**Abstract**

Recent advances like StyleGAN have promoted the growth of controllable facial editing. To address its core challenge of attribute decoupling in a single latent space, attempts have been made to adopt dual-space GAN for better disentanglement of style and content representations. Nonetheless, these methods are still incompetent to obtain plausible editing results with high controllability, especially for complicated attributes. In this study, we highlight the importance of interaction in a dual-space GAN for more controllable editing. We propose TransEditor, a novel Transformer-based framework to enhance such interaction. Besides, we develop a new dual-space editing and inversion strategy to provide additional editing flexibility. Extensive experiments demonstrate the superiority of the proposed framework in image quality and editing capability, suggesting the effectiveness of TransEditor for highly controllable facial editing. Code and models are publicly available at https://github.com/BillyXYB/TransEditor.

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1. Introduction

High-fidelity generative modeling has made a dramatic leap thanks to the progress of Generative Adversarial Networks (GANs) [13, 22, 23]. These efforts have expedited the advancement in facial editing [14, 16, 40], an important downstream task with many practical applications, circumventing the cumbersome manual editing processes. Nevertheless, highly controllable facial attribute editing remains challenging when applying current approaches [23–25].

The main challenge of highly controllable facial editing lies in the clean disentanglement of attributes in the latent space. For instance, it is expected to maintain the consistent face characteristic when manipulating the head pose of a portrait. Representative GAN-based methods [23, 24] explored the single latent space representation, and the style modulation technique of generators for better image generation and semantic editing. On another note, some studies [6, 39] focus on the local-region editing for specific facial parts in a fine-grained manner. However, under the single latent space design, these works still suffer from the latent entanglement of certain complicated attributes, such as facial pose.

Working towards these challenges, recent studies [4, 25] have presented preliminary attempts that leverage the idea of dual latent spaces for style and content disentanglement within the StyleGAN [22] architecture, achieving plausible semantic separation in each space. However, these attempts may not be adequate to take full advantage of the potential of a dual-space GAN. We empirically observed that these methods fail to obtain decent facial editing results, especially in complicated attributes, as shown in Fig. 6. Altering the pose of a face may produce dissatisfactory artifacts, and a drastic change in hue easily occurs when interpolating the style code of DAT [25] by fixing the content code. Accordingly, we conjecture that the underlying cause is the lack of interaction between the two latent spaces, and thus editing one space may distort the other, making the controllable facial editing infeasible.

In this paper, we show that the latent space interaction in a dual-space GAN plays a significant role in facial editing. Inspired by recent immense success of Transformers [5, 9, 20, 27, 38] in vision tasks, we propose a novel Transformer-based dual-space GAN, named TransEditor, to strengthen the dual latent space interaction. The two latent spaces in our generator, i.e., \( P \)-space and \( Z \)-space, serve as the initial input feature map of the generator and the style modulation [23] for all layers, respectively. Specifically, we propose a Transformer-Based Cross-Space Interaction module, where we incorporate a cross-space attention mechanism based on the Transformer to enhance the interaction between these two spaces, facilitating highly controllable facial editing. The design of interaction is non-trivial since potential entanglement might be aggravated via the interaction. We propose to use the \( P \)-space as the query and the \( Z \)-space as the key and value. Therefore, \( P \)-space is only exploited to re-weight the value matrix from \( Z \)-space through the Cross-Space Interaction module, hence still being disentangled with the refined code from \( Z \)-space. Thanks to the design of the interaction module, our dual spaces allow flexible editing while maintaining disentanglement semantically in an expressive manner, with \( P \)-space mainly controlling the structural information and \( Z \)-space determining the texture representation. Then, different from previous methods [32–34] that perform editing in a single space, we devise a novel Dual-Space Editing strategy to leverage the controllability brought by TransEditor (Fig. 1).

Further, to enable the real image editing, we also extend existing inversion techniques [31] to fit the proposed dual-space design.

The contributions of this work can be summarized as follows. We propose TransEditor, a novel Transformer-based dual-space GAN for highly controllable facial attribute editing. Through the introduced cross-space attention mechanism, the two latent spaces can establish meaningful interaction in a disentangled manner. Additionally, we develop a novel flexible dual-space image editing and inversion strategy to leverage the improved controllability provided by TransEditor. Extensive experiments demonstrate the effectiveness of TransEditor in highly controllable and stable facial attribute editing, outperforming state-of-the-art approaches especially for complicated attributes.

