We introduce a machine-in-the-loop pipeline that aims to address root causes of unwanted bias in natural language based supervised machine learning tasks in the education domain. Learning from the experiences of students is foundational for education researchers, and academic administrators. 21st-century skills learned from experience are becoming a core part of college and career readiness as well as the hiring process in the new knowledge economy. Minoritized students demonstrate these skills in their daily lives, but documenting, assessing, and validating these skills is a huge problem for educational institutions. As an equity focused online platform, LivedX translates minoritized students’ lived experiences into the 21st century skills, issues micro-credentials, and creates personal 21st century skills portfolio. To automate the micro credential mining from the natural language texts received from the students’ submitted essays, we employed a bag-of-word model to construct a multi-output classifier. Despite our goal, our model initially exacerbated disparate impact on minoritized students. We used a machine-in-the-loop model development pipeline to address the problem and refine the aforementioned model to ensure fairness in its prediction.

Keywords: Machine-in-the-loop, Ethical AI, Soft-skills

1 Introduction

The problem of data annotations from academic environments: As the result of a long and complex history of marginalization (e.g., racism, classism, oppression), minoritized students consistently lag behind their majority peers in academic achievement and career readiness. This lag has been influenced by structural inequalities such as those framed by poverty, migration, and/or undocumented status or homelessness [Massey and Denton, 1993]. This lag has also been called an opportunity gap because, in part, minoritized students lack access to the majority peers’ experiences and the discourses upon which educational achievement is defined [Carter and Welner, 2013]. As such, the lived experiences of minoritized students are often defined in terms of deficits and do not carry the cultural capital found in more privileged students’ experiences like attending AP courses, or early college, received funded extracurricular experiences. This
Improving ethical outcomes for our LivedX online platform: From deficit to asset mindset. In the Pilot phase of this work, the equity focused LivedX online platform was created, and is accessible at [https://livedx.com/](https://livedx.com/). In addition, the core ideas were pilot tested by guiding students to document their lived experiences. A robust LivedX research framework was developed using a phenomenological perspective ([Heidegger et al., 1962]) and a Funds of Knowledge framework ([Moll et al., 1992]) and used to interpret students’ experiences. Micro-credentials were issued to create a portfolio of soft/power skills. This iterative process helped revise and update the LivedX framework. As of now, a total of 170 micro-credentials can be awarded using the LivedX framework.

The purpose of the LivedX framework is to improve outcomes for minoritized students, but we found unintentional and unwanted bias within the framework. We improved our model and the outcomes for minoritized students by creating a dialog between our annotators and our model. Our annotators shape the data used by the model, and our model provides valuable feedback to our human annotators. This feedback provides annotators the opportunity to reconsider their own inherent biases and to account for the way the models leverage their annotations. The only way to achieve ethical results in use cases such as these is to view the entire process iteratively—from end to end. The annotators do not simply decide on annotations once and for all. Rather, they are privy to the sorts of mistakes the machine learning model makes from their annotations in order to consider possible biases in their own annotation work. They consider how to address the root (rather than superficial) of the unwanted bias ([Corbett-Davies and Goel, 2018] [Fazelpour and Lipton, 2020] [Estrada, 2020]). The alternative is to ensure that the unfairness generated by an algorithm on particular annotations is distributed equally among all groups. This does not usually improve the situation much because it fails to account for and address the characteristics of the data that are leading to the unwanted bias in the first place. Further, such superficial alternative approaches fail to provide guidance on how the machine learning fueled platform like LivedX should address the root cause of the unwanted biases ([Fazelpour and Lipton, 2020]). In this paper, we examine the machine-in-the-loop strategy to understand the intersection of machine and human bias for an effective and fair micro-credentialing process.

## 2 Materials and Methods

### 2.1 Dataset

We collected data through our LivedX interface. Users responded to four prompts with which they can narrate a small experience that took place in their life. The focus of this experience is asset based (e.g., helping others, conflict resolution, taking care of physical health) as we wanted to capture users’ positive experiences and reward them for participating in these experiences. As of 2021-08-10, we have collected 2,974 experience essays from 621 student users from our LivedX platform. The length of each natural language text in the collected experience corpus ranges from 9 to 2,649 characters.

The LivedX framework is built to assign from a pool of 152 *a priori* microcredentials that we refer to as “level-3 codes”. The codes are then grouped into 39 disjoint code groups, we call “level-2 codes” in an agglomerative fashion. We further introduced 8 disjoint code groups, we named “level-1 codings” from the level-2 codes naturally formed groups of eight which we call the “level-1 codes”. Each submitted experience usually gets 1–5 level-3 codes based on the robustness of the submitted experience. These codes could be in various categories such as global citizenship, social emotional learning, collaboration, and communication.

