# Contrastive Learning for Individual Fairness

Michael Xiang
michaelxiang@college.harvard.edu

Corwin Cheung
corwincheung@college.harvard.edu

***Abstract*—In recent years, contrastive learning has emerged as a powerful technique for training machine learning models, particularly due to its potential to learn rich representations of the data without explicit labeling. Contrastive learning operates by using positive and negative pairs to push similar data points closer together and dissimilar data points further apart within the context of the contrastive learner's embedding space. This principle, though, is strikingly similar to the definition of individual fairness within the algorithmic fairness literature. This paper, thus, aims to explore how contrastive learning could potentially boost the individual fairness of a model.**

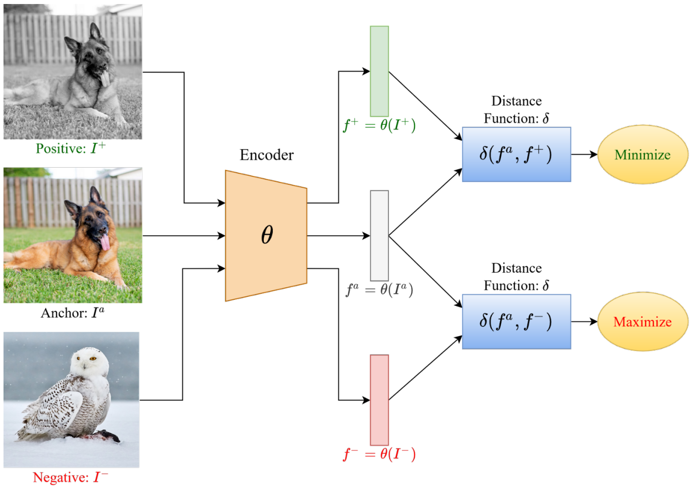

Fig. 1: This image shows how the contrastive learning process works. There are positive images that should be embedded close to the embedding of the anchor image and negative images that should be embedded farther apart. The encoder is trained with a loss function that aims to minimize the distance between the positive and anchor image embeddings while maximizing that for the negative and anchor image.

## I. Introduction

Individual fairness, within the context of algorithmic fairness, is defined as treating similar individuals with respect to some task similarly in terms of their classification by the model [1]. One notable challenge, however, lies in finding an effective representation of the data. The way that the data gets introduced inherently introduces bias - certain features may ”propogate” over into other features, e.g. someone may infer one's race from other factors, like one's neighborhood. Thus, it is important that we do not remove sensitive features like race and sex from consideration of our data, and that we actively ensure that people of different sensitive attributes are treated fairly.

To help with the problem of feature representation, we introduce the concept of contrastive learning. Within the context of training on images, contrastive learning operates by selecting some anchor image, performing an augmented version of that image to create a positive pair, and picking some other image within the dataset to act as a negative pair [2]. The idea is that, because the positive pair is formed from the anchor image, the embeddings for the two images should be very similar. And since the negative pair is formed from two different images, the embeddings should be vastly distant in terms of the embedding space. The images do not need to be labeled, and contrastive learning usually operates in an unsupervised learning environment. We observe that this training concept seems similar to the goal of individual fairness - ideally, similar images should be mapped to the embedding space similarly, while different images should be mapped farther apart in the embedding space. Thus, it is our goal that we can exploit this training concept to optimize a model's individual fairness.

We note that, since contrastive learner uses an embedder, any model that uses the embeddings instead of the actual data loses some information because the embeddings are not lossless. Thus, there may be some loss in accuracy when we train models on embeddings generated by a contrastive learner rather than the original data. Within the algorithmic fairness literature, though, there are a lot of algorithms that have been developed recently that use the concept of boosting [3]. Boosting is a machine learning ensemble technique that combines multiple weak learners to create a strong learner. Weights are updated such that each weak learner fixes the mistakes of the the previous weak learner [4]. We hope that the loss in accuracy that comes with contrastive learning to be offset by the increase in model power with boosting.

