MLSeg: Image and Video Segmentation as Multi-Label Classification and Selected-Label Pixel Classification

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Abstract. For a long period of time, research studies on segmentation have typically formulated the task as pixel classification that predicts a class for each pixel from a set of predefined, fixed number of semantic categories. Yet standard architectures following this formulation will inevitably encounter various challenges under more realistic settings where the total number of semantic categories scales up (e.g., beyond 1k classes). On the other hand, a standard image or video usually contains only a small number of semantic categories from the entire label set. Motivated by this intuition, in this paper, we propose to decompose segmentation into two sub-problems: (i) image-level or video-level multi-label classification and (ii) pixel-level selected-label classification. Given an input image or video, our framework first conducts multi-label classification over the large complete label set and selects a small set of labels according to the class confidence scores. Then the follow-up pixel-wise classification is only performed among the selected subset of labels. Our approach is conceptually general and can be applied to various existing segmentation frameworks by simply adding a lightweight multi-label classification branch. We demonstrate the effectiveness of our framework with competitive experimental results across four tasks including image semantic segmentation, image panoptic segmentation, video instance segmentation, and video semantic segmentation. Especially, with our MLSeg, Mask2Former gains +0.8%/+0.7%/+0.7% on ADE20K panoptic segmentation/YouTubeVIS 2019 video instance segmentation/VSPW video semantic segmentation benchmarks respectively. Code will be available at: https://github.com/openseg-group/MLSeg

Keywords: Semantic Segmentation, Panoptic Segmentation, Video Instance Segmentation, Video Semantic Segmentation

1 Introduction

Image and video segmentation, i.e., partitioning images or video frames into multiple meaningful segments, is a fundamental computer vision research topic

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Most of the existing studies formulate the image and video segmentation problem as a pixel classification task. We mainly take image semantic segmentation as an example for analysis in the following discussion for convenience. For example, image semantic segmentation needs to select the label of each pixel from the complete category set that is predefined in advance. However, it is unnecessary to consider the complete category set for every pixel in each image as most standard images only consist of objects belonging to a few categories. Figure 2 plots the statistics on the percentage of images that contain no more than the given class number in the entire dataset vs. the number of classes that appear within each image. Accordingly, we can see that 100.00%, 99.99%, 99.14%, and 99.85% of images contain less than 25 categories on PASCAL-Context [57], COCO-Stuff [8], ADE20K-Full [18,89], and COCO+LVIS [28,38] while each of them contains 60, 171, 847, and 1,284 predefined semantic categories respectively. Besides, Figure 1 shows an example image that only contains 7 classes while the complete label set consists of 171 predefined categories.

To take advantage of the above observations, we propose to re-formulate the segmentation task into two sub-problems including multi-label image/video classification and pixel classification over a subset of selected labels. To verify the potential benefits of our method, we investigate the gains via exploiting the ground-truth multi-label of each image or video. In other words, the pixel classifier only needs to select the category of each pixel from a collection of categories presented in the current image or video, therefore, we can filter out all other categories that do not appear. Figure 3 summarizes the comparison results based

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1 We use “label”, “category”, and “class” interchangeably.
Fig. 2: Illustrating the cumulative distribution of the number of images that contain no more than the given class number: The x-axis represents the class number presented in the image and the y-axis represents the percentage of images that contain no more than the given class number in the entire dataset. We plot the cumulative distribution on four benchmarks. We can see that more than 99% of all images only contain less than 25 categories on four benchmarks, which are marked with dark purple bars. The above four benchmarks contain 60, 171, 847, and 1,284 predefined semantic categories respectively.

Fig. 3: Illustrating the effectiveness of multi-label image classification: The segmentation results of exploiting the ground-truth multi-label during only evaluation or both training and evaluation on (a) PASCAL-Context, COCO-Stuff, ADE20K-Full, and COCO+LVIS (for image semantic segmentation)/(b) ADE20K (for image panoptic segmentation)/(c) VSPW (for video semantic segmentation). Refer to Sec. 3.4 for more details. YouTubeVIS results are not included as we cannot access the ground-truth on Segmenter [65] and Mask2Former [17]. We can see that the segmentation performance is significantly improved given the ground-truth multi-label prediction. In summary, multi-label classification is an important but long-neglected sub-problem towards more accurate segmentation.

Motivated by the significant gains obtained with the ground-truth multi-label, we propose two different schemes to exploit the benefit of multi-label image predictions including the independent single-task scheme and joint multi-task scheme. For the independent single-task scheme, we train one model for multi-label image/video classification and another model for segmentation. Specifically, we first train a model to predict multi-label classification probabilities for each image/video, then we estimate the existing label subset for each image/video based on the multi-label predictions, last we use the predicted label subset to train the segmentation model for selected-label pixel classification during both training and testing. For the joint multi-task scheme, we train one model to support both multi-label image/video classification and segmentation based on a shared backbone. Specifically, we apply a multi-label prediction head and a segmentation head over the shared backbone and train them jointly. For both schemes, we need to send the multi-label predictions into the segmentation head.
for selected-label pixel classification, which enables selecting a collection of categories that appear according to the image/video content adaptively.

