OneFormer: One Transformer to Rule Universal Image Segmentation

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https://github.com/SHI-Labs/OneFormer

Abstract

Universal Image Segmentation is not a new concept. Past attempts to unify image segmentation include scene parsing, panoptic segmentation, and, more recently, new panoptic architectures. However, such panoptic architectures do not truly unify image segmentation because they need to be trained individually on the semantic, instance, or panoptic segmentation to achieve the best performance. Ideally, a truly universal framework should be trained only once and achieve SOTA performance across all three image segmentation tasks. To that end, we propose OneFormer, a universal image segmentation framework that unifies segmentation with a multi-task train-once design. We first propose a task-conditioned joint training strategy that enables training on ground truths of each domain (semantic, instance, and panoptic segmentation) within a single multi-task training process. Secondly, we introduce a task token to condition our model on the task at hand, making our model task-dynamic to support multi-task training and inference.

Thirdly, we propose using a query-text contrastive loss during training to establish better inter-task and inter-class distinctions. Notably, our single OneFormer model outperforms specialized Mask2Former models across all three segmentation tasks on ADE20k, Cityscapes, and COCO, despite the latter being trained on each task individually. We believe OneFormer is a significant step towards making image segmentation more universal and accessible.

1. Introduction

Image Segmentation is the task of grouping pixels into multiple segments. Such grouping can be semantic-based (e.g., road, sky, building), or instance-based (objects with well-defined boundaries). Earlier segmentation approaches\cite{6,19,32} tackled these two segmentation tasks individually, with specialized architectures and therefore separate research effort into each. In a recent effort to unify semantic and instance segmentation, Kirillov et al.\cite{23} proposed panoptic segmentation, with pixels grouped into an
amorphous segment for amorphous background regions (labeled “stuff”) and distinct segments for objects with well-defined shape (labeled “thing”). This effort, however, led to new specialized panoptic architectures [9] instead of unifying the previous tasks (see Fig. 1a). More recently, the research trend shifted towards unifying image segmentation with new panoptic architectures, such as K-Net [47], MaskFormer [11], and Mask2Former [10]. Such panoptic/universal architectures can be trained on all three tasks and obtain high performance without changing architecture. They do need to, however, be trained individually on each task to achieve the best performance (see Fig. 1b). The individual training policy requires extra training time and produces different sets of model weights for each task. In that regard, they can only be considered a semi-universal approach. For example, Mask2Former [10] is trained for 160K iterations on ADE20K [13] for each of the semantic, instance, and panoptic segmentation tasks to obtain the best performance for each task, yielding a total of 480K iterations in training, and three models to store and host for inference.

In an effort to truly unify image segmentation, we propose a multi-task universal image segmentation framework (OneFormer), which outperforms existing state-of-the-arts on all three image segmentation tasks (see Fig. 1c), by only training once on one panoptic dataset. Through this work, we aim to answer the following questions:

(i) **Why are existing panoptic architectures [10,11] not successful with a single training process or model to tackle all three tasks?** We hypothesize that existing methods need to train individually on each segmentation task due to the absence of task guidance in their architectures, making it challenging to learn the inter-task domain differences when trained jointly or with a single model. To tackle this challenge, we introduce a task input token in the form of text: “the task is [task]”, to condition the model on the task in focus, making our architecture task-guided for training, and task-dynamic for inference, all with a single model. We uniformly sample [task] from {panoptic, instance, semantic} and the corresponding ground truth during our joint training process to ensure our model is unbiased in terms of tasks. Motivated by the ability of panoptic [23] data to capture both semantic and instance information, we derive the semantic and instance labels from the corresponding panoptic annotations during training. Consequently, we only need panoptic data during training. Moreover, our joint training time, model parameters, and FLOPs are comparable to the existing methods, decreasing training time and storage requirements up to 3x, making image segmentation less resource intensive and more accessible.

