

# Language-Guided Image Tokenization for Generation



Kaiwen Zha



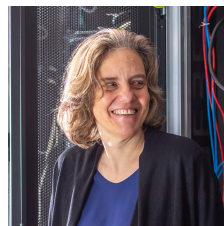
Lijun Yu



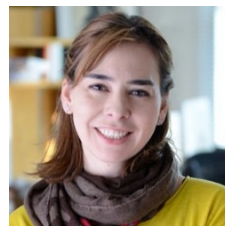
Alireza Fathi



David Ross



Cordelia Schmid



Dina Katabi



Xiuye Gu

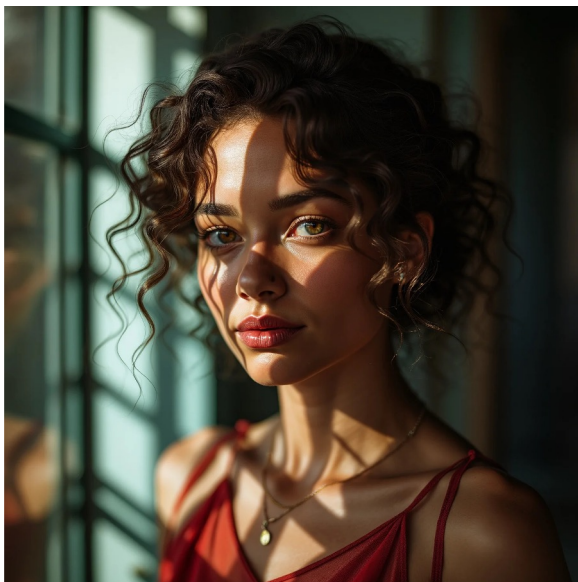


CVPR 2025

<https://kaiwenzha.github.io/textok/>



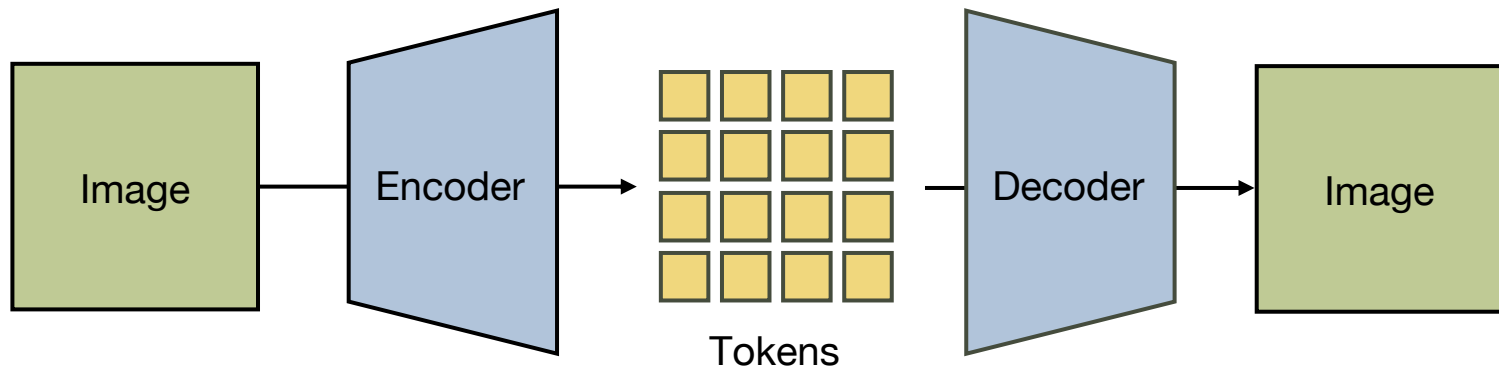
# Image Generation Made Great Progress



\*Examples generated by FLUX ([https://www.reddit.com/r/StableDiffusion/comments/1ehiz51/flux\\_image\\_examples/](https://www.reddit.com/r/StableDiffusion/comments/1ehiz51/flux_image_examples/))

# Tokenization is Key to Image Generation

**Tokenization:** Compresses raw image data into a compact low-dimensional latent representation (we call it “token”) through training an autoencoder



# Problem: Tradeoff between Compression and Quality

- **High** compression rate:

Low computational cost, bad reconstruction quality

- **Low** compression rate:

Good reconstruction quality, high computational cost

Can we achieve the best of both worlds,  
i.e., **low cost** and **high quality**?

# Our idea: Use Text during Tokenization

**Tokenization:** Finding a compact and comprehensive representation of an image

The most compact and comprehensive representation available of an image is its **caption**.

# Our idea: Use Text during Tokenization

**Tokenization:** Finding a compact and comprehensive representation of an image

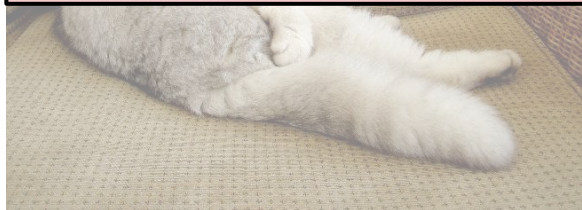


A fluffy, silver-and-white Persian cat lounges comfortably on a beige, textured sofa, its long, luxurious fur creating a soft cloud-like texture. The cat's round body and plush tail are relaxed, its paws tucked gently beneath it, and its green eyes are partially visible in a somewhat pensive expression. It appears content and at ease in its domestic environment.

# Our idea: Use Text during Tokenization

**Tokenization:** Finding a compact and comprehensive representation of an image

Using text (i.e., image caption) during tokenization can **simplify semantic learning.**



paws tucked gently beneath it, and its green eyes are partially visible in a somewhat pensive expression. It appears content and at ease in its domestic environment.

# Our idea: Use Text during Tokenization

**Tokenization:** Finding a compact and comprehensive representation of an image

Using text (i.e., image caption) during tokenization can **simplify semantic learning.**

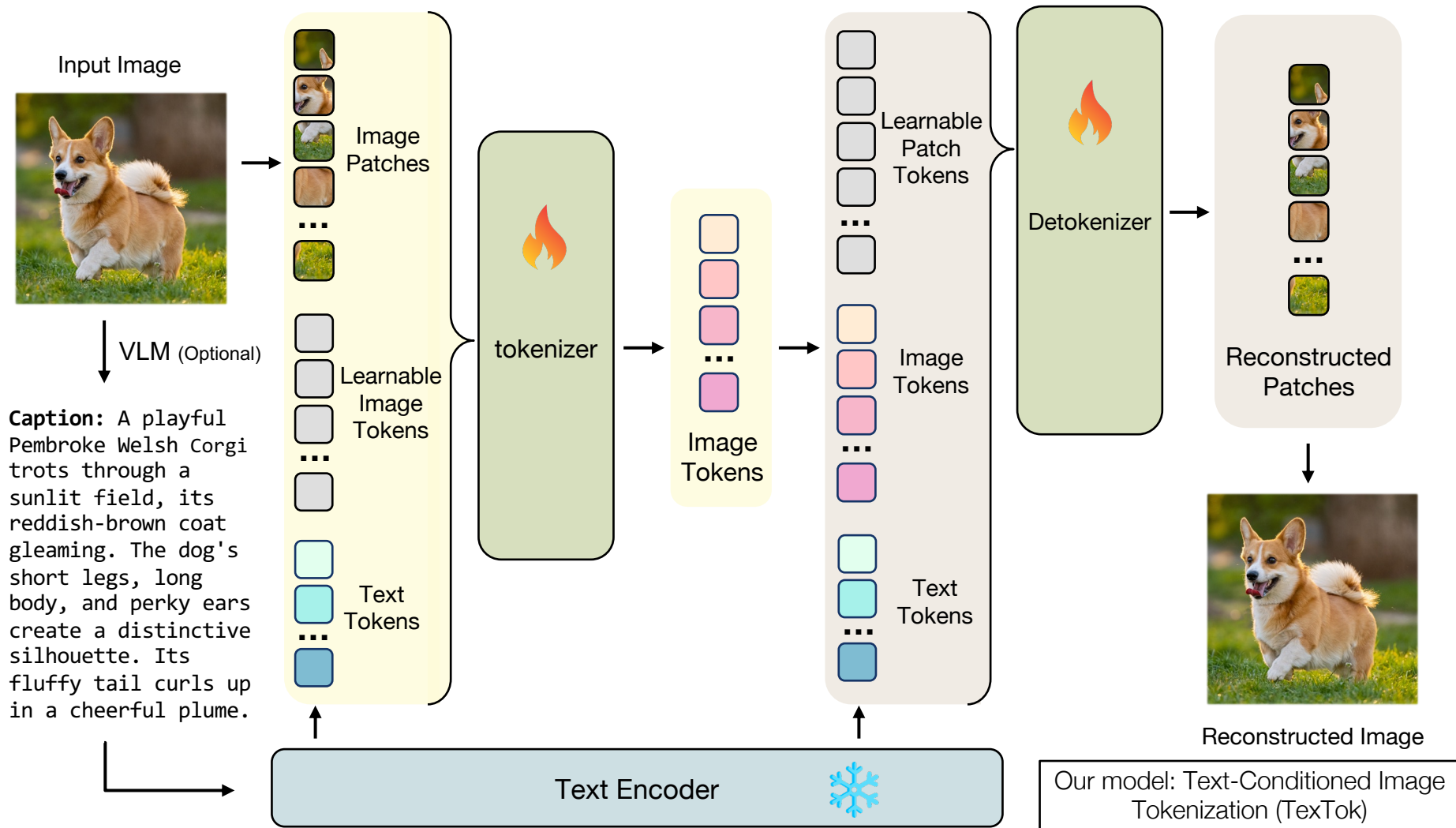


paws tucked gently beneath it, and its green eyes are partially visible in a somewhat pensive

**Achieve better quality without compromising cost!**



Our model: Text-Conditioned Image Tokenization (TexTok)

