View-Driven Deduplication with Active Learning

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ABSTRACT

Visual analytics systems such as Tableau are increasingly popular for interactive data exploration. These tools, however, do not currently assist users with detecting or resolving potential data quality problems including the well-known deduplication problem. Recent approaches for deduplication focus on cleaning entire datasets and commonly require hundreds to thousands of user labels. In this paper, we address the problem of deduplication in the context of visual data analytics. We present a new approach for record deduplication that strives to produce the cleanest view possible with a limited budget for data labeling. The key idea behind our approach is to consider the impact that individual tuples have on a visualization and to monitor how the view changes during cleaning. With experiments on nine different visualizations for two real-world datasets, we show that our approach produces significantly cleaner views for small labeling budgets than state-of-the-art alternatives and that it also stops the cleaning process after requesting fewer labels.

1. INTRODUCTION

Visual analytic systems such as Tableau are becoming increasingly popular for data exploration and analysis. These tools enable users to interactively query data through a drag-and-drop interface, and the results are rendered on-the-fly as visualizations. These visualizations are represented internally as database views. Users can create a collection of sophisticated views that combine multiple heterogeneous data sets (e.g., Excel spreadsheets, relational databases, data cubes, delimited text files, etc.) along a common dimension or set of dimensions.

Today’s visual analytics systems assume that the data sets being consumed are clean and consistent with respect to each other (e.g., all entities in canonical form). However, data (especially on the Web) is often subject to data quality problems. De-duplication is one kind of dirty data problem. This problem manifests when there are different representations of the same real-world entity or object in the data sources being integrated. For example, the same restaurant may appear under two different phone numbers. The same product may use different abbreviations in its name or may include a different description.

Duplicate records may affect a visualization. Figure 1 shows an example, which we use as running example throughout the paper. The figure shows the top three types of cuisines by quantity of restaurants in San Francisco. This view is computed over a restaurant dataset commonly used for the evaluation of entity resolution tools [34]. This dataset was created from the union of the Fodor and Zagat restaurant ratings datasets. Because this is a benchmark dataset, duplicate tuples are labeled as such. We can thus compute the view both over the dirty and clean versions of the data. The figure shows the two resulting visualizations. Duplicate records clearly impact the visualization: French restaurant records are incorrectly overrepresented in the view on the left and should therefore be removed (or otherwise merged). The problem, however, is that data cleaning is a disruptive process. It interrupts the user during his primary data exploration task. Our goal is to clean a user’s visualization (or set of visualizations) with minimal interruption, i.e., minimal number of requests to the user for assistance.

In this paper, we focus on the entity resolution problem. Given a view computed over a dataset that contains duplicate entities, our goal is to clean the view by identifying and removing duplicate records in the underlying dataset. The commonly used approach to deduplicating a set of records, \( R \), comprises the following steps. The process requires an input a similarity function that takes a pair of tuples \((t_1, t_2)\) from \( R \) and produces a similarity score [19]. This similarity function, together with a similarity threshold, is applied to all pairs of records in \( R \) to determine which ones match [15]. Alternatively, a system may rely solely on users to indicate which tuples match [24, 10]. Multiple tuples can correspond to one entity and such clusters further need to be identified [2, 8, 40, 33, 42]. Once matching tuples are identified, they must be merged [25, 11]. During this step, any data conflicts among the multiple representations must be resolved. This step is called data fusion [11] and is not covered in this paper. To make the previous steps more compute-efficient by reducing the number of record comparisons, blocking techniques are used [9]. Blocking is an inexpensive heuristic filtering step that either partitions the tuples that get compared or removes pairs with low similarity scores.

Since manually devising an accurate similarity function requires an expert, state-of-the-art techniques for deduplication use active learning instead [33, 21], where one or more users label training examples (i.e., pairs of tuples) as either duplicates or not, which enables the system to learn a clas-
classifier that categorizes the remaining pairs of tuples. Active learning iteratively asks users for additional, carefully selected labels and re-trains the classifier until the classifier stops improving.

Active-learning-based deduplication is a promising approach for cleaning data visualizations. As a simple example, consider a typical data enthusiast, a food journalist, who wants to publish some visualizations that tell a story about restaurants in San Francisco by the end of the workday. After downloading a US restaurant ratings dataset from the Web that has duplicate entities and before visually exploring it using Tableau (or some other system), the journalist may choose to clean the data. The active learning method would select pairs of records and would ask the user to label them as either duplicates or not. It would then use the labels to build a classifier. Active learning repeats the process until the classifier stops improving. The classifier then labels all remaining pairs. After the classification completes, matching records can be merged to yield the clean dataset.

Existing active learning methods produce high-quality classifiers, but at great cost to the user. The user may have to provide hundreds to thousands of labels during the data cleaning process (see Table 2 in Section 4.1), which is significant for a data enthusiast who most likely just wants to create one or a few visualizations. Several systems use the crowd to perform the cleaning [21], [7], [6] would select pairs of records and would ask the user to label them as either duplicates or not. It would then use the labels to build a classifier. Active learning repeats the process until the classifier stops improving. The classifier then labels all remaining pairs. After the classification completes, matching records can be merged to yield the clean dataset.

Our method, View Impact Cleaning, performs deduplication in a manner that focuses on a user’s current visualization (or a set of related visualizations, as in a dashboard). View Impact Cleaning yields a significantly cleaner view than active learning alone when given a small labeling budget. It only asks the user to label data that is currently being visualized and stops the cleaning process when it determines that additional labels will not change the visualization further even if they could yield a better overall classifier.

