Dynamic Clustering Network for Unsupervised Semantic Segmentation

Kehan Li\textsuperscript{1}    Zhennan Wang\textsuperscript{2}    Zesen Cheng\textsuperscript{1}    Runyi Yu\textsuperscript{1}    Yi’an Zhao\textsuperscript{1}
Guoli Song\textsuperscript{2}    Li Yuan\textsuperscript{1,2}    Jie Chen\textsuperscript{1,2}

\textsuperscript{1} School of Electronic and Computer Engineering, Peking University
\textsuperscript{2} Peng Cheng Laboratory

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{t-SNE visualization of the pixel-level representations produced by self-supervised ViT and the corresponding cluster centers discovered by the proposed dynamic clustering network (DCN). It can be found that these pixel representations present different groups in the representation space, which are associated with the semantics of the pixels. We mark the underlying groups found by the DCN by different colors. Based on the pixel embeddings produced by self-supervised ViT, the proposed DCN successfully finds the underlying semantic groups dynamically for different images with scenes of different complexity.}
\end{figure}

\section*{Abstract}

Recently, the ability of self-supervised Vision Transformer (ViT) to represent pixel-level semantic relationships promotes the development of unsupervised dense prediction tasks. In this work, we investigate transferring self-supervised ViT to unsupervised semantic segmentation task. According to the analysis that the pixel-level representations of self-supervised ViT within a single image achieve good intra-class compactness and inter-class discrimination, we propose the Dynamic Clustering Network (DCN) to dynamically infer the underlying cluster centers for different images. By training with the proposed modularity loss, the DCN learns to project a set of prototypes to cluster centers for pixel representations in each image and assign pixels to different clusters, resulting in dividing each image to class-agnostic regions. For achieving unsupervised semantic segmentation task, we treat it as a region classification problem. Based on the regions produced by the DCN, we explore different ways to extract region-level representations and classify them in an unsupervised manner.

We demonstrate the effectiveness of the proposed method through experiments on unsupervised semantic segmentation, and achieve state-of-the-art performance on PASCAL VOC 2012 unsupervised semantic segmentation task.

\section{1. Introduction}

Semantic segmentation is one of the basic tasks in computer vision, which has been widely used in many domains, such as autonomous driving and medical images. With the development of deep learning and the increasing amount of data [11, 23, 45], uplifting performance has been achieved on this task by optimizing deep neural networks with pixel-level annotations [24]. However, large-scale pixel-level annotations are expensive and laborious to obtain. To solve this problem, different kinds of weak supervisions have been explored for achieving label efficiency [32], e.g., image-level supervision [1, 41], scribble-level supervision [22] and box-level supervision [28]. More than this, there are also some methods which achieve semantic segmentation without relying on any labels [15, 16],
It is obvious that the cosine similarity between pixels within the same image is more related for semantic comparing with pixels across images.

namely unsupervised semantic segmentation.

Early approaches for unsupervised semantic segmentation are based on pixel-level self-supervised representation learning by introducing cross-view consistency [7, 16], edge detection [15, 44] or saliency prior [37]. Recently, the self-supervised ViT [5] provides a new paradigm for unsupervised semantic segmentation, for its property of containing semantic information in pixel-level representations as shown in Figure 1. The feasible solutions for transferring the self-supervised ViT to unsupervised semantic segmentation task are varied. The most intuitive way is to cluster all the representation of pixels in the dataset, or further treat these representations as pseudo label [12]. However, we find that the semantic discrimination of pixel representations is most pronounced within pixels in the same image but confusing across images. Specifically, it is the pixels in the same image that fuse information with each other, during the forward process of ViT. Besides, the self-supervised learning process does not establish explicit connections for pixel representations across different images.

We further demonstrate this view through qualitative and quantitative analysis. Firstly we visualize the cosine similarity between the query pixel and other pixels in different scopes, i.e., in the same image or across different images, in Figure 2. It can be intuitively found that the cosine similarity between embeddings of semantically consistent pixels is relatively large within the same image. However, when observing it across different images, the cosine similarity between the query pixel and a pixel belonging to a different class is even larger than the one for two semantically consistent pixels in some cases. For quantitative analysis, we introduce the concepts of intra-class angle and inter-class angle [8]. The intra-class angle is defined by the average angle between each embedding and the corresponding class center, and the smaller the angle, the better the intra-class compactness. The inter-class angle is defined by the minimum angle between the center of one class and the center of other classes, averaging for all classes, and the larger the angle, the better the inter-class discrimination. Here we use the 21 classes and the ground-truth defined in PASCAL VOC 2012 to calculate the two metrics. We count them using pixels in a single image and get the averages of 49.27° and 51.55° in the dataset for intra-class angle and inter-class angle, respectively. For comparison, the intra-class angle and inter-class angle of all pixels in the whole dataset is 49.28° and 24.91°, respectively. These statistics reflect that pixels of different semantic classes are easier to distinguish, within the confines of a single image, due to the smaller intra-class angle and the significantly larger inter-class angle. In conclusion, pixel representations within the same image is closer related and reflect their semantic relationship more accurately, comparing with pixels in different images. Therefore, it is more precise to cluster the pixel representations of self-supervised ViT separately for each image.

