MetaCube: A Crypto-Based Unique User-Generated Content Editor for Web3 Metaverse

Haihan Duan, Zhonghao Lin, Xiao Wu, and Wei Cai

Existing user-generated content editors in Web3 metaverse face two challenges: they cannot guarantee the uniqueness of UGC; and they are hard-pressed to find a trade-off between model granularity and 3D modeling difficulty. In this article, the authors design a novel UGC editor for the Web3 metaverse, named MetaCube, to address these challenges.

Abstract

Web3 (also known as Web 3.0) metaverse is a blockchain-driven networked, decentralized, and open virtual world. The key feature of the Web3 metaverse is that the ownership of digital assets is recorded by non-fungible token (NFT) protocol on the blockchain. Thus, users are better encouraged to construct Web3 metaverse due to the ownership of their user-generated content (UGC). However, the existing UGC editors mainly face two challenges: they cannot guarantee the uniqueness of UGC; and they are hard-pressed to find a trade-off between model granularity and 3D modeling difficulty. In this article, we design a novel UGC editor for the Web3 metaverse, named MetaCube, to address these challenges. MetaCube applies an artificial intelligence (AI) method to assist the UGC creation for decreasing the 3D modeling difficulty while maintaining the model granularity. To guarantee the uniqueness of UGC, this article proposes 3D Crypto-dropout, a specially designed dropout that can utilize user information to control the UGC creation process and generate unique fine-grained 3D models. Our experimental results demonstrate that the proposed 3D Crypto-dropout can effectively guarantee the uniqueness of UGC from both numerical and human-centered evaluation. Moreover, the existing challenges and open research topics for the uniqueness of UGC are also profoundly discussed.

Introduction

Web3 (also known as Web 3.0) metaverse is a networked, decentralized, and open virtual world, which could be regarded as the next-generation Internet that connects millions of people based on the blockchain [1]. Compared with the traditional virtual world, the key feature of the Web3 metaverse is that the ownership of digital assets can be guaranteed by smart contracts as non-fungible tokens (NFTs), for example, ERC-721 and ERC-1155 [2]. As a result, the NFTs' public certificate of authenticity or proof of ownership is recorded in the blockchain and can be transferred by the owners, allowing NFTs to be sold and traded in online markets, and be reused in different Web3 metaverse projects, and so on.

Incentivized by the ownership of the digital assets, users are better motivated to construct the Web3 metaverse by creating user-generated content (UGC), which is any form of content that has been created by users rather than the developers of online platforms [3]. In the Web2 era, the UGC mostly denotes images, videos, texts, and audio that is created and uploaded to social media and forums by their users, while 3D metaverse can contain more UGC compared with Web2, especially 3D shapes or models. In fact, there are already some enthusiasts that have become metaverse architects, landscape designers, fashion and clothing designers, and so on. Moreover, the pandemic also accelerated the digital transformation of society. Thus, the participating creators have more interaction and communication with the Web3 metaverse, which plays a crucial role in bridging and attracting people outside their communities and motivates them to join the Web3 metaverse. Therefore, a promising, effective, and sustainable creator economy in the Web3 metaverse can be built by positive circulation, and the UGC is the lifeblood of the positive circulation with increasing importance.

The industry early perceives the necessity of UGC in the Web3 metaverse. Thus, most existing notable Web3 metaverse projects (e.g., *Cryptovoxels*, *Decentraland*, *The Sandbox*, etc.) provide internal or external UGC editors. In general, these metaverse operators will build centralized servers to support the operation of the metaverse, such as network connection and virtual world rendering, and distribute blank spaces or lands that users can buy or rent. Then, the users can construct the lands according to their creativity and imagination by creating UGC using the provided editors, introducing external NFTs, and so on. However, the UGC editors of the existing Web3 metaverse projects have two major challenges:

The Uniqueness of UGC Creations: Mature communication and network technologies provide convenient connections for millions of users, so it is inevitable that there exists identical UGC even though they are created by different users. Nevertheless, in some cases, digital assets can represent the users' personalities, lifestyles, and experiences. For instance, the profile picture (PFP) is a typical example of a digital asset that high-

