OBJECT-AWARE SELF-SUPERVISED MULTI-LABEL LEARNING

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ABSTRACT

Multi-label Learning on image data has been widely exploited with deep learning models. However, supervised training on deep CNN models often cannot discover sufficient discriminative features for classification. As a result, numerous self-supervision methods are proposed to learn more robust image representations. However, most self-supervised approaches focus on single-instance single-label data and fall short on more complex images with multiple objects. Therefore, we propose an Object-Aware Self-Supervision (OASS) method to obtain more fine-grained representations for multi-label learning, dynamically generating auxiliary tasks based on object locations. Secondly, the robust representation learned by OASS can be leveraged to efficiently generate Class-Specific Instances (CSI) in a proposal-free fashion to better guide multi-label supervision signal transfer to instances. Extensive experiments on the VOC2012 dataset for multi-label classification demonstrate the effectiveness of the proposed method against the state-of-the-art counterparts.

Index Terms— Multi-label Learning, Self-Supervised Learning, Multi-instance Learning

1. INTRODUCTION

DCNNs (Deep Convolutional Neural Networks) have recently gained great success on a variety of computer vision tasks [1–3], and have shown preliminary achievements on different Multi-label classification benchmarks [4–6] compared to traditional image processing counterparts [7, 8], thanks to the strong capability of discovering high-level imaging features. Despite the power of deep learning, multi-label learning (MLL) poses a more challenging scenario, where an image can contain multiple objects, each associated with a distinct class/label. Recent MLL works harness self-supervised representation learning (SSL) to tackle this problem. However, most of them did not overlap the capability of SSL and the objectives of MLL well, which will be discussed below.

This paper aims to improve the MLL performance by enhancing the model capacity to recognize more detailed local contextual features of the visual instances. Many Self-supervised Learning works [9–17] explored to learn strong representations of the images to facilitate various tasks. Our baseline method PuzzleCAM [12] tackles this by splitting the image into 4 even patches along the horizontal and vertical centers of the image and narrowing the discrepancy between the representation learned from the patch-level feature image-level ones. This poses a self-supervised constraint on the model to learn such local contextual information of the visual instance without knowing the global information.

However, as illustrated in Fig. 1, one major drawback of this approach is that it would only impose sufficient supervision under the assumption that objects always fall in the center, i.e., single-object scenario. However, such assumption no longer stands in MLL, where instead the objects' location and scale are uncertain. According to our statistical analysis (Fig. 2), objects locations and scales become drastically unpredictable under the MLL setting. As a result, [12] may not provide sufficient supervision. Therefore, we propose to generate tiled images more robustly under the MLL scenario and force the objects, i.e., visual instances be more evenly broken into each patch, so that the auxiliary supervision can effectively impose on the objects, i.e., Object-Aware Self-supervision (OASS). To further promote robust contextual knowledge learning, we adopt EMA [18] method...
in knowledge distillation for patch-level feature extraction.

Besides, since one label only corresponds to an/some instance(s) in the above setting, it is more ideal to explicitly optimize multi-label learner with instance-level representations, so that each semantic can focus on a fine-grained set of class-specific and instance-related traits rather than being exposed to less decisive image-level features. Therefore we perform MLL at instance-level in opposed to previous MLL works [19, 20]. Since the abovementioned OASS module provides robust object related visual cues from the image, we can efficiently generate such class-specific instance-level representations by leveraging class-wise attention maps on OASS features. Existing weakly-supervised object detection works [21–23] follow the similar idea, however, they require to manually extract objects from the image which is much less efficient. Experiments show the effectiveness of our method and its superiority against the baselines.

We summarize our contributions in this paper as below:

- We propose a new self-supervised constraint to serve the MLL task, i.e., Object-Aware Self-supervision (OASS) module to better learn local contextual representations under the multi-label scenarios.
- We generate Class-specific Instance (CSI) from rich representations learned by the OASS and perform instance-level MLL efficiently.
- We conduct extensive experiments on multi-label classification dataset, demonstrating the advances in performance against various counterparts.

2. MULTI-LABEL REPRESENTATION LEARNING AND RELATION LEARNING

2.1. Object-Aware Self-supervision

As stated in the above sections, our motivation is to impose effective self-supervision on objects under the MLL scenario. Hence we propose to generate object-Aware patches for the auxiliary task in SSL. Note that the advances of our self-supervision approach from the one proposed in [12] are not only in the patch generation strategy but also reflected in the modified so-called puzzle module, which will be elaborated below.

