DenseCLIP: Extract Free Dense Labels from CLIP

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Abstract

Contrastive Language-Image Pre-training (CLIP) has made a remarkable breakthrough in open-vocabulary zero-shot image recognition. Many recent studies leverage the pre-trained CLIP models for image-level classification and manipulation. In this paper, we further explore the potentials of CLIP for pixel-level dense prediction, specifically in semantic segmentation. Our method, DenseCLIP, in the absence of annotations and fine-tuning, yields reasonable segmentation results on open concepts across various datasets. By adding pseudo labeling and self-training, DenseCLIP+ surpasses SOTA transductive zero-shot semantic segmentation methods by large margins, e.g., mIoUs of unseen classes on PASCAL VOC/PASCAL Context/COCO Stuff are improved from 35.6/20.7/30.3 to 86.1/66.7/54.7. We also test the robustness of DenseCLIP under input corruption and evaluate its capability in discriminating fine-grained objects and novel concepts. Our finding suggests that DenseCLIP can serve as a new reliable source of supervision for dense prediction tasks to achieve annotation-free segmentation.

1. Introduction

Through learning from massive data, large-scale visual-language pre-training models such as CLIP [45] capture expressive visual and language features. Various downstream vision tasks, e.g., text-driven image manipulation [42], image captioning [25], view synthesis [30], and object detection [19], have attempted to exploit such features for improved generality and robustness. For instance, conducting zero-shot image classification based on raw CLIP features leads to a competitive approach that matches the performance of fully-supervised counterparts [45].

In this paper, we take a step further to explore the applicability of CLIP features for pixel-level dense prediction tasks such as semantic segmentation. This investigation is meaningful in that previous studies mainly leverage CLIP features as a global image representation. In contrast, our exploration wishes to ascertain if CLIP features encapsulate object-level and local semantics for dense prediction. Different from the conventional pre-training task of image classification on iconic images, CLIP learns from images of complex scenes and their descriptions in natural language, which (1) encourages it to embed local image semantics in its features, (2) enables it to learn concepts in open vocabulary, and (3) captures rich contextual information, such as the co-occurrence/relation of certain objects and priors of the spatial locations. We believe all these merits contribute significantly to its potential for dense prediction tasks.

In this paper, we summarize both our success and failure experience on leveraging CLIP features for dense prediction. We find it essential to not break the visual-language association in the original CLIP feature space. In our earlier exploration, we experienced failures with the attempt to fine-tune the image encoder of CLIP for the segmenta-
2. Related Work

Transferable Representation Learning. Pre-training is widely used for dense prediction tasks. Yosinski et al. [52] show that ImageNet [11] pre-training greatly speeds up the convergence of the downstream object detection task. Later, extensive research is conducted on making the pre-training a human-labor-free process. In particular, self-supervised representation learning constructs pretext tasks [13, 14, 39] or relies on contrastive learning [7, 9, 22], clustering [3], and bootstrapping [18] to obtain supervision signals. Another line of work seeks to learn visual representation from natural language. Some studies [12, 16, 17, 44, 47, 53] propose to learn from image-caption pairs. Recently, CLIP [45] and ALIGN [31] perform contrastive learning on very large-scale web-curated image-text pairs and show promising pretrained representations with impressive zero-shot transferability. The success of CLIP inspires a new way of studies that transfer the pre-trained CLIP model to various downstream tasks such as text-driven image manipulation [42], image captioning [25], view synthesis [30], and object detection [19]. Different from these methods that typically apply CLIP right off the shelf for image encoding, we explore ways to adapt CLIP for pixel-level dense prediction.

Zero-Shot Visual Recognition. Zero-shot learning aims at classifying instances of those categories that are not seen during training. Common clues to infer unseen categories include shared attributes and visual-semantic mapping. As the latter does not require extra annotations, the paradigm is well-suited for zero-shot dense prediction tasks. Zhao et al. [54] project image pixel features and word concepts into a joint space. Kato et al. [32] fuse semantic features into visual features as guidance. ZS3Net [1] proposes to generate fake pixel-level features from semantic features for the unseen. SPNet [50] learns a projection from visual space to semantic space. Other studies like [26], [34], and [20], improve the generative ZS3Net in terms of uncertainty, structural consistency, and context, respectively, while STRICT [41] boosts the SPNet through self-training. We show that the proposed DenseCLIP not only achieves new SOTA on the zero-shot segmentation setting but can also deal with more difficult settings where all the categories are unseen during training.

