Unsupervised Contrastive Learning Hashing with Adaptive Distribution Balanced Feature Learning for Image Retrieval*

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Abstract. Hashing methods are increasingly used for unsupervised image retrieval task due to their high efficiency and low storage. Inspired by the success of contrastive learning in feature learning, some contrastive learning technology has been applied to unsupervised hashing approaches, but existing approaches cannot consider the adverse effects of chaotic feature distribution on the generation of hash codes. To solve the above problem, we propose a novel unsupervised hashing method based on contrastive learning framework named *Feature Distribution Balanced Hashing* (FDBH) that fully considers the characteristics of unsupervised hash code learning. First, we design a improved contrastive learning framework for unsupervised hash codes learning, which improved the structure of the learning framework and added polarization module to make it more suitable for the retrieval task. Second, a distribution optimization strategy named *Feature Distribution Optimization* (FDO) is proposed to adjust the feature distribution before the quantization process. Therefore, the features is optimized in the direction that is conducive to the generation of high-quality hash codes as much as possible without losing information. Finally, we design a new loss function, which is composed of the contrastive similarity loss and reconstruction loss. Experiments on the CIFAR-10 and MS COCO dataset show that the performance of our method is superior to the state-of-the-art unsupervised hashing method.

— 背景
— 痛点
— 创新点
— 1,2,3,4
— 实验

Keywords: Contrastive learning · Image retrieval · Unsupervised hashing · Distribution balanced.

1 Introduction

I 交待 xxx 背景下 xxx 问题及解决方法

With the rapid production of various photographing devices, the number of images is growing faster and faster in the world [11]. It is very important to mine effective information from large-scale images [1, 10]. Therefore, image retrieval has attracted more and more attention in the computer vision field. *Approximate Nearest Neighbor* (ANN) is widely used in image retrieval tasks. For existing ANN methods, hash technology plays an increasingly important role due to its low storage and fast retrieval [22, 24].

— 背景
— 问题
— 主流方法
主流技术

II 分析既存方法

Hashing methods for image retrieval are mainly divided into supervised hashing methods and unsupervised hashing methods. Because supervised hashing

— 总：2种方式
— 分1：有监督劣势
— 分2：无监督优势

* Supported by organization x.

分1 分2

过渡句：无监督好

总：无监督分3类

needs a lot of labeled data, its practical application has great limitations. The unsupervised hash method without annotation has more advantages in real world. Existing unsupervised hashing methods can be summarized as three types, encoder-decoder based methods, graph based methods and *Generative Adversarial Network* (GAN) based methods. It is a straightforward way to use encoder-decoder models compacting images into binary representations.Lin *et al.* [12] proposed DeepBit, a deep neural network to learn hash codes of images in an unsupervised way. It is a straightforward way to use encoder-decoder models compacting images into binary representations. Dai *et al.* [5] proposed *Stochastic Generative Hashing* (SGH) to learn hash functions with auto-encoding framework and discrete stochastic neurons. Shen *et al.* [18] proposed an auto-encoder based *Twin-Bottleneck Hashing* (TBH), guiding the reconstruction with an adaptive code-driven graph. As a widely used tool, similarity graphs can be used to generate hash codes. Spectral Hashing [21] is an early proposed unsupervised hashing method. Liu *et al.* [15] proposed *Anchor Graph Hashing* (AGH), exploring the neighborhood structure inherent in the data with graphs. Yang *et al.* [23] proposed to distill data pairs with confident semantic similarity, which is helpful for overcoming the lack of supervisory similarity signals in unsupervised hashing. Due to the excellent performance in various of fields, *Generative Adversarial Network* (GAN) [8] has been applied to unsupervised hashing. Dizaji *et al.* [6] proposed an unsupervised hashing function named HashGAN. Zieba *et al.* [25]. adopted similar concepts and learned compact binary descriptor with a regularized GAN.

1类

总结目前相关工作

2类

3类

指出痛点

Although unsupervised hashing methods have developed surprisingly, there are still some problems in the existing methods. The existing methods do not fully consider the impact of the feature before quantization on the quality of the hash code. It is generally believed that a better mapping from image data to binary hash code can be constructed is the key to the success of hashing methods. It can also be understood as whether the established model can extract features that can be quantified into a high-quality binary hash code. And the distribution of features before quantization plays a vital role in the quality of binary codes after quantization. For solving above problem, we propose a novel unsupervised hashing method based on contrastive learning framework named *Feature Distribution Balanced Hashing* (FDBH) that fully considers the characteristics of unsupervised hash code learning. The basic contrastive learning method is not directly applicable to unsupervised hashing methods. We design a improved contrastive learning framework for unsupervised hash code learning. We improved the structure of the learning framework and added polarization method to make it more suitable for the task. And a distribution optimization strategy named *Feature Distribution Optimization* (FDO) is proposed which can adjust the feature distribution before the quantization process, so that the feature is optimized in the direction that is conducive to the generation of high-quality hash codes as much as possible without losing information. In addition, we design a new loss function, which is composed of the contrast similarity loss and reconstruction loss. Experiments on the CIFAR-10 dataset and the MS COCO dataset show

v.模拟

n.量化

四 卖点

(解决xxx痛点

xxx方法

xxx效果)

创新点

实验效果