QUANTIFYING AND MITIGATING THE IMPACT OF LABEL ERRORS ON MODEL DISPARITY METRICS

Anonymous authors
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ABSTRACT

Errors in labels obtained via human annotation adversely affect a trained model's performance. Existing approaches propose ways to mitigate the effect of label error on a model's downstream accuracy, yet little is known about its impact on a model's group-based disparity metrics[1]. Here we study the effect of label error on a model's group-based disparity metrics like group calibration. We empirically characterize how varying levels of label error, in both training and test data, affect these disparity metrics. We find that group calibration and other metrics are sensitive to train-time and test-time label error—particularly for minority groups. For the same level of label error, the percentage change in group calibration error for the minority group is on average 1.5 times larger than the change for the majority group. Towards mitigating the impact of training-time label error, we present an approach to estimate how changing a single training input's label affects a model's group disparity metric on a test set. We empirically assess the proposed approach on a variety of datasets and find a 10-40% improvement, compared to alternative approaches, in identifying training inputs that improve a model's disparity metric. The proposed approach can help surface training inputs that may need to be corrected for improving a model's group-based disparity metrics.

1 INTRODUCTION

Label error (noise) — mistakes associated with the label assigned to a data point — is a pervasive problem in machine learning (Northcutt et al., 2021). For example, thirty percent of a random one thousand samples from the Google Emotions dataset (Demszky et al., 2020) had label errors (Chen, 2022). Similarly, an analysis of the MS COCO dataset found that up to thirty seven percent (273,834 errors) of all annotations are erroneous (Murdoch, 2022). Yet, little is known about the effect of label error on a model's group-based disparity metrics like equal odds (Hardt et al., 2016), group calibration (Pleiss et al., 2017), and false positive rate (Barocas et al., 2019).

It is now common practice to conduct 'fairness' audits (see: (Buolamwini and Gebru, 2018; Raji and Buolamwini, 2019; Bakalar et al., 2021)) of a model's predictions to identify data subgroups where the model underperforms. Label error in the test data used to conduct a fairness audit renders the results unreliable. Similarly, label error in the training data, especially if the error is systematically more prevalent in certain groups, can lead to models that associate erroneous labels to such groups. The reliability of a fairness audit rests on the assumption that labels are *accurate*; yet, the sensitivity of a model's disparity metrics to label error is still poorly understood. Towards such end, we ask:

what is the effect of label error on a model's disparity metric?

We address the high-level question in a two-pronged manner via the following questions:

1. **Research Question 1**: What is the sensitivity of a model's disparity metric to label errors in training and test data? Does the effect of label error vary based on group size?
2. **Research Question 2**: How can a practitioner identify training points whose labels have the most *influence* on a model's group disparity metric?

[1]Group-based disparity metrics like subgroup calibration, false positive rate, false negative rate, equalized odds, and equal opportunity are more often known, colloquially, as *fairness metrics* in the literature. We use the term group-based disparity metrics in this work.

CONTRIBUTIONS & SUMMARY OF FINDINGS

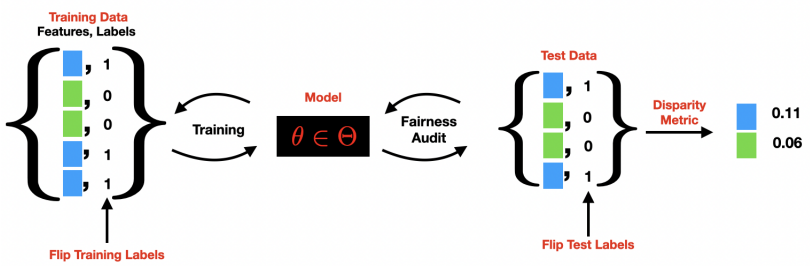

Figure 1: **A schematic of the test and train-time empirical sensitivity tests**. Here we show the model training and fairness audit pipeline. Our proposed sensitivity tests capture the effect of label error, in both stages, on the disparity metric. In the Test-time sensitivity test, we flip the label of a portion of the test data and then compare the corresponding disparity metric (group calibration for example) for the flipped dataset to the metrics for a standard model where the test labels were not flipped. In the Train-time sensitivity test, we flip the labels of a portion of the training set, and then measure the change in disparity metric to a standard model.

In addressing these questions, we make two broad contributions: First, we conduct comprehensive empirical sensitivity tests across several datasets and model classes to quantify the impact of labels errors—for test and training data—on a series of disparity metrics. Second, we propose a method, based on the influence function, to identify training points that have a high effect on a model's test disparity metric. We now discuss these contributions.

