Chapitre 4

Attribute manipulation

As illustrated in Figure 4.1, Generative Adversarial Networks showed good results on semantic face editing that aims at manipulating facial attributes of a given image.

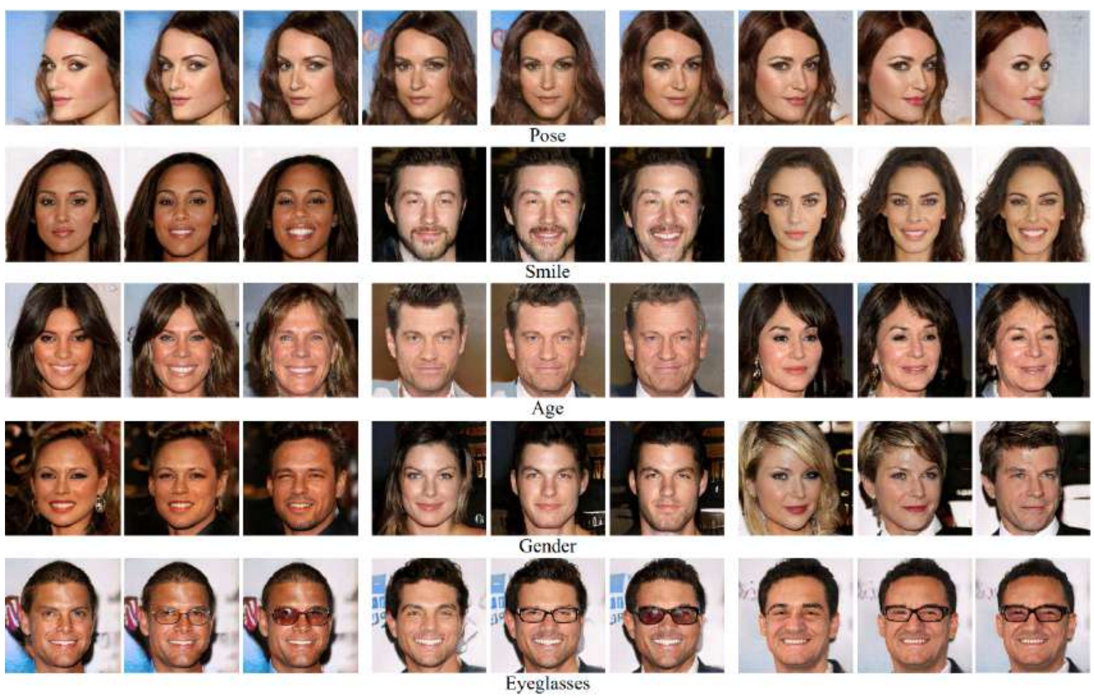


FIGURE 4.1 – Attribute manipulation using GANs[3]

In this chapter we will experiment on the attribute manipulation (gender and glasses) using two methods : the means and the difference methods. For each method, we will experiment in adding the glasses, removing them and changing the gender.

4.1 Means method

4.1.1 Description

In this first method, we used labeled pictures from the FFHQ dataset [3].

For each picture, we know the gender (Male or Female) and the glasses type (None, Normal or Dark).

We grouped latent representations by their labels, and after taking the mean of each category, we built a vector from the difference that mapped the direction of the change.

We can define X_1 as the set of latent representations of images with a given binary feature that we want to manipulate (e.g. female, with glasses) and X_2 the complementary feature (e.g. Male, without glasses).

