

CAN ACTIVE LEARNING PREEMPTIVELY MITIGATE FAIRNESS ISSUES?

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ABSTRACT

Dataset bias is one of the prevailing causes of unfairness in machine learning. Addressing fairness at the data collection and dataset preparation stages therefore becomes an essential part of training fairer algorithms. In particular, active learning (AL) algorithms show promise for the task by drawing importance to the most informative training samples. However, the effect and interaction between existing AL algorithms and algorithmic fairness remain under-explored. In this paper, we study whether models trained with uncertainty-based AL heuristics such as BALD are fairer in their decisions with respect to a protected class than those trained with identically independently distributed (i.i.d.) sampling. We found a significant improvement on predictive parity when using BALD, while also improving accuracy compared to i.i.d. sampling. We also explore the interaction of algorithmic fairness methods such as gradient reversal (GRAD) and BALD. We found that, while addressing different fairness issues, their interaction further improves the results on most benchmarks and metrics we explored.

1 INTRODUCTION

Machine learning applications are commonly used in various spheres of our lives but, until recently (Caton & Haas, 2020), the fairness or the accountability of these applications were not questioned. Even today, non-technical users find those algorithms to be unfair and impartial (Saha et al., 2020). A major cause of algorithmic unfairness is introduced by the large-scale datasets commonly used to train deep learning models (Deng et al., 2009). Due to their scale, these datasets are difficult to curate and they tend to mimic our societal biases. While the current literature in algorithmic fairness focuses on removing the effects of a known bias from the algorithms (Datta et al., 2017), there are many scenarios where these biases are unknown or hidden. For example, an algorithm that is designed to approve or reject loan requests could be biased in favor of university degree holders as their place of employment, type of position, zip code, or other seemingly impersonal attributes might fit the training set better.

BALD, an AL heuristic, is known to create balanced datasets in terms of classes (Gal et al., 2017; Atighehchian et al., 2020). Hence, it is reasonable to question whether it can mitigate some biases in the data used to train machine learning models, resulting in fairer models. Moreover, it is possible that BALD reduces the effect of unknown biases.

In this paper, we explore whether data collection with AL using BALD improves group fairness (Jacobs & Wallach, 2019), i.e., different groups are treated similarly. This is especially important as we often do not know *a priori* the sensitive attributes of a dataset that could be harmful to different communities (Mehrabi et al., 2019). For example, the ImageNet (Deng et al., 2009) was crawled from image databases without considering sensitive attributes such as race or gender. In consequence, models trained (or pre-trained) on this dataset are prone to mimic societal biases (Yang et al., 2020).

Experiments on Symbols (Lacoste et al., 2020) demonstrate that BALD improves the model fairness in multiple scenarios¹. Concretely, we test BALD in the scenario where the sensitive attribute is

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¹<https://github.com/ElementAI/active-fairness>

known, showing it is fairer than uniform sampling and balanced uniform sampling. Moreover, we show that BALD is competitive when compared with methods that require knowing the sensitive attribute. In the second scenario, we explore the interaction between AL and fairness methods for the case where the sensitive attribute is known. Our results show that fairness methods such as gradient reversal (Raff & Sylvester, 2018) combined with AL heuristics like BALD achieve significant improvement. Note that the scope of this work is not to *solve* fairness issues but to explore the effect of AL on algorithmic fairness.

2 BACKGROUND

Our work lies in the intersection of Bayesian AL and Fairness. First we provide a brief description of AL with BALD. Second, we focus on metrics for FEAT. Third, we introduce a fairness method related to our work. Finally, we focus on methods at the intersection between AL and fairness.

BALD An effective algorithm in AL is to greedily search for the most informative samples i.e. how much information we obtain by labelling sample \mathbf{x} with label y . Specifically, given the model parameters w and the current labelled dataset D , we can measure the mutual information between the posterior distribution $p(w|D)$, and the model prediction $p(y|\mathbf{x}, w)$ (Houlsby et al., 2011):

$$I[y, w|\mathbf{x}, D] = H[p(y|\mathbf{x}, D)] - \mathbb{E}_{p(w|D)} H[p(y|\mathbf{x}, w)], \quad (1)$$