Empirical Sensitivity Tests. We assess the sensitivity of model disparity metrics to label errors with a label flipping experiment. First, we iteratively flip the labels of samples in the test set, for a fixed model, and then measure the corresponding change in the model disparity metric compared to an unflipped test set. Second, we fix the test set for the fairness audit but flip the labels of a proportion of the training samples. We then measure the change in the model disparity metrics for a model trained on the data with flipped labels. We perform these tests across a datasets and model combinations.

Training Point Influence on Disparity Metric. We propose an approach, based on a modification to the influence of a training example on a test example's loss, to identify training points whose labels have undue effects on any disparity metric of interest on the test set. We empirically assess the proposed approach on a variety of datasets and find a 10-40% improvement, compared to alternative approaches that focus solely on model's loss, in identifying training inputs that improve a model's disparity metric.

2 SETUP & BACKGROUND

In this section, we discuss notation, and set the stage for our contributions by discussing the disparity metrics that we focus on. We also provide an overview of the datasets and models used in the experimental portions of the paper.

Overview of Notation. We consider prediction problems, i.e, settings where the task is to learn a mapping, $\theta : \mathcal{X} \times \mathcal{A} \rightarrow \mathcal{Y}$, where $\mathcal{X} \in \mathbb{R}^d$ is the feature space, $\mathcal{Y} \in \{0, 1\}$ is the output space, and $\mathcal{A}$ is a group identifier that partitions the population into disjoint sets e.g. race, gender. We can represent the tuple (x_i, a_i, y_i) as z_i. Consequently, the n training points can be written as: $\{z_i\}_{i=1}^n$. Throughout this work, we will only consider learning via empirical risk minimization (ERM), which corresponds to: $\hat{\theta} := \arg\min_{\theta \in \Theta} \frac{1}{n} \sum_i^n \ell(z_i, \theta)$. Similar to Koh and Liang (2017), we will assume that the ERM objective is twice-differentiable and strictly convex in the parameters. We focus on binary classification tasks, however, our analysis can be easily generalized.

Disparity Metrics. We define a group disparity metric to be a function, $\mathcal{GD}$, that gives a performance score given a model's probabilistic predictions (θ outputs the probability of belonging to the positive class) and 'ground-truth' labels. We consider the following metrics:

Dataset	Classes	n	d	Group	Test acc.	Source
CivilComments	2	$1,820,000$	768	Sex	97.4%	Koh and Liang (2017)
ACSIncome	2	$195,665$	10	Sex, Race	74.5%	Ding et al. (2021)
ACSEmployment	2	$378,817$	16	Sex, Race	73.2%	Ding et al. (2021)
ACSPublic Coverage	2	$138,554$	19	Sex, Race	72.9%	Ding et al. (2021)
Credit Dataset	2	$405,032$	6	Sex	67.4%	De Montjoye et al. (2015)

Table 1: Dataset characteristics and the test accuracies that logistic regression achieves (with regularization λ selected by cross-validation). n is the training set size and d is the number of features.

1. **Calibration**: defined as $\mathbb{P}\left(\hat{y} = y | \hat{p} = p\right), \forall p \in [0, 1]$. In this work, we measure calibration with two different metrics: 1) Expected Calibration Error (ECE) (Naeini et al., 2015; Pleiss et al., 2017), and 2) the Brier Score (Rufibach, 2010) (BS). If we group predictions into M interval bins (each size $1/M$) and calculate the accuracy of each bin. Let B_m be the set of indices of samples whose prediction confidence falls into the interval $I_m = [\frac{m-1}{M}, \frac{m}{M}]$. Here the accuracy of B_m is then: $\text{acc}(\text{B}_\text{m}) = \frac{1}{|B_m|}\sum_{i \in B_m} \mathbb{1}(\hat{y}_i = y_i)$, where y_i is the true label for sample x_i derived from a model θ with prediction $\hat{y}_i = \theta(x_i)$. Similarly, we can define the average confidence within a bin B_m as: $\text{conf}(\text{B}_\text{m}) = \frac{1}{|B_m|}\sum_{i \in B_m} \hat{p}_i$. ECE approximates a notion of miscalibration, so it is defined as: $\mathcal{GD}_{\text{ece}} = \sum_{m=1}^{M} \frac{|B_m|}{n} |\text{conf}(\text{B}_\text{m}) - \text{acc}(\text{B}_\text{m})|$, while the Brier Score is the mean squared error between the labels and a models' predicted probabilities: $\mathcal{GD}_{\text{bs}} = \sum_{i=1}^{n} (\hat{y}_i - y_i)^2$. We report results for the ECE in the main text, and defer Brier Score results to the appendix.
2. **(*Generalized*) False Positive Rate (FPR)**: is $\mathcal{GD}_{\text{fpr}}(\theta) = \mathbb{E}[\theta(x_i) \mid y_i = 0]$ (see Guo et al. (2017)),
3. **(*Generalized*) False Negative Rate (FNR)**: is $\mathcal{GD}_{\text{fnr}}(\theta) = \mathbb{E}[(1 - \theta(x_i)) \mid y_i = 1]$,
4. **Error Rate (ER)**: is the $\mathcal{GD}_{\text{er}}(\theta) = 1 - \text{acc}(\theta)$.