Self-Training. Self-training leverages the model trained on labeled data to generate pseudo labels for the unlabeled, which then are used to iteratively improve the previous model. Self-training has firstly become popular in the semi-supervised classification task [29, 33, 35, 43] and is also recently applied in the semi-supervised/zero-shot semantic segmentation settings [4, 10, 27, 28, 36, 37, 40, 56]. Our DenseCLIP+ adopts the same philosophy where the pseudo labels are obtained from both frozen DenseCLIP and DenseCLIP+ itself.
3. Methodology

In this paper, we aim at leveraging CLIP for semantic segmentation. Our study serves as an early attempt that explores the applicability of CLIP features for pixel-level dense prediction tasks. We start with a brief introduction of CLIP and a na"ïves solution as the preliminary, followed by presenting the proposed DenseCLIP in detail.

3.1. Preliminary on CLIP

CLIP [45] is a visual-language pre-training method that learns both visual and language representations from largescale raw web-curated image-text pairs. Specifically, CLIP consists of an image encoder \( V(\cdot) \) and a text encoder \( T(\cdot) \), both jointly trained to respectively map the input image and text into a unified representation space. CLIP adopts contrastive learning as its training objective, where ground-truth image-text pairs are regarded as positive samples, and mismatched image-text pairs are constructed as negative ones. In practice, the text encoder is implemented as a Transformer [49]. As for the image encoder, CLIP provides two alternative implementations, namely a Transformer and a ResNet [23] with global attention pooling layer. In the following, we focus on the ResNet-based image encoder, as ResNet is commonly used in representative segmentation methods.

We believe CLIP has inherently embedded local image semantics in its features as it learns to associate image content with natural language descriptions, the latter of which contain complex and dense semantic guidance across multiple granularities. For example, to correctly identify the image corresponds to the description \textit{the man at bat readies to swing at the patch while the umpire looks on} [8], CLIP must divide image semantics into local segments and properly align image semantics with singular mentioned concepts like \textit{man}, \textit{bat}, \textit{swing}, \textit{patch}, \textit{man at bat}, \textit{man at patch}, and \textit{man readies to swing}, instead of handling the image as a whole. Such uniqueness is absent from training with solely image labels.

3.2. Conventional Fine-Tuning Fails with CLIP

The current de facto pipeline of training a segmentation network is (1) initializing the backbone network with the ImageNet [11] pre-trained weights, (2) adding segmentation-specific network modules with randomly initialized weights, and (3) jointly fine-tuning the backbone and newly added modules.

It is natural to follow these standard steps to adapt CLIP for segmentation. Here, we start our exploration by applying this pipeline on DeepLab [5] with two CLIP-specific modifications. As shown in Figure 2, we first replace the ImageNet pre-trained weights with weights of the image encoder of CLIP. Second, we adopt a mapper \( \mathcal{M} \) that maps text embeddings of CLIP to the weights of DeepLab classifier (the last \( 1 \times 1 \) convolutional layer). The modified model can be formulated as follows:

\[
\text{DeepLab}(x) = C_\phi(\mathcal{H}(V_{\text{cl}}(x))),
\]

(1)

\[
\phi = \mathcal{M}(t),
\]

(2)

where \( V_{\text{cl}}(\cdot) \) denotes the DeepLab backbone, which is a ResNet dilated by a factor of \( l \). \( H(\cdot) \) denotes the randomly initialized ASPP module [5], and \( C_\phi(\cdot) \) is the DeepLab classifier, whose weights, denoted as \( \phi \), are determined by the text embedding of CLIP via the mapper \( \mathcal{M} \). Ideally, by updating the classifier weights with the corresponding text embedding, the adapted DeepLab is able to segment different classes without re-training.

To evaluate the segmentation performance of this modified DeepLab on both seen and unseen classes, we train it on a subset of classes in the dataset, considering the remaining classes as unseen ones. We have tried a series of mapper architectures. Although they perform well on seen classes, in all these cases the modified DeepLab fails to segment unseen classes with satisfying performance. We hypothesize that this is mainly because the original visual-language association of CLIP features has been broken: (1) the backbone is slightly different from the image encoder in terms of network architecture; (2) weights initialized from the image encoder have been updated during fine-tuning; (3) an extra mapper, which is trained only on data of seen classes, is introduced therefore leading to insufficient generality.

3.3. DenseCLIP

Failing the fine-tuning attempt, we turn to a solution that avoids introducing additional parameters and modifying the feature space of CLIP. To this end, we carefully revisit the image encoder of CLIP, especially its unique global attention pooling layer. As shown in Figure 3(b), different from conventional global averaged pooling, the image encoder of CLIP adopts a Transformer-style multi-head attention layer where globally average-pooled feature works as the query, and feature at each spatial location generates a key-value
Compared to the conventional fine-tuning method, the key to the success of DenseCLIP is keeping the pre-trained weights frozen and making minimal adaptation to preserve the visual-language association. Besides, to compensate for the weakness of using the CLIP image encoder for segmentation, which is designed for classification, DenseCLIP+ uses the outputs of DenseCLIP as pseudo labels and trains a more advanced segmentation network such as DeepLabv2 [5].