(ii) **How can the multi-task model better learn inter-task and inter-class differences during the single joint training process?** Following the recent success of transformer frameworks [2,10,17,18,21,30,46] in computer vision, we formulate our framework as a transformer-based approach, which can be guided through the use of query tokens. To add task-specific context to our model, we initialize our queries as repetitions of the task token (obtained from the task input) and compute a query-text contrastive loss [33,43] with the text derived from the corresponding ground-truth label for the sampled task as shown in Fig. 2. We hypothesize that a contrastive loss on the queries helps guide the model to be task-sensitive and reduce category mispredictions.

We evaluate OneFormer on three major segmentation datasets: ADE20K [13], Cityscapes [12], and COCO [27], each with all three segmentation tasks. OneFormer sets the new state of the arts for all three tasks with a single jointly trained model. To summarize, our main contributions are:

- We propose OneFormer, the first transformer-based multi-task universal image segmentation framework that needs to be trained only once with a single universal architecture, a single model, and on a single dataset to outperform existing frameworks across the semantic, instance, and panoptic segmentation tasks, despite the latter need to be trained separately on each task.
- OneFormer uses a task-conditioned joint training strategy, uniformly sampling different ground truth domains (semantic, instance, or panoptic) by deriving all GT labels from panoptic annotations to train its multi-task model. Thus, OneFormer actually achieves the original unification goal of panoptic segmentation [23].
- We validate OneFormer through extensive experiments on three major benchmarks: ADE20K [13], Cityscapes [12], and COCO [27]. OneFormer sets a new state-of-the-art performance on all three segmentation tasks compared with methods using the standard Swin-L [30] backbone and improves even more with new ConvNeXt [31] and DiNAT [17] backbones.

2. Related Work

2.1. Image Segmentation

Image segmentation is one of the most fundamental tasks in image processing and computer vision. Traditional works usually tackle one of the three image segmentation tasks with specialized network architectures (Fig. 1a).

**Semantic Segmentation.** Semantic segmentation was long tackled as a pixel classification problem with CNNs [5, 6, 8, 20, 32]. More recent works [21, 34, 42] have shown the success of transformer-based methods in semantic segmentation following its success in language and vision [2, 37]. Among them, MaskFormer [11] treated semantic segmentation as a mask classification problem following early works [3, 14, 16], through using a transformer decoder with object queries [2]. We also formulate semantic segmentation as a mask classification problem.
Instance Segmentation. Traditional instance segmentation methods [1, 4, 19] are also formulated as mask classifiers, which predict binary masks and a class label for each mask. We also formulate instance segmentation as a mask classification problem.

Panoptic Segmentation. Panoptic Segmentation [23] was proposed to unify instance and semantic segmentation. One of the earliest architectures in this scope was Panoptic-FPN [22], which introduced separate instance and semantic task branches. Works that followed significantly improved performance with transformer-based architectures [10, 11, 38, 39, 45, 46]. Despite the progress made so far, panoptic segmentation models are still behind in performance compared to individual instance and semantic segmentation models, therefore not living up to their full unification potential. Motivated by this, we design our OneFormer to be trained with panoptic annotations only.

2.2. Universal Image Segmentation

The concept of universal image segmentation has existed for some time, starting with image and scene parsing [35, 36, 44], followed by panoptic segmentation [23]. More recently, promising architectures [10, 11, 47] designed specifically for panoptic segmentation have emerged which also perform well on semantic and instance segmentation tasks. K-Net [47], a CNN, uses dynamic learnable instance and semantic kernels with bipartite matching. Inspired by DETR’s [2] reformulation of object detection with proposals based on queries, MaskFormer [11] used transformer-based architecture as a mask classifier. Mask2Former [10] improved upon MaskFormer with learnable queries, deformable multi-scale attention [51] in the decoder, a masked cross-attention and set the new state of the art on all three tasks. Unfortunately, it requires training the model individually on each task to achieve the best performance. Therefore, there remains a gap in truly unifying the three segmentation tasks. To the best of our knowledge, OneFormer is the first framework to beat state of the art on all three image segmentation tasks with a single universal model.

