Importance-Based Token Merging for Efficient Image and Video Generation

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Abstract

Token merging can effectively accelerate various vision systems by processing groups of similar tokens only once and sharing the results across them. However, existing token grouping methods are often ad hoc and random, disregarding the actual content of the samples. We show that preserving high-information tokens during merging—those essential for semantic fidelity and structural details—significantly improves sample quality, producing finer details and more coherent, realistic generations. To do so, we propose an importance-based token merging method that prioritizes the most critical tokens in computational resource allocation, leveraging readily available importance scores, such as those from classifier-free guidance in diffusion models. Experiments show that our approach significantly outperforms baseline methods across multiple applications, including text-to-image synthesis, multi-view image generation, and video generation with various model architectures such as Stable Diffusion, Zero123++, AnimateDiff, or PixArt-α.

1. Introduction

The rise of powerful diffusion models such as DALL-E [76], Stable Diffusion (SD) [79], or Imagen [80] has dramatically changed the landscape of generative AI [2, 17, 26, 79, 80, 90]. At their core, these models operate by iteratively denoising through multiple passes of a backbone network, processing a substantial number of tokens, which are particularly computationally intensive. To reduce the computational demands, prior work [3, 4, 36] has explored merging similar tokens and sharing the results across member tokens.

However, such a merging process can also significantly degrade image quality, losing some important details and structure. This typically happens when merging occurs in highly informative image regions, where critical visual details are compressed or discarded. One major reason is that existing methods rely on ad hoc heuristics for grouping tokens, often based on spatial proximity or fixed patterns.

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Prompt: "*A cute owl wearing a wizard hat.*"

(a) Spatial [3] (b) Importance-based (Ours)

Figure 1. **Importance-based Token Merging.** Our method prioritizes important tokens during token merging, resulting in images with greater details in essential areas compared to ToMeSD [3]. In the second row, we show the regions (in white) where computation (*e.g.*, attention) will take place after token merging.

Thus, the destination tokens, where the other tokens will merge into, are chosen randomly within predefined regions, sometimes pushing important visual elements into less relevant areas. This leads to suboptimal resource allocation, where crucial textures, edges, or fine-grained structures are lost, while regions that are less important retain more detail than necessary, as can be seen in Fig. 1 (a).

To address this limitation, we propose a novel token selection method that prioritizes computational resources in areas of high visual and semantic importance. Compared to existing approaches, our method ensures more effective merging decisions by using guidance from actual content relevance. Rather than treating all tokens equally, we use per-token importance signals to identify key or salient regions and ensure that the merging procedure prioritizes preserving more important tokens. Note that there are many proxies for importance, such as attention scores, saliency maps, or user-provided bounding boxes, all of which can be integrated into our merging method. Specifically in our case, we point out that an excellent choice is the classifier-free guidance (CFG) [25], as it inherently highlights regions that strongly influence model outputs and is obtainable with no additional cost.

More specifically, instead of merging tokens arbitrarily across the image, we first construct a pool of high-importance tokens. Then, token partitioning is only performed within this pool using a soft-matching strategy. This ensures that the most relevant tokens serve as anchors for merging, preserving key details while also maintaining diversity among the anchor tokens. Doing so facilitates a more efficient allocation of computational resources, preventing redundancy and ensuring that merging decisions are both meaningful and effective. Compared to simply selecting the top-k important tokens—which can lead to redundancy and suboptimal token assignments—our method strikes a balance between relevance and diversity, resulting in more coherent and detailed generations.

We apply our token merging strategy across three key applications: text-to-image generation, multi-view generation, and text-to-video generation, as well as across various model structures such as U-Net or transformers. Compared to baseline methods, our method consistently demonstrates superior performance, delivering results with higher fidelity and significantly improves image details across all tested scenarios.

Our contributions are as follows:

- We propose a novel importance-based token merging paradigm for diffusion models, designed to preserve crucial image content. The importance score can be easily obtained from CFG at no additional cost.
- We design a novel token-partitioning strategy based on a pool of important tokens to improve generation quality.
- Our method achieves state-of-the-art performance across various diffusion model tasks, including text-to-image synthesis, multi-view generation, and video generation, as well as across model architectures including U-Net and transformers.