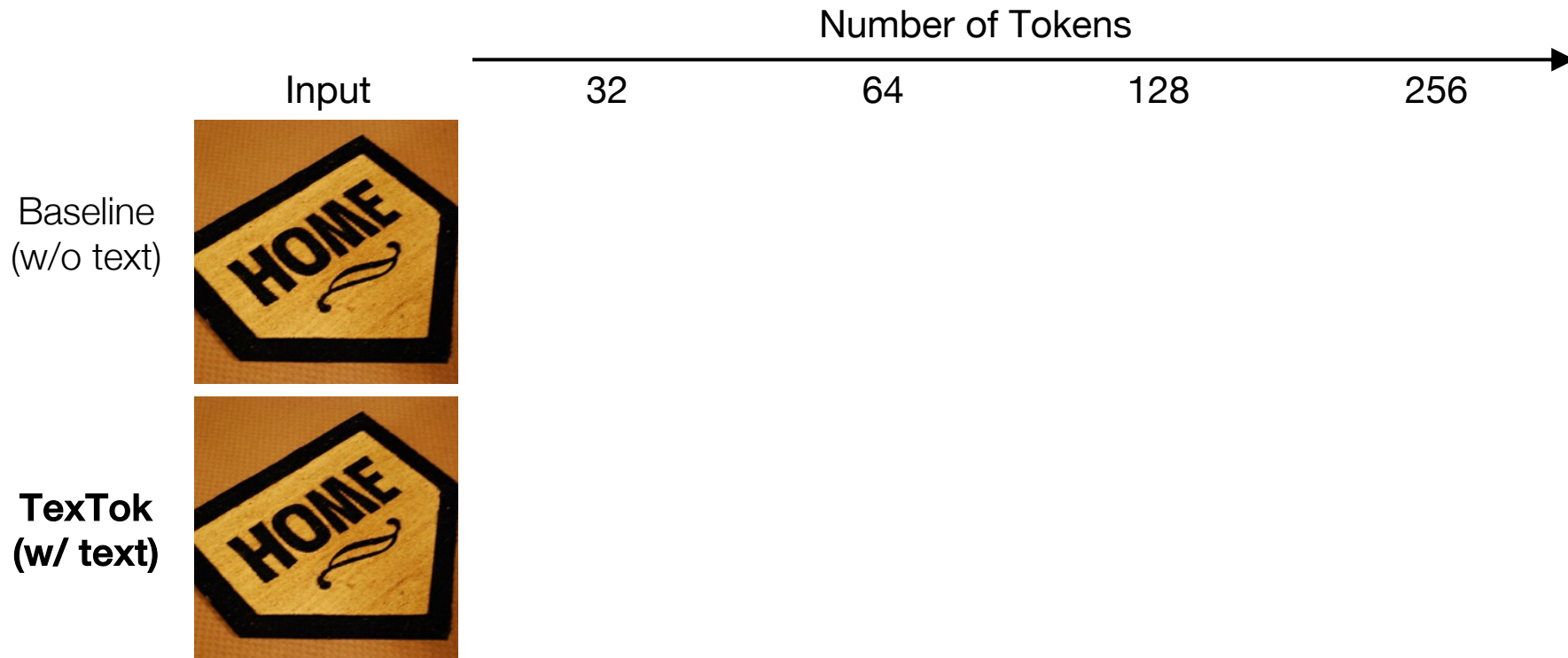


# Reconstruction Results

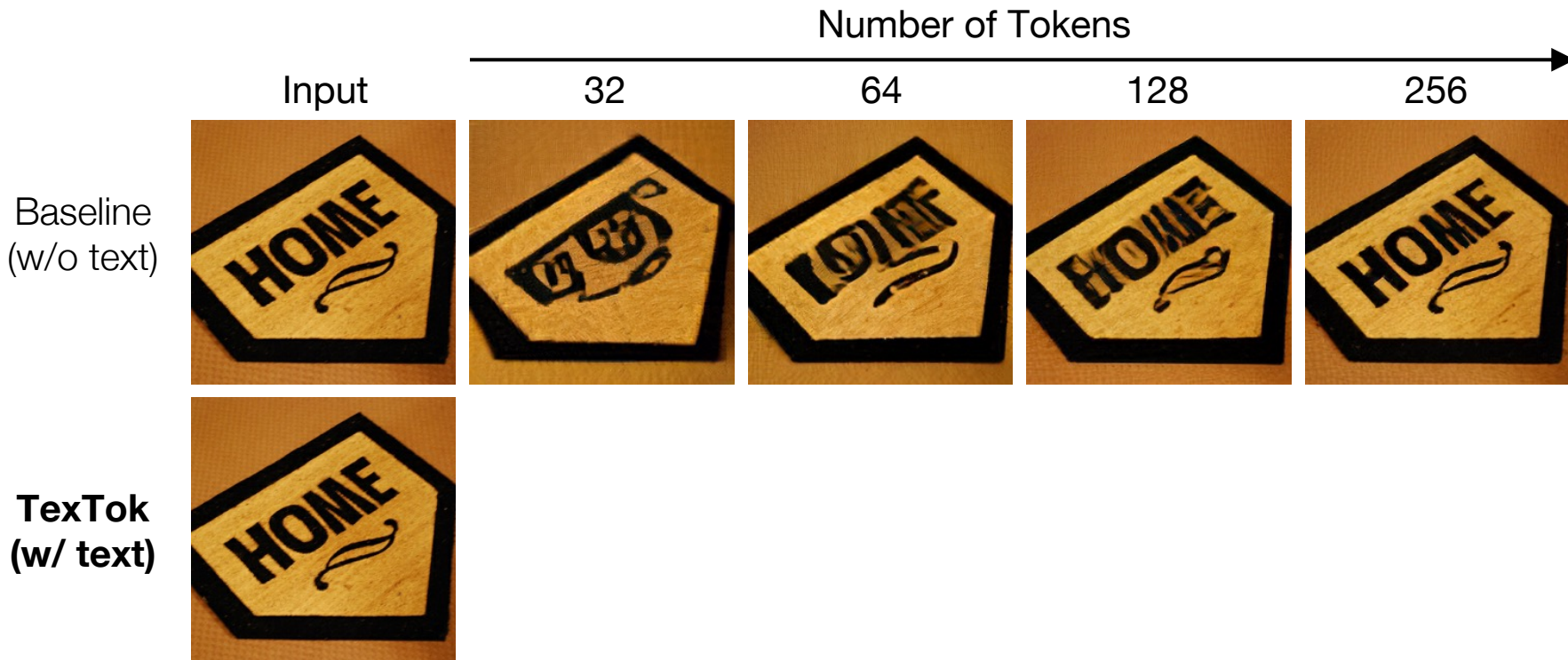


Input Image

# Reconstruction Results



# Reconstruction Results



# Reconstruction Results





# Reconstruction Results



# Reconstruction Results

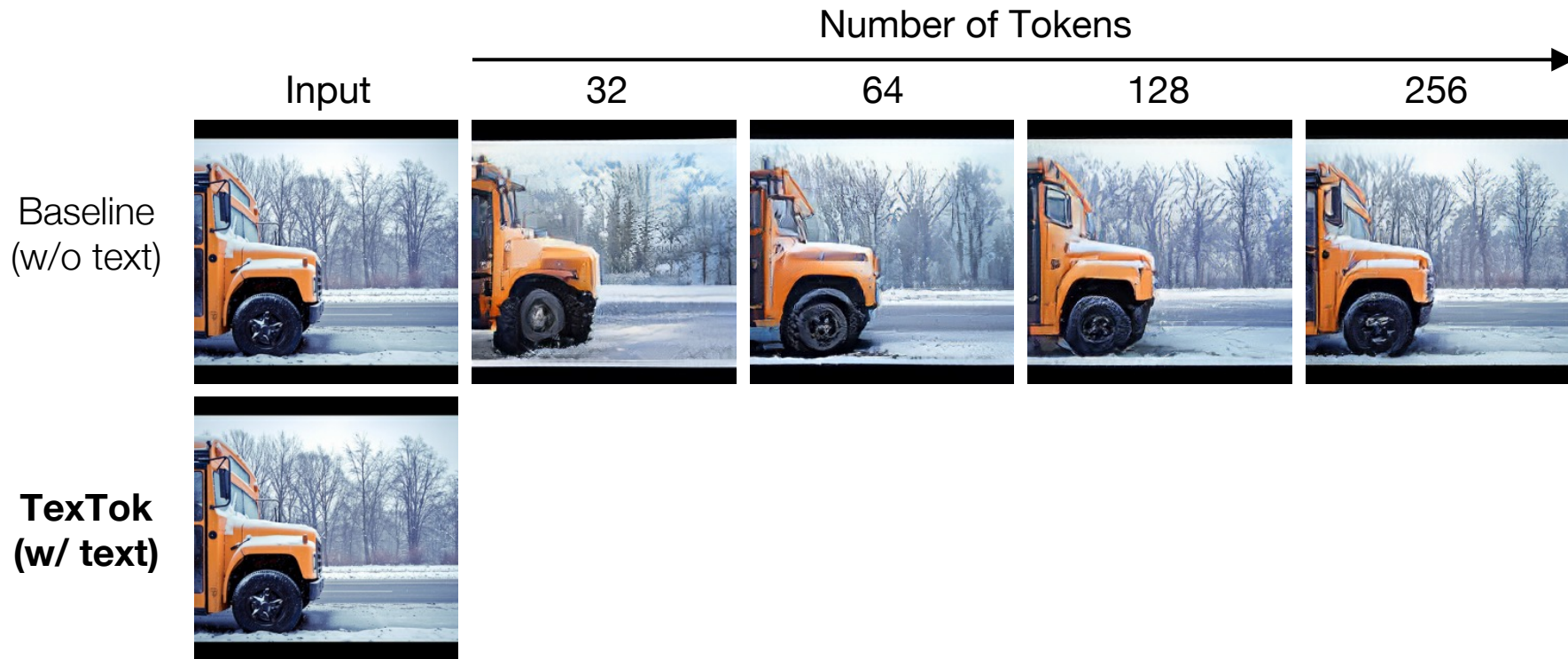


# Reconstruction Results

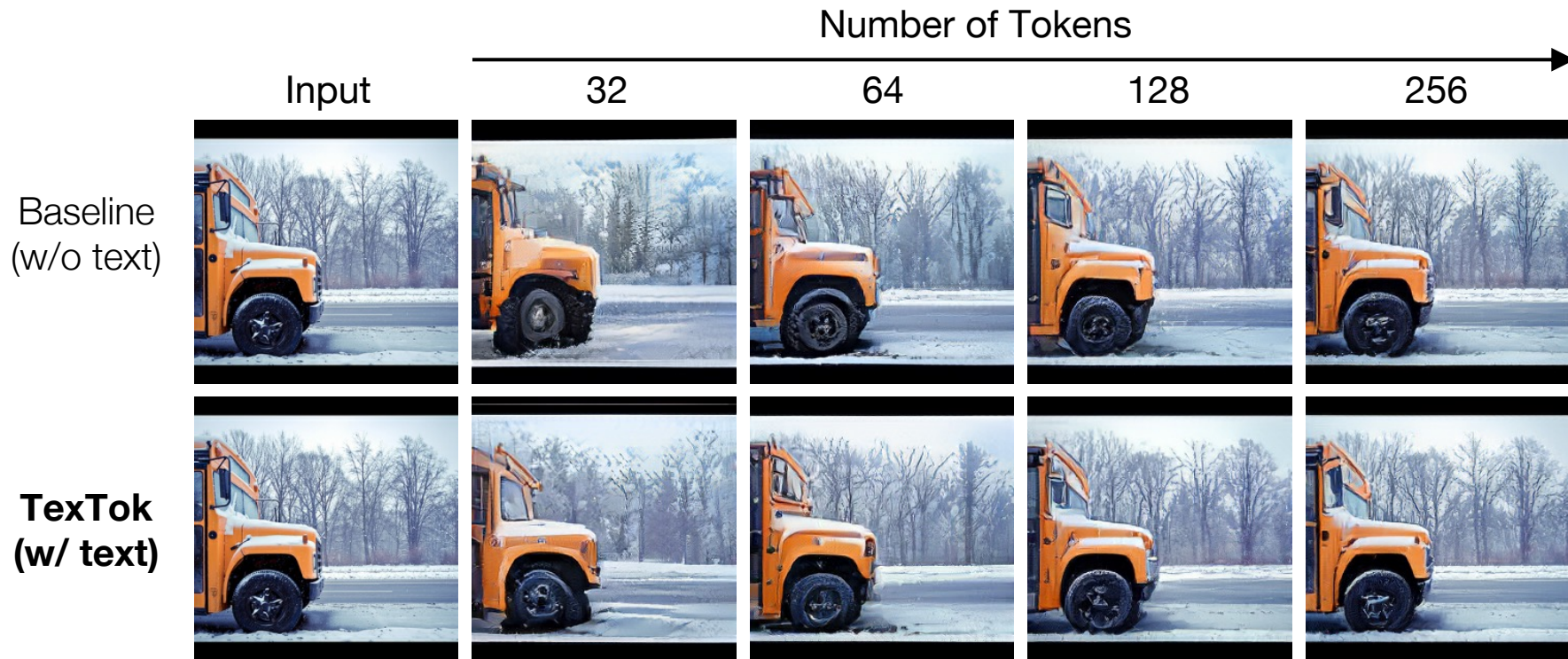


Input Image

# Reconstruction Results

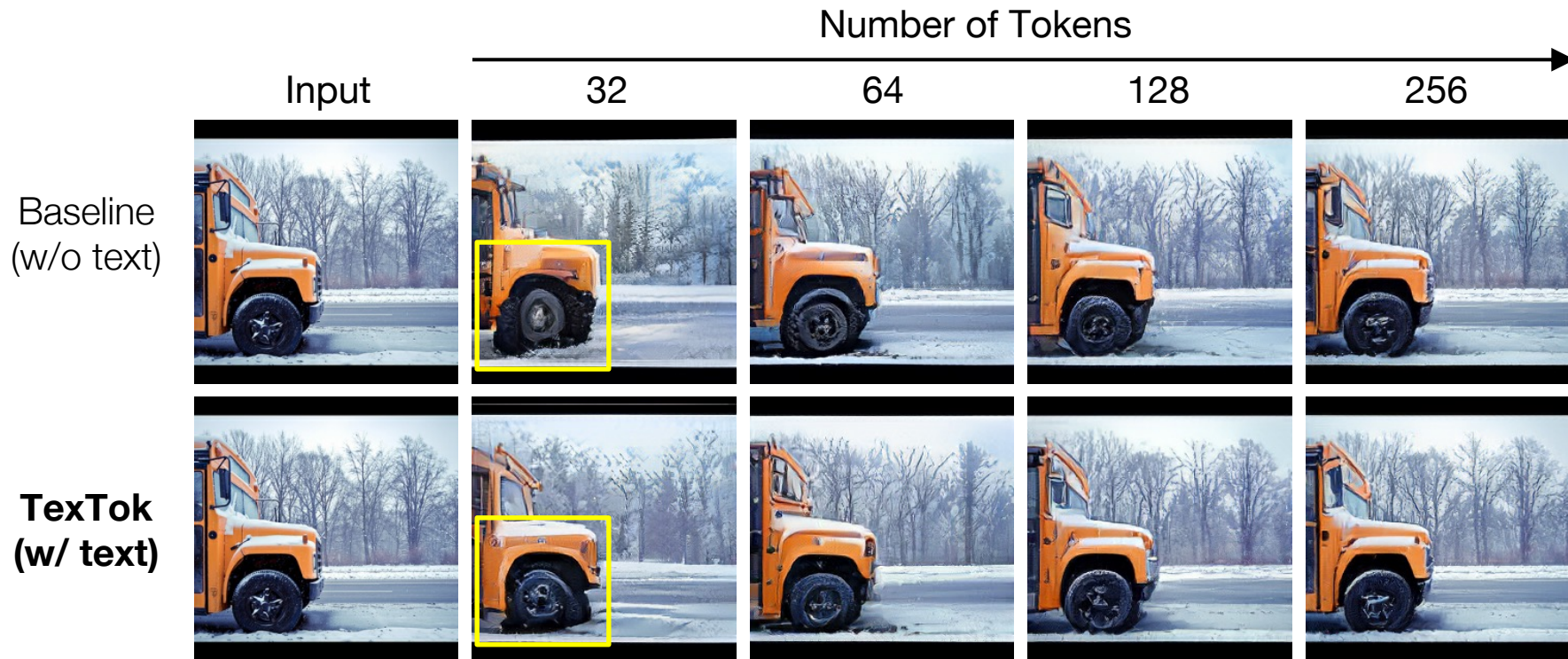


# Reconstruction Results



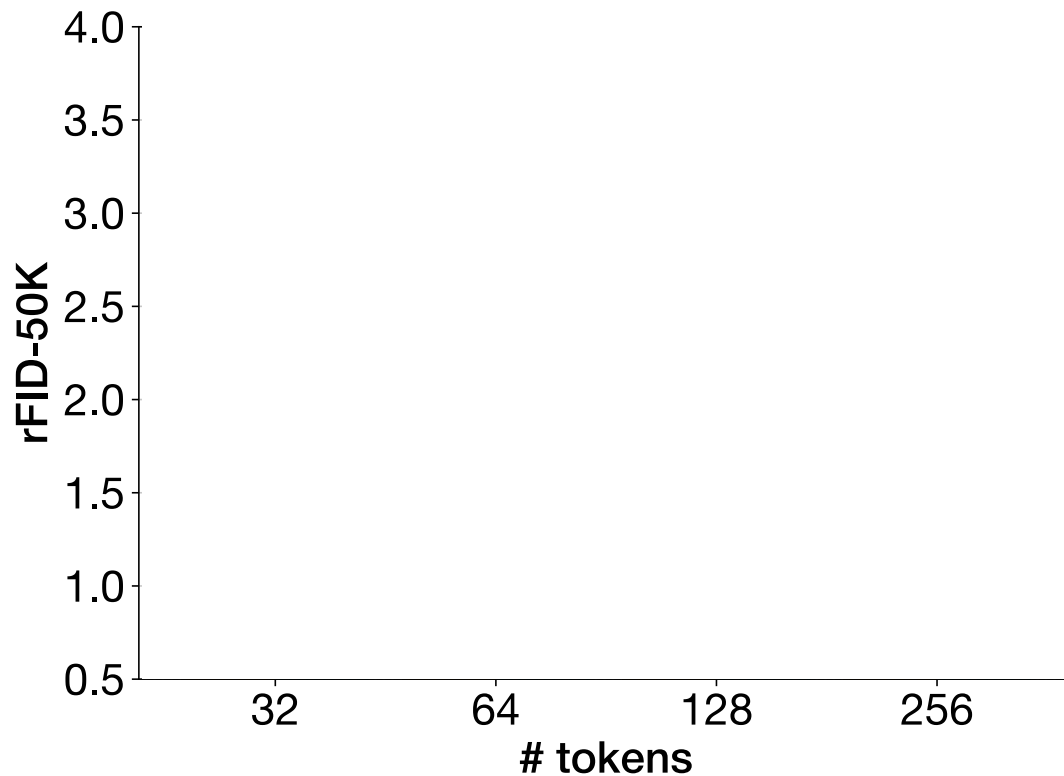


# Reconstruction Results



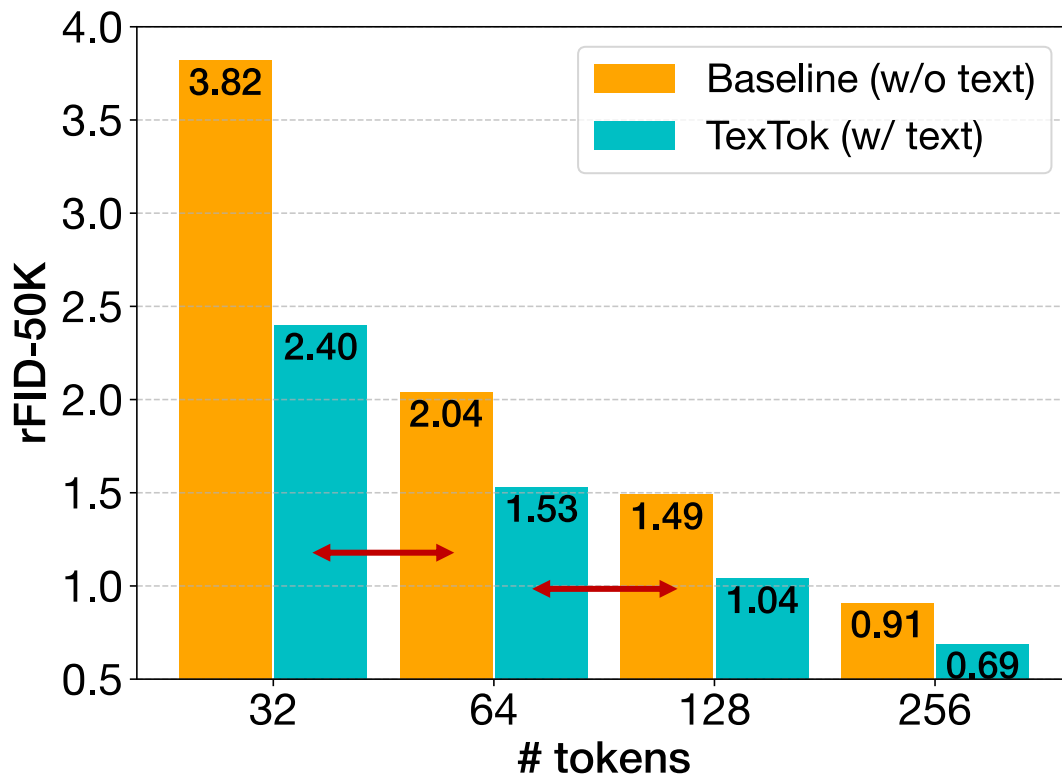