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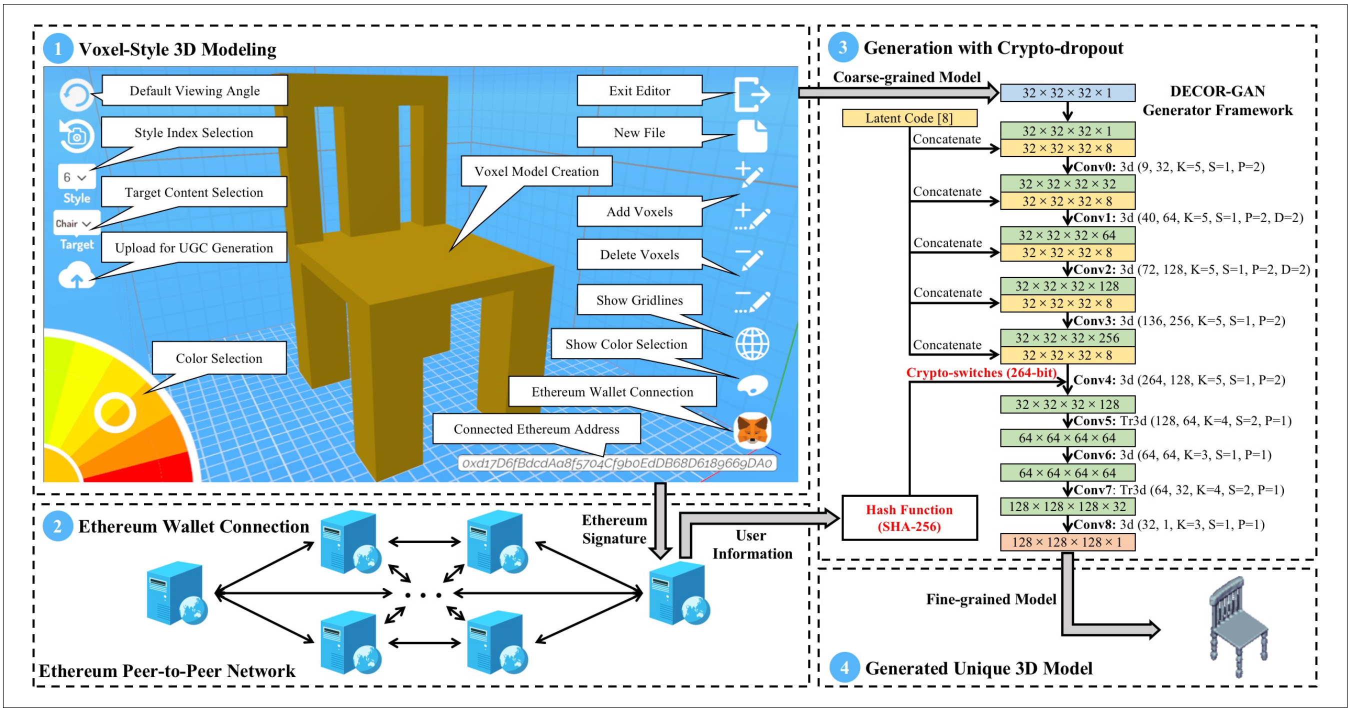

FIGURE 1. Workflow of MetaCube.

ly emphasizes uniqueness. Therefore, the users may hope to independently and solely possess the ownership of their created UGC. However, due to the transparent and open-sourced feature of Web3 metaverse, for example, file storage protocol InterPlanetary File System (IPFS), malicious users can easily reproduce or plagiarize an identical model based on someone's UGC, which can be regarded as a break of the UGC ownership. Therefore, it is imperative to design a mechanism to guarantee the uniqueness and scarcity of UGC in the Web3 metaverse.

The Trade-Off Between Model Granularity and Modeling Difficulty: Theoretically, the modeling difficulty of reproduction is proportionate to the model granularity, so an effective method for preventing reproduction is to create fine-grained models. However, building complex models also have a higher threshold since most normal metaverse users do not have the professional ability in 3D modeling. In *Cryptovoxels* and *The Sandbox*, they borrowed the successful experiences from *Minecraft* and provided voxel-style UGC editors to the users, which is a beneficial idea that could effectively reduce the learning cost, lower the modeling threshold, and avoid the uncanny valley problem. Nevertheless, voxel-style modeling also faces some issues: the coarse-grained models are easier to reproduce, the freedom of motion is relatively limited, and many users prefer realistic models rather than voxel-style models, and so on. Therefore, finding an approach to better balance model granularity and modeling difficulty is necessary.

