Rank-sensitive Deep Metric Learning
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Deep metric learning has shown significantly increasing values in a wide range of domains, such as image retrieval, face recognition, zero-shot learning, to name a few. When evaluating the methods for deep metric learning, *top-k precision* is commonly used as a key metric, since few users bother to scroll down to lower-ranked items. Despite being widely studied, how to directly optimize top-k precision is still an open problem. In this thesis, we proposed novel methods on how to optimize top-k precision in a rank-sensitive manner for deep metric learning. Given the cutoff value k, our key idea is to impose different weights to further differentiate misplaced images sampled according to the top-k precision.

To validate the effectiveness of the proposed methods, we conducted a series of experiments on three widely used benchmark datasets with discrete labels and one benchmark dataset with continuous labels. The experimental results on datasets with discrete labels demonstrate that: our proposed method (RS-TopK-Pre) outperforms all baseline methods on two datasets, namely CUB200-2011, Cars196, which shows the potential value of rank-sensitive optimization of top-k precision for deep metric learning. The experimental results on the dataset with continuous labels demonstrate that: our proposed method (RS-TopK-Pre) outperforms the baseline method (TopK-Pre). In view of the unique property of continuous labels, we further modified RS-TopK-Pre by imposing different weights to further differentiate misplaced images based on continuous rank information. We refer to this variant as CRS-TopK-Pre. Unfortunately, CRS-TopK-Pre failed to achieve better performance than the baseline method (TopK-Pre).

Overall, both the results on datasets with discrete labels and the results on the dataset with continuous labels show that: the factors, such as batch size and cutoff value k, significantly affect the performance of approaches that rely on optimizing top-k precision for deep metric learning. Careful examinations of these factors are thus recommended.

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