# Quantitative Reconstruction Results

ImageNet 256x256



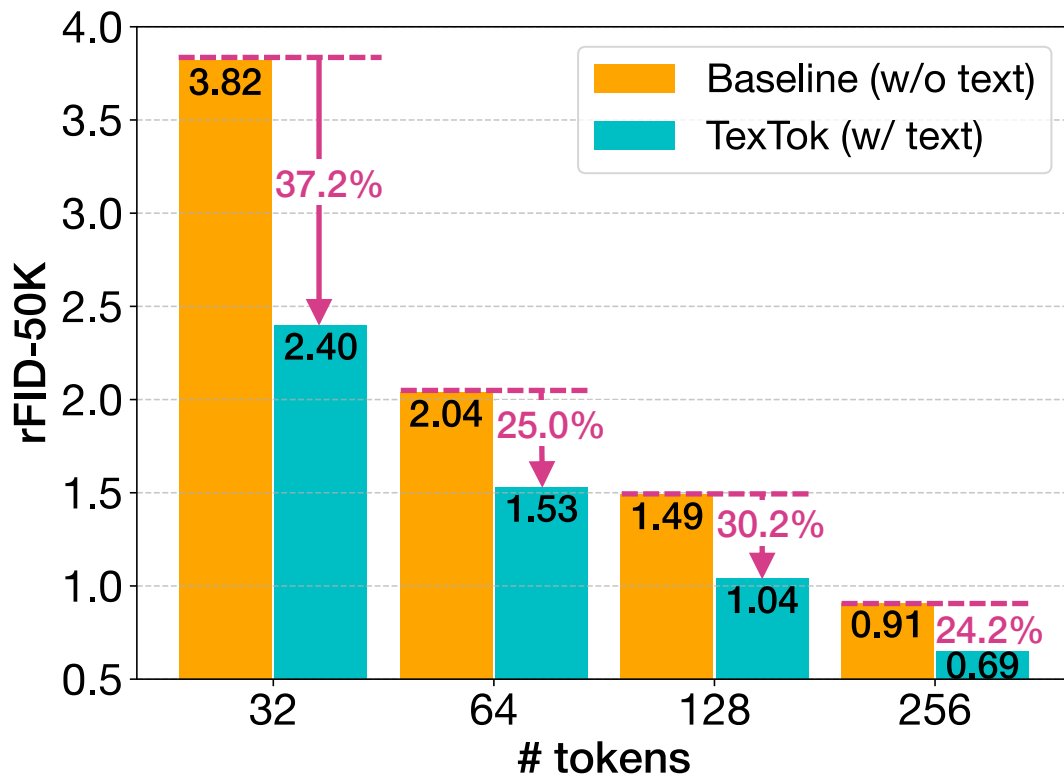
# Better Quality at High Compression

ImageNet 256x256



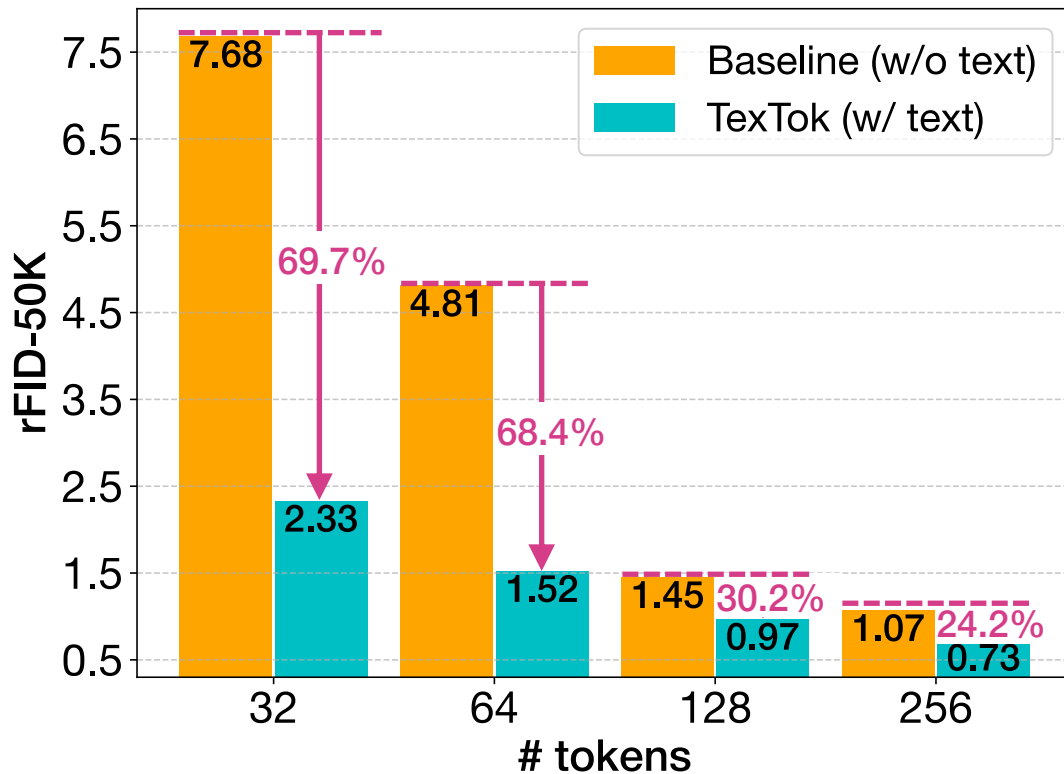
# Better Quality at High Compression

ImageNet 256x256



# Better Quality at High Compression

ImageNet 512x512





# More Detailed Reconstruction Results

Reconstruction						
tokenizer	# tokens	rFID ↓	rIS ↑	PSNR ↑	SSIM ↑	LPIPS ↓
(a) ImageNet 256×256						
SD-VAE-f8 [37]	1024 (d=4)	1.20 <sup>†</sup>	-	-	-	-
Baseline-32 (w/o text)	32 (d=8)	3.82	117.1	17.67	0.4281	0.3270
<b>TexTok-32 (w/ text)</b>		<b>2.40</b>	<b>156.2</b>	<b>18.32</b>	<b>0.4463</b>	<b>0.2884</b>
Baseline-64 (w/o text)	64 (d=8)	2.04	147.2	19.52	0.4801	0.2343
<b>TexTok-64 (w/ text)</b>		<b>1.53</b>	<b>169.8</b>	<b>20.10</b>	<b>0.4971</b>	<b>0.2126</b>
Baseline-128 (w/o text)	128 (d=8)	1.49	160.5	20.51	0.5102	0.1913
<b>TexTok-128 (w/ text)</b>		<b>1.04</b>	<b>183.3</b>	<b>22.05</b>	<b>0.5618</b>	<b>0.1499</b>
Baseline-256 (w/o text)	256 (d=8)	0.91	178.3	23.05	0.5950	0.1225
<b>TexTok-256 (w/ text)</b>		<b>0.69</b>	<b>192.6</b>	<b>24.38</b>	<b>0.6454</b>	<b>0.0998</b>

