ActiveClean:

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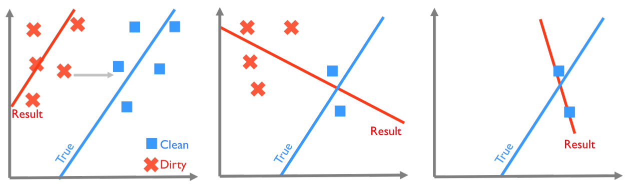
ABSTRACT

Data cleaning is often an important step to ensure that predictive models, such as regression and classification, are not affected by errors such as inconsistent, out-of-date, or outlier data. Identifying dirty data is often a manual and iterative process, and can be challenging on large datasets. However, many data cleaning workflows can introduce subtle biases into the training processes due to violation of independence assumptions. We propose ActiveClean, a progressive cleaning approach where the model is updated incrementally instead of re-training and can guarantee accuracy on partially cleaned data. ActiveClean supports a popular class of models called convex loss models (e.g., linear regression and SVMs) and record-by-record user-defined data cleaning operations. ActiveClean also leverages the structure of a user's model to prioritize cleaning those records likely to affect the results. Evaluation on four real-world datasets suggests that for a fixed cleaning budget, ActiveClean returns more accurate models than uniform sampling and Active Learning when corruption is systematic and sparse.

1. INTRODUCTION

Building distributed frameworks to facilitate model training on large and growing datasets is a key data management challenge with significant interest in both industry and academia [**?**, **?**, **?**, **?**]. While these frameworks abstract much of the difficult details of distributed Machine Learning (ML), they seldom offer the analyst any support in terms of constructing the model itself, i.e., which features to use, how to clean the data, and how to evaluate the results. Data often arrive *dirty*, including missing, incorrect, or inconsistent attributes, and analysts widely report that data cleaning and other forms of pre-processing account for up to 80% of their effort [**?**, **?**]. While data cleaning is an extensively studied problem, the high dimensionality of many models can amplify even a small amount of erroneous records [**?**], and the relative complexity (in comparison to SQL analytics) can make it difficult to trace the consequnces of an error.

Consequently, in prior work, we have noted the choice of data cleaning algorithm can significantly affect results even when using robust ML techniques [**?**, **?**]. In one fraud prediction example, we found that simply applying Entity Resolution before model training improved true positive detection probabilities from 62% to 91%. Despite this importance, in theory and in practice, the academic community has decoupled the data cleaning problem from featurization and ML. This is problematic because many ML techniques often make assumptions about data homogeneity and the consistency of



(a) Systematic Error (b) Mixed Dirty and Clean (c) Sampled Clean Data

Figure 1: (a) Systematic corruption in one variable can lead to a shifted model. (b) Mixed dirty and clean data results in a less accurate model than no cleaning. (c) Small samples of only clean data can result in similarly inaccurate models.

sampling, which can be easily violated if the analyst applies data cleaning in an arbitrary way.

To understand how this may happen, consider an anlyst training a regression model on dirty data. At first, she may not realize that there are outliers and train an initial model directly on the dirty data. As she starts to inspect the model, she may realize that some records have a large residual value (not predicted accurately). Once she confirms that those records are indeed dirty, she has to design data cleaning rules or scripts to fix or remove the offending records. After cleaning, she re-trains the model–iterating until she no longer finds dirty data. This iterative process is the de facto standard, and in fact encouraged by the design of the increasingly popular interactive "notebook" ML development environments (e.g., IPython), but makes the implicit assumption that model training commutes with incremental data cleaning. This assumption is wholly incorrect; due to the well-known Simpson's paradox, models trained on a mix of dirty and clean data can have very misleading results even in simple scenarios (Figure 1).

In a parallel trend, the dimensionality of the features used in ML models is also rapidly increasing. It is now common to use 100,000s of features in image processing processing problems with techniques such as Deep Learning. Empirically, such feature spaces have facilitated breakthroughs in previously hard classification tasks such as image classification, robot actuation, and speech recognition. However, the pitfall is that the standard approaches for debugging and reasoning about data error may lose their intuition for higher dimensions. In other words, it is often not obvious how an analyst should select which records to clean.

