MeshAnything V2: Artist-Created Mesh Generation With Adjacent Mesh Tokenization

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https://buaacyw.github.io/meshanything-v2/

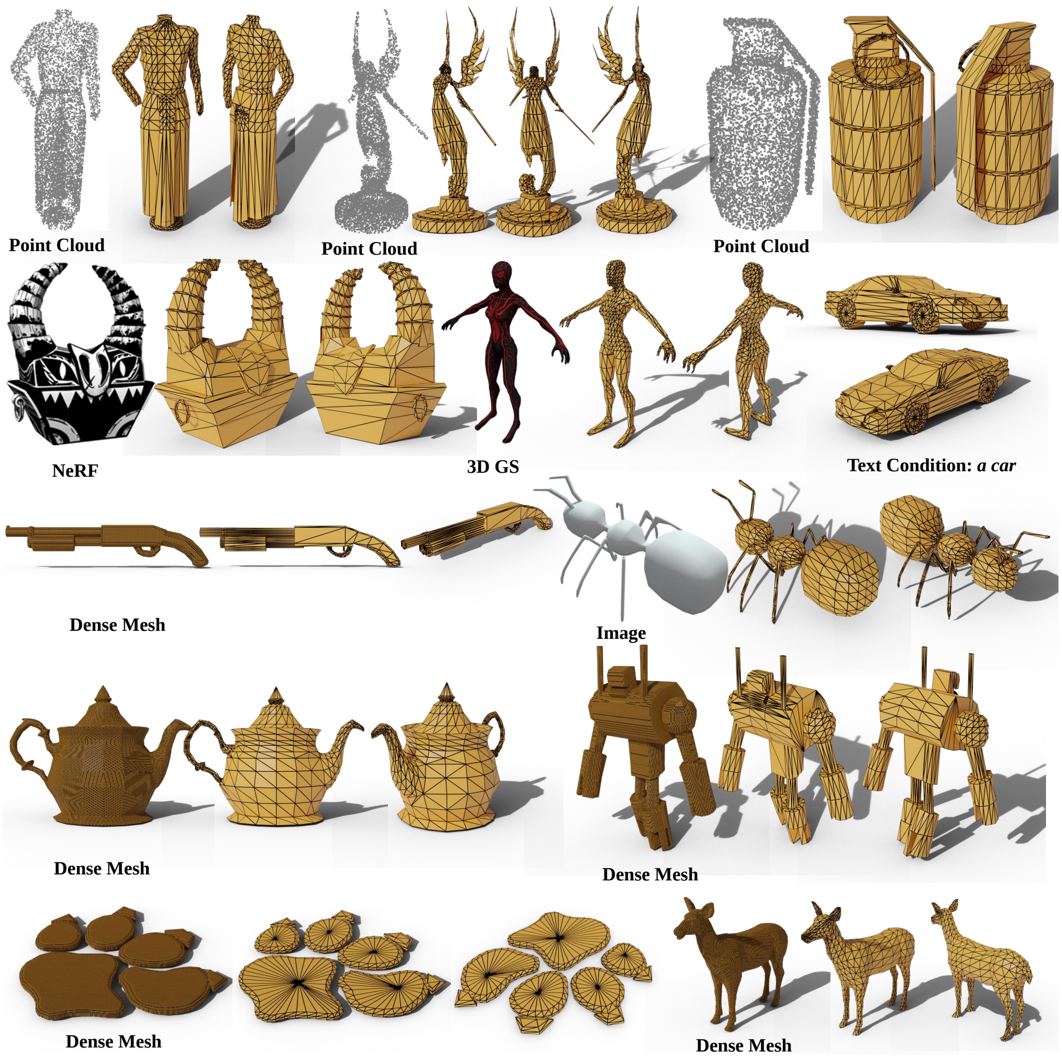

Figure 1: **Equipped with the newly proposed Adjacent Mesh Tokenization (AMT), MeshAnything V2 significantly surpasses MeshAnything (Chen et al., 2024b) in both performance and efficiency.** MeshAnything V2 generates Artist-Created Meshes (AM) up to 1600 faces aligned with given shapes. Combined with various 3D asset production pipelines, it efficiently achieves high-quality, highly controllable AM generation.

