The document presents a study on debiasing semi-supervised learning models for crisis tweet classification during disasters. The authors, Henry Peng Zou, Yue Zhou, Weizhi Zhang, and Cornelia Caragea from the University of Illinois Chicago, introduce DeCrisisMB, a novel debiasing method that utilizes a memory bank for equal sampling of pseudo-labels across classes during training iterations. This approach addresses the issue of bias in semi-supervised models, which can negatively impact disaster monitoring and rescue efforts by favoring certain classes over others.

The paper begins by highlighting the importance of social media data in crisis management and the limitations of fully supervised learning due to the need for extensive annotated data. Semi-supervised models, while practical, can suffer from bias towards certain classes. The authors analyze two existing debiasing methods, LogitAdjust and SAT, and find them lacking in debiasing performance.

DeCrisisMB is proposed as an alternative, using a memory bank to store pseudo-labels and sample equally from each class during training. The method is evaluated extensively against other debiasing methods and shows superior performance in both in-distribution and out-of-distribution settings. The authors also provide insights into the impact of pseudo-label quality and quantity on model performance.

Key contributions of the work include:

1. Analysis of bias in semi-supervised learning due to imbalanced pseudo-label generation.
2. Proposal of DeCrisisMB, a debiasing method based on memory bank and equal sampling.
3. Extensive experiments demonstrating the effectiveness of DeCrisisMB over other methods.

The paper also discusses related work in disaster tweet classification and semi-supervised learning, highlighting the need for debiasing in semi-supervised models. The authors conduct experiments using datasets from HumAID, which include tweets from hurricanes and other crises. They demonstrate that DeCrisisMB outperforms existing methods, including Pseudo-Labeling, MixMatch, FlexMatch, LogitAdjust, and SAT, in various settings.

In conclusion, the authors suggest that DeCrisisMB can serve as an effective debiasing module for semi-supervised learning in different domains. They acknowledge limitations in the context of classification settings and suggest future exploration in generative tasks and large language models. The broader impact of the work is seen in its potential to improve real-time situational awareness for crisis responders, aiding in more effective disaster management.