

“Principal Components” Enable A New Language of Images

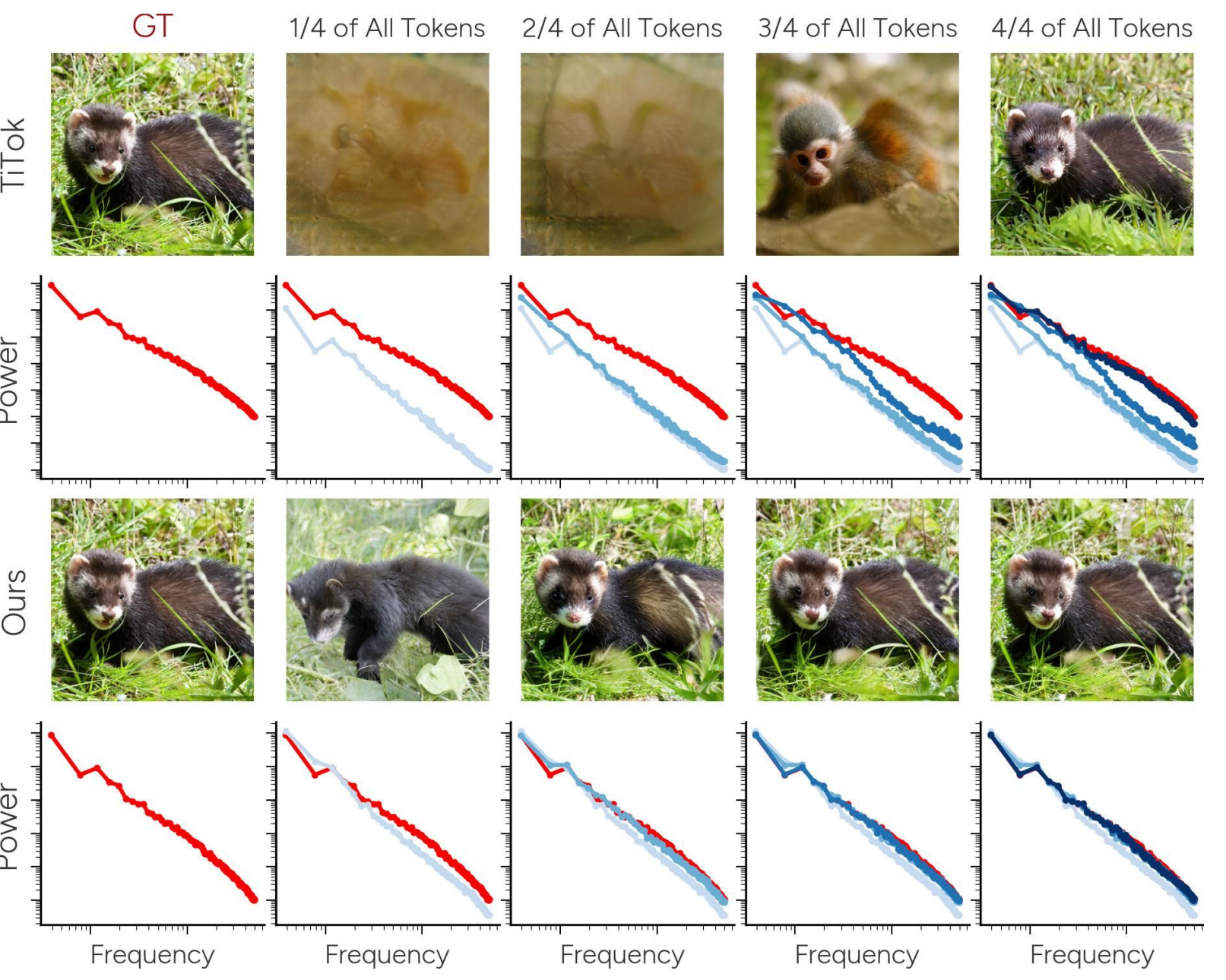
by *Xin Wen**, *Bingchen Zhao**, *Ismail Elezi*, *Jiankang Deng*, and *Xiaojuan Qi*



What makes this tokenizer different?