2. Related Work

2.1. Structured Latent Space for Disentanglement

Single Latent Space. ProgressiveGAN [21] uses a latent code as the input feature map to control the generation of the whole image. StyleGAN [22, 23] improves the disentanglement using a mapping network that maps the initial distribution to an intermediate latent space \( w \), thus the distribution of latent codes can be reformed to the given real image distribution. Besides, the layer-wise Adaptive Normal Instance (AdaIN) [11, 18] is used to improve the disentanglement further. StyleMapGAN [24] reshapes the latent code into a tensor with spatial structure. The method achieves good reconstruction results but poor semantic editing performance, known as the Editability-Distortion trade-off [2, 36, 44]. Its encoder also needs to be trained together, the training will fail otherwise. The reason is that the network relies on the encoder to make the projected style map of the real images achieve local correspondence [24].

Dual Latent Spaces. To achieve better disentanglement or spatial awareness, some studies that explore dual latent spaces design have been proposed. SNI [4] separates the latent space into spatially-variable and spatially-invariable parts. The separation allows a certain degree of local editing. However, the limited capacity of the spatial code (4×4 or 8×8) may cause failure when performing content control [25]. DAT [25] improves the structure by introducing a symmetric space similar to the origin latent space and utilizing separate operations during the generating process for disentanglement. However, the content space pro-
posed by DAT [25] operates on each pixel individually, so it lacks a global structure connection and cannot perform well on some attributes with large structural changes like pose. There are other flavors of dual latent spaces for various tasks. Zhu et al. [43] propose \( F \)-space and \( S \)-space for image compositing. Park et al. [29] use a style code vector and a structure code with spatial dimension. [3, 26] disentangle the pose and style for virtual try-on.

### 2.2. GAN-Based Image Editing

**Latent Space Manipulation.** Since the latent space of GAN is semantic-aware, it is possible to manipulate the attributes of the generated image through latent space navigation [42]. Previous works aiming at finding semantic directions can typically be divided into the supervised ones [12, 32], the self-supervised ones [19, 35], and the unsupervised ones [15, 34]. InterfaceGAN [32] finds hyper-planes in the latent space that corresponds to particular attributes by using attribute classifiers and SVM. Jahanian et al. [19] need a large set of paired examples to fit the image transformations. SeFa [34] performs decomposition on eigenvectors and finds interpretable directions without extra labels. Meanwhile, there are some studies [6, 39] that focus on local editing for specific facial parts. StyleSpace [39] proposes a space of channel-wise style parameters to perform highly localized and disentangled attribute editing.

**GAN Inversion.** To edit a real image using Latent Space Manipulation, the image should be projected back into the latent space of the generator [42]. Optimization-based methods [1, 28] directly optimize the latent code to minimize the pixel-wise reconstruction loss. However, the optimization process is slow and the inverted code may land out of the original semantic manifold, making the editing process suffer from meaningful semantic manipulation. This problem is resolved by learning-based methods [31, 36], which use an extra encoder trained and guided by the generator to directly embed the image into a latent code, offering benefit during real image editing.

### 2.3. Transformer-Based Interaction

Multi-head attention module is often used in some multi-modality tasks to establish the inter-modal interaction between text modalities and visual modalities, such as image captioning [7, 17] and text-to-image translation [8, 30]. TransStyleGAN [27] introduces a Transformer structure to model the correlation between different layers of style codes within a single latent space based on the StyleGAN2 architecture. In this work, we leverage the multi-head attention module in the Transformer [37] to establish the interaction between the proposed dual latent spaces (i.e., \( Z \)-space and \( P \)-space), facilitating more flexible and controllable attribute editing.

### 3. Methodology

Our goal is to achieve more controllable facial attribute editing through the disentangled but collaborative dual spaces. Fig. 2 (a) shows the structure of our model. We propose two latent spaces \( Z \) and \( P \) with separate mappings (Sec. 3.1), which are used as the initial input feature map of the generator and the layer-wise style modulation, respectively. Then, an interaction module based on the Transformer (Sec. 3.2) is proposed to model the interaction between these two spaces, making them more balanced during editing. Further, we develop a new dual-space image editing and inversion strategy (Sec. 3.3) for real image editing.

