GMM Diffusion: Gaussian Mixture Masks for Diffusion Models

Chang Liu, Karim Habashy, Peter Yuchen Pan, Hadi Sepanj

University of Waterloo

Motivation

- Diffusion models require significant computation and training time
- Our method proposes 2 novel modifications to allow small diffusion models generate similar quality images to their larger counterparts

Previous Work

- FreeU: Reweight U-Net's skip connections and backbone feature maps for diffusion models to improve image generation quality [1]
- GMM: Gaussian Mixture Masks applied to Retentive Networks [3]
- U-ViT: ViT-based architecture for diffusion models [2]

Proposed Methods

To the best of our knowledge, our work is the first to apply both Gaussian Mixture Mask and U-Net scale factors to diffusion models.

Specifically, our work is novel in 2 following ways.

1. Gaussian mixture mask

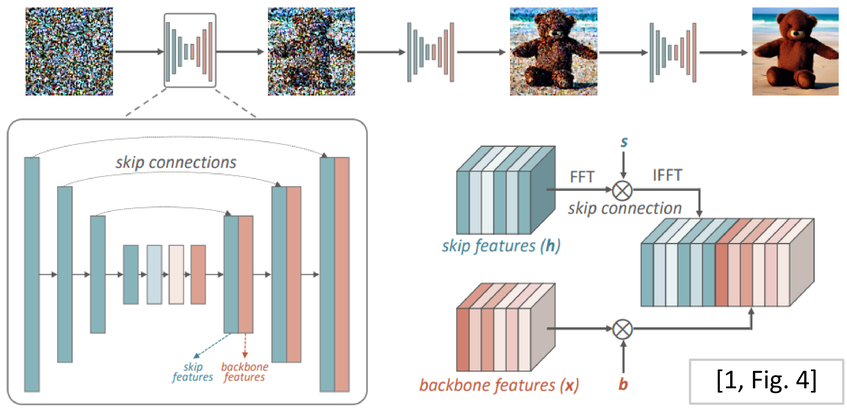
- Proposes Gaussian mixture mask to boost image generation capabilities for small dataset with almost zero additional parameters and computational cost
- Learn 2 parameters to implicitly generate Gaussian mixture mask on the attention heads

$$\text{GMMAttention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}} \circ M\right)V$$

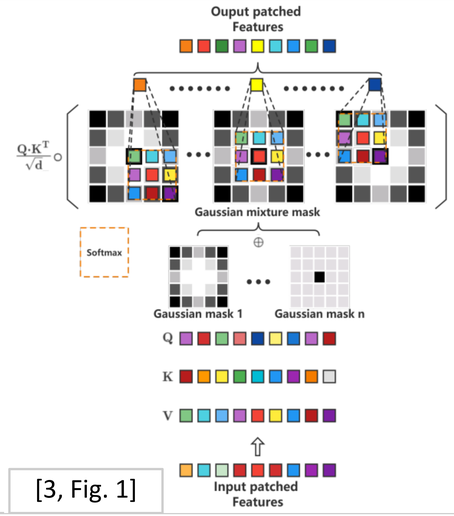
2. Skip connections during inference

- Re-scales U-Net's skip connection feature maps and backbone feature maps to improve image quality without additional training or finetuning
- Adjusts 2 scaling factors (scaling backbone based on averaged feature maps and scaling long skip connections across different decoder blocks).

Model Architecture



[1, Fig. 4]



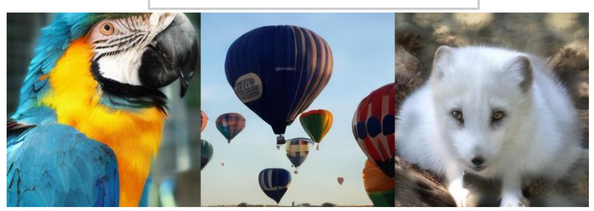
[3, Fig. 1]