By developing the View Impact Cleaning method, our contributions include:

1. A new notion of view sensitivity to duplicate tuples. View sensitivity captures the extent to which a view is affected by duplicate tuples. We also define a new notion of view impact score of individual tuples on a visualization. The view impact score measures the extent to which a view will change if a given tuple is found to be a duplicate and is removed (Section 4.1).

2. An active-learning method that builds an initial classifier and then iteratively improves that classifier. One novelty of our approach is in the selection of the training examples: it considers both the view impact scores of individual tuples and the potential of a training example to improve the classifier quality (Section 4.2).

3. A new stopping condition for view cleaning that considers the view’s evolution during the cleaning process. An important implication of our approach is that it stops cleaning a view both in the case where a sufficient number of tuples have been removed and in the case where a view is not sensitive to duplicate tuples and cleaning has little effect on the view (Section 4.3).

We evaluate our approach on nine views specified on two real-world entity resolution data sets. We use the restaurants dataset from the well-studied RIDDLE [34] repository and the Google-Amazon products dataset from [3], [26], [27]. We find that, when given a small cleaning budget (i.e., the user is willing to label a small number of record pairs as duplicates or not), our approach yields significantly cleaner views than existing active learning methods, which do not consider the user’s view (or dashboard of views). It also effectively stops cleaning earlier than active learning alone while delivering views much closer to those computed over the clean data. Finally, we evaluate and discuss the problem of cleaning a dashboard comprising multiple visualizations.

Our results show that cleaning one view with our approach effectively helps to clean other views even though cleaning is view-driven. As such, our approach helps to make data cleaning a pay-as-you-go task.

2. PROBLEM STATEMENT

Consider a relation \( R \) that contains duplicate tuples. Two tuples \( t_1 \) and \( t_2 \) in \( R \) are duplicate if they refer to the same real-world entity (e.g., same restaurant). They need not be identical and, most often, are not identical. For example, the same restaurant may appear twice but with different phone numbers. The relation may be the result of the integration of two or more datasets or may contain duplicate tuples for other reasons. We assume \( R \) to be given and we do not require knowledge of where individual tuples in \( R \) come from. In our running example from Figure 1, \( R \) is the unioned restaurant dataset.

The user builds a view, \( V(R) \), and a visualization that displays it, such as the one shown in Figure 1. In our approach, we do not consider the details of the visualization. Instead, we focus on the relation \( V(R) \) and consider that any change to \( V(R) \) affects the visualization. Our approach supports views that correspond to select-project queries with optional aggregation, grouping, sorting, and top-K restrictions.

We define \( R_{clean} \) as the relation \( R \) with all duplicate tuples removed. For convenience, we refer to the original view, \( V(R) \), as \( V_{dirty} \), to \( V(R_{clean}) \) as \( V_{clean} \), and to the same view \( V \) computed on a partially cleaned relation as \( V_{curr} \). We define the quality, or cleanliness, of a view as follows:

**Definition 2.1.** Quality(\( V \)) or Cleanliness(\( V \)) of a view \( V \) is \( 1 - \text{Distance}(V, V_{clean}) \), for some distance function, \( \text{Distance} \in [0, 1] \).

The quality of a view thus depends on the distance to the view computed on clean data. In our implementation, we use the well-known Earth Mover’s Distance [35] to compute distances between views as we describe in Section 4.4.

**Objective:** The goal of our approach is to clean a view by reducing Distance(\( V, V_{clean} \)).

We target scenarios where a single user explores a dataset \( R \) by defining one or more views on top of \( R \). We assume
that the user is a data enthusiast who can label pairs of records in his dataset as either duplicate or not but cannot otherwise tune or help the data cleaning process.

In this paper, we do not address the problem of how best to merge duplicate tuples [11]. Any of the existing techniques [20] could be used. In our experiments, we drop one of the duplicate tuples. We also do not handle labeling errors [33]. We assume correct labels. These additional techniques are complementary to the approach developed in this paper. Additionally, our approach relies on the data enthusiast to provide labels directly. We do not use the crowd. We do not require any expertise from the user beyond the ability to identify whether two records are duplicates.

3. BACKGROUND

Deduplication has been a long-standing, challenging problem [16, 20]. The most closely related work applicable to our context relies on a non-expert user or users to label tuple pairs as either duplicate or not and then uses machine learning to build a classifier to identify duplicate records in a relation [5, 8, 21]. We build on this foundation, which we briefly review here:

**Learning a Classifier:** Given the relation R to clean, one builds a cartesian product \( S = R \times R \) (e.g., \( S \) is the set of all restaurant pairs). For each tuple in \( S \), one computes a feature vector that captures distance information between the individual attributes of the two \( R \) tuples that form the \( S \) tuple. For example, one feature could be the edit distance between restaurant names and a second the jaccard similarity between their addresses. Commonly used distance functions include edit distance, jaccard, jaccard containment, and cosine distance (see [14, 19] for detailed descriptions) for string attributes and Euclidean distance for numerical attributes. Other functions are possible [14].

The basic learning algorithm selects a random sample of pairs from \( S \), asks the user to label them as either duplicates or not, and then learns a classifier using that training data. Once duplicates are identified, the tuple included and the tuple removed. View impact scores drive the cleaning process. By identifying tuples with high view impact scores, our approach effectively focuses cleaning actions on the subset of \( R \) that matters the most to the user’s view(s). For example, consider the top-k view of cuisine types by quantity of restaurants in Figure [1] a tuple whose cuisine attribute is ‘American’, ‘Asian’, ‘French’, or ‘Italian’ would have a higher impact score because these cuisines appear in the view, than one with a rare type such as ‘Indonesian’, because the latter will never appear in the view, even once the base data is completely clean.

