

1 We thank all reviewers for their helpful comments and feedback.

2 **Reviewer 1** 1. We will add the concurrent related works (CPCv2, MoCov2).

3 2. Parameter  $\tau^+$  and  $M$ : We agree that picking  $\tau^+$  could be domain-dependent and will add this clarification. Our  
4 results show that larger  $M$  consistently leads to better results regardless of domain. Scaling it up is indeed an interesting  
5 future direction. We will add these points of discussion.

6 **Reviewer 2** 1. QT baseline: Yes, the baseline (QT) in 5.3 also uses 2 positive samples.

7 2. Full ImageNet: Indeed, with a larger number of classes, the number of collisions naturally shrinks. We will work on  
8 adding larger-scale experiments.

9 3. Positive distribution: Section 5.5 provides a discussion about the “surrogate” positive distribution. We will state this  
10 at the beginning of section 3 and section 5 to improve the clarity.

11 **Reviewer 3** 1. To improve the clarity, we will explicitly state the difference between true and approximated positive  
12 distribution at the beginning of section 3 and section 5.

13 2. To probe the effect of debiased objective when the number of negative sample increases, we increase the batch size  
14 to 512 ( $N = 1022$ ) for the experiments in Figure 4ab and show the results in Figure 1 ab. The debiased objective still  
15 outperforms the biased baseline when the negative sample size is doubled.

16 3. We run biased SimCLR for 50% more epochs (600 epochs) and compare it with the debiased objective ( $M > 1$ ) in  
17 Figure 4c. The results are shown in Figure 1 c. The debiased objective ( $M > 1$ ) still outperforms the biased baseline  
18 even it is trained with 50% more epochs.

19 4. We will add the missing references on contrastive learning, e.g., PIRL and CPC v2, in the related work section.

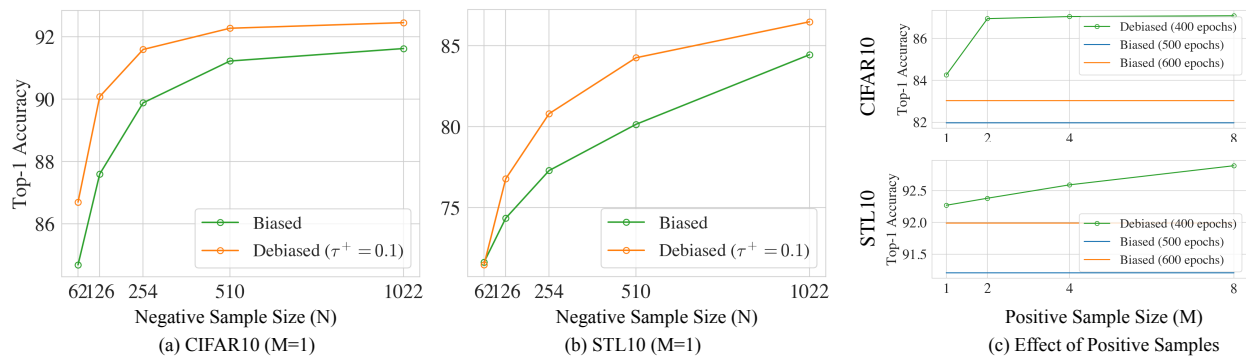


Figure 1: **Classification accuracy on CIFAR10 and STL10.** (a,b) Biased and Debiased ( $M = 1$ ) SimCLR with larger negative sample size  $N$ . (c) Comparison with biased SimCLR with 50% more training epochs (600 epochs) while fixing the training epoch for Debiased ( $M \geq 1$ ) SimCLR to 400 epochs.

20 **Reviewer 4** 1. Indeed, we derive the new objective by looking at the asymptotic version with large  $N$ . Interestingly,  
21 and very useful, the objective also works with smaller  $N$ . The bound in Theorem 3 analyzes the approximation error  
22 for smaller  $N$ .

23 2. Pseudocode: We show the  $M = 1$  version to give a clear comparison with the standard (biased) contrastive loss. We  
24 will add the  $M$  dependent version by changing the “pos” in line 8 of Figure 3 with an average of exponentials for  $M$   
25 positive samples.

26 3. We follow Kiros et al. [2015], Logeswaran and Lee [2018] in choosing these datasets. We agree that the improvements  
27 in our NLP experiments are not as significant as the CV and RL experiments and we will work on extending our method  
28 to other NLP benchmarks.

## 29 References

30 Ryan Kiros, Yukun Zhu, Russ R Salakhutdinov, Richard Zemel, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. Skip-thought  
31 vectors. In *Advances in Neural Information Processing Systems*, pages 3294–3302, 2015.

32 Lajanugen Logeswaran and Honglak Lee. An efficient framework for learning sentence representations. *International Conference on*  
33 *Learning Representations*, 2018.