2.3. Transformer-based Architectures

Architectures based on the transformer encoder-decoder structure [2, 25, 28, 51] have proved effective in object detection since the introduction of DETR [2]. Mask2Former [10, 11] demonstrated the effectiveness of such architectures for image segmentation with a mask classification formulation. Inspired by this success, we also formulate our framework as a query-based mask classification task. Additionally, we claim that calculating a query-text contrastive loss [33, 43] on the task-guided queries can help the model learn inter-task differences and reduce the category mispredictions in the model outputs. Concurrent to our work, LMSeg [50] uses text derived from multiple datasets’ taxonomy to calculate a query-text contrastive loss and tackle the multi-dataset segmentation training challenge. Unlike LMSeg [50], our work focuses on multiple tasks and uses the classes in the training sample’s GT label to calculate the contrastive loss.

3. Method

In this section, we introduce OneFormer, a universal image segmentation framework jointly trained on the panoptic, semantic, and instance segmentation and outperforms individually trained models. We provide an overview of OneFormer in Fig. 2. OneFormer uses two inputs: sample image and task input of the form “the task is {task}”. During our single joint training process, the task is uniformly
sampled from \{panoptic, instance, semantic\} for each image. Firstly, we extract multi-scale features from the input image using a backbone and a pixel decoder. We tokenize the task input to obtain a 1-D task token used to condition the object queries and, consequently, our model on the task for each input. Additionally, we create a text list representing the number of binary masks for each class present in the GT label and map it to text query representations. Note that the text list depends on the input image and the \{task\}. For supervision of the model’s task-dynamic predictions, we derive the corresponding ground-truths from panoptic annotations. As the ground truth is task-dependent, we calculate a query-text contrastive loss between the object and text queries to ensure there is task distinction in the object queries. The object queries and multi-scale features are fed into a transformer decoder to produce final predictions. We provide more details in the following sections.

### 3.1. Task Conditioned Joint Training

Existing semi-universal architectures for image segmentation [10, 11, 47] face a significant drop in performance when jointly trained on all three segmentation tasks (Tab. 7). We attribute their failure to tackle the multi-task challenge to the absence of task-conditioning in their architecture.

We tackle the multi-task train-once challenge for image segmentation using a task-conditioned joint training strategy. Particularly, we first uniformly sample the \text{task} from \{panoptic, semantic, instance\} for the GT label. We realize the unification potential of panoptic annotations [23] by deriving the \text{task}-specific labels from the panoptic annotations, thus, using only one set of annotations.

Next, we extract a set of binary masks for each category present in the image from the task-specific GT label, \textit{i.e.}, semantic task guarantees only one amorphous binary mask for each class present in the image, whereas, instance task signifies non-overlapping binary masks for only thing classes, ignoring the stuff regions. Panoptic task denotes a single amorphous mask for stuff classes and non-overlapping masks for thing classes as shown in Fig. 3. Subsequently, we iterate over the set of masks to create a list of text (\text{T}_{\text{list}}) with a template “a photo with a [CLS]”, where CLS is the class name for the corresponding binary mask. The number of binary masks per sample varies over the dataset. Therefore, we pad \text{T}_{\text{list}} with “an [\text{task}] photo” entries to obtain a padded list (\text{T}_{\text{pad}}) of constant length \text{N}_{\text{text}} with padded entries representing no-object masks. We later use \text{T}_{\text{pad}} for computing a query-text contrastive loss (Sec. 3.3).

We condition our architecture on the task using a task input (\text{T}_{\text{task}}) with the template “the task is \{\text{task}\}”, which is tokenized and mapped to a task-token (\text{Q}_{\text{task}}). We use \text{Q}_{\text{task}} to condition OneFormer on the \text{task} (Sec. 3.2).

### 3.2. Query Representations

During training, we use two sets of queries in our architecture: text queries (\text{Q}_{\text{text}}) and object queries (\text{Q}). \text{Q}_{\text{text}} is the text-based representation for the segments in the image, while \text{Q} is the image-based representation.