## II. Current Issues with Fair Models

We have already noted above that a huge problem within the algorithmic fairness community is the issue of fair representation of data. One of the fundamental goals of fair representation is to ensure that the features used by machine learning models to make predictions are not inadvertently encoding biases present in the data. Biases can manifest in various forms, including historical disparities, societal prejudices, and systemic inequalities, and they can permeate the data in subtle ways. Additionally, another issue with supervised learning in general is how expensive it can be to label datasets. Since contrastive learning is a form of unsupervised learning, it is less expensive to do, and we may also be able to utilize synthetic data (since we do not need labels) to train the model, which would both help dramatically cut costs and provides the model with much more data to work with.

## III. Proposed Approach

As explained above, we hope to utilize contrastive learning to generate embeddings for the data, and then evaluate how those embeddings perform as training and testing data in comparison to the original dataset. We will compare this 3 ways. First, we will evaluate a logistic regression model on the original training data. Then, we will evaluate a logistic regression model trained on the embeddings of the data provided by the contrastive learner. Finally, we will evaluate a boosting model trained on the embeddings on the data provided by the contrastive learner. We will evaluate in terms of both accuracy and fairness.

Our datasets are tabular, and we will implement SCARF, a state of the art contrastive learner on tabular data [5]. SCARF works by taking the original training set and ”corrupting” it slightly to create synthetic positive pairs. The idea is that, for a singular data point, it creates slight perturbations within that data point to generate a positive pair, and the synthetic perturbed data point should classify similarly to the original data point. We will tweak the training process, however, to train for individual fairness as well. For each training batch, we will create a copy of the batch and flip each of the protected attributes of each data point within the copied batch, so that the original and copied batch are similar except in terms of protected attributes. We will train the SCARF model to treat the data points within the two batches as positive pairs. For individual fairness evaluation, we will follow the guideline established in the paper, Individually fair gradient boosting, where we generate synthetic data and check to ensure that the ”flipped” version of the synthetic data (where everything is the same except for the protected attributes) is classified the same as the original synthetic data [3]. We classify the fairness metric as the percentage of synthetic pairs where the flipped version was classified the same as the original. Our boosting model is the classical XGBoost model, which we import from a well-documented library.

## IV. Experiments

We will train our contrastive learner, SCARF, and then classification models on two datasets, the Adult dataset and the COMPAS dataset, both well-documented within the algorithmic fairness literature and found on AIF360 datasets. We train for 2000 epochs total and batch size 128 for each dataset. We plotted the loss curves and obtained the classification reports for each dataset. The classification report contains our accuracy scores, which includes precision, recall, and F1 score. The fairness score, as mentioned before, is just the percentage of synthetic positive pairs predicted similarly by the model.

## V. Results

We have attached all charts in the appendix. For the adult dataset, we get the metrics for accuracy seen in 2. We observe that, overall, the logistic regression model trained on the original data has the best accuracy metrics while the booster trained on the embeddings slightly edges out the logistic regression model trained on the embeddings. In terms of fairness, all 3 models are on par with one another, with logistic regression on the original data slightly beating out the other two models by just over $0.01\%$ I. We also observe that the boosting model and logistic regression trained on embeddings have very similar fairness scores.

For the COMPAS dataset, we get the metric for accuracy seen in 3. For accuracy, the logistic regression model trained on the original data is still be the best across the board, but the other classifiers, such as the booster trained on embeddings, are in contention, as, for example, the booster has better recall for class 0. For fairness, however, we observe that the logistic regression model trained on the embeddings has the best fairness score, with the booster trained on the embeddings falling closely behind, while the logistic regression model trained on the original dat is $9\%$ behind the logistic regression model trained on embeddings II.

Thus, to sum it up, we see that, for the adult dataset, the logistic regression model on the original dataset has the best accuracy and fairness scores, but the booster model trained on the embeddings has slightly worse accuracy and fairness scores barely below that of the logistic regression model on the original dataset. For the COMPAS dataset, the logistic regression model on the embeddings has the best fairness score, but the booster model has better accuracy and on-par fairness. The logistic regression model on the original dataset has drastically worse fairness scores, but it still has the best accuracy.