We consider these metrics separately for each group, a_i, in the data as opposed to relative differences. We do this because we are primarily interested in the behavior of these metrics as more label error is induced either in the test or training data.

Datasets. We consider datasets across different modalities: 4 tabular, and a text dataset. A description of these datasets along with test accuracy is provided in Table 2. Each dataset contains annotations with a group label for both training and test data, so we are able to manipulate these labels for our empirical sensitivity tests. For the purposes of this work, we assume that the provided labels are the ground-truth—a strong assumption that nevertheless does not impact the interpretation of our findings.

Model. We consider three kinds of model classes in this work: 1) a logistic regression model, 2) a Gradient-boosted Tree (GBT) classifier for the tabular datasets, and 3) a ResNet-18 model. These three classes of models allow us to also test whether the sensitivity of a model's disparity metric depends on the amount of overparametrization and the model class (i.e. Logistic regression vs Neural Networks). We refer readers to the Appendix for details of model training and hyper-parameters.

3 Empirical Assessment of Label Sensitivity

In this section, we perform empirical sensitivity tests to quantify the impact of label error on test group disparity metrics. We report here results on a logistic regression model for subgroup calibration error (ECE) since these results demonstrate the critical empirical insights we observed from the tests. In addition, we provide a high-level summary of results on other model classes.

We conduct tests on data from two different stages of the ML pipeline: 1) Test-time (test dataset) and 2) Training-time (training data). We use as our primary experimental tool: label flipping, i.e., we flip the labels of a percentage of the samples, uniformly at random in either the test or training set, and then measure the concomitant change in the model disparity metric. We assume that each dataset's labels are the ground truth and that flipping the label results in label error for the samples whose labels have been overturned. Recent literature has termed this setting synthetic noise, i.e., the

label flipping simulates noise that might not be representative of real-world noise in labels (Arpit et al., 2017; Zhang et al., 2021; Jiang et al., 2020).

3.1 Sensitivity to Test-time Label Error

Overview & Experimental Setup. The goal of the test-time empirical test is to measure the impact of label error on the group calibration error of a fixed model. Consider the setting where a model has been trained, and a fairness assessment is to be conducted on the model. What impact does label error, in the test set used to conduct the audit, have on the calibration error on the test data? The test-time empirical tests answer this question. Given a fixed model, we iteratively flip a percentage of the labels, uniformly at random, ranging from zero to 30 percent in the test data. We then estimate the model's calibration using the modified dataset. Critically, we keep the model fixed while performing these tests across each dataset.