To obtain \text{Q}_{\text{text}}, we first tokenize the text entries \text{T}_{\text{pad}} and pass the tokenized representations through a text-encoder [43], which is a 6-layer transformer [37]. The en-
coded \( N_{\text{txt}} \) text embeddings represent the number of binary masks and their corresponding classes in the input image. We further concatenate a set of \( N_{\text{ctx}} \) learnable text context embeddings (\( \mathbf{Q}_{\text{ctx}} \)) to the encoded text embeddings to obtain the final \( N \) text queries (\( \mathbf{Q}_{\text{txt}} \)), as shown in Fig. 4. Our motivation behind using \( \mathbf{Q}_{\text{ctx}} \) is to learn a unified textual context [48, 49] for a sample image. We only use the text queries during training; therefore, we can drop the text mapper module during inference to reduce the model size.

To obtain \( \mathbf{Q} \), we first initialize the object queries (\( \mathbf{Q}' \)) as a \( N - 1 \) times repetitions of the task-token (\( \mathbf{Q}_{\text{task}} \)). Then, we update \( \mathbf{Q}' \) with guidance from the flattened 1/4-scale features inside a 2-layer transformer [2, 37]. The updated \( \mathbf{Q}' \) from the transformer (rich with image-contextual information) is concatenated with \( \mathbf{Q}_{\text{task}} \) to obtain a task-conditioned representation of \( N \) queries, \( \mathbf{Q} \). Unlike the vanilla all-zeros or random initialization [2], the task-guided initialization of the queries and the concatenation with \( \mathbf{Q}_{\text{task}} \) is critical for the model to learn multiple segmentation tasks (Sec. 4.3).

### 3.3. Task Guided Contrastive Queries

Developing a single model for all three segmentation tasks is challenging due to the inherent differences among the three tasks. The meaning of the object queries, \( \mathbf{Q} \), is task-dependent. Should the queries focus only on the thing classes (instance segmentation), or should the queries predict only one amorphous object for each class present in the image (semantic segmentation) or a mix of both (panoptic segmentation)? Existing query-based architectures [10, 11] do not take such differences into account and hence, fail at effectively training a single model on all three tasks.

To this end, we propose calculating a query-text contrastive loss using \( \mathbf{Q} \) and \( \mathbf{Q}_{\text{txt}} \). We use \( \mathbf{T}_{\text{pad}} \) to obtain the text queries representation, \( \mathbf{Q}_{\text{txt}} \), where \( \mathbf{T}_{\text{pad}} \) is a list of textual representations for each mask-to-be-detected in a given image with "a/an \{task\) photo" representing the no-object detections in \( \mathbf{Q} \) [2]. Thus, the text queries can be aligned with the purpose of object queries, representing the objects/segments present [2] in an image. Therefore, we can successfully learn the inter-task distinctions in the query representations using a contrastive loss between the ground truth-derived text and object queries. Moreover, contrastive learning on the queries enables us to attend to inter-class differences and reduce category misclassifications.

\[
\mathcal{L}_{\mathbf{Q} \rightarrow \mathbf{Q}_{\text{txt}}} = -\frac{1}{B} \sum_{i=1}^{B} \log \frac{\exp(q_{i}^{\text{obj}} \odot q_{i}^{\text{txt}} / \tau)}{\sum_{j=1}^{B} \exp(q_{i}^{\text{obj}} \odot q_{j}^{\text{txt}} / \tau)},
\]

\[
\mathcal{L}_{\mathbf{Q}_{\text{txt}} \rightarrow \mathbf{Q}} = -\frac{1}{B} \sum_{i=1}^{B} \log \frac{\exp(q_{i}^{\text{txt}} \odot q_{i}^{\text{obj}} / \tau)}{\sum_{j=1}^{B} \exp(q_{i}^{\text{txt}} \odot q_{j}^{\text{obj}} / \tau)},
\]

\[
\mathcal{L}_{\mathbf{Q} \rightarrow \mathbf{Q}_{\text{txt}}} = \mathcal{L}_{\mathbf{Q} \rightarrow \mathbf{Q}_{\text{txt}}} + \mathcal{L}_{\mathbf{Q}_{\text{txt}} \rightarrow \mathbf{Q}}
\]

Considering that we have a batch of \( B \) object-text query pairs \( (q_{i}^{\text{obj}}, q_{i}^{\text{txt}}) \), where \( q_{i}^{\text{obj}} \) and \( q_{i}^{\text{txt}} \) are the correspond-
Table 1. SOTA Comparison on the ADE20K val set. \(^1\): backbones pretrained on ImageNet-22K; \(^2\): trained with batch size 32; \(^3\): 0.5 confidence threshold; \(^4\): batch size 64. OneFormer outperforms the individually trained Mask2Former [10]. Mask2Former’s performance with 250 queries is not listed, as its performance degrades with 250 queries. We compute FLOPs using the corresponding crop size.

