B. Truncation trick in $\mathcal{W}$

If we consider the distribution of training data, it is clear that areas of low density are poorly represented and thus likely to be difficult for the generator to learn. This is a significant open problem in all generative modeling techniques. However, it is known that drawing latent vectors from a truncated [42, 5] or otherwise shrunk [34] sampling space tends to improve average image quality, although some amount of variation is lost.

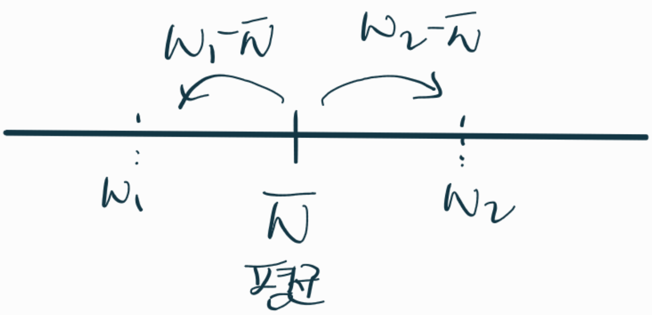
We can follow a similar strategy. To begin, we compute the center of mass of $\mathcal{W}$ as $\bar{\mathbf{w}} = \mathbb{E}_{\mathbf{z} \sim P(\mathbf{z})}[f(\mathbf{z})]$. In case of FFHQ this point represents a sort of an average face (Figure 8, $\psi = 0$). We can then scale the deviation of a given $\mathbf{w}$ from the center as $\mathbf{w}' = \bar{\mathbf{w}} + \psi(\mathbf{w} - \bar{\mathbf{w}})$, where $\psi < 1$. While Brock et al. [5] observe that only a subset of networks is amenable to such truncation even when orthogonal regularization is used, truncation in $\mathcal{W}$ space seems to work reliably even without changes to the loss function.

ψ가 0 이면 variation X

어떤 분포 z에서 or z를 가공한 $f(z)$에서 data를 sampling 하는데 좋은 example을 뽑고 싶은 게 상황.

$E_{z \sim p(z)}[f(z)] = \bar{w}$ 라고 정의.

good example $w' = \bar{w} + \psi(w - \bar{w})$



을 ψ를 고려해서 계산.

즉, 가장 잘 나오는 평균인 $\bar{w}$를 중심으로 뽑는다.