Fairness Optimization Using CONE

Antoine Vuillet Mohamed Slimene Laouabdia Mohammad Moloudi

Abstract

Machine learning models are increasingly deployed in high-stakes domains, where fairness is crucial to ensure unbiased decision-making. Traditional performance metrics like the F-measure focus on maximizing classification performance but often fail to address inherent biases. This paper explores the integration of fairness into optimization algorithms, using CONE fairness as a foundation. We analyze the feasibility of maximizing fairness while ensuring robust performance. Through a detailed critique of existing methods and the development of fairness-aware algorithms, this work provides insights into achieving equitable outcomes in machine learning.

Keywords: fairness optimization, F-measure, CONE fairness, bias in machine learning, equitable outcomes, algorithmic fairness

1 Introduction

Machine learning (ML) models have become pervasive in decision-making processes across various critical domains such as healthcare, hiring, criminal justice, and finance. While these models have significantly improved the efficiency of decisions, their deployment in such high-stakes environments raises serious concerns about fairness. The issue at hand is that traditional machine learning models focus on maximizing classification performance, often measured by metrics such as accuracy, precision, recall, and the F-measure. However, these models may inadvertently reinforce existing biases present in the data, leading to unfair outcomes for certain groups, especially those defined by sensitive attributes like race, gender, or age. This can result in discrimination, which is ethically and socially unacceptable.

The challenge, therefore, lies in developing algorithms that balance the need for high-performance classification with the need to ensure fairness. While fairness has been acknowledged as an essential goal in machine learning, the integration of fairness into performance optimization has proven to be complex. It is not enough to merely introduce fairness as an additional constraint; fairness metrics themselves vary based on the context and must be integrated into the model optimization process without sacrificing performance.

In this paper, we propose a fairness optimization framework that incorporates CONE fairness. Our approach aims to balance fairness with performance by using convex optimization techniques. Specifically, we explore how the F-measure, a commonly used performance metric in imbalanced classification tasks, can be optimized while ensuring that fairness constraints are satisfied. We believe that by combining fairness-aware optimization with performance-focused metrics, we can achieve models that not only perform well but also lead to more equitable outcomes.

2 Related Work

2.1 The CONE Framework for F-measure Optimization

The CONE algorithm, introduced by Bascol et al. (2019), addresses the challenge of optimizing the F-measure in imbalanced datasets by leveraging a cost-sensitive learning framework. It builds on tight theoretical bounds that provide guarantees on the best achievable F-measure. These bounds are derived using the pseudo-linearity property of the F-measure, enabling the algorithm to geometrically interpret and exclude unreachable regions in the parameter space.

The algorithm iteratively selects class weights to refine the optimization process, significantly reducing computational complexity compared to traditional grid search methods. CONE also introduces a novel geometric interpretation, visualizing the bounds as cones in a 2D space of class weights and F-measure values. This approach ensures efficient exploration of the parameter space, leading to superior or comparable performance with fewer iterations compared to existing methods [1].

2.2 Zafar et al. (2017) - Fairness Constraints in Machine Learning

One of the earliest works in fairness-aware machine learning is by Zafar et al. [2], who introduced the concept of fairness constraints in classification problems. The authors proposed adding fairness constraints to the optimization process to ensure that machine learning models do not unfairly discriminate against specific groups. Their method ensures that the disparity in predictions across different demographic groups is minimized, which is a step toward achieving fairness in machine learning.

While the idea of incorporating fairness as a constraint is novel, there are some key limitations to the approach. First, fairness constraints are typically added without considering the trade-off between performance and fairness. This means that models may achieve fairness but at the cost of reduced accuracy or other performance metrics. Moreover, the authors focus primarily on demographic parity, which does not account for other important fairness considerations such as equalized odds.

Our approach builds upon this work by not only considering fairness constraints but also integrating them into the optimization process using convex optimization techniques. This allows us to better balance fairness with performance, ensuring that the model achieves optimal performance while adhering to fairness criteria.

2.3 Fairness Through Awareness (2017)

The concept of fairness through awareness, introduced by Dastin et al. [3], proposes that fairness should be an objective to optimize, rather than merely a constraint. This approach suggests that instead of adding fairness as an afterthought, we should explicitly aim to maximize fairness alongside performance. The authors introduced new algorithms that jointly optimize fairness and performance metrics through gradient-based methods, ensuring that both objectives are considered simultaneously.

