Self-Supervised Object Localization with Joint Graph Partition

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Abstract
Object localization aims to generate a tight bounding box for the target object, which is a challenging problem that has been deeply studied in recent years. Since collecting bounding-box labels is time-consuming and laborious, many researchers focus on weakly supervised object localization (WSOL). As the recent appealing self-supervised learning technique shows its powerful function in visual tasks, in this paper, we take the early attempt to explore unsupervised object localization by self-supervision. Specifically, we adopt different geometric transformations to image and utilize their parameters as pseudo labels for self-supervised learning. Then, the class-agnostic activation map is used to highlight the target object potential regions. However, such attention maps merely focus on the most discriminative part of the objects, which will affect the quality of the predicted bounding box. Based on the motivation that the activation maps of different transformations of the same image should be equivariant, we further design a siamese network that encodes the paired images and propose a joint graph partition mechanism in an unsupervised manner to enhance the object co-occurrent regions. To validate the effectiveness of the proposed method, extensive experiments are conducted on CUB-200-2011, Stanford Cars and FGVC-Aircraft datasets. Experimental results show that our method outperforms state-of-the-art methods using the same level of supervision, even outperforms some weakly-supervised methods.

Introduction
Recently, deep convolution neural networks have achieved impressive results in many visual tasks such as recognition (He et al. 2016; Su et al. 2020) and segmentation (Chen et al. 2017; Su et al. 2022), etc. This is due to the strong learning ability under supervision. Object localization aims to locate the object of interest within an image. However, collecting bounding-box labels is very time-consuming and labor-intensive, thereby some of these methods are often unavailable in practice.

To relax the demand for expensive annotations, some recent researches (Zhou et al. 2016; Choe and Shim 2019; Lin et al. 2020) focus on weakly-supervised object localization (WSOL), which only utilizes image-level labels. As the recent self-supervised learning techniques (He et al. 2020; Chen et al. 2020b,a; Gidaris, Singh, and Komodakis 2018) arising, image visual representations can be learned without labels in an unsupervised way. To this end, we make the early attempt to explore unsupervised object localization with self-supervised learning, which not only outperforms previous unsupervised works (Zhang et al. 2018a; Zhao et al. 2020), but also even outperforms some weakly-supervised methods (Zhou et al. 2016; Zhang et al. 2018b; Baek, Lee, and Shim 2020) (see in Figure 1).

In this work, we introduce a novel and simple framework for unsupervised object localization by self-supervision. Specifically, inspired by RotNet (Gidaris, Singh, and Komodakis 2018), the network can extract visual features by a classification task. The core intuition is that it is essentially impossible for a network to effectively perform the recognition task unless it has first learned to recognize and detect classes of objects as well as their semantic parts in images. But different from it, we consider predicting sim-
The mainstream and representative methods for WSOL are based on CAM (Zhou et al. 2016), which produced localization maps by aggregating deep feature maps using a class-specific fully connected layer. However, such the CAM-based methods only discover small discriminative parts of objects. To tackle this drawback, EIL (Mai, Yang, and Luo 2020) and ADL (Choe and Shim 2019) proposed to mine objects by integrating discriminative region mining and adversarial erasing in a single forward-backward propagation. ACoL (Zhang et al. 2018b) used multiple parallel classifiers that were trained adversarially. CutMix (Yun et al. 2019) and CDA (Su et al. 2021b) also explored the strategy and forced the network to focus on more relevant parts of objects. Besides, there are some works (Xue et al. 2019; Zhang, Wei, and Yang 2020a) focused on the intra and inter pixel-level correlations to help the network learn divergent activation maps. In recent work, TS-CAM (Gao et al. 2021) took the full advantage of the self-attention mechanism in visual transformer for long-range dependency extraction for object mining. SPA (Pan et al. 2021) proposed a two-stage approach to leverage the structure information incorporated in convolutional features for WSOL.

