# Pixel-Level BPE Encoding for Auto-Regressive Image Generation

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## Abstract

The topic of image generation is very hot today. The most impressive results are obtained by GANs and diffustion-based models, or codebook-level autoregression (VQVAE+GPT). Also it is possible to generate images autoregressively on pixel level (image-GPT), however it is too memory-consuming approach due to the resulting total length of modeling pixel-sequence and hence this method is not very popular.

In our research we propose to adopt Byte-Pair-Encoding (BPE) for pixel-level encoding to drastically reduce the length of modeled sequence. Our experiments demonstrate that auto-regressive image generation might be understudied due to the lack of optimal sequence encoding techniques for images.

## 1. Introduction

There are plenty approaches to image generation: GANs, auto-encoders, auto-regression over discrete features, diffusion models, energy models and optimal transport. One of understudied approaches is auto-regressive pixel-level generating. The main challenge in this kind of models is the length of the modeling sequences. For example for 128x128 RGB image the pixel sequence length is equal to

$$128 \cdot 128 \cdot 3 = 49152$$

which is infeasible to model with standard auto-regressive architectures (RNN, GPT). But in contrast to extremely large sequence length the size of vocabulary is fairly small (255 values) compared to text-based models. We suggest to exploit this fact and to improve the trade-off between the sequence length and the vocabulary size.

We conducted several experiments with different types of sequence tokenization: Byte-Pair-Encoding (BPE), byte-level BPE, color-adapted BPE and spacial-adapted BPE. The proposed tokenization methods efficiently squeeze the length of the pixel sequences and give a green-light for further study of autoregressive pixel-level image generation. In addition we provide experimental results on CelebA and CIFAR datasets.

*Figure 1.* One of the worst examples :)

Main contributions of this paper:

- Image-GPT implementation
- Suggested several BPE-based tokenization techniques for pixel sequence length squeezing.

## 2. Related Work

Transformer-based (Vaswani et al., 2017) models are extremely successful in natural language generation and understanding fields. GPT (Alec Radford, 2018) demonstrated human-level performance text generating and zero-shot tasks via prompt engineering. There were attempts in using GPT architecture for image generation, which can be divided into two groups: discrete feature based regression DALLE (Ramesh et al., 2022) or pixel-level regression iGPT (Chen et al., 2020). The second type of models is not fairy popular, as it is too memory-expensive due to the length of the pixel context. However, iGPT model demonstrated decent results in low-resolution image generation and downstream tasks over contextualized features. From the other side, in NLP there are plenty of methods for sequence length compression — different tokenization techniques, which expoit the precomputer merge dictionaries for optimal encoding of words or byte groups. One of the most efficient methods is Byte-Pair-Encoding (Shibata et al., 1999). In GPT models it is used special modification of this algorithm which works at byte-level (blB) which is a one more step for optimal sequence squeezing.

## References


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