## VI. Discussion of Results and Conclusion

We think our results showed promise of contrastive learning boosting individual fairness. Specifically, for the COMPAS dataset, we saw that the individual fairness was better for the logistic regression model trained on the embeddings rather than the one trained on the original data. For the adult dataset, we saw that individual fairness of the models trained on the original data was on par with that of the models trained on the embeddings. We think that this supports the idea that contrastive learning can improve individual fairness due to its training mechanism, in which we explicitly direct the embeddings to map similar people with respect to a task similarly in the embedding space regardless of their protected attribute. We also saw that the accuracy dropped when we trained on the embeddings rather than the original dataset. For us, this was to be expected, as embedding the data to a lower dimension loses information, so some loss of accuracy was to be expected. Boosting also slightly improved the accuracy of the model trained on embeddings while retaining the same levels of individual fairness, which we think supports the idea discussed that boosting can help increase accuracy without hurting fairness too much, due to its concept of combining weak learners and improving on the previous learner's failures. Thus, we conclude that it is probable that a contrastive learning method improves individual fairness while losing some accuracy due to its unique method of training on positive and negative pairs, and that a booster trained on the contrastively-learned embeddings can retain the levels of individual fairness while increasing accuracy. We think further investigation into this phenomenon will significantly help validate our hypothesis, and that further training with, for instance, more epochs, may lead to more drastic results.

We have attached the code along with the paper for reproducibility, as well as the model weights. We hope that this project nudges people to look into contrastive learning as a computationally inexpensive yet optimal way to train models to be more individually fair. Synthetic data provides an easy way to fit the model with a lot of data while preventing the need for labels, and contrastive learning provides a promising way to ensure that models align with the definition of individual fairness. With more time, we think it would be worth observing how our code works on other datasets and exploring different classification models to train our embeddings on.

## VII. Related Work

We build upon existing papers that explore contrastive learning and boosting within the realm of algorithmic fairness. We build upon existing approaches that attempt to both improve individual fairness via boosting and evaluate individual fairness [3]. Additionally, we further analyze contrastive learning to learn fair representations. Previously within the literature, such contrastive learners are only used on image or text, not tabular data [6], so we explore further how contrastive learning works on tabular data [5]. Further, those papers also seem to be interested in the fairness of contrastive learning in terms of group fairness metrics, not individual fairness [6], something that our project delves into.

## VIII. Group Contribution

Michael came up with the project idea to explore contrastive learning and boosting in the context of individual fairness. He also coded up the preprocessing required for the datasets, training for the contrastive learner, the booster, the evaluation code needed to assess accuracy, and the synthetic data generator to assess fairness. He also planned the project, came up with the reasoning behind the results, and wrote up the results.

## References

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[3] Alexander Vargo, Fan Zhang, Mikhail Yurochkin, and Yuekai Sun. 2021. Individually fair gradient boosting. *arXiv preprint arXiv:2103.16785*.

[4] Yoav Freund and Robert E. Schapire. 1999. A Short Introduction to Boosting.

[5] Dara Bahri, Heinrich Jiang, Yi Tay, and Donald Metzler. 2021. Scarf: Self-supervised contrastive learning using random feature corruption. *arXiv preprint arXiv:2106.15147*

[6] Aili Shen, Xudong Han, Trevor Cohn, Timothy Baldwin, and Lea Frermann. 2021. Contrastive learning for fair representations. *arXiv preprint arXiv:2109.10645*

## Appendix

### A. Fairness Scores

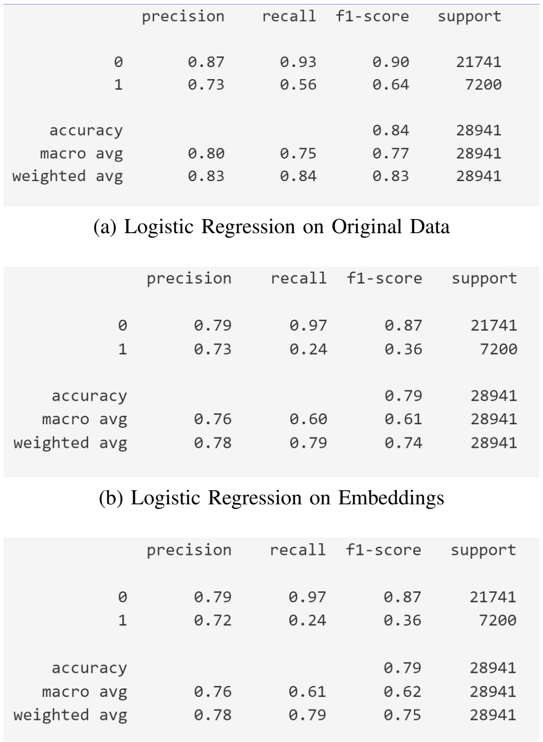
TABLE I: Individual Fairness for Adult Dataset

| Logistic Regression on Original Data | Logistic Regression on Embeddings | Booster on Embeddings |
|---|---|---|
| 0.9960076162397887 | 0.9848289417111971 | 0.9842761501136293 |

