Dense Contrastive Learning for Self-Supervised Visual Pre-Training

Xinlong Wang\textsuperscript{1}, Rufeng Zhang\textsuperscript{2}, Chunhua Shen\textsuperscript{1*}, Tao Kong\textsuperscript{3}, Lei Li\textsuperscript{3}
\textsuperscript{1}The University of Adelaide, Australia \textsuperscript{2}Tongji University, China \textsuperscript{3}ByteDance AI Lab

Abstract
To date, most existing self-supervised learning methods are designed and optimized for image classification. These pre-trained models can be sub-optimal for dense prediction tasks due to the discrepancy between image-level prediction and pixel-level prediction. To fill this gap, we aim to design an effective, dense self-supervised learning method that directly works at the level of pixels (or local features) by taking into account the correspondence between local features. We present dense contrastive learning, which implements self-supervised learning by optimizing a pairwise contrastive (dis)similarity loss at the pixel level between two views of input images.

Compared to the baseline method MoCo-v2, our method introduces negligible computation overhead (only <1% slower), but demonstrates consistently superior performance when transferring to downstream dense prediction tasks including object detection, semantic segmentation and instance segmentation; and outperforms the state-of-the-art methods by a large margin. Specifically, over the strong MoCo-v2 baseline, our method achieves significant improvements of 2.0% AP on PASCAL VOC object detection, 1.1% AP on COCO object detection, 0.9% AP on COCO instance segmentation, 3.0% mIoU on PASCAL VOC semantic segmentation and 1.8% mIoU on Cityscapes semantic segmentation.

Code is available at: \url{https://git.io/AdelaiDet}

1. Introduction
Pre-training has become a well-established paradigm in many computer vision tasks. In a typical pre-training paradigm, models are first pre-trained on large-scale datasets and then fine-tuned on target tasks with less training data. Specifically, the supervised ImageNet pre-training has been dominant for years, where the models are pre-trained to solve image classification and transferred to downstream tasks. However, there is a gap between image classification pre-training and target dense prediction tasks, such as object detection \cite{8, 24} and semantic segmentation \cite{4}. The former focuses on assigning a category to an input image, while the latter needs to perform dense classification or regression over the whole image. For example, semantic segmentation aims to assign a category for each pixel, and object detection aims to predict the categories and bounding boxes for all object instances of interest. A straightforward solution would be to pre-train on dense prediction tasks directly. However, these tasks’ annotation is notoriously time-consuming compared to the image-level labeling, making it hard to collect data at a massive scale to pre-train a universal feature representation.

Recently, unsupervised visual pre-training has attracted much research attention, which aims to learn a proper visual representation from a large set of unlabeled images. A few methods \cite{16, 1, 2, 13} show the effectiveness in downstream tasks, which achieve comparable or better results compared to supervised ImageNet pre-training. However, the gap between image classification pre-training and target dense prediction tasks still exists. First, almost all recent

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Comparisons of pre-trained models by fine-tuning on object detection and semantic segmentation datasets. ‘Sup. IN’ denotes the supervised pre-training on ImageNet. ‘COCO’ and ‘ImageNet’ indicate the pre-training models trained on COCO and ImageNet respectively. (a): The object detection results of a Faster R-CNN detector fine-tuned on VOC trainval07+12 for 24k iterations and evaluated on VOC test2007; (b): The semantic segmentation results of an FCN model fine-tuned on VOC train_aug2012 for 20k iterations and evaluated on val2012. The results are averaged over 5 independent trials.}
\end{figure}
self-supervised learning methods formulate the learning as image-level prediction using global features. They all can be thought of as classifying each image into its own version, i.e., instance discrimination [38]. Moreover, existing approaches are usually evaluated and optimized on the image classification benchmark. Nevertheless, better image classification does not guarantee more accurate object detection, as shown in [17]. Thus, self-supervised learning that is customized for dense prediction tasks is on demand. As for unsupervised pre-training, dense annotation is no longer needed. A clear approach would be pre-training as a dense prediction task directly, thus removing the gap between pre-training and target dense prediction tasks.