Despite the simplicity of DenseCLIP in comparison to existing segmentation approaches, the proposed method enjoys multiple unique merits inherited from CLIP. First, DenseCLIP can be used as a free segmentation annotator to provide rich and novel supervision signals for segmentation methods working with limited labels. Second, since the visual-language association of CLIP is retained in DenseCLIP, it naturally possesses the ability to segment open vocabulary classes, as well as fine-grained classes described by free-form phrases, such as white car and red bus. Third, since the CLIP is trained on raw web-curated images, CLIP demonstrates great robustness to natural distribution shift [45] and input corruptions [46]. We verify that DenseCLIP preserves such robustness to some extent.

3.4. DenseCLIP+

While DenseCLIP does not require any training, its network architecture is rigid because it adopts the image encoder of CLIP. To relax it from this constraint and benefit from more advanced architectures tailored for segmentation, such as DeepLab [5] and PSPNet [55], we propose DenseCLIP+. Instead of directly applying DenseCLIP for test-time prediction, DenseCLIP+ regard its predictions as training-time pseudo ground-truth labels. Together with an adopted self-training strategy, DenseCLIP+ is thus free from the restriction on its backbone architecture. As shown in Figure 3(a), we take DeepLabv2 [5] as the backbone of DenseCLIP+ to ensure a fair comparison with previous segmentation methods. The complete training process of DenseCLIP+ is illustrated in algorithm 1.

DenseCLIP-Guided Learning. In DenseCLIP+, we leverage the predictions of DenseCLIP to guide the train-
ing of another target network comprising an architecture tailored to segmentation task. In parallel to the target network, we feed the same pre-processed image input to the DenseCLIP+ pseudo code

\[
P \leftarrow \text{DenseCLIP model};
\]

\[
T \leftarrow \text{text embeddings of target classes};
\]

\[
V_1 \leftarrow \text{target model initialized w/ IN pre-trained};
\]

\[
V_1 \leftarrow \text{load } T \text{ to classifier weights of } V_1;
\]

\[
D \leftarrow \text{images for training};
\]

\[
N_g \leftarrow \text{DenseCLIP-guided learning iterations};
\]

\[
N_s \leftarrow \text{self-training iterations};
\]

\[
\text{for } i = 1, 2, \ldots, N_g \text{ do}
\]

\[
\hat{y} \leftarrow \text{model prediction } V_1(D_i);
\]

\[
y \leftarrow \text{pseudo labels from DenseCLIP } P(D_i);
\]

\[
L \leftarrow \text{cross entropy loss } \mathcal{L}_{CE}(\hat{y}, y);
\]

\[
V_{i+1} \leftarrow \text{SGD model update};
\]

\[
\text{end}
\]

\[
\text{for } j = N_g + 1, N_g + 2, \ldots, N_g + N_s \text{ do}
\]

\[
y \leftarrow \text{model prediction } V_j(D_j);
\]

\[
y \leftarrow \text{self-generated pseudo labels } V_j(D_j);
\]

\[
L \leftarrow \text{cross entropy loss } \mathcal{L}_{CE}(\hat{y}, y);
\]

\[
V_{j+1} \leftarrow \text{SGD model update};
\]

\[
\text{end}
\]

\[
\text{end}
\]

contrary, by adopting pseudo labels in DenseCLIP+, we do not observe any performance drop on seen classes.

**Self-Training.** It is expected that after certain training iterations, the target network guided by DenseCLIP will outperform DenseCLIP, rendering the latter suboptimal for further guidance as it gradually becomes an inferior model over time. Empirically, we also find that DenseCLIP-guided learning reaches an upper bound at around 1/10 of the standard training schedule. To further improve the performance, we swap out DenseCLIP and let the target model generate pseudo labels for itself. This is commonly referred to as self-training. Note that, model drifting is a long-standing problem in self-training where the model gradually collapses, because small errors occurring in early stages might be amplified during training in the absence of external correction. We also observe such phenomenon here, especially on semantically similar classes. We are aware of some effective techniques, such as early stopping [48] and data augmentation [56], to mitigate the problem but as this is not the focus of our paper, we simply abandon self-training when model drifting occurs.

### 4. Experiments

**Datasets.** We conduct experiments on three standard segmentation benchmarks, namely PASCAL VOC 2012 [15], PASCAL Context [38], and COCO Stuff [2]. PASCAL VOC 2012 contains 1,426 training images with 20 object classes plus a background class. Following common practice, we augment it with the Semantic Boundaries Dataset [21]. PASCAL Context labels PASCAL VOC 2010 (4,998/5,105 train/validation images) with segmentation annotations of 520 object/stuff classes, from which the most common 59 classes are treated as foreground while the rest are regarded as background. COCO Stuff extends the COCO dataset, which contains segmentation annotations of 80 object classes on 164K images, with additional 91 stuff classes.