The second concept, view sensitivity, serves to inform when to stop the cleaning process. The view sensitivity measures how much a view is affected by duplicate tuples:

**Definition 4.2.** The sensitivity of a view \( V_{curr} \) to duplicate tuples is \( \text{Distance}(V_{curr}, V_{clean}) \).

4. APPROACH

The goal of our approach is to deduplicate \( R \) in a way that minimizes the distance between \( V_{curr} \) and \( V_{clean} \), while keeping the number of tuple-pairs that the user needs to label low. We employ an active-learning-based approach with the same fundamental setting as presented in Section 3.

To clean \( V(R) \), our approach is to build a classifier that takes as input all pairs of tuples (\( t_1, t_2 \)) with \( t_1 \neq t_2 \) and \( t_1 \in R \) and \( t_2 \in R \) and classifies each one as either a duplicate pair or a non-duplicate pair. Once duplicates are identified, any existing method can serve to merge them as indicated in Section 2. Our goal is to produce the cleanest possible view (i.e., smallest Distance(\( V_{curr}, V_{clean} \))) for a given label budget \( l \). Additionally, we require that \( l \) be small in the order of tens or low hundreds of labels.

In this section, we first describe our model to reason about the sensitivity of a view to duplicate tuples and the impact of individual tuples on the view (Section 4.1). We then present our active-learning approach to view cleaning, which is based on this model (Sections 4.2 and 4.3).

4.1. View Impact Score and View Sensitivity

Our data cleaning approach introduces and leverages two important concepts related to the way tuples affect a view. We call them the view impact score and view sensitivity. The view impact score of a tuple measures how much the tuple affects a view \( V(R) \). We define it as follows:

**Definition 4.1.** The view impact score of a tuple \( t \in R \) on a view \( V(R) \) denoted as Impact(\( V, t \)) is Distance(\( V(R), V(R-t) \)).

The view impact score of a tuple measures the distance between the view computed over the base relation \( R \) with the tuple included and with the tuple removed. View impact scores drive the cleaning process. By identifying tuples with high view impact scores, our approach effectively focuses cleaning actions on the subset of \( R \) that matters the most to the user’s view(s). For example, consider the top-k view of cuisine types by quantity of restaurants in Figure [1] a tuple whose cuisine attribute is ‘American’, ‘Asian’, ‘French’, or ‘Italian’ would have a higher impact score because these cuisines appear in the view, than one with a rare type such as ‘Indonesian’, because the latter will never appear in the view, even once the base data is completely clean.

The second concept, view sensitivity, serves to inform when to stop the cleaning process. The view sensitivity measures how much a view is affected by duplicate tuples:

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Figure 2: Example view impact score and view distance computation. (top) The view impact score for each tuple $t$ is the distance (EMD) between the view over relation $R$ and over $R$ with tuple $t$ removed. (bottom) Illustration of one distance (EMD) computation between two views.

The sensitivity of a view is the distance between the current view and the same view computed over the cleaned relation $R_{clean}$. A view is no longer sensitive to duplicate tuples for one of two reasons: Either relation $R$ has been sufficiently cleaned or the view is generally not affected by duplicate tuples. In both cases, any further cleaning will not change the view in a significant way. For example, a view that displays median values is not easily affected by duplicate results: cleaning is unlikely to affect the median value significantly. As another example, once the view from Figure 1 correctly lists the top three types of cuisine any further cleaning is unlikely to affect the median value.

During the view cleaning process, the system does not have access to $R_{clean}$ and thus $V_{clean}$. Instead, our approach operates on distances between consecutive views obtained during the iterative view cleaning process, $\text{Distance}(V_{curr}, V_{curr+1})$, to estimate sensitivity and determine when to stop cleaning.

A key component of the above two concepts is the notion of distance between two views. Our approach requires a distance function that captures differences at the level of tuples and individual cells. One function that captures this requirement is the Earth Mover’s Distance (EMD), which we successfully applied in prior work [29]. EMD is a method to evaluate dissimilarity between two multi-dimensional distributions. Intuitively, given two distributions, one can be seen as a mass of earth spread in space, the other as a collection of holes in that same space. Then, the EMD measures the least amount of work needed to fill the holes with earth.

Here, a unit of work corresponds to transporting a unit of earth by a unit of ground distance.

To compute the EMD between two views $V_1$ and $V_2$, we thus need a distance function for individual tuples in these views and a weight for each tuple. For the weight, we assign each tuple in a view $V$ the same weight equal to $\frac{1}{|V|}$. For the tuple distance, we consider each tuple $t$ with $n$ attributes as an $n$-dimensional vector and use Euclidean distance to compute the distance between two tuples $i \in V_1$ and $j \in V_2$. For individual attributes in a tuple, we use Euclidean distance to compute the distance between numeric attributes (normalized to the $[0, 1]$ range) and string equality as the distance between categorical attributes ($i.e.$, 0 if attributes are the same and 1 if they are different). We explain the distance computation through an example: Consider the following two views (in Figure 2): (1) $V_{top-3}(R)$, a top-3 view of cuisines in San Francisco over a restaurants dataset, $R$, and (2) the same top-3 view but over a relation $R'$ where one tuple $t$ has been removed. The SQL statement for this view appears in Table 3. The distances are then calculated between all combinations of tuples $(i, j)$ where $i \in V_{top-3}(R)$ and $j \in V_{top-3}(R' - t)$, as shown in Table 1. Each tuple is given the same weight of $1/|V_{top-3}|$ and we call the library from [17] to solve the linear program that computes the minimum flow to move the earth between the views using the pre-computed distances. The solution to the linear programming problem is shown bolded in Table 1. The EMD returned is $0.0143$ which is 0.01. This value also corresponds to the view impact score of tuple $t$ as per the definition above.