Inspired by the supervised dense prediction tasks, e.g., semantic segmentation, which performs dense per-pixel classification, we propose dense contrastive learning for self-supervised visual pre-training. DenseCL views the self-supervised learning task as a dense pairwise contrastive learning rather than the global image classification. First, we introduce a dense projection head that takes the features from backbone networks as input and generates dense feature vectors. Our method naturally preserves the spatial information and constructs a dense output format, compared to the existing global projection head that applies a global pooling to the backbone features and outputs a single, global feature vector for each image. Second, we define the positive sample of each local feature vector by extracting the correspondence across views. To construct an unsupervised objective function, we further design a dense contrastive loss, which extends the conventional InfoNCE loss [28] to a dense paradigm. With the above approaches, we perform contrastive learning densely using a fully convolutional network (FCN) [25], similar to target dense prediction tasks.

Our main contributions are thus summarized as follows.

- We propose a new contrastive learning paradigm, i.e., dense contrastive learning, which performs dense pairwise contrastive learning at the level of pixels (or local features).
- With the proposed dense contrastive learning, we design a simple and effective self-supervised learning method tailored for dense prediction tasks, termed DenseCL, which fills the gap between self-supervised pre-training and dense prediction tasks.
- DenseCL significantly outperforms the state-of-the-art MoCo-v2 [2] when transferring the pre-trained model to downstream dense prediction tasks, including object detection (+2.0% AP), instance segmentation (+0.9% AP) and semantic segmentation (+3.0% mIoU), and far surpasses the supervised ImageNet pre-training.

2. Related Work

Self-supervised pre-training. Generally speaking, the success of self-supervised learning [38, 16, 39, 44, 15, 13] can be attributed to two important aspects namely contrastive learning, and pretext tasks. The objective functions used to train visual representations in many methods are either reconstruction-based loss functions [6, 29, 11], or contrastive loss that measures the co-occurrence of multiple views [36]. Contrastive learning, holds the key to most state-of-the-art methods [38, 16, 1, 39], in which the positive pair is usually formed with two augmented views of the same image (or other visual patterns), while negative ones are formed with different images.

A wide range of pretext tasks have been explored to learn a good representation. These examples include colorization [43], context autoencoders [6], inpainting [29], spatial jigsaw puzzles [27] and discriminate orientation [10]. These methods achieved very limited success in computer vision. The breakthrough approach is SimCLR [1], which follows an instance discrimination pretext task, similar to [38], where the features of each instance are pulled away from those of all other instances in the training set. Invariances are encoded from low-level image transformations such as cropping, scaling, and color jittering. Contrastive learning and pretext tasks are often combined to form a representation learning framework. DenseCL belongs to the self-supervised pre-training paradigm, and we naturally make the framework friendly for dense prediction tasks such as semantic segmentation and object detection.

Pre-training for dense prediction tasks. Pre-training has enabled surprising results on many dense prediction tasks, including object detection [32, 30] and semantic segmentation [25]. These models are usually fine-tuned from ImageNet pre-trained model, which is designed for image-level recognition tasks. Some previous studies have shown the gap between ImageNet pre-training and dense prediction tasks in the context of network architecture [23, 21, 35, 34]. YOLO9000 [31] proposes to joint train the object detector on both classification and detection data. He et al. [17] demonstrate that even we pre-train on extremely larger classification dataset (e.g., Instagram [26], which is 3000× larger than ImageNet), the transfer improvements on object detection are relatively small. Recent works [22, 45] show that pre-trained models utilizing object detection data and annotations (e.g, MS COCO [24]) could achieve on par performance on object detection and semantic segmentation compared with ImageNet pre-trained model. While the supervised pre-training for dense prediction tasks has been explored before DenseCL, there is little work on designing an unsupervised paradigm for dense prediction tasks.

Visual correspondence. The visual correspondence prob-
3. Method

3.1. Background

For self-supervised representation learning, the breakthrough approaches are MoCo-v1/v2 [16, 2] and SimCLR [1], which both employ contrastive unsupervised learning to learn good representations from unlabeled data. We briefly introduce the state-of-the-art self-supervised learning framework by abstracting a common paradigm. DenseCL learns general representations that could be shared among multiple dense prediction tasks.