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Abstract

We introduce MeshAnything V2, an autoregressive transformer that generates Artist-Created Meshes (AM) aligned to given shapes. It can be integrated with various 3D asset production pipelines to achieve high-quality, highly controllable AM generation. MeshAnything V2 surpasses previous methods in both efficiency and performance using models of the same size. These improvements are due to our newly proposed mesh tokenization method: Adjacent Mesh Tokenization (AMT). Different from previous methods that represent each face with three vertices, AMT uses a single vertex whenever possible. Compared to previous methods, AMT requires about half the token sequence length to represent the same mesh in average. Furthermore, the token sequences from AMT are more compact and well-structured, fundamentally benefiting AM generation. Our extensive experiments show that AMT significantly improves the efficiency and performance of AM generation.

1 Introduction

Due to the controllable and compact advantages of meshes, they serve as the predominant 3D representation in various industries, including games, movies, and virtual reality. For decades, the 3D industry has relied on human artists to manually create meshes, a process that is both time-consuming and labor-intensive.

To address this issue, very recently, a line of work (Nash et al., 2020; Alliegro et al., 2023; Siddiqui et al., 2023; Weng et al., 2024; Chen et al., 2024a;b) has focused on automatically generating Artist-Created Meshes (AMs) to replace manual labor. Inspired by the success of large language models (LLMs), these approaches treat AMs as sequences of faces and learn to generate them with autoregressive transformers (Vaswani et al., 2017) in a manner similar to LLMs. Unlike methods that produce dense meshes in a reconstruction manner, these methods learn from the distribution of meshes created by human artists, thereby generating AMs that are efficient, beautiful, and can seamlessly replace manually created meshes.

Although these methods have achieved some success, they still face significant challenges. One major limitation is that current methods (Nash et al., 2020; Alliegro et al., 2023; Siddiqui et al., 2023; Weng et al., 2024; Chen et al., 2024a;b) cannot generate meshes with a large number of faces. Specifically, the maximum number of faces that can be generated is currently limited to 800. The primary reason for this limitation is the inefficiency of the current tokenization methods. These methods treat a mesh as a sequence of faces, where each face consists of three vertices, and each vertex typically requires three tokens to represent. Consequently, each mesh is tokenized into a sequence nine times the number of its faces, resulting in substantial computational and memory demands. Besides, the resulting token sequence is highly redundant, which harms sequence learning and reduces performance.

This work aims to address this issue. We introduce a novel mesh tokenization method named Adjacent Mesh Tokenization (AMT), which processes meshes into more compact and well-structured token sequences, thereby improving both efficiency and performance. AMT achieves this by representing each face with one vertex instead of three whenever possible. As shown in Fig. 1 and Alg. 1, during the tokenization process, after encoding a face, AMT finds and encodes its adjacent face, which shares an edge, requiring only one additional vertex to represent the adjacent face. When an adjacent face cannot be found, AMT adds a special token & to the sequence to mark this event and restarts from a face that has not been encoded yet. Ideally, because AMT uses only one vertex to represent a face, the sequence length can be reduced to nearly one-third.

To test the effectiveness of AMT, we conducted extensive experiments in the MeshAnything (Chen et al., 2024b) setting. Our experiments on Objaverse (Deitke et al., 2023) demonstrated that AMT can, on average, reduce the sequence length by half, thereby reducing the computational load and memory usage of the attention block by nearly four times. Moreover, the performance of our model also improved due to the compact and well-structured token sequence from AMT. Besides, AMT can also be applied to unconditional or other conditional mesh generation settings (Siddiqui et al., 2023), and its effectiveness is not affected by the use of VQ-VAE (Van Den Oord et al., 2017).