As it stands, there are two key problems in interactive model construction, (1) correctness, and (2) dirty data identification. We address these to problems in a system called ActiveClean which facilitates interactive training-cleaning iteration in a safe way (with expected monotone convergence guarantees) and automatically selects the most valuable data for the analyst to inspect. ActiveClean is implemented as a Python middleware library that connects IPython notebooks to the Berkeley Data Analytics Stack. The analyst initializes an ActiveClean with an ML model, a featurization function, and the base data, and the ActiveClean initially returns the model trained on the dataset. ActiveClean also returns an array of data sampled from the model that are possibly dirty. The analyst can apply any value transformations to the data and then prompt the system to iterate. As the analyst cleans more data, ActiveClean learns a internal model to predict which data are likely dirty.

In our demonstration, we will present two experimental datasets

2. ARCHITECTURE

This section presents the ActiveClean architecture.

2.1 Overview

Figure 2 illustrates the ActiveClean architecture. The dotted boxes describe optional components that the user can provide to improve the efficiency of the system.

2.1.1 *Required User Input*

Model: The user provides a predictive model (e.g., SVM) specified as a convex loss optimization problem $\phi(\cdot)$ and a featurizer $F(\cdot)$ that maps a record to its feature vector x and label y.

Cleaning Function: The user provides a function $C(\cdot)$ (implemented via software or crowdsourcing) that maps dirty records to clean records as per our definition in Section **??**.

Batches: Data are cleaned in batches of size b and the user can change these settings if she desires more or less frequent model updates. The choice of b does affect the convergence rate. Section **??** discusses the efficiency and convergence trade-offs of different values of b. We empirically find that a batch size of 50 performs well across different datasets and use that as a default. A cleaning budget k can be used as a stopping criterion once $C(\dot{})$ has been called k times, and so the number of iterations of ActiveClean is $T = \frac{k}{b}$. Alternatively, the user can clean data until the model is of sufficient accuracy to make a decision.

2.1.2 *Basic Data Flow*

The system first trains the model $\phi(\cdot)$ on the dirty dataset to find an initial model $\theta^{(d)}$ that the system will subsequently improve. The *sampler* selects a sample of size b records from the dataset and passes the sample to the *cleaner*, which executes $C(\cdot)$ for each sample record and outputs their cleaned versions. The *updater* uses the cleaned sample to update the weights of the model, thus moving the model closer to the true cleaned model (in expectation). Finally, the system either terminates due to a stopping condition (e.g., $C(\cdot)$ has been called a maximum number of times k, or training error convergence), or passes control to the *sampler* for the next iteration.

2.1.3 *Optimizations*

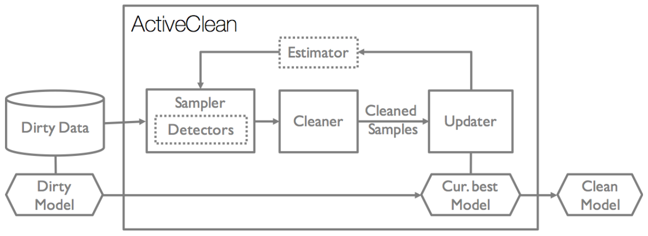


Figure 2: ActiveClean allows users to train predictive models while progressively cleaning data. The framework adaptively selects the best data to clean and can optionally (denoted with dotted lines) integrate with predefined detection rules and estimation algorithms for improved conference.

In many cases, such as missing values, errors can be efficiently detected. A user provided *Detector* can be used to identify such records that are more likely to be dirty, and thus improves the likelihood that the next sample will contain true dirty records. Furthermore, the *Estimator* uses previously cleaned data to estimate the effect that cleaning a given record will have on the model. These components can be used separately (if only one is supplied) or together to focus the system's cleaning efforts on records that will most improve the model. Section **??** describes several instantiations of these components for different data cleaning problems. Our experiments show that these optimizations can improve model accuracy by up-to 2.5x (Section **??**).

2.2 Example

The following example illustrates how a user would apply ActiveClean to address the use case in Section **??**:

EXAMPLE 1. *The analyst chooses to use an SVM model, and manually cleans records by hand (the $C(\cdot)$). ActiveClean initially selects a sample of 50 records (the default) to show the analyst. She identifies a subset of 15 records that are dirty, fixes them by normalizing the drug and corporation names with the help of a search engine, and corrects the labels with typographical or incorrect values. The system then uses the cleaned records to update the the current best model and select the next sample of 50. The analyst can stop at any time and use the improved model to predict donation likelihoods.*