Unlike the previous attempts which only consider foreground-background partition [36, 38, 40], or divide each image into a fixed number of clusters [26], we argue that it is important to consider different images distinguishably, due to the complexity of various scenarios. We thus propose the Dynamic Clustering Network (DCN) to cluster the pixels into dynamic semantic groups for each image. In the DCN, cluster centers are explicitly encoded to learnable prototypes and dynamically updated for different images, which is implemented by iteratively applying scaled dot-product attention [39] on these prototypes and pixel embeddings in the image to be processed. Through such a structure, the DCN learns to project the initial prototypes to cluster centers depends on the input pixel embeddings. With the cluster centers, segmentation of an image is achieved by assigning each pixel to the nearest cluster. The dynamic is reflected in two aspects. First, the cluster centers are detected based on different pixel embeddings in different images. Second, we propose a novel loss function to optimize the DCN considering the complexity of different scenarios, which does not constrain the number of semantic groups and results on dynamic number of segmented regions for different images.

The DCN is end-to-end optimized without any annotations, by the proposed modularity loss. We first construct an affinity graph taking input pixel embeddings as vertices and the cosine similarity of them as edges. Motivated by modularity [27] in community detection, we use the connection relationship of two pixels in the affinity graph to adjust the strength of assigning two pixels to the same cluster. After optimizing, the DCN realize fast and accurate inference on unseen images, successfully extracting the implicit pixel-level knowledge of self-supervised ViT.

We consider unsupervised semantic segmentation, which
requires classifying each pixel, as an region classification problem, and achieve it by classifying the regions produced by DCN in several unsupervised ways. (a) With the help of the image-level discriminating ability of the self-supervised ViT, we input the images masked by the binary mask of a region to the self-supervised ViT to get region embeddings, which are then clustered using k-means. (b) Based on the region embeddings, we adopt k-NN classifier to assign each region the same label as its nearest regions. (c) We introduce language-image pre-training models [30], and classify each region using texts of pre-defined categories. The experimental results demonstrate that the proposed DCN is able to segment an image accurately, and finally the proposed method achieves sate-of-the-art performance on unsupervised semantic segmentation task of PASCAL VOC 2012 dataset without post-processing or re-training.

2. Related works

Unsupervised semantic segmentation. With the development of self-supervised and unsupervised learning in deep learning, unsupervised methods for semantic segmentation tasks start to emerge. Among them, Ji et al. [16] and Ouali et al. [29] learn a segmentation model by maximizing the mutual information between augmented views. Cho et al. [7] propose to incorporate geometric consistency as an inductive bias to learn invariance and equivariance for photometric and geometric variations and exploit a clustering objective. Van et al. [37] introduce a salient object detector and exploit contrastive learning for salient pixels to learn pixel-level representations. Ke et al. [18] solve the unsupervised hierarchical semantic segmentation problem based on the idea that a good representation reveal any level of grouping in a consistent and predictable manner. Ziegler et al. [47] propose a pixel-level self-supervised learning algorithm, and then cluster learned prototypes by Infomap [31]. Recently, Caron et al. [5] find that the pixel embeddings of self-supervised ViT are well suited for semantic segmentation, which promotes the emergence of a series of methods based on pixel embeddings extracted by self-supervised ViT. We review these methods in the following.