In this article, we design a novel Web3 metaverse UGC editor, named MetaCube, to address the aforementioned challenges. Focusing on the trade-off challenge between model granularity and modeling difficulty, MetaCube allows users to apply voxel-style 3D modeling to reduce the threshold, like *Minecraft*. Then, MetaCube utilizes the artificial intelligence-generated content (AIGC) method, especially generative adversarial network (GAN) [4], to generate fine-grained 3D models based on the coarse-grained voxel models created by the users. To guarantee the uniqueness of created UGC, this article proposed a 3D version of Crypto-dropout [5], a specially designed dropout [6], to integrate the users' crypto information on the blockchain network into the generation process of AIGC, which can guarantee the uniqueness of generated UGC based on the difficulty of the hash collision. With 3D Crypto-dropout, only the original user can create an identical UGC using MetaCube since malicious users are hard to obtain identical user information through the blockchain network, which significantly protects the digital ownership of users in the Web3 metaverse. Note that, Crypto-dropout is a general idea that can be applied to any generative models based on neural networks [7], which denotes the proposal of Crypto-dropout still has much potential for further improvement.

Design of MetaCube

Voxel-Style User-Generated Content Editor: MetaCube

In this work, we design a voxel-style UGC editor named MetaCube, whose workflow is shown in Fig. 1. The UGC creation in MetaCube contains four steps:

1. Voxel-style 3D Modeling
2. Ethereum Wallet Connection
3. Generation with Crypto-dropout
4. Generated Unique 3D Model.

In this subsection, we will introduce the 3D modeling procedure of MetaCube in detail, and the proposal about unique UGC generation will be discussed later.

The proposed MetaCube is implemented by Unity, a cross-platform game development engine. Currently, MetaCube can support both personal computers (PCs) and mobile platforms

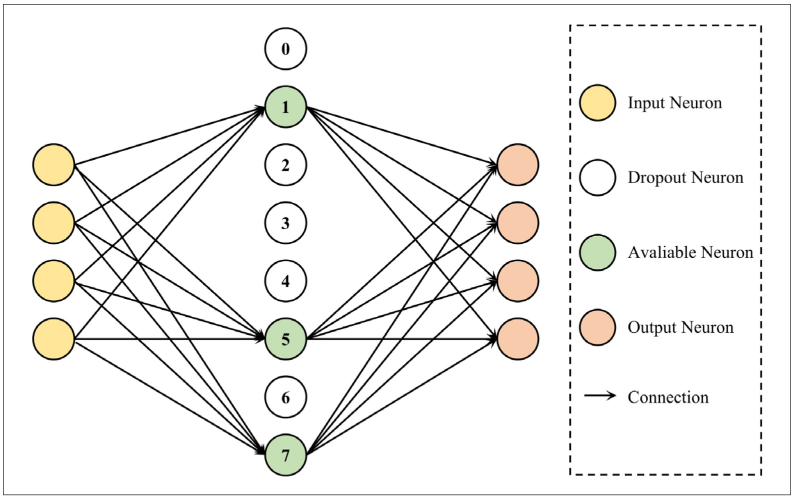

FIGURE 2. Crypto-dropout in a fully connected layer.

(e.g., smartphones, tablets, etc.). As shown in the first step of Fig. 1, MetaCube has a concise and intuitive graphic user interface (GUI). The central part of MetaCube is the area for voxel model creation, which is a space with a resolution of 32 ×32 × 32 that allows the users to place or remove blocks to create coarse-grained models. Besides, the left and right areas are set with penal buttons using recognizable icons, in which the key buttons are annotated in Fig. 1.