2. Related Work

2.1. Diffusion Models

Diffusion models [12, 26, 88, 90] are a class of generative models that iteratively transform random noise into complex data structures, such as images, by gradually reversing a diffusion process. In these models, data is progressively corrupted by adding noise, and the model learns to recover the original data through iterative denoising with learned parameters. This approach has demonstrated impressive results in generating high-quality, realistic images [1, 6, 16, 33, 67, 69, 72, 76, 79, 80, 105], videos [2, 5, 17, 39, 84, 114], 3D content [42, 53, 58, 62, 70, 74, 83], and audio [27, 37]. A popular diffusion model architecture is introduced by Stable Diffusion [79], which uses a U-Net with transformer blocks. It first encodes a noisy image as latent tokens, which are processed through transformer blocks comprising self-attention, MLP, and cross-attention layers. This design has been extended for multi-view generation with multi-view attention [83] and for video generation with temporal layers [17]. More recent approaches [6, 114] replace the U-Net with a fully transformer-based architecture for improved scalability.

In diffusion models, classifier-free guidance (CFG) [25] is a technique that enhances fidelity and detail in generation by guiding the model toward conditioned inputs without the need for an external classifier. Recent work [98, 110] suggests a connection between CFG and saliency. Our study advances this by identifying CFG as an indicator of token importance, enabling more effective token merging.

To reduce the cost of diffusion inferences, various techniques have been proposed. Some approaches require retraining, including better model structures [35, 73, 79], model pruning [14], model compression [48, 106, 113], step distillation [18, 54, 68, 81, 82], and consistency regularization [63, 91]. Others avoid retraining, such as improved sampling to reduce inference steps [52, 59, 60, 90], caching [8, 31, 44, 64, 65, 86, 101, 112], model quantization [7, 11, 22, 46, 87, 95], and token reduction [3, 4, 32]. In this work, we focus on improving token reduction. Notably, our method is compatible with other diffusion acceleration techniques, enabling combined use for further speedup.

2.2. Token Reduction

Token reduction [4, 20, 93] decreases the number of tokens to process by pruning or merging them. It is widely applied in tasks such as classification [4, 20, 50, 66], segmentation [34, 103], detection [56], video understanding [10], and large language models [30, 45, 89]. Token pruning methods include removing tokens based on attention scores [15, 20, 50, 57, 100, 102, 104], using the Gumbel-Softmax trick for selective pruning [29, 38, 56, 77, 100], developing sampling methods [15, 107], integrating sparsity in the model [9, 43], and reinforcement learning-based methods [71]. For token merging [4, 19, 40, 78, 92, 97, 103, 115], approaches include bipartite soft matching [3, 4], K-Means [66], K-Medoids clustering [66], and Density-Peak Clustering with K-Nearest Neighbors (DPC-KNN) [108]. Additionally, soft merging methods assign tokens to multiple clusters before merging them [19, 78, 115].

Recent studies have applied token reduction to diffusion model inference [3, 21, 32, 36, 47, 49, 61, 85, 94, 96, 111]. ToMeSD [3] introduced token merging to Stable Diffusion [79] with a training-free method. The typical token merging procedure for diffusion models selects destination tokens from input feature tokens and utilizes bipartite soft matching to merge redundant tokens. The reduced token set is processed by operations like attention, and is then copied back to the merged token locations, ensuring the final token count matches the input. Although this token merging approach performs well, its selection of destination tokens is not optimal, *i.e.*, spatially random across the image. ToFu [36] combines token pruning and merging but still follows similarly suboptimal destination token selection strategy. In our work, we propose that selecting destination tokens based on their importance improves the fidelity and quality in generation, and this importance can be easily obtained via classifier-free guidance without additional cost. AT-EDM [94] uses self-attention maps to derive token importance, but this requires first performing full self-attention and increases peak memory usage. ATC [21] applies bottom-up hierarchical clustering for better token merging, but we show it is costly for generative tasks.

3. Method

We propose a novel importance-based token-merging method, summarized in Fig. 2, allowing for a more efficient allocation of computing resources. We highlight that classifier-free guidance serves as an effective importance indicator. Further, we propose using a dynamic pool of important tokens, where the pool size adapts to the token merging ratio, optimizing resource allocation and reducing redundancy.

Important Tokens. Selecting which tokens to serve as anchors (destination tokens) for merging is critical for generating high-quality content. This is because these tokens correspond to the primary image regions where subsequent computations, such as attention, are applied. In principle, all reliable per token importance signals, such as cross attention maps, user provided bounding boxes, or saliency maps, can be integrated with our method. We find that classifier-free guidance (CFG) [25] serves as an excellent indicator. CFG modifies the noise prediction to improve sample control. It is designed to steer the predicted noise in a direction more aligned with the condition:

$$\tilde{\epsilon}_\theta(\mathbf{x}_t, t) = \epsilon_\theta(\mathbf{x}_t, t) + w \cdot (\epsilon_\theta(\mathbf{x}_t \mid y, t) - \epsilon_\theta(\mathbf{x}_t, t)), \quad (1)$$

where $\epsilon_\theta(\mathbf{x}_t \mid y, t)$ is the noise prediction conditioned on input y, $\epsilon_\theta(\mathbf{x}_t, t)$ is the unconditional noise prediction, and w is the guidance weight. It is widely used in diffusion models and incurs no additional computational cost. For each token, we calculate its importance as the absolute value