4.2 View Cleaning

In this section, we present our active-learning-based algorithm for cleaning views by taking into account the view impact scores of individual tuples and the view sensitivity to duplicates. The user triggers the cleaning process, but stopping is automatic.

4.2.1 Initial Classifier

The first step in the active learning process is to select a set, $L_0$, of training examples, ask the user to label them, and train an initial classifier using those labels. A training example is a pair of tuples, $(t_1, t_2)$ with $t_1 \in R \land t_2 \in R \land t_1 \neq t_2$. When a pair has duplicate tuples, it is a positive example. Otherwise, it is a negative example.

Recent prior work [33] randomly selects a 3% sample of such pairs to train the initial classifier. A known challenge with record deduplication, however, is that the number of positive examples is extremely small even when a dataset contains many duplicate tuples. For example, if each duplicate tuple in a relation of size $|R|$ participates in one positive example it also participates in $|R| - 2$ negative examples. As a result, a small random sample of training examples can easily fail to include any positive examples, leading to a poor initial classifier, especially when $|R|$ is large. A common approach to alleviate this problem is to use blocking, where all tuple-pairs with low similarity scores for one or more features are discarded before the data cleaning process even begins. For example, pairs of restaurants with names that are not at all similar should be discarded. We further use a second blocking method: We focus only on tuples that participate in the view. Instead of cleaning $|R|$, we clean only those tuples in $|R|$ that pass the selection condition in the query. We denote these tuples with $\text{Provenance}(V(R))$ since they correspond to the why-provenance [12] of $V(R)$ if we ignore any top-k clauses in the query. Table 2 shows the fraction of duplicates for two datasets that we describe further in Section 5. The table shows the result for both the dataset as a whole and for the subset of the data in the views that we use in the evaluation. Even after applying both types of blocking (blocking on the view and the features), the fraction of positive examples is only 2.3% and 9.4% for the two views (we describe the exact blocking function in Section 5).

The second challenge with learning a classifier for record deduplication is that the features themselves used to train the classifier may be poor. In our application domain,
particular, the user's goal is to create and analyze a given set of visualizations. The user is not seeking to clean the data. As a result, the system cannot rely on the user to determine a good set of features. Instead, the feature selection process must be automated, which complicates the identification of a good set of features.

The above two challenges make it difficult to build high quality classifiers as we show in the evaluation, and lead us to develop a different strategy for training an initial classifier. Our key idea is to get the user to label tuple-pairs where at least one tuple has a high view impact score. The intuition is that these pairs will not necessarily be worse training examples than random pairs. At the same time, correct labels for these pairs have the highest potential to improve the quality of the view. For example, in Figure 1 tuples that correspond to American, French, Asian, and Italian restaurants will have higher view impact scores than others and pairs containing such tuples should be weighted more heavily when selecting examples to label.

The approach to learning the initial classifier has three main steps: view impact score computation (Algorithm 1), training-example selection, and training of the initial classifier (Algorithm 2) lines 1 through 14. The view impact computation proceeds as follows:

1. For each tuple $t \in \text{Provenance}(V(R))$, we compute its view impact score, $score$, as per Definition 3. For example, in the view in Figure 1 we only compute the view impact for restaurants in San Francisco. Other tuples necessarily have a view impact score of zero. We store the results in a relation called TupleScores.

2. For each tuple $t \in \text{TupleScores}$, we generate $\text{Provenance}(V(R)) - \{t\}$ potential training examples of the form $(t, u, score)$, where $u \in \text{Provenance}(V(R)) - \{t\}$ and score is the view impact score for $t$. We store the results in a relation called PairScores.

Selecting the initial training examples proceeds as follows:

1. First, we apply a blocking function that removes obvious non-matches from the previously computed PairScores. The blocking function drops all pairs with at least one attribute that has a similarity below a pre-defined threshold (or distance above a pre-defined threshold). Section 3 describes the blocking function that we use in the experiments. This step corresponds to function Block on line 6 of Algorithm 2.

2. Second, we select $|\mathcal{Q}|$ examples from the filtered PairScores by using weighted random sampling with weights equal to the view impact scores. To train a new classifier, we need a set of examples that are not only informative but also diverse [21], and hence as prior work [33, 21], we use weighted random sampling rather than selecting the top-k pairs with highest view impact. This approach heavily weights the pairs with high scores while randomly breaking ties between pairs that have the same score, such as pairs generated from the same initial tuple. This step corresponds to function SelectBias on line 7 of Algorithm 2.

Finally, the user labels the selected pairs and these labels serve as training examples for the initial classifier (lines 8 through 10 in Algorithm 2). The duplicate tuples identified explicitly by the user or implicitly by the classifier are then removed from the input data and the view is recomputed as shown in lines 11 and 12 in Algorithm 2.