where I is the mutual information, H the entropy, and $p(y|\mathbf{x}, D) = \mathbb{E}_{p(w|D)} p(y|\mathbf{x}, w)$. Finally, we query the label for the sample x in the unlabelled set U that maximizes this mutual information, and we add to the set D . Finally, we update the posterior $p(w|D)$ with the new set. This approach is referred to as BALD and it greedily reduces the model uncertainty, a.k.a. *epistemic uncertainty*. We note that the model uncertainty can converge to 0 by adding more samples. This can be seen in Equation 1 when the two terms on the right hand side are equal. In contrast, the inherent noise in the data cannot be reduced by obtaining more samples. This is referred to as the *aleatoric uncertainty* and is measured by the term $H[p(y|\mathbf{x}, D)]$ in Equation 1. In order to estimate this quantity, we need to perform expectations over $p(w|D)$, which is often intractable. As common procedure, we approximate these quantities using MC-Dropout (Gal & Ghahramani, 2016). Other approaches can be used such as using ensembles (Beluch et al., 2018). Other heuristics such as computing the entropy of the prediction are not able to discriminate between epistemic and aleatoric uncertainty. In consequence, these heuristics may select examples with high aleatoric uncertainty, but low information gain.

Equalized Odds is satisfied when the prediction and the sensitive attribute a conditioned on the target are independent. In a hiring scenario, this would be satisfied when the true positive rate and the false positive rate are equal across all protected groups (Hardt et al., 2016)

$$P(\hat{y} = 1 | y = \gamma, a = 0) = P(\hat{y} = 1 | y = \gamma, a = 1) \forall \gamma \in \{0, 1\}.$$

Equal opportunity is a similar metric that is measured with respect to a particular negative outcome (Hardt et al., 2016)

$$P(\hat{y} = 1 | y = 1, a = 0) = P(\hat{y} = 1 | y = 1, a = 1).$$

Predictive parity is used when there is no "good outcome" to a problem. While both *Equalized odds* and *Equal opportunity* are centered around the outcome of the model, *Predictive parity* will be satisfied when A_a , the accuracy of group a , is equal across the set of groups \mathcal{G} (Verma & Rubin, 2018):

$$\delta_A = \max_{a \in \mathcal{G}}(A_a) - \min_{a \in \mathcal{G}}(A_a).$$

Gradient Reversal Against Discrimination (GRAD) (Raff & Sylvester, 2018) is a simple approach to improve group fairness in deep learning models. It builds upon Gradient Reversal (Ganin & Lempitsky, 2015). The aim is to obtain an intermediate representation $z = h(x)$ that minimizes the information about a sensitive variable a . Next, $\hat{y} = f_y(z)$ can be used as an estimate of the label y without using any sensitive information. To achieve this, an extra network $f_a(z)$ is trained

to predict the sensitive variable a . Using gradient reversal one can minimize the mutual information between a and z to make sure that the estimation of \hat{y} using z does not contain any direct or indirect information about variable a . With GRAD, the overall loss to optimize is:

$$l_y(f_y(z)) + \lambda \cdot l_a(f_a(z)), \quad (2)$$

where l_y and l_a are the loss functions to optimize f_y and f_a , and λ is an hyperparameter to weight the adversarial regularizer.

3 RELATED WORK

Our work is related with active fairness methods (Noriega-Campero et al., 2019; Sharaf & Daumé III; Anahideh et al., 2020), high-skew AL methods (Vijayanarasimhan & Grauman, 2014; Wallace et al., 2010; Aggarwal et al., 2020), and resampling methods (Amini et al., 2019; Li & Vasconcelos, 2019). Different from the two first families of methods, instead of introducing new AL strategies, we study the interaction of already existing AL algorithms with the fairness of the resulting models. The main difference with respect to re-sampling methods and our work is that in the AL setup we start with no labels whereas resampling algorithms start with fully labelled datasets.

4 EXPERIMENTS

We investigate whether training a model with AL reduces two types of biases:

- **Minority group.** The minority class is not associated with y (given x), but there are fewer samples for training the model in that subspace (since the distribution is uneven). With infinite data, this would be less of a problem since there could be enough data to converge to the optimal classifier, but since the aleatoric uncertainty could remain, it may still induce fairness issues. This is best addressed in the data collection process and goes beyond the scope of this paper.
- **Sensitive attribute.** There is a feature that correlates with y but it is considered sensitive and not authorized for use in making the prediction. Even with an infinite amount of data and a perfect predictor, the model would still use that feature and may produce unfair predictions.

With Symbols, we generate datasets that mimic both bias types while controlling every other aspect of the problem. This allows us to isolate the bias issue from other issues like labelling errors, aleatoric uncertainty or mis-specified problems. Concretely, we generate a binary classification dataset with two groups for each type of bias. In *minority group*, the two groups have the same proportion in each class, so that the minority group does not have good support for the model to learn. In *sensitive attribute*, we generate a spurious correlation by assigning most of each class to a specific group. The model will probably learn this pattern and make wrong predictions on items that do not follow this correlation.

