**GLeaD: Improving GANs with A Generator-Leading Task**

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**Supplementary Material**

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**Overview**

This supplementary material is organized as follows. Sec. A introduces the detailed discriminator network structure of GLeaD. Sec. B provides comparisons on the computational between our method and the baseline [1].

**A. Discriminator Network Structure**

Recall that, our D concludes a backbone \(D_{enc}\), a head predicting realness scores, and a decoder \(h\) for predicting representative features \(f\) and \(w\). Taking images whose resolution are \(256 \times 256\) as an instance, the backbone \(D_{enc}\) is first employed to extract features from the input image. The very last feature map of \(4 \times 4\) is sent to the scoring head to extract the realness score while the multi-level feature maps are sent to the decoder \(h\) to predict the representative features adequate for G to reconstruct the original images. As described in the submission, the representative features consist of latent codes \(w\) and the spatial representations \(f\), which concludes a low-level representation and a high-level representation. Recall that, these spatial representations will be sent to the fixed generator to serve as the basis of the reconstruction and will be modulated by latent codes to predict the final results. We illustrate the architectures of the three aforementioned components of D in Tab. S1, Tab. S2, and Tab. S3, respectively.

**B. Computational Costs**

We first compute the discriminator parameter amounts of the baseline and our method. As in Tab. S4, our method merely brings 7.4% additional parameters over baseline, which is brought by the proposed lightweight design of \(h\) composed of \(1 \times 1\) convolutions. Then we compare the inference time of the discriminators with a single A6000 GPU. At last, we make comparisons on the training time. We separately train the baseline model [1] and our model with 8 A100 GPUs on LSUN Church and record how much time the training costs. From the numbers in Tab. S4, we

<table>
<thead>
<tr>
<th>Stage</th>
<th>Block</th>
<th>Output Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>input</td>
<td>-</td>
<td>(3 \times 256 \times 256)</td>
</tr>
</tbody>
</table>
| block\(_1\) | \[
1 \times 1 \text{Conv}, 128 \\
2 \times 3 \times 3 \text{Conv}, 128 \\
1 \times 1 \text{Conv}, 128 \\
\text{Downsample} \\
\text{LeakyReLU}, 0.2
\] | \(128 \times 128 \times 128\) |
| block\(_2\) | \[
2 \times 3 \times 3 \text{Conv}, 256 \\
1 \times 1 \text{Conv}, 256 \\
\text{Downsample} \\
\text{LeakyReLU}, 0.2
\] | \(256 \times 64 \times 64\) |
| block\(_3\) | \[
2 \times 3 \times 3 \text{Conv}, 512 \\
1 \times 1 \text{Conv}, 512 \\
\text{Downsample} \\
\text{LeakyReLU}, 0.2
\] | \(512 \times 32 \times 32\) |
| block\(_4\) | \[
2 \times 3 \times 3 \text{Conv}, 512 \\
1 \times 1 \text{Conv}, 512 \\
\text{Downsample} \\
\text{LeakyReLU}, 0.2
\] | \(512 \times 16 \times 16\) |
| block\(_5\) | \[
2 \times 3 \times 3 \text{Conv}, 512 \\
1 \times 1 \text{Conv}, 512 \\
\text{Downsample} \\
\text{LeakyReLU}, 0.2
\] | \(512 \times 8 \times 8\) |
| block\(_6\) | \[
2 \times 3 \times 3 \text{Conv}, 512 \\
1 \times 1 \text{Conv}, 512 \\
\text{Downsample} \\
\text{LeakyReLU}, 0.2
\] | \(512 \times 4 \times 4\) |

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* This work was done during an internship at Ant Group.
† Corresponding author.
Table S2. Network structure of the decoder \( h \) predicting the low-level spatial representation, the high-level spatial representation and the 512-channel latent codes. Note that \( h \) receives multi-level features as inputs due to its feature pyramid architecture \([2]\). The output size is with order \( \{C \times H \times W\} \).

<table>
<thead>
<tr>
<th>Stage</th>
<th>Block</th>
<th>Output Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>input</td>
<td>–</td>
<td>512 \times 32 \times 32</td>
</tr>
<tr>
<td></td>
<td></td>
<td>512 \times 16 \times 16</td>
</tr>
<tr>
<td></td>
<td></td>
<td>512 \times 8 \times 8</td>
</tr>
<tr>
<td></td>
<td></td>
<td>512 \times 4 \times 4</td>
</tr>
<tr>
<td>block(_1)</td>
<td>( [\begin{array}{l} 1 \times 1 \text{Conv}, 512 \ \text{Upsample} \end{array} ] )</td>
<td>512 \times 8 \times 8</td>
</tr>
<tr>
<td>block(_2)</td>
<td>( [\begin{array}{l} 1 \times 1 \text{Conv}, 512 \ \text{Upsample} \end{array} ] )</td>
<td>512 \times 16 \times 16</td>
</tr>
<tr>
<td>block(_3)</td>
<td>( [\begin{array}{l} 1 \times 1 \text{Conv}, 512 \ \text{Upsample} \end{array} ] )</td>
<td>512 \times 32 \times 32</td>
</tr>
<tr>
<td>block(_4)</td>
<td>( [\begin{array}{l} 1 \times 1 \text{Conv}, 3 \ 2 \times 1 \times 1 \text{Conv}, 512 \ \text{Downsample} \ \text{FC}, 512 \ \text{LeakyReLU}, 0.2 \ \text{FC}, 1 \end{array} ] )</td>
<td>3 \times 32 \times 32</td>
</tr>
<tr>
<td></td>
<td></td>
<td>512 \times 32 \times 32</td>
</tr>
<tr>
<td></td>
<td></td>
<td>512</td>
</tr>
</tbody>
</table>

Table S3. Network structure of the head predicting realness scores which are scalars. The output size is with order \( \{C \times H \times W\} \).

<table>
<thead>
<tr>
<th>Stage</th>
<th>Block</th>
<th>Output Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>input</td>
<td>–</td>
<td>512 \times 4 \times 4</td>
</tr>
<tr>
<td>block(_1)</td>
<td>( [\begin{array}{l} \text{Mbstd}, 1 \ 3 \times 3 \text{Conv}, 512 \ \text{LeakyReLU}, 0.2 \ \text{Downsample} \ \text{FC}, 512 \ \text{LeakyReLU}, 0.2 \ \text{FC}, 1 \end{array} ] )</td>
<td>1</td>
</tr>
</tbody>
</table>

Table S4. Computational cost comparisons.

<table>
<thead>
<tr>
<th>Method</th>
<th># params</th>
<th>inference time(s)</th>
<th>training time(h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>24.00M</td>
<td>0.0184</td>
<td>43.83</td>
</tr>
<tr>
<td>GLLeaD</td>
<td>25.77M</td>
<td>0.0219</td>
<td>55.78</td>
</tr>
</tbody>
</table>

can conclude that our method improves the synthesis quality without much additional computational burden.

**References**
