Learning a Deep Reinforcement Learning Policy Over the Latent Space of a Pre-trained GAN for Semantic Age Manipulation

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Abstract

Learning a disentangled representation of the latent space has become one of the most fundamental problems studied in computer vision. Recently, many generative adversarial networks (GANs) have shown promising results in generating high fidelity images. However, studies to understand the semantic layout of the latent space of pre-trained models are still limited. Several works train conditional GANs to generate faces with required semantic attributes. Unfortunately, in these attempts often the generated output is not as photo-realistic as the state of the art models. Besides, they also require large computational resources and specific datasets to generate high fidelity images. In our work, we have formulated a Markov Decision Process (MDP) over the rich latent space of a pre-trained GAN model to learn a conditional policy for semantic manipulation along specific attributes under defined identity bounds. Further, we have defined a semantic age manipulation scheme using a locally linear approximation over the latent space. Results show that our learned policy can sample high fidelity images with required age variations, while at the same time preserve the identity of the person.

1. Introduction

The task of performing attribute manipulation in human face images has multiple applications. For example, face aging has often been used for cross face verification [35] and even in forensic art [13]. There have been various supervised and unsupervised approaches proposed for age-specific semantic manipulation [18, 50, 52, 51]. But unfortunately, the outputs are low in resolution or not comparable to the images generated by the state of the art GANs like ProgressiveGAN [22], StyleGAN [23] or BigGAN [7]. This often limits the application of such models in downstream tasks, which require high-resolution images with particular facial attributes. A custom generative model can generate high-resolution images with required facial attributes, but it is an arduous task requiring enormous computational resources and specific datasets.

Recent studies have tried to understand and utilize the latent structure of generative models. Radford et al., [43] have shown that the vector arithmetic over the latent space has a direct association with the semantic changes over the generated output. Shen et al., [50] in their work InterfaceGAN have shown promising results in generating semantically rich high resolution images by traversing the latent space of ProgressiveGAN [22] and StyleGAN [23]. InterfaceGAN [50] proposes a linear traversal scheme over the latent space defined by the $d$-dimensional standard normal distribution, the base distribution used to train the ProgressiveGAN. This method has a lot of potential as it allows us to utilize the existing (pre-trained) state of the art models for downstream tasks.
Though InterfaceGAN does generate a rich set of high-quality images, it is often noticed that the generated images are semantically monotonic and sometimes even fail to preserve the identity. Even the authors of InterfaceGAN, have pointed out that a linear traversal for age-based manipulation has a high correlation with gender and leads to undesired changes in the gender of the generated output. Such variations directly impact the identity of the person in the generated images and that makes it unsuitable for many downstream tasks. As a solution, the authors have proposed a complement scheme to negate such unwanted changes, under which the projection of age based hyperplane along the gender hyperplane is subtracted from the original direction. However, considering the number of unwanted variations generated in such a trajectory, it becomes impractical to train a hyperplane for all the attributes. Moreover, an equivalent linear trajectory over an irregular latent space often fails to generalize and may not introduce the desired semantic change. It is also important to note that a linear traversal may also sample intermediate vectors which lie in the low-density regions of a high dimensional normal distribution.

In this work, we have proposed a non-linear traversal scheme (Figure 1) over the rich latent space of ProgressiveGAN using Reinforcement Learning (RL). Our approach generates a path through the latent space using locally linear approximations of the desired manifold as shown in Figure 2 over the typical set of a standard normal distribution. Unlike the InterfaceGAN, our formulation places an explicit emphasis on identity preservation over the sampled trajectory. We have formulated a Markov Decision Process (MDP) for such a traversal, which incentivizes the sampling of images with the required age variation while preserving identity.

Our contribution can be summarized in the following:

- We propose a non-linear traversal scheme over the latent space of the pre-trained ProgressiveGAN using Reinforcement Learning (RL). Our policy is conditioned on the base state and the required age changes, giving it additional freedom to learn different manipulation schemes for different latent vectors.

- We have formulated a Markov Decision Process (MDP) for semantic manipulation without making any inherent assumption about the network architecture of the pre-trained GAN and the attribute over which the manipulation is performed. This approach provides the additional flexibility of easily extending our formulation to other state of the art GAN models and other semantic attributes like head pose transfer.

- Our approach utilizes the local linear property of a manifold to generate a trajectory that would sample images with the required age variation while preserving the base image’s identity. The results show the efficacy of this approach compared to InterfaceGAN.