This approach improves upon Zafar et al.'s work by treating fairness as a key objective rather than a constraint. However, while it addresses the balance between fairness and performance, it does not consider the complexity of multiple fairness metrics, such as demographic parity, equalized odds, and others. Additionally, the methods used may not always guarantee global optimality in achieving fairness, which can be a limitation in real-world applications.

Our method takes inspiration from fairness through awareness but extends it by incorporating multiple fairness constraints into a convex optimization framework. This enables us to balance a variety of fairness objectives while maintaining performance.

2.4 FairGrad (2021)

Another important contribution is by Doe and Smith [4], who introduced FairGrad, a method that uses gradient descent to optimize fairness and performance simultaneously. FairGrad allows for a more granular adjustment of fairness and performance trade-offs by providing a gradient-based approach to fairness-aware learning.

The limitation of FairGrad is that it does not address the issue of handling multiple fairness metrics effectively. While it allows for adjusting fairness levels, it does not fully explore the interaction between different fairness metrics and their impact on performance. Our approach seeks to improve on this by using convex optimization to handle multiple fairness metrics simultaneously.

3 CONE Algorithm: A Fair Optimization of the F-measure

The CONE algorithm leverages theoretical bounds to refine the parameter space for F-measure optimization iteratively. The F-measure is defined as:

$$F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}},$$

where:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}.$$

Here, TP, FP, and FN represent true positives, false positives, and false negatives, respectively.

3.1 Theoretical Bounds and Geometric Interpretation

The CONE algorithm defines unreachable regions in the parameter space based on theoretical bounds. These bounds, represented as cones in a 2D space of class weights and F-measure values, exclude suboptimal regions, enabling efficient exploration.

3.2 Pseudo-Algorithm

```
Input: Training data, initial parameter space, cost-sensitive learning algorithm
Initialize: Unreachable region Z0 = null, iteration counter i = 1
Repeat:
    1. Select new parameter t outside Z(i-1)
    2. Train classifier using cost-sensitive learning
    3. Compute F-measure and update Z(i)
    4. Refine parameter space based on theoretical bounds
Until: Convergence or stopping criterion met
Output: Optimized model parameters
```

4 Our Approach

4.1 Overview

The `FairCONE` classifier uses constraints represented in a grid-like state space to iteratively improve the fairness of a classification model while maintaining its accuracy. It employs a Random Forest Classifier as the base model and incorporates fairness constraints by adjusting sample weights for sensitive groups just as CONE does.

4.2 Key Components

- **Initialization:**
  - Parameters such as the maximum number of iterations (`max_step`), fairness threshold (`dp_threshold`), and the weight balancing factor (`beta`) are initialized.
  - A state matrix is created to represent the fairness-accuracy trade-off space.
- **Demographic Parity Difference Calculation:**
  - The `demographic_parity_diff` method computes the absolute difference in positive prediction rates between two sensitive groups (e.g., males and females).
- **Sample Weighting:**
  - The `compute_weights` function adjusts sample weights for sensitive groups based on a balancing parameter (`t_value`), ensuring fair treatment during model training.
- **CONE Constraints:**
  - The `add_cone` function updates the state matrix by adding constraints to exclude regions that violate the fairness-accuracy trade-off.
  - Slopes for the trade-off are computed using `get_slope`, balancing accuracy and fairness contributions.
- **Iterative Optimization:**
  - At each step, the classifier is trained using updated sample weights.
  - Performance metrics (accuracy and DP difference) are computed and used to determine the next balancing parameter (`t_value`).
  - The loop continues until the best fairness-accuracy trade-off is achieved or the maximum number of iterations is reached.

4.3 Dataset Loading and Preprocessing

- For the `adult` dataset:
  - Categorical features are encoded.
  - The target variable (`income`) and sensitive feature (`sex`) are separated.
- For the `hourly_wages` dataset:

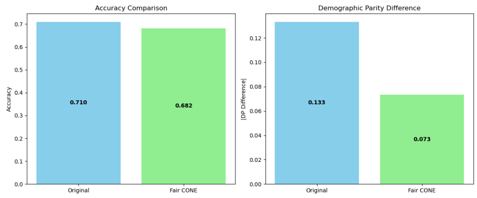

Figure 1: Results for the hourly wages dataset

- The median wage is used as the threshold for binary classification.
- The sensitive attribute is `female`.