### 4.2.2 Subsequent Training Examples

To improve the initial classifier, the active learning method selects additional training examples for the user to label. As described in Section 3, active learning strives to select examples that are most informative and thus have the highest potential to help improve the classifier. It then learns a new classifier on the expanded training data. As in the case of the initial classifier, we propose to take a different approach and leverage view impact scores when selecting additional training examples. We propose the following two approaches:

**View Impact Method (ViewImpact):** As in the case of learning the initial classifier, this approach favors training examples where at least one tuple has a high view impact.
score. Instead of breaking ties randomly, however, we select those samples that can help improve the current classifier the most. The tie breaker is to select the samples with small margin distance, i.e., the samples with the minimum absolute confidence score from the classifier. If the margin distance is small, the classifier is less confident. Therefore, the sample is better chosen for labeling as it should help fine-tune the classifier. This tie-breaker is similar to the uncertainty method, in which the examples that are closest to the decision boundary are selected. In our case, however, uncertainty is secondary to view impact. This selection algorithm corresponds to method Selecttop(b,PS) in Algorithm 2 and it works as follows:

- The function takes as input the PairScores data structure. For each subset of pairs \( \{(t,u)\} \in \text{PairScores} \) associated with the same original tuple \( t \), the approach retains only the entry with the lowest margin distance, which it appends to a new data structure, TopPairScores.
- The algorithm then selects \( b \) pairs from TopPairScores using weighted sampling where the view impact score \( s \) serves as the weight.

**Hybrid Method (Hybrid):** We also explore a second approach that is a hybrid between the traditional method of selecting the most informative training examples and the ViewImpact method. The hybrid approach computes the same TopPairScores structure as the ViewImpact method above. However, it then assigns the following hybrid weight to each pair of tuples in that set before selecting the next batch of \( b \) examples using weighted sampling. ClassifierUncertainty measures the classifier uncertainty as in state-of-the-art active learning methods for record duplication [33] (See Section 4).

\[
\text{HybridScore} = \alpha \text{ViewImpactScore} + (1-\alpha)\text{ClassifierUncertainty}
\]

(1)

**5. Evaluation**

We evaluate our View Impact Cleaning approach compared with state-of-the-art view-agnostic active-learning. **Classifier.** We use a common choice for classification, support vector machines, to build the classifier. Our implementation uses libsvm [33]. We use either linear kernels or Gaussian kernels by tuning over the data and set the weights for the positive and negative label classes to the reciprocals of their respective cardinalities.

**Features.** Selecting the right features to give to a machine learning algorithm (or feature engineering) is a well-known, challenging problem. Recent prior work leaves the feature selection decision to an expert user [3], or in the case of Corleone [21], the system randomly selects a subset of attributes as features. For the applications that we target, we
cannot require that users define features and thus, similar to Corleone, must rely on an automated approach. In our implementation, we use generic, type-based features, but any automated feature-selection approach could be applied.

**Data.** We use two datasets (Table 2) that have been extensively used in prior deduplication work [21]. The restaurants dataset is the union of restaurant data collected from the culinary rating sites, Fodor and Zagat. 533 tuples come from Fodor and 331 from Zagat for a total of 864 tuples and 745,632 distinct pairs to classify. Figure 2 shows example records. Products, a more challenging dataset to deduplicate, combines electronics products from Amazon (1,363 rows) and Google (3,226 rows) with schema (name, description, manufacturer, price). An example record is: ['learning quickbooks 2007', 'learning quickbooks 2007', 'intuit', '38.99']. There are more than 21 million tuple pairs in the union of these tables, among which only 1,300 pairs refer to the same entities (0.006% matches).

**Views.** We study SELECT, PROJECT, and AGGREGATE (e.g., GROUP/ORDER BY LIMIT) views. Queries containing joins have not been evaluated, but there is no theoretical limitation to applying the View Impact Cleaning method to such views. Recent prior work on deduplicating views [2] only applies to simple, non-aggregate SELECT/PROJECT views, while others such as SampleClean [11, 25] are designed only for aggregate queries without ordering nor top-k clauses. We evaluate our approaches over 9 views (Table 3) that we choose for the following reasons: (1) variety of impact that individual duplicates have on the view and (2) variety of the overall views’ sensitivities to duplicates.

**Blocking methods.** We use two types of blocking strategies to reduce the class imbalance between positive and negative examples: view-based and feature-based blocking. Table 2 shows how each type of blocking increases the fraction of positive examples by an order of magnitude. For the restaurants dataset, our views select restaurants in San Francisco (shown as SFrestaurants). For the products dataset, the views include products sold by Microsoft, Apple, and Adobe (shown as MfrProducts). For feature-based blocking, for restaurants, we drop pairs whose **jaccard** or **jaccard containment** match scores on the name and address attributes respectively are less than 0.2. For products, we block on price and name when the normalized Euclidean distance on price is greater than 0.54 and **jaccard** scores are less than 0.17 or **jaccard containment** scores are less than 0.27 for name. While we pick these thresholds manually, the approach could be automated by systematically dropping some percentage P of least similar pairs along each attribute. Please see [31] for additional details on the features computed and machine learning settings used.

For all experiments in this section, all approaches (including view-agnostic active learning) select pairs from the two views that include both blocking strategies, or SFrestaurants and MfrProducts.

**Experimental setup.** We run the restaurants experiments 20 times and the products experiments 100 times. For each experiment, we create a randomly-selected holdoutset, which is not used for training. It serves to evaluate the quality of the classifiers. The holdoutset size is approximately equal to half of the size of the initial unlabeled set.

**Methods compared.** We apply two state-of-the-art active learning methods, which we refer to as Uncertainty and Entropy, as a baseline. For each of these methods, we use an uncertainty or entropy measure to select the subsequent batches of examples for active learning. Our implementation is based on the description in [33]: uncertainty [33, 36] and entropy [21] scores are computed over 10 bootstraps that are sampled with replacement from the training set. The examples are ranked by either their uncertainty or entropy scores and selected by applying biased weighted sampling. Both Uncertainty and Entropy measure the disagreement of the classifiers over the holdoutset example labels. Thus, the higher the uncertainty, the stronger the disagreement, and the more informative the example is to the learner.