In the following sections, we address the following two questions: (i) Can AL improve fairness by re-balancing datasets to reduce the predictive parity between two groups without knowing the groups? (ii) How well does AL compare with other existing algorithms such as GRAD for removing sensitive variables?

To answer our first question, we must determine whether an algorithm with no knowledge of bias is better than uniform labelling. In addition, we compare our results with an *Oracle*, an upper-bound for uniform sampling. This *Oracle* will balance the queried examples across groups thus improving the Predictive parity of the model. To evaluate our results we will use the Accuracy and the Predictive parity on a balanced test set.

Experimental setup We follow the same methodology as Atighehchian et al. (2020) with a VGG-16 trained on the labelled dataset for 20 epochs. Then we estimate the uncertainty of all unlabelled examples using 20 Monte Carlo iterations. We label 50 items per retraining which we find is a good trade-off between performance and efficiency. After each retraining, we evaluate our model on a held-out set for evaluation and we reset the weights to their initial value pretrained on ImageNet.

@ 10%	Sensitive attribute		Minority group	
	Predictive parity	Accuracy %	Predictive parity	Accuracy %
Uniform	10.73 \pm 2.70	87.23 \pm 1.77	4.67 \pm 0.76	88.53 \pm 1.66
Uniform + GRAD $\lambda = 0.5$	7.58 \pm 2.16	87.37 \pm 0.98	2.03 \pm 1.46	84.98 \pm 0.88
Uniform + GRAD $\lambda = 1$	5.50 \pm 1.51	83.69 \pm 2.79	1.38 \pm 0.00	86.52 \pm 1.81
AL-Bald	3.56 \pm 1.70	91.66 \pm 0.36	2.11 \pm 0.19	94.08 \pm 0.10
AL-Bald + GRAD $\lambda = 0.5$	2.16 \pm 1.13	92.34 \pm 0.26	0.74 \pm 0.15	93.38 \pm 0.84
AL-Bald + GRAD $\lambda = 1$	1.27 \pm 0.88	90.31 \pm 0.84	0.75 \pm 0.65	91.72 \pm 0.67
Balanced Uniform(Oracle)	10.34 \pm 1.97	86.91 \pm 1.83	2.40 \pm 0.65	90.66 \pm 0.41
Balanced Uniform(Oracle) GRAD $\lambda = 0.5$	5.15 \pm 1.39	88.40 \pm 2.02	1.88 \pm 0.01	90.24 \pm 0.70
REPAIR (Li & Vasconcelos, 2019)	0.54 \pm 0.11	94.52 \pm 0.19	1.06 \pm 0.44	92.84 \pm 0.33

Table 1: Comparison between BALD and uniform labelling after 10% of the dataset has been labelled. λ is the weight of the gradient reversal term. Both metrics are evaluated on a balanced held out set. Standard deviation is reported by repeating the experiment with 3 different random seeds.

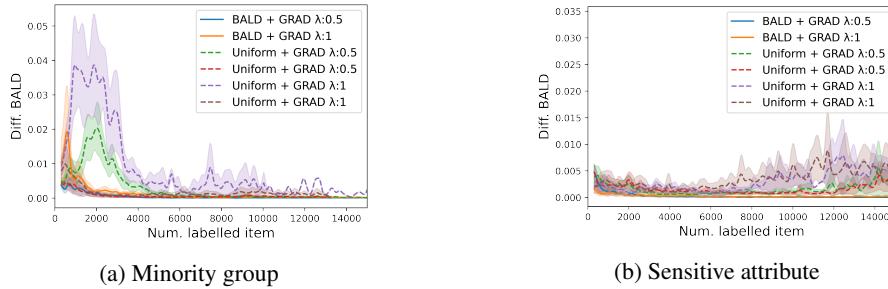


Figure 1: Absolute difference in epistemic uncertainty between groups for both datasets.

Does AL improve fairness? We test our hypothesis on both datasets. The results in Table 1 show that, with no knowledge of biases, Bayesian AL reduces the performance gap between groups. This is in accord with our hypothesis that BALD would help to lower the epistemic uncertainty on both types of biases, resulting in better predictive parity for both datasets. We also note that rebalancing the dataset using the unknown attribute (*Oracle*) leads to only minor improvement (or no improvement). We provide plots of the labelling progress in Appendix A.1. In addition, we note that our method is competitive with REPAIR (Li & Vasconcelos, 2019) which has access to the fully labelled dataset.