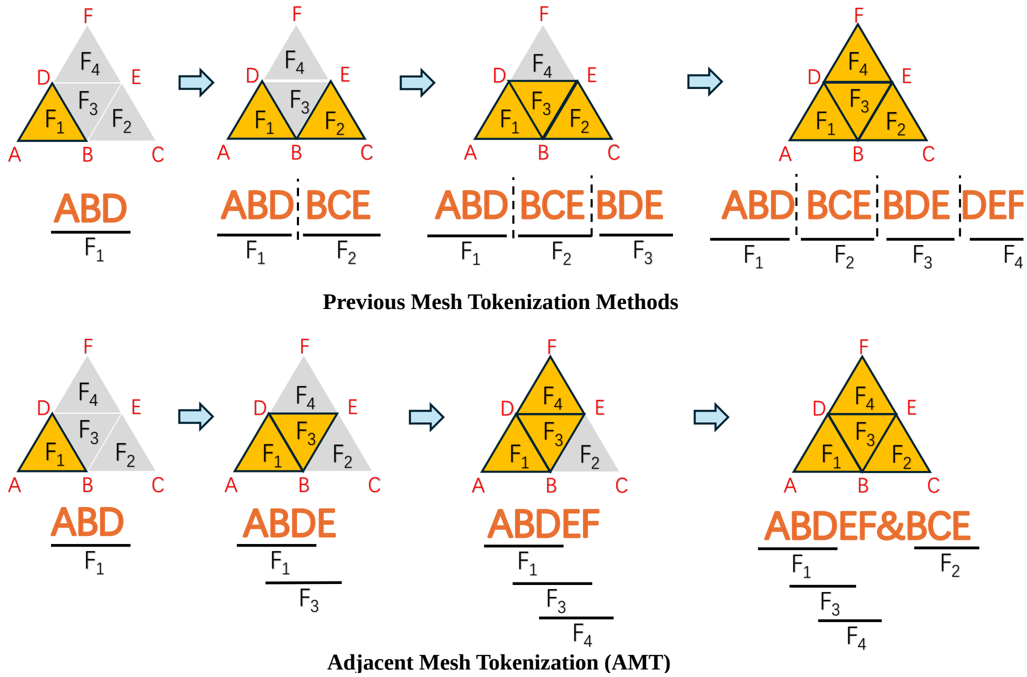

Figure 2: **Illustration of Adjacent Mesh Tokenization (AMT).** Unlike previous methods that use three vertices to represent a face, AMT uses a single vertex whenever possible. When this is impossible, AMT adds a special token & and restarts. Our experiments demonstrate that AMT reduces the token sequence length by half on average. Its compact, and well-structured sequence representation enhances sequence learning, thereby significantly improving both the efficiency and performance of mesh generation.

Additionally, we introduce MeshAnything V2, which is equipped with AMT. V2 increases the maximum face count from 800 to 1600. Thanks to AMT, the performance and efficiency of V2 both significantly outperform its previous version (Chen et al., 2024b). We open-source MeshAnything V2 to the community.

In summary, our contributions are:

1. We introduce a novel mesh tokenization method, named Adjacent Mesh Tokenization (AMT). Compared to previous tokenization methods, AMT requires approximately half the token sequence length to represent the same mesh, thereby fundamentally reducing the computational burden of Artist-Created Mesh generation.
2. We equip MeshAnything with AMT and introduce MeshAnything V2. V2 doubles the maximum number of faces that can be generated while achieving significantly better accuracy and efficiency.
3. Extensive experiments show that AMT significantly improves the efficiency and performance of mesh generation.

2 Related Work

2.1 Artist-Created Mesh Generation

Diverging from previous works that produce dense meshes, recent works have focused on generating meshes created by human artists, i.e., Artist-Created Meshes (AMs) (Nash et al., 2020; Alliegro et al., 2023; Siddiqui et al., 2023; Chen et al., 2024a; Weng et al., 2024; Chen et al., 2024b). These methods process meshes into ordered face sequences and learn to generate this sequence. (Nash et al., 2020) first proposed using autoregressive transformers to sequentially generate vertices and faces. (Siddiqui et al., 2023) use VQ-VAE to learn a mesh vocabulary and then learn this vocabulary

Algorithm 1: Adjacent Mesh Tokenization (AMT)

Input: $\mathcal{M}$: a triangle mesh
Output: A token sequence Seq that represents $\mathcal{M}$
Sort the vertices of $\mathcal{M}$ in ascending order by their coordinates;
Sort the faces of $\mathcal{M}$ in ascending order by their vertex indices;
Initialize an empty token sequence Seq;
Initialize a face list $UnvisitedFaces$ as the faces of $\mathcal{M}$;
Remove the first face from $UnvisitedFaces$;
Append the three vertices of the removed face to Seq;
while $UnvisitedFaces$ *is not empty* **do**
  if *the last token in Seq is "&"* **then**
    Remove the first face from $UnvisitedFaces$;
    Append the three vertices of the removed face to Seq;
  else
    $AdjacentVertices \leftarrow$ vertices adjacent to both the last two vertices in Seq;
    Filter out vertices from $AdjacentVertices$ that form faces with the last two vertices in Seq that are not in $UnvisitedFaces$;
    if $AdjacentVertices$ *is not empty* **then**
      Sort $AdjacentVertices$ in ascending order by their coordinates;
      Append the first vertex in $AdjacentVertices$ to Seq;
    else
      Append "&" to Seq;
return Seq;

