Interpreting the Latent Space of GANs via Correlation Analysis for Controllable Concept Manipulation

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Abstract—Generative adversarial nets (GANs) have been successfully applied in many fields like image generation, inpainting, super-resolution and drug discovery, etc., by now, the inner process of GANs is far from been understood. To get deeper insight of the intrinsic mechanism of GANs, in this paper, a method for interpreting the latent space of GANs by analyzing the correlation between latent variables and the corresponding semantic contents in generated images is proposed. Unlike previous methods that focus on dissecting models via feature visualization, the emphasis of this work is put on the variables in latent space, i.e. how the latent variables affect the quantitative analysis of generated results. Given a pretrained GAN model with weights fixed, the latent variables are intervened to analyze their effect on the semantic content in generated images. A set of controlling latent variables can be derived for specific content generation, and the controllable semantic content manipulation be achieved. The proposed method is testified on the datasets Fashion-MNIST and UT Zappos50K, experiment results show its effectiveness.

I. INTRODUCTION

GANs[1] have achieved great success in many tasks like image generation[2][3], super resolution[4] and image translation[5][6], etc. However, due to the great amount of parameters and complex cascade of nonlinear activations, hardly can we understand the intrinsic logic of GANs and the quantitative relationship between input values of variables in latent space and semantic content in output generated images. Moreover, GANs still suffer some severe issues, such as unstable training, mode drop and mode collapse, etc. Many works toward mitigating these issues have been proposed: designing new architectures[7][2], new loss functions[8][9] or new training methodologies[7][3]. Compared to the large amount of works that aiming at improving train stablity and generation quality, few works have been done to explore the intrinsic working mechanism of GANs, i.e. the interpretability of GANs. This motivated the work of this paper.

Recently, along with the success of deep learning, interpreting deep neural models become a hot topic in research. The methods can be generally divided into three categories according to the corresponding interpreting results: visualizing pre-trained models[10][11], diagnose pre-trained models[12][13] and construct interpretable models[14][15]. The first kind of methods use activation maximization or de-convolution techniques to visualize neurons or derive an input that maximize semantic outputs, the second kind of methods diagnose pre-trained deep models by adding understandable disturbance to the inputs or quantify the importance of features, the last kind of methods impose constraints on neurons or reconstruct deep models to make deep models more interpretable. As for GANs, researchers proposed various methods to make it more interpretable and controllable, such as concatenating latent code with conditional information[16][17], interpolating in latent manifolds[18][19] and latent disentanglement[5][20]. Bau et.al[21] proposed to quantify the effect or importance of

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different layer nodes on content changes by utilizing a pre-trained segmentation model to calculate IoU scores on generated image variations. However, previous methods did not give any quantitative evaluation of contribution each variable in latent space provide for generating specific semantic contents.

For the interpretability of GANs, due to the black-box property of deep neural models, hardly can we understand how the latent variables affect the generation process. To investigate if the variables in latent space contain the necessary information to distinguish different semantic contents in generated images, we use t-SNE[22] to analyze the latent representations of Fashion-MNIST samples and find that the latent representations of samples from different classes can be well-separated, as shown in Figure 1. This indicates that for samples from same one class, there may exist closely-related latent variables that made their latent representations distinguishable. This motivated us to quantify the importance of different latent dimensions for specific concept generation.

We propose to analyze the correlation between the latent inputs and the corresponding generated outputs by utilizing a pretrained classifier to provide quantitative evaluations on the semantic content changes in generated images, then to interpret the meaning of variables in latent space of GANs. We also propose two methods for locating high-correlated latent dimensions for specific concept generation or manipulation: one is by sequential intervention and the other is by optimization. Moreover, given a specific class concept, we can also intervene the generated outputs.

The remaining part of this paper is organized as follows: in section 2, we give an brief introduction to the backgrounds of this work. In section 3, we introduced the proposed method for interpreting the latent space of GANs in detail. The experiment results and implementation details were given in section 4 and finally was the conclusion of this paper.