- We propose a low-rank traversal scheme over the typical set of a standard normal distribution to prevent out-of-distribution sampling, thereby preventing mode collapse in the sampled output, especially for a non-linear trajectory.

2. Related work

Ever since their inception in 2014, GANs have been one of the most popular frameworks for image generation with their variants achieving the state of the art results in almost every subdomain including face synthesis, image translation and attribute manipulation. This is because of their tremendous ability to learn the distribution over the target space, capture its various aspects in a rich and expressive latent space, and generate higher subjective perceptual quality images when compared to other generative models like Variational Autoencoders. There are works which have attempted to make GANs useful for real world images by either introducing an additional encoder to get the latent space representation of the required image or by inverting the mapping from latent space of the GAN to the image space. However, studies to understand how the semantic features of images are embedded in latent space, are yet to be explored and utilized to their full potential.

In recent years, several works have shown excellent results in the synthesis of images with a tweaked attribute while preserving the identity. However, these approaches have some significant drawbacks. These big models, with a large number of parameters, not just require a well-annotated attribute-specific dataset but are also computationally expensive. Therefore, a resourceful way to approach such tasks is to harness the rich latent space of pre-trained GANs.

Latent space for attribute manipulation: Latent space of GANs has been modeled as Riemannian manifold in many works. Jahanian et al., studied the possibilities and limitations of GAN models to generalize beyond the training distribution and produce simple image transformations by exploring walks in the latent space. InterfaceGAN, a recently proposed framework by Shen et al., strives to disentangle the different semantics encoded in the latent space of GANs, using subspace projection, to control the facial features by training distinct SVM models for each attribute. This approach demands several simplifying assumptions to be made.

Learning a disentangled representation can reduce the supervision required for semantic editing. In a concurrent
work, Nitzan et al., [44] have done this by mapping the disentangled latent representation to a pre-trained generator’s latent space. This approach still requires learning an encoding of a feature and its complement by training two encoders.

**Face aging with identity preservation:** There have been several works specific to facial attribute manipulation in recent years [18, 20, 52, 51]. A necessary requirement in this task is to preserve the person’s identity, which can be extremely challenging. Dual conditional GANs proposed by Song et al., [51] attempt to learn identity-preserving face aging from unlabelled datasets of various age groups. Siamese GANs by Hsu et al., [20] can transform a low resolution input of a face to a high resolution output while preserving identity using Siamese networks. IPCGAN [52] forces the high level features of the input image and synthesized image to be similar to preserve identity and uses an age classifier module to ensure that the generated image lies in the target age group. While these variants of conditional GANs do not rely on sequential training data and preserve identity, they still require training large networks involving long hours of extensive computation.

A semi-supervised learning method for age progression and regression proposed recently by Pham et al., [40] involves training a conditional GAN to learn facial aging. While the model produces realistic human faces and scores better than IPCGANs, it requires training of two GANs and does not perform well at learning local aging features, such as skin irregularities and wrinkles, in the elderly age group.

An essential aspect of semantic attribute manipulation is the subjective nature of perception of a person’s age. Angulu et al., [2] have provided an extensive analysis of popular age estimation algorithms, comparison of their performance, and the basis of evaluation.

### 3. Method

Recently, there have been multiple successful applications of reinforcement learning algorithms in real-life problems [26, 39, 30]. Unfortunately, such applications are limited to solving low dimensionality formulations. Learning policies directly over visual input is still far from being plausible and often requires an intermediate representation learning procedure to learn a condensed embedding of the necessary visual information. Once such a representation is learned, a complete MDP is defined over the low dimensional representation to learn the required policy over the latent space. For the task of representation learning, the deep generative models have shown a lot of promise. Researchers have used Variational Autoencoders (VAEs) [57, 58, 19] to learn such representations. Kurutach et al., [29] have even shown that the latent space of InfoGAN [9] is rich enough to learn goal-directed visual plans.

Contrary, to learning a condensed representation of visual input. Our work proposes an MDP formulation to exploit the semantics of representations in pre-trained GANs to generate high fidelity images for facial aging. For this task, we have binned the continuous range of plausible age variations into consecutive buckets. Taking inspiration from goal-reaching RL problems, we learn a conditional policy which samples face images belonging to different age bins; conditioned on the base latent vector (defines the base identity to be generated) and the order of aging i.e., making the face older (ascending) or making the face younger (descending). In our MDP formulation, the states and the transition function are defined over the latent space of the ProgressiveGAN [22].