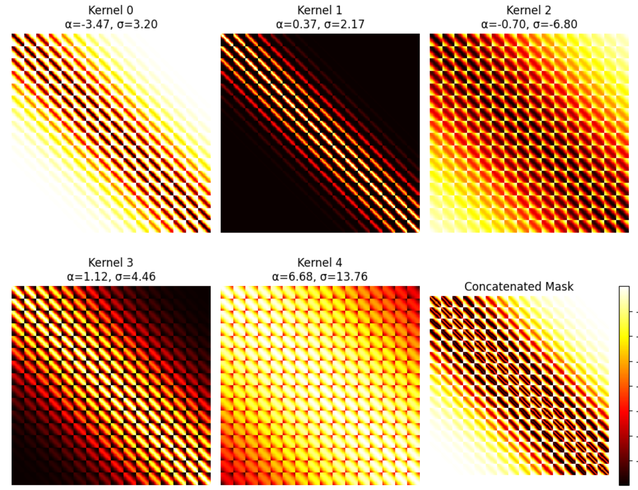
Experiments

Model 1: b=1.0, s=1.0

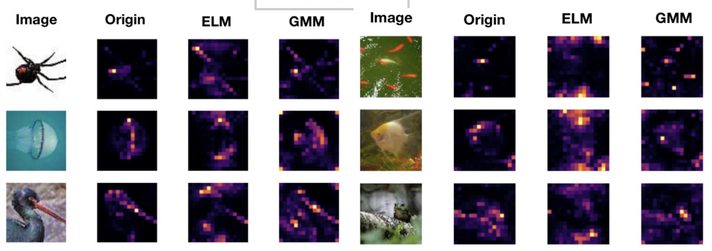
Model 2: b=1.3, s=1.0

Model 3: b=1.0, s=0.8





[3, Fig. 7]



References

[1] C. Si, Z. Huang, Y. Jiang, and Z. Liu, "FreeU: Free Lunch in Diffusion U-Net," *https://arxiv.org/pdf/2309.11497.pdf*, Sep. 2023.

[2] F. Bao *et al.*, "All are worth words: A VIT backbone for diffusion models," *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. doi:10.1109/cvpr52729.2023.02171

[3] C. Li and C. Zhang, *Toward a deeper understanding: Retnet viewed through convolution*, 2023. doi:10.2139/ssrn.4637493