II. PRELIMINARIES

A. Generative Adversarial Networks

Generative adversarial nets (GANs) aimed at modeling the train data distribution through an adversarial process. It mainly contains of two models that play against with each other, a generator G and a discriminator D. G mapping noise inputs from latent space to image space and try to let D classify the generated samples as true, whereas D wants to clearly distinguish real data from generated ones. The adversarial process can be formulated as below:

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} \left[ \log D(x) \right] + \mathbb{E}_{z \sim p_z(z)} \left[ \log (1 - D(G(z))) \right]$$  \hspace{1cm} (1)

where \( V(D, G) \) is the value function of the min-max game, \( p_{data}(x) \) and \( p_z(z) \) represent the distribution of train data and latent noise respectively. In practice, people tend to train G to maximize \( \log D(G(z)) \) rather than to minimize \( \log(1 - D(G(z))) \) for the reason that equation 1 may not provide sufficient gradient for G in the early training stage. In this paper, we choose a pre-trained WGAN[8] model for latent space analysis.

B. GAN Dissection

In [21], the author proposed an analytic framework to visualize and understand GANs at unit-, object- and scene level respectively by identifying interpretable units that are closely related to some object concepts through a segmentation network. Moreover, the author also quantify the causal effect of interpretable units and offer an empirical method to mitigate the artifacts problem in generation results. The method for characterizing units by dissection can be formulated as below:

$$IoU_{u,c} \equiv \frac{\mathbb{E}_x \left[ r_{u,P} > t_{u,c} \right] \wedge s_c(x)}{\mathbb{E}_x \left[ r_{u,P} > t_{u,c} \right] \vee s_c(x)}$$  \hspace{1cm} (2)

where \( u \) denote the layer node in GANs and \( c \) means concepts like classes, \( r_{u,P} \) denote the feature map of unit \( u \), \( \wedge \) and \( \vee \) represent intersection and union operation respectively, \( t_{u,c} \) is a chosen threshold for producing binary mask and \( s_c(x) \) is the segmentation result of the generated image \( x \). This method use the IoU(Intersection of Union) score to quantify the spatial agreement between a unit’s feature map and the segmentation map of a generated image, which can reflect the importance of an unit for generating a specific concept.

III. CORRELATION ANALYSIS BETWEEN LATENT AND OUTPUT SPACES

In this paper, we propose to interpreting the latent space of GANs by analyzing the correlation between latent dimensions and the corresponding content changes in generated image. A thing need to notice is that the proposed method aimed at analyzing a pre-trained GAN model other than training a new one during the correlation analysis. The target was to semantically interpreting the latent space and quantify the importance of different latent dimensions, below are the details of the proposed method.

A. Problem Statement

Given a pre-trained generator \( G(z) \), the target was to analyze the latent space and quantify the importance of different latent dimensions for generation. As for specific semantic concepts like classes or objects, we want to analyze which
dimensions influence contents of the generated results most. The problem can be formulated as below:

\[
X = G(Z) = G([z_1, z_2, \ldots, z_N])
\]

\[
\Delta z_i \implies \Delta X \implies \Delta C_i, \quad \text{for } i = 1, \ldots, N
\]

where \([z_1, z_2, \ldots, z_N] = z \in \mathbb{R}^N\) was denoted as the latent variable, \(\Delta X\) and \(\Delta C_i\) (\(C \in \mathbb{R}^L, L\) classes) represent the content change and concept (here we choose class labels as different concepts) change in the corresponding generated image. For each latent dimension, we adjust the value of this dimension and observe how much can the intervention influence the generation results. Practically, as will be introduced in the later part, for most concepts, there may be more than one latent dimension that closely related to that concept, thus we also try to find these controlling dimensions for different concept. The problem can be simply formulated as:

\[
\alpha_i \in \{0, 1\}, \quad i = 1, \ldots, N
\]

\[
[\alpha_1 \cdot z_1, \ldots, \alpha_N \cdot z_N] \iff \Delta X \iff \Delta C_i
\]

where \(\alpha_i \in \{0, 1\}\) represent whether the corresponding dimension is high-correlated with a given concept \(C_i\) or not. In the next two subsection, we will introduce the proposed method for finding important latent dimension by quantifying the semantic content change and finding controlling dimensions for given concept through optimization.