Self-supervised Learning

Self-supervised learning is an important technique in unsupervised tasks. By setting up different proxy-tasks, the network itself can learn meaningful image feature representations. (Larsson, Maire, and Shakhnarovich 2016) performed image colorization pretext to establish a mapping from objects to colors. In (Pathak et al. 2016), they learned objects features by predicting the missing parts of the images. In recent studies, some works (Noroozi and Favaro 2016; Wei et al. 2019a) tried to solve jigsaw problems to learn the information of different patches in the images. RotNet (Gidaris, Singh, and Komodakis 2018) proposed a simple rotation transformation and achieved remarkable results. Besides, video information is also widely used for training unsupervised models (Misra, Zitnick, and Hebert 2016; Pathak et al. 2018a). Localizing objects from video sequences is often referred to as weakly-supervised object localization (WSOL). Our main contributions are the following:

- We take the early attempt to conduct unsupervised object localization by self-supervision, which to our best knowledge, has not been well explored.
- We introduce a network to encode paired images with different transformations and propose an unsupervised joint graph partition mechanism to enhance the co-occurrence regions of the target object.
- Extensive experimental results on three benchmark datasets show the effectiveness of our proposed method and it can outperform the state-of-the-art unsupervised methods by a large margin, even outperforms some weakly-supervised methods.

**Related Work**

**Weakly-supervised Object Localization**

Weakly-supervised Object Localization (WSOL) aims to learn the localization of objects with only image-level labels. Unlike the mainstream and representative methods for WSOL, the work itself can learn meaningful image feature representations for WSOL. (Larsson, Maire, and Shakhnarovich 2016) performed image colorization pretext to establish a mapping from objects to colors. In (Pathak et al. 2016), they learned objects features by predicting the missing parts of the images. In recent studies, some works (Noroozi and Favaro 2016; Wei et al. 2019a) tried to solve jigsaw problems to learn the information of different patches in the images. RotNet (Gidaris, Singh, and Komodakis 2018) proposed a simple rotation transformation and achieved remarkable results. Besides, video information is also widely used for training unsupervised models (Misra, Zitnick, and Hebert 2016; Pathak et al. 2018a). Localizing objects from video sequences is often referred to as weakly-supervised object localization (WSOL). Our main contributions are the following:

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Figure 3: The overview of our method. Paired training images that contain the same object with different geometric transformations are first encoded into feature representations by a share-weight network. The joint graph partition module is responsible for dividing the two joint image features into two optimal sub-graphs and yields the masks to reinforce the co-occurrent object regions for enhancement followed by a standard convolutional layer. The final classification loss $L_{cls}$ and equivariant regularization loss $L_{ER}$ are used to update the gradient propagation to train the network in an end-to-end manner.

et al. 2017; Mahendran, Thewlis, and Vedaldi 2018). Recently, contrastive learning (Tian, Krishnan, and Isola 2020; Su, Lin, and Wu 2021; Su et al. 2021a) by constructing pairs using different augmentations of image achieved great success. The core idea in contrastive learning is to strengthen the invariance of the network to various data augmentations. MoCo (He et al. 2020; Chen et al. 2020b) further improved the performance by using the memory bank and relaxing the big batch size for training. In this paper, we focus on self-supervised object localization that learns the potential image object feature representations with self-supervised strategy.

Unsupervised Object Discovery

Traditional unsupervised object learning methods are based on the similarity between image pixels such as superpixels (Wang et al. 2016) and Grabcut (Rother, Kolmogorov, and Blake 2004). In terms of deep learning, due to the need for a large number of ground-truth for training, there have been only a few unsupervised learning works in these years. (Cho et al. 2015) used off-the-shelf region proposals to form a set of candidate bounding boxes for objects and adopted probabilistic Hough transform to select the final prediction. MO (Zhang et al. 2019), DDT (Wei et al. 2019b), SCDA (Wei et al. 2017a) and PSY (Baek, Lee, and Shim 2020) all utilized the models pre-trained on ImageNet (Rusakovsky et al. 2015) that use class-level labels for post-process generation. Therefore, these are not strictly unsupervised object localization approaches. Another common method is to employ adversarial networks (Goodfellow et al. 2014) to find the objects. ReDraw (Chen, Artières, and Denoyer 2019) proposed to segment the objects by redrawing the masks of the targets based on an adversarial architecture. In this work, we compare our proposed method with the above mentioned unsupervised and weakly supervised methods to validate the effectiveness of our approach.