After the voxel modeling, the user needs to connect their cryptocurrency wallet (we use Ethereum wallet MetaMask in this work) by sending a crypto signature to obtain the user information (e.g., Ethereum address, Ethereum Name Service (ENS) address, etc.). Then, the user can select a specific target and style index, where we select "Chair" and style "6" as an example in Fig. 1. After determining the target content and style index, MetaCube will call a GAN model to refine the coarse-grained model created by the user to a fine-grained model. In this work, we apply DECOR-GAN [8] to refine the model from 32 × 32 × 32 to 128 × 128 × 128. The structured framework and parameters can be found in Fig. 1, where the "3d" and "Tr3d" after the layer number "ConvX" means 3D convolution and transposed 3D convolution, and the content in rounded bracket denotes "(input kernel number, output kernel number, kernel size, step size, padding, dilation)." At last, the user can obtain the generated unique 3D model, whose ownership will be confirmed as an NFT on the blockchain.

Guarantee of Uniqueness: Crypto-Dropout

In 2012, G. E. Hinton *et al.* first proposed dropout [6], an efficient trick that could relieve the over-fitting problem by randomly omitting some neurons to prevent complex co-adaptations during the training of neural network models. Moreover, previous works also discussed the details of the dropout technique in convolutional neural networks (CNNs) [9]. Generally, dropout is used in the training process of neural network models, but, in this work, we innovatively apply dropout in the prediction/generation process to generate unique UGC. The core idea is to integrate crypto information into the generation process of neural network models. Specifically, we encode the user information as a hash value to impact or control the activation of neural network neurons/kernels using dropout, which is named Crypto-dropout [5].

As shown in Fig. 1, the MetaCube prototype is implemented based on Ethereum Peer-to-Peer (P2P) network. For wallet connection, MetaCube will send an Ethereum signature to obtain the user information of the author through a smart contract, such as the Ethereum address. Then, the proposed 3D version of the Crypto-dropout algorithm applies a hash function (e.g., SHA-256 in this work) to encode the user information and other messages from the user as a hash value. The hash value can control which neurons/kernels will be dropped (0: dropout; 1: retain) during the generation process, where the hash value is called Crypto-switches, which has a certain length corresponding to the number of neurons/kernels [5].

Theoretically, the uniqueness can be guaranteed by two aspects: the low probability of hash collision (e.g., the probability of two hashes accidentally colliding is approximately 4.3×10^{-60}); and the low probability of identical user input coarse-grained model (e.g., the collision probability in a space with a resolution of 32 × 32 × 32 is even lower than the probability of hash collision, about 1.4×10^{-9864}). Due to the difficulty of the two conditions, the activated neurons/kernels of GAN using Crypto-dropout are hard to be identical, which guarantees the generated UGC of different users is unique.

Then we will illustrate two representative cases to explain Crypto-dropout, including Crypto-dropout in a fully connected layer and Crypto-dropout in a 3D convolutional layer:

Crypto-Dropout in a Fully Connected Layer: In Fig. 2, we illustrate an example of setting Crypto-Dropout in a fully connected layer. In this case, the hidden layer has eight neurons, so the corresponding Crypto-switches also need 8 bits. Here, we assume the Crypto-switches are "01000101," so the 0*th*, 2*nd*, 3*rd*, 4*th*, 6*th* neurons will be dropout neurons, and the 1*st*, 5*th*, 7*th* neurons will be retained.

Crypto-Dropout in a 3D Convolutional Layer: For applying dropout to a convolutional layer, there are various methods that could achieve different performances, for example, drop-neuron, drop-channel, drop-path, and so on [9]. In this article, the proposed 3D Crypto-dropout used the 3D convolutional kernels as the dropout units. Figure 3 shows an example that has 8 kernels in the 3D convolutional layer. Similarly, we also assume the Crypto-switches are "01000101." Thus, only the 1st, 5th, 7th kernels would be available during the prediction/generation process of the neural network model.

Therefore, MetaCube applies the 3D Crypto-dropout technique in the model generation from coarse-grained voxel to fine-grained model, which can build a crypto connection between the user and their UGC. More importantly, the 3D crypto-dropout can be regarded as a protocol to guarantee the uniqueness of UGC. For example, the difficulty of hash collision guarantees that only the user can generate an identical UGC using MetaCube. Even if other users can reproduce an identical coarse-grained model, MetaCube can guarantee that the generated fine-grained results are different from the original one, because other users cannot share the same user information as the original owner. Thus, if a Web3 metaverse only allows its users to create UGC using MetaCube, the mechanism of 3D Crypto-dropout can guarantee UGC in the metaverse is unique with a high probability. Furthermore, an extreme case can also be achieved if the timestamp is considered as a part of the user information during the model generation using 3D Crypto-dropout. In this case, even the original creators are hard to reproduce their UGC, since the lost time is never found again.