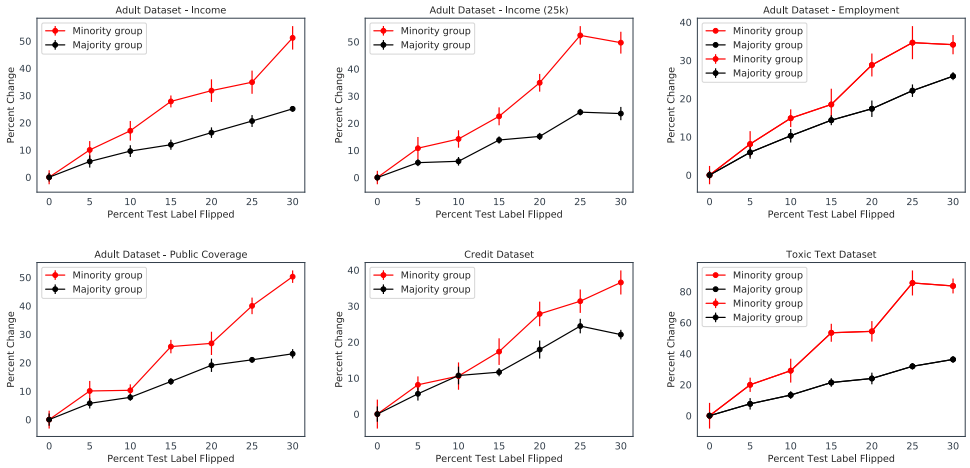

Figure 2: **Test-time Label Flipping Results across 6 datasets**. For each dataset, we plot the percent change in calibration error versus the corresponding percentage change in label error. Here, we plot the minority (smallest) group as well as the majority (largest) group. These two groups represent two ends of the spectrum for the impact of label error. We observe that across all datasets, the minority group incurs higher percentage change in group calibration compared to the majority group.

Results. In Figure 2, we report results of the label flipping experiments across 6 tasks. On the horizontal axis, we have the percentage of labels flipped in the test dataset, while on the vertical axis, we have the percentage change in the model's calibration. For each dataset, we compute model calibration for two demographic groups in the dataset, the majority and the minority—in size–groups. We do this since these two groups constitute the two ends of the spectrum in the dataset. As shown, we observe a more distinctive effect for the minority group across all datasets. This is to be expected since flipping even a small number samples in the minority group can have a dramatic effect on test and training accuracy within this group. For both groups, we observe a super-linear effect on the calibration error. For example, for the Income prediction task on the Adult dataset, a 10 percent label error induces a 20 percent change in the model's test calibration error. These results suggest that test-time label error has more pronounced effects for minority groups. Further, these results imply that - for calibration error - one can expect a change at least as large as the percentage of label error present in the test dataset. Similarly, we observe for other disparity metrics across all model classes that increases in percentage of labels flipped disproportionately affects the minority group (See Appendix E).

3.2 Sensitivity to Training Label Error

Overview & Experimental Setup. The goal of the training-time empirical tests is to measure the impact of label error on a trained model. More specifically, given a training set in which a fraction of the samples' labels have been flipped, what effect does the label error have on the calibration error compared to a model trained on data without label error? We simulate this setting by creating multiple

copies of each of the datasets where a percentage of the training labels have been flipped uniformly at random. We then assess the model calibration of these different model using the same fixed test dataset. Under similar experimental training conditions for these models, we are then able to quantify the effect of training label error on a model's test calibration error. We conduct this analysis across all dataset-model task pairs.

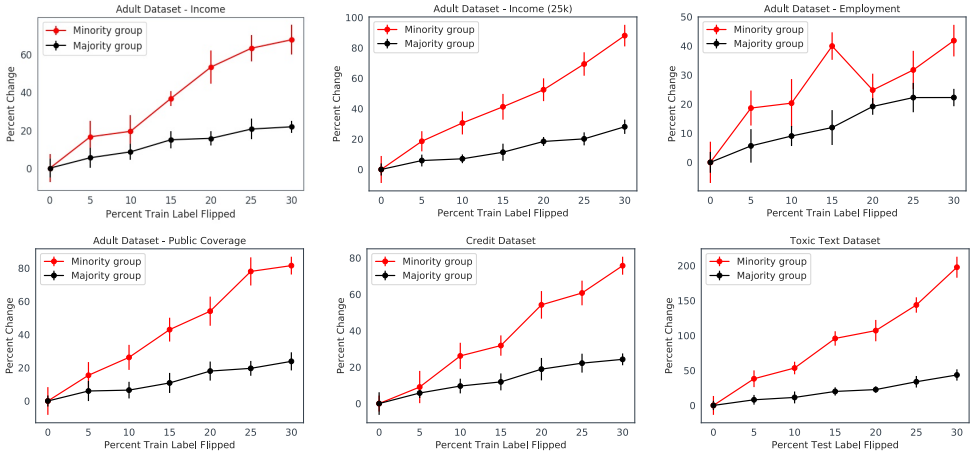

Figure 3: **Training-time Label Flipping Results across 6 datasets**. For each dataset, we plot the percent change in calibration error versus the corresponding percentage change in label error for the training set. Here, we plot the minority (smallest) group as well as the majority (largest) groups by size. Similar to the test-time setting, we observe that across all datasets, the minority group incurs higher percentage change in group calibration compared to the majority group. However, we observe a larger magnitude change for the minority groups.