Methodology

We address unsupervised object localization in a self-supervised manner, and the core idea is to learn the potential object features that cover the entire region by predicting transformation task. In particular, we present a simple yet powerful framework to mine the object and propose an unsupervised joint graph partition strategy for object mining. In the following sections, we first give an overview of the entire architecture, and then introduce the joint graph partition method and objective functions in detail.

Overall Architecture

The entire framework of our proposed method is shown in Figure 3. Formally, given an unlabeled image $I$, we adopt two different random geometric transformations $T_1, T_2$ to it and form two new images $I_1$ and $I_2$. Note that the new images can also be the original image without transformations. We first adopt the backbone network (i.e., VGG16 (Simonyan and Zisserman 2014)) as the encoder to extract their features denoted as $F_1$ and $F_2$, by removing the fully-connected layers and softmax layer. Since these two transformed images contain the same objects but with different parts of activation as we show in Figure 2, we then design a joint graph partition mechanism with learnable parameters, which is able to model the relationship between similar and dissimilar pixels for co-occurrent object regions mining for enhancement. The partition module yields two optimal solution masks that highlight the co-objects. Afterward, we add the masks to the former features $F_1$ and $F_2$ and followed by a $1 \times 1$ convolutional layer. Finally, we apply an average pooling along the channel axis to form the class-agnostic activation map. The prediction loss $L_{cls}$ and equivariant regulari-
Joint adjacency Matrix

The raw text is a bit scattered, but it seems to be discussing a method for approximating a matrix $F$ using normalized channel features for both inter and intra images. Specifically, the text mentions constructing a graph $G$ with nodes representing features of paired images, and then cutting the graph to optimize for different subgraphs. The goal is to make the different subgraphs as far from each other as possible and as similar internally as possible. In this way, the text suggests that we can aggregate the co-occurrence regions.

**Joint Graph Partition**

As depicted in Figure 4 left, we transform the initial CAMs into grayscale maps, which show the potential foreground object pixels. We aim to use these two different maps to mine the semantic features in the co-occurrent part. As depicted in Figure 4 left, we transform the initial activation maps. (Right) The paradigm of the unsupervised joint graph partition, which views the two feature maps as graph nodes and the edge represents the distance between each other. The similar object nodes are close while the dissimilar ones are distant. We aim to cut the graph and divide it into two optimal sub-graphs by using the subgraph indicator. The final optimal solution is then reshaped into two masks representing the co-occurrent regions.

The joint graph partition mechanism for better object mining as shown in Figure 4 right. Formally, the paired image feature maps $(F_1, F_2) \in \mathbb{R}^{w \times h \times c}$ are viewed as graph nodes, where $w$ and $h$ denote the spatial size of the feature map and $c$ is the feature map dimension. We then construct a graph $G(V, E)$, where $V$ represents the feature nodes in the graph, and $E$ represents edges between nodes. In graph $G$, we have $2wh$ nodes $N \in \mathbb{R}^{2wh \times N}$ in total for paired images. We then use the paired images nodes to jointly construct a adjacency matrix $A$ that represents the similarity of each node across inter and intra images. Specifically, we utilize Euclidean distance: $d_{i,j} = ||x_i - x_j||^2$ to measure the distance between the two arbitrary nodes in $G$. Since we use normalized channel features for both $F_1$ and $F_2$, which satisfies $||x_i||^2 = 1$. By removing the constant, the adjacency matrix can be approximated to $A \in \mathbb{R}^{2wh \times 2wh} = N^T N$. As for the degree matrix $D$, since we consider both inter and intra information between paired images, nodes are fully connected between each other, $D = \text{diag}(\sum A_{i,i}, ..., \sum A_{i,j}) \in \mathbb{R}^{2wh \times 2wh}$. After converting the image features to a graph, we then cut the graph. Our goal is to make the different subgraphs as far apart as possible from each other and as similar internally as possible. In this way we can aggregate the co-occurrence category of prospects for subsequent enhancement. Inspired by (Ng, Jordan, and Weiss 2002), we will have the following function:

$$L_m = \text{RatioCut}(V_1, ..., V_k) = \sum_{i} \frac{W(V_i, V_i)}{|V_i|}, \quad (1)$$

where $\{V_1, V_2, ..., V_k\}$ represents a subset of $V$. In our task, we aim to divide the foreground object $O$ and background $\bar{O}$, thus, $k = 2$. $W(O, \bar{O})$ represents the sum of edges of $O$ and its complementary set, which equals to $\sum_{m \in O, n \in \bar{O}} A_{m,n} |O|$. The nodes cardinality in $O$ subset.

In order to solve the optimal graph cut problem and avoid the occurrence of a single sample node as a subset, we then introduce the subgraph indicator $h = [h_1, ..., h_{2wh}]^T \in \mathbb{R}^{2wh \times h}$ as follows:

$$h_i = \begin{cases} \frac{1}{|O|} & \text{if } V_i \in O \\ 0 & \text{if } V_i \notin O \end{cases} \quad (2)$$

Since $D$ is a diagonal matrix, only the elements on the diagonal multiplied by the vector $h_i$ have a value, where $D_{m,m} = \sum_{n=1} A_{m,n}$. And known from the property of the Laplace matrix, we then can put Eq 2 into Eq 1. The function $L_m$ can be reformulated as:

$$L_m = \frac{1}{2} \left( \sum_{m \in O, n \in \bar{O}} A_{m,n} \frac{1}{|O|} + \sum_{m \in \bar{O}, n \in O} A_{m,n} \frac{1}{|O|} \right)$$

$$= \frac{1}{2} \left( \sum_{m \in O, n \in \bar{O}} A_{m,n} \left( \frac{1}{|O|} - 0 \right)^2 + \sum_{m \in \bar{O}, n \in O} A_{m,n} \left( \frac{1}{|O|} \right) \right)$$

$$= \sum_{m=1}^{2wh} \sum_{n=1}^{2wh} h_m h_n D_{m,n} - \sum_{m=1}^{2wh} h_m h_n A_{m,n}$$

$$= h^T (D - A) h \quad (3)$$

Following (Zhang et al. 2020) that the continuous solution of the indicator vector is the principal component, we can finally get the optimal co-occurrence mask $h^*$ by optimizing Eq 3. Afterward, we reshape it into $\{h_1, h_2\} \in \mathbb{R}^{w \times h \times 1}$ as the enhancement features and add them to the $F_1$ and $F_2$ respectively followed by a new standard convolutional layer for information updating. Note that except for tensor addition for features fusion, other alternatives like multiplication and concatenation will be discussed in our ablation studies.
Objective Function

Prediction Loss. For self-supervised learning, we provide the network \( N(\cdot) \) pretext task to update the gradient propagation and learn the object features. Specifically, we adopt different geometric transformations including the unchanged original images, random rotation \( (90^\circ, 180^\circ, 270^\circ) \), random flipping, random scaling \( (1/4, 1/2, 2, 4) \) size of the original ones and translation. Then, we use the Cross-Entropy loss for transformation prediction as follows:

\[
L_{cls} = \text{Cross-Entropy}(N(T_i(I)), y_i),
\]

where \( y_i \) is the artificial label of each transformation \( T_i \).