We demonstrate the effectiveness of our approach on various strong baseline methods including DeepLabv3 [12], Segmenter [65], Swin-Transformer [53], BEiT [4], MaskFormer [18], and Mask2Former [17] across multiple segmentation benchmarks including PASCAL-Context [57], ADE20K [89], COCO-Stuff [8], ADE20K-Full [89,18], COCO+LVIS [28,38], YouTubeVIS [78], and VSPW [56].

2 Related Work

Image segmentation. We can roughly categorize the existing studies on image semantic segmentation into two main paths: (i) region-wise classification methods [1,7,26,25,74,58,7,67], which first organize the pixels into a set of regions (usually super-pixels), and then classify each region to get the image segmentation result. Several very recent methods [18,86,69] exploit the DETR framework [10] to conduct region-wise classification more effectively. (ii) pixel-wise classification methods, which predict the label of each pixel directly and dominate most previous studies since the pioneering FCN [54]. There exist extensive follow-up studies that improve the pixel classification performance via constructing better contextual representations [87,12,83,81] or designing more effective decoder architectures [3,64,13]. Image panoptic segmentation [41,40] aims to unify image semantic segmentation and image instance segmentation tasks. Some recent efforts have introduced various advanced architectures such as Panoptic FPN [40], Panoptic DeepLab [16], Panoptic Segformer [47], K-Net [86], and Mask2Former [17]. Our MLSeg is complementary with various paradigms and consistently improves several representative state-of-the-art methods across both image semantic segmentation and image panoptic segmentation tasks.

Video segmentation. Most of the previous works address the video segmentation task by extending the existing image segmentation models with temporal consistency constraint [71]. Video semantic segmentation aims to predict the semantic category of all pixels in each frame of a video sequence, where the main efforts focus on two paths including exploiting cross-frame relations to improve the prediction accuracy [43,35,39,24,59,11] and leveraging the information of neighboring frames to accelerate computation [55,77,46,33,52]. Video instance segmentation [78] requires simultaneous detection, segmentation and tracking of instances in videos and there exist four mainstream frameworks including tracking-by-detection [68,48,9,23,31], clip-and-match [6,2], propose-and-reduce [49], and segment-as-a-whole [72,36,75,15]. We show the effectiveness of our method on both video semantic segmentation and video instance segmentation tasks via improving the very recent state-of-the-art method Mask2Former [15].

Multi-label classification. The goal of multi-label classification is to identify all the categories presented in a given image or video over the complete label set. The conventional multi-label image classification literature partitions the existing methods into three main directions: (i) improving the multi-label classification loss functions to handle the imbalance issue [76,5], (ii) exploiting the
label co-occurrence (or correlations) to model the semantic relationships between different categories \([32,45,14,79]\), and (iii) localizing the diverse image regions associated with different categories \([73,27,80,44,51]\). In our independent single-task scheme, we choose the very recent state-of-the-art method Query2Label \([51]\) to perform multi-label classification on various semantic segmentation benchmarks as it is a very simple and effective method that exploits the benefits of both label co-occurrence and localizing category-dependent regions. There exist few efforts that apply multi-label image classification to address segmentation task. To the best of our knowledge, the most related study EncNet \([85]\) simply adds a multi-label image classification loss w/o changing the original semantic segmentation head that still needs to select the label of each pixel from all predefined categories. We empirically show the advantage of our method over EncNet in the ablation experiments. Besides, our proposed method is naturally suitable to solve large-scale semantic segmentation problem as we only perform pixel classification over a small subset of the complete label set based on the multi-label image prediction. We also empirically verify the advantage of our method over the very recent ESSNet \([38]\) in the ablation experiments.

3 Our Approach

We first introduce the overall framework of our method in Sec. 3.1, which is also illustrated in Figure 4. Second, we introduce the details of the independent single-task scheme in Sec. 3.2 and joint multi-task scheme in Sec. 3.3. Last, we conduct analysis experiments to investigate the advantages of our method in Sec. 3.4.

