Contextual Similarity Aggregation with Self-attention for Visual Re-ranking <Supplementary Material>

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Abstract

This is the supplementary material for the paper "Contextual Similarity Aggregation with Self-attention for Visual Re-ranking" accepted to the NeurIPS 2021. This supplementary document first report the results of ablation experiments evaluated on validation set rSfM120k. Then, we analyse the limitation of our method. After that, we show the influence of different random seeds by repeating the experiment multiple times. Finally, we include the NeurIPS Paper Checklist in the supplemental material.

1 Ablation Experiments on Validation Set

In the manuscript, we follow the common practice in the literature to directly validate the choice of hyperparameters on the testing set. To validate the hyperparameters on the validation set to verify the merits of our choice, in this experiment, we follow HOW [6] to split the training data into a train set and a validation set. This validation set is composed of 162 3D models from rSfM120k, which is denoted as rSfM120k-HOW. This validation set is more challenging and more responsive to the target task than the original one in GeM [3]. Please refer to HOW [6] for more details. Besides, we make an additional experiment on the influence of temperature parameter. The result is shown in Figure 1. Compared with Figure 2 in the manuscript, we can find that most of the optimal parameters validated directly on ROxf (Hard) and rSfM120k-HOW are consistent.

2 Limitations

Our re-ranking method relies on the first-round retrieval. If the performance of the initial retrieval results is poor, our re-ranking method still works but the performance improvement is limited. However, the performance of most re-ranking methods heavily relies on the first-round retrieval, therefore this limitation is the common drawback of most re-ranking methods.

Our method just requires the affinity feature as the network input, which is generated by comparing the image with anchor images, and is not directly related to the original feature. It can be accomplished with different visual features. We use the fine-tuned R-GeM feature for the first-round retrieval and compute the affinity features for top candidates to train the re-ranking model. Then we test our model on various (type of features, fine-tuned or not) features. The result is showed in Table 4 in the

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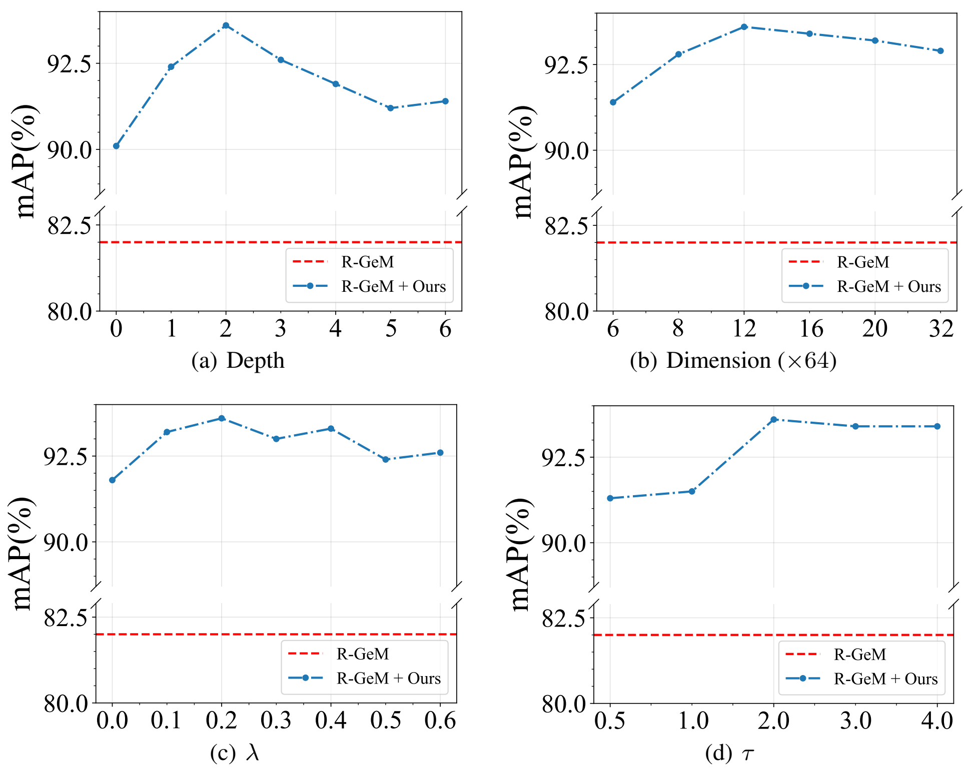