$$\text{Vector}[i] = \text{mean}(X_1)[i] - \text{mean}(X_2)[i]$$

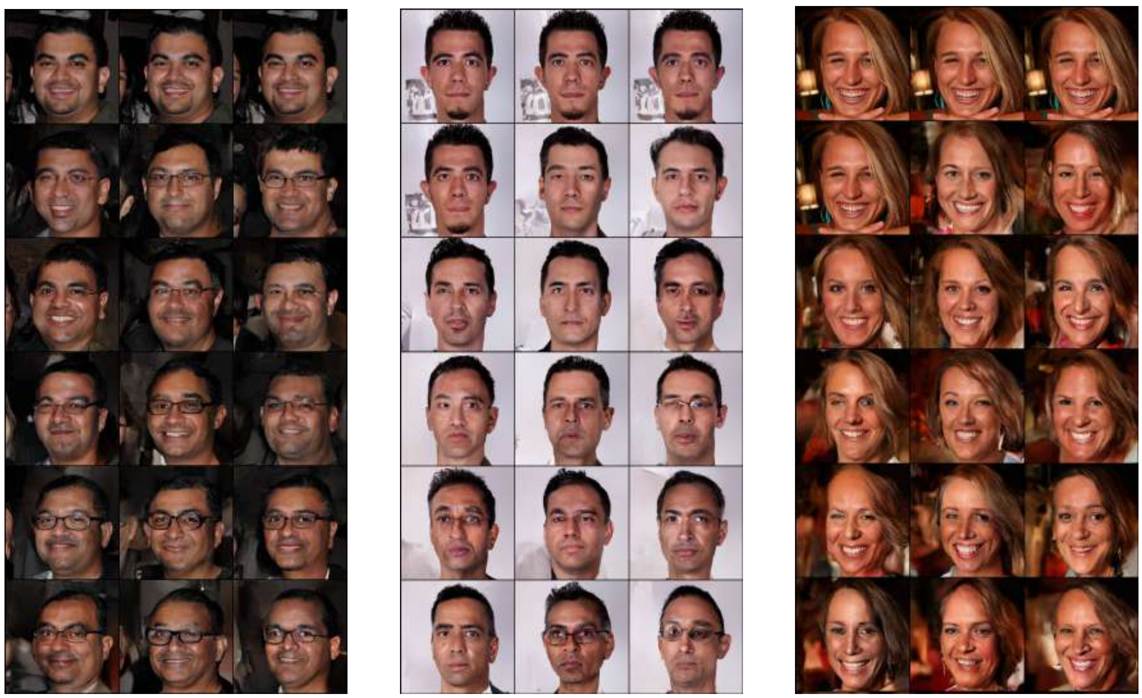
Using k=5, the number of groups of latent variables, achieved the best results. We make the assumption that the attribute we are looking to manipulate is encoded within 5 first latent variables.

We will interpolate starting from an image i with latent code z_i and translate along the vector :

$$z_{t(i)} = z_i + t(\bar{X}_2 - \bar{X}_1), \text{ with } t \in [0, 1]$$

4.1.2 Glasses manipulation

Adding glasses



(a) Picture n° 1 (b) Picture n° 2 (c) Picture n° 3

FIGURE 4.2 – Adding glasses using means method

While adding glasses, the first method changes the ethnicity and age of the person as illustrated in Figure 4.2 (maybe due to the correlation between wearing glasses and getting older), and doesn't work consistently on all faces (women and children).