Experiments

As we discussed earlier, the proposed 3D Crypto-dropout is the key technique that guarantees the uniqueness of the generated UGC. In this section, we will study the performance of the 3D Crypto-dropout, especially the numerical and visual differences between the generated results.

Experimental Settings

Theoretically, thanks to the adaptability of the proposed 3D Crypto-dropout, MetaCube can use various generative models (e.g., GAN, variational autoencoder (VAE) [10], etc.) that receive voxel shapes as input and generate fine-grained voxel, mesh, or cloud point. In this work, we apply DECOR-GAN [8], a state-of-the-art 3D shape detailization method by conditional refinement, as the experimental generative neural network to generate fine-grained 3D models from coarse-grained 3D models, which allows the user to select a generation target (including car, chair, laptop, motor, plane, plant, and table) with a preferred style as a condition to generate a corresponding model. DECOR-GAN was well-trained on ShapeNet [11], and its open-source codes and models are utilized for our experiments.

Setting Crypto-Dropout in Different Layers

In this subsection, we will evaluate the performance when setting Crypto-dropout in different convolutional layers. In fact, the difference between the generated models is easy to prove using the numerical method. For example, we can calculate the absolute subtraction value of two model tensors and then calculate their sum. If the sum is not equal to 0, the two models would be different. In our experiment, all generated models are numerically different compared with others. However, the numerical difference cannot provide a macroscopic perception for people to understand, so we intend to compare the similarity of generated models when setting 3D Crypto-dropout in different convolutional layers.

In this experiment, we utilize two different Ethereum addresses as the different user information for 3D Crypto-dropout. Then we build 10 models for car, chair, laptop, motor, plane, plant, and tablet, and randomly select 10 styles to generate fine-grained models when setting 3D Crypto-dropout in "Conv1" to "Conv8" layer respectively. Thus, 100 pairs of fine-grained models for each Crypto-dropout layer are created, totally $7 \times 10 \times 10 \times 8 = 5600$ pairs of models. Then we calculate the intersection over union (IoU) of a pair of models as their similarity. For one category of each Crypto-dropout layer, the mean similarity value of 100 pairs of models is presented as the experimental result.

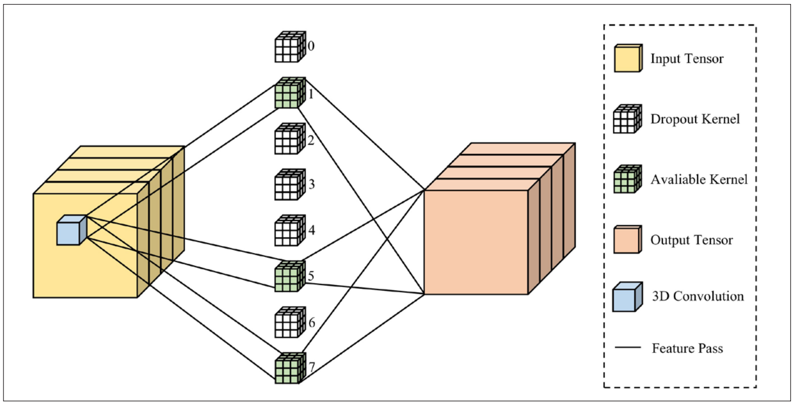

FIGURE 3. Crypto-dropout in A 3D convolutional layer.