Results & Implications. We show the results of the training-time experiments in Figure 3. Similar to the test-time experiments, we find minority groups are more sensitive to label error than larger groups. Specifically, we find that even a 5 percent label error can induce significant changes in the disparity metrics, of a model trained on such data, for these groups.

A conjecture for the higher sensitivity to extreme training-time error is that a model trained on significant label error might have a more difficult time learning patterns in the minority class where there are not enough samples to begin with. Consequently, the generalization performance of this model worsens for inputs that belong to the minority group. Alternatively, in the majority group, the proportion of corrupted labels due to label error is smaller. This might mean that uniform flipping does not affect the proportion of true labels compared to the minority group. Even though the majority group exhibits label error, there still exists enough samples with true labels such that a model can learn the underlying signal for the majority class.

A second important finding is that overparameterization seems to confer more resilience to training label error. We find that for the same levels of training label error, an overparametrized model is less sensitive to such change compared to a model with a smaller number of parameters. Recent work suggests that models that learn functions that are more aligned with the underlying target function of the data generation process are more resilient to training label error (Li et al., 2021). It might be that compared to linear and tree-based models, an overparametrized deep net is more capable of learning an aligned function.

4 Influence of Training Label on Test Disparity Metric

In this section, we present an approach for estimating the 'influence' of perturbing a training point's label on a disparity metric of interest. The approach is based on a modification to the influence functions method of Koh and Liang (2017). First, we discuss the results of Koh and Liang (2017), and then present extensions that we derive in this work. We consider two primary effects: 1) up-weighting a training point, and 2) perturbing the training label.

Upweighting a training point. Let $\hat{\theta}_{-z_i}$ be the ERM solution when a model is trained on all data points, $\{z_j\}_{j=1}^n$, except z_i. The influence, $\mathcal{I}_{\text{up,params}}$, of datapoint, z_i, on the model parameters is then defined as the change: $\hat{\theta}_{-z_i} - \hat{\theta}$. This measure indicates how much the parameters change when the model is 'refit' on all training data points except z_i. Koh and Liang (2017) give a closed-form estimate of this quantity as:

$$\mathcal{I}_{\text{up,params}} \stackrel{\text{def}}{=} \left.\frac{d\hat{\theta}_{\epsilon,\, z_i}}{d\epsilon}\right|_{\epsilon=0} = -H_{\hat{\theta}}^{-1} \nabla_\theta \ell(z_i, \hat{\theta}), \tag{1}$$

where H is the hessian, i.e., $H_{\hat{\theta}} \stackrel{\text{def}}{=} \frac{1}{n}\sum_{i=1}^n \nabla_\theta^2 \ell(z_i, \theta)$.

The loss on a test example, $\ell(z_t, \hat{\theta})$, is a function of the model parameters, so using the chain-rule, we can estimate the influence, $\mathcal{I}_{\text{up,loss}}(z_i, z_t)$, of a training point, z_i, on $\ell(z_t, \hat{\theta})$ as:

$$\mathcal{I}_{\text{up,loss}}(z_i, z_t) \stackrel{\text{def}}{=} \left.\frac{d\ell(z_t, \hat{\theta}_{\epsilon,\, z_i})}{d\epsilon}\right|_{\epsilon=0} = -\nabla_\theta \ell(z_t, \hat{\theta})^\top H_{\hat{\theta}}^{-1} \nabla_\theta \ell(z_i, \hat{\theta}). \tag{2}$$

Perturbing a training point's label. A second notion of influence that Koh and Liang (2017) study is how perturbing a training point leads to changes in the model parameters. Specifically, given a training input, z_i, that is a tuple (x_i, y_i), how would the perturbation, $z_i \to z_{i,\delta}$, which is defined as $(x_i, y_i) \to (x_i, y_i + \delta)$, change the model's predictions? Koh and Liang (2017) give a closed-form estimate of this quantity as:

$$\mathcal{I}_{\text{pert,loss,y}}(z_j, z_t) \approx -\nabla_\theta \ell(z_t, \hat{\theta}_{z_{j,\delta}, -z_j})^\top H_{\hat{\theta}}^{-1} \nabla_y \nabla_\theta \ell(z_j, \hat{\theta}). \tag{3}$$

Adapting influence functions to group disparity metrics. We now propose modifications that allow us to compute the influence of a training point on a test group disparity metric. We note that our discussion here is brief, so we refer readers to Section D of the appendix for a careful walk through. Let S_t be a set of test examples. We can then denote $\mathcal{GD}(S_t, \hat{\theta})$ as the group disparity metric of interest, e.g., the estimated ECE for the set S_t given parameter setting $\hat{\theta}$.