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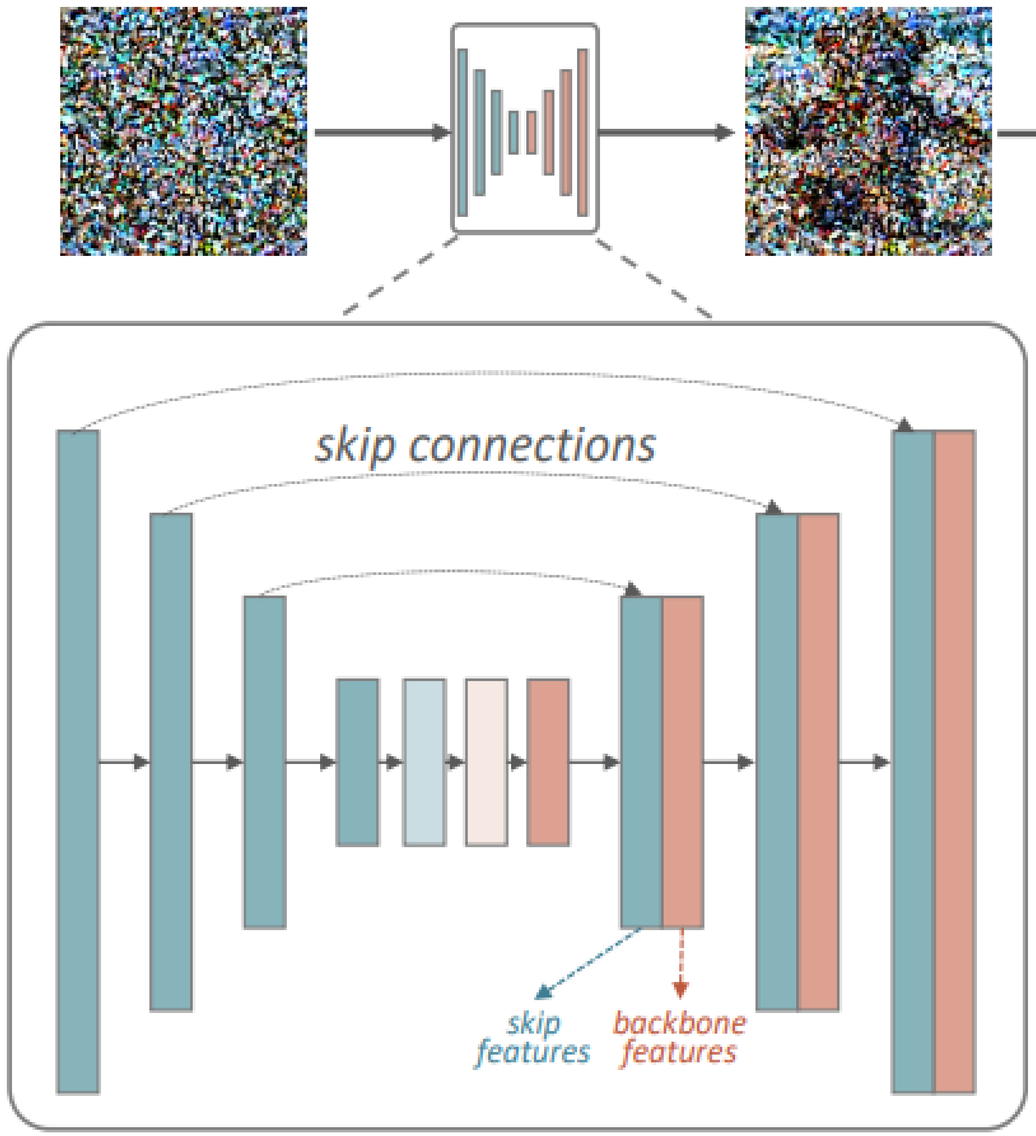