- **1D Causal Tokenization** – An ordered structure where token importance follows a hierarchical pattern.
- **PCA-Like Structure** – Earlier tokens contain most significant information, while later tokens refine details.
- **Semantic-Spectrum Decoupling** – ensuring tokens capture high-level rather than low-level artifacts.

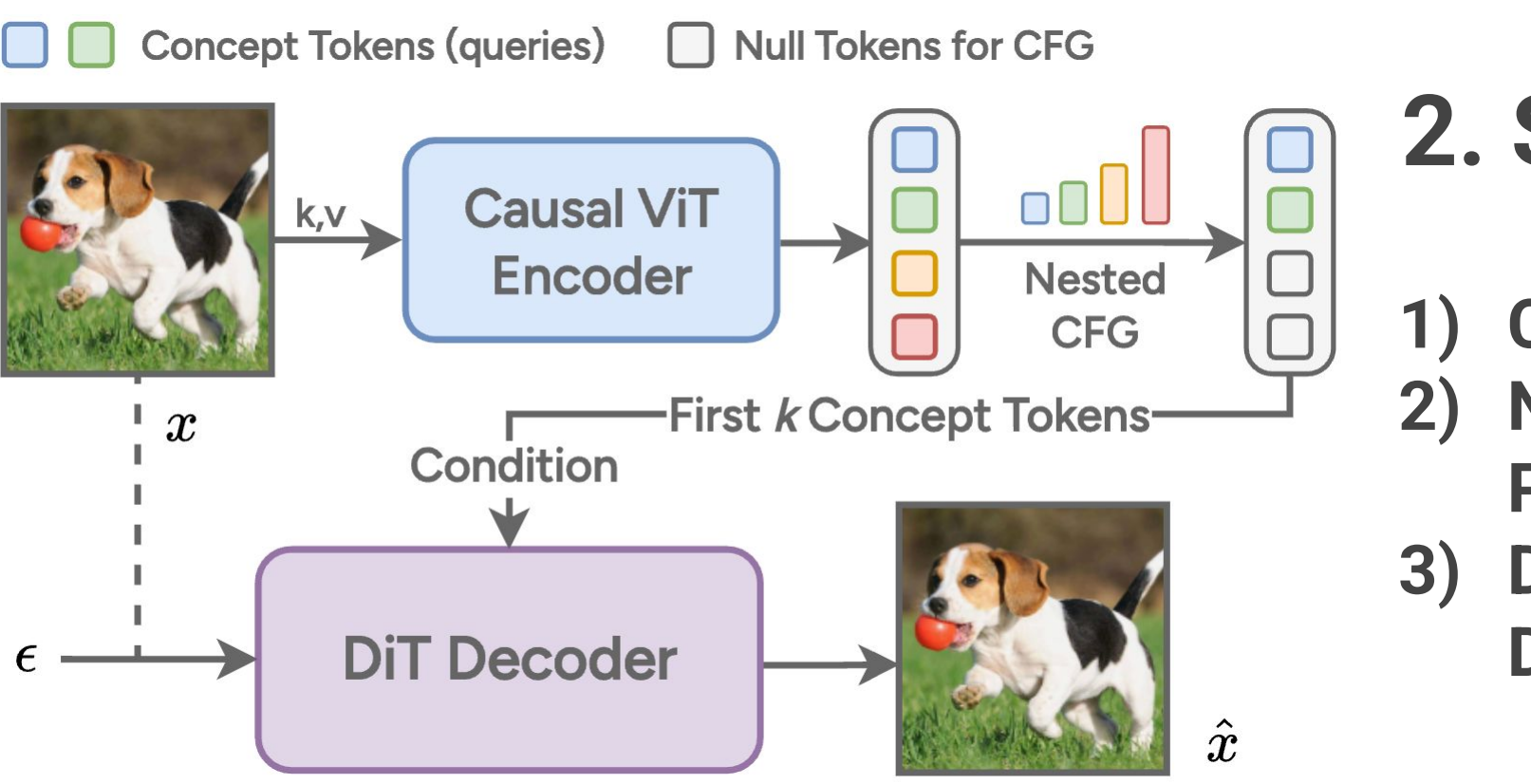
1. Semantic-Spectrum Decoupling



TiTok: both semantic details and spectral power increase simultaneously.

