

Interpreting the Latent Space of Generative Adversarial Networks using Supervised Learning

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Understanding GAN's latent space

2 branches of questions

- Are scalar variables of GAN's latent vector entangled? If they are, would it be beneficial to disentangle them? If yes, how to do that? And what feature of an image that those scalar variables capture?

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- How to manipulate GAN's latent space to observe desired generated images?

In our paper, we focus on the 2nd questions for facial images

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Linear interpolation

Interpolate between 2 points in latent space (corresponding to 2 pictures) to observe the change in interpolated images.

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Linear interpolation

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- Pros: Easy implementation
- Cons:
 - Does not make any implication about GAN's latent scalar variables.
 - Can not manipulate GAN's latent space as desire

Vector Arithmetic

Add or subtract vectors in latent space to get desired generated images

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Vector Arithmetic

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- Cons:
 - Hand-select generated images with desired characteristics used for manipulation

InfoGAN

Used another easily, semantically understandable hidden variable in a lower dimension to encode the latent variables

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- Pros:
 - Unsupervised learning (saving human effort)
- Cons:
 - Require training a new GAN model (difficult)
 - Cannot know in advance the characteristics encoded in hidden variables

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Idea

Create a linear mapping from GAN's latent space to the predefined, semantically meaningful characteristic space.

$$y = zW^T + b; \quad (1)$$

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$$y = zW^{\top} + b; \quad (1)$$

Image manipulation and obstacles

Image manipulation

$$z^0 = z + w_i$$

$$y^0 = z^0 W^> + b$$

$$y + y = (z + w_i) W^> + b$$

$$y_2 + y_3 = (z W^>_2 + b) + w_i W^>_3$$

$$\begin{array}{c}
 y_1 \\
 y_2 \\
 \vdots \\
 y_n
 \end{array}
 = w_i
 \begin{array}{c}
 w_1^> \\
 w_2^> \\
 \vdots \\
 w_n^>
 \end{array}
 =
 \begin{array}{c}
 w_1^> w_i \\
 w_2^> w_i \\
 \vdots \\
 w_n^> w_i
 \end{array}$$

$$y_i > 0$$

Image manipulation and obstacles

Obstacle: if w_i is similar to other coefficients, changing z to z^0 also changes cause changes to other attributes

Overcome: Orthogonality Regularization

$$J(w) = \text{MSE}(f_w(z); y) + \|w\|_2^2$$

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Image manipulation

Orthogonality Regularization effectiveness

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Contribution summary

- Supervised method to explicitly map the latent space with a meaningfully pre-defined semantic space with advantages compared to existing methods:

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- Supervised method to explicitly map the latent space with a meaningfully pre-defined semantic space with advantages compared to existing methods:
 - Utilize pre-trained GAN model, easy to implement
 - Allow to change the intensity of images' characteristic
- More robust image manipulation with orthogonality regularization

Thank you for listening!