**Zero-shot Setups.** Traditionally, zero-shot segmentation methods train on a subset of classes, named seen classes, with ground-truth annotations, and during inference, both seen and unseen classes are evaluated. Depending on whether the unlabeled pixels are observed during training, the setting can be split into inductive (not observed) and transductive. The selection of seen classes varies among previous works and we follow the most common setups, whether the unlabeled pixels are observed during training, the setting can be split into inductive (not observed) and transductive. The selection of seen classes varies among previous works and we follow the most common setups, where for PASCAL VOC, the background class is ignored and **potted plant**, **sheep**, **sofa**, **train**, **tv monitor** are chosen as the 5 unseen classes; for PASCAL Context, the background is not ignored and **cow**, **motorbike**, **sofa**, **cat**, **boat**, **fence**, **bird**, **tv monitor**, **keyboard**, **aeroplane** are unseen; and for COCO Stuff, **frisbee**, **skateboard**, **cardboard**, **carrot**, **scissors**, **suitcase**, **giraffe**, **cow**, **road**, **wall concrete**, **tree**, **grass**, **river**, **clouds**, **playing field** are unseen. Besides, we also
Table 1. Zero-shot segmentation performances. "ST" stands for self-training.

| Method            | PASCAL-VOC | COCO-Stuff | PASCAL-Context | mIoU(S) | mIoU(U) | mIoU | hIoU|
|-------------------|------------|------------|----------------|--------|--------|------|-----|
| Inductive         |            |            |                |        |        |      |     |
| SPNet [50]        | 75.8       | 0.0        | 56.9           | 34.6   | 0.7    | 31.6 | 1.4 |
| SPNet-C [50]      | 78.0       | 15.6       | 63.2           | 35.2   | 8.7    | 32.8 | 14.0|
| ZS3Net [1]        | 77.3       | 17.7       | 61.6           | 34.7   | 9.5    | 33.3 | 15.0|
| CaGNet [20]       | 78.4       | 26.6       | 65.5           | 35.7   | 12.2   | 33.5 | 18.2|
| Transductive      |            |            |                |        |        |      |     |
| SPNet [50]+ST     | 77.8       | 25.8       | 64.8           | 34.6   | 26.9   | 34.0 | 30.3|
| ZS3Net [1]+ST     | 78.0       | 21.2       | 63.0           | 34.9   | 10.6   | 33.7 | 16.2|
| CaGNet [20]+ST    | 78.6       | 30.3       | 65.8           | 35.6   | 13.4   | 33.7 | 19.5|
| STRICT [41]       | 82.7       | 35.6       | 70.9           | 35.3   | 30.3   | 34.9 | 32.6|
| DenseCLIP+ (ours) | 88.8       | 86.1       | 88.1           | 87.4   | 38.2   | 54.7 | 45.0|
|                  | (+6.1)     | (+50.5)    | (+17.2)        | (+37.6)| (+2.9) | (+24.4)| (+4.7)| (+12.4)| (+17.4)| (+46.0)| (+22.1)| (+29.9)|
| Fully Supervised  |            |            |                |        |        |      |     |
|                  | -          | -          | 88.2           | -      | 39.9   | -    |     |

evaluate a new more challenging setting named annotation-free segmentation where all classes are considered as unseen thus no annotation is provided. We report the mean Intersection over Union (mIoU) of seen, unseen, and all classes as well as the harmonic mean (hIoU) of seen and unseen mIoUs as evaluation metrics.

**Text Embedding.** We follow the same process to construct text embeddings as Xu *et al.* [19]. In specific, we feed prompt engineered texts into the text encoder of CLIP with 85 prompt templates, such as there is a {class name} in the scene, and average the resulting 85 text embeddings of the same class. Note that, for background embedding, instead of inserting the word background into the prompt templates, we adopt a learnable background embedding with random initialization.

**Implementation Details.** We implement our method on the MMSegmentation² codebase and inherit its training configurations. DenseCLIP requires no training and we train DenseCLIP+ on 4 Tesla V100 GPUs with a batch size of 16. We choose the lightest training schedule provided by MMSegmentation, which is 20k/40k/80k for PASCAL VOC/PASCAL Context/COCO Stuff. The first 1/10 training iterations adopt DenseCLIP-guided learning and the rest adopts self-training. For fair comparisons, we choose DeepLabv2 as the target model for PASCAL VOC and COCO Stuff and DeepLabv3+ for PASCAL Context. All use the ResNet-101 backbone initialized with the ImageNet pre-trained weights. Finally, unless explicitly specified, we use the CLIP-ResNet-50³ model by default.