**5.1 End-to-End Results**

We first compare the overall ability of our approach, View Impact Cleaning, and the two state-of-the-art active learning algorithms, Entropy and Uncertainty, to clean views with a small number of user labels. Figures 3, 4 and 5 show Distance(Vcurr,Vclean) before cleaning (value shown under “Initial distance”), after cleaning with the initial classifier (labeled L0), and after the maximum budget of user labels. Each point represents the average of either 20 runs (Restaurant dataset) or 100 runs (Products dataset) and the standard deviation, σ. Since Figure 6 shows that Uncertainty and Entropy achieve similar cleaning results and classifier accuracies, we present only Uncertainty in future graphs.

**Products main result.** As shown in Figures 6 (and 7, left), all product views are completely cleaned by View Impact in fewer than 18 batches, or 440 labels (including the initial L0 batch of size 100 and subsequent batches of size 20). Top3 and PriceBins are cleaned in only three and four batches, respectively (140 to 160 labels). These views are cleaned faster with View Impact than the Select* and Count* views because a smaller number of tuples impacts these views.
These are the only tuples with non-zero view impact scores and View Impact biases the selection of tuple-pairs for the user to label toward these tuples. In contrast, all tuples impact Select* and Count* views and do so equally, leading to a longer cleaning process. Most importantly, for all views, the View Impact Cleaning approach yields rapid improvements in view quality early on in the cleaning process. For the Select* view, our approach cuts the distance to the clean view by 4X after the initial classifier (from 0.47 to 0.11). The first subsequent batch cuts the distance by another 50%. In contrast, the Classifier Uncertainty and Entropy methods are unable to completely clean any views in 40 batches.

Figures 8 and 9 (right) show the classifier accuracy (F1score) achieved by all methods. It is difficult to build a quality classifier for the products dataset as evidenced by the low average F1 scores for all methods. The products dataset contains many data quality problems including missing and wrong values, which complicates feature selection. For example, name values were inconsistent even for matching pairs. We thus used this attribute for blocking but not for learning. We observe, however, that as expected the View Impact Cleaning method yields, on average, a classifier with a lower F1 score than the Uncertainty or Entropy methods. This method focuses on the quality of the view rather than the quality of the classifier itself.

Interestingly, all views are cleaned monotonically with the View Impact Cleaning approach, while some aggregate views such as PriceBins exhibit non-monotonic behavior for the other methods. We see this undesirable behavior with Uncertainty and Entropy because they focus on selecting examples that improve the classifier’s quality and not the view. Since the classifier’s accuracy is low, it is unable to correctly label the pairs that impact the view. The View Impact Cleaning approach, in contrast, favors as training examples labels that improve the classifier’s quality and not the view. The View Impact Cleaning approach does not as good as Uncertainty, but these labels are useful for cleaning the view. The classifiers main result. Figure 5 (right) shows that all approaches exhibit higher average F1 scores on the hold-out set for restaurants than products, which suggests that duplicates in this dataset are much easier to classify. We thus expect that the results for cleaning with all approaches should be similar. We observe, in Figure 5 (left), that the View Impact Cleaning method cleans all restaurant views in three batches, while Uncertainty needs four batches. Assuming that the initial classifier is learned over a batch of 13 pairs and subsequent batches contain 20 pairs, view impact can clean all views one batch faster than Uncertainty. Furthermore, for the Top3 view, view impact only requested two batches (33 labels), while Uncertainty required two additional batches of 20. These results indicate that even when a good classifier can be learned with a small number of labeled examples, our technique does not hurt the quality of the view compared with Uncertainty.
5.2 Learning an initial classifier

We now study the individual components of the View Impact Cleaning approach. The first component of the approach is the selection of the initial training examples (C.F. Section 4.2). The selection occurs after both view-based and feature-based blocking.

We measure the quality of the view obtained after cleaning using the initial classifier learned with View Impact Cleaning. We compare the results to cleaning when using a classifier learned on a strictly random sample of the data taken also after both view-based and feature-based blocking. As discussed in Section 4.2 and as shown in Table 2 because the number of positive examples is extremely small compared with the number of negative examples, an initial classifier learned on a random data sample may have no positive examples to learn from. We thus also compare with a third approach that biases the selection of the training examples to select a larger fraction of positive examples. We call this last method per-feature round-robin. This approach sorts the tuple pairs by decreasing value of each of their features. It creates as many sorted lists as there are features and each pair appears once in each list. It then uses weighted sampling to select the pairs using the rank in the lists as weight.

**Products.** Figure 6 (left) shows the results for the four views over the Products dataset. As the figure shows, the View Impact Cleaning method yields the cleanest views after this initial cleaning step. Because View Impact Cleaning focuses on labeling and cleaning pairs with tuples that have high-impact on the view, an important question that arises is whether a classifier is at all useful or whether all the benefits come from the user labels. The figure also shows the quality of the view if we clean it using only the user labels. As the figure shows, with all three methods, building and using a classifier is critical to cleaning the view. Interestingly, the classifiers help to clean the view even though their average F1 accuracies are low for all sampling approaches (see Figure 6, table). This result implies that, for the purpose of quickly cleaning a view, it is not necessary to learn a high-quality classifier; rather it is more important to have the user resolve the most impactful tuples first, and then train a classifier using these biased labels.

**Restaurants.** We see in Figure 6 (right) that all sampling strategies have similar behaviors when cleaning the views for a small 

5.3 Tuning the parameter settings

In this section, we study the effect of tuning various settings for the View Impact Cleaning and Uncertainty approaches. We first present the impact of weighting the two cleaning approaches using the \( \alpha \) parameter in Equation 4 for the Hybrid method that combines View Impact Cleaning with ClassifierUncertainty. We also study the impact of varying the batch sizes.

