High-Resolution Image Synthesis with Latent Diffusion Models

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The Development of AI-Generated Content (AIGC)

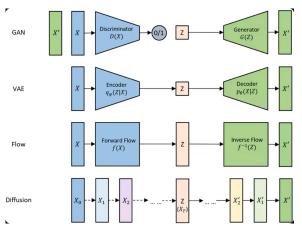


Figure 1: The development of AIGC and mobile edge computing network [1].

^[1] M. Xu, et al., "Unleashing the power of edge-cloud generative AI in mobile networks: A survey of AIGC services," IEEE Commun. Surv. Tutor., Early Access, 2024.

Diffusion Model

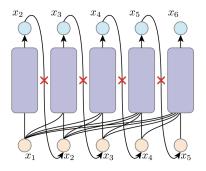


Figure 2: An illustration of diffusion model [2].

- With Gaussian noise as input
- The quality of generated images gets progressively better.

^[2] H. Du, et al., "Enhancing deep reinforcement learning: A tutorial on generative diffusion models in network optimization," arXiv preprint arXiv:2308.05384, 2023.

AIGC in Mobile Edge Computing (MEC)

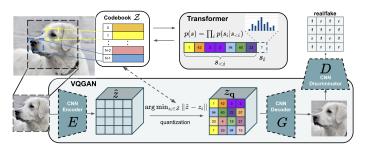


Figure 3: An overview of a mobile AIGC network [1].

• AIGC models can be deployed at edge servers.

^[1] M. Xu, et al., "Unleashing the power of edge-cloud generative AI in mobile networks: A survey of AIGC services," IEEE Commun. Surv. Tutor., Early Access, 2024.

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MEC Network

Local Processing Model

Home BS Processing Model



Neighbor BS Processing Model

Yingjian Zhu (UCAS)

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Weighted Cost

Offloading Problem

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Deep Reinforcement Learning based OSI Algorithm

• State:

$$s_n^{(l)} = \left(B_n^{(l)}, q_n^{(l)}, f_n^{U,(l)}, g^{B,(l)}, h_n^{(l)}\right)$$

• Action:

$$a_n^{(l)} = \left(x_n^{(l)}, y_n^{(l)}, c_n^{(l)}\right)$$

• Reward:

$$r_n^{(l)} = -\sum_{n \in \mathcal{N}} \left(\omega_1 T_n^{(l)} + \omega_2 E_n^{(l)} + \omega_3 \epsilon_n^{(l)}\right) - r_n^{P,(l)}$$

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Acknowledgements

Thanks for your listening!

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