3.1 Framework

The overall framework of our method is illustrated in Figure 4, which consists of one path for multi-label image classification and one path for semantic segmentation. The multi-label prediction is used to sort and select the top \(\kappa\) category embeddings with the highest confidence scores which are then sent into the selected-label pixel classifier to generate the semantic segmentation prediction. We explain the mathematical formulations of both multi-label image classification and selected-label pixel classification as follows:

**Multi-label image classification.** The goal of multi-label image classification is to predict the set of existing labels in a given image \(x \in \mathbb{R}^{H \times W \times 3}\), where \(H\) and \(W\) represent the input height and width. We generate the image-level multi-label ground truth \(y^{gt}\) from the ground truth segmentation map and we represent \(y^{gt}\) with a vector of \(K\) binary values \([y_1^{gt}, y_2^{gt}, ..., y_K^{gt}]^T, y_i^{gt} \in \{0, 1\}\), where \(K\) represents the total number of predefined categories and \(y_i^{gt} = 1\) represents the existence of pixels belonging to \(i\)-th category and \(y_i^{gt} = 0\) otherwise.

The prediction \(y \in \mathbb{R}^K\) is a vector that records the existence confidence score of each category in the given image \(x\). We use \(g(\cdot; \theta_1)\) to represent the
Fig. 4: **Illustrating the framework of our approach:** Given an input image that contains person, grass, and railing, which are marked with ●, ●, and ●, respectively. First, we use the multi-label image classification model $g(\cdot; \theta_1)$ and multi-label image classifier to predict the presence probabilities of all categories. Second, we sort the labels according to the predicted presence probabilities and select the top $\kappa$ most probable category embeddings. Last, we send the selected subset of category embeddings into the selected-label pixel classifier to identify the label of each pixel based on the pixel embeddings output by the semantic segmentation model $f(\cdot; \theta_2)$. 

backbone for the multi-label image classification model. We estimate the multi-label predictions of input $x$ with the following sigmoid function:

$$ y_k = \frac{e^{\xi(g(x;\theta_1), h_k)}}{e^{\xi(g(x;\theta_1), h_k)} + 1}, \quad (1) $$

where $y_k$ is the $k$-th element of $y$, $g(x;\theta_1)$ represents the output feature map, $h_k$ represents the multi-label image classification weight associated with the $k$-th category, and $\xi(\cdot)$ represents a transformation function that estimates the similarity between the output feature map and the multi-label image classification weights. We supervise the multi-label predictions with the asymmetric loss that operates differently on positive and negative samples by following [5,51].

**Selected-label pixel classification.** The goal of semantic segmentation is to predict the semantic label of each pixel and the label is selected from all predefined categories. We use $z \in \mathbb{R}^{H \times W \times K}$ to represent the predicted pixel classification probability map for the input image $x$. We use $f(\cdot;\theta_2)$ to represent the semantic segmentation backbone and $z^{gt} \in \mathbb{R}^{H \times W}$ to represent the ground-truth segmentation map. Instead of choosing the label of each pixel from all $K$ predefined categories, based on the previous multi-label prediction $y$ for image $x$, we introduce a more effective selected-label pixel classification scheme:

- Sort and select the top $\kappa$ elements of the classifier weights according to the descending order of multi-label predictions $y = [y_1, y_2, \ldots, y_K]$:

$$ [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_K] = \text{Top-}\kappa(\mathbf{y}), \quad (2) $$

- Classification of pixel $(i, j)$ over the top $\kappa$ selected categories:

$$ z_{i,j,k} = \frac{e^{\psi(f(x;\theta_2)_{i,j}, \mathbf{w}_k)/\tau_k}}{\sum_{l=1}^{\kappa} e^{\psi(f(x;\theta_2)_{i,j}, \mathbf{w}_l)/\tau_l}}, \quad (3) $$
Multi-label image classification backbone \( g(\cdot; \theta_1) \) is set as Swin-L by default. The transformation \( \xi(\cdot) \) is implemented as two transformer decoder layers followed by a linear layer that prepares the refined category embeddings for the multi-label image classifier. (b) Illustrating the framework of Segmenter w/ selected category embeddings: The semantic segmentation backbone \( f(\cdot; \theta_2) \) is set as ViT-B/16 or ViT-L/16. The transformation \( \psi(\cdot) \) is implemented as two transformer encoder layers followed by \( \ell_2 \)-normalization before estimating the segmentation map.

where \([w_1, w_2, \cdots, w_K]\) represents the pixel classification weights for all \( K \) pre-defined categories and \([w_1, w_2, \cdots, w_\kappa]\) represents the top \( \kappa \) selected pixel classification weights associated with the largest multi-label classification scores. \( f(x; \theta_2) \) represents the output feature map for semantic segmentation. \( \psi(\cdot) \) represents a transformation function that estimates the similarity between the pixel features and the pixel classification weights. \( \kappa \) represents the number of selected category embeddings and \( \kappa \) is chosen as a much smaller value than \( K \). We apply a set of rank-adaptive learnable temperature parameters \([\tau_1, \tau_2, \cdots, \tau_\kappa]\) to adjust the classification scores over the selected top \( \kappa \) categories. The temperature parameters across different selected classes are shared in all of the baseline experiments by default\(^2\). We analyze the influence of \( \kappa \) choices and the benefits of such an adjustment scheme in the following discussions and experiments.