Rather than learning a policy defined over the full $R^d$ dimension space, we have restricted the search space to the typical set [33] of a $d$-dimensional standard normal distribution (the base distribution used to train ProgressiveGAN [22]). We have used a locally linear approximation of manifold to learn a linear affine subspace to generate a new state under the Markovian assumption. As a reward scheme, our agent gets a positive reward if it samples from a new age bin (to improve image generation with age diversity) while respecting the defined identity bound (to preserve identity) and the typical set of the distribution (to avoid mode collapse). In later sub-sections, we will discuss each of these components individually.

#### 3.1. Latent Space and Goal

The latent space of ProgressiveGAN, defined over the $d$-dimensional standard normal distribution, is rich enough to generate high fidelity images with required semantic variation [50]. In our work, the RL policy learns a sampling scheme that can sample the required latent vector and thereby generate the corresponding image with the necessary facial properties. For this, we have defined our state space to be the same as the $d$-dimensional latent space of ProgressiveGAN ($\mathcal{G}_{\text{model}}$), where each latent vector $s$ is associated with its corresponding image based on the following equation.

$$ I \leftarrow \mathcal{G}_{\text{model}}(s) \quad (1) $$

For the given sampling-based policy, we have also defined the corresponding goal $g$ as the task of preserving the identity ($I^{\text{base}}$) while inducing age variations over the set of generated images. We represent our goal ($g$) as a concatenation of latent vector associated with the given base image ($s^{\text{base}}$) and a one hot embedding $R^d$, to define whether we want to make the base image younger ($C^{\text{dsc}}$) or older ($C^{\text{asc}}$). Hence, the goal ($g$) for a given base image and required age manipulation is represented as $[s^{\text{base}}, C]$ where $C \in \{C^{\text{asc}}, C^{\text{dsc}}\}$. Taking inspiration from goal-based RL
achieved generalization. Based on defined age condition generated by such a direction and also the level of the manifold, as shown in Figure 2. This approximation, over the typical set of a Gaussian normal distribution from point A to point B.

3.2. Locally linear approximation

Shen et al., [50] (InterfaceGAN) have shown that a linear traversal across a hyperplane defined over the latent space of ProgressiveGAN, can generate the required semantic variation for a given base image. Often, such a linear traversal isn’t generic enough to sample images across different age groups while preserving the person’s identity. Also, the linear traversal scheme often fails to consider the latent space’s manifold structure and can even lead to traversing low-density region where, by definition, the model has not been trained well [25, 4].

In our work, we circumvent this issue by generating a non-linear trajectory using a locally linear approximation of the manifold, as shown in Figure 2. This approximation strategy gives the model an additional freedom to learn a shared local manifold structure across different latent vectors and utilize it for a given task. Manifold structures for face aging around a given conditioned base state can be approximated to be locally Euclidean and the geometry can be estimated using linear approximations (planar subspace) [1, 24, 58]. Any planar approximation of a d-dimensional latent space requires at least two R^d dimensional basis vector, which can span the full space.

For the given problem, we have taken inspiration from InterfaceGAN and have used one of the basis as the planar hyperplane direction learned for facial aging (K^{hyp}). This choice is motivated by the accuracy of disentanglement generated by such a direction and also the level of achieved generalization [50]. Based on defined age conditioning, we have used K^{gen} as K^{hyp} if C = C^{asc} or −K^{hyp}

if C = C^{desc}. The other basis for the local approximation, (K^{gen}), is generated by our policy network πθ(α|s_t), as part of the action required at a given state. Our action space α_t is R^{d+2} dimensional. Here, the d-dimensions provide the predicted basis vector and the other two dimensions provide the scalars, w_1^α and w_2^α, to weigh the principal basis and the generated basis vector. Therefore, the action α_t is the concatenation of [k_t^{gen}, w_1^α, w_2^α].

Hence the transition function for given action α_t at state s_t is defined as:

\[ s_{t+1} = T s_t + (1 - T)(s_t + w_1^α * k_g^{hyp} + w_2^α * k_t^{gen}) \] (2)

For our experiments, we have introduced an additional hyper parameter T which controls the smoothness of the generated trajectory [58, 55]. An episode starts with s_{base}, i.e., s_0 = s^{base} and the full trajectory is unrolled from there.