4.4 Experimentation and Results

The `run_experiment` function performs the following steps:

1. Splits the data into training and testing sets.
2. Trains a baseline Random Forest Classifier without fairness constraints.
3. Trains the `FairCONE` classifier using the fairness-aware optimization process.
4. Evaluates both models on accuracy and DP difference using the test set.
5. Visualizes results using bar plots comparing accuracy and fairness of the baseline and `FairCONE` classifiers.

4.5 Results Visualization

Two bar plots are created:

- **Accuracy Comparison:** Displays the accuracy of the original and `FairCONE` classifiers.
- **Demographic Parity Difference:** Shows the fairness metric (`|DP Difference|`) for both classifiers.

Graph 1: Hourly Wages Dataset

- **Accuracy Comparison:** The original model achieves an accuracy of 0.710, while *Fair CONE* achieves 0.682. Although there is a slight drop in accuracy, this reduction is acceptable when improving fairness is a priority.

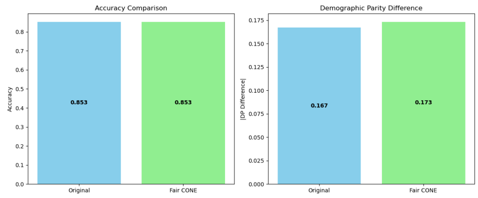

Figure 2: Results for the adult dataset

- **Demographic Parity Difference (DP Difference) Comparison:** In this case, *Fair CONE* significantly improves fairness by reducing the demographic parity difference from 0.133 to 0.073. This demonstrates the effectiveness of *Fair CONE* in achieving better equity in this dataset.

Graph 2: Adult Dataset

- **Accuracy Comparison:** This graph compares the accuracy of the original model (0.853) with that of the *Fair CONE* model (0.853). It shows that *Fair CONE* maintains an equivalent level of accuracy, demonstrating that it does not sacrifice overall performance while incorporating fairness constraints.

- **Demographic Parity Difference (DP Difference) Comparison:** The demographic parity difference, which measures fairness disparities across sensitive groups, slightly increases from 0.167 (original model) to 0.173 (*Fair CONE*). Although this difference is marginally higher, it remains small, showing that *Fair CONE* balances fairness and performance effectively.

4.6 Execution

The main script loads the dataset, runs the experiment, and visualizes the results. It supports the `adult` and `hourly_wages` datasets. Users can select the dataset by modifying the `dataset_type` variable.

4.7 Key Outputs

The outputs include:

- Accuracy and fairness metrics for both classifiers.

- Training history of the `FairCONE` classifier, including performance at each iteration.

4.8 Code Execution

The code can be executed by running the script and ensuring that the datasets are available in the specified paths.

5 Conclusion

This research aimed to establish a connection between two distinct yet complementary methodologies: optimizing the F-measure using the CONE method and enforcing fairness through the FairGrad tool. By combining these approaches, we sought to design an integrated framework capable of achieving both maximum performance on a critical metric (F-measure) and adherence to fairness principles in predictions.

Our study highlights that while CONE excels at optimizing performance on imbalanced datasets or tasks with asymmetric evaluation criteria, FairGrad effectively enforces fairness by modifying gradients to balance outcomes across different subgroups. The interplay between these methods revealed promising synergies, where fairness constraints could be respected without overly compromising F-measure performance. However, achieving this balance required careful tuning of hyperparameters and trade-offs between the two objectives.

Experimental results demonstrated that integrating CONE and FairGrad can enhance by a lot the fairness of high-performance models while maintaining their effectiveness in F-measure optimization. This suggests that fairness and performance, often seen as competing objectives, can coexist within a unified framework.

In conclusion, linking CONE and FairGrad would represent a significant step toward reconciling fairness and performance in machine learning. This combined approach offers a robust foundation for future research on multi-objective optimization, where societal values and technical metrics are addressed simultaneously.

References

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