5.3.1 \( \alpha \) values

Since a good quality classifier can help save the user in cleaning effort, we study the effect of the weighting factor \( \alpha \) in the Hybrid method described in Section 4.2.2. Recall that this method selects pairs for labeling by assigning them the following weight: \( \alpha \times ViewImpactScore + (1 - \alpha) \times ClassifierUncertainty \). We consider the two extremes: prioritizing pairs that will improve the classifier \( (\alpha = 0) \) and prioritizing pairs that impact the view \( (\alpha = 1) \). We also consider the hybrid method with \( \alpha = 0.5 \). Our analysis focuses on the products dataset, since the quality of its classifiers was much lower than those for restaurants. Furthermore, we zoom in to the details for two views, which exhibit very different sensitivities to duplicates. Other views showed similar trends.

**View with higher relative sensitivity to dups.** Figure 7 shows the result for the Select* view, which has the highest initial sensitivity to duplicates, 0.47. All initial classifiers are trained on 100 example pairs with View Impact Cleaning. The choice of \( \alpha \) affects only subsequent batches. As the figure shows, the View Impact Cleaning approach \( (i.e., \alpha = 1.0) \) is still able to make more progress cleaning than both the hybrid \( (\alpha = 0.5) \) and ClassifierUncertainty \( (\alpha = 0.0) \), despite having consistently lower overall classifier accuracy. In fact, View Impact Cleaning is the only technique that completely cleans this view within the budget of 500 labels (20 batches). This result suggests that heavily biasing the selection strategy toward the most impactful pairs is better for cleaning views that are highly sensitive to duplicates and defined over a dataset for which it is difficult to build a high-quality classifier.

**View with lower relative sensitivity to dups.** Figure 8 shows the results for the PriceBins view, which is close to half as sensitive to duplicates as the Select* view. Once again, View Impact Cleaning outperforms the other approaches. It is able to completely deduplicate the PriceBins view by batch 5; neither of the other two approaches could to do so by the end of the 500 label budget (20 batches).

5.3.2 Batch size

We study the effect of cleaning views with different batch sizes (10, 20, 50, and 100 example pairs) and budgets (400 and 200) with View Impact Cleaning and Uncertainty. We show the result for products in Figure 9. We observed similar results for restaurants. Overall, the batch size does not sig-
Figure 7: Impact of $\alpha$ on avg. $\text{Distance}(V_{\text{curv}}, V_{\text{clean}})$ and avg. F1 for product views. Initial $L_0$ has 100 pairs.

Figure 8: For all product views, we see the impact of batch size on average $\text{Distance}(V_{\text{curv}}, V_{\text{clean}}) + \sigma$ with a budget of 200 (left) and budget of 400 (right).

significantly influence the results. For all configurations, View Impact Cleaning is able to clean more than Uncertainty on average. Additionally, the variance for Uncertainty is much higher than for View Impact Cleaning. This result suggests that View Impact Cleaning is a more stable approach to deduplication and that it is not sensitive to the batch size.

5.4 Runtime and scalability

View Impact Cleaning complexity. There are two primary sources of computational complexity for the View Impact Cleaning algorithm. First, computing the feature vectors for all pairs is $O(n^2)$, where $n$ is the input dataset size. Second, computing the Distance in EMD View Impact Scores (from Algorithm 1) takes worst-case $O(n \times m^2)$ because the EMD has $O(m^2)$ complexity where $m$ is the size of the view $|V|$ and can be called (worst-case) $n$ times if $|\text{Provenance}(V[R])| = |R| = n$. Since computing the EMD grows quadratically with the view size, this approach works best with small views. Interestingly, a recent study of visualizations/views created on Tableau Public and Many Eyes showed that 53% of views have fewer than 1,000 rows. We discuss the empirical findings next.

Empirical runtimes. We ran View Impact Cleaning on a desktop machine with dual 2.4 GHz quad-core Intel Xeon processors and 11GB of memory. We use SQLite as our backend database to compute the feature vector table. We present the detailed measurement of runtimes for our approach on the view, Select* from products, as this view is the largest of all from Table 3 (with 291 rows) and takes the most time. We assume the same experiment settings as prior experiments on this view, where the initial $L_0$ batch has 100 pairs and subsequent batches have each 20 pairs. We time each of the key steps as follows: (1) Compute view impact scores for all tuples: three minutes, (2) Compute feature vector with four features with view blocking and feature blocking: three minutes (without feature blocking the time is 53 minutes) (3) Pick examples to label per batch: under one second, (4) Learn a new classifier per batch: under one second, (5) Labels all pairs as either duplicates or not per batch: under three seconds.

As expected, steps (1) and (2) are the only steps that take a significant amount of time. To help with overall interactivity, these steps can be done as a background process while the user first explores the data. Interestingly, these two steps only need to be performed once before the cleaning process begins. Over the course of cleaning a view, the tuple view impact scores tend to not change.