### 4.1. Results on Zero-Shot Segmentation

We compare DenseCLIP+ with SOTA methods including SPNet [50], ZS3Net [1], CaGNet [20], and STRICT [41]. We did not include results of DenseCLIP because it does not require training thus cannot make use of the ground-truth of seen classes. ZS3Net and CaGNet are generative approaches, while SPNet is non-generative and more simple but requires post-possessing step of calibration (SPNet-C). STRICT improves SPNet by a self-training strategy and is free of calibration. Compare with these methods, our DenseCLIP+ does not rely on any particular network architecture nor post-possessing. Despite being simple, DenseCLIP+ achieves a strikingly good result. As shown in Table 1, it surpasses all methods on all datasets with large margins. On PASCAL VOC, PASCAL Context, and COCO Stuff, in terms of unseen mIoUs, DenseCLIP+ improves the previous SOTA by 50.5, 24.4, and 46.0 respectively (on a scale of 100). Furthermore, DenseCLIP+ does not suffer from degradation on the seen classes as well. Note that the overall mIoU of DenseCLIP+ is on par with that of fully supervised baselines. Therefore, we can almost claim these setups of zero-shot segmentation are solved. Please refer to Table 1 for more specific numbers.

### 4.2. Ablation Studies

We perform ablation studies on the PASCAL VOC zero-shot segmentation setting. As shown in Table 2a, we first examine the two proposed strategies in DenseCLIP+. Compared to the adapted DeepLabv2, whose classifier is replaced with the DenseCLIP classifier, DenseCLIP-guided learning improves the unseen mIoU from 3.7 to 72.8 and the result is further improved by self-training to 86.1. However, there is a slight degradation on seen classes when using self-training (from 89.5 to 88.8) partially due to model drifting. Overall, DenseCLIP+ performs better than DenseCLIP on unseen classes and surpasses the baseline DeepLabv2 on seen classes in the same time.

In addition, we vary the pre-trained CLIP models from

²https://github.com/open-mmlab/mmsegmentation
³https://github.com/openai/CLIP
Table 2. Ablations. All experiments are evaluated on PASCAL VOC under the traditional zero-shot setting.

| Method                        | S   | U   | hIoU |
|-------------------------------|-----|-----|------|
| DenseCLIP                    | -   | -   | -    |
| Adapted DeepLabv2            | 83.4| 3.7 | 7.0  |
| + DenseCLIP-Guided           | 89.5| 72.8| 80.3 |
| + Self-Training              | 88.8| 86.1| 87.4 |

(b) CLIP models

| CLIP   | S   | U   | hIoU |
|--------|-----|-----|------|
| r50    | 88.8| 86.1| 87.4 |
| r101   | 88.2| 86.6| 87.4 |
| r50x4  | 88.4| 86.6| 87.5 |
| r50x16 | 88.3| 86.0| 87.1 |

(c) Segmentation methods and backbones

| Seg. Method | Backbone | S   | U   | hIoU |
|-------------|----------|-----|-----|------|
| DeepLabv2 [5] | r50-d8  | 87.9| 87.1| 87.5 |
| DeepLabv2 [5] | r101-d8 | 88.8| 86.1| 87.4 |
| DeepLabv3+ [6] | r101-d8 | 89.9| 85.5| 87.6 |
| PSPNet [55]   | r101-d8 | 89.7| 84.9| 87.2 |

Table 3. Annotation-free segmentation (mIoU).

| Method          | CLIP | P-VOC | P-Context | COCO-Stuff |
|-----------------|------|-------|-----------|------------|
| DenseCLIP       | r50  | 41.5  | 18.5      | 10.2       |
|                 | r50x16| 50.9  | 20.3      | 13.6       |
| DenseCLIP+      | r50  | 58.4  | 23.9      | 13.6       |
|                 | r50x16| 67.5  | 25.1      | 17.3       |

ResNet-50 to ResNet-50x16 (Table 2b) and also experiment with different segmentation methods and their backbones (Table 2c). We do not observe obvious differences in hIoUs among these variants. We think this is mainly because a standard DenseCLIP+ already reach near the fully supervised upper bound. However, in the following more challenging annotation-free setting, the capacity of the CLIP models starts to matter.

4.3. Annotation-Free Segmentation

The impressive performance of DenseCLIP+ on traditional zero-shot segmentation encourages us to further evaluate DenseCLIP(+) in a more challenging setup where during training, no annotation is provided. In Table 3, both DenseCLIP and DenseCLIP+ clearly benefit from more powerful CLIP models, e.g., the CLIP-ResNet-50x16 improves the mIoU of DenseCLIP+ on PASCAL VOC by 9.1% compared to CLIP-ResNet-50. Note that the target models of the two variants are both DeepLabv2-ResNet-101 thus the performance gain introduces no extra cost during inference. In addition, DenseCLIP+ consistently outperforms DenseCLIP across all datasets.