B. High-correlated latent dimensions for specific concept generation

To analyze the correlation between latent space and the output image space, we adopted a pre-trained classifier \(Q(x)\) to assign score on the generated image and its variations. The pre-trained classifier \(Q\) can quantify the content change of the base generated image as an softmax score, which can be used for latent dimension importance analysis. For i-th latent dimension and j-th class

\[
Z^k = Z + k \cdot \delta \cdot [0, \ldots, 1, \ldots, 0] \quad k \in [-m, m]
\]

\[
X^k = G(Z^k) = G([z_1, \ldots, z_i + \delta \cdot k, \ldots, z_N])
\]

\[
S_{i,j}^k = Q_j(X^k) = Q_j(G(Z^k))
\]

where \(Z^k, X^k\) and \(S_{i,j}^k\) represent the latent variable intervened the i-th dimension), the generated image and the corresponding classification softmax score of class j while \(k\) means adjust the value of i-th latent dimension bi-directional k steps (the stepsize was \(\delta\)). It’s easy to find that when \(k = 0\), \(Z^0\) and \(X^0\) is just the same as \(Z\) and \(X\), i.e., the base reference generated image and latent variable. To measure the i-th latent dimension’s effect on the generation of j-th class contents, we use the averaged probability change ratio (APCR) as the quantitative evaluation metric.

\[
APCR_{i,j} = \frac{\left\| \sum_{k=1}^{m} (S_{i,j}^k - S_{i,j}^{k-1}) \right\|_1}{2 \cdot m} + \frac{\left\| \sum_{k=-m}^{-1} (S_{i,j}^k - S_{i,j}^{k+1}) \right\|_1}{2 \cdot m}
\]

As can be seen from the above equation, the metric calculate the averaged value changes of the probability that the generated image variations belong to a specified class over the latent
dimension changes. Here we use L-1 norm to calculate the probability changes separately along two variation directions. Then, for each class, we will get \( n \) (dimension of the latent space) APCR scores and find the most correlated dimension for this class by ranking the scores. Similarly, we can also derive \( L \) APCR scores for each latent dimension.

C. Controlling set of latent dimensions for controllable concept manipulation

As mentioned above, for a given specific class, there may have multi latent dimensions that closely related to it, hence we propose to find these important dimensions, which we called controlling latent dimension here. We propose to intervene all the latent dimensions by assigning different weights to these dimensions and observe the corresponding classification score changes. The optimization objective was to maximize the classification score changes by updating the coefficients on the latent dimensions. The model weights were keep frozen during the optimization process. To derive the controlling dimensions for j-th class, we firstly add differentiated distortions to the latent dimensions by utilizing a weight vector \( w = [w_1, \ldots, w_N] \):

\[
Z' = Z + w * \xi = [z_1 + w_1 \cdot \xi, \ldots, z_N + w_N \cdot \xi]
\]

where \( \xi \) represent an experimental constant for latent intervention, and \( w_i \in [-1,1] \) represent the latent intervention coefficients. Positive coefficients denote positive intervention direction and vise versa. For j-th class to be analyzed, we first calculate the probability changes with respect to latent interventions. Then we can derive the optimization objective of weight vector \( w \):

\[
\Delta S_j = S'_j - S_j = Q_j \left( G \left( Z' \right) \right) - Q_j \left( G \left( Z \right) \right)
\]

\[
w^* = \arg \max L_w = \arg \max (|\Delta S_j|) \tag{11}
\]

For easy optimization and make the coefficients on latent dimensions sparse, we add a L-2 norm regularization and rewrite the optimization objective, the optimal \( w \) can be derived through the optimization of equation (12). Finally, we add a threshold \( t_j \) on the optimized coefficients \( w \) to filter out uncorrelated dimensions for each class \( j \), hence the controlling dimensions for can be derived.

\[
w^* = \arg \min (1 - |\Delta S_j| + \lambda \cdot \|w\|_2) \tag{12}
\]

\[
w_{>t_j} \iff [|w_{j,1}| > t_j, \ldots, |w_{j,N}| > t_j] \tag{13}
\]

Moreover, for controllable concept manipulation, we can just modify the optimization objective as below and derive the controlling set of latent dimensions for class-to-class translation (class \( j \) and class \( k \)).