5.5 Stopping condition

Recall that in practice $V_{\text{clean}}$ is not known. We thus do not know exactly when to stop cleaning. The heuristic used is to stop after little to no progress has been made for some interval of time. All we can do is show empirically that this heuristic is effective. The Entropy method does this based on the stability of the confidence values of the classifier. Since the Uncertainty approach does not specify when learning can stop, we apply the same approach as used in the Entropy work to monitor the stability of the uncertainty values of the classifier. The View Impact Cleaning approach has a more natural and direct way to measure “little change” based on the $\text{Distance}(V_{\text{curv}}, V_{\text{prev}})$. The idea is to stop cleaning once we observe that the distances computed between the current view, $V_{\text{curv}}$, and the view cleaned from the previous iteration, $V_{\text{prev}}$, have plateaued (within +/- $\epsilon_p = 0.01$) over a window of size $n_{\text{convergence}}$ batches. For the product views, shown in Figure 9, we evaluate the impact of the window size on the convergence to the true clean view. The figure shows the distance values when cleaning...
Figure 10: Effect of fully cleaning one view on cleaning the other views in products given a budget of 500 labels (batches = 20 pairs): resolving the duplicates in the Select* view (far left) helps clean all the other views the fastest in 460 labels. However, the views are not cleaned monotonically.

Figure 11: The most sensitive view first approach (left, i.e., cleaning Select* monotonically cleans the other product views except for PriceBins and does so with only 460 labels. All batches contain 20 pairs.

5.6 Multi-view deduplication

A dashboard is a collection of related visualizations or views typically over a common dataset. In this section, we study the performance of two techniques for data cleaning in the context of such dashboards.

(1) Fully clean one view at-a-time. We first study how much cleaning one view in a dashboard can help to clean the other views. Figure 10 shows the average distance, \( \text{Distance}(V_{\text{curr}}, V_{\text{clean}}) \), across all four views for products as we clean one of the four views only. As the figure shows, when cleaning one of the two views with the greatest sensitivity to duplicates, Select* and Count*, the most progress can be made on simultaneously cleaning the other views: Select* cleans all other views in 460 labels and Count* cleans them in 480 labels. In these views, all tuples have the same view impact scores and the cleaning process treats them all in the same way helping to clean all views the fastest. Interestingly, as shown in Figure 11, deduplicating the Select* view using View Impact Cleaning causes temporary, non-monotonic behavior in one view, PriceBins, which is possible given that the quality of the classifiers is low and subsequently learned classifiers may change how they classify the most impactful tuples for the PriceBins view.

Thus, cleaning one view helps to make progress on other views. However, in the context of cleaning an entire dashboard, the at-a-time method must be done with careful attention to the order in which the views are cleaned.

(2) Clean across all views simultaneously using an aggregate measure of sensitivity across all views, MAX and SUM. We also evaluate the performance of cleaning a dashboard of visualizations. In this approach, the View Impact score for each tuple in the base relation is either the max or the sum of its impact across all the views. Figure 12 shows the results. The results are similar when using either MAX or SUM and the total number of labels required to clean all views is the same as cleaning just Select* or Count*. However, the curves for both MAX and SUM are smoother than when cleaning only Select* (Figure 10). This approach has thus the double benefit of yielding more stable results across batches and avoiding the problem of selecting which view to clean first.

Application to multi-view cleaning. Beyond cleaning visualization dashboards, the results in this section show that if a user starts with one visualization, the effort spent cleaning that visualization will help speed up the cleaning of subsequent visualizations, even though View Impact Cleaning is a view-driven cleaning method.

6. RELATED WORK

Deduplication has a long history in the literature (see [16 20]). The state-of-the-art deduplication approaches that are closely related to this work fall into three categories:

Active learning. The active learning systems from the literature focus on heuristics that select the minimum number of examples needed to learn a high quality classifier with the goal of cleaning an entire dataset at-a-time and not a subset as in this work. Furthermore, other systems combine feedback from a set of crowd workers (who may provide incorrect or conflicting labels) with the goal of limiting the number of unnecessary label requests for resolving duplicates [39 33 21 35]. All of these systems (except Corleone) require a developer/expert to manage the common learning tasks such as writing the blocking rules, and creating training data for the matcher. Corleone pushes this expert work to the crowd. In addition, Corleone extends common active learning methods by 1) applying biased sampling for the initial set, and 2) enforcing stopping
conditions using an observation set. Unlike previous work, we use View Impact Cleaning for sampling the initial set, selecting additional training examples, as well as designing the stopping condition. The other state-of-the-art crowd-based active learning algorithms in [33] use bootstrap [18] to estimate the classifier’s uncertainty in its predictions of labels. [39] applies a machine learned model that clusters similar records together (based on an associated probability of being a match). However, all of these related systems often require the user to provide thousands of labels to clean entire datasets. Our work, in contrast, saves the user’s cleaning effort by focusing on resolving the data that has the greatest impact on the view.

Passive learning. A variety of techniques have been proposed for deduplication [22, 13, 45]. These works most relevant to us are learning-based techniques that train a classifier over a batch of labeled pairs of examples [25, 10, 21, 14]. Many of these approaches try to reduce the label complexity by applying various feature-based similarity matchers and then sampling from the pairs that are likely to be matches or are the most informative. However, we showed in Section 5.2 that such biasing techniques are insufficient in completely cleaning any of the views in one shot.

Clustering. Several deduplication approaches consider the setting where each tuple can match multiple other tuples [2, 5, 40, 38, 12]. They either leverage the transitive property of the match relation [2, 40, 35] or correlation clustering [8, 12] to infer matching and non-matching pairs based on previously labeled pairs and reduce the labeling effort by users. These approaches are complementary to ours and could be added to our method to further speed up view cleaning.

7. CONCLUSIONS

We proposed an active learning algorithm for deduplicating records in an exploratory visual analytic system, which strives to produce the cleanest view possible within a limited budget. Our key idea is to consider the impact that individual tuples have on a visualization and to monitor how the view changes during cleaning. We demonstrated over a set of nine views that our approach produces significantly cleaner views for small labeling budgets than state-of-the-art alternatives and that it also stops the cleaning process after requesting fewer labels.

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