We now explain the procedure of OASS. Given the input image $I$ and the classification model $g(f(x; \theta); \phi)$, where $f(.)$ denotes the encoder part of the model parameterized by $\theta$, and $g$ denotes the classification head. The $A = f(x; \theta)$ be the output activation from the encoder $f$. The $A_c = \text{CAM}(A; g) \in \mathbb{R}^{C \times h \times w}$ represents the Class Attention Maps (CAMs) associated with feature maps $A$, where $C$ is the number of the label. Next, we cut the image into 4 patches, but instead of cutting them evenly as in [12], we first calculate a keypoint $k'$ on the CAMs as follows:

$$k' = (k'_x, k'_y) = \arg \max \{\max (A_{c1}^{0}, A_{c1}^{1}, ..., A_{c1}^{C-1})\},$$

which means $k'$ is the coordinate of the peak value on the merged CAM. We then obtain the corresponding location on the original image $k = s \cdot k'$ where $s$ is the scaling factor of the encoder $f$ posed on the image ($e.g$, $s = 16$ for ResNet-50).

Then we cut the images into 4 patches. Apart from the above key point detecting strategy ($\text{Max}$), we explore 3 additional strategies to potentially find more robust key points as below.

The illustration of the below strategies is shown in Fig. 4.

Channel-wise Max ($\text{cMax}$) Instead of performing self-supervision on the merged CAM $\max (A_{c1}^{0}, A_{c1}^{1}, ..., A_{c1}^{C-1})$, we apply such a strategy to each channel of CAM $A_c$ and generate $C$ reconstruction loss $L_{r_c}$ and reconstructed classification loss $L_{p-cl}$.

Channel-wise Top-k ($\text{cTopk}$) Similar to $\text{cMax}$, for each CAM channel, we select $k$ local maxima $\{p_c^k\}_{k=1}^K$ on CAM with the top CAM values and calculate the keypoint as their geometric center:

$$k'_c = \text{round} \left( \frac{1}{k} \sum_{k} p_c^k \right).$$

Channel-wise weighted Top-k ($\text{cTopk-w}$) Similar to $\text{cTopk}$, we calculate the geometric center by weighted averaging, where the weights are the corresponding normalized CAM responses:

$$k'_c = \text{round} \left( \frac{1}{k} \sum_{k} A_c(p_c^k) \sum_{i} A_c(p_i^c) \cdot p_c^k \right).$$

This will desirably split the object into each patch even when it doesn’t fall on the center of the image. After generating the patches, we then have to resize them into unified sizes before entering the encoder again to get the patch-level feature maps hence all patches become the size of $(H/2, W/2)$. Next, we tile the generated patch-level feature maps similar to [12], but we cannot tile them directly since the images patches are no longer the same size to begin with. Hence we resize each patch feature map back to the size of its original image patch divided by $s$ before patch-level features tiling.

EMA for Patch-level Feature Extraction. Inspired by recent knowledge distillation [18] and semi-supervised learning
approaches, we extract patch-level features using the Exponential Moving Average (EMA) of the encoder \( f \) instead of sharing weight strategy in [12], so that the patch-level features generated by a self-ensemble teacher is more stable and accurate. 

**Loss Design.** We preserve the loss terms definitions from [12], including reconstruction loss \( L_{re} = \| A^s - A^{re} \|_1 \) between original features \( A^s \) and tiled ones \( A^{re} \), and additional classification loss of logits from \( A^{re} \): \( L_{p-cls} = l_{cls}(Y^{re}, Y) \). The final total training loss for latter 3 channel-wise strategies is:

\[
    L = L_{cls} + \sum_{c=1}^{C} \mathbb{I}(y_c = 1)(\alpha_p L_{p-cls} + \alpha_{re} L_{re})/\mathbb{I}(y_c = 1), \quad 1 \leq c \leq C
\]

where \( \alpha_{re}, \alpha_p \) is the loss weights for \( L_{re}, L_{p-cls} \) respectively, and \( y_c \) is the classification label for class \( c \).

To this end, the proposed Object-Aware Self-supervision forces the encoder feature maps to contain as much object-related information to facilitate the classification on the reconstructed feature maps, which in turn helps the encoder to extract more discriminative features.