Loss function. Following the principle of MoCo [16], the contrastive learning can be considered as a dictionary look-up task. For each encoded query \( q \), there is a set of encoded keys \( \{k_0, k_1, \ldots\} \), among which a single positive key \( k_+ \) matches query \( q \). The encoded query and keys are generated from different views. For an encoded query \( q \), its positive key \( k_+ \) encode different views of the same image, while the negative keys encode the views of different images. A contrastive loss function InfoNCE [28] is employed to pull \( q \) close to \( k_+ \) while pushing it away from other negative keys:

\[
\mathcal{L}_q = - \log \frac{\exp(q \cdot k_+ / \tau)}{\exp(q \cdot k_+ / \tau) + \sum_{k_-} \exp(q \cdot k_- / \tau)},
\]

where \( \tau \) denotes a temperature hyper-parameter as in [38].

3.2. DenseCL Pipeline

We propose a new self-supervised learning framework tailored for dense prediction tasks, termed DenseCL. DenseCL extends and generalizes the existing framework to a dense paradigm. Compared to the existing paradigm revisited in 3.1, the core differences lie in the encoder and loss function. Given an input view, the dense feature maps are extracted by the backbone network, e.g., ResNet [18] or any other convolutional neural network, and forwarded to the following projection head. The projection head consists of two sub-heads in parallel, which are global projection head and dense projection head respectively. The global projection head can be instantiated as any of the existing projection heads such as the ones in [16, 1, 2], which takes the dense feature maps as input and generates a global feature vector for each view. For example, the projection head...
in [2] consists of a global pooling layer and an MLP which contains two fully connected layers with a ReLU layer between them. In contrast, the dense projection head takes the same input but outputs dense feature vectors.

Specifically, the global pooling layer is removed and the MLP is replaced by the identical 1×1 convolution layers [25]. In fact, the dense projection head has the same number of parameters as the global projection head. The backbone and two parallel projection heads are end-to-end trained by optimizing a joint pairwise contrastive (dis)similarity loss at the levels of both global features and local features.

### 3.3. Dense Contrastive Learning

We perform dense contrastive learning by extending the original contrastive loss function to a dense paradigm. We define a set of encoded keys \( \{t_0, t_1, \ldots\} \) for each encoded query \( r \). However, here each query no longer represents the whole view, but encodes a local part of a view. Specifically, it corresponds to one of the \( S_h \times S_w \) feature vectors generated by the dense projection head, where \( S_h \) and \( S_w \) denote the spatial size of the generated dense feature maps. Note that \( S_h \) and \( S_w \) can be different, but we use \( S_h = S_w = S \) for simpler illustration. Each negative key \( t_- \) is the pooled feature vector of a view from a different image. The positive key \( t_+ \) is assigned according to the extracted correspondence across views, which is one of the \( S^2 \) feature vectors from another view of the same image. For now, let us assume that we can easily find the positive key \( t_+ \). A discussion is deferred to the next section. The dense contrastive loss is defined as:

\[
L_r = \frac{1}{S^2} \sum_s \log \frac{\exp(r^s \cdot t^s_+) / \tau}{\sum_{t^s_-} \exp(r^s \cdot t^s_- / \tau)},
\]

where \( r^s \) denotes the \( s \)th out of \( S^2 \) encoded queries.

Overall, the total loss for our DenseCL can be formulated as:

\[
\mathcal{L} = (1 - \lambda)\mathcal{L}_q + \lambda \mathcal{L}_r,
\]

where \( \lambda \) acts as the weight to balance the two terms. \( \lambda \) is set to 0.5 which is validated by experiments in Section 4.3.

### 3.4. Dense Correspondence across Views

We extract the dense correspondence between the two views of the same input image. For each view, the backbone network extracts feature maps \( F \in \mathbb{R}^{H \times W \times K} \), from which the dense projection head generates dense feature vectors \( \Theta \in \mathbb{R}^{S_h \times S_w \times E} \). Note that \( S_h \) and \( S_w \) can be different, but we use \( S_h = S_w = S \) for simplicity. The correspondence is built between the dense feature vectors from the two views, i.e., \( \Theta_1 \) and \( \Theta_2 \). We match \( \Theta_1 \) and \( \Theta_2 \) using the backbone feature maps \( F_1 \) and \( F_2 \). The \( F_1 \) and \( F_2 \) are first downsampled to have the spatial shape of \( S \times S \) by an adaptive average pooling, and then used to calculate the cosine similarity matrix \( \Delta \in \mathbb{R}^{S^2 \times S^2} \). The matching rule is that each feature vector in a view is matched to the most similar feature vector in another view. Specifically, for all the \( S^2 \) feature vectors of \( \Theta_1 \), the correspondence with \( \Theta_2 \) is obtained by applying an argmax operation to the similarity matrix \( \Delta \) along the last dimension. The matching process can be formulated as:

\[
c_i = \arg\max_j \text{sim}(f_i, f'_j),
\]

where \( f_i \) is the \( i \)th feature vector of backbone feature maps \( F_1 \), and \( f'_j \) is the \( j \)th of \( F_2 \). \( \text{sim}(u, v) \) denotes the cosine similarity, calculated by the dot product between \( \ell_2 \) normalized \( u \) and \( v \), i.e., \( \text{sim}(u, v) = u^\top v / \|u\|\|v\| \). The obtained \( c_i \) denotes the \( i \)th out of \( S^2 \) matching from \( \Theta_1 \) to \( \Theta_2 \), which means that \( i \)th feature vector of \( \Theta_1 \) matches \( c_i \)th of \( \Theta_2 \). The whole matching process could be efficiently implemented by matrix operations, thus introducing negligible latency overhead.

For the simplest case where \( S = 1 \), the matching degenerates into the one in global contrastive learning as the single correspondence naturally exists between two global feature vectors, which is the case introduced in Section 3.1.

According to the extracted dense correspondence, one can easily find the positive key \( t_+ \) for each query \( r \) during the dense contrastive learning introduced in Section 3.3.

### 4. Experiments

We adopt MoCo-v2 [2] as our baseline method, as which shows the state-of-the-art results and outperforms other methods by a large margin on downstream object detection task, as shown in Table 1. It indicates that it should serve as a very strong baseline on which we can demonstrate the effectiveness of our approach.

#### Technical details.

We follow the most settings of [2]. A ResNet [18] is adopted as the backbone. The following global projection head and dense projection head both have a fixed-dimensional output. The former outputs a single 128-D feature vector for each input and the latter outputs dense 128-D feature vectors. Each \( \ell_2 \) normalized feature vector represents a query or key. For both the global and dense contrastive learning, the dictionary size is set to 65536. The momentum is set to 0.999. Shuffling BN [16] is used during the training. The temperature \( \tau \) in Equation (1) and Equation (2) is set to 0.2. The data augmentation pipeline consists of \( 224 \times 224 \)-pixel random resized cropping, random color jittering, random gray-scale conversion, gaussian blurring and random horizontal flip.

#### 4.1. Experimental Settings

#### Datasets.

The pre-training experiments are conducted on two large-scale datasets: MS COCO [24] and ImageNet [5].
Only the training sets are used during the pre-training, which are \( \sim 118k \) and \( \sim 1.28 \) million images respectively. COCO and ImageNet represent two kinds of image data. The former is more natural and real-world, containing diverse scenes in the wild. It is a widely used and challenging dataset for object-level and pixel-level recognition tasks, such as object detection and instance segmentation. While the latter is heavily curated, carefully constructed for image-level recognition. A clear and quantitative comparison is the number of objects of interest. For example, COCO has a total of 123k images and 896k labeled objects, an average of 7.3 objects per image, which is far more than the ImageNet DET dataset’s 1.1 objects per image.

**Pre-training setup.** For ImageNet pre-training, we closely follow MoCo-v2 [2] and use the same training hyper-parameters. For COCO pre-training including both baseline and ours, we use an initial learning rate of 0.3 instead of the original 0.03, as the former shows better performance in MoCo-v2 baseline when pre-training on COCO. We adopt SGD as the optimizer and we set its weight decay and momentum to 0.0001 and 0.9. Each pre-training model is optimized on 8 GPUs with a cosine learning rate decay schedule and a mini-batch size of 256. We train for 800 epochs for COCO, which is a total \( \sim 368k \) iterations. For ImageNet, we train for 200 epochs, a total of 1 million iterations.