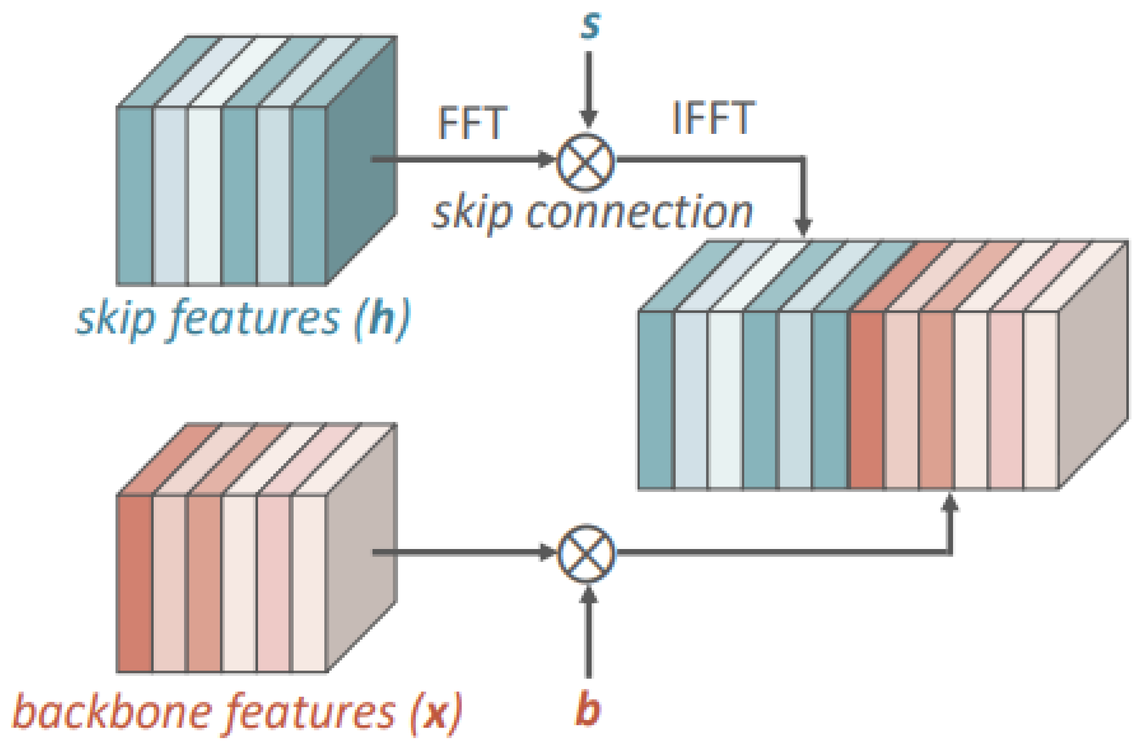
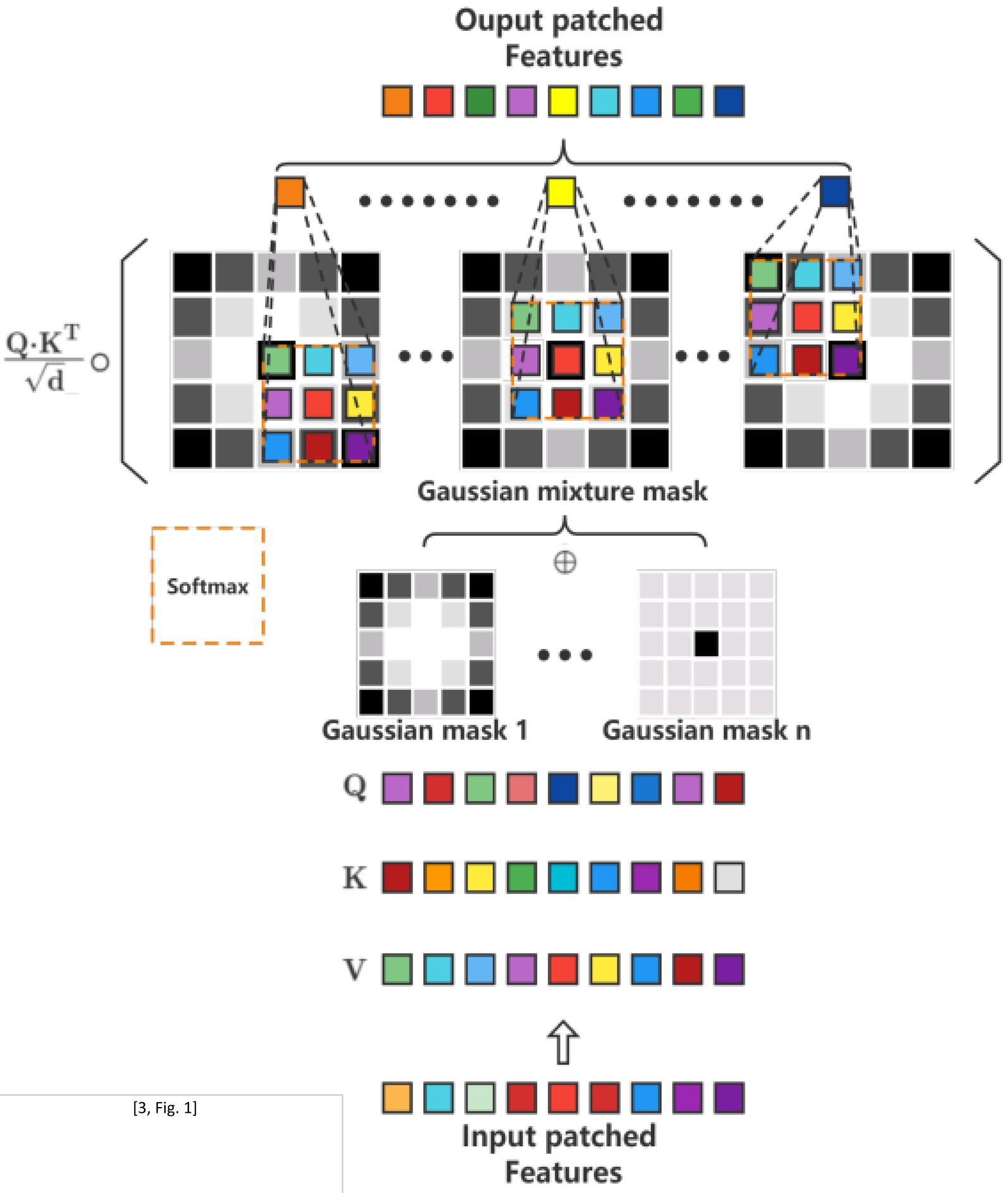


