Self-Supervised Ranking for Representation Learning

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Abstract

We present a new framework for self-supervised representation learning by positing it as a ranking problem in an image retrieval context on a large number of random views from random sets of images. Our work is based on two intuitive observations: first, a good representation of images must yield a high-quality image ranking in a retrieval task; second, we would expect random views of an image to be ranked closer to a reference view of that image than random views of other images. Hence, we model representation learning as a learning-to-rank problem in an image retrieval context, and train it by maximizing average precision (AP) for ranking. Specifically, given a mini-batch of images, we generate a large number of positive/negative samples and calculate a ranking loss term by separately treating each image view as a retrieval query. The new framework, dubbed S2R2, enables computing a global objective compared to the local objective in the popular contrastive learning framework calculated on pairs of views. A global objective leads S2R2 to faster convergence in terms of the number of epochs. In principle, by using a ranking criterion, we eliminate reliance on object-centered curated datasets (e.g., ImageNet). When trained on STL10 and MS-COCO, S2R2 outperforms SimCLR and performs on par with the state-of-the-art clustering-based contrastive learning model, SwAV, while being much simpler both conceptually and implementation-wise. Furthermore, when trained on a small subset of MS-COCO with fewer similar scenes, S2R2 significantly outperforms both SwAV and SimCLR. This indicates that S2R2 is potentially more effective on diverse scenes and decreases the need for a large training dataset for self-supervised learning.

1 Introduction

Self-supervised visual representation learning (SSRL) has advanced quickly, thanks to the contrastive learning principle and extensive research on the problem. Contrastive learning has a simple, intuitive objective: to assure that similar images are mapped to a compact neighborhood in the representation space. In practice, contrastive representation learning methods operate on pairs of views extracted from images, so implicitly, they assume that there is a dominant object that defines each image. Based on this assumption, then either image instance ID \[4, 6, 7, 11, 14, 16\] or a simultaneously generated cluster code for each image \[2, 3, 9, 17\] is used to define a cross-entropy objective for training an encoder such that pairs of augmentations from an image are classified as the same compared to a set of negative representations. However, in a real-world scene, it is natural to have very different objects at different spatial locations \[12\], such that forcing them to have the same representation in isolation would not make sense.

In this work, we propose a new framework for SSRL that naturally lends itself to compare and contrast a large number of views from images. In our framework, S2R2, we formulate representation learning as a retrieval task with the objective of optimizing the ranking of random views of a random set of
images in terms of average precision. Ranking is a stronger criterion than the contrastive learning loss, as it goes beyond a local objective that forces pairs of positive samples to be close to each other and far from the negatives. With such a local objective, it is inevitable to regularly pull together a pair of positive samples, while moving either one away from other related samples, or by pulling them closer to the space of negative samples. This significantly slows down the optimization process. In contrast, by simultaneously ranking a large number of views, the global objective adapted in S2R2 avoids such conflicting optimization steps. The issue of locality in contrastive loss is illustrated in [15], where representations learned by SimCLR [4] are not disentangled enough semantically, and a mixture model is deployed to push apart the representations at the category level.

A remedy for the locality issue could be extending the pairwise contrastive objective to use more crops for computing the loss, a technique adopted by a recent state-of-the-art model, SwAV [3]. Our experiments show that this makes SwAV more efficient on a cluttered dataset than its more basic counterpart, SimCLR [4]. However, SwAV relies on a multi-stage algorithm that needs solving a cluster assignment problem at every optimization step. Moreover, technically, the multi-crop technique is not a global objective; rather, it accumulates loss for multiple pairs.

We summarise our contributions as follows:

- We propose a new framework, S2R2, for self-supervised representation learning by ranking random image views. S2R2 employs a global optimization objective and fundamentally does not rely on object-centered curated images.
- We empirically show that S2R2 outperforms the standard contrastive learning model, SimCLR, and performs on par with its relatively more complicated recent alternative, SwAV.
- S2R2 delivers outstanding performance when trained on a small and diverse set of scenes compared to SimCLR and SwAV.

2 Methodology

We first review the formal definition of ranking in image retrieval, and how to maximize ranking average precision end-to-end using the recent work of Brown et al. [1]. Then we proceed to describe S2R2 in terms of maximizing ranking AP.

