Adaptive Data-Free Quantization

Supplementary Material

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Due to page limitation of the main body, as indicated, the supplementary material offers further discussion on the hyper-parameters and more visual results with higher resolution, which are summarized below:

- Additional parameter studies about the hyper-parameters α_{ds} and α_{as} in Eq.(9) as well as β and γ in Eq.(12), as mentioned in Sec.3.1 of the main body (Sec.A).
- Additional ablation study about the number of generated samples from the generator (G) during the training phase (Sec.B).
- Visualization of real and generated samples with *higher resolution*, as mentioned in Sec.3.5 of the main body (Sec.C).

A. Additional Parameter Studies

A.1. α_{ds} and α_{as} in Eq.(9)

In this section, we further study the parameters α_{ds} and α_{as} in Eq.(9) of the main body on the balance process. We perform that via varied $\alpha_{ds} \in \{0, 0.1, 0.2, 0.3, 0.4, 0.6, 0.8\}$ with $\alpha_{as} = 0.1$ (Fig.1(a)) and $\alpha_{as} \in \{0, 0.1, 0.2, 0.3, 0.4, 0.6, 0.8\}$ with $\alpha_{ds} = 0.2$ (Fig.1(b)), where the ablation studies are carried out under 3-bit precision upon ResNet-18, to serve as full-precision (P) and quantized network (Q) on ImageNet. It is observed that the optimal performance is achieved with $\alpha^*_{ds} = 0.2$ and $\alpha^*_{as} = 0.1$ (as adopted in the main experiments), confirming the effectiveness of balancing disagreement with agreement sample. Accordingly, the results offer an *evidence* that the balance process is conducive to generating the sample with adaptive adaptability (*i.e.*, neither too large nor small $\mathcal{H}^{'}_{info}(p_{ds})$) to Q under varied bit widths, which address the over-and-under fitting issues.

A.2. β in Eq.(12)

The parameter β in Eq.(12) of the main body is utilized to balance the disagreement and agreement samples. To validate the effectiveness of the balance process, we further perform the experiments over varied β (*i.e.*, 0, 0.2, 0.4, 0.6, 0.8, 1.0, 2.0, 5.0) under 5-bit precision upon ResNet-18, to serve as P and Q on ImageNet. Fig.2(a) illustrates that AdaDFQ obtains the best result given $\beta^* = 0.8$, implying that carefully adjusting β can earn the extra accuracy gains. By contrast, the accuracy for AdaDFQ drops sharply when β exceeds 1, in that G focuses more on the disagreement and agreement samples with a larger β, which leads to the generated samples with either too large or small $\mathcal{H}^{'}_{info}(p_{ds})$ beyond the capacity of the balance process.

A.3. γ in Eq.(12)

γ is the balance parameter for $\mathcal{L}_{BNS}$ in Eq.(12) of the main body, which aims to balance the distribution information about the training data from P on the generated samples from G. We testify $\gamma \in \{0, 0.2, 0.4, 0.6, 0.8, 1.0, 2.0, 5.0, 10\}$ to perform

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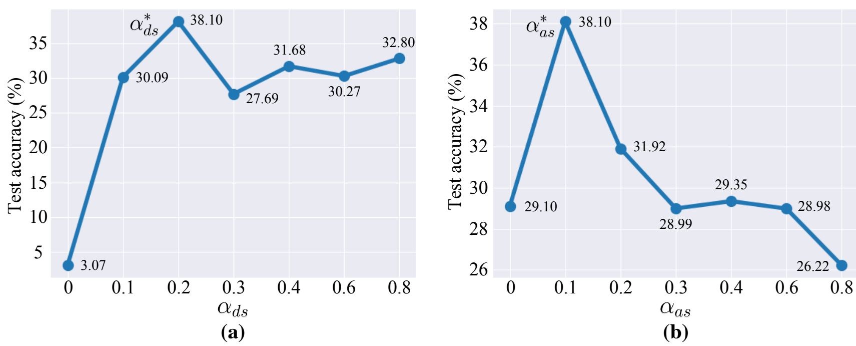

Figure 1. Parameter studies about the effectiveness of α_{ds} and α_{as} in Eq.(10) on ImageNet.