For the purpose of interrater reliability (IRR), we had a group of 3 coders (i.e., human annotators) who annotated each of the submitted experience texts to receive level-3 microcredentials. All three coders had different racial and ethnic backgrounds. Two coders could be classified as people of color and the third coder is identified as Caucasian. In addition, all three coders had diverse professional backgrounds. One coder is trained in Science, Technology, Engineering, and Mathematics (STEM) education and the other two in research methodology. Diverse professional background also brought richness to the coding process. The coders discussed each experience and shared their interpretation of the experience and then the coding team came to a consensus by creating shared meaning ascribed to particular text.

### 2.2 Predicting microcredentials

We adapted a bag-of-word model approach to solve the multi-label text classification problem of predicting a set of appropriate level-3 codes out of 152 codes for a given experience text. To obtain such a model, we first removed
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Figure 1: Our proposed machine-in-the-loop fairness pipeline emphasizes two forms of revisions based upon fairness outcomes: (1) a re-evaluation of annotations based upon predictive outcomes and (2) model revision. Note that the Dataset and Machine Learning Algorithm nodes are nodes where human and machine collaborate iteratively.

common English stop words. We converted the text dataset into the term frequency inverse document frequency (TF-IDF) matrix [Ramos et al., 2003]. For simplicity, we chose to build a multi-output classifier. This strategy consists of fitting one binary classifier, e.g., logistic regression, per target; and we have 152 level-3 targets. We conducted a 10-fold cross validation on a split training set to decide on the hyper-parameters of the model.

2.3 Evaluation with fairness metrics

We evaluated the microcredential predictions using conditional statistical parity (CSP). CSP measures whether particular groups have equal probability of receiving a favorable outcome (in this case a credential) while permitting a legitimate factor to affect the prediction fairly [Ruf and Detyniecki, 2021]. In our case, we consider students who have submitted fewer than 5 experiences to be too inexperienced and exclude them from consideration. For level-1 and level-2 credentials, we see CSP for many—but not all—credentials.

We found that CSP exists for most credentials between most groups, but occasionally a group achieves substantially fewer credentials than other groups. For example, the students who identified as white achieved a CSP of 0.1049 for the "working with others" credential, whereas students who identify as black or African American achieved a CSP of 0.0368 (see 2). If we take the data annotations to be authoritative, we might suspect that students who identify as black or African American are somehow deficient (perhaps due to systemic discouragement of these experiences). A second possibility also exists, however. Students who identify as black or African American may express how they work with others in ways that are different from white students and in ways that the annotators might have missed. These questions cannot be answered by the outputs of the model alone. They need to be answered by the subject experts (in this case, the annotators).

For our problem, we mark differences in CSP of greater than 0.05 as credentials of concern.

2.4 Machine-in-the-loop Pipeline

Figure 1 illustrates our proposed iterative pipeline to refine the machine learning models by sending the intermediate predictions by the model back to the human annotators considering fairness outcomes. Many approaches to enforce fairness across machine learning model prediction emphasize strategies related to algorithm manipulation or dataset balancing to address discrepancies of fairness [Mehrabi et al., 2021]. We propose that data annotation should also be an iterative process included in the machine learning pipeline, since annotations are frequently problematic insofar as they can encode societal norms [Schumann et al., 2021]. Annotations should periodically be reconsidered in light of fairness metric outcomes, especially for high bias models. High bias models can identify trends in the annotations that result from the annotators’ unwanted bias. The predictions of these models can identify trends that need to be explored by the annotators.
3 Results and Discussion

3.1 Microcredential Assignment Experiments

We trained three models for predicting level-3 microcredentials: Logistic Regression, Naïve Bayes and Support Vector Machines with linear kernel on a 5000 dimensional “term frequency inverse document frequency” scores of the experience text corpus that we retrieved from the LivedX platform. We conducted a 10-fold cross-validation for each of the models, and the evaluation results are presented in Table 1. Each of the three classifiers show promising prediction performance where Logistic Regression based multi-output classification demonstrated slightly faster performance than the rest on an average. Currently, the model is being used at the LivedX platform to automate the microcredential assignment problem to assist the human annotators.