### 3. EXPERIMENTS

**3.1. Implementation Details**

We validate our proposed framework on Pascal VOC2012 dataset [4] to align with our major baseline PuzzleCAM [12]. For fairness, we train our models on only train split same as [12] throughout the experiments and evaluate the models on val split (10,582 training and 1,449 validation images). Same with [12], firstly, all images are randomly resized between 320 and 540 followed by horizontal flipping. All samples are padded to 512 \( \times \) 512 for training and inference. We set target loss weights \( \alpha_{re} = \alpha_p = 1/15 \) for \( L_{re} \) and \( L_{p-cls} \) respectively, and ramped up both \( \alpha_{re} \) and \( \alpha_p \) linearly to 100 epochs. We adopt ResNet-50 pre-trained on ImageNet as the backbone feature extractor throughout and optimize the model with Adam optimizer. We conduct all experiments on Nvidia’s A100 GPUs with 48G VRAM.

**3.2. Comparison with existing methods**

We conducted extensive experiments on VOC2012 benchmark dataset to demonstrate our advances in Multi-label Classification.

As shown in Tab. 1, our approach with Max achieves 92.45 mAP scores on val split, which greatly outperform our strong baseline PuzzleCAM [12] for both splits.
Fig. 5: Visualizations of the CAMs generated on val split. The first row is generated by PuzzleCAM method, and the second row is generated by our method (cTopk-w w/o CSI).

Table 1: Comparison of classification mAP on VOC2012 val split with state-of-the-art methods.

| Method           | Architecture  | mAP w/o CSI |
|------------------|---------------|-------------|
| SSGRL [19]       | ResNet-101    | 91.9        |
| SSGRL [19]       | ResNet-50     | 91.4        |
| MCAR [23]        | ResNet-50     | 90.04       |
| PuzzleCam [12]   | ResNet-101    | 92.60       |
| PuzzleCam [12]   | ResNet-50     | 89.3        |
| Ours (w/ gt-bbox)| ResNet-50     | 92.62       |
| Ours (Max)       | ResNet-50     | **92.45**   |
| Ours (cTopk-w)   | ResNet-50     | 92.20       |

Table 2: mAP on test split compared to baseline.

| Method                           | mAP w/o CSI |
|----------------------------------|-------------|
| PuzzleCAM [12]                   | 81.37       |
| Ours (Max) w/ CSI                | **84.27**   |
| Ours (cTopk-w) w/o CSI           | **88.43**   |

Table 3: Ablation studies on keypoint detection strategies.

| Method                           | w/o CSI | w/ CSI |
|----------------------------------|---------|--------|
| Ours (w/ gt-bbox)                | 92.65   | 92.62  |
| Ours (Max)                       | **92.38** | **92.45** |
| Ours (cMax)                      | 91.58   | 92.08  |
| Ours (cTopk)                     | 92.21   | 92.05  |
| Ours (cTopk-w)                   | 92.02   | 92.20  |

3.3. Ablation Studies

Effect of different keypoint detection strategies. First, we explore the effect of different keypoint detection strategies for Object-Aware Self-supervision. We first remove the CSI module and test different strategies in OASS module. As shown in Tab. 3, among different proposed keypoint detecting strategies, Max performed the best on val split, while Tab. 2 shows that cTopk-w generalizes the best on test split. As can be seen from Fig. 4, this is because cTopk-w has less chance to be misled by low-quality global maxima on CAMs by considering other local maxima as in the case of Max.

Fig. 6 presents the improvements of per-class AP scores on our method (cTopk-w w/o CSI) against baseline [12] on test 1. Compared with the variances of the object location shifts statistics of different classes (red curve) derived from the statistics in Fig. 2, we can easily observe that they roughly follow the same trend. In other words, the larger the location of the object of certain class varies in images, the more likely the precision performance (AP) of this class benefits from our method, supporting the effectiveness of our proposed Object-Aware Self-supervision.

Effect of Class-specific Instance. Comparing w/o CSI and w/ CSI methods for both cTopk-w and Max strategies in Tab. 3, w/ CSI method constantly performs better than w/o CSI ones, proving the effectiveness of CSI.

4. CONCLUSIONS

In this paper, we proposed Object-Aware Self-supervision to facilitate local contextual representation learning for multi-label circumstances. To facilitate instance-level MLL, we proposed to generate Class-specific Instance harnessing the self-supervision outcome. Extensive experiments and ablation studies validated the proposed approach for multi-label learning. We plan to apply a stronger CNN backbone and adapt our method to weakly supervised segmentation in the future.
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