with a decoder-only transformer. (Alliegro et al., 2023) differ from other methods by using a discrete diffusion model to generate AMs instead of an autoregressive transformer. (Chen et al., 2024a) propose directly using the discretized coordinates of the vertex as the token index, bypassing the need for VQ-VAE as in (Siddiqui et al., 2023). (Weng et al., 2024) use pivot vertices as a coarse mesh representation and then generate the complete mesh tokens. (Chen et al., 2024b) generate AMs aligned with given shapes, which can be integrated with various 3D asset production methods to convert their results into AMs.

As shown in Fig. 2, all of these methods process meshes into face sequences and use three vertices to represent a single face, resulting in highly redundant representations. Different from these methods, our newly proposed Adjacent Mesh Tokenization (AMT) uses a single vertex to represent a single face, providing a more compact and well-structured mesh representation, thereby significantly improving the efficiency and performance of mesh generation.

2.2 3D Generation

In recent years, 3D generation has gradually become one of the mainstream research directions in the field of 3D research. This area focuses on generating diverse, high-quality 3D assets for the 3D industry. Generative Adversarial Networks (GANs) (Wu et al., 2016; Achlioptas et al., 2018; Goodfellow et al., 2020) produce synthetic 3D data by training a generator and a discriminator network to distinguish between generated and real data. Very recently, a new line of works (Hong et al., 2023; Liu et al., 2024; Shi et al., 2023; Li et al., 2023; Tang et al., 2024; Wang et al., 2024; Tochilkin et al., 2024; Wei et al., 2024; Xu et al., 2024) directly generate 3D assets in a feed-forward manner. (Hong et al., 2023) pioneer these methods and use a transformer to directly regress the parameters of 3D models given conditions. Besides, applying diffusion models (Ho et al., 2020) to directly generate 3D assets has also been widely researched (Zhou et al., 2021; Nichol et al., 2022; Alliegro et al., 2023; Lyu et al., 2023; Liu et al., 2023; Zhang et al., 2024). (Zhang et al., 2024) lead the SOTA of current 3D generation methods by first generating high-quality 3D shapes with DiT and then producing detailed textures with material diffusion models.

As mesh is a crucial component in 3D generation, Artist-Created Mesh Generation (Nash et al., 2020; Alliegro et al., 2023; Siddiqui et al., 2023; Chen et al., 2024a; Weng et al., 2024; Chen et al., 2024b) is closely related to 3D generation. However, it differs significantly from previous 3D generation methods as it mainly focuses on sequence learning, which is rarely seen in other 3D generation methods, to produce high-quality mesh topology.

3 Method

3.1 Adjacent Mesh Tokenization

In this section, we detail Adjacent Mesh Tokenization (AMT), a novel tokenization method for Artist-Created Mesh (AM) generation. Compared to previous methods, AMT processes the mesh into a more compact and well-structured token sequence by representing each face with a single vertex whenever possible. For simplicity, we describe AMT on triangle mesh. But it is worth noting that AMT can be easily generalized to the generation of meshes with variable polygons.

Tokenization is a crucial part of sequence learning, as it processes various data formats, such as text, images, and audio, into token sequences. The processed tokens are then used as ground truth inputs for training the sequence model. During inference, the sequence model generates a token sequence that is subsequently detokenized into the target data format. Therefore, tokenization plays a vital role in sequence learning, determining the quality of the data sequence that the sequence model learns from.

We first illustrate the tokenization methods used in previous methods (Nash et al., 2020; Alliegro et al., 2023; Siddiqui et al., 2023; Chen et al., 2024a; Weng et al., 2024; Chen et al., 2024b). Although there are slight differences in detail, the previous tokenization methods can be unified as follows: Given a mesh $\mathcal{M}$, vertices are first sorted in ascending order based on their z-y-x coordinates, where z represents the vertical axis. Next, faces are ordered by their lowest vertex index, then by the next lowest, and so on. The mesh is then viewed as an **ordered** sequence of faces:

$$\mathcal{M} := (f_1, f_2, f_3, \ldots, f_N), \tag{1}$$

where f_i represents the i-th face in the mesh, and N is the number of faces in $\mathcal{M}$.