### 3.2 Independent single-task scheme

Under the independent single-task setting, the multi-label image classification model \( g(\cdot; \theta_1) \) and the semantic segmentation model \( f(\cdot; \theta_2) \) are trained separately and their model parameters are not shared, i.e., \( \theta_1 \neq \theta_2 \). Specifically, we first train the multi-label image classification model \( g(\cdot; \theta_1) \) to identify the top \( \kappa \) most likely categories for each image. Then we train the selected-label pixel classification model, i.e., semantic segmentation model, \( f(\cdot; \theta_2) \) to predict the label of each pixel over the selected top \( \kappa \) classes.

**Multi-label image classification model.** We choose the very recent SOTA multi-label classification method Query2Label [51] as it performs best on multiple multi-label classification benchmarks by the time of our submission according to paper-with-code.\(^3\) The key idea of Query2Label is to use the category embeddings as the query to gather the desired pixel embeddings as the key/value, which is output by an ImageNet-22K pre-trained backbone such as Swin-L, adaptively.

\(^2\) We set \( \tau_1 = \tau_2 = \cdots = \tau_\kappa \) for all baseline segmentation experiments.

\(^3\) https://paperswithcode.com/task/multi-label-classification
Fig. 6: Illustrating the framework of joint multi-task scheme: $g(\cdot; \theta_1)$ and $f(\cdot; \theta_2)$ are set as the shared multi-task backbone and $\theta_1 = \theta_2$. $\xi(\cdot)$ is implemented as one transformer encoder layer or two transformer decoder layers or global average pooling + linear projection. $\psi(\cdot)$ is implemented as two transformer encoder layers followed by L2-normalization before estimating the segmentation map.

with one or two transformer decoder layers. Then Query2Label scheme applies a multi-label image classifier over the refined category embeddings to predict the existence of each category. Figure 5a illustrates the framework of Query2Label framework. Refer to [51] and the official implementation for more details. The trained weights of Query2Label model are fixed during both training and inference of the following semantic segmentation model.

Selected pixel classification model. We choose a simple yet effective baseline Segmenter [65] as it achieves even better performance than Swin-L\(^4\) when equipped with ViT-L. Segmenter first concatenates the category embedding with the pixel embeddings output by a ViT model together and then sends them into two transformer encoder layers. Last, based on the refined pixel embeddings and category embeddings, Segmenter computes their $\ell_2$-normalized scalar product as the segmentation predictions. We select the top $\kappa$ most likely categories for each image according to the predictions of the Query2Label model and only use the selected top $\kappa$ category embeddings instead of all category embeddings. Figure 5b illustrates the overall framework of Segmenter with the selected category embeddings.

3.3 Joint multi-task scheme

Considering that the independent single-task scheme suffers from extra heavy computation overhead as the Query2Label method relies on a large backbone, e.g., Swin-L, we introduce a joint multi-task scheme that shares the backbone for both sub-tasks, in other words, $\theta_1 = \theta_2$ and the computations of $g(\cdot; \theta_1)$ and $f(\cdot; \theta_2)$ are also shared.

Figure 6 shows the overall framework of the joint multi-task scheme. First, we apply a shared multi-task backbone to process the input image and output the pixel embeddings. Second, we concatenate the category embeddings with the down-sampled pixel embeddings\(^5\), send them into one transformer encoder layer, and apply the multi-label image classifier on the refined category embeddings to estimate the multi-label predictions. Last, we sort and select the top $\kappa$ category embeddings, concatenate the selected category embeddings with the

\(^4\) Segmenter w/ ViT-L: 53.63\% vs. Swin-L: 53.5\% on ADE20K.

\(^5\) Different from the semantic segmentation task, the multi-label image classification task does not require high-resolution representations.
pixel embeddings, send them into two transformer encoder layers, and compute the semantic segmentation predictions based on $\ell_2$-normalized scalar product between the refined selected category embeddings and the refined pixel embeddings. We empirically verify the advantage of the joint multi-task scheme over the independent single-task scheme in the ablation experiments.

### Table 1: Ablation of the improvements with our method

| Method                  | Image semantic seg. | Image panoptic seg. | Video semantic seg. |
|-------------------------|---------------------|---------------------|---------------------|
|                         | PASCAL-Context/COCO-Stuff/ADE20K-Full/COCO+LVIS | ADE20K              | VSPW                |
| Baseline                | 53.85               | 41.85               | 17.93               | 19.41               | 48.1               | 59.4               |
| + MT                    | 54.05               | 42.38               | 17.81               | 20.26               | 48.2               | 59.5               |
| + MT + LS               | 54.27               | 44.31               | 18.26               | 21.13               | 48.8               | 59.6               |
| + MT + LS + RA          | 54.76               | 44.98               | 18.78               | 21.26               | 48.9               | 60.1               |

### 3.4 Analysis experiments

**Oracle experiments.** We first conduct several groups of oracle experiments based on Segmenter w/ ViT-B/16 on four challenging image semantic segmentation benchmarks (PASCAL-Context/COCO-Stuff/ADE20K-Full/COCO+LVIS), Mask2Former w/ Swin-L on both ADE20K panoptic segmentation benchmark and VSPW video semantic segmentation benchmark.