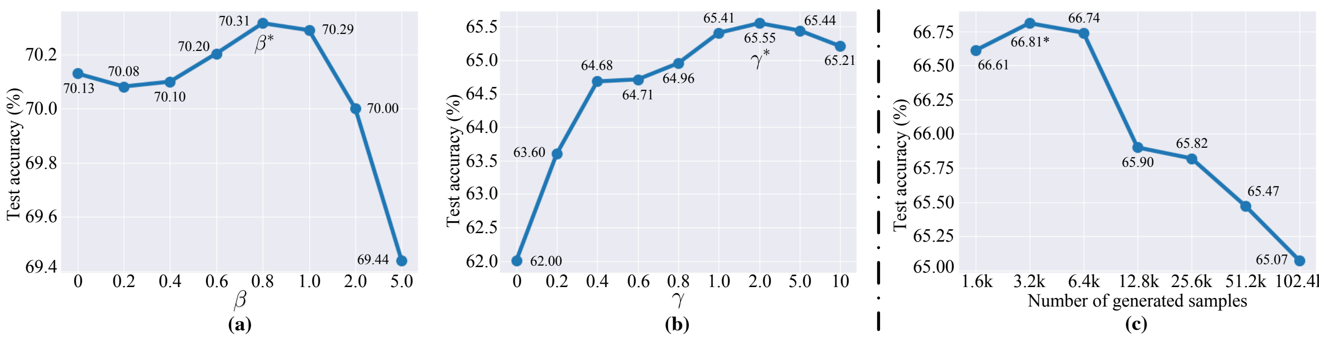

Figure 2. (a)(b) Ablation studies about the parameters β and γ in Eq.(13) on ImageNet. (c) Illustration of how the number of generated samples from G affects AdaDFQ on CIFAR-100.

the experiments under 4-bit precision with MobileNetV2, to serve as P and Q on ImageNet. Fig.2(b) illustrates that the *peak* appears at $\gamma^* = 2.0$, while the accuracy remains stable (ranging from 65.41% to 65.55%) around $\gamma = 2.0$ (ranging from 1.0 to 5.0), implying that AdaDFQ can maximally recover the performance of Q via the generated samples from G within a *batch* by exploiting the distribution information about the training data from P.

B. Additional Ablation Study about the Number of Generated Samples

We further investigate the effect of the number of generated samples over the calibration process of Q for AdaDFQ. In particular, we generate different numbers of generated samples, *i.e.*, 1.6k, 3.2k (as adopted in the main experiments), 6.4k, 12.8k, 25.6k, 51.2k and 102.4k, under 4-bit precision upon ResNet-20, to serve as P and Q on CIFAR-100. Fig.2(c) illustrates that AdaDFQ obtains the superior performance (ranging from 66.61% to 66.81%) around 3.2k (ranging from 1.6k to 6.4k), while suffers from a large performance degradation when the number of generated samples continues to increase. The *intuition* is that, it can't be guaranteed that all generated sample (especially for large number of generated samples) are informative to Q, owing to the limited capacity of G, which, in turn, highlights the *importance* of generating the sample with adaptive adaptability to Q.

C. Visual Analysis on Generated Samples with Higher Resolution

As mentioned in Sec.3.5, we further offer the visual results of real and generated samples with *higher resolution* due to page limitation; see Fig.3. The results show that, the generated samples from varied categories (*i.e.*, varied rows) that correspond to the real samples, differ greatly from each other, confirming the effectiveness of the category information extracted from P; while the generated samples under different bit-width scenarios (*i.e.*, 3 bit, 4 bit and 5bit) vary greatly, confirming that AdaDFQ succeeds in generating the sample with adaptive adaptability to Q with varied bit widths, which are consistent with our analysis in the main body.