However, in this setting, we have to discard the self-training of DenseCLIP+ since it always leads to severe model drifting. To figure out the reason why self-training is applicable in traditional zero-shot segmentation but not the annotation-free setting, we plot the confusion matrix on PASCAL VOC in Figure 4. Lighter colors on the diagonal and darker colors on the rest indicate better performance. First, hard cases cannot be solved despite DenseCLIP+ and more power CLIP models mitigating the confusion. We investigate the exact pairs that cause the most mistakes and find out they are mostly semantically close (horse and cow) or inclusive (chair and sofa). Second, we highlight the unseen classes in the traditional zero-shot setting with blue boxes. Mistake rarely occurs within the highlighted region, which explains the good performance of DenseCLIP+ on this setting.

4.4. Open Vocabulary Segmentation

DenseCLIP inherits the open-vocabulary ability from CLIP and does not require annotations. Therefore, we can deploy it on several interesting setups where the target classes are (1) more fine-grained, such as red car, yellow car; (2) of certain imagery properties, e.g., blurry; (3) novel concepts like Batman, Joker. We collect images from Flickr then directly evaluate these images on DenseCLIP and train DenseCLIP+ with only DenseCLIP-guided learning. Results in Figure 5 are impressive given the open-vocabulary targets and being annotation-free. Besides, results from DenseCLIP+ are less noisy and more accurate than DenseCLIP, which is complementary to the quantitative results.

4.5. Robustness Under Corruption

CLIP is trained on web-curated images, whose quality and distribution are more diverse than well-pre-processed datasets. Radford et al. [45] and Ravula et al. [46] demonstrate the robustness of CLIP on natural distribution shift and artificial corruption respectively. While these explorations are done for image classification, we benchmark its
Figure 5. **Qualitative results.** Here we show the segmentation results of DenseCLIP and DenseCLIP+ on various unseen classes, including fine-grained classes such as cars in different colors/imagery properties, celebrities, and animation characters. All results are obtained without any annotation.

| Correlation | level 1 | level 5 |
|-------------|---------|---------|
|             | r50     | r50x16  | r50     | r50x16  |
| None        | 41.5    | 50.9    | 41.5    | 50.9    |
| Gaussian Noise | 26.5    | 48.1    | 4.0     | 23.5    |
| Shot Noise  | 27.6    | 48.4    | 4.8     | 25.5    |
| Impulse Noise | 16.8    | 42.4    | 4.6     | 25.3    |
| Speckle Noise | 30.9    | 49.8    | 11.5    | 34.6    |
| Gaussian Blur | 37.9    | 50.0    | 5.7     | 20.7    |
| Defocus Blur | 31.7    | 47.2    | 9.5     | 26.7    |
| Spatter      | 39.6    | 49.4    | 16.6    | 31.7    |
| JPEG         | 30.7    | 46.9    | 12.8    | 36.0    |

Given these observations, we encourage using more powerful CLIP pre-trained models when robustness particularly matters.

5. **Conclusion**

In this paper, we present our exploration of applying CLIP in semantic segmentation, as an early attempt that studies the applicability of pre-trained visual-language models in pixel-level dense prediction tasks. While the conventional fine-tuning paradigm fails to benefit from CLIP, we find the image encoder of CLIP already possesses the ability to directly work as a segmentation model. The resulting model, termed DenseCLIP, can be readily deployed on various semantic segmentation settings without re-training. On top of the success of DenseCLIP, we further propose DenseCLIP+ that leverages DenseCLIP to provide training-time pseudo labels for unlabeled pixels, which thus can be applied to more segmentation-tailored architectures beyond just the image encoder of CLIP. On standard transductive zero-shot segmentation benchmarks, DenseCLIP+ significantly improves previous SOTA results, even doubles the mIoU of unseen classes. More importantly, DenseCLIP+ can be readily employed for segmenting more challenging unseen classes, including fine-grained concepts such as celebrities and animation characters.

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\(^4\)The severity level is controlled by certain coefficients, such as kernel size, specified in ImageNet-C [24].
Figure 6. **More qualitative results.** DenseCLIP and DenseCLIP+ can yield reasonable segmentation results of different car brands and sports without any annotation.