- **Segmenter/Mask2Former + GT (train + eval):** the upper-bound segmentation performance of Segmenter/Mask2Former when training & evaluating equipped with the ground-truth multi-label of each image or video, in other words, we only need to select the category of each pixel over the ground-truth existing categories in a given image or video.

- **Segmenter/Mask2Former + GT (eval):** the upper-bound segmentation performance of Segmenter/Mask2Former when only using the ground-truth multi-label of each image or video during evaluation.

Figure 1 illustrates the detailed comparison results. We can see that only applying the ground-truth multi-label during evaluation already brings considerable improvements and further applying the ground-truth multi-label during training significantly improves the segmentation performance across all benchmarks. For example, when compared to the baseline Segmenter or Mask2Former, Segmenter + GT (train + eval) gains +17%/+24%/+19%/+27% absolute mIoU scores across PASCAL-Context/COCO-Stuff/ADE20K-Full/COCO+LVIS and Mask2Former + GT (train + eval) gains +11%/+13% on ADE20K/VSPW.

**Improvement analysis of MLSeg.** Table 1 reports the results with different combinations of the proposed components within our joint multi-task scheme. We can see that: (i) multi-task learning (MT) introduces the auxiliary multi-label image classification task and brings relatively minor gains on most benchmarks,
Fig. 7: Illustrating the values of learned $1/\tau$ with rank-adaptive-$\tau$ manner on four semantic segmentation benchmarks. We can see that the values of $1/\tau$ are almost monotonically decreasing, thus meaning that the pixel classification scores of the category associated with larger multi-label classification scores are explicitly increased.

(ii) combining MT with label sorting & selection (LS) achieves considerable gains, and (iii) applying the rank-adaptive-$\tau$ manner (shown in Equation 3) instead of shared-$\tau$ achieves better performance. We investigate the possible reasons by analyzing the value distribution of learned $1/\tau$ with the rank-adaptive-$\tau$ manner in Figure 7, which shows that the learned $1/\tau$ is capable of adjusting the pixel classification scores based on the order of multi-label classification scores. In summary, we choose “MT + LS + RA” scheme by default, which gains +0.91%/+3.13%/+0.85%/+1.85%/+0.8%/+0.7% over the baseline methods across these six challenging segmentation benchmarks respectively.

4 Experiment

4.1 Datasets

ADE20K/ADE20K-Full. The ADE20K dataset [89] consists of 150 classes and diverse scenes with 1,038 image-level labels, which is divided into 20K/2K/3K images for training, validation, and testing. Semantic segmentation treats all 150 classes equally, while panoptic segmentation considers the 100 thing categories and the 50 stuff categories separately. The ADE20K-Full dataset [89] contains 3,688 semantic classes, among which we select 847 classes following [18].

PASCAL-Context. The PASCAL-Context dataset [57] is a challenging scene parsing dataset that consists of 39 semantic classes and 1 background class, which is divided into 4,998/5,105 images for training and testing.

COCO-Stuff. The COCO-Stuff dataset [8] is a scene parsing dataset that contains 171 semantic classes divided into 9K/1K images for training and testing.

COCO+LVIS. The COCO+LVIS dataset [28,38] is bootstrapped from stuff annotations of COCO [50] and instance annotations of LVIS [28] for COCO 2017 images. There are 1,284 semantic classes in total and the dataset is divided into 100K/20K images for training and testing.

VSPW. The VSPW [56] is a large-scale video semantic segmentation dataset consisting of 3,536 videos with 251,633 frames from 124 semantic classes, which is divided into 2,806/343/387 videos with 198,244/24,502/28,887 frames for training, validation, and testing. We only report the results on val set as we can not access the test set.
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**YouTubeVIS.** YouTube-VIS 2019 [78] is a large-scale video instance segmentation dataset consisting of 2,883 high-resolution videos labeled with 40 semantic classes, which is divided into 2,238/302/343 videos for training, validation, and testing. We report the results on val set as we cannot access the test set.