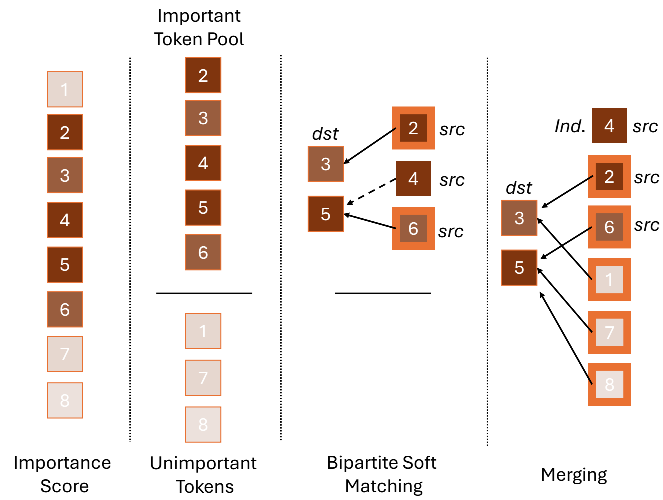


Figure 2. **Overview.** We propose an importance-based token merging method. The importance of each token can be determined using classifier-free guidance. These scores, visualized with colors ranging from light to dark (indicating less to more important tokens), are used to construct a pool of important tokens. We randomly select a set of destination (*dst*) tokens from this pool and the remaining important tokens become source (*src*) tokens. Bipartite soft matching is then performed between the *dst* tokens and *src* tokens. *src* tokens without a suitable match are considered independent tokens (*ind.*). All other *src* tokens and unimportant tokens are merged with the destination tokens for subsequent computational steps.

of its CFG score:

$$\begin{aligned} \text{importance} &= |\epsilon_\theta(\mathbf{x}_t \mid y, t) - \epsilon_\theta(\mathbf{x}_t, t)| \\ &\approx |-\sigma_t \nabla_{\mathbf{x}_t} \log p(y \mid \mathbf{x}_t)|, \end{aligned} \quad (2)$$

where σ_t is the noise scale. The guidance term effectively estimates the gradient of the log-likelihood of the conditioning variable y (e.g., a text prompt) with respect to the noisy sample $\mathbf{x}_t$ [25]. Thus, the CFG magnitude can be interpreted as a saliency or importance measure: tokens with a high CFG magnitude have stronger influences in steering the generation toward satisfying the condition y. In Fig. 3, we provide an example of the resulting importance maps.

Importance-based Token Merging. With the token importance scores, a naive approach is to pick the top-k tokens as destination tokens (*dst*) and merge the rest tokens that are similar to them. However, this approach produces low-quality outputs due to merging inefficiency, as shown in Fig. 4 (a). More specifically, there are two particular issues about this:

1. **Redundancy**. The top-k tokens can be very similar - but all important tokens, leading to redundancy and less intra-variant among the selected destination tokens.
2. **Unimportant Independent Tokens**. In the token merging pipeline, some tokens lack similar destination to-

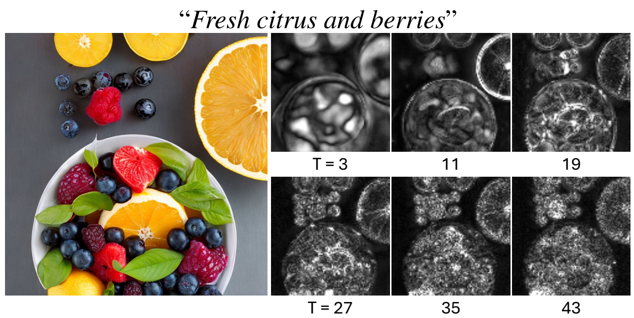


Figure 3. **Importance Maps.** We present token importance maps derived from classifier-free guidance (CFG) across diffusion inference timesteps. These maps highlight areas significantly align with the user prompt. In the early steps, they capture the semantics and structure of the image relevant to the prompt, while in later steps, they focus on finer details of the objects the user intends to generate. The generated image is shown on the left for reference.

(a) Top-k (b) Ours

Figure 4. We compare our method with an approach that uses the top-k important tokens as destination tokens (*dst*) for token merging. The computation locations after token merging are illustrated as non-black pixels in the bottom-right windows. They include locations of *dst* tokens, which are shown in white, and independent tokens (some other tokens that lack a similar *dst* token for merging), which are shown in orange. Our method produces more structured and detailed image, as highlighted in the red box.

kens, making them "independent" and remain unmerged. In the top-k approach, background or irrelevant tokens often become independent due to the absence of suitable matches among the important tokens, as shown in Fig. 4.