| Corruption         | level 1 | level 2 | level 3 | level 4 | level 5 |
|--------------------|---------|---------|---------|---------|---------|
|                    | r50     | r50x16  | r50     | r50x16  | r50     | r50x16  | r50     | r50x16  | r50     | r50x16  |
| None               | 41.5    | 50.9    | 41.5    | 50.9    | 41.5    | 50.9    | 41.5    | 50.9    | 41.5    | 50.9    |
| Gaussian Noise     | 26.5    | 48.1    | 20.7    | 45.5    | 14.0    | 40.6    | 8.9     | 33.0    | 4.0     | 23.5    |
| Shot Noise         | 27.6    | 48.4    | 21.1    | 45.5    | 14.9    | 40.0    | 8.0     | 31.5    | 4.8     | 25.5    |
| Impulse Noise      | 16.8    | 42.4    | 14.1    | 40.6    | 12.3    | 38.8    | 8.2     | 32.6    | 4.6     | 25.3    |
| Speckle Noise      | 30.9    | 49.8    | 27.1    | 48.3    | 18.6    | 43.0    | 15.2    | 39.4    | 11.5    | 34.6    |
| Gaussian Blur      | 37.9    | 50.0    | 27.1    | 45.1    | 18.0    | 38.2    | 11.7    | 31.3    | 5.7     | 20.7    |
| Defocus Blur       | 31.7    | 47.2    | 26.5    | 44.2    | 19.2    | 38.2    | 13.5    | 32.1    | 9.5     | 26.7    |
| Spatter            | 39.6    | 49.4    | 30.0    | 42.2    | 24.5    | 38.3    | 22.0    | 36.3    | 16.6    | 31.7    |
| JPEG               | 30.7    | 46.9    | 26.8    | 45.7    | 24.0    | 45.0    | 17.7    | 41.3    | 12.8    | 36.0    |

### A. More Qualitative Results

In Figure 5, we show qualitative results of fine-grained classes (*red car, yellow car*), objects with certain imagery properties (*blurry car*), and novel concepts (*Batman, Bill Gates*). Since DenseCLIP preserves the open-vocabulary ability, we can evaluate it on many interesting setups. In Figure 6, we test whether DenseCLIP can segment out different car brands and sports. The evaluation images are crawled from Flickr and all results are obtained without any annotation. DenseCLIP and DenseCLIP+ again demonstrate powerful open-vocabulary ability on subtle concepts. Note that, in the *basketball* and *football* examples, DenseCLIP not only correctly distinguishes athletes playing different sports, but also separates audience and players.

### B. More Robustness Results

In Section 4.5, we show the robustness of DenseCLIP under artificial corruptions. We use corrupting operations provided by the official code of ImageNet-C [24]. In particular, the severity levels are controlled by a series of coefficients of corruption operators. Limited by space, in Section 4.5, we only include results of level 1 and level 5. Here, we extend the table to all levels. As shown in Table 5, CLIP-ResNet-50x16 consistently outperforms CLIP-ResNet-50 by large margins and shows decent robustness.
Table 6. Zero-shot segmentation performances (pAcc & mAcc). "ST" stands for self-training.

| Method         | PASCAL-VOC | COCO-Stuff | PASCAL-Context |
|----------------|------------|------------|----------------|
|                | pAcc(S)    | pAcc(U)    | pAcc(S)        | pAcc(U)    | pAcc(S)    | pAcc(U)    | pAcc |
| Inductive      |            |            |                |            |            |            |      |
| SPNet [50]     | 94.8       | 0.0        | 76.9           | 65.6       | 1.7        | 51.3       | -    |
| SPNet-C [50]   | 88.8       | 29.6       | 77.6           | 61.8       | 24.5       | 53.4       | -    |
| ZS3Net [1]     | 93.0       | 21.5       | 79.4           | 64.3       | 22.8       | 54.7       | 53.5 |
| CaGNet [20]    | 89.5       | 43.0       | 80.7           | 65.6       | 25.5       | 56.6       | 55.2 |
| Transductive   |            |            |                |            |            |            |      |
| ZS3Net [1]+ST  | 91.9       | 34.1       | 81.0           | 65.8       | 24.9       | 56.3       | 46.8 |
| CaGNet [20]+ST | 87.0       | 58.6       | 81.6           | 65.9       | 26.7       | 56.8       | -    |
| DenseCLIP+ (ours) | 94.6      | 91.4       | 94.0           | 64.2       | 79.4       | 67.6       | 73.9 |
| Fully Supervised| -          | -          | 94.0           | -          | 68.1       | -          | 74.8 |

| Method         | PASCAL-VOC | COCO-Stuff | PASCAL-Context |
|----------------|------------|------------|----------------|
|                | mAcc(S)    | mAcc(U)    | mAcc(S)        | mAcc(U)    | mAcc(S)    | mAcc(U)    | mAcc |
| Inductive      |            |            |                |            |            |            |      |
| SPNet [50]     | 94.6       | 0.0        | 70.9           | 50.3       | 0.0        | 45.9       | -    |
| SPNet-C [50]   | 87.9       | 23.9       | 71.9           | 46.3       | 16.1       | 43.6       | -    |
| ZS3Net [1]     | 87.7       | 15.8       | 73.5           | 50.4       | 27.0       | 48.4       | 23.8 |
| CaGNet [20]    | 88.7       | 39.4       | 76.4           | 50.7       | 27.0       | 48.5       | 35.7 |
| Transductive   |            |            |                |            |            |            |      |
| ZS3Net [1]+ST  | 85.7       | 26.4       | 73.8           | 50.4       | 27.2       | 48.6       | 32.3 |
| CaGNet [20]+ST | 83.9       | 50.7       | 75.6           | 50.6       | 27.3       | 48.5       | 35.7 |
| DenseCLIP+ (ours) | 93.7      | 92.6       | 93.4           | 50.8       | 72.4       | 52.7       | 55.4 |
| Fully Supervised| -          | -          | 93.4           | -          | 53.0       | -          | 59.5 |