# Tokenization Improvements Translate to Generation

Reconstruction							Generation	
tokenizer	# tokens	rFID ↓	rIS ↑	PSNR ↑	SSIM ↑	LPIPS ↓	gFID ↓	gIS ↑
(a) ImageNet 256 × 256								
SD-VAE-f8 [37]	1024 (d=4)	1.20 <sup>†</sup>	-	-	-	-	9.62	121.5
Baseline-32 (w/o text)	32 (d=8)	3.82	117.1	17.67	0.4281	0.3270	4.97	170.3
<b>TexTok-32 (w/ text)</b>		<b>2.40</b>	<b>156.2</b>	<b>18.32</b>	<b>0.4463</b>	<b>0.2884</b>	<b>3.55</b>	<b>205.3</b>
Baseline-64 (w/o text)	64 (d=8)	2.04	147.2	19.52	0.4801	0.2343	3.30	188.9
<b>TexTok-64 (w/ text)</b>		<b>1.53</b>	<b>169.8</b>	<b>20.10</b>	<b>0.4971</b>	<b>0.2126</b>	<b>2.88</b>	<b>209.2</b>
Baseline-128 (w/o text)	128 (d=8)	1.49	160.5	20.51	0.5102	0.1913	3.19	190.1
<b>TexTok-128 (w/ text)</b>		<b>1.04</b>	<b>183.3</b>	<b>22.05</b>	<b>0.5618</b>	<b>0.1499</b>	<b>2.75</b>	<b>210.9</b>
Baseline-256 (w/o text)	256 (d=8)	0.91	178.3	23.05	0.5950	0.1225	2.91	197.2
<b>TexTok-256 (w/ text)</b>		<b>0.69</b>	<b>192.6</b>	<b>24.38</b>	<b>0.6454</b>	<b>0.0998</b>	<b>2.68</b>	<b>219.6</b>

# System-level Generation Benchmarking

			(a) ImageNet 256×256						(b) ImageNet 512×512				
Model	#Params (G)	#Params (T)	FID↓	IS↑	Precision↑	Recall↑	#tokens	FID↓	IS↑	Precision↑	Recall↑	#tokens	
<i>latent diffusion</i>													
LDM-4 [37]	400M	55M	3.60	247.7	0.87	0.48	4096 <sub>(d=3)</sub>	-	-	-	-	-	
U-ViT-H [2]	501M	84M	2.29	263.9	0.82	0.57	1024* <sub>(d=4)</sub>	4.05	263.8	0.84	0.48	4096* <sub>(d=4)</sub>	
DiT-XL/2 [32]	675M	84M	2.27	278.2	0.83	0.57	1024* <sub>(d=4)</sub>	3.04	240.8	0.84	0.54	4096* <sub>(d=4)</sub>	
DiffiT [14]	-	-	1.73	276.5	0.80	0.62	-	2.67	252.1	0.83	0.55	-	
MDTv2-XL/2 [12]	676M	84M	1.58	314.7	0.79	0.65	1024* <sub>(d=4)</sub>	-	-	-	-	-	
REPA + SiT-XL/2 [51]	675M	84M	1.80	284.0	0.81	0.61	1024* <sub>(d=4)</sub>	-	-	-	-	-	
EDM2-XXL [21]	1.5B	84M	-	-	-	-	-	1.81	-	-	-	4096 <sub>(d=4)</sub>	
<i>Ours</i>													
TexTok-32 + DiT-XL	675M	176M	2.75	294.6	0.83	0.56	32 <sub>(d=8)</sub>	2.74	303.2	0.83	0.56	32 <sub>(d=8)</sub>	
TexTok-64 + DiT-XL	675M	176M	2.06	290.0	0.81	0.60	64 <sub>(d=8)</sub>	1.99	301.9	0.82	0.6	64 <sub>(d=8)</sub>	
TexTok-128 + DiT-XL	675M	176M	1.66	294.4	0.80	0.61	128 <sub>(d=8)</sub>	1.80	305.4	0.81	0.63	128 <sub>(d=8)</sub>	
TexTok-256 + DiT-XL	675M	176M	<b>1.46</b>	303.1	0.79	0.64	256 <sub>(d=8)</sub>	<b>1.62</b>	313.8	0.80	0.64	256 <sub>(d=8)</sub>	

**Our model achieves state-of-the-art generation performance at the time of submission**

# System-level Generation Benchmarking

			(a) ImageNet 256×256					(b) ImageNet 512×512				
Model	#Params (G)	#Params (T)	FID↓	IS↑	Precision↑	Recall↑	#tokens	FID↓	IS↑	Precision↑	Recall↑	#tokens
<i>latent diffusion</i>												
LDM-4 [37]	400M	55M	3.60	247.7	0.87	0.48	4096 <sub>(d=3)</sub>	-	-	-	-	-
U-ViT-H [2]	501M	84M	2.29	263.9	0.82	0.57	1024* <sub>(d=4)</sub>	4.05	263.8	0.84	0.48	4096* <sub>(d=4)</sub>
<b>DiT-XL/2 [32]</b>	675M	84M	<b>2.27</b>	<b>278.2</b>	<b>0.83</b>	<b>0.57</b>	<b>1024*<sub>(d=4)</sub></b>	<b>3.04</b>	<b>240.8</b>	<b>0.84</b>	<b>0.54</b>	<b>4096*<sub>(d=4)</sub></b>
DiffiT [14]	-	-	1.73	276.5	0.80	0.62	-	2.67	252.1	0.83	0.55	-
MDTv2-XL/2 [12]	676M	84M	1.58	314.7	0.79	0.65	1024* <sub>(d=4)</sub>	-	-	-	-	-
REPA + SiT-XL/2 [51]	675M	84M	1.80	284.0	0.81	0.61	1024* <sub>(d=4)</sub>	-	-	-	-	-
EDM2-XXL [21]	1.5B	84M	-	-	-	-	-	1.81	-	-	-	4096 <sub>(d=4)</sub>
<i>Ours</i>												
<b>TexTok-32 + DiT-XL</b>	675M	176M	2.75	294.6	0.83	0.56	32 <sub>(d=8)</sub>	2.74	303.2	0.83	0.56	32 <sub>(d=8)</sub>
<b>TexTok-64 + DiT-XL</b>	675M	176M	<b>2.06</b>	<b>290.0</b>	<b>0.81</b>	<b>0.60</b>	<b>64<sub>(d=8)</sub></b>	<b>1.99</b>	<b>301.9</b>	<b>0.82</b>	<b>0.6</b>	<b>64<sub>(d=8)</sub></b>
<b>TexTok-128 + DiT-XL</b>	675M	176M	1.66	294.4	0.80	0.61	128 <sub>(d=8)</sub>	1.80	305.4	0.81	0.63	128 <sub>(d=8)</sub>
<b>TexTok-256 + DiT-XL</b>	675M	176M	<b>1.46</b>	<b>303.1</b>	<b>0.79</b>	<b>0.64</b>	<b>256<sub>(d=8)</sub></b>	<b>1.62</b>	<b>313.8</b>	<b>0.80</b>	<b>0.64</b>	<b>256<sub>(d=8)</sub></b>

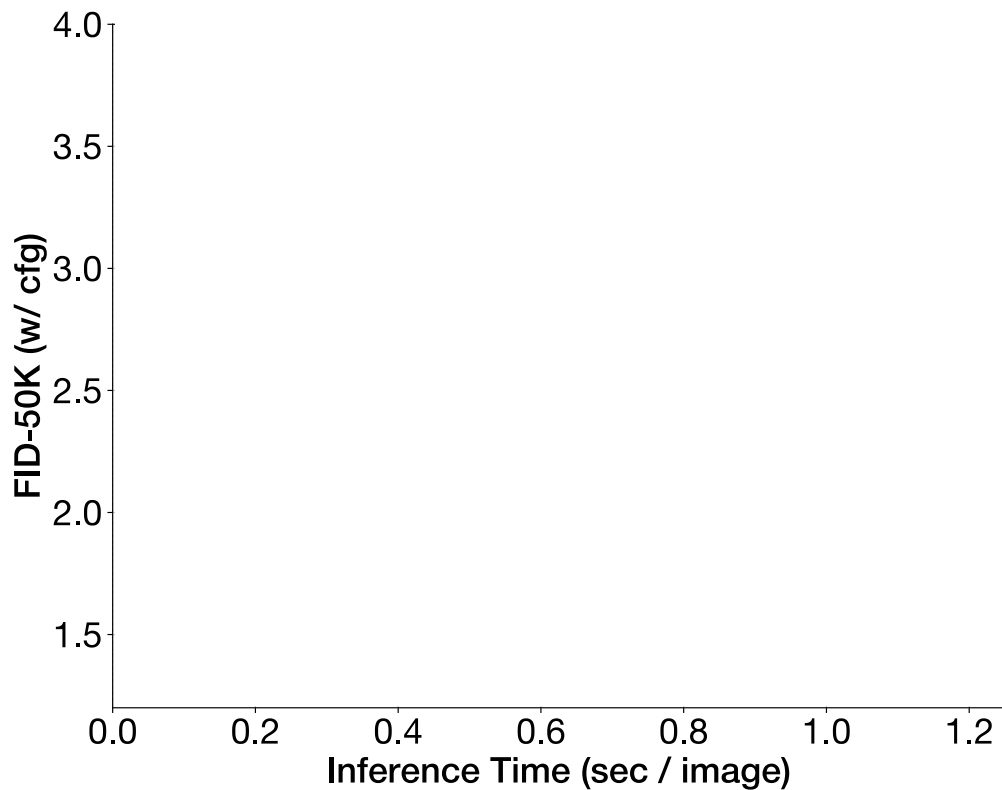
Our model with 64 tokens perform better than vanilla DiT with 1024 tokens on ImageNet-256