3.5. Losses

In addition to the contrastive loss on the queries, we calculate the standard classification CE-loss (\(L_{\text{cls}}\)) over the class predictions. Following [10], we use a combination of binary cross-entropy (\(L_{\text{bce}}\)) and dice loss (\(L_{\text{dice}}\)) over the mask predictions. Therefore, our final loss function is a weighted sum of the four losses (Eq. (2)). We empirically set \(\lambda_{\text{q}}\) = 0.5, \(\lambda_{\text{cls}} = 2\), \(\lambda_{\text{bce}} = 5\) and \(\lambda_{\text{dice}} = 5\). To find the least cost assignment, we use bipartite matching [2, 11] between the set predictions and the ground truths. We set \(\lambda_{\text{cls}}\) as 0.1 for the no-object predictions [10].

\[
L_{\text{final}} = \lambda_{\text{q}}L_{\text{q}} + \lambda_{\text{cls}}L_{\text{cls}} + \lambda_{\text{bce}}L_{\text{bce}} + \lambda_{\text{dice}}L_{\text{dice}}
\]  
(2)

4. Experiments

We illustrate that OneFormer, when trained only once with our task-conditioned joint-training strategy, generalizes well to all three image segmentation tasks on three widely used datasets. Furthermore, we provide extensive ablations to demonstrate the significance of OneFormer’s components. Due to space constraints, we provide implementation details in the appendix.

4.1. Datasets and Evaluation Metrics

Datasets. We experiment on three widely used datasets that support all three: semantic, instance, and panoptic segmentation tasks. Cityscapes [12] consists of a total 19 (11 “stuff” and 8 “thing”) classes with 2,975 training, 500 validation and 1,525 test images. ADE20K [13] is another benchmark dataset with 150 (50 “stuff” and 100 “thing”) classes among the 20,210 training and 2,000 validation images. COCO [27] has 133 (53 “stuff” and 80 “thing”) classes with 118k training and 5,000 validation images.

Evaluation Metrics. For all three image segmentation tasks, we report the PQ [23], AP [27], and mIoU [15] scores. Since we only have a single model for all three tasks, we use the value of the task token to decide the scores to consider. For e.g., when task is panoptic, we report the PQ score and similarly we report AP and mIoU scores when task is instance and semantic, respectively.

4.2. Main Results

ADE20K. We compare OneFormer with the existing state-of-the-art pseudo-universal and specialized architectures on the ADE20K [13] val dataset in Tab. 1. With the standard Swin-L\(^8\) backbone, OneFormer, while being trained only once, outperforms Mask2Former’s [10] individually trained models on all three image segmentation tasks and sets a new state-of-the-art performance when compared with other methods using the same backbone.

Cityscapes. We compare OneFormer with the existing state-of-the-art pseudo-universal and specialized architectures on the Cityscapes [13] val dataset in Tab. 2. With Swin-L\(^8\) backbone, OneFormer outperforms Mask2Former with a +0.6% and +1.9% improvement on the PQ and AP metrics, respectively. Additionally, with ConvNeXt-L\(^1\) and ConvNeXt-XL\(^1\) backbone, OneFormer sets a new state-of-the-art of 68.5% PQ and 46.7% AP, respectively.