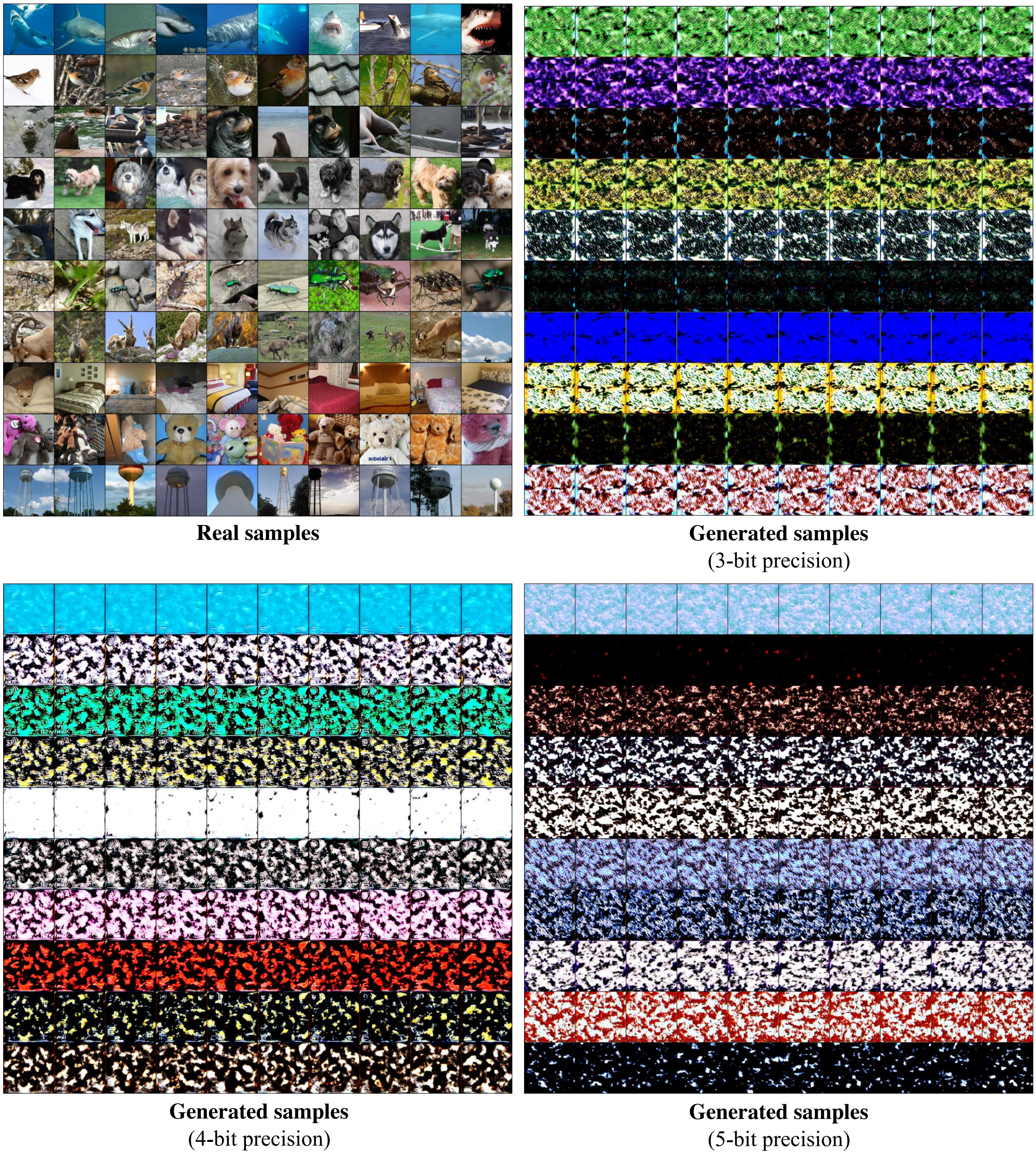

Figure 3. Visualization of real and generated samples, as an *extension* of Fig.6 in the main body, where each row denotes one of 10 randomly chosen classes from ImageNet.