# System-level Generation Benchmarking

			(a) ImageNet 256×256					(b) ImageNet 512×512				
Model	#Params (G)	#Params (T)	FID↓	IS↑	Precision↑	Recall↑	#tokens	FID↓	IS↑	Precision↑	Recall↑	#tokens
<i>latent diffusion</i>												
LDM-4 [37]	400M	55M	3.60	247.7	0.87	0.48	4096 (d=3)	-	-	-	-	-
U-ViT-H [2]	501M	84M	2.29	263.9	0.82	0.57	1024* (d=4)	4.05	263.8	0.84	0.48	4096* (d=4)
DiT-XL/2 [32]	675M	84M	2.27	278.2	0.83	0.57	1024* (d=4)	3.04	240.8	0.84	0.54	4096* (d=4)
DiffiT [14]	-	-	1.73	276.5	0.80	0.62	-	2.67	252.1	0.83	0.55	-
MDTv2-XL/2 [12]	676M	84M	1.58	314.7	0.79	0.65	1024* (d=4)	-	-	-	-	-
REPA + SiT-XL/2 [51]	675M	84M	1.80	284.0	0.81	0.61	1024* (d=4)	-	-	-	-	-
EDM2-XXL [21]	1.5B	84M	-	-	-	-	-	1.81	-	-	-	4096 (d=4)
<i>Ours</i>												
TexTok-32 + DiT-XL	675M	176M	2.75	294.6	0.83	0.56	32 (d=8)	2.74	303.2	0.83	0.56	32 (d=8)
TexTok-64 + DiT-XL	675M	176M	2.06	290.0	0.81	0.60	64 (d=8)	1.99	301.9	0.82	0.6	64 (d=8)
TexTok-128 + DiT-XL	675M	176M	1.66	294.4	0.80	0.61	128 (d=8)	1.80	305.4	0.81	0.63	128 (d=8)
TexTok-256 + DiT-XL	675M	176M	1.46	303.1	0.79	0.64	256 (d=8)	1.62	313.8	0.80	0.64	256 (d=8)

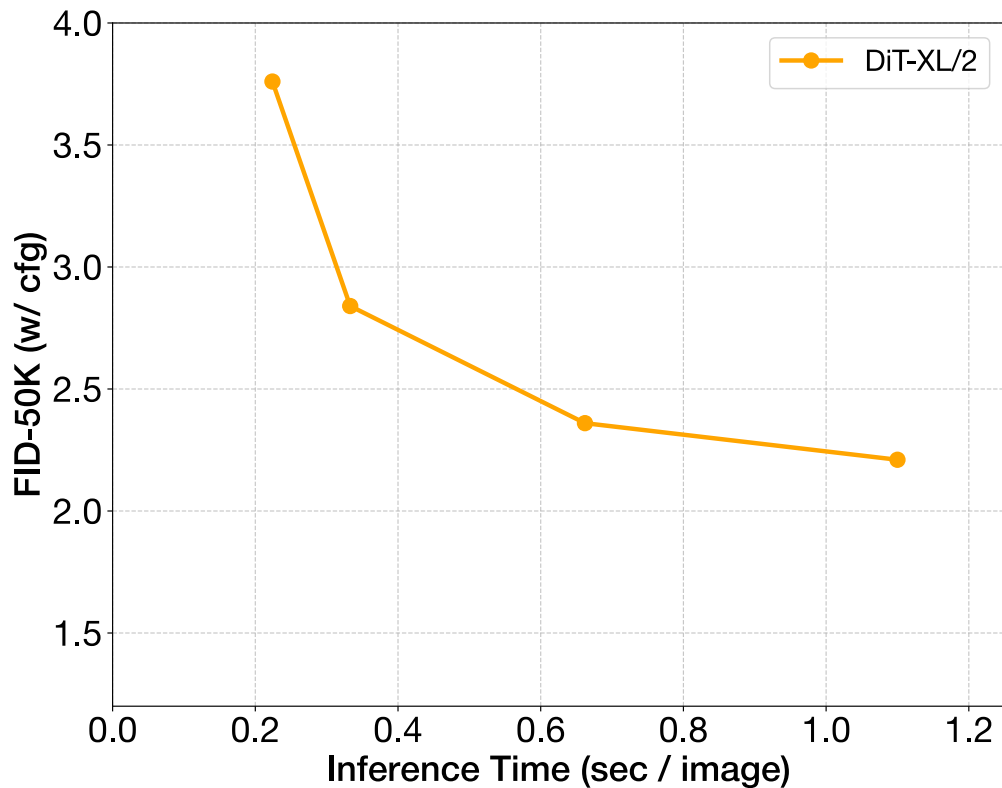
Our model with 32 tokens perform better than vanilla DiT with 4096 tokens on ImageNet-512

# Improved Generation Speed/Quality Frontier



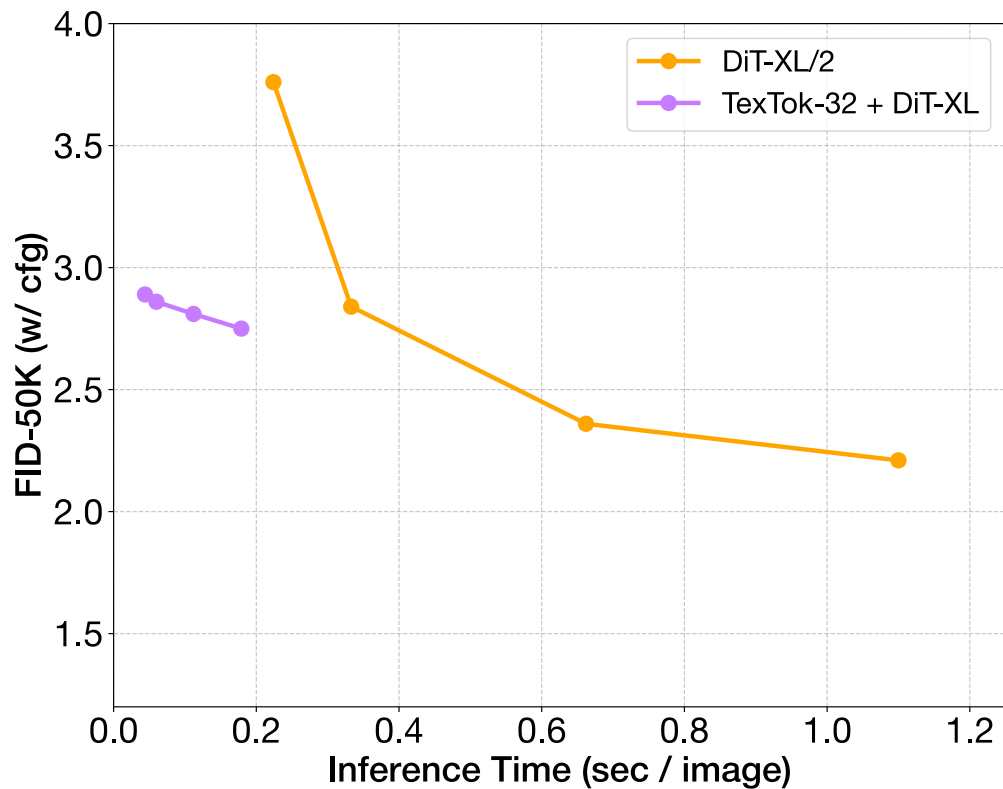
ImageNet 256x256

# Improved Generation Speed/Quality Frontier



ImageNet 256x256

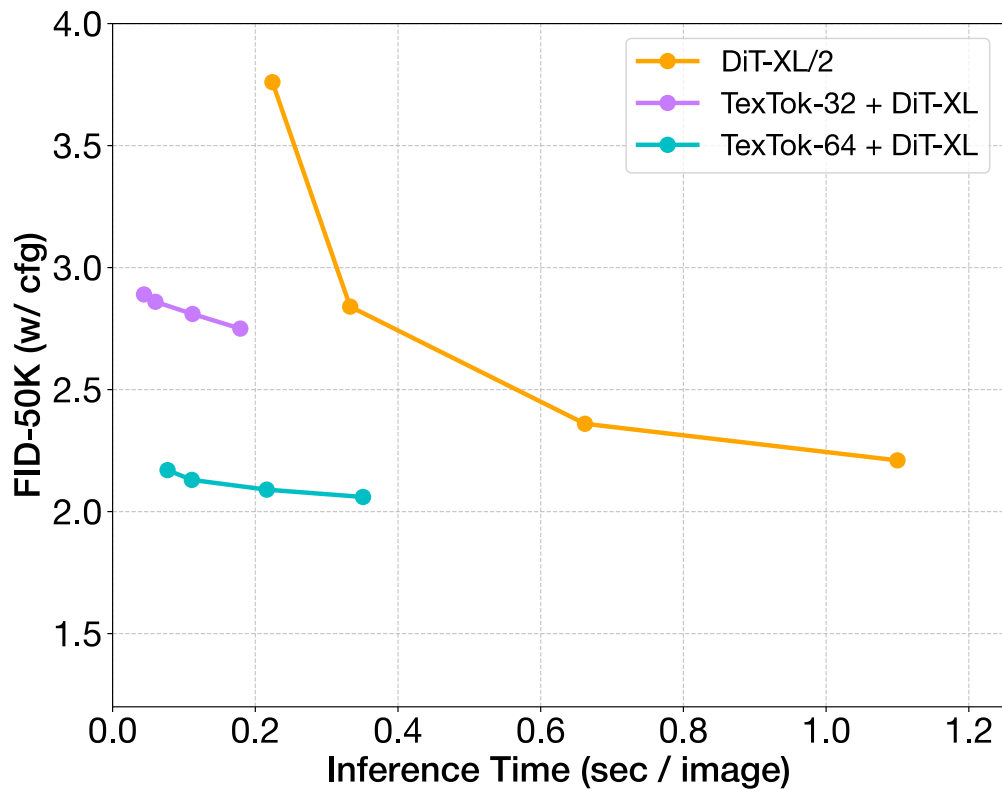
# Improved Generation Speed/Quality Frontier