Then, each f_i is represented as an ordered sequence of three vertices v:

$$f_i := (v_{i1}, v_{i2}, v_{i3}), \tag{2}$$

where v_{i1}, v_{i2}, and v_{i3} are the vertices that form the i-th face f_i in the mesh. It is worth noting that v_{i1}, v_{i2}, and v_{i3} have already been sorted and have a fixed order.

Substituting Equation equation 2 into Equation equation 1 gives:

$$\mathcal{M} := ((v_{11}, v_{12}, v_{13}), (v_{21}, v_{22}, v_{23}), \ldots, (v_{N1}, v_{N2}, v_{N3})) = \text{Seq}_V \tag{3}$$

Due to the sorting, the resulting Seq_V is unique and its length is three times the number of faces in the mesh. It is evident that Seq_V contains a significant amount of redundant information, as each vertex appears as many times as the number of faces it belongs to.

To resolve this issue, we propose Adjacent Mesh Tokenization (AMT) to obtain a more compact and well-structured Seq_V than previous method. Our key observation is that the main redundancy of Seq_V comes from representing each face with three vertices as in equation 2. This results in vertices that have already been visited appearing redundantly in Seq_V. Therefore, AMT aims to represent each face using only a single vertex whenever possible. As shown in Fig. 2 and Alg. 1, AMT efficiently encodes adjacent faces during tokenization, using only one additional vertex. When no adjacent face is available, as illustrated in the last step of Fig. 2, AMT inserts a special token & into the sequence to denote this event and restarts the process from a face that has not yet been encoded. To detokenize, simply reverse the tokenization algorithm as described in Alg. 1.

In the ideal case, where the special token "&" is rarely used, AMT can reduce the length of Seq_V obtained by previous methods to nearly one-third. Of course, in extreme cases, such as when each face in the mesh is completely disconnected from others, AMT performs worse than previous methods. However, since the datasets Deitke et al. (2023); Chang et al. (2015) used for AM generation are created by human artists, the meshes generally have well-structured topologies. Thus, the overall performance of AMT is significantly better than previous methods. As shown in Sec. 4.3, on the Objaverse test set, AMT can reduce the length of Seq_V by half on average.

Discussion on Sorting in Mesh Tokenization. Both previous methods and AMT initially sort the vertices and faces of the mesh. The primary goal is to process the mesh data into a sequence with a fixed pattern, making it easier for the learning of the sequence model. In AMT, to maintain this design, we consistently choose the face with the earlier index in the sorted list whenever there are multiple choices. Besides, thanks to this design, the token sequence processed by AMT is unique for each mesh. Additionally, AMT prioritizes visiting adjacent faces whenever possible. In contrast, previous methods naively follow the sorted order, often resulting in token sequences where spatially distant vertices are adjacent in the sequence, potentially increasing sequence complexity. As shown in Sec. 4.3, compared to previous methods, AMT demonstrates significant advantages in both speed and memory usage, as well as improved accuracy, proving that the sequences generated by AMT are more compact and well-structured.

Discussion on AMT and the use of VQ-VAE. After obtaining Seq_V, mesh generation methods then need to process it into a token sequence for sequence learning. (Siddiqui et al., 2023) propose to train a VQ-VAE (Van Den Oord et al., 2017) to achieve this. They take Seq_V as input and learn a vocabulary of geometric embeddings with the VQ-VAE. After training the VQ-VAE, they then use the VQ-VAE's quantized features as the input for the transformer (Vaswani et al., 2017). Very recently, (Chen et al., 2024a) proposed another method to process Seq_V into a token sequence. They discard VQ-VAE and directly use the discretized coordinates of the vertex as the token index. It is important to emphasize that whether or not VQ-VAE is used does not affect AMT's effectiveness. This is because AMT operates before the aforementioned methods. For example, in the case of using VQ-VAE, AMT first shortens the Seq_V that represents $\mathcal{M}$, and the shortened Seq_V is then quantized into an embedding sequence with the VQ-VAE.

3.2 MeshAnything V2

In this section, we introduce MeshAnything V2. It is equipped with AMT and scales up its maximum generated face count from 800 to 1600. Without increasing the number of parameters, MeshAnything V2 achieves shape conditioned Artist-Created Mesh (AM) generation with significantly better performance and efficiency. We also use it as an example to demonstrate how AMT can be applied to mesh generation.