Figure 1: Impact of transformer model variants, the weight of the MSE loss, and the value of temperature on mAP on rSfM120k-HOW. All model variants are evaluated with re-ranking length $K = 1024$ and anchor image list length $L = 512$. (a) Comparisons of different transformer depth n. The hidden size $L' = 768$, and head number $N_h = 12$. (b) Impact of the hidden size L'. Transformer depth is kept as 2. (c) Impact of the weight of the MSE loss. (d) Impact of the value of temperature. The model takes the default settings.

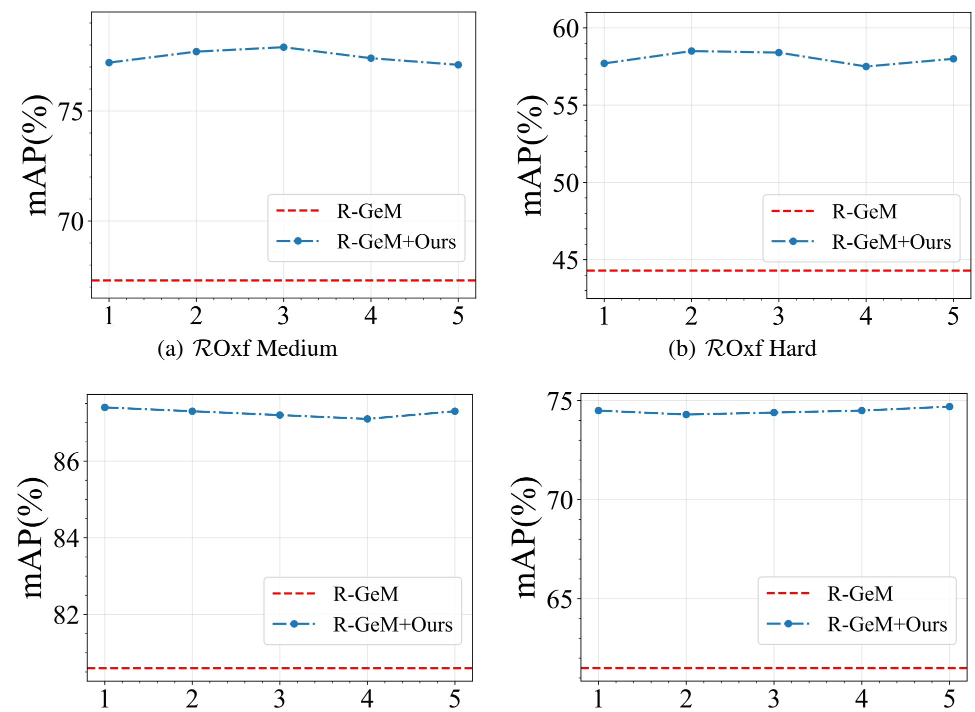
manuscript. Our re-ranking method improves the mAP of various features with the trained re-ranking model by a large margin.

Besides, we want to confirm whether our method still works when the performance of first-round retrieval is poor, so we perform cross feature testing on two features: the off-the-shelf version of ResNet101 with R-MAC pooling and without whitening (R-RMAC[O]), the off-the-shelf version of ResNet101 with GeM pooling and without whitening (R-GeM[O]). The performance of the first-round retrieval using these two features is extremely unsatisfactory especially on the hard evaluation of $\mathcal{R}$Oxf [2] dataset. We re-rank the retrieval results of these two features with the re-ranking model trained by the fine-tuned version of R-GeM feature.

The result is shown in Table 1. The performance is enhanced by our re-ranking method for all testing features. However, the improvement is limited when using features with lower initial performance compared with the re-ranking results for features with high initial retrieval performance. We think there are two main reasons. The first point is that we only re-rank the top-K candidates. When the results of the first-round retrieval are poor, there are fewer relevant images in the top-K candidates. Secondly, we use affinity features as the input of our re-ranking model by calculating the similarity between the candidates and the anchor images. We directly select the top-L images in the ranking list as the anchor images. When the results of the first-round retrieval are poor, the selected anchor images are far from the query, and the variance of their distances to the candidate images is relatively small, which cannot provide useful information for distinguishing the candidate images.