ImageNet 256x256

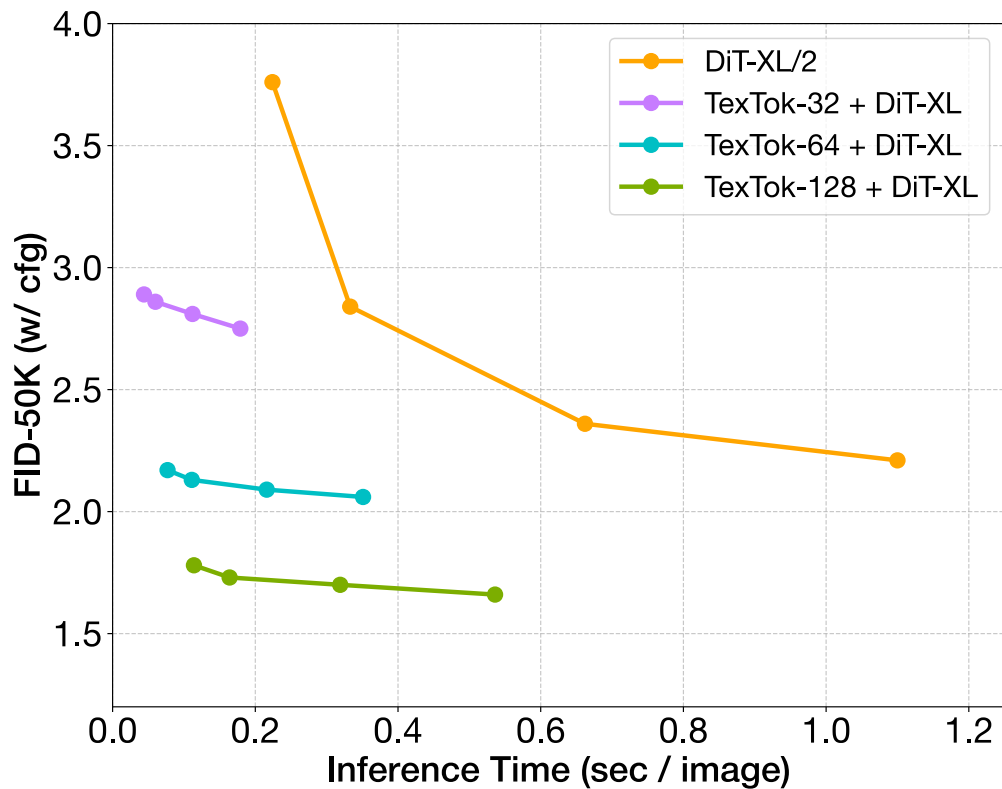


# Improved Generation Speed/Quality Frontier



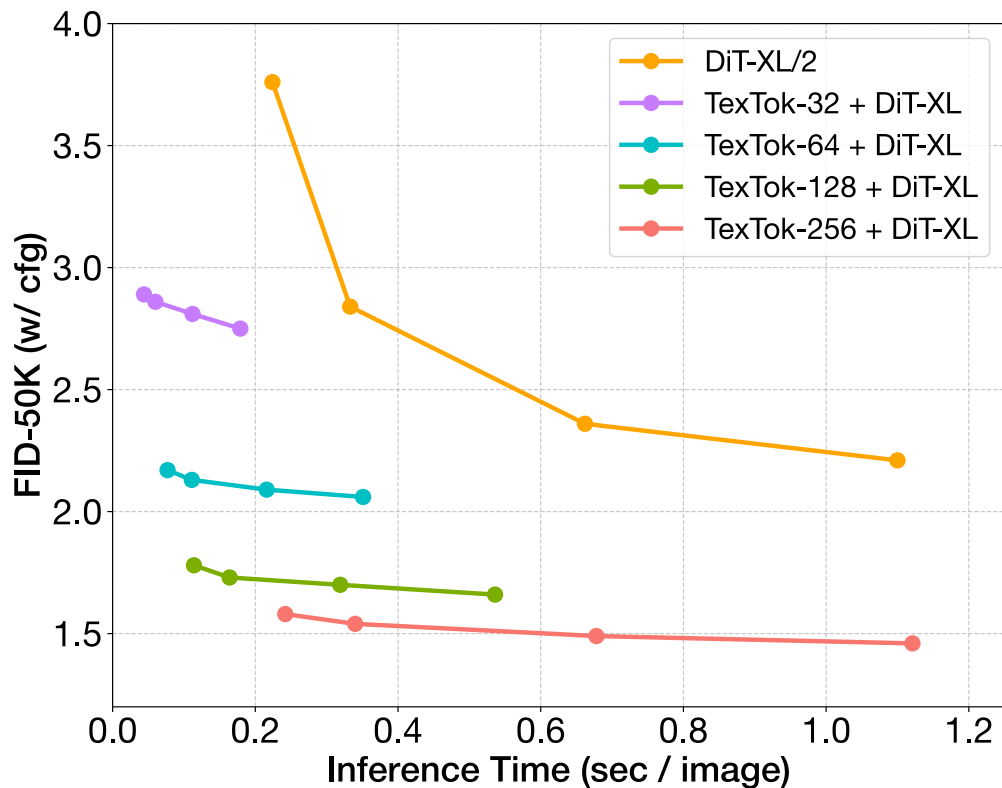
ImageNet 256x256

# Improved Generation Speed/Quality Frontier



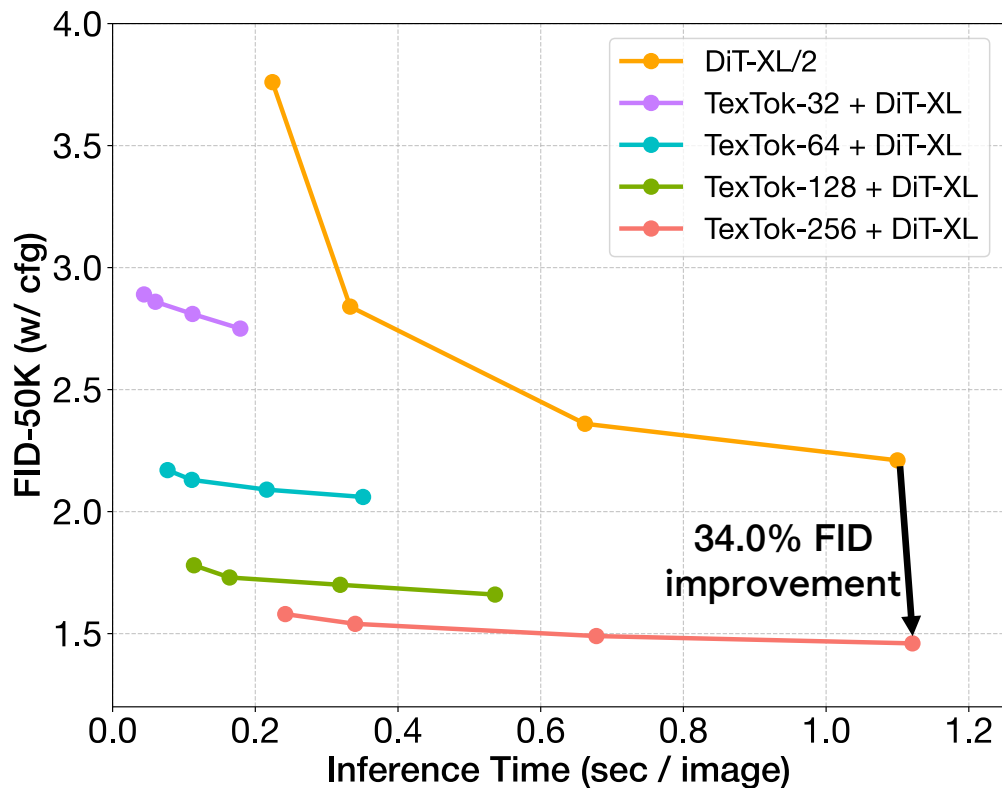
ImageNet 256x256

# Improved Generation Speed/Quality Frontier



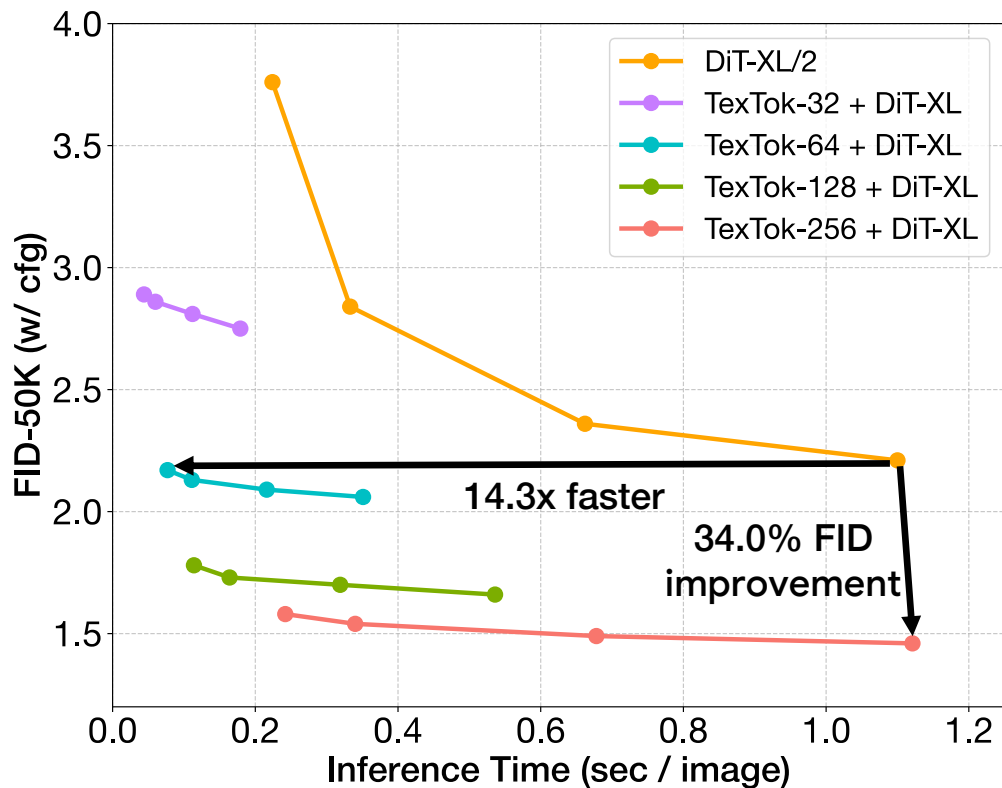
ImageNet 256x256

# Improved Generation Speed/Quality Frontier



ImageNet 256x256

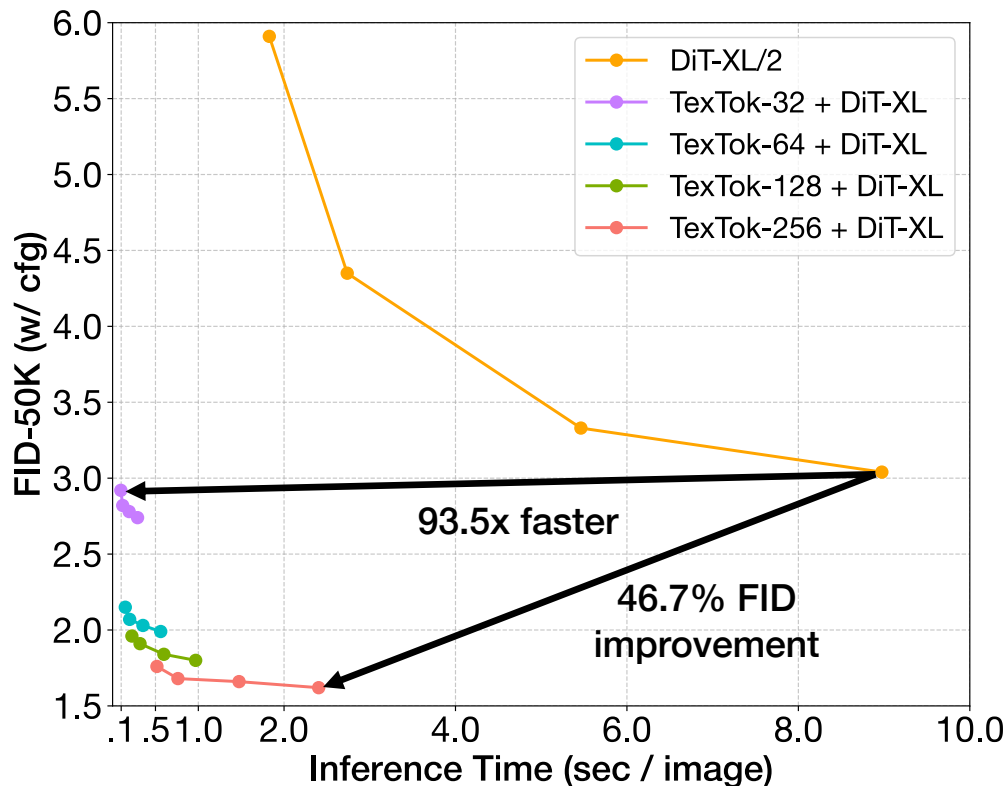
# Improved Generation Speed/Quality Frontier



ImageNet 256x256

# Improved Generation Speed/Quality Frontier

ImageNet 512x512



# Generation Samples on ImageNet 512x512



# Text-to-Image Generation

- Take the text used in generation also to tokenization
- No additional annotation cost, free performance boost



# Text-to-Image Generation



**Caption (Prompt):** A vibrant scarlet macaw, with a striking black and white beak, perches on a weathered, grey wooden branch against a backdrop of lush green foliage. Its feathers display a gradient of red, with hints of blue and green near its tail, creating a textured and iridescent effect. The macaw's large size and bright colors make it stand out in its natural-looking environment, appearing alert and possibly watchful of its surroundings.

# Text-to-Image Generation

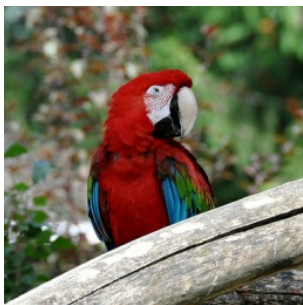
Number of Tokens

32

64

128

Reference  
Image



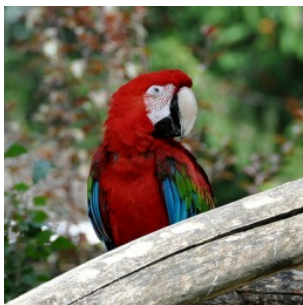
Baseline  
(w/o text)

**TextTok  
(w/ text)**

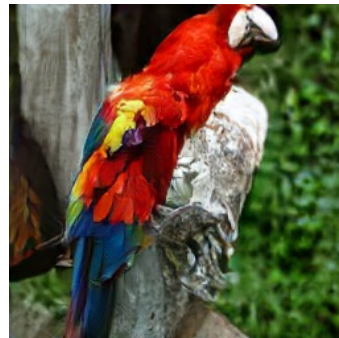