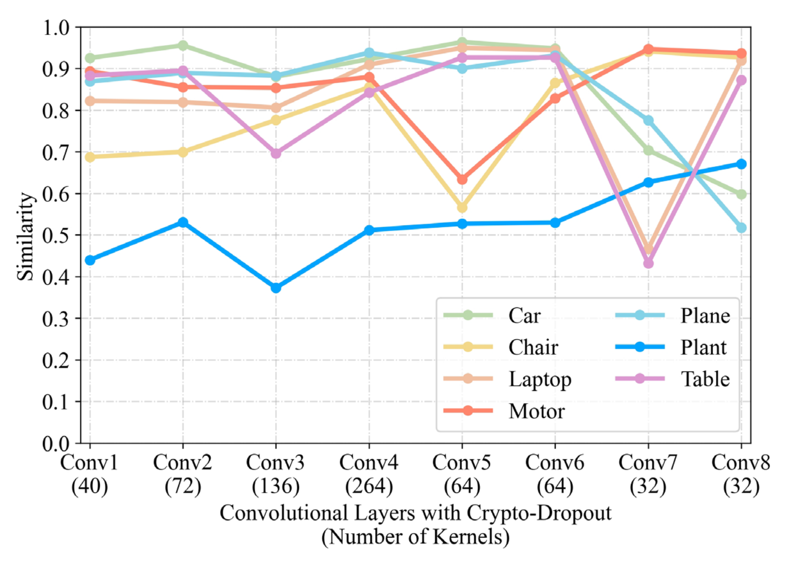

FIGURE 4. Similarity of generated results when setting Crypto-dropout in different convolutional layers.

A line chart is drawn in Fig. 4 to illustrate the similarity fluctuation of different generation targets when setting 3D Crypto-dropout in different convolutional layers. In this figure, the convolutional layers are numbered according to Fig. 1 (from "Conv1" to "Conv8"), and the numbers of kernels for each layer are annotated in the brackets. Note that, the "Conv0" layer was avoided since the dropout of this layer would influence the semantic understanding of the neural network.

As shown in Fig. 4, according to the trend of chair, motor, table, and laptop, there are apparent drops when setting 3D Crypto-dropout in "Conv5" and "Conv7," which seems unstable compared with the results of other layers. As shown in Fig. 1, we can find that "Conv5" and "Conv7" are transposed 3D convolution (also known as deconvolution [12]). Therefore, we consider that the transposed 3D convolution may not be suitable for setting Crypto-dropout. Besides, the experimental results also show that different target categories have different responses when applying 3D Crypto-dropout. For example, the similarity of car and plane shows a significant decrease when setting 3D Crypto-dropout close to the output layer, which has a contrary trend compared with motor and chair. Moreover, the similarity of the plant is obviously lower than other lines, which means the plant is more sensitive to 3D Crypto-dropout,

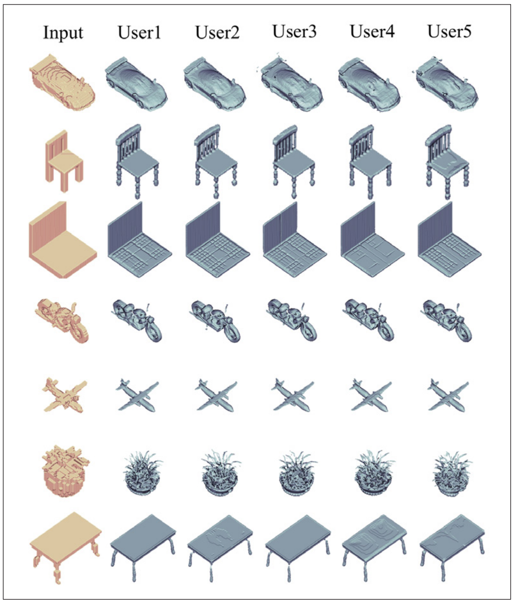

FIGURE 5. Generated results when applying 3D Crypto-dropout by different users.

which can cause more diversity in the generated models.

Overall, we can find that some similarity values of generated models are higher than 0.9, which means they may have very similar visual appearances, because the generation process of DECOR-GAN is conditionally controlled by a specific target and style index. To address this issue, some potential solutions will be discussed below.

On the other hand, the numbers of kernels are another key parameter that would impact the uniqueness of generated models, since more kernels can decrease the probability of hash collision of the Crypto-switches. For example, the length of Crypto-switches when setting 3D Crypto-dropout in "Conv4" is 264 bits, so the theoretical probability of hash collision of "Conv4" is significantly lower than "Conv8" (32 bits). Therefore, in implementing MetaCube, we apply 3D Crypto-dropout to "Conv4" to better guarantee the uniqueness of generated results with a low probability of hash collision.