Ours:

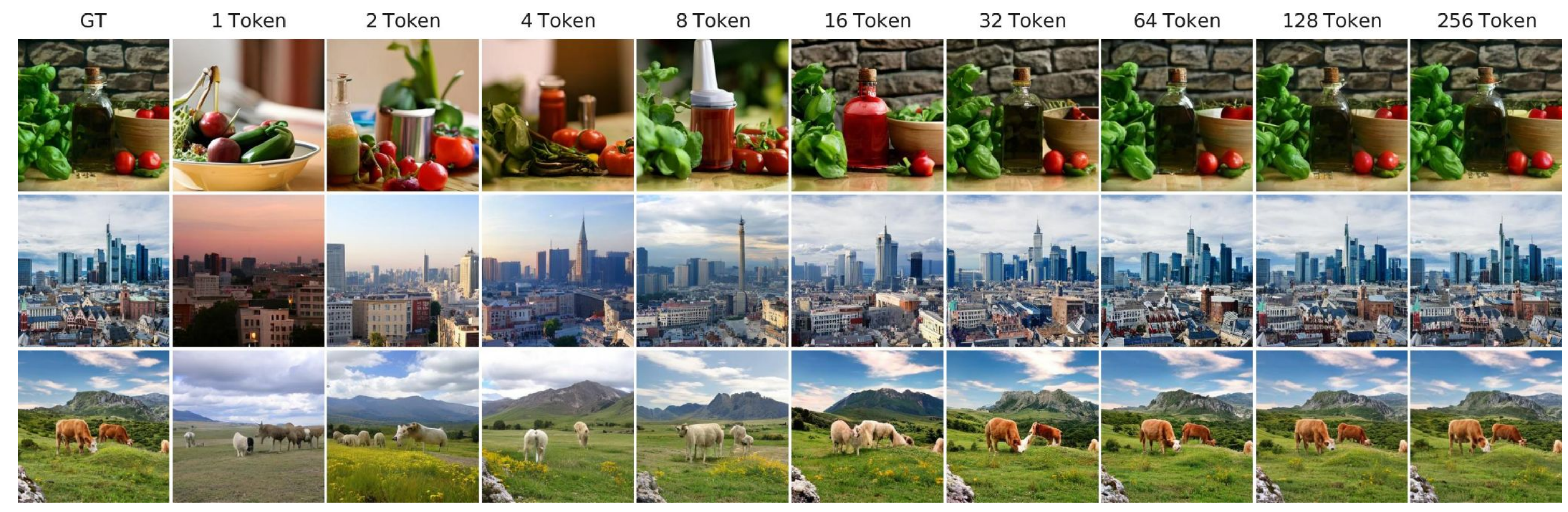
- 1) Semantic clarity w/ few tokens.
- 2) Consistent spectrum across token counts.
- 3) Coarse-to-fine hierarchy, mirroring global precedence effect in human vision.



2. Semanticist

- 1) Causal ViT Encoder
- 2) Nested Dropout for PCA-like Structure
- 3) Diffusion-Based DiT Decoder