To avoid these issues, we propose to first create a pool of the most important tokens and then, ensure that both destination tokens and independent tokens are drawn from this set. To do so, destination tokens are randomly sampled from the pool, while independent tokens are selected as those in the important token pool that are most dissimilar to the chosen destination tokens. This approach ensures that all computations following the merging step operate on important tokens, leading to improved detail preservation, as illustrated in Fig. 4 (b).

To determine the optimal pool size, we adapt it based on the token merging ratio r. Specifically, we set the pool size as $\mathbf{P} = (1-r)\cdot(1+p)$, where p is a hyper-parameter of our method. With a constrained token processing budget, *i.e.*, a high token merging ratio r, the pool size remains small, ensuring the selection of only the most critical tokens. Conversely, with a larger compute budget, the pool size increases, reducing the likelihood of selecting redundant tokens as destination tokens.

Token Merging in Diffusion Inference. At time-step t of the diffusion inference, a diffusion model layer, *e.g.* a transformer layer, takes $\mathbf{N}$ tokens as input. The token merging ratio is r. Based on the token importance derived from the previous timestep's classifier-free guidance, we select the top $\mathbf{K} = \mathbf{N}\cdot(1-r)\cdot(1+p)$ tokens as the important token pool, denoted as $\mathbf{A}$. From $\mathbf{A}$, we randomly pick $\mathbf{D} = \mathbf{N}\cdot k$ tokens to form the destination (*dst*) set. Here, p, k are hyper-parameters. The remaining tokens in $\mathbf{A}$ become the source (*src*) set.

Next, we perform bipartite soft matching by computing pairwise cosine similarities between *src* and *dst* tokens. Each *src* token is linked to its most similar *dst*. Then, in *src* set, we select the top $\mathbf{I} = \mathbf{N}\cdot(1-k-r)$ tokens with the smallest similarity to their closest *dst* tokens to serve as independent tokens. The remaining *src* tokens and unimportant tokens are merged into their corresponding *dst* tokens. The merging is performed via averaging all grouped tokens. After merging, the number of tokens reduces to $\mathbf{I}+\mathbf{D} = \mathbf{N}\cdot(1-r)$ tokens. The diffusion model layer then processes this reduced token set, the merged locations are filled with the corresponding processed *dst* tokens, maintaining the same output shape as the input.

4. Experiments

4.1. Experimental Settings

Text-to-image Generation. We use Stable Diffusion 2 (SD) [79] as the base model, a text-to-image latent diffusion model with a U-Net architecture that generates 768x768 images. Our token merging method is compared to ToFu [36], ToMeSD [3] and ATC [21]. Due to ATC's slow inference (several minutes per image), we only display its visual results. For quantitative comparison, we follow previous studies [1, 76, 80, 105] and report FID [24] and CLIP scores [23, 75] for zero-shot image generation on the MS-COCO 2014 validation dataset [51], with 30K randomly sampled image-caption pairs.

We also experiment with a diffusion transformer, PixArt-α [6], for text-to-image generation. We compare our method with ToMeSD and similarly evaluate on the MS-COCO dataset. Unless otherwise stated, "text-to-image" in this paper refers to generation based on Stable Diffusion.

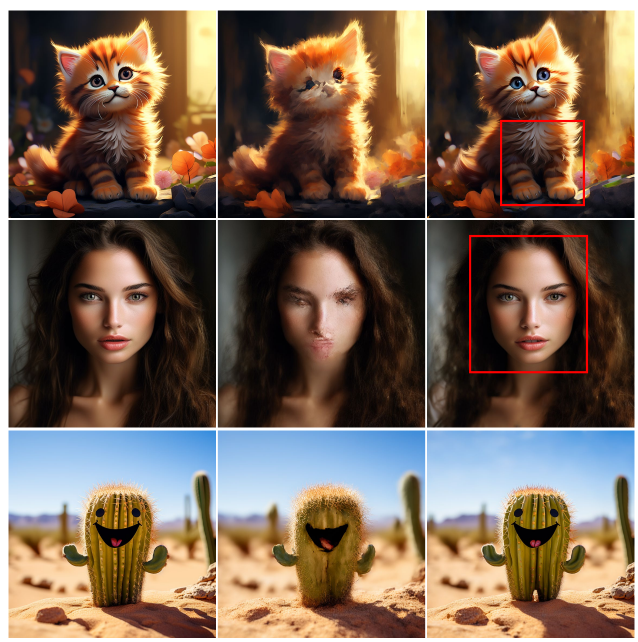
(a) SD [79] $\sim$ 8s (b) ATC [21] $\sim$ mins (c) ToFu [36] $\sim$ 5s (d) ToMe. [3] $\sim$ 5s (e) Ours $\sim$ 5s

Figure 5. **Qualitative comparison of text-to-image generation.** The first column shows results from Stable Diffusion (SD) [79], while the subsequent columns show SD combined with various token merging methods. As highlighted in red boxes, our approach consistently produces finer details with coherent structures. Note that ATC requires minutes to generate an image, whereas other methods, including ours, complete the task in seconds. The token merging ratio is 0.7. Please see the supplementary for prompts. Best viewed with zoom-in.