Applying Crypto-Dropout by Different Users

In this subsection, we will illustrate some representative examples and discuss the different appearances of generated results from a human-centered perspective. In this experiment, we utilize some coarse-grained voxel to generate fine-grained models with "Conv4" as the Crypto-dropout layer. Specifically, we fix the coarse-grained input models and change the user information using 5 different Ethereum addresses to generate fine-grained models. As shown in Fig. 5, we visualize some representative cases for each category. Zooming in on the rendered image, we can find some details that can be utilized to distinguish the uniqueness of each model.

Texture: The texture difference of the generated models seems intuitive for people to distinguish. For example, the laptop is an excellent case to show the texture difference, in which the generated models show evident diversity on their generated "keyboard." Also, at the bottom of Fig. 5, different decorative patterns on the table models are generated by different users. On the contrary, the texture difference of car, motor, and plane are relatively hard to be perceived. For instance, there are some subtle texture differences on the wings of the plane models.

Shape: Although the generated models share very similar shapes, we can still find some detailed points to distinguish the models. For example, the heads of the generated car models are different. Specifically, the models of "User3" and "User4" have a round front bumper, but the "User1" and "User5" seem sharper. The plant models are more distinguishable than other categories if we carefully check the density and direction of their leaves. For instance, the plant model of "User4" seems to have more leaves than the model of "User3." The generated flowerpots of plant models are also different, for example, the flowerpot of "User4" is round, but the flowerpots of "User1," "User2," and "User5" have a gap on the right bottom.

Size: In some cases, the composition of generated models also shows different sizes. For example, about the chair models, we can notice that the legs of the chairs have different diameters and shapes, in which the models of "User2" and "User4" can intuitively show the difference. Moreover, the back of the chairs has different intervals, for example, from the rendering of "User3," we can find that the back of the chair blocks the background light, while others do not. Looking at the plant, the generated model of "User4" has longer and wider leaves compared with the nearby two plant models.

In fact, the illustration images are only renderings of the generated model from a single perspective, but the difference is much easier to be distinguished by looking around their 3D visualization. Overall, the difference between generated models with 3D Crypto-dropout can be perceived from a human-centered perspective, which could better fulfill the users' psychological needs of their UGC uniqueness.

Challenges and Open Research Topics

According to our experimental results, the proposed UGC editor MetaCube with 3D Crypto-dropout can effectively guarantee the uniqueness of UGC in the Web3 metaverse. However, this solution is not a perfect method, so we raise three representative challenges and promising research topics that are worthy of further study.

Better Guaranteeing the Uniqueness

The core motivation of the proposed 3D Crypto-dropout is based on the feature of the hash function: it has a very low probability of finding a new input that can obtain the identical hash value for a hash function. Therefore, the Crypto-dropout can theoretically guarantee that the Crypto-switches generated by different users are different, so the corresponding dropped neurons/layers/kernels are unique for each user.

In fact, compared with other modules, the dropout technique has a special advantage that it can easily achieve one-by-one mapping with the hash value generated by encoding the user information, while other modules need numerical methods to achieve approximate one-by-one mapping. For example, for a hash value, the impact of every bit is equal, which means there is not one bit of a hash value that is more important than others. However, something is different when we use a hash value to control the activation of neural network models. To the best of our knowledge, the deep neural network is still a block box that is hard to explain [13]. In recent years, some researchers have found that different neurons/layers/kernels play different roles in neural networks [14], so the impact of the neurons/layers/kernels is highly different.

According to the aforementioned characteristic of neural network models, there might be some dropped neurons/layers/kernels that have less impact on the generated results. An intuitive and potential solution to better guarantee the uniqueness of UGC is to apply Crypto-dropout to multiple layers rather than only one layer, but this method may also lead to poor generated results if a large number of necessary neurons/layers/kernels are dropped. Another potential solution is to filter some neurons/layers/kernels that control the appearance (texture, shape, size, etc.) rather than the semantic information for Crypto-dropout, while the co-adaptation of the neurons/layers/kernels might also cause unexpected influence on the generated results. Therefore, how to reasonably apply Crypto-dropout is a promising research topic for better guaranteeing the uniqueness of UGC.