3. Reconstruction with A Variable Number of Tokens

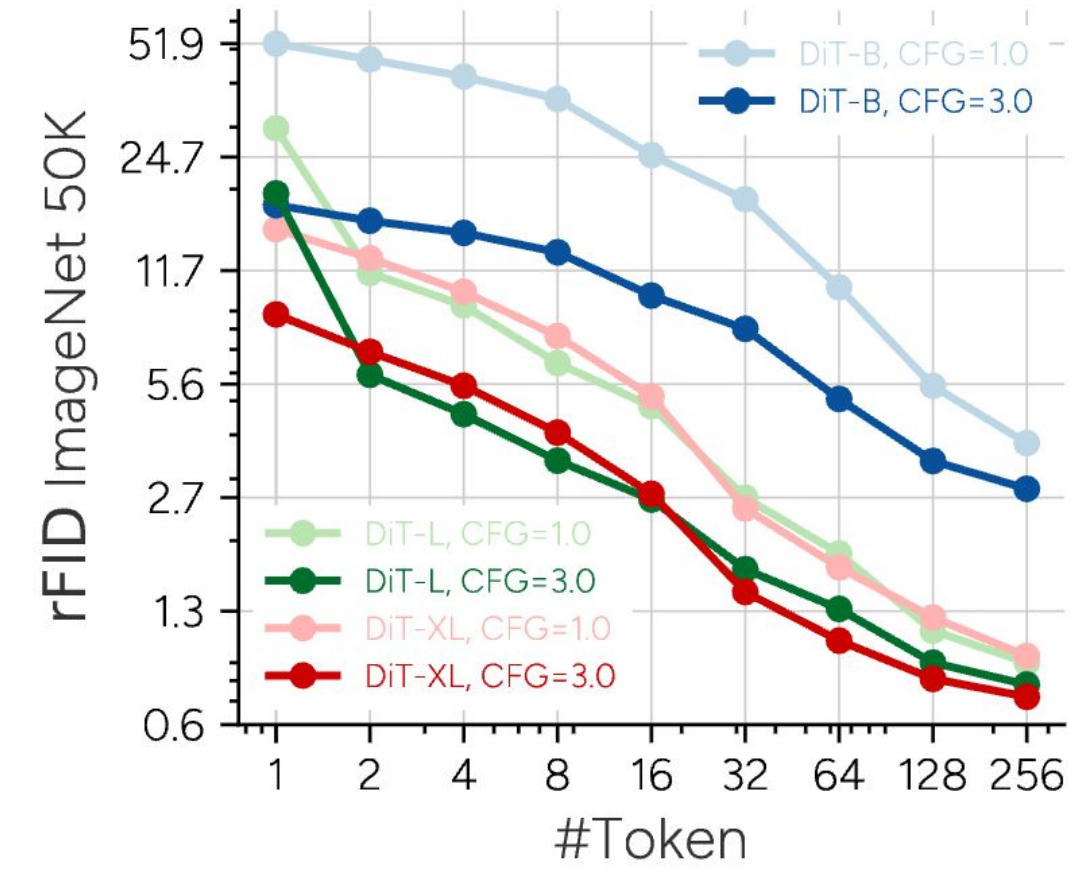
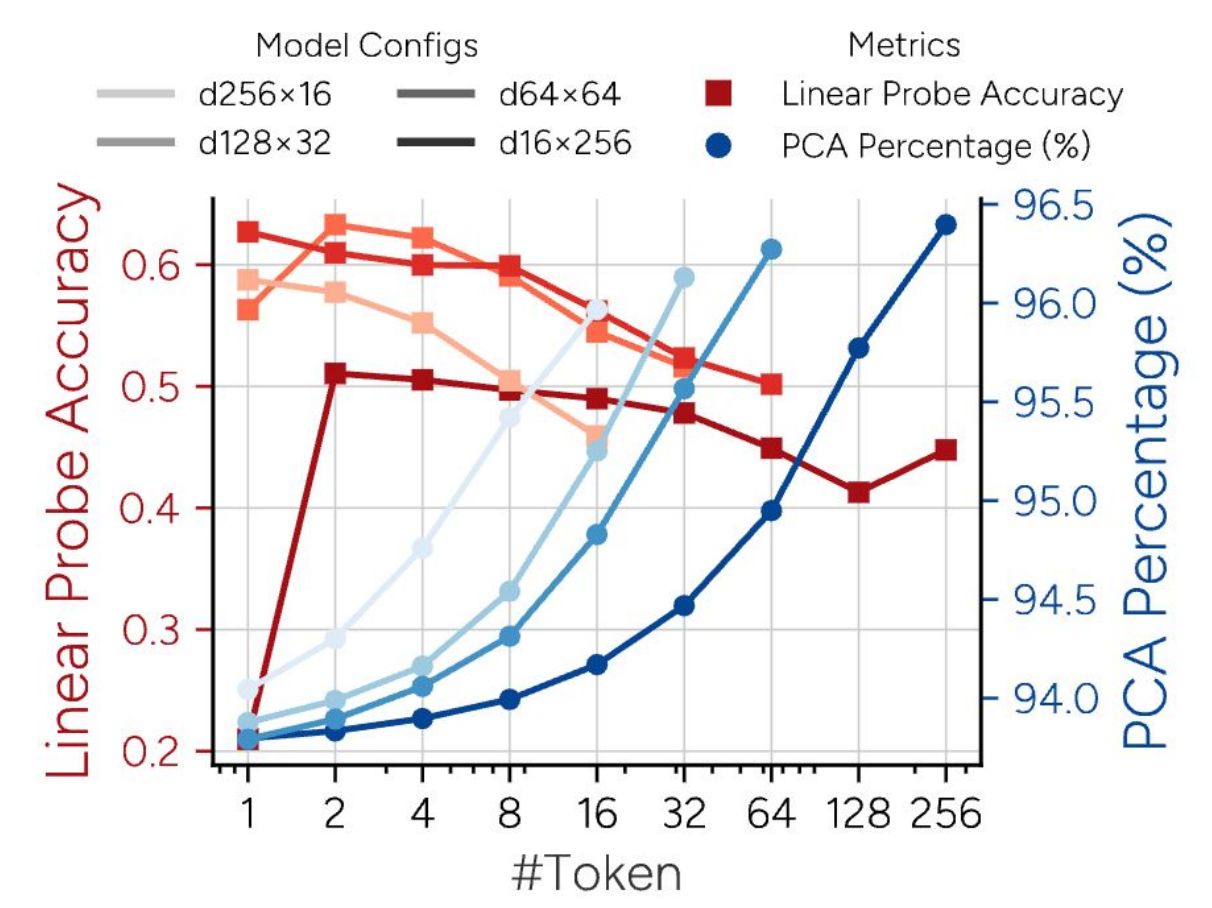