How does AL interact with fairness methods? In Section 2, we introduced GRAD (Raff & Sylvester, 2018) as a way to prevent the model from basing its predictions on attributes that could be harmful to certain groups. Our hypothesis is that, although BALD reduces the *minority group* bias by reducing the epistemic uncertainty, it is still affected by the *sensitive group* bias. To reduce the later bias, we apply gradient reversal to prevent our model from using the spurious attribute and explore its interaction with AL. BALD computation is still only applied to the classification head. In Table 1, we report results for different strengths of the gradient reversal weight λ . We observe that BALD obtains comparable or better performances than Uniform GRAD without requiring the knowledge of the group variable. Moreover, the best results are obtained by combining BALD and GRAD showing an overall improvement on predictive parity. It is not clear however why BALD helps the GRAD algorithm in the case of sensitive variables. To investigate this, we show in Fig. 1 the absolute difference in epistemic uncertainty between groups on both datasets. We observe that GRAD without BALD leads to a growing epistemic uncertainty difference with the value almost doubling over time, which is different for other baselines.

5 DISCUSSION AND CONCLUSION

We have shown that Bayesian AL with BALD as heuristic can mitigate group fairness issues. By training a model that is confident on all groups, we create a model that has better predictive parity. In addition, we see that using GRAD makes the model less confident in both cases. We make the hypothesis that by limiting the ability of the model to learn the sensitive attribute it increases the difficulty. This is an initial step in analyzing selection bias in actively learned datasets, future work includes studying the effect of AL with pretrained large transformer models.

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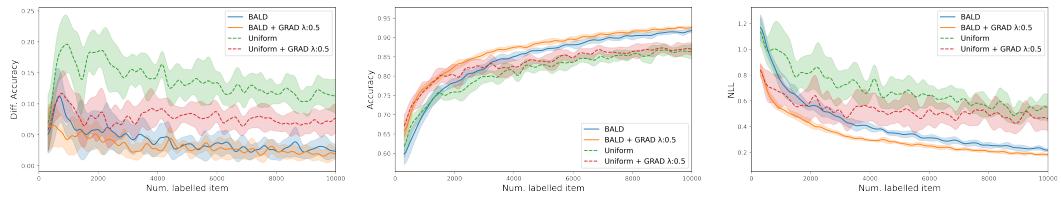


Figure 2: Performance comparison between uniform labelling and BALD on *Sensitive attribute*. We present the Predictive parity (left), the test accuracy (middle) and the negative log-likelihood (right).

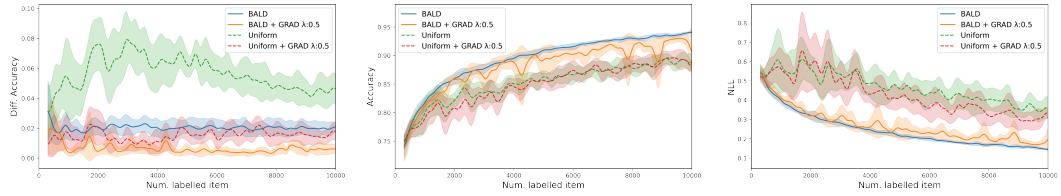


Figure 3: Performance comparison between uniform labelling and BALD on *Minority group*. We present the Predictive parity (left), the test accuracy (middle) and the negative log-likelihood (right).

A APPENDIX

A.1 LABELLING PROGRESS

In Table 1, we compared all methods after 10% of the dataset has been labelled. In Fig. 3 and Fig. 2, we have the metrics for all steps leading to this point.

B DATASET GENERATION

We used Symbols (Lacoste et al., 2020) to generate all of our datasets. We kept the default parameters (as of version 1.0.1) and limited the choice of color to {red, blue} to create our groups. The classes were sampled from {’a’, ’d’}. In Fig. 4, we present some examples.

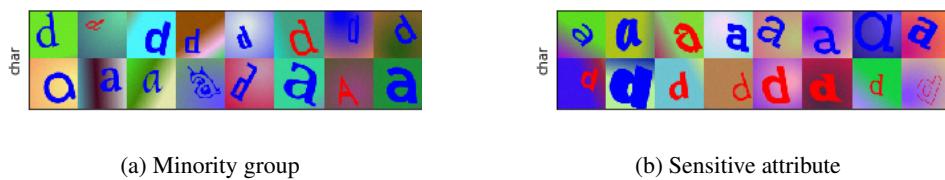


Figure 4: Absolute difference in epistemic uncertainty between groups for both datasets.