Following (Chen et al., 2024b), MeshAnything V2 also targets generating AMs aligned to a given shape, allowing integration with various 3D asset production pipelines to achieve highly controllable AM generation. That is, we aim to learn the distribution: $p(\mathcal{M}|\mathcal{S})$, where $\mathcal{M}$ represents the AM and $\mathcal{S}$ represents the 3D shape condition.

As in (Chen et al., 2024b), V2 uses point clouds as the shape condition input $\mathcal{S}$. We also use the same point cloud–Artist-Created Mesh data pairs $(\mathcal{M}, \mathcal{S})$ collected in (Chen et al., 2024b). The target distribution $p(\mathcal{M}|\mathcal{S})$ is learned with a decoder-only transformer with the same size and architecture as in (Chen et al., 2024b). To inject $\mathcal{S}$ into the transformer, we first encode it with a pretrained point cloud encoder (Zhao et al., 2024) into a fixed-length token sequence $\mathcal{T}_S$ and then set it as the prefix of the transformer's token sequence. We then process paired $\mathcal{M}$ into mesh token sequence $\mathcal{T}_M$. It is concatenated to the point cloud token sequence as the transformer's ground truth sequence. After training the transformer with cross-entropy loss, we input $\mathcal{T}_S$ and let the transformer autoregressively generate the corresponding $\mathcal{T}_M$, which is then detokenized into $\mathcal{M}$.

The key difference between (Chen et al., 2024b) and our method is the way we obtain $\mathcal{T}_M$. Instead of the naive mesh tokenization method used in (Chen et al., 2024b), we process $\mathcal{M}$ with the newly proposed Adjacent Mesh Tokenization (AMT) and obtain a more compact and efficient sequence Seq_V. Following (Chen et al., 2024a), we discard the VQ-VAE and directly use the discretized coordinates from Seq_V as token indices. We then add a newly initialized codebook entry to represent the & in the AMT sequence. Finally, we sequentially combine the coordinate token sequence and the special token for & to obtain the mesh token sequence $\mathcal{T}_M$ for transformer input. As mentioned in Sec. 3.1, it is worth noting that whether or not VQ-VAE is used does not affect the application and effectiveness of AMT.

Table 1: **Ablation Study on AMT.** We compare MeshAnything V2 with its variant without AMT. Please refer to Section 4.3 for detailed explanation.

Method	**CD**$\downarrow$ ($\times 10^{-2}$)	**ECD**$\downarrow$ ($\times 10^{-2}$)	**NC**$\uparrow$	**#V**$\downarrow$	**#F**$\downarrow$	**V_Ratio**$\downarrow$	**F_Ratio**$\downarrow$
V2 W.O. AMT	1.454	5.867	0.913	**297.4**	**561.6**	**1.132**	**1.124**
V2	**0.802**	**4.587**	**0.935**	314.7	590.7	1.207	1.192

To facilitate the transformer's learning of the sequence patterns of AMT, in addition to the absolute positional encoding used in (Chen et al., 2024b), we add the following embeddings for Adjacent Mesh Tokenization (AMT): when representing a face with three vertices, we add a specific embedding for the three new vertices; when representing a face with one vertex, we add a different embedding for the single new vertex. Additionally, we provide a distinct embedding for the & token.

4 Experiments

4.1 Implementation Details

The main experimental setting of MeshAnything V2 remains consistent with (Chen et al., 2024b), except we equipped it with the newly proposed Adjacent Mesh Tokenization (AMT). We still use OPT-350M (Zhang et al., 2022) as our autoregressive transformer (Vaswani et al., 2017) and the pre-trained point encoder from (Zhao et al., 2024). We trained on the same combined dataset collected in (Chen et al., 2024b), except this time we used meshes with fewer than 1600 faces as the experiment dataset instead of 800. This resulted in a dataset containing 100K point cloud and mesh pairs. We randomly sampled 2K data samples as the evaluation dataset. To accommodate meshes with more faces, we sampled 8192 points instead of 4096 for each point cloud. Besides, unlike (Chen et al., 2024b), we update the point encoder from (Zhao et al., 2024) during training because we find its accuracy insufficient for handling complex meshes with up to 1600 faces.

MeshAnything V2 is trained with 32 A800 GPUs for four days. The batch size per GPU is 8, resulting in a total batch size of 256.