Method	#Token	Dim.	VQ	rFID↓	PSNR↑	SSIM↑	Gen. Model	Type	#Token	#Step	gFID↓	IS↑
MaskBit [55]	256	12	✓	1.61	—	—	MaskBit	Mask.	256	256	1.52	328.6
RCG (cond.) [27]	1	256	✗	—	—	—	MAGE-L	Mask.	1	20	3.49	215.5
MAR [28]	256	16	✗	1.22	—	—	MAR-L	Mask.	256	64	1.78	296.0
TiTok-S-128 [60]	128	16	✓	1.71	—	—	MaskGIT-L	Mask.	128	64	1.97	281.8
TiTok-L-32 [60]	32	8	✓	2.21	—	—	MaskGIT-L	Mask.	32	8	2.77	194.0
VQGAN [13]	256	16	✓	7.94	—	—	Tam. Trans.	AR	256	256	5.20	280.3
ViT-VQGAN [57]	1024	32	✓	1.28	—	—	VIM-L	AR	1024	1024	4.17	175.1
RQ-VAE [26]	256	256	✓	3.20	—	—	RQ-Trans.	AR	256	64	3.80	323.7
VAR [49]	680	32	✓	0.90	—	—	VAR-d16	VAR	680	10	3.30	274.4
ImageFolder [29]	286	32	✓	0.80	—	—	VAR-d16	VAR	286	10	2.60	295.0
LlamaGen [48]	256	8	✓	2.19	20.79	0.675	LlamaGen-L	AR	256	256	3.80	248.3
CRT [39]	256	8	✓	2.36	—	—	LlamaGen-L	AR	256	256	2.75	265.2
Causal MAR [28]	256	16	✗	1.22	—	—	MAR-L	AR	256	256	4.07	232.4
SEMANTICIST w/ DiT-L	256	16	✗	0.78	21.61	0.626	εLlamaGen-L	AR	32	32	2.57	260.9
SEMANTICIST w/ DiT-XL	256	16	✗	0.72	21.43	0.613	εLlamaGen-L	AR	32	32	2.57	254.0