Self-supervised vision transformers and applications. Transformer, a model mainly based on self-attention mechanism, is first proposed by Vaswani et al. [39] for machine translation and is widely used in natural language processing tasks [3, 9] and cross-modal tasks [17, 20, 21, 30]. ViT [10] is the first pure visual transformer model to process images. For self-supervised learning, Chen et al. [6] explore self-supervised learning on ViT using contrastive learning and show inspiring performance. Caron et al. [5] propose self-distillation with no labels (DINO) to train the ViT, and found a property of self-supervised ViT that its features contain explicit information about the semantic segmentation of an image. Based on DINO, a lot of researchers extends this property to varies application. For example, Simeoni et al. [36] proposed a series of hand-made rules to chose pixels belonging to same object according to their feature similarity, achieving unsupervised object discovery and detection. Wang et al. [40] introduce normalized cuts [33] on the affinity graph constructed by pixel embeddings from DINO to divide foreground and background in an image, for unsupervised object discovery and saliency detection task. For semantic segmentation task, Hamilton et al. [12] train a segmentation head by distilling the feature correspondences, which further encourages pixel features to form compact clusters and learn better pixel-level representations. Melas et al. [26] adopt spectral decomposition on the affinity graph to discover meaningful parts in an image and implement semantic segmentation of an image. [38] also design some hand-made rule based on pixel embeddings to find objects and train a Mask R-CNN [14] to generate more accurate pseudo labels.

Text-supervised semantic segmentation. Language-image pre-training models enable learning without annotations or zero-shot transfer on vision tasks. For semantic segmentation, Zhou et al. [46] modify the visual encoder of CLIP [30] and apply the text-based classifier on pixel level. Xu et al. [42] propose a hierarchical grouping vision transformer, and train it with image-to-text contrastive loss. Finally, the semantic segmentation results can be obtained by the grouping result and text embeddings. Shin et al. [35] leverage the retrieval abilities of CLIP and the robust correspondences offered by modern image representations to co-segment entities. Shin et al. [34] use CLIP to construct category-specific images, and produce pseudo-label with a category-agnostic salient object detector bootstrapped from DINO.

3. Dynamic clustering network

As mentioned above, the self-supervised ViT projects pixels to a high dimensional embedding space, where the semantically similar pixels in the same image are relatively close. For dynamically mining underlying semantic groups for each image in the fixed pixel embeddings generated by the self-supervised ViT, we propose the Dynamic Clustering Network (DCN).

The overall structure of DCN is shown in Figure 3. The DCN adaptively generate pixel assignments for different images by three steps: (a) Take a series of learnable prototypes as input, which represent the cluster centers. (b) Iteratively update the prototypes through interacting with the pixel embeddings and with each other. (c) Assign pixels to the cluster centers. The DCN is trained end-to-end without any annotations. To ensure that the updated cluster centers accurately reflect the semantic distribution of pixel embeddings, we propose a novel modularity loss motivated by modularity [27], which has been widely used to mea-
ensure the quality of a graph partition. We now explain each component of DCN and the optimization of it in details.

### 3.1. Prototype update

In the DCN, cluster centers are generated from some prototypes, which are randomly initialized and optimized through training. In order to map these prototypes to potential cluster centers dynamically for pixels in each image, we introduce the scaled dot-product attention [39] to construct the main body of the DCN. Specifically, we update the prototypes by applying dynamic update block and self-update block iteratively on the prototypes and pixels embeddings.

**Dynamic update block** is used to update prototypes according to the pixel embeddings. Let \( C^l \in \mathbb{R}^{k \times d} \) denote \( k \) prototypes after \( l \)-th update and \( X \in \mathbb{R}^{n \times d} \) denote \( n \) pixel embeddings from an image, the dynamic update process can be formulated as

\[
\bar{C}^l = \text{Softmax} \left( \frac{C^{l-1}W_q(XW_k)^T}{\sqrt{d}} \right) \left( XW_o \right),
\]

\[
C^l = C^{l-1} + \bar{C}^lW_o, \quad (1)
\]

where \( W_q, W_k, W_e, W_o \in \mathbb{R}^{d \times d} \) are learnable linear projections. The dynamic update adaptively chose the relative pixel embeddings for each prototypes and update it, which makes it possible to generate cluster centers dynamically for different image.

**Self-update block** is designed for modeling the connections for different cluster centers. Formulaically, it can be expressed as

\[
C^l = \text{Softmax} \left( \frac{C^{l-1}W_q(C^{l-1}W_k)^T}{\sqrt{d}} \right)(C^{l-1}W_e),
\]

\[
C^l = C^{l-1} + C^lW_o. \quad (4)
\]

Different from dynamic update block, the self-update block updates each prototype by other prototypes and make it aware of the presence of others, for the purpose of better adjusting their relative positions in the embedding space.

The whole update progress is done by applying dynamic update block and self-update block alternately. For implementation, we adopt the Feed-forward Network (FFN) after each update following the transformer [39], which is omitted in Figure 3 for brevity. In addition, the two update blocks and the FFN are followed by layer normalization [2].