\[
\Delta S_{k \rightarrow j} = Q_j \left( G \left( Z_k - w \cdot \xi \right) \right) - Q_j \left( G \left( Z_k \right) \right)
\]

\[
\Delta S_{j \rightarrow k} = Q_k \left( G \left( Z_j + w \cdot \xi \right) \right) - Q_k \left( G \left( Z_j \right) \right) \tag{14}
\]

\[
w^* = \arg \max L_w = \arg \max (|\Delta S_{k \rightarrow j}| + |\Delta S_{j \rightarrow k}|) \tag{15}
\]

Thus for \( Z_j \) and \( Z_k \) that belong to class \( j \) and \( k \), we can achieve class \( j \leftrightarrow k \) translation by \( Z_j \pm w \cdot \xi \) and \( Z_k - w \cdot \xi \) respectively. The proposed method was depicted in Figure 2, where the top part denote the process of finding high-correlated latent dimensions for specific concept by sequential intervention and adding weights on latent variables. The bottom part denote the process of controllable manipulation through latent intervention on top-ranked and bottom-ranked dimensions.

IV. Experiments

In this section, we will present the experiment results to demonstrated the effectiveness of the proposed method along with some interesting findings. The experiments can be divided into four parts, the first one was designed to find high-correlated latent dimensions for specific concept by intervening latent dimensions sequentially, the second one solving the same problem as the first but with optimization-based method, the third experiment was about controllable concept manipulation using controlling latent dimensions and the last one was about class2class image translations.

A. Datasets and Implementation Details

In this paper, we conducted the designed experiments on two datasets: Fashion-MNIST[23] and UT Zappos50K[24]. Fashion-MNIST is a dataset of Zalando’s article images—consisting of 60k training samples and 10k testing samples, just the same with the original MNIST dataset. Each example is a 28x28 grayscale image, associated with a label from 10 classes: [T-shirt, Trouser, Pullover, Dress, Coat, Sandal, Shirt, Sneaker, Bag, Ankle boot]. UT Zappos50K is a large shoe dataset consisting of 50,025 catalog images collected from Zappos.com. The images are divided into 4 major categories — shoes, sandals, slippers, and boots — followed by functional types and individual brands. As for the implementation, we use a pre-trained WGAN_GP model for correlation analysis. Moreover, we adopt the LeNet-5 model as the choice for classification network and EmbedNet. The length of latent variables is set to 100.

B. Find High-Correlated Latent Dimensions by Sequential Latent Intervention

As having been introduced in Secton 3.2, given a specific class concept, we intervene the latent dimensions sequentially and get corresponding APCR scores for each latent dimension. Then we rank the latent dimensions for each concept according to the APCR values, thus high-correlated latent dimensions can be derived. Here we use softmax score to indicate the concept changes in generated images. The softmax score changes w.r.t latent offsets for each latent dimension was shown in Figure 3, from which we can clearly see that the slope of different curves varies greatly. It indicate that semantic concepts are sensitive to several latent dimensions, i.e., intervening on some high-correlated latent dimensions will lead to greater semantic concept changes compared to interven on less important dimensions. Moreover, we also give the APCR distribution
information in Figure 4, where the x-axis denote the range-index number (larger index number represent larger APCR values) of APCR values and the y-axis denote the number of dimensions belong to each range. It furthermore demonstrated that the amount of high-correlated latent dimensions for each concept is small.