#### 3.1. Dual Latent Spaces

Instead of learning a generator \( G \) that maps a single Gaussian distribution to an image \( x \), i.e., \( x = G(z) \), \( z \in \mathcal{N}(0, I) \), two separated latent spaces are used in our method, denoted as \( Z \) and \( P \). Thus, our generation process can be reformulated as:

\[
x = \text{TransEditor}(z, p),
\]

where \((z, p) \in Z \times P\).

Note that it is non-trivial to determine how the two spaces should be integrated with the generator. For the StyleGAN2-based architecture [23], at each layer, the generation process can be expressed as:

\[
F_{i+1} = \text{ModuConv}(T_{w_i}F_{i}),
\]

where \(F_i\) denotes the feature map produced from the previous \(i - 1\) layer, and \(T_{w_i}\) is the modulation and demodulation process determined by the layer style code \(w_i\). Although the modulation and demodulation are performed at every layer, each feature map is the convoluted result from the previous layer. Thus, the initial feature map \(F_0\) is the foundation that the whole generation process is based on. Therefore, compared with StyleGAN2 in Fig. 2(b), to provide more controllability, we replace the learned constant input with the latent input from \(P\)-space. Besides, the additional latent capacity provided by \(P\)-space allows us to remove the noise inputs.

In addition, we consider that reshaping a single sampled vector for the entire latent input is inherently entangled [4], hence our two spaces \( Z \) and \( P \) consist of separate sub-vectors, \(i.e., z \in \mathbb{R}^{n \times 512}, p \in \mathbb{R}^{n \times 512}\). To further encourage a desirable disentanglement property, we exploit separate mappings for the dual spaces: \((z^+, p^+) \in M_z(Z) \times M_p(P)\), which can be written as:

\[
z^+ = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} = \begin{bmatrix} 0 & \ldots & 0 & M_{z_1} \\ 0 & \ldots & 0 & M_{z_2} \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \ldots & 0 & M_{z_n} \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}
\]

\[
p^+ = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix} = \begin{bmatrix} 0 & \ldots & 0 & M_{p_1} \\ 0 & \ldots & 0 & M_{p_2} \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \ldots & 0 & M_{p_n} \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix}
\]
Network architecture of TransEditor. (a) shows the structure of our model, which contains two separate latent spaces $Z$ and $P$, a Cross-Space Interaction module based on the Transformer, and a generator. Compared to (b) StyleGAN2 [23] that leans a constant input, our generator uses the $p^+$ code as the input and the interaction result $(z^+)^L(w)$ for style modulation.

Figure 2. Network architecture of TransEditor. (a) shows the structure of our model, which contains two separate latent spaces $Z$ and $P$, a Cross-Space Interaction module based on the Transformer, and a generator. Compared to (b) StyleGAN2 [23] that leans a constant input, our generator uses the $p^+$ code as the input and the interaction result $(z^+)^L(w)$ for style modulation.

Note that each $M_z$ or $M_p$ is a MLP [10] module, and the mapped space $z^+ \times p^+ \in \mathbb{R}^{n \times 512} \times \mathbb{R}^{n \times 512}$. In our experiments, we set $n = 16$.

3.2. Transformer-Based Cross-Space Interaction

In a dual-space GAN, naive generation using two separated latent codes might be problematic. SNI [4] shows that adding the style code at all layers influences the disentanglement performance, i.e., changing the style code at early layers of the generator affects the structural information. Although DAT [25] achieves better disentanglement than SNI, we find that when fixing DAT’s content code and interpolating its style code, drastic changes in hue could easily appear and cause artifacts. We attribute this phenomenon to the lack of interaction in the dual latent spaces, as they are not correlated by any means.