In ranking based image retrieval, given a query image $I_q$ and a set of $m$ images $I = \{I_1 ... I_m\}$, an ideal ranking algorithm should rank set of all relevant (positive) images $I_P$ above the set of unrelated (negative) images $I_N$, where $I = I_P \cup I_N$ and $I_P \cap I_N = \emptyset$. In a retrieval context, AP is the standard metric used to measure the quality of a ranking algorithm. Following [13] and [1], the definition of AP is shown in eq. 1, where $R_q(i, X)$ denotes the rank of image $I_i$ among all images in $X$ with respect to the query image $I_q$. This metric is maximized once all positive images are ranked higher than any negative image.

$$AP_q = \frac{1}{|I_P|} \sum_{i \in I_P} \frac{R_q(i, I_P)}{R_q(i, I)}$$

The rank function $R_q(i, X)$ returns the number of images in $X$ that are more similar to the query image $I_q$ than image $I_i$. This is formally defined in eq. 2, where $s_i$ denotes the similarity between $I_i$ and $I_q$. One can use any standard similarity metric for computing $s_i$. In this work, we choose to use cosine similarity on the representation vectors $r_i$ and $r_q$ corresponding to $I_i$ and $I_q$, respectively.

$$R_q(i, X) = 1 + \sum_{j \in X, j \neq i} 1 \{ (s_{q,j} - s_{q,i}) < 0 \} \quad s.t. \quad s_{q,i} = \langle \frac{r_i}{||r_i||}, \frac{r_q}{||r_q||} \rangle$$

Unlike the contrastive loss, the AP loss does not force all positive images to have the same representation; neither expects them all to have the same identity. Instead, it guides them to be closer to a given related query image than the negative samples are.

Optimizing the AP loss above is not trivial, as it is not differentiable due to the presence of the indicator function $1 \{ \}$. However, recently Brown et al. [1] have proposed a simple modification to this formulation that results in a highly accurate approximation of eq. 2. That is, by replacing the
indicator function with the sigmoid function as shown in eq. 3, where $\tau$ is a temperature parameter. With this modification, eq. 1 becomes differentiable, and we can train a ranking model by directly maximizing AP. Brown et al. [1] report significant and reliable improvements for image retrieval in various settings using this approximation.

$$\phi(d; \tau) = \frac{1}{a + e^{-d/\tau}}$$

In S2R2, we adapt this objective and maximize AP by simulating a retrieval setting where the positive samples are obtained by means of aggressive augmentation of an image. Similarly, negatives are obtained by applying similar augmentations to other images. In our mini-batch gradient descent optimization setting, first, we sample $B$ images and then generate $K$ views for each of them, following the same aggressive augmentation setup as in SimCLR [4]. At every SGD step, each of the $B \times K$ views is once used as a query image; with the other $k-1$ views from the same reference image constituting positive samples ($|S_P| = k - 1$), and the $k \times (B - 1)$ views of the other images constituting negatives ($|S_N| = k \times (B - 1)$)). Then the AP term in eq. 1 is averaged across $K \times B$ query images to produce the final optimization target.

3 Experiments

We compare S2R2 against two recent state-of-the-art models, SimCLR [4] and SwAV [3], on both object-centered and cluttered datasets. For a cluttered dataset, we use the MS-COCO dataset [10]. To analyze all models’ behavior in response to dataset size, we separately train models on its train split (COCO-Train) that includes about 118k images, and validation split (COCO-Val) that has only 5k images. For an object-centered curated dataset, we use STL10 [5], a subset of ImageNet designed specifically for research on unsupervised methods. It includes 100k unlabeled images, from 10 known and "some" unknown categories. It also has labeled train and test splits (STL10-Train and STL10-Test), with 5k and 8k images, respectively, from the ten known categories. For STL10, we use the combination of the unlabeled and train splits (105k images) for training representation encoders.

To evaluate a given representation encoder (trained on either MS-COCO or STL10), we adopt the standard linear classification setting [16]. A linear classifier is trained on STL10-Train after detaching (freezing) the encoder. Then the Top-1 accuracy on STL10-Test is reported.

Given that we have access to limited computational infrastructure, we resize the random image views to 96x96 (the original size for STL10 images) for training on all datasets. We experiment with both ResNet18 and ResNet50 convolutional backbones [8]. Following the best practice in SSRL [4], we use a non-linear projection layer on top of the representations before computing the AP loss. All models in this paper are trained from scratch, and we report the best performance we achieve for each model (including SimCLR and SwAV). For SwAV especially, we have tried to find the best multi-crop setting for each dataset separately, rather than using its default 6x crops. However, for neither of the methods, we do a comprehensive grid search to find the best hyperparameters. In particular, training S2R2 with larger batch sizes has not been possible using our limited computational resources.

Table 1 shows linear classification accuracy for each model when trained on COCO-Train, STL10, and COCO-Val. On COCO-Train, S2R2 outperforms SimCLR, especially at a lower number of epochs, and matches the accuracy of SwAV. On a lower number of epochs, though, it still significantly outperforms SwAV. The trend is similar on STL10, but S2R2 slightly exceeds SwAV.

When training on COCO-Val, however, we observe that neither SimCLR nor SwAV can reach the performance of S2R2. This difference between COCO-Train and COCO-Val is not trivially expected. We hypothesize that this could be due to the presence of many human-centered images in the COCO dataset, which would mean that the larger COCO-Train split does not necessarily provide an equally more learning signal. On the contrary, the presence of many similar scenes prevents the ranking model from working properly, so it does not perform better than SwAV. Note that the equal performance of S2R2 and SwAV on STL10 is not surprising, as the contrastive loss already suits that setting. Besides, SwAV deploys a multi-crop technique, which is enough to mimic a global metric on a curated dataset.