**Evaluation protocol.** We evaluate the pre-trained models by fine-tuning on the target dense prediction tasks end-to-end. Challenging and popular datasets are adopted to fine-tune mainstream algorithms for different target tasks, i.e., VOC object detection, COCO object detection, COCO instance segmentation, VOC semantic segmentation, and Cityscapes semantic segmentation. When evaluating on object detection, we follow the common protocol that fine-tuning a Faster R-CNN detector (C4-backbone) on the VOC trainval107+12 set with standard 2x schedule in [37] and testing on the VOC test2007 set. In addition, we evaluate object detection and instance segmentation by fine-tuning a Mask R-CNN detector (FPN-backbone) with on COCO train2017 split (\( \sim 118k \) images) with standard 1x schedule and evaluating on COCO 5k val2017 split. For semantic segmentation, an FCN model [25] is fine-tuned on VOC train_aug2012 set (10582 images) for 20k iterations and evaluated on val2012 set. We also evaluate semantic segmentation on Cityscapes dataset by training an FCN model on train_fine set (2975 images) for 40k iterations and test on val set.

### 4.2. Main Results

**PASCAL VOC object detection.** In Table 1, we report the object detection result on PASCAL VOC and compare it with other state-of-the-art methods. When pre-trained on COCO, our DenseCL outperforms the MoCo-v2 baseline by 2% AP. When pre-trained on ImageNet, the MoCo-v2 baseline has already surpassed other state-of-the-art self-supervised learning methods. And DenseCL still yields 1.7% AP improvements, strongly demonstrating the effectiveness of our method. The gains are consistent over all three metrics. It should be noted that we achieve much larger improvements on more stringent AP\(_{75}\) compared to those on AP\(_{50}\), which indicates DenseCL largely helps improve the localization accuracy. Compared to the supervised ImageNet pre-training, we achieve the significant 4.5% AP gains.

**COCO object detection and segmentation.** The object detection and instance segmentation results on COCO are reported in Table 2. For object detection, DenseCL outperforms MoCo-v2 by 1.1% AP and 0.5% AP when pre-trained on COCO and ImageNet respectively. The gains are 0.9% AP and 0.3% AP for instance segmentation. Note that fine-tuning on COCO with a COCO pre-trained model is not a typical scenario. But the clear improvements still show the effectiveness.

**PASCAL VOC semantic segmentation.** We show the largest improvements on semantic segmentation. As shown in Table 2a, DenseCL yields 3% mIoU gains when pre-training on COCO and fine-tuning an FCN on VOC semantic segmentation. The COCO pre-trained DenseCL achieves the same 67.5% mIoU as ImageNet pre-trained MoCo-v2. Note that compared to 200-epoch ImageNet pre-training, 800-epoch COCO pre-training only uses \( \sim 1/10 \) images and \( \sim 1/3 \) iterations. When pre-trained on ImageNet, DenseCL consistently brings 1.9% mIoU gains. It should be noted that the ImageNet pre-trained MoCo-v2 shows no trans-

| pre-train       | AP | AP\(_{50}\) | AP\(_{75}\) |
|-----------------|----|------------|------------|
| random init.    | 32.8 | 59.0 | 31.6 |
| super. IN       | 54.2 | 81.6 | 59.8 |
| MoCo-v2 CC      | 54.7 | 81.0 | 60.6 |
| DenseCL CC      | 56.7 | 81.7 | 63.0 |
| SimCLR IN [1]   | 51.5 | 79.4 | 55.6 |
| BYOL IN [13]    | 51.9 | 81.0 | 56.5 |
| MoCo IN [16]    | 55.9 | 81.5 | 62.6 |
| MoCo-v2 IN [2]  | 57.0 | 82.4 | 63.6 |
| MoCo-v2 IN\(^*\)| 57.0 | 82.2 | 63.4 |
| DenseCL IN      | 58.7 | 82.8 | 65.2 |