Equivariant Regularization Loss. At the last layer of our network, we adopt an average pooling along the channel axis \( (i.e., P_1 = \text{AvgPool}(N(T_i(I))|B;w,h)) \), \( B \) is batch size) to yield the class-agnostic activation map (CAAM) followed by the Softmax function for classification. To further guarantee the consistency of input paired images for learning, we propose an equivariance regularization loss for regularizing the network prediction as follows:

\[
L_{ER} = ||P_1 - P_2||_1.
\]

Training. Finally, we train our network in an end-to-end manner, all the network parameters are jointly learned by minimizing the following multi-task loss function:

\[
L_{total} = L_{cls} + L_{ER} + L_m.
\]

Experiments

Experimental Setup

Datasets. To evaluate the proposed approach, three datasets are adopted, including CUB-200-2011 (Wah et al. 2011), FGVC-Aircraft (Maji et al. 2013) and Stanford Cars (Krause et al. 2013). Among them, CUB-200-2011 is the largest dataset that contains 200 categories of birds with 5,994 training images and 5,794 testing images. We strictly follow the train-list and test-list of the datasets for training and evaluating images and 5,794 testing images. We strictly follow the original ones and translation. Then, we use the Cross-Entropy loss for transformation prediction as follows:

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Experiments

Table 1: The ablation study for each proposed loss of our method.

|                         | \( L_m \) | \( L_{ER} \) | GT-Known Loc |
|-------------------------|-----------|--------------|--------------|
| ✓                       | ✓         | 54.6         |              |
| ✓                       | ✓         | 57.9         |              |
| ✓                       | ✓         | 60.4         |              |

Table 2: Experiments of various transformations for self-supervised learning. Aggregating different affine transformations can bring significant improvement.

| Rotation | Flip | Rescale | Translation | GT-Known Loc |
|----------|------|---------|-------------|--------------|
| ✓        | ✓    | ✓       | ✓           | 57.9         |
| ✓        | ✓    | ✓       | ✓           | 58.1         |
| ✓        | ✓    | ✓       | ✓           | 58.2         |
| ✓        | ✓    | ✓       | ✓           | 60.0         |
| ✓        | ✓    | ✓       | ✓           | 60.2         |
| ✓        | ✓    | ✓       | ✓           | 60.4         |

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Ablation Studies

In this section, we explore the effectiveness of each component in our proposed method. Since CUB-200-2011 is a more challenging dataset, we conduct ablative analysis on it with the VGG16 backbone pretrained without using class-level labels if there is no special declaration.

Comparison with Baseline. Table 1 gives an ablation study of each loss in our approach. Note that in our method, baseline denotes using only prediction loss \( L_{cls} \) and using single image for training since it does not have \( L_m \) for graph partition. As can be seen, paired images mining boosts the network performance by \( 3.3\% \), which reveals that joint graph partition is effective. Furthermore, when we introduce to use equivariant regularization loss \( L_{ER} \), we can further improve the localization accuracy achieving \( 60.4\% \). This shows the effectiveness of the proposed losses in our self-supervised object localization learning, which can help the network to mine and regularize the potential object features. Besides, compared with baseline, we insert the joint graph partition module into the network structure. Since the module works at the top layer with a relatively small spatial size, thus the overhead is marginal compared with the baseline network. More detailed information about the computation complexity can be referred to supplementary material.
Table 3: Comparison between our method and the previous state-of-the-arts in terms of GT-Known Loc performance on CUB-200-2011, Stanford Cars and FGVC-Aircraft datasets. ‘*’ indicates our reimplemented results using their publicly released code since they do not report the results.

Table 4: Experiments of various features fusion strategies.

Table 5: Localization error statistics.

The Effect of Different Transformations. As we mentioned in the introduction, too simple pretext tasks may degrade the learning features. As shown in Table 2, we explore different numbers of transformations for network learning. Only using rotation means the network has totally 4 classes to predict (i.e., self image, 90°, 180° and 270° rotated images, respectively), which achieves 57.9% GT-Known Loc. When we utilize more geometric transformations, it makes the network harder to predict the class. As we finally use four different transformations, we can yield the best results to 60.4%. This also shows that different geometric transformations can drive the network to activate objects in different areas, and the variety of transformations can help the network to mine more useful object regions by our proposed joint graph partition and regularization strategies.

The Effect of Different Features Fusion. Table 4 gives different features fusion strategies in our network. Among them, features addition yields the best performance. We conjecture that because the optimal masks have zero values, matrix multiplication turns some features to zero sharply, which may affect the features learning. And the concatenation operation can not well integrate the features globally.