Multi-view Diffusion. We use Zero123++ v1.2 [83] as the base model. Zero123++ is an image-conditioned multi-view latent diffusion model that generates six novel views at a resolution of 320×320. We compare our method to ToMeSD. Following evaluation protocols of prior work [55, 58], we test on GSO dataset [13], which comprises 30 everyday objects, and compute PSNR, SSIM [99], and LPIPS metrics [109] to evaluate the similarity between the generated images and ground truth. We also include visual comparisons using in-the-wild images as input.

Video Diffusion. We adopt AnimateDiff v3 [17] as the base model, which adds temporal attention layers to turn the text-to-image model, *i.e.* Stable Diffusion, into a video diffusion model. This model generates 16-frame videos at a resolution of 512×512. We compare our token merging method with ToMeSD and evaluate using VBench [28]. We report the semantic, quality, and total scores from VBench. The semantic score assesses alignment between the generated videos and the user prompt, focusing on entity types, attributes, and styles. The quality score evaluates the temporal consistency and visual quality of the generated videos.

Other Metrics. We report TFLOPs, latency, and GPU memory usage, with and without memory-efficient atten-



(a) PixArt-α [6] (b) ToMeSD [3] (c) Ours

Figure 6. **Token merging for diffusion transformer.** We apply ToMeSD [3] and our method to PixArt-α [6] with a merging ratio of 0.3. Detailed generations are highlighted with red boxes. Best viewed with zoom-in. Please see the supplementary for prompts.