### 4.2 Implementation details

**Multi-label image classification.** For the independent single-task scheme, following the official implementation of Query2Label, we train multi-label image classification models, e.g., ResNet-101 [30], TResNetL [62], and Swin-L [53], for 80 epochs using Adam solver with early stopping. Various advanced tricks such as cutout [21], RandAug [20] and EMA [29] are also used. For the joint multi-task scheme, we simply train the multi-label image classification models following the same settings as the segmentation models w/o using the above-advanced tricks that might influence the segmentation performance. We illustrate more details of the joint multi-task scheme in the supplementary material.

**Segmentation.** We adopt the same settings for both independent single-task scheme and joint multi-task scheme. For the segmentation experiments based on Segmenter [65], DeepLabv3 [12], Swin-Transformer [53], and BEIT [4], we follow the default training & testing settings of their reproduced version based on mmsegmentation [19]. For the segmentation experiments based on MaskFormer or Mask2Former, we follow their official implementation.

**Hyper-parameters.** We set $\kappa$ as 25, 50, 50, 100, and 100 on PASCAL-Context, ADE20K, COCO-Stuff, ADE20K-Full, and COCO+LVIS respectively as they consist of a different number of semantic categories. We set their multi-label image classification loss weights as 5, 10, 10, 100, and 300. The segmentation loss weight is set as 1. We illustrate the hyper-parameter settings of experiments on MaskFormer [18] or Mask2Former [17] in the supplementary material.

**Metrics.** We report mean average precision (mAP) for multi-label image classification task, mean intersection over union (mIoU) for image/video semantic segmentation task, panoptic quality (PQ) for panoptic segmentation task, and mask average precision (AP) for instance segmentation task.

### 4.3 Ablation experiments

We conduct all ablation experiments based on the Segmenter w/ ViT-B and report their single-scale evaluation results on COCO-Stuff test and COCO+LVIS test if not specified. The baseline with Segmenter w/ ViT-B achieves mIoU=41.85% and mIoU=19.41% on COCO-Stuff and COCO+LVIS respectively.

**Influence of the multi-label classification accuracy.** We investigate the influence of multi-label classification accuracy on semantic segmentation tasks based on the independent single-task scheme. We train multiple Query2Label models based on different backbones, e.g., ResNet101, TResNetL, and Swin-L.

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7 [https://github.com/SlongLiu/query2labels](https://github.com/SlongLiu/query2labels)
8 [https://github.com/facebookresearch/Mask2Former](https://github.com/facebookresearch/Mask2Former)
Table 2: Influence of the multi-label image classification accuracy (mAP) on semantic segmentation accuracy (mIoU) based on independent single-task manner.

| Backbone       | COCO-Stuff | COCO+LVIS |
|----------------|------------|-----------|
|               | mIoU (%)   | mIoU (%)  |
| ResNet101 [63]| 55.17      | 60.10     |
| TResNetL [69] | 64.79      | 26.54     |
| ResNet101 [63]| 31.04      | 34.93     |

|                      | COCO-Stuff | COCO+LVIS |
|----------------------|------------|-----------|
|                      | mIoU (%)   | mIoU (%)  |
| Swin-L [53]          | 21.19      | 21.19     |
| TResNetL [63]        | 19.88      | 19.88     |
| Swin-L [53]          | 16.30      | 16.30     |
|                    | +2.57      | -3.11     |
|                    | +0.47      | +1.78     |

Table 3: Independent single-task scheme vs. Joint multi-task scheme: we adopt Swin-L as the backbone for the multi-label predictions in the independent single-task scheme.

| Method                       | COCO-Stuff | COCO+LVIS |
|-----------------------------|------------|-----------|
| Indep. single-task.         | 343.21M    | 182.8G    |
| Joint multi-task.           | 109.73M    | 78.71G    |

Table 4: Influence of the size of the selected label set, i.e., $\kappa$.

| $\kappa$ | COCO-Stuff | COCO+LVIS |
|----------|------------|-----------|
|         | mIoU (%)   | mIoU (%)  |
| 25       | 44.65      | 44.98     |
| 50       | 44.58      | 44.67     |
| 75       | 44.41      | 44.37     |
| 100      | 44.20      | 44.20     |
| 125      | 20.36      | 20.36     |
| 150      | 21.26      | 20.99     |
| 171      | 20.93      | 20.93     |

Table 5: Influence of the multi-label classification loss weight.

| multi-label cls. loss weight | 1  | 5  | 10 | 20 |
|-----------------------------|----|----|----|----|
| mAP (%)                     | 59.14 | 62.38 | 62.52 | 62.18 |
| mIoU (%)                    | 44.11 | 44.90 | 44.98 | 44.04 |

Table 6: Influence of multi-label prediction head architecture.

| Method                       | COCO-Stuff | COCO+LVIS |
|-----------------------------|------------|-----------|
| GAP+Linear                  | 103.24M    | 76.94G    |
| 2x TranDec                  | 114.27M    | 78.83G    |
| 1x TranEnc                  | 109.73M    | 78.71G    |