Inspired by the cross-domain Transformer model [30], we correlate the two separated spaces via a cross-attention-based interaction module. The mapped latent code $z^+$ is used as the key ($K$) and value ($V$), and the latent code $p^+$ as the query ($Q$). The interaction in the $l$-th layer transformer can be written as:

$$Q = p^+ W^Q, K = (z^+)^l W^K, V = (z^+)^l W^V, \quad (5)$$

$$z^+)^{l+1} = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V + (z^+)^l, \quad (6)$$

where $W^Q, W^K, W^V$ are linear projection matrices, and $d_k$ is the common dimensionality of the latent code. In other words, an attention process queried by $p^+$ will be operated on $z^+$. Since $p^+$ acts as the query only, the two spaces are still separated, yet $z^+$ has adopted to the query $p^+$. This design enables better disentanglement of the dual spaces while maintaining global consistency during editing (see Sec. 4.3).

The refined latent code $(z^+)^L$, that is $w$, serves as the style modulation parameters of the generator $G$. The generation process of image $x$ is thus formulated as:

$$x = G(w, F_0), \quad (7)$$

where $w$ is the modulation input produced from Eq. (6), and the Reshape module (see Fig. 2(a)) reshapes the mapped $p^+$ code into the initial feature map $F_0$ whose spatial dimension is suitable as the input to the generator. The training of our generator is entirely unsupervised, which only applies the adversarial loss and path length regularization following StyleGAN2 [23].

3.3. Dual-Space Image Editing and Inversion

Intuitively, some complicated attributes (e.g., age) may involve changes in both the facial structure and the texture. With our disentangled dual latent spaces, we propose to edit such complex attributes using $Z$ and $P$ together. To our knowledge, this is the first study that performs attribute editing through the two latent spaces simultaneously.

As enforcing the semantic distribution to fit the original Gaussian distribution is undesirable [22], the editing procedure of our model via the latent manipulation is operated on the product space $Z^+ \times P^+$. Hence, our dual-space manipulation procedure can be written as:

$$I_{(z^+ \times p^+)}(z^+, p^+) = (I_z(z^+), I_p^+(p^+)), \quad (8)$$
where $z^+ \in \mathcal{Z}^+$, $p^+ \in \mathcal{P}^+$, and $I_i$ represents the manipulation operated on space $i$.

It is noteworthy that the two operations $I_{\mathcal{Z}^+}$ and $I_{\mathcal{P}^+}$ could be different. In our case, we utilize the linear latent manipulation method by InterfaceGAN [33] for both spaces. Specifically, for each attribute, we use an SVM classifier to train two hyper-planes represented by the normal vectors in the two separated latent spaces $\mathcal{Z}^+$ and $\mathcal{P}^+$. Therefore, for known latent codes $z^+$ and $p^+$, we can move $\lambda_z$ steps along $n_z$ and $\lambda_p$ steps along $n_p$ to get the new latent codes $(z^+ + \lambda_z \ast n_z, p^+ + \lambda_p \ast n_p)$. For the attributes that are fully contained in one space only, we edit them by operating on that space solely (e.g., $\lambda_p = 0$). More complicated attributes like gender will be better manipulated if the two spaces are used simultaneously. The manipulated codes will then be used for generating the edited image.

To edit real images, it is necessary to invert the images back into the dual latent spaces. We adopt a pSp [31] encoder architecture for our dual-space image inversion. As shown in Fig. 3, three levels of feature maps of the input real image are first extracted using a feature pyramid. Since our $z^+$ space has a layer-wise structure, different features are used to produce each $z^+_i$. The $p^+$ latent code is only mapped from the highest-level feature in the encoder and injected as the initial feature map input of the generator.

The aforementioned inversion strategy maps real images into our trained dual latent spaces, and thereby we can apply linear latent manipulation to perform dual-space editing.

4. Experiments

In our experiments, we first evaluate the effectiveness of our method in highly controllable facial editing (Sec. 4.1). Then, we compare our method with three representative state-of-the-art methods (Sec. 4.2), i.e., the single-space methods (StyleGAN2 [23], StyleMapGAN [24]), and the dual-space method (DAT [25]), on both qualitative (Sec. 4.2.1) and quantitative (Sec. 4.2.2) aspects. In addition, we perform an ablation study (Sec. 4.3) to isolate each pivotal component of our method. We trained TransEditor on CelebA-HQ [21] and FFHQ [22] at a resolution of $256 \times 256$. Details of experiment settings and implementation can be found in our supplementary material. The quantitative metrics used in this section are shown as follows.

