A Additional implementation details

The high-level architecture is depicted in Fig. 1.

**VQ-SEG.** VQ-SEG is trained for 600k iterations, with a batch size of 48, dictionary size of 1024. The number of segmentation categories per-group are $m_p = 133$ for the panoptic segmentation, $m_h = 20$ for the human parsing, and $m_f = 5$ for the face parsing. The per-category weight function follows the notation:

$$
\alpha_{cat} = \begin{cases} 
20, & \text{if } \text{cat} \in [154, ..., 158] \\
1, & \text{otherwise},
\end{cases}
$$

(1)

where $\text{cat} \in [154, ..., 158]$ are the face-parts categories eyebrows, eyes, nose, outer-mouth, and inner-mouth.

**VQ-IMG.** VQ-IMG$_{256}$ and VQ-IMG$_{512}$ are trained for 800k and 940k iterations respectively, with a batch size of 192 and 128, a channel multiplier of $[1, 1, 2, 4]$ and $[1, 1, 2, 4, 4]$, while both are trained with a dictionary size of 8192.

The per-layer normalizing hyperparameter for the face-aware loss is $\alpha_f^l = [\alpha_{f1}, \alpha_{f2} \times 0.01, \alpha_{f2} \times 0.1, \alpha_{f2} \times 0.2, \alpha_{f2} \times 0.02]$ corresponding to the last layer of each block of size $1 \times 1, 7 \times 7, 28 \times 28, 56 \times 56, 128 \times 128$, where $\alpha_{f1} = 0.1$ and $\alpha_{f2} = 0.25$. We experimented with two settings, the first where $\alpha_{f1} = \alpha_{f2} = 1.0$, and the second, which was used to train the final models, where $\alpha_{f1} = 0.1, \alpha_{f2} = 0.25$. The remaining face-loss values were taken from the work of [2]. The per-layer normalizing hyperparameter for the object-aware loss, $\alpha_o^l$ were taken from the work of [1], based on LPIPS [4].

**Scene-based transformer.** The $512 \times 512$ and $256 \times 256$ models both share all implementation details, excluding the VQ-IMG used for token encoding and decoding, and the object-aware loss that was applied to the $512 \times 512$ model only. Both transformers share the architecture of 48 layers, 48 attention heads, and an embedding dimension of 2560. The models were trained for a total of 170k iterations, with a batch size of 1024, Adam [3] optimizer, with a starting
learning-rate of $4.5 \times 10^{-4}$ for the first $40k$ iterations, transitioning to $1.5 \times 10^{-4}$ for the remainder, $\beta_1 = 0.9, \beta_2 = 0.96$, weight-decay of $4.5 \times 10^{-4}$, and a loss ratio of $7/1$ between the image and text tokens. For classifier-free guidance, we fine-tune the transformer, while replacing the text tokens with padding tokens in the last $30k$ iterations, with a probability of $p_{CF} = 0.2$. At inference-time we set the guidance scale to $\alpha_c = 5$, though we found that $\alpha_c = 3$ works as well.

At each inference step, the next token is sampled by (i) selecting half the logits with the highest probabilities, (ii) applying a softmax operation over the selected logits, and (iii) sampling a single logit from a multinomial probability distribution.

![Fig. 1. The scene-based method high-level architecture. Given an input text and optional scene layout, a corresponding image is generated. The transformer generates the relevant tokens, encoded and decoded by the corresponding networks.](image)

**B Additional samples**

Additional samples generated from challenging text inputs are provided in Figs. 2-3, while samples generated from text and scene inputs are provided in Figs. 4-7. The different text colors emphasize the large number of different objects/scenarios being attended. As there are no ‘octopus’ or ‘dinosaur’ categories, we use instead the ‘cat’ and ‘giraffe’ categories respectively. We did not attempt to use other classes in this case. However, we found that generally there are no “one-to-one” mappings between absent and existing categories, hence several categories may work for an absent category.
"a painting of a Unicorn lemur in the Sahara desert" "a painting of a dog raking autumn leaves" "a painting of a ghost picking apples" "a painting of an image of a white giraffe"

"a sloth eating oatmeal" "a panda walking slowly in his dirt enclosure" "a panda bear carrying some grocery bags" "blue elephant"

"a painting of roses blooming on a cloud" "a painting of a human being eating money." "a painting of a panda with horns" "a painting of humanoid"

"Duke University men's basketball Coach K smiling" "purple coffee" "a dog is lying on a blanket on top of a couch" "fuzzy lizard"

"a painting of dachshund in a hot air balloon" "a painting of singing eggplant" "a painting of horse riding a scooter" "a painting of A turtle eating grapefruit"

Fig. 2. Additional samples generated from challenging text inputs.
Fig. 3. Additional samples generated from challenging text inputs.
C  Additional comparisons and ablation studies

A comparison of challenging generations (faces) is shown in Fig. 8. This challenging comparison emphasizes the necessity of the face-aware component in the VQ-IMG network.

To further establish the necessity of model large-scaling, we provide an ablation study of two smaller models (Small-0.4B, Medium-1.4B) in Tab. 1.

| Model   | FID↓   | Text↑   | Quality↑      |
|---------|--------|---------|---------------|
| Obj512  | 8.70   | -       | -             |
| +S / M  | 19.08 / 15.49 | 34.4% / 39.5% | 30.5% / 42.9% |

Table 1. An ablation study (FID and human preference) of the small (S, 0.4B parameters) and medium (M, 1.4B) models. Human preference (text-alignment and image-quality) of S and M are compared with Obj512 (4B model).
Fig. 5. Additional samples generated (b) from text and segmentation inputs (a).

Fig. 6. Additional samples generated (b) from text and segmentation inputs (a).
Fig. 7. Additional samples generated (b) from text and segmentation inputs (a).

Fig. 8. A qualitative comparison emphasizing the advantage of our method in challenging generations (where available). [5] is denoted as Long et al.
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