Influence of upweighting a training point on a test group disparity metric. A group disparity metric on the test set is a function of the model parameters; consequently, we can apply the chain rule to $\mathcal{I}_{\text{up,params}}$ (from Equation 1) to estimate the influence, $\mathcal{I}_{\text{up,disparity}}$, of up-weighting a training point on the disparity metric as follows:

$$\begin{aligned}\mathcal{I}_{\text{up,disparity}}(z_i, S_t) &\stackrel{\text{def}}{=} \left.\frac{d\mathcal{GD}(S_t, \hat{\theta}_{\epsilon,\, z_i})}{d\epsilon}\right|_{\epsilon=0} = -\nabla_\theta \mathcal{GD}(S_t, \hat{\theta})^\top \left.\frac{d\hat{\theta}_{\epsilon,\, z_i}}{d\epsilon}\right|_{\epsilon=0}, \\ &= -\nabla_\theta \mathcal{GD}(S_t, \hat{\theta})^\top H_{\hat{\theta}}^{-1} \nabla_\theta \ell(z_i, \hat{\theta}).\end{aligned} \tag{4}$$

We now have a closed-form expression for a training point's influence on a test group disparity metric.

Influence of perturbing a training point's label on a test group disparity metric. We now consider the influence of a training label perturbation on a group disparity metric of interest. To do this, we simply consider the group disparity metric function as the quantity of interest instead of the test loss. Consequently, the closed-form expression for the influence of a modification to the training label on disparity for a given test set is:

$$\mathcal{I}_{\text{pert,disparity,y}}(z_j, S_t) \approx -\nabla_\theta \mathcal{GD}(S_t, \hat{\theta})^\top H_{\hat{\theta}}^{-1} \nabla_y \nabla_\theta \ell(z_j, \hat{\theta}). \tag{5}$$

With Equations 12 and 13, we have the key quantities of interest that allows us to rank training points, in terms of influence, on the test group disparity metric. We can then use these quantities to prioritize samples that should be more carefully inspected.

5 Identifying and Correcting Training Label Error

In this section, we empirically assess the modified influence expressions for calibration across these datasets for prioritizing mislabelled samples. We find a 10-40 percent improvement, compared to alternative approaches that estimate influence on test loss (Kong et al., 2021) and other uncertainty estimation based approaches. In addition, we propose an approach to automatically correct the labels identified by our proposed approach.

5.1 Identifying Label Error

Overview & Experimental Question. We are interested in surfacing training points whose change in label will induce a concomitant change in a test disparity metric like group calibration. Specifically, we ask: When the training points are ranked by influence on test calibration, are the most highly influential training points most likely to have the wrong labels? We conduct our experiments to directly measure a method's ability to answer this question.

Experimental Setup. For each dataset, we randomly flip the labels of 10 percent of the training samples. We then train our standard logistic regression classifier on this modified dataset. In this task, we have direct access to the ground-truth and knowledge of the exact samples whose labels were flipped. This allows us to directly compare the performance of our proposed methods to each of the baselines on this task. We then rank training points using a number of baseline approaches as well as the modified influence approaches. For the top 50 examples, we consider what fraction of these examples had flipped labels in the training set.

Approaches & Baselines. We consider the following methods:

- **IF-Calib**: The closed-form approximation to the influence of a training point on the test calibration;
- **IF-Calib-Label**: The closed-form approximation to the influence of a training point's label on the test calibration;
- **Loss**: A baseline method which is the training loss evaluated at each data point in the training set. The intuition is that, presumably, more difficult training samples will have higher training loss;
- **Uncertainty Estimation Based Approaches**: We also consider methods two uncertainty estimation algorithms: 1) an approach htat estimate a sample's uncertainty based on a K-fold validation score, and 2) a logit-based approach (Wu and Klabjan, 2021).