**Re-scoring Calculation.** We designed this metric given by $C_e/C_i$ to quantitatively evaluate the editing performance, where $C_e$ and $C_i$ denote the cumulative change of attribute score of the edited and the influenced attributes, respectively. It effectively measures how the editing of one attribute affects other attributes. Details of this metric are included in the supplementary material. A lower value represents a less entangled (better) editing result.

**Learned Perceptual Image Patch Similarity (LPIPS).** LPIPS [41] measures the diversity of a latent space. A larger LPIPS score indicates a more diverse space.

### 4.1. Latent Space Interpolation and Editing

Our dual latent spaces achieve a certain degree of semantic separation, with $\mathcal{P}$-space controlling structural information like pose and $\mathcal{Z}$-space controlling texture information.

**Disentangled and Balanced Dual Spaces.** The two latent spaces in our architecture are both semantically meaningful while achieving desirable disentanglement. Specifically, the head pose is entirely controlled by the $\mathcal{P}$-space. As shown in Fig. 4a, when re-sampling the $z$ code, all the generated images share the same head pose. On the other hand, when $z$ code is fixed, a similar texture, i.e., color, makeup, race, will appear on all results (Fig. 4b). Besides, under the dual space setting, it is often desirable to have more balanced spaces rather than being dominant by a single space. DAT [25] uses a diversity loss to encourage the diversity of its content space. In Tab. 1, our dual spaces achieve a more balanced space separation than DAT while obtaining a higher overall diversity. The diversity difference between our dual spaces ($\Delta_{LPIPS}$) is 0.0662, which is half of that of DAT [25]. This is consistent with our qualitative observation that both spaces of TransEditor shows higher controllability since they are more balanced.

**Latent Space Interpolation.** The two spaces are both smooth and semantic-aware, thus it is possible to change certain face attributes by interpolating towards a specific direction. Fig. 4c shows a fixed head pose at each row and a smooth change in texture when $z$ code is being interpolated. Similarly, Fig. 4d shows small changes in texture information at each row with fixed $z$ code, and the consistency in the head pose of each column with the same $p$ code. The smoothness and semantic-aware property of the latent space allows better attribute editing.

**Dual Latent Space Editing.** Using the dual-space latent manipulation method (Sec. 3.3), attribute editing can be per-
Figure 4. **Dual Latent Spaces of TransEditor.** Each row in (a) is generated by a fixed $p$ code and a randomly sampled $z$ code. Similarly, each row in (b) is generated by a fixed $z$ code and a randomly sampled $p$ code. In (c), each column starts from the same $z$ code and interpolates towards the same direction. Each row has the same sampled $p$ code. Similarly, each column in (d) starts from the same $p$ code then interpolates in the same way. Each row in (d) shares the same $z$ code.

Figure 5. **Dual-Space Editing of attribute Male.** When editing using the $p$ code (first row), the hair volume will decrease. And the face will gradually grow a small beard if using the $z$ code (second row). The third row shows the result of editing the male attribute jointly via both spaces.

formed through linear interpolation towards a normal direction of the trained hyper-planes. The result in Fig. 5 indicates that $p$ code controls the structural information such as hair volume, and $z$ code controls the texture information like the beard, and the joint editing results in the third row demonstrate the cooperation between the two latent spaces can achieve better editing performance. More editing results in Fig. 1 further demonstrate the flexibility of our dual-space editing strategy.

### 4.2. Comparison to State-of-the-art Methods

#### 4.2.1 Qualitative Evaluation

**Sampled Image Editing.** Fig. 6 shows the editing results of some sampled images. Since the change in gender may involve variation in both texture and structure information, the editing of gender is accomplished by editing on both $Z$-space and $P$-space (Content and Style space for DAT [25]). For pose editing, only content space of DAT [25] and $P$-space of ours are used. Compared with other methods, our method achieves better editing results. As mentioned in Sec. 2, when the editing involves the style space of DAT [25], the image tone could be easily changed (the third row of Fig. 6a). The manipulation of the head pose is even a more challenging task, as the texture and structure information need to stay aligned to preserve the identity. Fig. 6b shows the advantage of TransEditor. Dur-
ing pose editing, the \( p \) code is being manipulated when fixing the \( z \) code. However, the interaction process ensures that the style modulation parameter received by the generator has been aligned with the \( p \) code (Eq. (6)), thus producing a consistent texture throughout manipulation.