C. Find Controlling Set of Latent Dimensions via Optimization

We use the optimization-based method described in Section 3.2 to derive the coefficients vector \( w \in [-1, 1] \) on latent dimensions for each concept, then we impose thresholds on the coefficients to filter out positive and negative controlling set of latent dimensions. Larger positive values and smaller negative values denote higher correlation when intervene along the positive and negative direction respectively. We randomly select two classes for demonstrate the controlling latent dimensions, which can be seen in Figure 5 (top and bottom parts represent intervention results of class 8 and class 9 respectively). As illustrated in Figure 5, the first three rows represent the intervention results of \( R_0, R_{50}, R_{99} \) dimensions respectively, where the numbers denoted as the ranked order, thus \( R_0 \) and \( R_{99} \) represent most correlated latent dimension along bi-directional intervention. The bottom two rows give the intervention results of top-5 positive/ negative correlated dimensions. From top three rows we can see that positive intervention results of \( R_0 \) are similar to negative intervention results of \( R_{99} \) while intervene on \( R_{50} \) car hardly lead to any generation changes. Moreover, we intervene on top-5 positive and negative dimensions and get better results, which can be seen from bottom two rows. This indicate that for a given specific concept, we can derive the controlling set of latent dimensions of it, hence concept manipulation can be achieved by intervening on these dimensions (furthermore results can be seen in the next subsection).

![Fig. 5: Intervene on controlling set of latent dimensions.](image)

We also propose to use intersection ration \( IR_{ctrl} \) as a evaluation metric of the concordance of the controlling dimensions derived by sequential intervention and optimization. The results can be seen in Table I, it indicate that controlling dimensions derived by two methods were quite similar with an average IR score 0.75. It furthermore demonstrated that latent dimensions contribute differently to specific concept generation.

| Classes | class0 | class1 | class2 | class3 | class4 |
|---------|--------|--------|--------|--------|--------|
| \( IR_{ctrl} \) | 0.7    | 0.9    | 0.7    | 0.8    | 0.4    |

| Classes | class5 | class6 | class7 | class8 | class9 |
|---------|--------|--------|--------|--------|--------|
| \( IR_{ctrl} \) | 1      | 0.7    | 0.9    | 0.7    | 0.7    |

TABLE I: Intersection ration of high-correlated latent dimensions derived by sequential intervention and optimization

D. Controllable Concept Manipulation with Controlling Latent Dimensions

As introduced in the above section, we can achieve controllable concept manipulation by intervening the controlling set of latent dimensions. The controllable manipulation results of Fashion-MNIST and UT Zappos50k can be seen in Figure
6 and Figure 7 respectively. In Figure 6, the leftmost column denotes the reference images come from different classes of Fashion-MNIST, and the right 10 column denote the corresponding directional manipulation results, i.e. translate the reference image to different classes. Similarly, in Figure 7, the middle column in the yellow bounding-box denote the reference image in UT Zappos50k and other columns denote bi-directional manipulation results. From the results we can see that controllable concept manipulation can be achieved by intervention on controlling set of latent dimensions.

Fig. 6: Controllable concept manipulation on Fashion-MNIST through intervening on controlling set of latent dimensions (final manipulation results).

Fig. 7: Controllable concept manipulation on UT Zappos50k through intervening on controlling set of latent dimensions.

E. Interesting Findings of Extreme Intervention on Latent Dimensions

We also have some interesting findings about the latent interventions, which was demonstrated in Figure 8. Usually, the common choice of latent variables were drawn from a Gaussian normal distribution, by now, researchers have not explored extreme cases of latent values. We propose to add positive and negative impulse stimuli on latent dimensions and observe the corresponding semantic content change in the generated image. The results were demonstrated in Figure 8, where the middle row represent the original images come from different classes, the top and bottom row denote positive/ negative extreme intervention results respectively. From the results we can see that for images from different classes, if we extremely intervene some latent dimension (adding impulse stimuli), the final manipulation results will converge to some specific classes. Inspired by this finding, we can find these unique dimension for various class pairs and achieve controllable class-to-class translation (Figure 9).

Fig. 8: Extreme intervention results by adding impulse stimuli on specific latent dimensions bidirectionally.

Fig. 9: Controllable Class-to-Class translation by extreme intervening on some specific latent dimensions (final translation results).

V. CONCLUSION

In this paper, we proposed a method to interpret the latent space of GANs with correlation analysis for controllable concept manipulation. We utilized a pre-trained classifier to evaluate the concept changes in the generation variations. We first illustrated that the importance of different latent dimensions that contribute to specific concept generation varies greatly. Moreover, we also proposed two method to find the controlling set of latent dimensions for different concepts, with which we can fulfillize controllable concept manipulation. These interesting findings provide a new route for controllable generation and image editing, moreover, it also give us some thoughtful insight on the interpretability of GANs’ latent space.
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