(a) UNet Architecture



(b) FreeU Operations


Ouput patched
Features
$\frac{Q \cdot K^T}{\sqrt{d}}$ ○
Softmax
Gaussian mixture mask
⊕
Gaussian mask 1
Gaussian mask n
Q
K
V
Input patched
Features

[3, Fig. 1]

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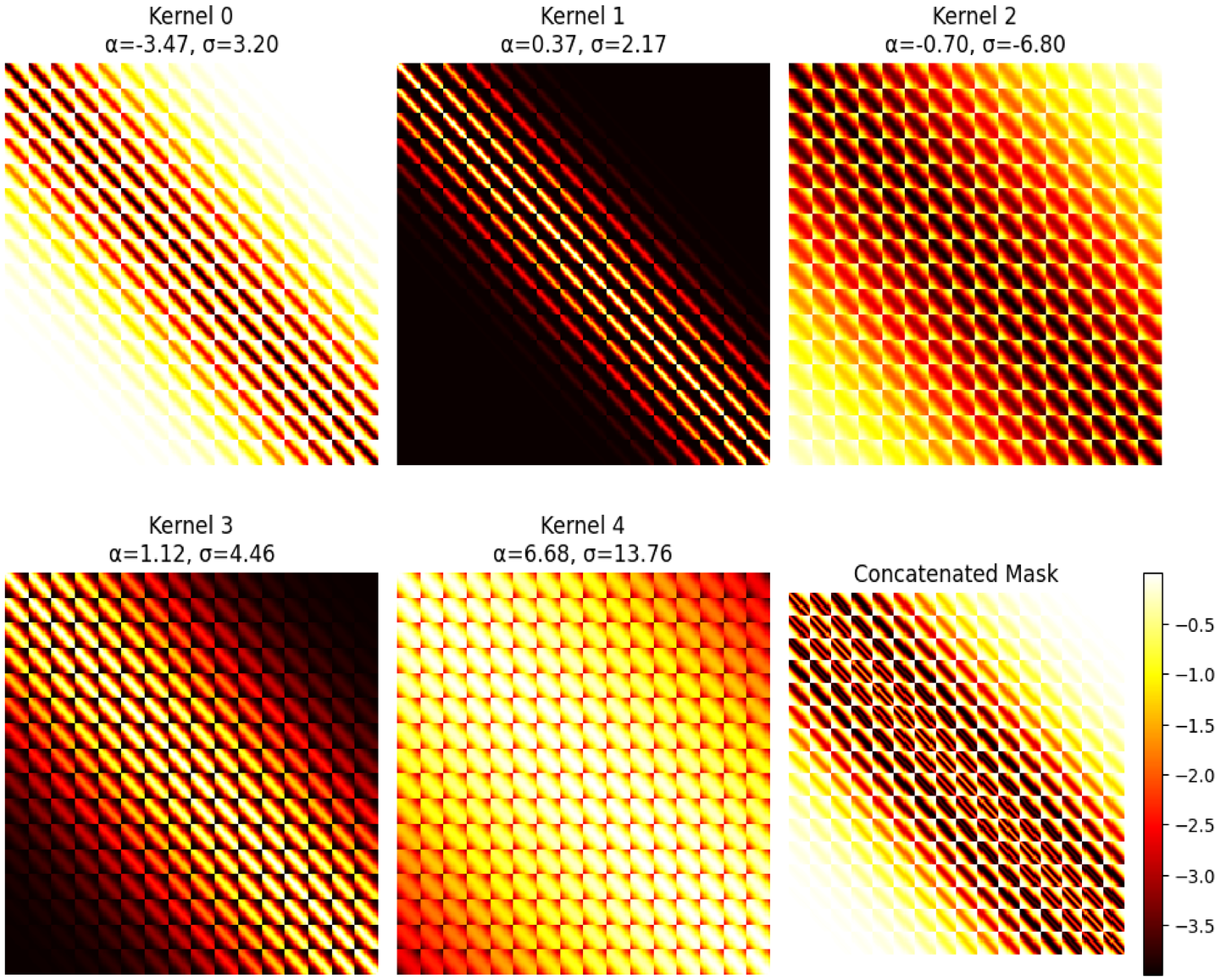
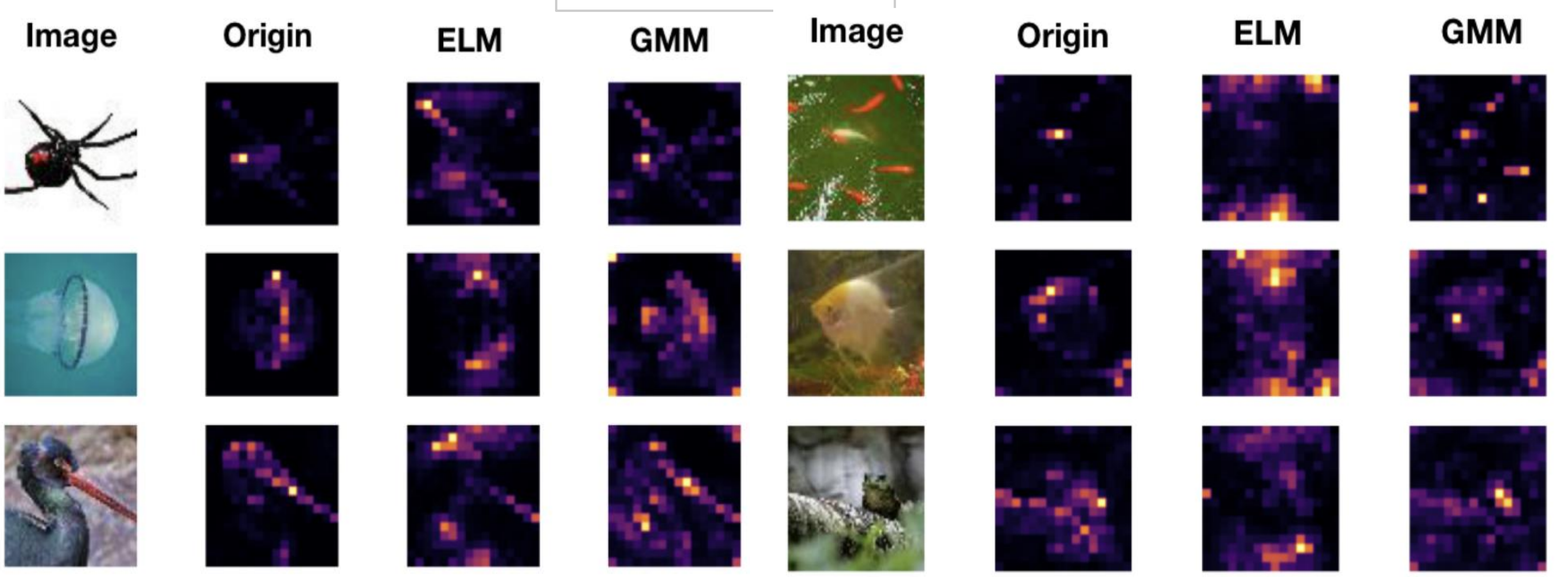


[3, Fig. 7]



References

[1] C. Si, Z. Huang, Y. Jiang, and Z. Liu, “FreeU: Free Lunch in Diffusion U-Net,” *https://arxiv.org/pdf/2309.11497.pdf*, Sep. 2023.