### 3.2. Pixel assignment

After updating, the prototypes become cluster centers conditional on the input pixel embeddings. Since the grouping structure of pixel embeddings is represented in hypersphere space [36,40], we consider the cluster also in hypersphere space. First we get a soft assignment for each pixel by calculating the cosine similarity between its embedding and the cluster centers

\[
S_{i,j} = \cos < x_i, c_j >,
\]

\[
S_{i,j} = \cos < x_i, c_j >, \quad (5)
\]

where \( S \in \mathbb{R}^{n \times k} \) is the assignment matrix, \( x_i = X_{i, :} \) is the \( i \)-th pixel embedding and \( c_j = C_{j, :} \) is the \( j \)-th cluster center. The soft assignment is differentiable and is used to optimize the network when training, which is described in Section 3.3. During inference, we assign each pixel to a definite cluster by the maximum similarity

\[
a_t = \arg\max_j \cos < x_i, c_j >. \quad (6)
\]

By doing that, an image is segmented to \( m \) regions. Each region is identified by a cluster and consists of pixels as-
signed to this cluster. It is worth noting that \( m \) is different for different images, because the assignment when inference is done by \( \arg \max \) operation which do no guarantee that every cluster center is assigned at least once. Due to the dynamic nature of this assignment as well as the dynamic update of prototypes for each image, we name the proposed network Dynamic Clustering Network.

### 3.3. Modularity loss

To optimize the network without any label, an intuitive way is making use of a metric that measures the quality of assignments. We introduce modularity [27] as the metric. Formulaically, it is calculated as

\[
q = \frac{1}{2m} \sum_{i,j} (A_{i,j} - \frac{k_i \cdot k_j}{2m}) \delta(i,j),
\]

where \( i, j \) is the index of vertices, \( A_{i,j} \) is the edge between \( i \) and \( j \), \( k_i \) is the sum of edges connected to vertex \( i \), \( 2m \) is the sum of all edges in the graph and \( \delta(i,j) \) is an indicator function which equals to 1 when \( i \) and \( j \) belong to the same cluster. Modularity measure the partition of a graph, based on the idea that the possible existence of clusters is revealed by the comparison between the actual density of connections between two vertices and the expected density in the graphs where all edges are randomly assigned. This is reflected in the fact that when preserving the degrees of vertices in the graph but connecting vertices randomly, the probability of an edge existing between vertices vertices \( i \) and \( j \) is \( k_i \cdot k_j / 2m \). We introduce the modularity for the following two reasons. First, no hyperparameters are required, which make it robust to different inputs. Second, it does not depend on the count of clusters, allowing the network to detect different count of groups in different images.

Based on how modularity reveals the existence of clusters, we propose the modularity loss to optimize the DCN. We first construct a fully connected undirected affinity graph for pixels from an image by treating them as vertices. The weight of edge between two pixels which represents their affinity is calculated by the cosine similarity of them

\[
A_{ij} = \max (0, \cos \langle \mathbf{x}_i, \mathbf{x}_j \rangle).
\]

Here we truncate the weight to a minimum of zero to avoid negative values in modularity calculation. At the same time we define the degree of two pixels belong to the same cluster

\[
\bar{S} = \max (0, S); \quad \delta(i,j) = \max_c \bar{S}_{i,c} \cdot \bar{S}_{j,c},
\]

where \( S \) is the soft assignment in equation 5, which makes the loss function differentiable. The soft assignment is calculated by cosine similarity so that we have \( S_{i,j} \in [-1, 1] \). Considering the indicator function in the original modularity, we make the value of \( \delta(i,j) \in [0, 1] \) by ignoring \( S_{i,j} \) which is less than zero. Since the pixel embeddings are fixed and only the prototypes are updated, the update of a prototype will be ambiguity if we take unrelated pixel pairs into account. Therefore, we chose the related prototype \( c \) for each pair by \( \max_c \bar{S}_{i,c} \cdot \bar{S}_{j,c} \) and calculating \( \delta(i,j) \) in the same way. At last, the modularity loss for an image is

\[
L = -\frac{1}{2m} \sum_{i,j} (A_{i,j} - \frac{k_i \cdot k_j}{2m}) \delta(i,j),
\]

where \( i, j \) denote pixels, \( A_{i,j} \) is the weight of edge \( (i, j) \) in the affinity graph, \( 2m, k_i, k_j \) are consistent with equation 7 and can be obtained by \( A \). Overall, the modularity loss adjusts the similarity of the prototypes to different pixel pairs according to the intensity of \( i, j \) belonging to the same cluster on the affinity graph, and then determines the position of different cluster centers in the embedding space. Meanwhile, the \( \max \) function in equation 9 adaptively chooses different cluster centers, which achieve the dynamic number of cluster centers for different images. Through optimizing the modularity loss, the DCN finally learn to predict potential grouping relationships among pixels for different images.