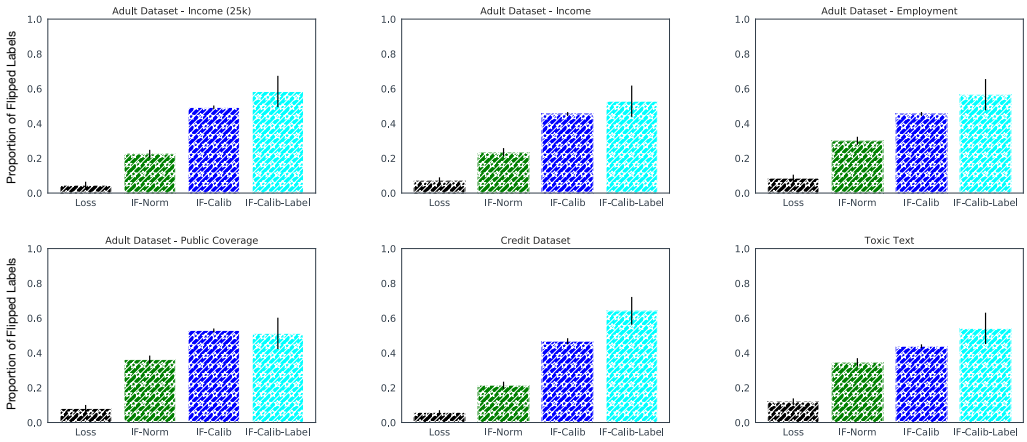

Figure 4: **Empirical Results for Training Point Ranking Across 6 datasets**. For the top 50 most influential examples, we show the proportion of samples whose labels were flipped in the training data. Confidence intervals is computed for N=5 different models.

Results: Prioritizing Samples. In Figure 4, we show the performance of the two approximations that we consider in this work as well as two baselines. We plot the fraction of inputs, out of the

top ranked 50 ranked training points, whose labels were flipped in the training set. The higher this proportion, then the more effective an approach is in identifying the samples that likely have wrong labels. In practice, the goal is to surface these training samples and have a domain expert inspect them. If a larger proportion of the items to be inspected are mislabeled, then a higher proportion of training set mistakes, i.e. label error, can be fixed. Across the different datasets, we find a 10-40 percent improvement, compared to baseline approaches, in identifying critical training data points whose labels need to be reexamined.

We find the loss baseline to be ineffective for ranking in our experiments. A possible reason is that modern machine learning models can typically be trained to 'memorize' the training data; resulting in settings where a model has low loss even on outliers or mislabeled examples. In such a case, ranking by training loss for a sample is an ineffective ranking strategy. We defer the results of the uncertainty-based baselines to Appendix (Section F). We find that these baselines also underperform our proposed approaches. For example, the 5-fold cross validation setting underperforms the standard influence functions approach by 50 percent.

5.2 Correcting Label Error

We take label error identification one step further to automatically relabelling inputs that have identified as critical. We restrict our focus to binary classification where the label set is $\{0, 1\}$, and the corresponding relabelling function is simply $1 - y_i$, where y_i is the predicted label.

Setup & Experiment: We consider the logistic regression model across all tasks for a setting with 20 percent training label error. We consider ECE (calibration) as the disparity function of interest. We then rank the top 20 percent of training points by label-disparity influence, our proposed approach. For these points, we apply the relabelling function, and then fine-tune the model for an additional epoch with the modified labels.

Results: First, we observe an average improvement of 8.7 percent improvement in group calibration across all groups, with larger (12.5 percent) improvement coming from the smallest group. As expected, we also observe an approximately 7 percent decrease in the average loss for the overall training set. These results point to increasing promise of automatic relabeling.

6 Related Work

We discuss directly related work here, and defer a longer discussion to Section A of the Appendix.

Impact of Label Error/Noise on Model Accuracy. Learning under label error falls under the category more commonly known as *learning under noise* Frénay and Verleysen (2013); Natarajan et al. (2013); Bootkrajang and Kabán (2012). *Noise* in learning can come from different components of the underlying data generation process, which include the input features and the labels. In this work, we focus exclusively on categorization mistakes associated with the label in both the test and training data. Previous work focused primarily on the effect of label error in the training data; however, we advance this line of work to investigate the effect of label error in the test data used to conduct a fairness audit on the reliability of the audit. Model resilience to training label error has been studied for both synthetic (Arpit et al., 2017; Zhang et al., 2021; Rolnick et al., 2017) and real-world noise settings (Jiang et al., 2020). Along these lines, a major line of inquiry is the development of mitigation strategies; these seek to produce accurate models and learning algorithms that are resilient to training label error. These strategies can be in the form of model regularization (Srivastava et al., 2014; Zhang et al., 2017), bootstrap (Reed et al., 2014), knowledge distillation (Jiang et al., 2020), instance weighting (Ren et al., 2018; Jiang and Nachum, 2020), robust loss functions (Ma et al., 2020; Ghosh et al., 2017), or trusted data (Hendrycks et al., 2018). In contrast to this line of work, instead of making the model resilient to label error, we take the approach of finding the 'problematic' training points, whose careful relabeling will most likely improve a model's disparity metric.