3.3. Typical set

The typical set for a probability distribution is defined as a set of elements whose information content is sufficiently close to the expected information content of the distribution [33, 4]. As mentioned in [33], an (ε, N) - typical set is defined as:

**Definition:** [33, 48] An (ε, N) - typical set for a distribution P(x) with support \( x \in X \) is defined as a set of all N-length sequence that satisfy

\[ \mathcal{H}[P(x)] - ε ≤ \frac{1}{N} \sum_{n=1}^{N} \log(P(x_n)) \leq \mathcal{H}[P(x)] + ε \] (3)

where \( \mathcal{H}[P(x)] \) represents the entropy of the distribution, \( P(x) \), and is defined as \( \int_X P(x) [-\log(P(x))] dx \). A simpler factorized formulation for the same equation can be written as

\[ \mathcal{H}[P(x)] - ε ≤ \frac{1}{N} \sum_{n=1}^{N} \log(P(x_n)) \leq \mathcal{H}[P(x)] + ε \] (4)

Nalisnick et al. [33], have shown that a high likelihood for an out of distribution dataset in a generative model results from a mismatch between the typical set of a distribution and the region with a high likelihood. During the training of the generative model, most of the latent vectors are sampled from a subset of the model’s full support and especially from the typical set of the distribution. For a d-dimensional standard normal distribution \( N(0, I) \) an (ε, 1) - typical set is defined as \( \frac{1}{2} ||d - ||x||^2 \leq ε \) [4]. Interestingly, this equation is similar to the Gaussian Anulus Theorem [55] defined over the same distribution. For a normal distribution this region lies at a \( σ/\sqrt{d} \) distance from the mode as shown in Figure 2. Even the authors of InterfaceGAN

\[ 1 \text{Proof has been provided in the supplementary material} \]
We have tackled this issue by restricting the learned trajectory to fall over the typical set of the normal distribution. For each newly generated state, a check is done to determine if the generated state is within the defined typical set of the distribution. If the new state is not in this region, then the episode is terminated with high negative reward. We have used the following function to formulate an $(\epsilon, 1)$-typical set defined over the $d$-dimensional latent space of ProgressiveGAN.

$$Z_g(t) = \begin{cases} 1 \text{ if } \frac{1}{2}d - \|s_t\|^2 \leq \epsilon \\ 0 \text{ otherwise} \end{cases} \quad (5)$$

where $\epsilon \in R^+$ and is a hyper parameter.

### 3.4. Age based Manipulation

In our reinforcement learning framework, we have associated the property age with each generated image (obtained from the sampled latent vector - equation $[I]$). For the task of predicting the age of a face image, we have trained an age regression ($A_{reg}$) model using a ResNet-50 [17] based model over IMDB Wiki Faces dataset [44]. The following equation enlists the prediction mechanism.

$$I_t \leftarrow G_{model}(s_t)$$

$$age_t \leftarrow A_{reg}(I_t) \quad (6)$$

Our reward scheme then incentivizes the policy to sample face images belonging to different age groups (bins). For example, say the base image is of a 30-year-old person and the policy is conditioned to generate older faces (ascending order). In such a scenario, the agent will receive its reward only if it samples images belonging to the higher age group, i.e., age $> 30$. The exact reward structure is described in Section 3.6.

As the ProgressiveGAN [22] is trained over CelebA-HQ dataset [51] [22], there is an age-associated bias over the learned latent space. Most of the generated images from the model have an associated age value that lies between 20-60 year group. Hence, for our experiments, we have sub-divided the given age range into multiple buckets ($S$) of equal size $B$, to group similarly aged face images into the same bucket.

To achieve the desired diverse age variation within a given episode, we incentivize the policy to cover as many buckets as possible, in a given order, while discouraging it from sampling images from the same bucket. For this, our policy is encouraged to generate one image from each of the buckets, under the given ascending or descending conditioning, while being within the set identity bound (described in the next Section). To ensure this, we reward the agent only when it transitions to an unvisited age bucket. This approach ensures that, for an episode, the policy looks for a diverse set of age variations and thereby not getting stuck into sampling images from the same age bucket. We define an indicator function $\delta(\text{age})$, which specifies, if the newly generated face image has an age value associated with an unvisited bucket. Using this formulation, we define a function $M_g(t)$, which indicates if the newly sampled face image qualifies for a reward.

$$M_g(t) = \begin{cases} 1 \text{ if age}_t > \text{age}_{base} \text{ and } \delta(\text{age}_t) = 1 \text{ and } C \subseteq C^{asc} \\ 1 \text{ if age}_t < \text{age}_{base} \text{ and } \delta(\text{age}_t) = 1 \text{ and } C \subseteq C^{desc} \\ 0 \text{ otherwise} \end{cases} \quad (7)$$

### 3.5. Identity preservation

One of the key components of our proposed formulation is the task of preserving identity during face sampling. To preserve the identity of the generated image during state transitions, we have defined a reward scheme where an incentive is given for sampling images for a new age bin under a given threshold over identity.

