

1 We thank the reviewers (R1, R2, R3, R4) for their thorough reading and constructive criticism. We
2 will fix the mentioned typos and representation issues.

3 **Curiosity about mapping points to group memberships for the two-color case and how the**
4 **choice of the function affects the experiments (R1):** This is indeed an interesting question which
5 we thought about as well. We believe the experiments in Appendix F.1 (Figure 10) provide some
6 information. There, the mapping function is varied from being completely random to deterministic.
7 As the colors become more deterministically assigned, the price of fairness becomes larger.

8 **Comparisons to previous fair clustering algorithms (R1,R4):** Since previous fair clustering
9 algorithms do not take probabilistic color assignments as an input, they are not directly applicable.
10 However, as R1 mentions, it is possible to assign points to their most likely color and then apply a
11 fair clustering algorithm. Due to the page limit, this is done in Appendix F.1 (Figure 11). We also
12 mention that it may not always be feasible to apply this method (see footnote in the appendix on
13 page 22). We would be happy to run further suggested experiments of this kind and include a brief
14 discussion of this point (and the preceding one from R1) in the main paper.

15 Large Cluster Assumption Issues

16 (R1,R2,R3,R4): Reviewers have expressed concerns for the large cluster assumption &
17 Algorithm 2. We acknowledge that the large cluster assumption is a limitation in our work.
18 We consider our full solution to the two color case to be significant and this special case is
19 commonly studied in the fair ML literature. Further, although the idea of sampling and then
20 applying a fair clustering algorithm is simple, we show that arguably more elaborate methods do not seem to lead to better results under this
21 assumption. Please see Appendix D where we present another solution based on dependent rounding
22 for the k -center problem under the large cluster assumption and end up with similar guarantees.
23 At the request of R3, we ran the large cluster experiment for different values of k ; Fig. 1 shows a
24 reasonable (and expected) degradation in quality. We will add these new experiments to the paper.

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26 assumption. Please see Appendix D where we present another solution based on dependent rounding
27 for the k -center problem under the large cluster assumption and end up with similar guarantees.
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29 reasonable (and expected) degradation in quality. We will add these new experiments to the paper.

30 **Motivation for specific case of metric membership (R1):** One natural example is the case where
31 the membership is income. Clustering could be performed and different outcomes assigned to
32 different clusters. Forcing each cluster to have an average income around the global average prevents
33 the possibility of having low or high income individuals from being over or under represented in a
34 good or bad outcome. We will add this as motivation, and welcome other examples to include!

35 **What's the current best possible for gamma (R2):** As mentioned in Theorem 4.2, it is R for
36 metric membership and 1 for the two-color probabilistic case as mentioned at the end of the theorem.
37 We will be more clear about these values. Theorem 4.5 is for the large cluster multiple color setting;
38 the lower and upper bounds are relaxed by ϵ , the factor of 2 in 2ϵ is a typo, it is in fact just ϵ .

39 **Metric membership connection to the two-color case and a clear definition of the price of**
40 **fairness (R2):** Indeed we see that the reviewers agree on a more detailed explanation of metric
41 membership, which we will add. As you mentioned (comment about Figure 3) we will indicate
42 explicitly that the price of fairness is with respect to the output of the approximation algorithm not
43 the true optimal since the true optimal is prohibitive to obtain (since the problem is NP-hard).

44 **Presentation issues (R1):** The suggested improvements regarding Appendix C, the figures, and
45 the addition of proof sketches are all valid and would highly improve the presentation. We will try to
46 incorporate them as much possible in the camera ready version within the given page limit.

47 **Presentation issues and including further references (R4):** We thank the reviewer for bringing
48 up these issues and believe that fixing them in the camera ready version will significantly improve the
49 presentation. We will add a high level description of our algorithms as well as a smoother introduction
50 to metric membership and different notation. We were not aware of the paper by Ding and Xu, we
51 will include it in the related work section.

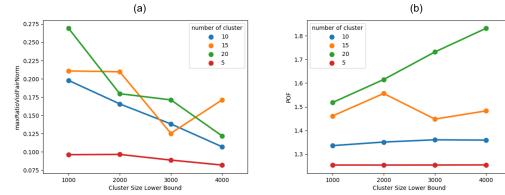


Figure 1: Results on the Census1990 dataset for different values of k . We see a reasonable degradation in the violation (a) and POF (b) for larger values of k .