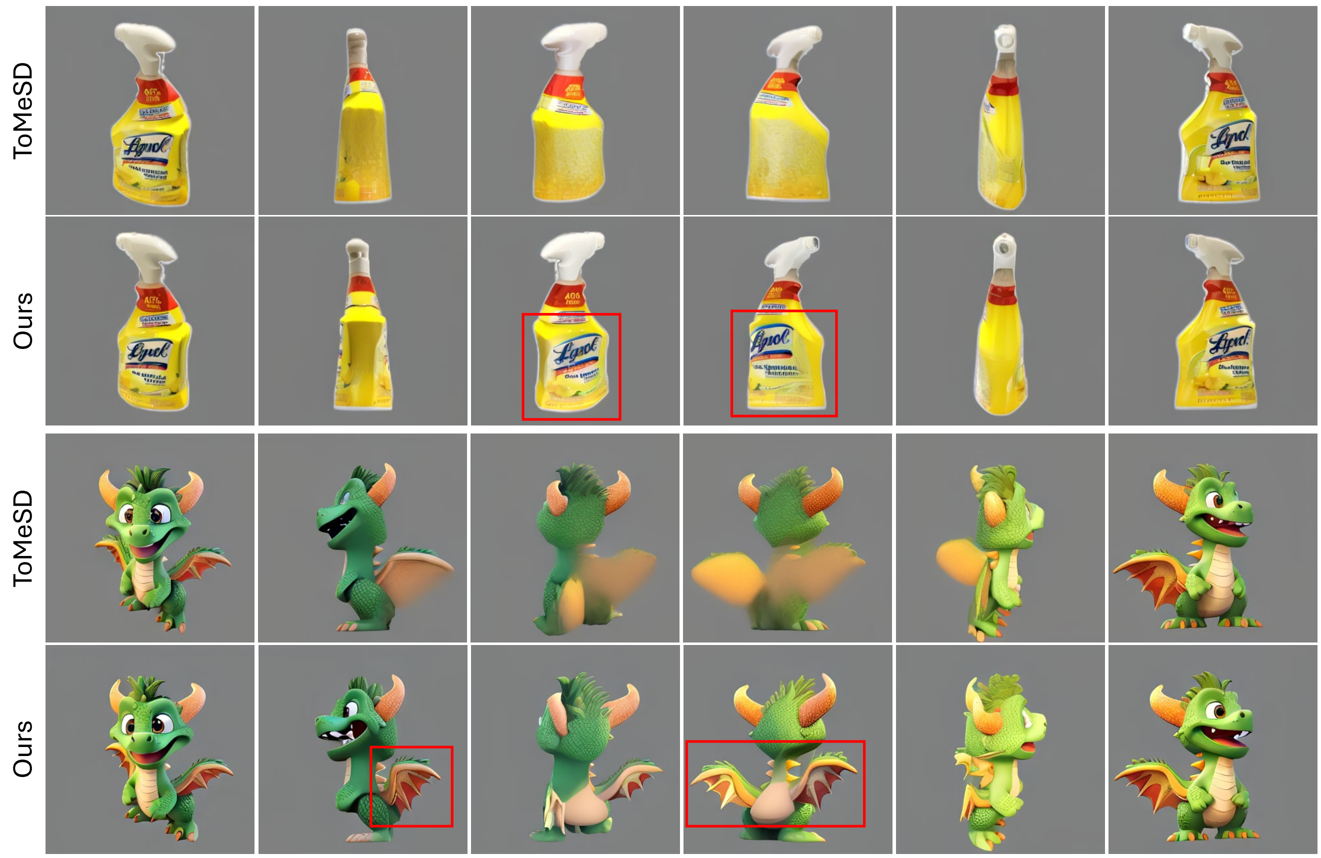


Figure 7. **Qualitative comparison of multi-view diffusion.** We apply ToMeSD [3] and our token merging method to the multi-view diffusion model. We use Zero123++ [83] as the base model and a merging ratio of 0.6. Our method outputs finer details, as highlighted in red boxes. Best viewed with zoom-in. Please refer to the supplementary for input images.

tion [41], on an NVIDIA A5000 GPU. Inference uses float16 precision. We estimate TFLOPs for a single diffusion sampling step. For latent diffusion models, the inference cost is measured exclusively in the latent space.

Implementation Details. For text-to-image synthesis with Stable Diffusion [79], we merge tokens in the self-attention layers of the first and last model blocks, similar to ToMeSD [3]. For PixArt-α [6], we apply token merging to self-attention and cross-attention in the middle half of the model layers (7–20 out of 28) for simplicity. For multi-view diffusion, we merge tokens in the self-attention layers of the first two and last two blocks of Zero123++ [83]. For video diffusion, we merge tokens in the first and last blocks of AnimateDiff [17]. The hyper-parameter p, which determines the size of our important token pool, is set to 0.4, 0.6, and 0.8 for image, multi-view, and video generation tasks, respectively. The number of destination tokens (k) remains consistent across all tasks and follows the setting used in ToMeSD, utilizing 25% of the total tokens.

4.2. Results

In Tab. 1 and Fig. 5, we compare different token merging methods applied to Stable Diffusion 2 [79] for text-to-image generation. Our method consistently outperforms baselines, especially at higher token merging ratios (r). For example, at $r = 0.75$, our method achieves an FID of 17.75 versus ToMeSD [3]'s 20.89. Agglomerative Token Clustering (ATC) [21] is not included due to its prohibitive computational cost, as it is CPU-bound and non-batched, making it impractical for large-scale evaluations. Notably, our method also performs well when used with cross-attention maps (Sec. 4.3). When the merging ratio is small, such as 0.3, our important token pool becomes the whole token set, making it functionally equivalent to ToMeSD.

In Tab. 2 and Fig. 6, we show our method significantly outperforms ToMeSD when applied to a diffusion transformer, achieving an FID improvement of 17–48%. This highlights the generalizability of our approach. In Tab. 3, we compare ToMeSD and our token merging method in the context of multi-view diffusion. Our importance-based token merging method consistently shows improved perfor-

r	FID ↓			CLIP ↑		
	ToFu	ToMe.	Ours	ToFu	ToMe.	Ours
0	-	-	11.88	-	-	31.83
0.30	13.48	12.20	12.20	31.82	31.82	31.82
0.50	15.81	13.50	**13.42**	31.81	31.79	**31.83**
0.60	17.32	14.81	**14.51**	31.81	31.80	**31.81**
0.70	18.94	17.46	**16.22**	31.78	31.78	**31.79**
0.75	19.29	20.89	**17.75**	31.76	31.71	**31.76**

Table 1. **Text-to-image generation.** We apply ToFu [36], ToMeSD [3] and our token merging method to Stable Diffusion [79] across various token merging ratios r.

r	FID ↓		CLIP ↑		Latency (s) ↓
	ToMe.	Ours	ToMe.	Ours	
0	27.51		31.30		9.14
0.3	34.23	**28.50**	30.76	**31.05**	8.96
0.5	65.46	**34.02**	29.85	**30.68**	7.54
0.7	95.46	**50.76**	28.67	**29.93**	7.14