**Real Image Editing.** To enable real image editing, we use the dual-space inversion method mentioned in Sec. 3.3. The latent manipulation method is identical to the sampled image editing. Fig. 7 shows the comparative results on real image editing with state-of-the-art methods. In Fig. 7a, StyleMapGAN [24] suffers from the global semantic editing, in which the face turns to male with long hair. The distortion of DAT [25] and attribute entanglement of StyleGAN2 [23] can be clearly observed. As shown in Fig. 7b, all the baselines fail to edit the head pose while our method obtains plausible results.

### 4.2.2 Quantitative Evaluation

For editing performance comparison, we chose three attributes: smile, head pose, and gender, which represent editing in \( Z \)-space, \( P \)-space, and both spaces, respectively. We use them to calculate our re-scoring metric. The comparative results of our method with StyleGAN2 [23], StyleMapGAN [24], and DAT [25] are presented in Tab. 2. We observe that when editing each specific attribute, the influence of our model on other attributes is minimal, indicating that our method is the least entangled when performing editing.

### 4.3. Ablation Study

**Space Interaction via Transformer.** The space interaction is crucial in our architecture for the semantic balance between the two spaces. Removing the interaction process (i.e., the generator receives two completely independent codes) produces an unbalanced result. Under this setting, the \( P \)-space controls the majority of information, leading to more entangled results during editing and joint changes in color and shape (the first row of Fig. 8).

In contrast, with the cross-space interaction mechanism, the tones of the images keep consistent in a successful pose editing (the third row of Fig. 8). Therefore, establishing a connection between the two spaces enables a more balanced setting, which benefits facial attribute editing.

**Dual-Space Design vs. Single-Space Design.** We then evaluate the role of the dual-space design. TransStyleGAN [37] employs the self-attention mechanism to establish connections between different style codes within the single-space design. However, as can be seen in the second row of Fig. 8, when the step size of pose-editing gets larger, the face orientation is still difficult to change, while the distortion of the face and the change of tone could be serious. This indicates the difficulty of editing pose in a single space, demonstrating the advantage of our dual latent spaces.

**Selection of K, Q, V Matrices.** For the Cross-space Interaction module, we need to consider the choice of the \( K, Q, V \) matrices for the cross-space attention. Some studies in the multi-modality field use the single-modality feature that needs to be refined as the query, and the other modality feature as the key and value. In our case, this is equivalent to using the \( z^+ \) space as the query matrix and the \( p^+ \) space as the key and value matrix. However, the output of the cross-space attention module, as the refined feature of the \( z^+ \) space, is a weighting of the value matrix (\( p^+ \) space), which may produce certain entanglement of the two spaces. This setting (Fig. 9a) shows a severe entanglement between \( P \)-space and \( Z \)-space that swapping \( p \) codes result in different textures, which is not desirable for editing. On the other hand, our setting shown in Fig. 9b is much better disentangled, since the \( p^+ \) space is only adopted to as query to help update the \( z^+ \) space. Therefore, this interaction method in Sec. 3.2 is more desirable for our design.
5. Conclusion and Discussion

This paper introduces TransEditor, a novel dual-space GAN architecture with a Cross-Space Interaction mechanism based on the Transformer. Besides, we propose a new dual-space image editing and inversion strategy for highly controllable facial editing. Extensive experiments show the effectiveness of TransEditor in attribute disentanglement and controllability, surpassing state-of-the-art baselines in complicated attribute editing. The proposed TransEditor is readily applicable to many real-world applications such as photo retouching and face manipulation, which however, might be used unethically. Devising better media forensics approaches could be countermeasures. As for limitations, the editing process relies on auxiliary classifiers (for semantic boundaries), whose quality and diversity may limit editable attributes. In addition, the improvement on the cross-space interaction of a dual-space GAN for editing tasks can be interesting future work.

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