Generally, an age-based manipulation over an image leads to multiple changes in the face; this makes the task of identity comparison even more challenging. Wang et al., [56] have shown that a Mean Square Error (MSE) in a pixel space between the base image and generated image does not capture the face aging attributes like hair color, beard, and wrinkles. Instead, a perceptual loss based on the image’s content was proposed as a surrogate for identity preservation during age change. The authors have used the lower feature layers of an AlexNet [28] model trained on ImageNet and have empirically shown that the conv5 feature vector is the best suited surrogate. Inspired by [56], we have also used an MSE based comparison of the conv5 layer of an AlexNet [28] model. The squared distance is computed between the feature vectors of the base image and all the associated images generated in the given trajectory. For each new state generated by the transition function, we generate the corresponding image using our ProgressiveGAN. This image is then passed through the AlexNet model to get the corresponding conv5 feature vector ($F$).

$$I_g(t) = ||F(I_t) - F(I_{base})||^2 \quad (8)$$

Preserving identity while transitioning over large age differences is challenging. This problem arises, as a lot of the facial attributes have to be modified. For example, an image in the (20-25) age bucket will not have wrinkles, but such attributes would be present in the older age group. This makes the sampling of images across extreme age differences difficult. It becomes extremely tough to distinguish it from a facial change from an identity-based modification, as these attributes have a very high correlation with the identity of
a person. One way of solving this is by having a more lenient threshold on the identity (8). However, this tends to introduce noisy intermediary samples.

To solve this issue, we define two thresholds: a soft threshold $P_1$, under which identity will be better preserved, and a hard threshold $P_2$, where an agent will be able to sample images from the extreme age differences without much deterioration in identity. The thresholds respect the $P_1 < P_2$ relationship. Our reward scheme thereby incentivizes the agent to make decisions by following the locally linear approximation to sample images under soft threshold while the hard threshold gives the flexibility to sample across extreme age variations.

### 3.6. Reward Scheme

For each transition, the corresponding $s_t$ is passed through ProgressiveGAN (1) to get the associated image $I_t$. This image, $I_t$, is further passed through age regressor ($\mathcal{A}_{reg}$) and through Alexnet (28) model to get the corresponding age and identity feature associated with it. If the generated state is associated with an unvisited bucket under given sampling order (ascending or descending) and within a given identity bound (based on equations 7 and 8), then the policy is credited with a positive reward.

As mentioned in Section 3.5, we have considered a dual thresholding scheme where $P_1$ is the soft threshold and $P_2$ is the hard threshold such that $P_1 < P_2$. If the MSE score based on equation 8 over the identity is less than $P_1$ and $M_{d}(t) = 1$, then the agent is credited with $mr$ reward. If it is between $P_1$ and $P_2$, we provide $r$ reward, and if it crosses over $P_2$ then we give a large negative reward and terminate the episode. The idea of having a reward scheme based on soft and hard margin is to promote sampling of images that have a large age difference. Such large variations cannot be captured under tighter identity bound. The $P_2$ margin over the trajectory also serves as a filter to remove spurious face images with plausibly different identity. Our reward scheme incentivizes the agent to reach an unvisited age bucket under $P_2$ identity bound while providing the flexibility to search for better identity preserving images under $P_1$ bound. If the model fails to generate a new state that satisfies the aforementioned conditions, it gets -1 reward. The concept of giving a negative reward is inspired by simulation-based goal-reaching reinforcement learning tasks like Fetch-Push (41) where the agent tries to finish the goal as early as possible. Once the agent samples from all the age buckets, under given conditioning, the episode is terminated. A sizeable negative reward is also given if the new state does not fall in the typical set of the isotropic Gaussian distribution. The maximum number of steps in an episode is set to $|elen|$.