Table 7: Comparison with EncNet and ESSNet based on Segmenter w/ ViT-B.

| Method                   | #params | FLOPs | mIoU (%) | #params | FLOPs | mIoU (%) |
|--------------------------|---------|-------|----------|---------|-------|----------|
| Baseline                 | 102.50M | 78.84G| 48.80    | 102.51M | 79.25G| 41.85    |
| EncNet                   | 109.15M | 84.89G| 49.06    | 109.18M | 85.29G| 42.81    |
| ESSNet                   | 101.42M | 78.05G| 48.91    | 101.43M | 78.42G| 42.13    |
| Ours                     | 109.74M | 78.71G| **49.68**| 109.70M | 78.55G| **44.98**|

Then we train three Segmenter w/ ViT-B segmentation models based on their multi-label predictions independently. According to the results in Table 2, we can see that more accurate multi-label classification prediction brings more semantic segmentation performance gains and less accurate multi-label classification prediction even results in worse results than baseline.

**Independent single-task scheme vs. Joint multi-task scheme.** We compare the performance and model complexity of the independent single-task scheme (w/ Swin-L) and joint multi-task scheme in Table 3. To ensure fairness, we choose the # of labels in the selected label set, i.e., $\kappa$, as 50 for both schemes, and the segmentation models are trained & tested under the same settings. According to the comparison results, we can see that joint multi-task scheme achieves better performance with fewer parameters and FLOPs, thus, we choose the joint multi-task scheme in the following experiments for efficiency if not specified.
Influence of different top $\kappa$. We study the influence of the size of selected label set, i.e., $\kappa$, in Table 4. According to the results, our method achieves the best performance on COCO-Stuff/COCO+LVIS when $\kappa=50/\kappa=100$, which achieves a better trade-off between precision and recall for multi-label predictions. Besides, we attempt to fix $\kappa=50$ during training and report the results when changing $\kappa$ during evaluation on COCO-Stuff: $\kappa=25$: 44.89% / $\kappa=50$: 44.98% / $\kappa=75$: 45.00% / $\kappa=100$: 45.01%. Notably, we also report the results with $\kappa=K$, in other words, we only sort the classifier weights, which also achieve considerable gains. Therefore, we can see that sorting the classes according to multi-label predictions is the key to the gains. In summary, our method consistently outperforms baseline with different $\kappa$ values. We also attempt to use dynamic $\kappa$ for different images during evaluation but observe no significant gains. More details are provided in the supplementary material.

Influence of the multi-label classification loss weight. We study the influence of the multi-label image classification loss weights with the joint multi-task scheme on COCO-Stuff and report the results in Table 5. We can see that setting the multi-label classification loss weight as 10 achieves the best performance.

Influence of $\xi(\cdot)$ choice. Table 6 compares the results based on different multi-label prediction head architecture choices including “GAP+Linear” (applying global average pooling followed by linear projection), “2× TranDec” (using two transformer decoder layers), and “1× TranEnc” (using one transformer encoder layer) on COCO-Stuff. Both “2× TranDec” and “1× TranEnc” operate on feature maps with $\frac{1}{16}$ resolution of the input image. According to the results, we can see that “1× TranEnc” achieves the best performance and we implement $\xi(\cdot)$ as one transformer encoder layer if not specified. We also attempt generating multi-label prediction (mAP=58.55%) from the semantic segmentation prediction directly but observe no performance gains, thus verifying the importance of relatively more accurate multi-label classification predictions.

Comparison with EncNet. Table 7 compares our method to EncNet [85] based on Segmenter w/ ViT-B/16 and reports the results on the second and last rows. We follow the reproduced EncNet settings in mmsegmentation and tune the number of visual code-words as 64 as it achieves the best result in our experiments. According to the comparison results, we can see that our method significantly outperforms EncNet by +0.62%/+2.17%/+1.94% on ADE20K/COCO-Stuff/COCO+LVIS, which further verifies that exploiting selected-label pixel classification is the key to our method.

Comparison with ESSNet. We compare our method to ESSNet [38] on ADE20K/COCO-Stuff/COCO+LVIS on the last two rows of Table 7. Different from the original setting [38] of ESSNet, we set the number of the nearest neighbors associated with each pixel as the same value of $\kappa$ in our method to ensure fairness. We set the dimension of the representations in the semantic space as 64. According to the results on COCO+LVIS, we can see that (i) our baseline achieves 19.41%, which performs much better than the original reported best result (6.26%) in [38] as we train all these Segmenter models with batch-size
respectively with slightly more parameters and GFLOPs. More details about

Table 8: Combination with DeepLabv3, Seg-Mask-L/16, Swin-B and BEiT.