## 4. Experiment

### 4.1. DCN for Unsupervised semantic segmentation

#### 4.1.1 Region classification

Since the DCN segments each image into a set of regions, we consider the unsupervised semantic segmentation task, which requires classifying each pixel, as a region classification problem. We exploit the ability to discriminate image categories of self-supervised ViT to determine the category of regions over the entire dataset. Specifically, for each region we use its binary mask and the corresponding image to produce a masked image, then input it to the self-supervised ViT to get a region embedding. Following the previous researches [26, 38, 43], we apply k-means clustering algorithm to embeddings of all foreground regions to classify each region in an unsupervised manner. Moreover, we also implement classification of regions by k-NN retrieval and language-image pre-training models [30]. The details are shown in Section 4.

#### 4.1.2 Foreground detection

Semantic segmentation aims at predicting the category of each pixel. In complex scenes, some datasets (e.g., Pascal VOC 2012 [11]) only define the foreground categories and give a pixel “background” status if it does not belong to any specified classes. For quantitative evaluation, the regions belonging to background are unsuitable for clustering or discriminating by language, because background actually contains a lot of categories such as water, sky, land,
Figure 4. **Qualitative results on PASCAL VOC 2012 dataset.** We show the segmentation results of DCN, semantic segmentation of DCN based on k-means clustering and the ground-truth in sequence. The proposed DCN is able to find different semantics within an image and realize precise semantic segmentation with image-level embedding from the self-supervised ViT.

Figure 5. **Visualization of k-NN region retrieval results.** We show the k regions with the highest similarity following each query region. Thanks to the accurate localization of the DCN, the region embeddings obtained from self-supervised ViT are unbiased, so that it is favourable to achieve retrieval according to the region embeddings.

wall, etc. Hence, we perform clustering and language-based classification only on the foreground regions. To identify whether a region is foreground, we first get a foreground score for each region by summing the attention value of pixels within it. The attention value of pixels are from the last self-attention layer of the self-supervised ViT, taking the minimum of each attention head, based on the idea that a pixel is likely to be foreground when it appears in at least one attention head. With the foreground score of regions in an image, we cluster them into two categories and chose the cluster with larger score as foreground.

**Implementation details.** We use ViT-small [10] trained with DINO [5] as the self-supervised ViT and set the patch size to 8. From the ViT, we take tokens except cls token from the last layer as corresponding pixel embeddings. For training and inference of the DCN, we resize the width and height of images to 224 and do not use additional data augmentation. During inference, we use bilinear upsampling to restore the soft assignment of pixels to the original resolution, before getting the hard assignment. The DCN is optimized by AdamW [25], with learning rate of 0.0001 and weight decay of 0.01. We train the DCN for 2500 it-
Table 1. Unsupervised semantic segmentation results on PASCAL VOC 2012 semantic segmentation dataset. The proposed method achieves state-of-the-art performance without re-training or additional post processing, showing the applicability of transferring self-supervised ViT to semantic segmentation task and the effect of the proposed DCN to mine the underlying semantic groups in embeddings of self-supervised ViT.

| Method            | mIoU | Acc.  |
|-------------------|------|-------|
| MoCo [13]         | 4.3  |       |
| SwAV [4]          | 4.4  |       |
| IIC [16]          | 9.8  |       |
| MaskContrast [37] | 35.0 |       |
| DSM [26]          | 30.8 ± 2.7 |       |
| DSM [26]          | 37.2 ± 3.8 |       |
| Leopart [47]      | 41.7 |       |
| MaskDistill [38]  | 42.0 |       |
| MaskDistill w/ self-training [38] | 45.8 |       |
| Ours              | 47.1 ± 2.4 |       |

Table 2. k-NN classification results on PASCAL VOC 2012.

| k     | mIoU | Acc.  |
|-------|------|-------|
| 1     | 55.06| 88.17 |
| 3     | 57.12| 89.69 |
| 5     | 57.53| 89.93 |
| 10    | 55.91| 89.69 |

4.2. Qualitative results of DCN

We show the semantic groups discovered by the DCN in Figure 4, where different groups are marked by different colors on the original images. The results reflect that the DCN successfully discover underlying semantic groups in images with considerable localization precision, e.g., birds, fence and tree branch in the first image. Moreover, dynamism is manifested in scenes of varying complexity, i.e., there are more detected groups in a complex scene (the first image) than the simple one (the second image), thanks to the flexible of the proposed modularity loss. The second line of Figure 4 shows the unsupervised semantic segmentation results. Through clustering, regions in different images are linked to further form region-level semantic groups. Thanks to the accurate localization of the DCN as well as image-level recognition capability of the self-supervised ViT, we get inspiring segmentation results without any annotations.