$$R_g(s_t, a_t, s_{t-1}) = \begin{cases} 
-n & \text{if } I_g(t) > P_2 \text{ or } Z_g(t) = 0 \\
nr & \text{if } I_g(t) \leq P_1 \text{ and } M_{d}(t) = 1 \text{ and } Z_g(t) = 1 \\
r & \text{if } P_1 < I_g(t) \leq P_2 \text{ and } M_{d}(t) = 1 \text{ and } Z_g(t) = 1 \\
-1 & \text{otherwise}
\end{cases}$$

where $r, n \in R^+$

### 4. Experiments

#### 4.1. Implementation Details

For our experiments, we use a ProgressiveGAN pre-trained on $1024 \times 1024 \times 3$ resolution face images from CelebA-HQ dataset (22). For the defined environment formulation, Proximal Policy Optimization (PPO) (47), a model-free RL algorithm, was trained to learn the corresponding conditioned policy. For the training of the RL policy, 60,000 latent vectors and its corresponding images were sampled. The starting state of an episode is chosen randomly from this set of 60,000 training samples. After every 100 episodes of training, the age manipulation order i.e., $c_{asc}, c_{dsc}$ is switched. The hyperparameters associated with training are listed in Table 1. The trained RL policy was tested on another unseen set of sampled vectors.

The proposed environment was defined and implemented in Pytorch (35). We used TensorFlow 2 (12) branch of the baselines (10) package to implement and test the model-free based reinforcement learning algorithm. The experiments were performed on a machine with Intel(R) Xeon(R) Silver 4114 Processor @ 2.20GHz, 40 cores, 128GB RAM, and 2 Nvidia GeForce RTX 2080Ti with 11016 MB.

#### 4.2. Identity preservation and catastrophe avoidance

The unfavourable conditions of leaving the typical set or failure to preserve identity has been termed as a catastrophe. As mentioned in equation [9] the agent is given a large negative reward when it generates states associated with a large identity difference from the base image. A negative reward is also given whenever the generated state does not fall in the defined $\epsilon-$typical set. Such negative rewards, particularly for identity preservation and for falling in the typical

| Parameter | $c$ | $n$ | $\epsilon_{len}$ | $P_1$ | $P_2$ | $T$ | $\epsilon$ | $d$ | $B$ | $m$ |
|-----------|----|----|------------------|-----|-----|-----|------|----|-----|----|
| Value     | 2  | 100| 60               | 750 | 900 | 0.3 | 3.5  | 512| 5   | 2   |

Table 1: Hyper-parameters used in our experiments
set, introduces a notion of fear [14] in the model to generate images in a limited sub-region where there is a better possibility to preserve identity while maintaining high generation quality. The negative reward hyperparameter, $n$, can be changed based on user-specific needs. In our experiments, we have explored the model’s feasibility to generate diverse age groups while respecting the above-mentioned conditions. Figure 3 shows the result of our PPO based RL model for age manipulation. The presented results are obtained after training the policy for 1 million steps.

4.3. Comparison with InterfaceGAN

Figure 5 shows the images generated by our model in comparison to the InterfaceGAN [50]. The initial rows are representative samples where the gender of the individual is changing while following the trajectory generated by InterfaceGAN, whereas our RL policy is able to preserve the gender of the base image. The middle rows empirically show that our policy does a better job of preserving the identity of the person. The last row shows that our non-linear trajectory does better at introducing the required facial features when compared against its linear counterpart. We have used the age basis, without any complement, as the primary basis in our model and the same is used as a hyperplane for linear traversal in InterfaceGAN. This setup would permit us to fairly compare the proposed non-linear RL based manifold learning approach against the linear traversal approach presented in InterfaceGAN. From Figure 5, it is evident that our output is quite different from InterfaceGAN. This also shows that the proposed non-linear traversal does a better job of preserving the identity while inducing the required age variation.

$\cos(\theta) = \frac{\vec{a}.\vec{b}}{||\vec{a}|| ||\vec{b}||}$

(10)

We perform a quantitative comparison of the trajectory obtained from our RL model against the linear traversal of InterfaceGAN. We do this by evaluating the cosine similarity (10) between the two feature vectors from the VGG Face model [42] obtained by passing the base image and the sampled images generated from the models. For this evaluation, we have sampled 300 base states, to generate images from InterfaceGAN and our proposed RL policy. From the results enlisted in Table 2, it is clear that our model performs better than InterfaceGAN in terms of preserving the identity of the base image along a trajectory while introducing the required semantic changes.

