

1 We thank the reviewers for their constructive and thorough feedback.

2 **Reviewer #1**

3 **1) BigGAN experiments not convincing:** Our submission demonstrates many directions for BigGAN that were not  
4 demonstrated by [8]: changing seasons, adding clouds, adding grass, day-night, warm lighting, pixelation, contrast,  
5 light direction, sharpness, owl height, background color, etc. (see Figure 7; Supplemental Material: Figure 1; and  
6 accompanying video: 4:00-4:40). While one can debate the merits of the entangling in Figure 7 (dogs photographed in  
7 snow may generally have heavier coats), we believe that these examples ought to be sufficient to convince the reader of  
8 the promise of our method for BigGAN. Moreover, we introduce style mixing for BigGAN, which is also novel.

9 **2) Canonical directions instead of PCA:** In our experiments with StyleGAN and BigGAN, we haven't been able  
10 to find canonical directions that were any more interpretable than random directions are (and random directions are  
11 sometimes somewhat interpretable). The published training algorithms do not give a specific role to canonical directions,  
12 making them no different from random directions. We are happy to mention this in the paper.

13 **3) Qualitative Evaluation:** It is true that some of our results are comparable to those of [8]. The main advantage of  
14 our method is that we can find many transformations that [8] cannot find, because that method requires hand-specified  
15 transformations as supervision. While we believe that the extensive demonstrations we provide in the paper, video, and  
16 supplement illustrate the promise of these ideas, we also believe that quantitative evaluation is useful. We are aware of  
17 no methods that would enable evaluation for large collections of interpretable directions, as demonstrated here, and  
18 think it is an extremely interesting direction for future work. We are happy to discuss this in the text.

19 **4) How to find layers:** Some effort is required to identify useful layer ranges. However, it does not require  $L^2$  search;  
20 e.g., we find that certain ranges tend to be useful, and that there is no need to try arbitrary subsets. Moreover, we argue  
21 that this effort is far less than that of gathering supervised data, especially when one doesn't even know what attributes  
22 are controllable within a given GAN. See also the response to Reviewer #4 re "How was comparison performed".

23 **5) Prior and concurrent work:** Thank you, we will add and discuss these references in the revised paper. Ramesh  
24 (ICLR 2020) is indeed relevant in the way R1 mentions; the paper addresses a different problem from us. The method  
25 of Plumerault (ICLR 2020) seems very similar to [8], which we discuss and compare to. Please note that the ICML  
26 2020 publication date was after the NeurIPS 2020 submission deadline.

27 **Reviewer #2:**

28 **How to evaluate quantitatively:** This is an interesting question; one possibility is to compare on a computer-generated  
29 dataset with known attributes. **How dataset affects components:** One observation we report in the paper is that  
30 translation is not discovered for StyleGAN faces, because FFHQ is already carefully aligned. This, together with the  
31 other entanglements we report, suggest that the components indeed are dataset-dependent. **Using this method in the  
32 supervised case:** One possibility is to linearly train on a small supervised dataset to use a sparse set of these PCA  
33 features. Another possibility, based on our layer-wise editing, is to learn a separate latent direction vector for each layer.  
34 We will mention this as future work.

35 **Reviewer #3:**

36 **Not clear if PCA helps on StyleGAN:** As shown by Figure 4 and the Supplemental Material (Figures 2–5), the  
37 PCA basis gives a useful content-style separation and ordering of directions. For example, all random directions  
38 seem to include some pose and appearance variation, whereas, in PCA, pose variations only occur in the first 20 or  
39 so components. **Role of StyleGAN demonstration:** We argue that the techniques we describe for StyleGAN are  
40 themselves useful, since we provide many ways to control StyleGAN models that have not been discovered before.

41 **Reviewer #4**

42 — **Using later layers for BigGAN:** We offer to add examples to the supplemental showing results using later layers of  
43 BigGAN.

44 — **Analysis in Figure 6:** See Figure 10 of the Supplement for more dramatic examples.

45 — **How was comparison to supervised methods performed:** Many of the comparisons were based on directions  
46 we'd already found, and some we found specifically for this comparison. For the latter, it took at most five minutes to  
47 pick a suitable component (often there were several good candidates to choose from) and choose the layer range.

48 The purposes of these examples is to show that some of the edits found by supervised methods also emerge in our  
49 technique. Some effort is required to sample our PCA directions and layers, but we argue that this is less than the effort  
50 of creating supervised data.

51 — **More investigation of which attributes can't be found:** This is an interesting avenue for future investigation.