C. More Evaluation Metrics on Zero-Shot Segmentation

Apart from Intersection over Union (IoU), some zero-shot segmentation methods also report pixel accuracy (pAcc) and mean accuracy (mAcc) as evaluation metrics. For comprehensive comparisons, we provide performance with the mentioned metrics in Table 6. In terms of the overall and unseen pAcc/mAcc, DenseCLIP+ still surpasses the previous SOTA methods by large margins and reaches near the fully-supervised baselines. However, its pAcc/mAcc of seen classes on PASCAL VOC and COCO-Stuff fall behind SPNet and CaGNet+ST by a bit. Different from mIoU, pAcc and mAcc punish only false negatives but not false positives (mIoU punishes both). Previous methods are much more confident on seen classes than unseen classes, therefore yields more predictions on seen classes, which consequently avoids false negatives on seen classes. In fact, SPNet biases towards seen classes so much that without calibration (reduce the confidence of seen classes by scaling factors), its performance on unseen classes is almost zero. DenseCLIP+, on the contrary, is more balanced between seen and unseen classes.

References

[1] Maxime Bucher, Tuan-Hung Vu, Matthieu Cord, and Patrick Pérèz. Zero-shot semantic segmentation. In NeurIPS, 2019.
[2] Holger Caesar, Jasper Uijlings, and Vittorio Ferrari. Coco-stuff: Thing and stuff classes in context. In CVPR, 2018.
[3] Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. In NeurIPS, 2020.
[4] Liang-Chieh Chen, Raphael Gontijo Lopes, Bowen Cheng, Maxwell D Collins, Ekin D Cubuk, Barret Zoph, Hartwig Adam, and Jonathon Shlens. Naive-student: Leveraging semi-supervised learning in video sequences for urban scene segmentation. In ECCV, 2020.
[5] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In ECCV, 2018.
[6] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In ECCV, 2018.
look at self-training for zero-label semantic segmentation. In CVPRW, 2021. 2, 6
[42] Or Patashnik, Zongze Wu, Eli Shechtman, Daniel Cohen-Or, and Dani Lischinski. Styleclip: Text-driven manipulation of stylegan imagery. In ICCV, 2021. 1, 2
[43] Hieu Pham, Zihang Dai, Qizhe Xie, and Quoc V Le. Meta pseudo labels. In CVPR, 2021. 2
[44] Ariadna Quattoni, Michael Collins, and Trevor Darrell. Learning visual representations using images with captions. In CVPR, 2007. 2
[45] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In ICML, 2021. 1, 2, 3, 4, 7
[46] Sriram Ravula, Georgios Smyrnis, Matt Jordan, and Alexandros G Dimakis. Inverse problems leveraging pre-trained contrastive representations. In NeurIPS, 2021. 4, 7
[47] Mert Bulent Sariyildiz, Julien Perez, and Diane Larlus. Learning visual representations with caption annotations. In ECCV, 2020. 2
[48] Parthipan Siva and Tao Xiang. Weakly supervised object detector learning with model drift detection. In ICCV, 2011. 5
[49] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In NeurIPS, 2017. 3
[50] Youngqin Xian, Subhabrata Choudhury, Yang He, Bernt Schiele, and Zeynep Akata. Semantic projection network for zero- and few-label semantic segmentation. In CVPR, 2019. 2, 6, 10
[51] Johnathan Xie and Shuai Zheng. Zsd-yolo: Zero-shot yolo detection using vision-language knowledge distillation. arXiv preprint, 2021. 5
[52] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks? In NeurIPS, 2014. 2
[53] Xin Yuan, Zhe Lin, Jason Kuen, Jianming Zhang, Yilin Wang, Michael Maire, Ajinkya Kale, and Baldo Faieta. Multimodal contrastive training for visual representation learning. In CVPR, 2021. 2
[54] Hang Zhao, Xavier Puig, Bolei Zhou, Sanja Fidler, and Antonio Torralba. Open vocabulary scene parsing. In ICCV, 2017. 2
[55] Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network. In CVPR, 2017. 2, 4, 7
[56] Yuliang Zou, Zizhao Zhang, Han Zhang, Chun-Liang Li, Xiao Bian, Jia-Bin Huang, and Tomas Pfister. Pseudoseg: Designing pseudo labels for semantic segmentation. In ICLR, 2021. 2, 5