COCO. We compare OneFormer with the existing state-of-the-art pseudo-universal and specialized architectures on the COCO [27] val2017 dataset in Tab. 3. With Swin-L\(^8\) backbone, OneFormer performs on-par with the individually trained Mask2Former [10] with a +0.1% improvement in the PQ score. Due to the discrepancies between the panoptic and instance annotations in COCO [27], we evaluate the AP score using the instance ground truths derived
| Method                  | Backbone                  | #Params | #FLOPs | #Queries | Crop Size | PQ   | AP   | mIoU (s.s.) | mIoU (m.s.) |
|------------------------|---------------------------|---------|--------|----------|-----------|------|------|-------------|-------------|
| Individual Training    |                           |         |        |          |           |      |      |             |             |
| CMT-DeepLab™ [45]      | Max-S™ [38]               | —       | —      | —        | 1025×2049| 60k  | 64.6| —           | —           |
| Axial-DeepLab-L™ [39]  | Axial ResNet-L™ [39]      | 45M     | 687G   | —        | 1025×2049| 60k  | 63.9| 35.8        | 81.0        |
| Axial-DeepLab-XL™ [39]| Axial ResNet-XL™ [39]     | 173M    | 2447G  | —        | 1025×2049| 60k  | 64.4| 36.7        | 80.6        |
| Panoptic-DeepLab™ [9]  | SWideRNet [7]             | 536M    | 10365G | —        | 1025×2049| 60k  | 66.4| 40.1        | 82.2        |
| Mask2Former-Panoptic [10] | Swin-L™ [30]         | 216M    | 514G   | 200      | 512×1024 | 90k  | 66.6| 43.6        | 82.9        |
| Mask2Former-Instance [10] | Swin-L™ [30]          | 216M    | 507G   | 200      | 512×1024 | 90k  | 64.6| —           | —           |
| Mask2Former-Semantic [10] | Swin-L™ [30]           | 215M    | 494G   | 100      | 512×1024 | 90k  | 66.6| 43.6        | 82.9        |
| kMaX-DeepLab™ [46]     | ConvNeXt-L™ [31]         | 232M    | 1673G  | 256      | 1025×2049| 60k  | 68.4| 44.0        | 83.5        |
| Joint Training         |                           |         |        |          |           |      |      |             |             |
| OneFormer              | Swin-L™ [30]             | 219M    | 543G   | 250      | 512×1024 | 90k  | 67.2| 45.6        | 83.0        |
| OneFormer              | ConvNeXt-L™ [31]         | 220M    | 497G   | 250      | 512×1024 | 90k  | 68.5| 46.5        | 83.0        |
| OneFormer              | ConvNeXt-XL™ [31]        | 372M    | 775G   | 250      | 512×1024 | 90k  | 68.4| 46.7        | 83.6        |
| DiNaTL™ [17]           |                         | 223M    | 450G   | 250      | 512×1024 | 90k  | 67.6| 45.6        | 83.1        |

Table 2. SOTA Comparison on Cityscapes val set. †: backbones pretrained on ImageNet-22K; ‡: trained with batch size 32; •: hidden dimension 1024. OneFormer outperforms the individually trained Mask2Former [10] models. Mask2Former’s performance with 250 queries is not listed, as its performance degrades with 250 queries. We compute FLOPs using the corresponding crop size.

