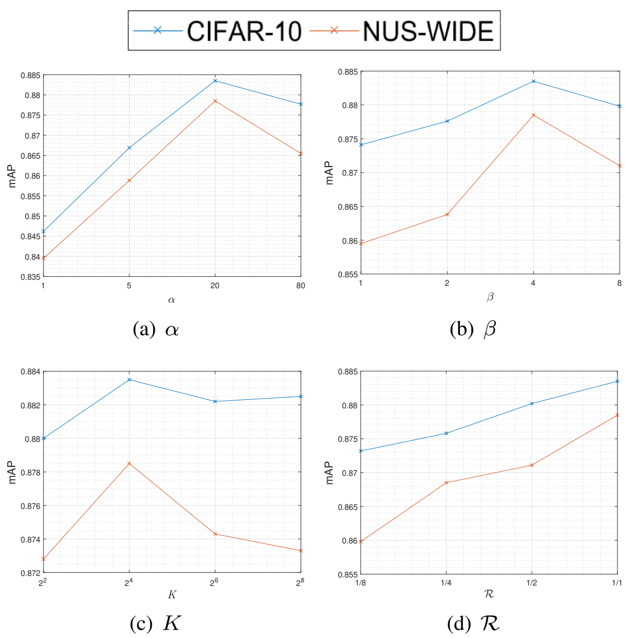
Generalized Product Quantization Network for Semi-supervised Image Retrieval
- Supplementary Material -



(a) α (b) β (c) K (d) $\mathcal{R}$

Figure 1. The results of hyper-parameter variants.

	Value			
α	1	5	20	80
β	1	2	4	8
K	2^2	2^4	2^6	2^8
R	1/8	1/4	1/2	1/1

Table 1. A list of Hyper-parameter values.

Analysis on Hyper-parameters As mentioned in section 4.2 of our original submission, we present additional information regarding hyper-parameters: α, β, and K. Besides, to see how GPQ actually uses unlabeled data, we set up a hyper-parameter $\mathcal{R}$ that determines the ratio of the total unlabeled data used for training. The default value is set as $\{\alpha, \beta, K, \mathcal{R}\} = \{20, 4, 2^4, 1/1\}$ in order, and we vary each hyper-parameters as listed in Table 1 while fixing others at defaults. We conduct experiments on CIFAR-10 and NUS-WIDE datasets for the binary code of 48-bits.

From Figure 1, we can see that trends of mAP scores according to variation of α and K are similar to those observed in other deep quantization methods [1, 2]. The hyper-parameter β that controls the randomness of predictions before applying softmax shows optimal performance at 4. The results of $\mathcal{R}$ related with the amount of unlabeled data justify that GPQ can fully utilize the unlabeled data to improve retrieval performance.

Algorithm We demonstrate our training process in Algorithm , where γ denotes learning rate. The result of entropy maximization and minimization can be observed in updating stage of θ_C and θ_F, respectively. Gradients generated from the unlabeled data in a batch do not flow directly into θ_Z, however, previous ones can be reflected by initializing θ_Z from θ_C.

Algorithm 1 GPQ training for batch size B

Input: Parameters of each component: $\theta_F, \theta_Z, \theta_C$
Input: Batch $\mathbf{B} = \{(I_1^L, y_1, I_1^U), ..., (I_B^L, y_B, I_B^U)\}$

```
Initialize θ_Z with θ_C by soft assignment
for i in 1...B do
    x̂_i^L, x̂_i^U ← F_{θ_F}(I_i^L, I_i^U)
    q̂_i^L ← Z_{θ_Z}(x̂_i^L)
    p̂_i^L, p̂_i^U ← C_{θ_C}(x̂_i^L, x̂_i^U)
end for
if label=true then
    ℓ_{N-PQ} ← L_{N-PQ} with {x̂_i^L, q̂_i^L, y_i}_{i=1}^B
    ℓ_cls ← L_cls with {p̂_i^L, y_i}_{i=1}^B
else
    ℓ_SEM ← L_SEM with {p̂_i^U}_{i=1}^B
end if
```

$$\theta_F \leftarrow \theta_F - \gamma \left(\frac{\partial \ell_{N\text{-}PQ}}{\partial \theta_F} + \frac{\partial \ell_{cls}}{\partial \theta_F} + \frac{\partial \ell_{SEM}}{\partial \theta_F} \right)$$

$$\theta_Z \leftarrow \theta_Z - \gamma \frac{\partial \ell_{N\text{-}PQ}}{\partial \theta_Z}$$

$$\theta_C \leftarrow \theta_C - \gamma \left(\frac{\partial \ell_{cls}}{\partial \theta_C} - \frac{\partial \ell_{SEM}}{\partial \theta_C} \right)$$

Output: Updated $\theta_F, \theta_Z, \theta_C$

References

[1] Benjamin Klein and Lior Wolf. End-to-end supervised product quantization for image search and retrieval. In *CVPR*, pages 5041–5050, 2019. 1

[2] Tan Yu, Junsong Yuan, Chen Fang, and Hailin Jin. Product quantization network for fast image retrieval. In *ECCV*, pages 186–201, 2018. 1