Enhancing the Visual Difference by Style Control

Previously, we discussed the experimental results of 3D Crypto-dropout generated by different users from a human-centered perspective. However, although the uniqueness can be guaranteed by the 3D Crypto-dropout, the subtle visual difference may not satisfy the psychological needs of users.

Motivated by the significant performance of StyleGAN [15], the state-of-the-art generative models usually have a latent code to control the style of generated results. The applied DECOR-GAN [8] also provides an 8-dimensional latent code for style control, as shown in Fig. 1. In this article, we also conduct a preliminary experiment to control the latent code for changing the generated results using Crypto-dropout. Specifically, we reshape a 64-bit Crypto-switches to 8×8 and multiply it with the style codes trained by ShapeNet [11].

Some generated results are shown in Fig. 6. In this figure, it is easier to perceive the visual difference even if we do not zoom in on the rendered images. We can find that the generated models of chair and plant are complete, and the differences between these models are distinguishable. However, there are also some undesirable results that seem incomplete, as shown in the red box of Fig. 6. Moreover, some cases seem to have extra noise, for example, the planes of "User3" and "User4" in the blue box of Fig. 6 have apparent noise around the models.

The reason for incompleteness and noise is that the latent code with Crypto-dropout may fall out of the learned latent space, which results in weird output. We further conduct experiments by assigning average weights according to the column sum of the 8×8 Crypto-switches matrix. We can find that the obvious incomplete screen and noise around the plane can be effectively alleviated, which means some numerical methods can be a potential solution to better help the style control

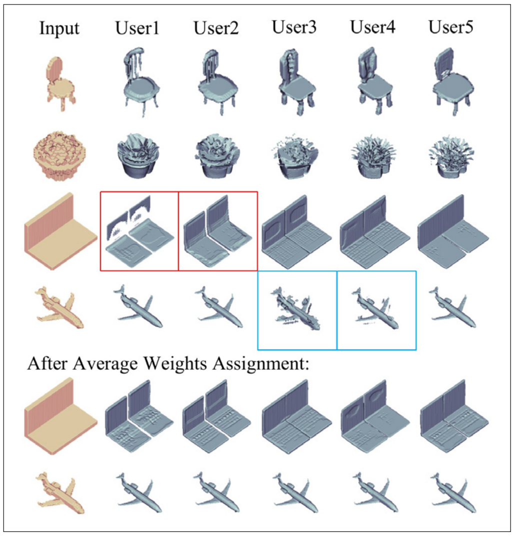

FIGURE 6. Generated results when setting Crypto-dropout in style-control latent space.

with Crypto-dropout.

Improving the Quality of Generated Results

According to the results shown in Fig. 5, most generated models are complete and can be recognized as specific categories. However, the idea of Crypto-dropout is to drop some neurons/layers/kernels according to the Crypto-switches, so the information passed in the generation process must have an inevitable loss due to the dropout. Thus, information loss is a weakness of Crypto-dropout that can be improved.

To solve this problem, a potential solution is to make the dropout procedure smoother. For example, we may assign the weights of the selected neurons/layers/kernels by the Crypto-Switches as their mean value, maximum, minimum, and so on. Moreover, we can also globally choose a neuron/layer/kernel according to some strategies to replace the selected neurons/layers/kernels by the Crypto-Switches. However, the performance of these smooth methods also might cause co-adaptation issues and influence the uniqueness of UGC. Therefore, it is imperative to propose more theoretical supports or practical experiments to improve the quality of generated results while guaranteeing the uniqueness of UGC.

Conclusions

In the future of the Web3 metaverse, the NFT-based UGC will play an increasingly essential role, and how to guarantee the uniqueness of UGC and find a good trade-off between model granularity and modeling difficulty needs to be attached importance seriously. This article proposes MetaCube for Web3 metaverse, a pioneer editor prototype for creating unique UGC using the creators' crypto information. The uniqueness of UGC is guaranteed by the 3D Crypto-dropout technique, a specially designed dropout that can take user information into account using a hash function. We believe the uniqueness problem of UGC in the Web3 metaverse has much space for study by both academia and industry, and our proposed MetaCube is a novel and insightful solution which has considerable potential for further improvement. Specifically, considering the multi-modal input is a promising direction to better help the UGC creators, such as applying Crypto-dropout in text-to-image, text-to-model, and image-to-model methods.

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