Impact of Label Error on Model *'Fairness'*. This work contributes to the burgeoning area that studies the impact of label error on a model's 'fairness' (termed 'group-based disparity' in this paper) metrics. Fogliato et al. (2020) studied a setting in which the labels used for model training are a noisy proxy for the true label of interest, e.g., predicting rearrest as a proxy for rearrest. Wang et al. (2021) introduce a method to account for group-dependent label noise by using new surrogate loss functions

that weight group-based disparity metrics. Similarly, Konstantinov and Lampert (2021) study the effect of adversarial data corruptions on fair learning in a PAC model and prove impossibility theorems under the adversarial model. Jiang and Nachum (2020) propose a re-weighting scheme that is able to correct for label noise. They then show that training a classifier on the re-weighted objective recovers models with group-disparity properties similar to a model trained on the unobserved noiseless labels.

Influence Functions & Their Uses. Influence functions originate from robust statistics where it is used as a tool to identify outliers Cook and Weisberg (1982); Cook (1986); Hampel (1974). Koh and Liang (2017) introduced influence functions for modern machine learning models, and used them for various model debugging tasks. Most similar to our work, Kong et al. (2021) propose RDIA, a relabelling scheme based on the influence function that is able to provably correct for label error in the training data. RDIA identifies training samples whose change in label has a high influence on the test loss for a validation set; however, we focus on identifying training samples whose change in label has a high influence on a group-disparity metric on a test/audit set. We compare to their approach in Section 5. In recent work, De-Arteaga et al. (2021) study expert consistency in data labeling and use influence functions to estimate the impact of labelers on a model's predictions. Along similar direction, Brunet et al. (2019) adapt the influence function approach to measure how removing a small part of a training corpus, in a word embedding task, affects test bias as measured by the word embedding association test Caliskan et al. (2017). Feldman and Zhang (2020) use influence functions to estimate how likely a training point is to have been memorized by a model. More generally, influence functions are gaining widespread use as a tool for debugging model predictions Barshan et al. (2020); Han et al. (2020); Yeh et al. (2018); Pruthi et al. (2020).

7 Conclusion

In this work, we study the effect of label error, both in the training and test set, on a model's disparity metric. Fairness audits are typically used to help surface disparate performance across groups in the data. However, if either the test data used to perform a fairness assessment or the training data used to fit the model contains label error, then it is unclear whether the conclusions of such a fairness assessment are reliable. Given the widespread presence of label error in the ML labeling pipeline, understanding the downstream effects of label error on a model's disparity metric is important. In this paper, we sought to address two key questions: *1) What is the impact of label error on a model's group disparity metric, especially for smaller groups in the data;* and *2) How can a practitioner identify training samples whose labels would also lead to a significant change in the test disparity metric of interest?*

To address the first question, we conducted empirical sensitivity tests. First, we flip the labels in the test set, to simulate label error, then measure the corresponding change to the disparity metric. Second, we fix a test set, but instead iteratively simulate varying levels of label error in the training set. We then measure the change in disparity metric, e.g., group calibration error for models trained on these 'contaminated' datasets compared to a model derived from data without label error.

We find that disparity metrics are, indeed, sensitive to test and training time label error. In addition, for the same level of label error, the percentage change in group calibration error for the minority group is on average 1.5 times larger than the change for the majority group. A possible explanation for the training-time results is that label error affects the ability of the model to easily learn patterns for the minority group even at lower fractions of label error in the training data.

Second, we present an approach for estimating the 'influence' of perturbing a training point's label on a disparity metric of interest. We empirically assess the proposed approach on a variety of datasets and find a 10-40% improvement, compared to alternative approaches, in identifying training inputs that improve a model's disparity metric.

Our findings come with certain limitations. In this work, we focused on the influence of label error on disparity metrics. However, other components of the ML pipeline can also impact downstream model performance. The proposed empirical tests simulate the impact of label error; however, it might be the case that real-world label error is less pernicious to model learning dynamics than the synthetic flipping results suggest.

Ultimately, we see our work as helping to provide insight and as an additional tool for practitioners seeking to address the challenge of label error particularly in relation to a disparity metric of interest.

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