilities have uniform edge noise. If the size distribution of clusters is skewed (i.e., there are few large clusters and a long tail of small clusters), we expect `vesd`() to be better than `wang`() and `hybrid`() to be comparable or better than `vesd`().

2. In the same setting, but with small clusters (for instance, in Clean-Clean ER tasks where most clusters have size 2), we expect `wang`() to be much better than `vesd`() and `hybrid`() to perform like `wang`().

3. Suppose now the error rate of answers is high and matching probabilities are correlated with the ground truth, that is, truly positive edges have high probability and truly negative edges have low probability. We expect `eager`() to perform better than `lazy`(), and `adaptive`() to perform like `eager`().

4. Similarly, if the error is high and matching probabilities are uncorrelated with the ground truth, we expect `eager`() to be better than `lazy`(), and `adaptive`() to be like `eager`().

5. Instead, when the error is low and matching probabilities are correlated with the ground truth, we expect `lazy`() to be better than `eager`(), and `adaptive`() to be like `lazy`().

6. In the less realistic case where the error is low and matching probabilities are uncorrelated with the ground truth, we still expect `lazy`() to be better, but we expect `adaptive`() to be like `eager`().

7. There can be mixed cases of reasonable error rate and matching probability noise. We expect the different edge expansion strategies to have similar progressive F-measure in such cases.

Figures 2(a) and 2(b) report an experimental comparison of the considered strategies, against the popular `cora` bibliographic dataset.[18] `cora` is an example of a dataset where matching probabilities are correlated with the ground truth and the cluster size distribution is skewed (the top three clusters account for more then one third of the records), thus matching with application scenarios 1) and 3). The plots confirm the expected behaviour of strategies, with `adaptive`(), `eager`(), `hybrid`(), and `vesd`() being close to `ideal`().

Mixed Consider the perfect oracle setting, for sake of simplicity. Suppose that the matching probabilities have, in addition to the noise observed in the experiments of Figures 2(a) and 2(b), also a new, systematic noise, which only affects specific clusters and "splits" them in two parts. This can happen in many applications, where real-world entities are represented in well-defined *variations*. Examples include different sweetness – dry, extra dry – of the same wine entity, or the ArXiv and conference versions of the same paper. They are not really different entities, but we can expect lower p_m values between records of the two variations, than between records of the same variation. Systematic "split" error is correlated with entity variations rather than ground truth, and is a challenging scenario for `hybrid`() strategy. After growing the first variation, indeed, if inter-variation p_m values are such that corresponding questions are skipped by `insert-node`() and deferred to the `merge-clusters`() phase, `hybrid`() would seed the new variation as a separate cluster and grow it as if it was a different entity, until the start of the second phase. Our framework enables the design of a new strategy, that we call `mixed`(), that at every step selects `insert-node`() or `merge-clusters`() depending on the realistic cluster benefit, rather than having two separated phases. Experimental comparison of `hybrid`() and `mixed`() is shown in Figure 2(c), against a synthetic version of the `cora` dataset. In the synthetic `cora`, we artificially add the systematic error in the largest cluster c and set $p_m(u, v)$ to 0.001, $u, v \in c$, if u is odd and v is even.[19] The `mixed`() strategy consists of a sequence of *realistic merge clusters* operations, with sporadic *realistic insert node* (with the same early termination as `hybrid`()). Specifically, whenever the next pair of clusters in non-increasing order of benefit (see Section 2) corresponds to two singleton nodes $\{u\}$ and

[18] We refer the reader to the original papers [6, 7] for more details about the dataset and the experimental methodology.

[19] We also augment inter-variation p_m values and re-scale all the other scores in the graph, so that ranking of nodes by expected cluster size does not change for the purpose of the experiment.

$\{v\}$ never seen before, `mixed()` substitutes `merge-clusters`$(\{u\}, \{v\})$ with `insert-node`(w), where w is the largest unprocessed node in non-increasing order of expected cluster size. We observed that `mixed()` performs like `hybrid()` with the original `cora` dataset. However, in the presence of systematic error, after growing the first entity variation c_a, as soon as the second variation of c – which we refer to as c_b – grows large enough that the `cbn`(c_a, c_b) becomes relevant, the two sub-clusters are merged early by `merge-clusters()` into c.

5 Related Work

Entity Resolution (ER) has a long history (see, e.g., [4, 8] for surveys), from the seminal paper by Fellegi and Sunter in 1969 [5], which proposed the use of a learning-based approach, to rule-based and distance-based approaches (see, e.g., [4]), to the recently proposed hybrid human-machine approaches (see, e.g., [17, 9]). We focus on the latter line of work, which we refer to as *crowdsourced ER*, where we typically have access to machine-generated probabilities that two records represent the same real-world entity, and can ask "are u and v matching?" questions to humans.

The strategies described in [16, 18, 6] abstract the crowd as a whole by an *oracle*, which can provide a correct YES/NO answer for a given pair of items. Traditional ER strategies consider ER to be an *offline* task that needs to be completed before results can be used, which can be extremely expensive in resolving billions of records. To address this concern, recent strategies [21, 13] propose to identify more duplicate records early in the resolution process. Such *online* strategies are empirically shown to enable higher recall (i.e., more complete results) in the event of early termination or if there is limited resolution time available. The strategies focus on different ER logics and their performances, which can be formally compared in terms of the number of questions asked for 100% recall [6, 12]. Unfortunately, the strategies do not apply to low quality of answers: if an answer involving two clusters C_1, and C_2, is wrong, the error propagates to all the pairs in $C_1 \times C_2$.

The oracle errors issue raised by [18, 16, 6] is addressed by recent works such as [10, 14, 15, 7]. The solution provided by these works consists of a brand new set of techniques for replicating the same question (i.e. about the same pair) and submitting the replicas to *multiple* humans, until enough evidence is collected for labeling the pair as matching or non-matching (see Section 5). New techniques include voting mechanisms [10], robust clustering methods [14], and query-saving strategies such as classifying questions into easy and difficult [15]. These algorithms show how to make effective use of machine-generated probabilities for generating replicas and correcting errors, sometimes for the specific pair-wise answers and sometimes for the entities as a whole. In this setting, each YES/NO answer for a given pair of items can be interpreted as a matching probability: $1 - p^E$ if the pair is supposed to be matching, and p^E otherwise. (An information theoretic perspective of it is provided in [11].) General purpose answer-quality mechanisms are described in the crowd-sourcing literature [2, 19].

6 Conclusions

In this paper, we considered the pipelines described in [18, 16, 6, 7] in the general CrowdOracle model. We summarized their goals, provable guarantees and application scenarios. Specifically, we described a common framework consisting of simple operations that combined together lead to the considered strategies. This framework raised the issue of a specific scenario, which can be challenging for strategies in [18, 16, 6, 7]. To this end, we leveraged the simple operations introduced in this paper for defining an original strategy, which is better than `hybrid()` in the challenging scenario (and comparable in the traditional setting).

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