TABLE II: Individual Fairness for COMPAS Dataset

| Logistic Regression on Original Data | Logistic Regression on Embeddings | Booster on Embeddings |
|---|---|---|
| 0.9046717171717171 | 0.9936868686868687 | 0.9842171717171717 |

### B. Accuracy Metrics



```
              precision    recall  f1-score   support

           0       0.87      0.93      0.90     21741
           1       0.73      0.56      0.64      7200

    accuracy                           0.84     28941
   macro avg       0.80      0.75      0.77     28941
weighted avg       0.83      0.84      0.83     28941
```

(a) Logistic Regression on Original Data

```
              precision    recall  f1-score   support

           0       0.79      0.97      0.87     21741
           1       0.73      0.24      0.36      7200

    accuracy                           0.79     28941
   macro avg       0.76      0.60      0.61     28941
weighted avg       0.78      0.79      0.74     28941
```

(b) Logistic Regression on Embeddings

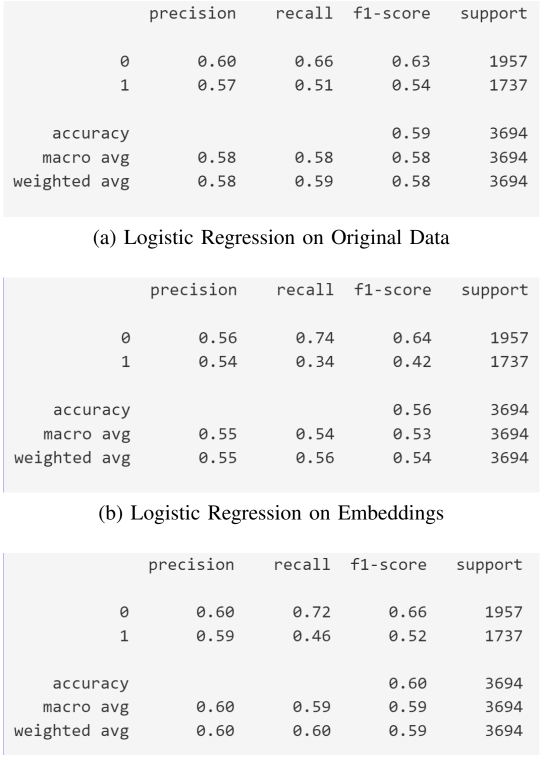
```
              precision    recall  f1-score   support

           0       0.79      0.97      0.87     21741
           1       0.72      0.24      0.36      7200

    accuracy                           0.79     28941
   macro avg       0.76      0.61      0.62     28941
weighted avg       0.78      0.79      0.75     28941
```

(c) Booster on Embeddings

Fig. 2: Accuracy Results for the Adult Dataset



```
              precision    recall  f1-score   support

           0       0.60      0.66      0.63      1957
           1       0.57      0.51      0.54      1737

    accuracy                           0.59      3694
   macro avg       0.58      0.58      0.58      3694
weighted avg       0.58      0.59      0.58      3694
```

(a) Logistic Regression on Original Data

```
              precision    recall  f1-score   support

           0       0.56      0.74      0.64      1957
           1       0.54      0.34      0.42      1737

    accuracy                           0.56      3694
   macro avg       0.55      0.54      0.53      3694
weighted avg       0.55      0.56      0.54      3694
```

(b) Logistic Regression on Embeddings

```
              precision    recall  f1-score   support

           0       0.60      0.72      0.66      1957
           1       0.59      0.46      0.52      1737

    accuracy                           0.60      3694
   macro avg       0.60      0.59      0.59      3694
weighted avg       0.60      0.60      0.59      3694
```

(c) Booster on Embeddings

Fig. 3: Accuracy Results for the COMPAS Dataset