Table 2. Comparison of our method with ToMeSD [3] when applied to the diffusion transformer PixArt-α [6].

r	PSNR ↑		SSIM ↑		LPIPS ↓	
	ToMe.	Ours	ToMe.	Ours	ToMe.	Ours
0.40	14.80	**14.82**	0.775	**0.777**	0.260	**0.259**
0.60	14.71	**14.85**	0.782	**0.783**	0.272	**0.263**
0.70	14.18	**14.80**	**0.787**	0.785	0.302	**0.274**
0.75	13.12	**14.58**	**0.789**	0.784	0.349	**0.283**

Table 3. **Multi-view diffusion.** We compare ToMeSD [3] with our token merging method when applied to Zero123++ [83].

mance over ToMeSD, especially at higher merging ratios. At $r = 0.75$, our method achieves a significant improvement in PSNR (14.58 vs. 13.12) and a much lower LPIPS (0.283 vs. 0.349), highlighting its ability to maintain high output quality even under aggressive token compression. Qualitative examples in Fig. 7 further validate this, showcasing finer geometrical and textual details in the objects generated by our method. A similar trend can be observed in Tab. 4 and Fig. 8, where we extend the comparison to video diffusion. Across these tests, our method consistently performs better than ToMeSD, both in numerical metrics and in visual quality, particularly in preserving object details. We observed that merging tokens in the temporal layers significantly reduces the generated dynamics. Nonetheless, we present results with token merging applied for both spatial and temporal layers in Tab. 5.

r	Semantic ↑		Quality ↑		Total ↑	
	ToMe.	Ours	ToMe.	Ours	ToMe.	Ours
0.40	75.40	75.40	81.69	81.69	80.44	80.44
0.60	74.03	**74.51**	81.58	**81.75**	80.07	**80.30**
0.70	72.03	**73.23**	**81.52**	81.23	79.62	**79.63**
0.75	69.67	**71.58**	80.82	**81.00**	78.59	**79.12**

Table 4. **Video diffusion (spatial).** Token merging applies on only spatial attention layers of AnimateDiff [17] with various token merging ratios r. We compare our method and ToMeSD [3] with VBench scores [28].

	Semantic ↑	Quality ↑	Total ↑
ToMeSD	72.71	81.35	79.62
Ours	**73.52**	**81.69**	**80.06**

Table 5. **Video diffusion (spatial and temporal)**. Token merging applies on both spatial and temporal attention layers of AnimateDiff [17] with a spatial merging ratio of 0.7 and a temporal merging ratio of 0.2. We report VBench scores [28] of our method in comparison to ToMeSD [3].

r	Latency (s)		Memory (GB)	TFLOPs
	ToMeSD	Ours		
0	8.5 (5.3)		7.63 (3.16)	4.30
0.3	8.0 (5.0)	8.0 (5.0)	5.20 (3.16)	3.83
0.5	6.0 (4.7)	6.1 (4.8)	4.05 (3.16)	3.55
0.7	5.7 (4.5)	5.8 (4.5)	3.55 (3.16)	3.36

Table 6. Comparison of inference costs when applying our token merging method and ToMeSD [3] to Stable Diffusion 2 [79]. Numbers in parentheses indicate measurements when memory-efficient attention [41] is enabled.

Inference Costs. We compare the inference costs of our method and ToMeSD when applied to Stable Diffusion 2 in Tab. 6. As can be seen, both methods show similar improvements in inference times, GPU usage, and TFLOPs. This demonstrates that our token merging strategy can enhance performance without incurring additional costs.

4.3. Ablation Study

We conduct ablation studies on the text-to-image generation task to examine alternative design choices in our method. As shown in Tab. 7, simply using top-k important tokens as destination tokens leads to worse results. Furthermore, not choosing independent tokens exclusively from the important set (w/ global *ind.*), leads to a performance drop.

Cross-Attention Maps for Token Importance. In principle, our method can be used with any per-token importance scores. As shown in Tab. 8, we use our method with