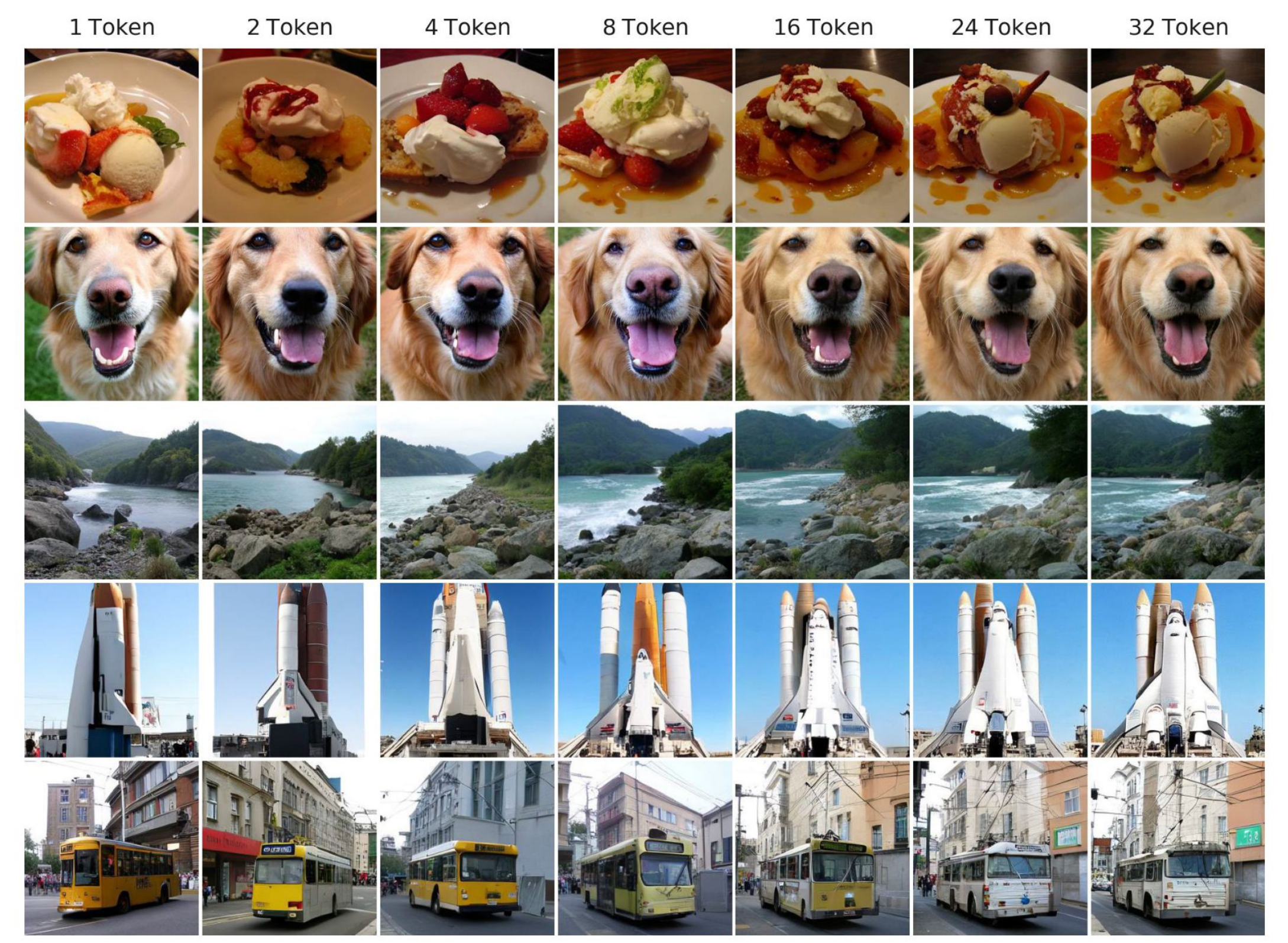
Competitive understanding, reconstruction, and AR generation.

Top: quantitative results on ImageNet reconstruction and autoregressive generation.

Left: linear probing; Right: reconstruction FID.



4. AR Generation with A Variable Number of Tokens (w/ LlamaGen)



5. Discussion

Potential Applications

- Unified understanding & generation, image compression, data analysis, etc.

Limitations/Future Work

- **Inference Speed:** Diffusion decoding is slower than direct pixel regression.
- **Alternative Architectures:** Flow-matching or consistency models could improve efficiency.
- **Random Ordering:** Compatible to random-ordered tokens could be useful.