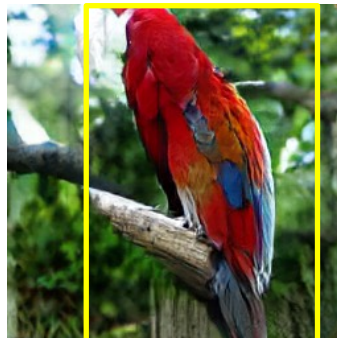
# Text-to-Image Generation

Number of Tokens →

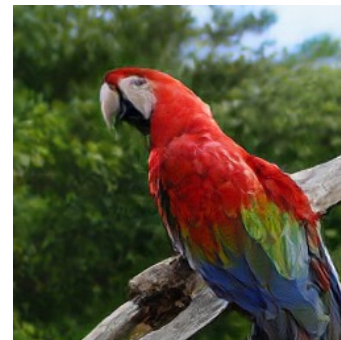
Reference  
Image



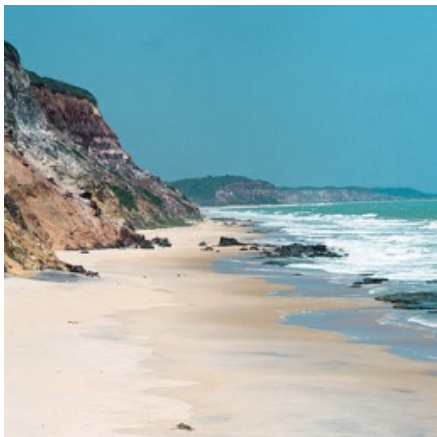
Baseline  
(w/o text)



**TextTok  
(w/ text)**



# Text-to-Image Generation



**Caption (Prompt):** A towering, multi-hued cliff of red, tan, and gray rock faces a serene, turquoise ocean under a brilliant blue sky. The cliff's rough, layered texture contrasts with the smooth, white sand beach below, where gentle waves lap against dark, rocky outcrops. The expansive beach stretches alongside the cliff, forming a picturesque coastal scene under the vast, clear sky.

# Text-to-Image Generation

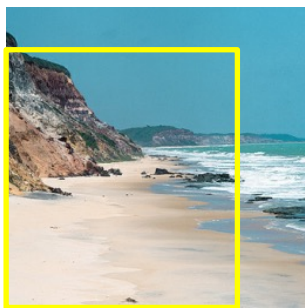
Number of Tokens →

32

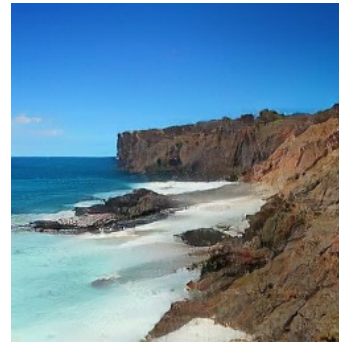
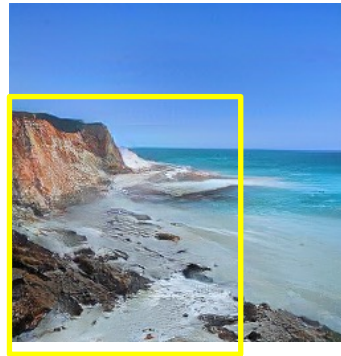
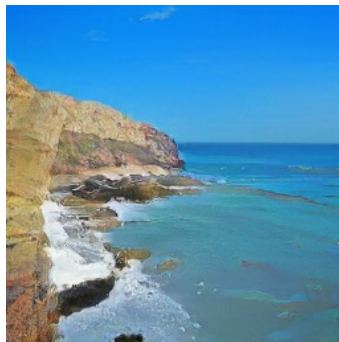
64

128

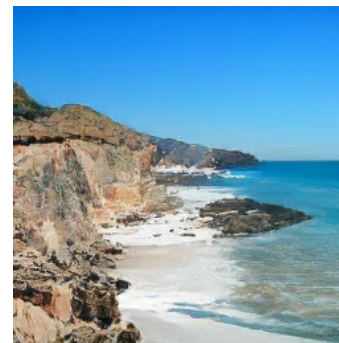
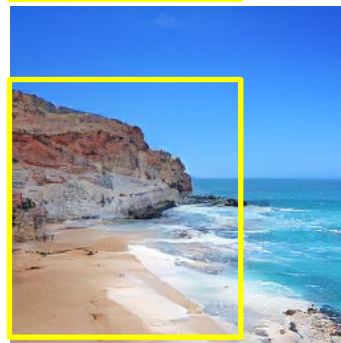
Reference  
Image



Baseline  
(w/o text)



**TextTok  
(w/ text)**



# TexTok Summary

- A tokenization framework that uses text during tokenization
- **Reconstruction**
  - better reconstruction quality
  - higher compression rate
- This leads to **generation** of
  - better generation performance
  - better computational efficiency

# Check Out the Concurrent and Follow-up Work!

- TA-TiTok: <https://tacju.github.io/projects/maskgen.html>
- QLIP: <https://nvlabs.github.io/QLIP/>
- SemHiTok: <https://arxiv.org/abs/2503.06764>