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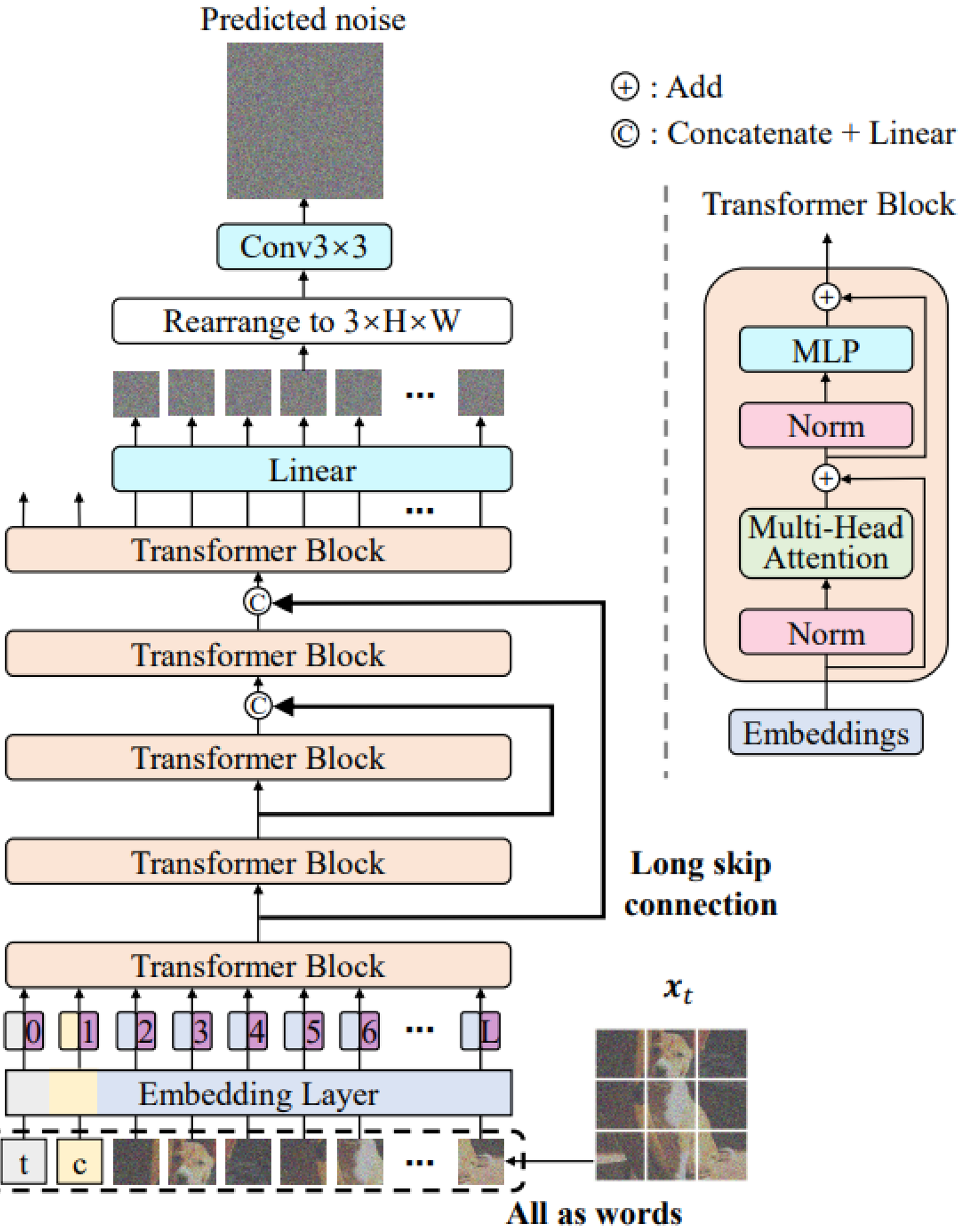
Predicted noise
Conv3×3
Rearrange to 3×H×W
Linear
Transformer Block
Transformer Block
Transformer Block
Transformer Block
Transformer Block
0
1
2
3
4
5
6
L
Embedding Layer
t
c
x_t
All as words
Long skip connection
⊕ : Add
© : Concatenate + Linear
Transformer Block
MLP
Norm
Multi-Head Attention
Norm
Embeddings