Error Analysis. To further reveal the effect of our method, we categorize the localization errors into localization part error (Part) and localization more error (More). Part indicates that the predicted bounding box only covers parts of the object, and IoU is less than a certain threshold. On the contrary, More indicates that the predicted bounding box is larger than the ground truth bounding box by a large margin. Table 5 lists localization error statistics. Our method effectively reduces Part, and More errors using different backbones, which indicates that our localization maps are much accurate. More detailed definitions of each metric can be referred to supplementary material.

Comparisons with State-of-the-arts

We compare the proposed approach with the state-of-the-arts on the GT-Known Loc performance by using tight bounding boxes. Table 3 reports the results of our method
and several methods on the three benchmark datasets. To be specific, we first list some weakly-supervised object localization approaches at the top of Table 3. Among them TS-CAM (Gao et al. 2021) yields the best result achieving 87.70% accuracy on CUB-200-2011 dataset, outperforming the latest SPA (Pan et al. 2021) by 10.3% and achieves more than 30% gains over the CAM (Zhou et al. 2016) in terms of \textit{GT-Known Loc}. It employs a visual transformer (Dosovitskiy et al. 2020) backbone network structure, which can help the network to learn the features globally.

Secondly, we compare our method with several methods under pseudo-unsupervised setting. As can be seen in the middle of Table 3, using the same VGG16 backbone, our method outperforms other SOTA methods by a large margin. On CUB-200-2011 dataset, we achieve \textbf{88.83\%} \textit{GT-Known Loc} performance gains compared with the second-best method PSY (Baek, Lee, and Shim 2020). On Stanford Cars and Aircraft datasets, we get remarkable performance achieving \textbf{97.73\%} and \textbf{96.72\%}, respectively. When we adopt a stronger InceptionV3 (Szegedy et al. 2016) backbone, we can further improve the \textit{GT-Known Loc} performance on Stanford Cars and Aircraft datasets achieving \textbf{98.62\%} and \textbf{97.94\%}. It is worth mentioning that our proposed method even outperforms the best weakly-supervised methods (Ours: \textbf{88.83\%} vs. TS-CAM: \textbf{87.70\%}) on CUB-200-2011 dataset. Although the backbone is pretrained using class-level labels, compared with the WOSL methods, we train the network by self-supervision without using annotations on the training datasets and achieve significant performance. This validates the effectiveness of our proposed method and further ease the burden of using class labels for training the networks.

Finally, we show the unsupervised learning results at the bottom of Table 3. Since there are few researches on unsupervised object localization, we adopt similar unsupervised saliency detection method DUSD (Zhang et al. 2018a) and unsupervised segmentation method ReDraw (Chen, Artières, and Denoyer 2019) in our task. We also compare our method with a recently published approach DiLo (Zhao et al. 2020), which utilizes distilling localization for self-supervised representation learning. As can be seen, the traditional method UODL (Cho et al. 2015) yields the best results on both CUB-200-2011 and Stanford Cars datasets by using off-the-shelf region proposals. As for deep learning methods, our approach achieves the best results \textbf{74.62\%} on Aircraft dataset. Besides, we achieve the second best performance on CUB-200-2011 approaching \textbf{60.4\%} and Stanford Cars approaching \textbf{70.37\%} in terms of \textit{GT-Known Loc} without using other auxiliary techniques.

Visualization comparisons of the proposed approach are shown in Figure 5. Compared with the WSOL method CAM (Zhou et al. 2016), our method can mine more complete object regions than only focuses on the most discriminative ones. Bounding boxes produced by our method not only localize object regions accurately but also are more compact, which verifies its superiority.

**Conclusion**

In this paper, we take the early attempt to explore unsupervised object localization by self-supervision. By providing different geometric transformation pretext tasks and introducing a novel joint graph partition module, we encode paired images with the same object and mine the co-occurrent regions for features learning. To validate the effectiveness of our approach, extensive experiments are conducted on three benchmark datasets, and the results show that our method outperforms state-of-the-art methods.
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