| Method                  | Backbone                  | #Params | #FLOPs | #Queries | Epochs | PQ   | PQθ | PQθ* | AP   | A instance | mIoU |
|------------------------|---------------------------|---------|--------|----------|--------|------|-----|------|------|------------|------|
| Individual Training    |                           |         |        |          |        |      |     |      |      |            |      |
| MaskFormer [11]        | Swin-L™ [30]              | 212M    | 792G   | 100      | 100    | 52.7| 58.5| 44.0 | —   | —          | 64.8 |
| K-Net [47]             | Swin-L™ [30]              | —       | —      | 100      | 100    | 54.6| 60.2| 46.0 | —   | —          | —    |
| Panoptic SegFormer [26] | Swin-L™ [30]              | 221M    | 816G   | 353      | 24     | 55.8| 61.7| 46.9 | —   | —          | —    |
| Mask2Former-Panoptic [10] | Swin-L™ [30]             | 216M    | 875G   | 200      | 100    | 57.8| 64.2| 48.1 | 48.7| 48.6       | 67.4 |
| Mask2Former-Instance [10] | Swin-L™ [30]            | 216M    | 868G   | 200      | 100    | 57.8| 64.2| 48.1 | 48.7| 48.6       | 67.4 |
| Mask2Former-Semantic [10] | Swin-L™ [30]            | 216M    | 891G   | 200      | 100    | 57.8| 64.2| 48.1 | 48.7| 48.6       | 67.4 |
| kMaX-DeepLab™ [46]     | ConvNeXt-L™ [31]         | 232M    | 749G   | 128      | 81    | 57.9| 64.0| 48.6 | —   | —          | —    |
| kMaX-DeepLab™ [46]     | ConvNeXt-XL™ [31]        | 232M    | 749G   | 256      | 81    | 58.0| 64.2| 48.6 | —   | —          | —    |
| Joint Training         |                           |         |        |          |        |      |     |      |      |            |      |
| OneFormer              | Swin-L™ [30]              | 219M    | 891G   | 150      | 100    | 57.9| 64.4| 48.0 | 49.0| 48.9       | 67.4 |
| OneFormer              | DiNaTL™ [17]             | 223M    | 736G   | 150      | 100    | 58.0| 64.3| 48.4 | 49.2| 49.2       | 68.1 |

Table 3. SOTA Comparison on COCO val2017 set. †: Imagenet-22k pretrained; ‡: retrained model; •: trained with batch size 64. OneFormer competes with the individually trained Mask2Former [10]. We evaluate the AP score on instance ground truths derived from the panoptic annotations. Mask2Former’s performance with 150 queries is not listed, as its performance degrades with 150 queries. We compute FLOPs using 100 validation COCO images (varying sizes). A instance represents evaluation on the original instance annotations.

from the panoptic annotations. We provide more information in the appendix. Following [10], we evaluate mIoU on semantic ground truths derived from panoptic annotations.

4.3. Ablation Studies

We analyze OneFormer’s components through a series of ablation studies. Unless stated otherwise, we ablate with Swin-L™ OneFormer on the Cityscapes [12] dataset.

Task-Conditioned Architecture. We validate the importance of the task token (Q_task), initializing the queries with repetitions of the task token (task-guided query init.) and the learnable text context (Q_ctx) by removing each component one at a time in Tab. 4. Without the task token, we observe a significant drop in the AP score (−2.7%). Furthermore, using a learnable text context (Q_ctx) leads to an improvement of +4.5% in the PQ score, proving its significance. Lastly, initializing the queries as repetitions of the task token (task-guided query init.) instead of using an all-zeros initialization [2] leads to an improvement of +1.4% in the PQ and +1.1% in the AP score, indicating the importance of task-conditioning the initialization of the queries.

Contrastive Query Loss. We report results without the query-text contrastive loss (L_Q−Q_ctx) in Tab. 5. We observe that the contrastive loss significantly benefits the PQ (+8.4%) and AP (+3.2%) scores. We also conduct experiments substituting our query-text contrastive loss with a classification loss (L_cls) on the queries. L_cls can be regarded as a straightforward alternative for L_Q−Q_ctx as both provide supervision for the number of masks for each class present in the image. However, we observe significant drops on all the metrics (−0.8% PQ, −0.9% AP, and −0.4% mIoU) using the classification loss instead of the contrastive loss. We attribute the drops to the inability of the classification loss to capture the inter-task differences effectively.

Input Text Template. We study the importance of the template choice for the entries in the text list (T_list) in Tab. 6. We experiment with “a photo with a [CLS] [TYPE]” template for our text entries where CLS is the class name for the object.
We present OneFormer, a transformer-based multi-task universal image segmentation framework with task-guided queries to unify the three image segmentation tasks with a single universal architecture, a single model, and training on a single dataset. Our jointly trained single OneFormer model outperforms the individually trained specialized Mask2Former models, the previous single-architecture state of the art, on all three segmentation tasks across major datasets. Consequently, OneFormer can reduce training time, weight storage, and inference hosting requirements to a third. We believe OneFormer is a significant step towards making image segmentation more universal and accessible.

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