| Models     | Mean-cos | Std-cos | Min-cos | Max-cos |
|------------|----------|---------|---------|---------|
| InterfaceGAN | 0.903    | 0.097   | 0.318   | 0.994   |
| Ours       | 0.919    | 0.065   | 0.624   | 0.997   |

Table 2: Comparison of the cosine similarity (cos) scores between the trajectory obtained from InterfaceGAN and the non-linear trajectory of our model.
According to Shen et al. [50], there is a high correlation between the age and gender variations. A linear traversal across a hyperplane, without considering its complement, causes an unnecessary change in other attributes like gender. This issue was significantly noticed when a linear traversal is performed for age manipulation (face aging) [3]. In our proposed RL framework, such discrepancy can easily be detected using identity-based comparison of the sampled image and the base image [8]. If such an issue is encountered, the episode is terminated [4,2], thereby preventing the agent from making major changes in identity while attempting to induce the required variations.

5. Conclusion

In this work, we have formulated a locally linear traversal scheme over the latent space of a ProgressiveGAN for the task of semantic age manipulation of a given image. Our approach is independent of the generative model’s architecture and can be easily extended to other state-of-the-art GAN models and facial attributes. We obtain comparable results with InterfaceGAN for the task of face ageing and have shown that the learned conditional policy does a better job of preserving the base state’s identity while introducing the required semantic variations. We have also shown our approach’s efficiency in learning a non-linear trajectory while generating samples that belong to the distribution’s typical set. In the future, we will extend this formulation to other attributes, like pose variation and smile change. We will also experiment with different GAN architectures and
generative models e.g. flow \cite{27} and autoregressive generative models \cite{54}.

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A. $(\epsilon, 1)$ - Typical set for Gaussian Isotropic Normal Distribution

For an independent and identically distributed (i.i.d.) samples of our generative model Definition-1 \[33\] can be simplified and re-written as

$$\left| \mathcal{H}[P(x)] - \frac{1}{N}\left( \sum_{n=1}^{N} -\log(P(x_n)) \right) \right| \leq \epsilon$$

(11)

where $\mathcal{H}$ defines the entropy of the distribution and $P$ denoted the density function of the distribution. The entropy for a multi-variant Gaussian distribution is defined as:

$$\mathcal{H}[P(x)] = \frac{1}{2}(\log(\det(2\pi e \Sigma)))$$

considering, a standard normal distribution where $\Sigma = \sigma^2 I$, this equation can further be simplified as

$$\mathcal{H}[P(x)] = \frac{1}{2}(\log((2\pi e \sigma^2)^d))$$

$$= \frac{d}{2}(\log(2\pi e) + (\log(\sigma^2)))$$

$$= \frac{d}{2}(1 + 2\pi) + d\log(\sigma)$$

(12)

Similarly the density function for the $d$-dimensional standard normal distribution is

$$P(x) = \frac{1}{(2\pi \sigma^2)^{\frac{d}{2}}} \exp \left( -\frac{||x - \mu||^2}{2\sigma^2} \right)$$

(13)

Substituting eqn [13] and eqn [12] in eqn [11] we get

$$\epsilon \geq \left| d\log(\sigma) + \frac{d}{2}(1 + 2\pi) - \left( d\log(\sigma) + \frac{d}{2}\log(2\pi) + \frac{1}{N}\sum_{n} \frac{||x_n - \mu||^2}{2\sigma^2} \right) \right|$$

$$= \frac{1}{2} \left| d - \frac{1}{N}\sum_{n} \frac{||x_n - \mu||^2}{\sigma^2} \right|$$

(14)

Since the Latent space for a ProgressiveGAN is defined over 512 dimensional $\mathcal{N}(0, 1)$ distribution. A $(\epsilon, 1)$ - Typical Set for the latent distribution can be defined as:

$$\epsilon \geq \frac{1}{2} \left| 512 - ||x||^2 \right|$$

$$\beta \geq \left| 512 - ||x||^2 \right|$$

(15)

where $\beta = 2\epsilon$
B. Comparison between InterfaceGAN and output of our RL based policy

This section contains a comparative analysis between the images generated by our RL-policy and the InterfaceGAN in terms of gender-based changes during sampling. As can be seen in Figure 5, our model does a better job in introducing the necessary age differences while at the same preserving the identity of the person without any explicit gender alterations.

Figure 5: Comparative result of (i) generated output from our RL-policy, and (ii) InterfaceGAN for various base images.