Table 1: Experimental evaluation of three Bag-of-Word Models in terms of average accuracy of each of predictions of 152 level-3 microcredential classes, and CPU time required for microcredential assignment of each experience text submitted.

| Model name           | Average accuracy | Average prediction time per essay (s) |
|----------------------|------------------|-------------------------------------|
| Logistic Regression  | 0.96 ± 0.066     | 0.089959                            |
| Support Vector Machines | 0.96 ± 0.006    | 0.093059                            |
| Naïve Bayes          | 0.94 ± 0.005     | 0.109604                            |

3.2 Evaluation based on Fairness Metrics and Model Refinement

When we isolate the possible race categories to "white" and "black or African American" for the sake of illustration, 12.8% of the level-2 microcredentials have a difference in CSP greater than or equal to 0.05. 60% of these differences favored white submissions. The annotators assessed these differences looking especially for initial annotations that might contain some annotator bias. For instance, Table 2 outlines effectiveness of model refinement through the proposed iterative pipeline on a particular level-2 microcredential, “Working with Others”.

After one iteration of training our model, we sent the outcomes back to annotators and asked them to reconsider the annotations for credentials exhibiting a difference in CSP greater than or equal to 0.05 between two demographic groups. This reconsideration was performed one demographic group at a time, so that the annotators could consider possible systemic bias as explanations. For example, the annotators discovered that black or African American students in the sample tend to talk about working with others passively, whereas white students tend to describe working with others actively.

Table 2: Conditional statistical parity for the "Working with Others" credential by race, before and after annotation re-assessment.

| Iteration               | White    | Black or African American |
|-------------------------|----------|---------------------------|
| Before Annotation Reassessment | 0.1049  | 0.0368                    |
| After Annotation Reassessment | 0.1049  | 0.0743                    |

4 Conclusion and Future Work

In this project, we shared an equity serving online platform (LivedX) that translates peoples’ everyday life experiences into micro credentials, which utilizes the machine learning pipeline proposed here. We found that iterative data annotation—with deliberate reflection on the fairness of outcomes for each subgroup—leads to more just outcomes. The project is still in its early stages in terms of scale of the data set and the diversity of population included in the experience essay corpus and the human annotators. The model could also be improved through using sequential neural network models, like BERT instead of bag of words. We hope, through this presentation, that we create a dialog in the community that would help us reflect on best practices for iterative annotations of data that leads to more equitable outcomes for marginalized groups.

References

Douglas Massey and Nancy A Denton. American apartheid: Segregation and the making of the underclass. Harvard university press, 1993.
Prudence L Carter and Kevin G Welner. *Closing the opportunity gap: What America must do to give every child an even chance*. Oxford University Press, 2013.

Martin Heidegger, John Macquarrie, and Edward Robinson. *Being and time*. New York, (Original work published in 1927), 1962.

Luis C Moll, Cathy Amanti, Deborah Neff, and Norma Gonzalez. Funds of knowledge for teaching: Using a qualitative approach to connect homes and classrooms. *Theory into practice*, 31(2):132–141, 1992.

Sam Corbett-Davies and Sharad Goel. The measure and mismeasure of fairness: A critical review of fair machine learning. *CoRR*, abs/1808.00023, 2018. URL [http://arxiv.org/abs/1808.00023](http://arxiv.org/abs/1808.00023).

Sina Fazelpour and Zachary C. Lipton. Algorithmic fairness from a non-ideal perspective. AIES ’20, page 57–63, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 9781450371100. doi [10.1145/3375627.3375828](https://doi.org/10.1145/3375627.3375828). URL [https://doi.org/10.1145/3375627.3375828](https://doi.org/10.1145/3375627.3375828).

Daniel Estrada. Ideal theory in AI ethics. *CoRR*, abs/2011.02279, 2020. URL [https://arxiv.org/abs/2011.02279](https://arxiv.org/abs/2011.02279).

Juan Ramos et al. Using tf-idf to determine word relevance in document queries. In *Proceedings of the first instructional conference on machine learning*, volume 242, pages 29–48. Citeseer, 2003.

Boris Ruf and Marcin Detyниеcki. Towards the right kind of fairness in AI. *CoRR*, abs/2102.08453, 2021. URL [https://arxiv.org/abs/2102.08453](https://arxiv.org/abs/2102.08453).

Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. A survey on bias and fairness in machine learning. *ACM Comput. Surv.*, 54(6), July 2021. ISSN 0360-0300. doi [10.1145/3457607](https://doi.org/10.1145/3457607). URL [https://doi.org/10.1145/3457607](https://doi.org/10.1145/3457607).

Candice Schumann, Susanna Ricco, Utsav Prabhu, Vittorio Ferrari, and Caroline Pantofaru. A step toward more inclusive people annotations for fairness. AIES ’21, page 916–925, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 9781450384735. doi [10.1145/3461702.3462594](https://doi.org/10.1145/3461702.3462594). URL [https://doi.org/10.1145/3461702.3462594](https://doi.org/10.1145/3461702.3462594).