Removing glasses

(a) Picture n° 1

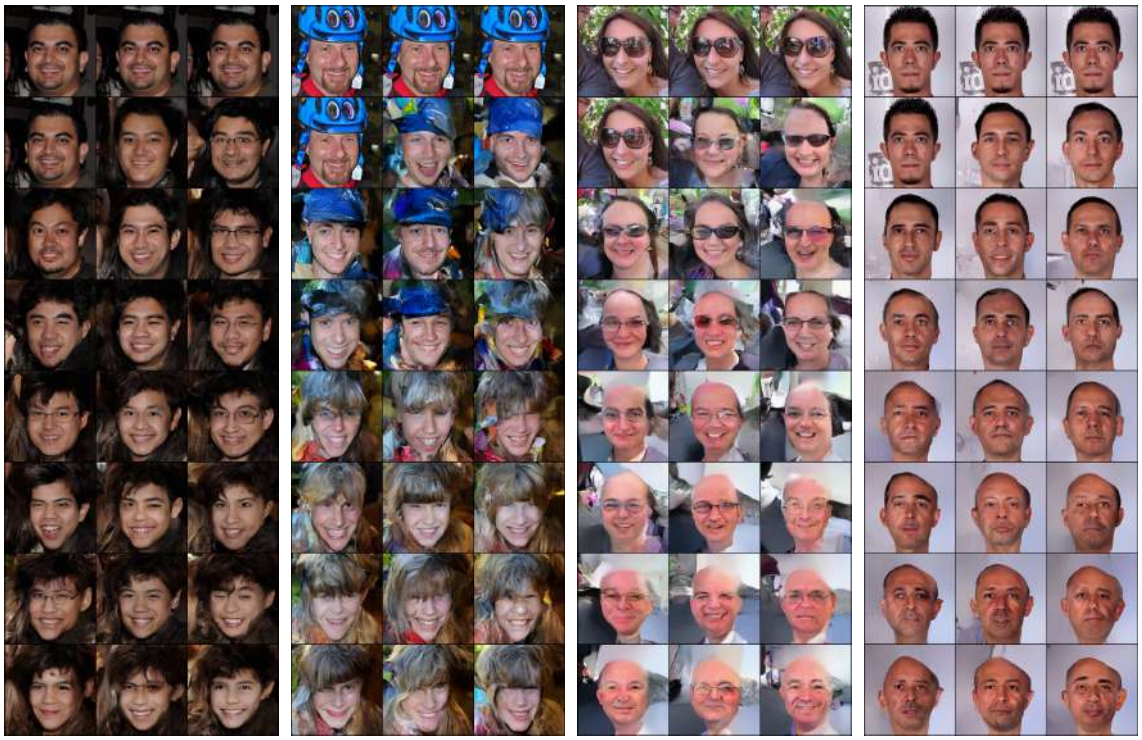
(b) Picture n° 2

(c) Picture n° 3

FIGURE 4.3 – Removing glasses using means method

On Figure 4.3, we can see that removing glasses preserves general attributes like the gender and the face orientation but fails in some detailed facial attributes (beard) resulting in a generation of younger faces.

4.1.3 Gender manipulation



(a) Picture n° 1 (b) Picture n° 2 (c) Picture n° 3 (d) Picture n° 4

FIGURE 4.4 – Changing gender using means method

Changing gender adds hair and removes beard in the two first examples (a) and (b) of Figure 4.4, but it makes faces younger and doesn't add relevant feminine traits.

In example (c), the change made the woman bald, removed sunglasses and made her older.

In Figure 4.4 (d), we considered the picture to be female and transformed it to male to visualize the extreme male version according to our model. The extreme male is therefore a bald old man.

4.2 Difference method

4.2.1 Description

The second method uses an external image editing tool. Using online tools [1] [2], we added manually glasses to an image in our dataset as shown below :

(a) Picture without glasses (b) Picture with glasses

FIGURE 4.5 – Modified image using Pixelied

We then encoded the latent variables of each image separately and used the difference as the vector for our translation.

Let z_1 be the latent representation of Figure 4.5 (a) and z_2 that of Figure 4.5 (b). The vector used in the translation will be mapped from the difference :

$$z_{t(i)} = z_i + t(z_2 - z_1), \text{ with } t \in [0, 1]$$

We tested our transformation on the same image to visualize the change :

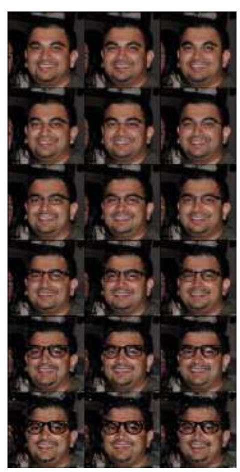


FIGURE 4.6 – Difference method applied to the same picture

1. Piexelied (see https ://pixelied.com/features/add-glasses-to-photo)
2. FaceApp Technology Limited

4.2.2 Gender manipulation

Reference Image :

(a) Picture of reference

(b) Picture transformed to female

Figure 4.7 – Modified image using FaceApp

Results :