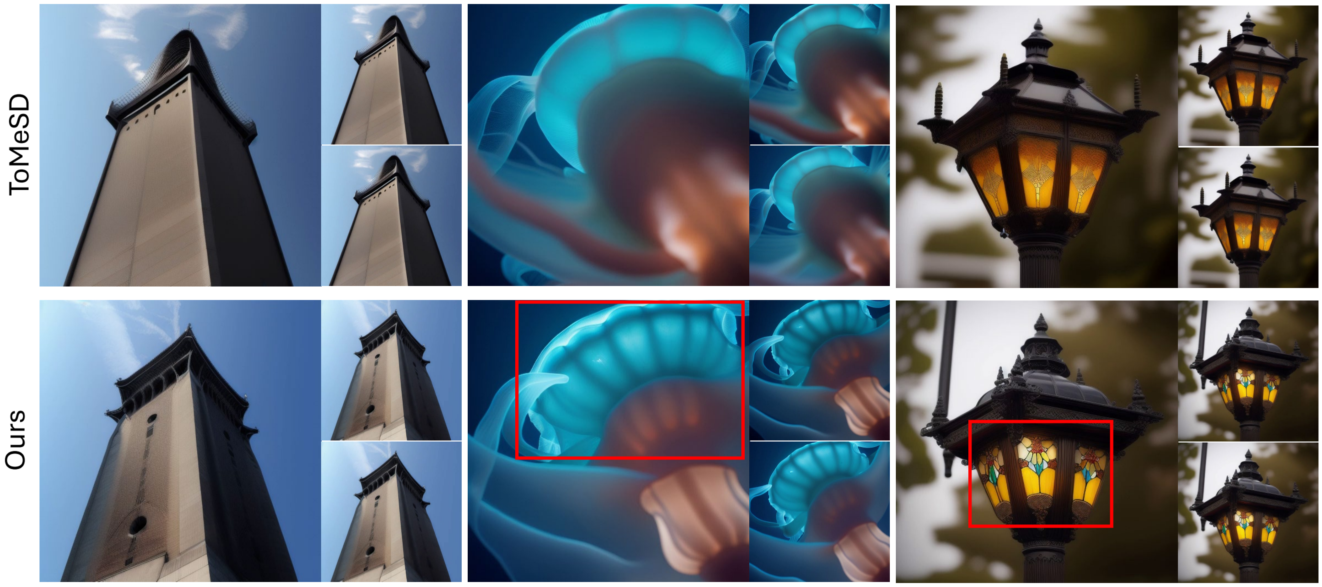


Figure 8. **Qualitative comparison of video diffusion.** We apply ToMeSD and our token merging method to the video diffusion model. For each generated video, we show three frames: the first on the left, the 8th at the top right, and the last 16th frame at the bottom right. We use AnimateDiff [17] as the base model and a merging ratio of 0.7. Best viewed with zoom-in. Please refer to supplementary for prompts.

r		Ours	w/ top-k *dst*	w/ global *ind.*
0.3	FID ↓	**12.20**	12.56	12.22
	CLIP ↑	31.82	31.82	31.82
0.7	FID ↓	**16.22**	16.29	16.43
	CLIP ↑	31.79	31.79	31.80

Table 7. Ablation studies of our method for text-to-image generation. 'w/ top-k *dst*' means top-k rather than random selection from the important token pool for destination tokens. 'w/ global *ind.*' means independent tokens may also be outside the important token pool, instead of solely within it.

r	p	0	0.2	0.4	0.8
0.3	FID ↓	12.87	12.32	**12.19**	**12.19**
	CLIP ↑	31.83	31.83	31.82	31.82
0.7	FID ↓	16.52	16.23	**16.22**	16.42
	CLIP ↑	31.78	31.78	31.79	31.79

Table 9. **Choice of p.** We show the results of our method for the text-to-image generation task with different values of p, which determines the important token pool size.

r	FID ↓			CLIP ↑		
	ToMe	Ours *(CA)*	Ours *(CFG)*	ToMe	Ours *(CA)*	Ours *(CFG)*
0.30	12.20	**12.17**	12.20	31.82	31.82	31.82
0.50	13.50	**13.38**	13.42	31.79	31.82	**31.83**
0.70	17.46	16.79	**16.22**	31.78	31.79	**31.79**
0.75	20.89	18.17	**17.75**	31.71	31.75	**31.76**

Table 8. Comparison of token merging methods applied to Stable Diffusion [79]. CA and CFG denote cross-attention and classifier-free guidance as importance signals, respectively.

cross-attention maps instead of CFG. While this may require additional memory to compute and store the attention matrices, it remains a strong alternative and also allows our method to remain applicable in scenarios where CFG is unavailable.

Choice of p. Our important token pool size is $(1-r)\cdot(1+p)$, where r is the token merging ratio. Tab. 9 shows that our method remains robust to the choice of p, provided that p is within a reasonable range.

5. Conclusions

We propose an importance-based token merging method for generation tasks, which maintains generation quality while reducing inference latency. We utilize token importance to dynamically allocate computational resources to regions of high relevance to the input condition, thereby enhancing the fidelity of the generated outputs. This novel, simple, and intuitive strategy accelerates various models for free with no modifications needed. Notably, we identify classifier-free guidance as an effective token importance indicator. Our method achieves state-of-the-art performance across diverse tasks, including text-to-image synthesis, multi-view generation, and video generation.

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