4.3. Region clustering

We evaluate the performance of DCN for fully unsupervised semantic segmentation, with the help of the image-level discriminating ability of self-supervised ViT. Following recent researches, we adopt k-means on region embeddings to classify foreground regions into 20 classes defined in PASCAL VOC 2012 and evaluate the quality of clusters with ground-truth via Hungarian matching [19]. Since the k-means algorithm is greatly affected by the initial value of cluster centers, we run it for 10 times and report the results by mean ± std in Table 1. Comparing with the methods which also adopt the region clustering pipeline [26, 38], we reach higher segmentation performance without re-training, demonstrating the superior of the DCN brought by its dynamic. In conclusion, we achieve state-of-the-art performance on unsupervised semantic segmentation task of PASCAL VOC 2012 dataset.

4.4. Region retrieval

In this section we evaluate the effect of the proposed method by k-NN region retrieval, to show the quality of region-level representation as well as the localization quality of the DCN. To implement that, we first obtain region embeddings on PASCAL VOC 2012 training set and validation set by the steps mentioned in Section 4.1.1. Based on the assumption that only region-level annotations are available in the training set, we obtain the label of each region in the training set by the most overlapping ground-truth region. Then we adopt the weighted k-NN classifier to classify regions in the validation set. Specifically, the soft label of a region is calculated by weighting one-hot labels of k most similar regions by their similarity, where we use the cosine distance between region embeddings as similarity. Finally, the category with the highest score in the soft label is used as the classification result of a region. We evaluate k-NN retrieval with different value of k and show the results in Table 2. To intuitively show the retrieval performance, we also show the query regions and their 5 nearest neighbors in Figure 5. Both the results demonstrate the effectiveness and applicability of the DCN and the combining of DCN and self-supervised ViT for region-level representation extraction.

4.5. Language guided segmentation

The emergence of language-image pre-training models helps the unsupervised classification in visual task, by constructing classifiers from prompt texts. A recent research [46] proposes to modify the visual encoder of
Our method gets higher performance with PASCAL VOC 2012.

| Method                  | mIoU  |
|-------------------------|-------|
| MaskCLIP [46]           | 50.9  |
| GroupViT [42]           | 51.2  |
| DCN + MaskCLIP (Ours)   | **51.68** |

Table 3. Comparison of text-guided semantic segmentation on PASCAL VOC 2012. Our method gets higher performance with the help of accurate localization of objects from the DCN.

CLIP [30] and apply the text-based classifiers to pixel level. However, the pixel-level classification results are relatively coarse, due to the image-level pre-training task. We demonstrate the effectiveness of combining the localization ability of the DCN and the classification ability of CLIP in this section. Specifically, based on a region produced by the DCN, its predicted category is determined by the mode of pixel classification results from MaskCLIP [46] within it. Table 3 shows the performance on PASCAL VOC 2012 dataset. For comparison, we report results of methods which achieve semantic segmentation using text supervision only. With the help of accurate localization of objects from the DCN, we get higher performance than the related works MaskCLIP [46] and GroupViT [42].

5. Conclusion

In this work, we propose the DCN and the compatible pipeline to solve the unsupervised semantic segmentation problem, with the help of the surprising properties of self-supervised ViT. For the purpose of directly clustering the pixel-level representations of self-supervised ViT, we first analyze the scope where the representation of pixels reflect their semantic accurately and draw the conclusion that the relationship between representation and semantic is applicable for pixels within the same image. Therefore, we propose the DCN, which dynamically divides pixels in an image to different semantic groups, taking into account different scene complexities in different images. Meanwhile, we propose a novel loss function motivated by modularity, which optimizes the DCN without relying on any annotations. We also explore the extraction of region-level representation, which achieves the unsupervised classification of regions. Qualitative and quantitative experimental results demonstrate the effectiveness and superior of the proposed method.

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