# Fair-SMOTE vs the AIF360 toolkit

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#### **ACM Reference Format:**

### 1 PROPOSAL

For my CSC-791 Project I will explore the universe of different algorithms made available in the AIF360 toolkit<sup>1</sup>. These different algorithms come from a myriad of different previous works in the literature of fairness. These algorithms will then be compared to the results obtained by Chakraborty et al. [2].

As stated by Chakraborty et al. fairness algorithms will usually fall within one of three categories:

- Pre-processing Optimized Preprocessing [1], Reweighing [4].
- In-processing Adversarial Debiasing [7], Prejudice Remover Regularizer [6].
- **Post-processing** Equalized Odds [3], Reject Option Classification [5].

On the opposite end of these algorithms, Fair-SMOTE [2] addresses the problem through all three steps, through pre, in and post processing. However the Fair-SMOTE paper fails to address comparisons to these existing algorithms. As such this work has the objective of running all 7 algorithms described above in different datasets and comparing the obtained results to those of Fair-SMOTE.

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 $<sup>^1</sup> A vailable\ at\ https://github.com/Trusted-AI/AIF360$