| Method       | ADE20K #params | COCO-Stuff FLOPs | mIoU(%) | COCO-Stuff #params | FLOPs | mIoU(%) | COCO+LVIS #params | FLOPs | mIoU(%) |
|--------------|----------------|------------------|---------|-------------------|-------|---------|------------------|-------|---------|
| DeepLabv3    | 87.21M         | 347.64G          | 45.19   | 87.22M            | 347.68G | 38.42   | 88.08M           | 550.02G | 11.04   |
| + MLSeg      | 91.87M         | 349.17G          | 46.61   | 91.75M            | 349.09G | 39.86   | 94.21M           | 559.47G | 12.76   |
| Seg-Mask-L/16| 333.23M        | 377.83G          | 53.63   | 333.26M           | 378.57G | 47.12   | 334.49M          | 420.2G  | 23.71   |
| + MLSeg      | 345.99M        | 377.18G          | 54.47   | 346.03M           | 377.46G | 47.93   | 348.31M          | 422.6G  | 24.60   |
| Swin-B       | 121.42M        | 299.81G          | 52.4    | 121.34M           | 299.98G | 47.16   | 122.29M          | 309.34G | 29.33   |
| + MLSeg      | 125.43M        | 300.18G          | 53.01   | 125.46M           | 300.56G | 47.85   | 126.89M          | 309.52G | 20.81   |
| BEiT         | 441.27M        | 1745.09G         | 57.0    | 441.30M           | 1746.54G | 49.9    | OOM              |        |         |
| + MLSeg      | 456.28M        | 1751.04G         | 57.8    | 456.35M           | 1751.34G | 50.3    | OOM              |        |         |

Table 9: Combination with Mask2Former based on Swin-L.

| Method       | Image semantic seg. #params | Image panoptic seg. FLOPs | mIoU(%) | Video semantic seg. FLOPs | mIoU(%) | Video instance seg. FLOPs | mIoU(%) |
|--------------|-----------------------------|---------------------------|---------|---------------------------|---------|---------------------------|---------|
| Mask2Former  | 205.54M                     | 669.02G                   | 57.3    | 205.55M                   | 677.98G | 48.1                       | 205.50M |
| + MLSeg      | 208.79M                     | 669.81G                   | 58.0    | 208.83M                   | 679.11G | 48.9                       | 208.78M |

T=2 means each video clip is composed of 2 frames during training/evaluation and we report the GFLOPs over 2 frames.

8 for 320K iterations. (ii) ESSNet achieves 19.11%, which performs comparably to our baseline and this matches the observation in the original paper that ESSNet is expected to perform better only when training the baseline method with much smaller batch sizes. In summary, our method outperforms ESSNet by +0.77%/+2.85%/+2.15% across ADE20K/COCO-Stuff/COCO+LVIS, which further shows the advantage of exploiting multi-label image classification over simply applying k-nearest neighbor search for each pixel embedding.

4.4 State-of-the-art experiments

Image semantic segmentation. We apply our method to various state-of-the-art image semantic segmentation methods including DeepLabv3, Seg-Mask-L/16, Swin-Transformer, and BEiT. Table 8 summarizes the detailed comparison results across three semantic segmentation benchmarks including ADE20K, COCO-Stuff, and COCO+LVIS, where we evaluate the multi-scale segmentation results on ADE20K/COCO-Stuff and single-scale segmentation results on COCO+LVIS (due to limited GPU memory) respectively. More details of how to apply our joint multi-task scheme to these methods are provided in the supplementary material. According to the results in Table 8, we can see that our MLSeg consistently improves DeepLabv3, Seg-Mask-L/16, Swin-Transformer, and BEiT across three evaluated benchmarks. For example, with our MLSeg, BEiT gains 0.8% on ADE20K with slightly more parameters and GFLOPs.

Image panoptic segmentation & Video semantic segmentation & Video instance segmentation. To verify the generalization ability of our method, we extend MLSeg to “selected-label region classification” and apply it to the very recent Mask2Former [17]. According to Table 9, our MLSeg improves the image semantic segmentation/image panoptic segmentation/video semantic segmentation/video instance segmentation performance by +0.7%/+0.8%/+0.7%/+0.7% respectively with slightly more parameters and GFLOPs. More details about
the Mask2Former experiments and the segmentation results of combining Mask2Former with MLSeg are provided in the supplementary material.

5 Conclusion

This paper introduces a general and effective scheme that formulates the segmentation task into two sub-problems including multi-label classification and selected-label pixel classification. We first verify the potential benefits of exploiting multi-label image/video classification to improve pixel classification. We then propose a simple joint multi-task scheme that is capable of improving various state-of-the-art segmentation methods across multiple benchmarks. We hope our initial attempt can inspire more efforts towards solving the challenging segmentation problem with a large number of categories. Last, we want to point out that designing & exploiting more accurate multi-label image/video classification methods is a long-neglected but very important sub-problem towards more general and accurate segmentation.

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