**Table 1 – Object detection fine-tuned on PASCAL VOC.** ‘CC’ and ‘IN’ indicate the pre-training models trained on COCO and ImageNet respectively. ‘\(^*\)’ means re-implementation. The results of other methods are either from their papers or third-party implementation. All the detectors are trained on trainval07+12 for 24k iterations and evaluated on test2007. The metrics include the VOC metric AP\(_{50}\) (i.e., IoU threshold is 50%) and COCO-style AP and AP\(_{75}\). The results are averaged over 5 independent trials.
| pre-train | AP\(^b\) | AP\(_{50}\) | AP\(_{75}\) | AP\(_m\) | AP\(_{50}^c\) | AP\(_{75}^c\) |
|----------|----------|----------|----------|----------|----------|----------|
| random init. | 32.8 | 50.9 | 35.3 | 29.9 | 47.9 | 32.0 |
| super. IN | 39.7 | 59.5 | 43.3 | 35.9 | 56.6 | 38.6 |
| MoCo-v2 CC | 38.5 | 58.1 | 42.1 | 34.8 | 55.5 | 37.3 |
| DenseCL CC | 39.6 | 59.3 | 43.3 | 35.7 | 56.6 | 38.4 |
| MoCo-v2 IN | 39.8 | 59.8 | 43.6 | 36.1 | 56.9 | 38.7 |
| DenseCL IN | 40.3 | 59.9 | 44.3 | 36.4 | 57.0 | 39.2 |

Table 2 – Object detection and instance segmentation fine-tuned on COCO. ‘CC’ and ‘IN’ indicate the pre-training models trained on COCO and ImageNet respectively. All the detectors are trained on train2017 with default 1× schedule and evaluated on val2017. The metrics include bounding box AP (AP\(^b\)) and mask AP (AP\(_m\)).

| pre-train | mIoU |
|----------|------|
| random init. | 40.7 |
| super. IN | 67.7 |
| MoCo-v2 CC | 64.5 |
| DenseCL CC | 67.5 |
| MoCo-v2 IN | 67.5 |
| DenseCL IN | 69.4 |

Table 3 – Semantic segmentation on PASCAL VOC and Cityscapes. ‘CC’ and ‘IN’ indicate the pre-training models trained on COCO and ImageNet respectively. The metric is the commonly used mean IoU (mIoU). Results are averaged over 5 independent trials.

Cityscapes semantic segmentation. Cityscapes is a benchmark largely different from the above VOC and COCO. It focuses on urban street scenes. Nevertheless, we observe the same performance boost with DenseCL. Even the COCO pre-trained DenseCL can surpass the supervised ImageNet pre-trained model by 1.9% mIoU.

4.3. Ablation Study

We conduct extensive ablation experiments to show how each component contributes to DenseCL. We report ablation studies by pre-training on COCO and fine-tuning on VOC0712 object detection, as introduced in Section 4.1. All the detection results are averaged over 5 independent trials. We also provide results of VOC2007 SVM Classification, following [12, 41] which train linear SVMs on the VOC train2007 split using the features extracted from the frozen backbone and evaluate on the test2007 split.

Loss weight \(\lambda\). The hyper-parameter \(\lambda\) in Equation (3) serves as the weight to balance the two contrastive loss terms, i.e., the global term and the dense term. We report the results of different \(\lambda\) in Table 4. It shows a trend that the detection performance improves when we increase the \(\lambda\). For the baseline method, i.e., \(\lambda = 0\), the result is 54.7% AP. The AP is 56.2% when \(\lambda = 0.3\), which improves the baseline by 1.5% AP. Increasing \(\lambda\) from 0.3 to 0.5 brings another 0.5% AP gains. Although further increasing it to 0.7 still gives minor improvements (0.1% AP) on detection performance, the classification result drops from 82.9% to 81.0%. Considering the trade-off, we use \(\lambda = 0.5\) as our default setting in other experiments. It should be noted that when \(\lambda = 0.9\), compared to the MoCo-v2 baseline, the classification performance rapidly drops (-4.8% mAP) while the detection performance improves for 0.8% AP. It is in accordance with our intention that DenseCL is specifically designed for dense prediction tasks.

Matching strategy. In Table 5, we compare three different matching strategies used to extract correspondence across views. 1) ‘random’: the dense feature vectors from two views are randomly matched; 2) ‘max-sim \(\Theta\)’: the dense correspondence is extracted using the dense feature vectors \(\Theta_1\) and \(\Theta_2\) generated by the dense projection head; (3) ‘max-sim \(F\)’: the dense correspondence is extracted according to the backbone features \(F_1\) and \(F_2\), as in Equation 4. The random matching strategy can also achieve 1.3% AP improvements compared to MoCo-v2, meanwhile the classification performance drops by 0.9% mAP. It may be because 1) the dense output format itself helps, and 2) part of the random matches are somewhat correct. Matching by the
outputs of dense projection head, i.e., $\Theta_1$ and $\Theta_2$, brings no clear improvement. The best results are obtained by extracting the dense correspondence according to the backbone features $F_1$ and $F_2$.