3 Impact of the random seed

The impact of different random seeds on mAP on $\mathcal{R}$Oxf and $\mathcal{R}$Par with Medium and Hard evaluation protocols is shown in Figure 2. We repeat the experiment five times. The model takes the default



(a) $\mathcal{R}$Oxf Medium (b) $\mathcal{R}$Oxf Hard

(c) $\mathcal{R}$Par Medium (d) $\mathcal{R}$Par Hard

Figure 2: Impact of different random seeds on mAP on $\mathcal{R}$Oxf and $\mathcal{R}$Par with Medium and Hard evaluation protocols. The re-ranking length $K = 1024$, and the anchor image length $L = 512$. The experiment is repeated five times.

Table 1: mAP performance of the proposed model with different feature types. The re-ranking model is trained by fine-tuned R-GeM. Re-ranking length $K = 1024$. Anchor image length $L = 512$. V: VGG16 [4]; R: ResNet101 [1]; [O]: off-the-shelf networks pretrained on ImageNet; W: With post-processing whitening [3]; RMAC: regional max-pooling [5]; GeM: generalized-mean pooling [3]; MAC: max-pooling [5].

Method	**Training feature**	**Medium**		**Hard**	
		$\mathcal{R}$Oxf	**$\mathcal{R}$Par**	**$\mathcal{R}$Oxf**	**$\mathcal{R}$Par**
R-RMAC[O] [5]	-	26.3	60.0	5.9	32.6
R-RMAC[O]+Ours	R-GeM	**29.3**	**69.7**	**9.6**	**46.3**
R-GeM[O] [3]	-	21.8	48.0	5.4	22.3
R-GeM[O]+Ours	R-GeM	**23.3**	**52.4**	**8.0**	**31.2**
R-RMAC[O]-W [5]	-	51.2	74.0	21.4	51.7
R-RMAC[O]-W+Ours	R-GeM	**56.8**	**81.9**	**30.5**	**65.7**
R-GeM[O]-W [3]	-	50.3	73.0	23.0	50.9
R-GeM[O]-W+Ours	R-GeM	**55.0**	**81.5**	**30.3**	**65.6**
R-MAC-W [5]	-	63.3	76.6	35.7	55.5
R-MAC-W+Ours	R-GeM	**73.2**	**86.0**	**52.8**	**72.1**
V-GeM-W [3]	-	61.6	69.3	34.3	44.9
V-GeM-W+Ours	R-GeM	**73.3**	**81.5**	**50.0**	**73.0**

settings. The re-ranking length is set to 1024 and the anchor image length is 512. From the figure, we can see that the variance of mAP values of the five-time experiments is relatively small. Our method is virtually unaffected by the random seed and achieves stable performance on the testing datasets.

Checklist

1. For all authors...

(a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] We have clearly stated the contributions and scope in the abstract and introduction.
(b) Did you describe the limitations of your work? [Yes] We describe the limitations in the supplementary material.
(c) Did you discuss any potential negative societal impacts of your work? [N/A] Our work concentrates on image retrieval.
(d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A] We do not have theoretical results and report the extensive experiment results.
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We include the all the necessary code, instructions and environment needed in the supplemental materials.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] The important training details are introduced in Section **??**.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] In the main paper, we show the results of a single experiment, and in the supplementary material, we show the error bars of our main experiments in the form of variance.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] We report the types of resources used in the experiments in Section **??**, but we do not report the total amount of computation required for each experiment because we did more experiments than reported in the paper and these times could not be calculated.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] In Section **??**, we cite corresponding papers for the asserts we use.
   (b) Did you mention the license of the assets? [Yes] The code, data, models the we used are under MIT License. They can be used and modified for free.
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] In the supplementary material, we provide the complete experiment code, the necessary commands and the corresponding environment for generating the training dataset, training the model, and testing the model.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] The training dataset rSfM120k and best-performing image retrieval model is public available. We cite the paper that provides the dataset and the model.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A] The dataset used in the experiment describes various landmarks and is not related to information about individuals and offensive events.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A] We use publicly available datasets provided by other work that did not require participants.
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A] Our experiments focus on image data and do not require participants.
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A] We do not hire any people to participate in our experiments.

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