(a) Picture n° 1

(b) Picture n° 2

(c) Picture n° 3

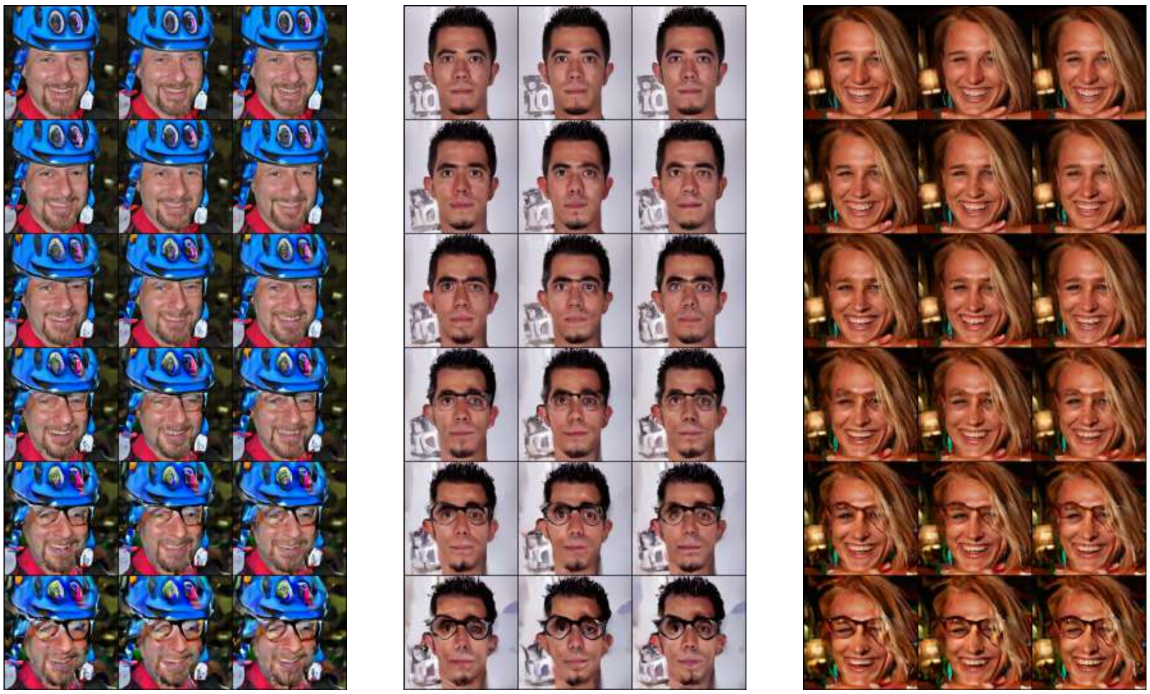
(d) Picture n° 4

Figure 4.8 – Changing gender using difference method

The results presented in Figure 4.8 are satisfying. The model successfully changes the gender of the image but we still can't clearly see all the attributes being preserved.

4.2.3 Glasses manipulation

Adding glasses

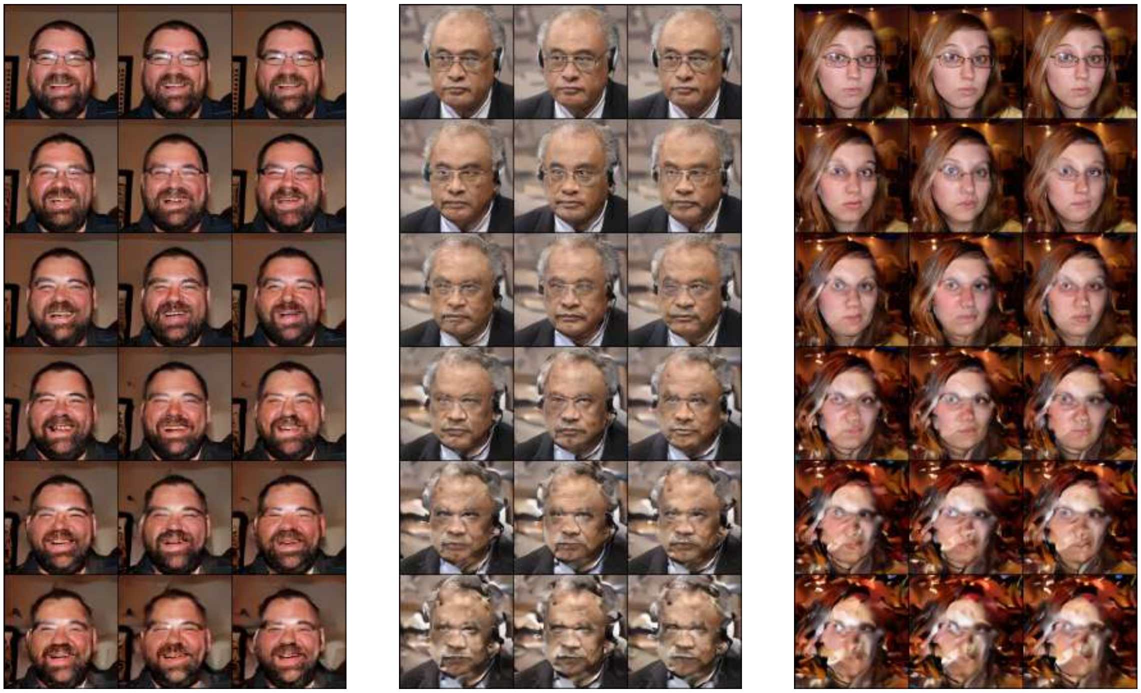


(a) Picture n° 1 (b) Picture n° 2 (c) Picture n° 3

FIGURE 4.9 – Adding glasses using difference method

While adding glasses, this method preserves a lot of information like hair color, beard, hats, and gender but doesn't work well on the last steps (t>0.9) resulting in a noisy generation as shown in Figure 4.9.

Removing glasses



(a) Picture n° 1 (b) Picture n° 2 (c) Picture n° 3

Figure 4.10 – Removing glasses using difference method

The removal of glasses is pretty good on the experiments (a) and (c) of Figure 4.10. It doesn't change the background or the general faces' attributes while successfully removing glasses, however it doesn't work on all images (as shown on the Figure 4.10 (b)).

4.3 Conclusion

In this experimentation, the attribute manipulation has promising results. This encourages future experimentation in this using different methods. The difference method has some good results on the semantic attribute manipulation, but results in noisy generation, however the means method changed age and race due to the entanglement in our dataset. A future lead would be to create a dataset of some images and their modified versions and learn the translation vector using a neural network.