Figure 1 shows the effect of varying the number of images and the views per image in a mini-batch on the performance of S2R2 for different datasets. As we can see, increasing the number of images not only does not help beyond a point but also degrades accuracy. We believe this happens at the point where images in a mini-batch are likely to become similar with respect to their visual
Table 1: Top-1 accuracy of a linear classifier trained on STL10-Train and evaluated on STL20-Test

| Training data          | Architecture | Model    | Setting #images | Setting #views | Epochs 10  | Epochs 50  | Epochs 100 | Epochs 200 | Epochs 400 | Epochs 600 |
|------------------------|--------------|----------|-----------------|----------------|-----------|-----------|-----------|-----------|-----------|-----------|
|                        |              |          |                 |                |            |            |            |            |            |            |
| COCO-Train             | ResNet18     | SimCLR   | 256             | 2              | 60.7      | 68.6      | 70.9      | 73.4      | 73.7      | 75.7      |
|                        |              | SwAV     | 128             | 6              | 64.1      | 72.6      | 75.4      | 77.0      | -         | -         |
|                        |              | S2R2 (ours) | 64             | 20             | 68.3      | 74.2      | 76.2      | 77.2      | -         | -         |
|                        | ResNet50     | SimCLR   | 256             | 2              | 60.4      | 68.1      | 74.9      | 77.5      | -         | -         |
|                        |              | S2R2 (ours) | 32          | 20             | 74.1      | 79.7      | 81.2      | 80.1      | -         | -         |
| STL10 (unlabeled + train) | ResNet18     | SimCLR   | 256             | 2              | 64.2      | 74.3      | 77.8      | 82.0      | 84.1      | 86.1      |
|                        |              | SwAV     | 256             | 8              | 69.1      | 80.4      | 83.9      | 85.3      | -         | -         |
|                        |              | S2R2 (ours) | 64          | 20             | 72.4      | 81.6      | 84.1      | 86.4      | -         | -         |
|                        | ResNet50     | SimCLR   | 256             | 2              | 63.7      | 76.6      | 81.1      | 85.2      | -         | -         |
|                        |              | S2R2 (ours) | 32          | 20             | 77.3      | 85.9      | 88.4      | 89.7      | -         | -         |
| COCO-Val               | ResNet18     | SimCLR   | 64              | 2              | 46.1      | 56.1      | 58.0      | 62.0      | 63.5      | 64.1      |
|                        |              | SwAV     | 32              | 40             | 43.1      | 58.6      | 63.5      | 66.2      | 66.4      | 66.7      |
|                        |              | S2R2 (ours) | 8           | 10             | 58.6      | 64.8      | 67.5      | 69.0      | 68.8      | 68.8      |
|                        | ResNet50     | SimCLR   | 256             | 2              | 39.0      | 48.0      | 53.4      | 59.4      | -         | -         |
|                        |              | S2R2 (ours) | 16          | 20             | 54.3      | 65.6      | 68.4      | 70.2      | -         | -         |

(a) COCO-Train  (b) COCO-Val  (c) STL10

Figure 1: Linear classification accuracy v.s. the number of images/views in a mini-batch (ResNet18)

content. Therefore, their random views can not be "ranked properly." Nevertheless, this demands more investigation by controlling the dataset content in terms of diversity of visual scenes.

4 Discussion

The initial results in this work show that our new ranking based framework for representation learning outperforms contrastive learning methods of SimCLR and SwAV. We chose to experiment with MS COCO as a cluttered dataset; however, as we discussed, we have noticed that it is not an ideal dataset to represent crowded real-world scenes. It is heavily biased towards person class, and more than half the images include humans. Moreover, most images are selected to cover objects at different scales, not necessarily bringing in more visual content. For example, it comes with a large number of baseball scenes that are extremely similar in terms of visual complexity. Therefore, we plan to run experiments on more challenging datasets like Places [18] or ADE20k [19] to better understand the performance gains of S2R2 compared to SimCLR or SwAV.

For the augmentation procedure, in this work, we only experimented with uniformly resized and scaled image crops; however, there might be a better cropping policy that needs further experiments. The AP objective we used here demands computing pairwise similarity of all positive-negative views in a batch. This results in a $O(B^2K^3)$ a tensor that prohibits training with a larger number of images and views in a mini-batch. However, it is possible to avoid memory consumption by doing the loss computation for each query in a loop rather than storing a large big matrix. We will explore this aspect in the future to enable training on larger mini-batches. Finally, S2R2 outperforms contrastive methods; however, it does not solve the problem of similar views of different images being considered as negative, a problem that needs further research.
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