4.2 Qualitative Experiments

We present the qualitative results of MeshAnything V2. As shown in Fig. 1, MeshAnything V2 effectively generates high quality Artist-Created Mesh aligned to given shapes. When integrated with various 3D assets production pipelines, V2 successfully achieves highly contrabllable AM generation.

4.3 Quantitative Experiments

Averaged Token Sequence Length. We randomly sample $10k$ mesh samples with fewer than 1600 faces from our dataset and tokenize them into token sequences using the previous tokenization method and AMT separately. In transformer Vaswani et al. (2017) learning, a vertex requires several tokens to represent it, whereas the special symbol & only requires one token. Therefore, the loss incurred by AMT when it cannot find the next adjacent face is relatively small. Since three tokens are used to represent a vertex in (Chen et al., 2024b;a) as well as in this paper, we calculate the final input token length for the transformer based on this standard. For each sample, we divide the length of the token sequence obtained by our method by the length obtained by the previous method, and then average the results to determine the average reduction in token sequence length achieved by AMT. Across the aforementioned $10k$ mesh samples, we found this ratio to be 0.4973, indicating that the AMT method significantly reduces length of token sequence. Additionally, this experiment only demonstrates the superiority of the AMT algorithm in shortening sequence length; its more compact and well-structured sequence characteristics also provide further advantages for sequence learning.

Ablation Study. We ablate the effectiveness of AMT by comparing the results of MeshAnything V2 with its variant without AMT. The variant follows exactly the same settings as V2, except that AMT is replaced with naive mesh tokenization as in previous methods (Siddiqui et al., 2023; Chen et al., 2024a;b). This also serves as a fairer comparison with (Chen et al., 2024b), as the original model of (Chen et al., 2024b) was trained on data with fewer than 800 faces rather than 1600. Moreover, (Chen et al., 2024b) is trained on a small total batch size of 64 while we observed a noticeable performance improvement when the batch size was increased to V2's 256.

We follow the evaluation metric settings of (Chen et al., 2024b) to quantitatively assess mesh quality. We uniformly sample $100K$ points from both the ground truth meshes and the generated meshes and compute the following metrics on our 2K evaluation dataset:

- **Chamfer Distance (CD):** Evaluates the overall quality of a reconstructed mesh by computing chamfer distance between point clouds.
- **Edge Chamfer Distance (ECD):** Assesses the preservation of sharp edges by sampling points near sharp edges and corners.
- **Normal Consistency (NC):** Evaluates the quality of the surface normals.
- **Number of Mesh Vertices (#V):** Counts the vertices in the mesh.
- **Number of Mesh Faces (#F):** Counts the faces in the mesh.
- **Vertex Ratio (V_Ratio):** The ratio of the estimated number of vertices to the ground truth number of vertices.
- **Face Ratio (F_Ratio):** The ratio of the estimated number of faces to the ground truth number of faces.

As shown in Table 1, our results indicate that V2 significantly outperforms its variant, demonstrating the effectiveness of AMT. It shows that AMT not only improves training speed and reduces memory pressure but also enhances generation quality. Notably, although V2 and its variant were trained for the same number of iterations, the variant consumed nearly two times the GPU hours of V2. Additionally, the table shows that AMT takes slightly more vertices and faces. A likely reason for this is that the variant's performance is still too weak, and it tends to ignore details and use a simpler topology when representing complex meshes with high face counts. We also observe that both AMT and the variant have vertex and face ratios greater than 1.0, meaning they use more faces on average relative to the ground truth, unlike the results in (Chen et al., 2024b), which were less than 1 (around 0.88). We suspect this is because the dataset for V2 contains more complex meshes with over 800 faces, which causes the model to occasionally produce more complex topologies for simple shapes.

5 Limitations and Conclusion

In this work, we present MeshAnything V2, a shape-conditioned Artist-Created Mesh (AM) generation model that generates AM aligned to given shapes. V2 significantly outperfroms MeshAnything (Chen et al., 2024b) in both performance and efficiency with our newly proposed Adjacent Mesh Tokenization (AMT). Different from previous methods that use three vertices to represent a face, AMT uses a single vertex whenever possible. Our experiments demonstrate that AMT averagely reduces the token sequence length by half. The compact, and well-structured token sequence from AMT greatly enhances sequence learning, thereby significantly improving the efficiency and performance of AM generation.

Limitations. Although there is a large improvement over V1, the accuracy of MeshAnything V2 is still insufficient for industrial applications. More efforts are needed to improve the model's stability and accuracy.

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