Evaluating the fairness of fine-tuning strategies in self-supervised learning

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Abstract

In this work we examine how fine-tuning impacts the fairness of contrastive Self-Supervised Learning (SSL) models. Our findings indicate that Batch Normalization (BN) statistics play a crucial role, and that updating only the BN statistics of a pre-trained SSL backbone improves its downstream fairness (36% worst subgroup, 25% mean subgroup gap). This procedure is competitive with supervised learning, while taking 4.4× less time to train and requiring only 0.35% as many parameters to be updated. Finally, inspired by recent work in supervised learning, we find that updating BN statistics and training residual skip connections (12.3% of the parameters) achieves parity with a fully fine-tuned model, while taking 1.33× less time to train.

1 Introduction

SSL is an effective pre-training strategy in the image (Chen et al., 2020; Grill et al., 2020; Caron et al., 2021, 2020; Zbontar et al., 2021; Bardes et al., 2021), language (Devlin et al., 2019), video (Alayrac et al., 2020) and audio (Deng et al., 2009) domains. These large scale SSL models are trained without the use of (potentially) biased human annotations, and attain better than supervised performance when fine-tuned on small sample supervised datasets. The performance guarantees for many of these large scale SSL models is strongly coupled with the use of BN (Chen et al., 2020; Zbontar et al., 2021; Caron et al., 2020; Alayrac et al., 2020; Fetterman and Albrecht, 2020). BN (Ioffe and Szegedy, 2015) tends to favor subgroups of the dataset which contain more samples, negatively impacting downstream model performance for under-represented subpopulations.

To understand how SSL model fairness is impacted by fine-tuning, we evaluate a number of tuning strategies. We find that the treatment of BN statistics is a dominant factor for determining downstream fairness. When tuning a linear task head, freezing BN statistics and backbone parameters reduces performance by up to 36% in the worst subgroup fairness metric, whereas allowing BN statistics to update reduces the performance gap against a fully fine-tuned model, while taking 4.4× less time to train and updating only 0.35% of the total model parameters.

2 Results

Our baseline SSL model uses the SimCLR framework and optimization procedure (Chen et al., 2020; Goyal et al., 2017), pre-trained (no labels) on the Celeb-A train split (162,770 samples). We then attach a linear head to the backbone and evaluate five scenarios inspired by analysis in supervised learning (Frankle et al., 2020): fully fine-tuned (Full FT); frozen backbone, updating residual skip connections and BN stats (BN Stats+Skip); frozen backbone, updating BN affine parameters and BN stats (BN Stats+Affine); frozen backbone, updating BN stats (BN Stats); and fully frozen backbone (Frozen). Updates are done using supervised information from the Celeb-A train split.

We evaluate Celeb-A test split (19,962 samples) using the 40-dimensional binary attribute prediction task. We baseline our SSL model against a strong supervised learning model, which uses the same ResNet50 (He et al., 2016) backbone. To choose hyper-parameters, we perform a random search (twenty trials) across optimizers (Hu et al., 2021; Kingma and Ba, 2015), learning rates and schedulers (Goyal et al., 2017; Smith and Topin, 2017), weight decay, training epochs, and linear
### Conclusion

Models that produce fair representation vectors can directly improve the fairness of any downstream task that uses them. These models have the ability to affect fairness at a large scale, through the use of

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2For example: $F_1$ (wearing hat | blurry) is the $F_1$ score for blurry images when predicting wearing hat.

3We omit on-diagonal ($t = c$) terms to ensure all metric components are well-defined.
of developer APIs. In this work, we quantify the the effect that various fine-tuning strategies play in downstream fairness, and observe the crucial role played by BN statistics. We demonstrate that only updating BN statistics minimizes the gap between an end-to-end trained model and a frozen SSL model, improving worst case subgroup fairness by $36\%$ and taking $4.4\times$ less time to train.
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