**Grid size.** In the default setting, the adopted ResNet backbone outputs features with stride 32. For a $224 \times 224$-pixel crop, the backbone features $F$ has the spatial size of $7 \times 7$. We set the spatial size of the dense feature vectors $\Theta$ to $7 \times 7$ by default, i.e., $S = 7$. However, $S$ can be flexibly adjusted and $F$ will be pooled to the designated spatial size by an adaptive average pooling, as introduced in Section 3.4. We report the results of using different numbers of grid in Table 6. For $S = 1$, it is the same as the MoCo-v2 baseline except for two differences. 1) The parameters of dense projection head are independent with those of global projection head. 2) The dense contrastive learning maintains an independent dictionary. The results are similar to those of MoCo-v2 baseline. It indicates that the extra parameters and dictionary do not bring improvements. The performance improves as the grid size increases. We use grid size being 7 as the default setting, as the performance becomes stable when the $S$ grows beyond 7.

| grid size | Detection AP | AP$_{50}$ | AP$_{75}$ | Classification mAP |
|-----------|--------------|-----------|-----------|--------------------|
| 1         | 54.6         | 80.8      | 60.5      | 82.2               |
| 3         | 55.6         | 81.3      | 61.5      | 81.6               |
| 5         | 56.1         | 81.4      | 62.2      | 82.6               |
| 7         | 56.7         | 81.7      | 63.0      | 82.9               |
| 9         | 56.7         | 82.1      | 63.2      | 82.9               |

Table 6 – Ablation study of grid size $S$. The results increase as the $S$ gets larger. We use grid size being 7 in other experiments, as the performance becomes stable when the $S$ grows beyond 7.

**Training schedule.** We show the results of using different training schedules in Table 7. The performance consistently improves as the training schedule gets longer, from 200 epochs to 1600 epochs. Note that the 1600-epoch COCO pre-trained DenseCL even surpasses the 200-epoch ImageNet pre-trained MoCO-v2 (57.2% AP vs. 57.0% AP). Compared to 200-epoch ImageNet pre-training, 1600-epoch COCO pre-training only uses $\sim$1/10 images and $\sim$7/10 iterations. In Figure 3, we further provide an intuitive comparison with the baseline as the training schedule gets longer. It shows that DenseCL consistently outperforms the MoCo-v2 by at least 2% AP.

**Pre-training time.** In Table 8, we compare DenseCL with MoCo-v2 in terms of training time. DenseCL is only 1s and 6s slower per epoch when pre-trained on COCO and ImageNet respectively. The overhead is less than 1%. It strongly demonstrates the efficiency of our method.

| #epochs | Detection AP | AP$_{50}$ | AP$_{75}$ | Classification mAP |
|---------|--------------|-----------|-----------|--------------------|
| 200     | 54.8         | 80.5      | 60.7      | 77.6               |
| 400     | 56.2         | 81.5      | 62.3      | 81.3               |
| 800     | 56.7         | 81.7      | 63.0      | 82.9               |
| 1600    | 57.2         | 82.2      | 63.6      | 83.0               |

Table 7 – Ablation study of training schedule. The results consistently improve as the training schedule gets longer. Although 1600-epoch training schedule is 0.5% AP better, we use 800-epoch schedule in other experiments for faster training.

Figure 3 – Different pre-training schedules on COCO. For each pre-trained model, a Faster R-CNN detector is fine-tuned on VOC trainval07+12 for 24k iterations and evaluated on test2007. The metric is the COCO-style AP. Results are averaged over 5 independent trials.

| time/epoch | COCO | ImageNet |
|------------|------|----------|
| MoCo-v2    | 1'45'' | 16'48'' |
| DenseCL    | 1'46'' | 16'54'' |

Table 8 – Pre-training time comparison. The training time per epoch is reported. We measure the results on the same 8-GPU machine. For either pre-training on COCO or ImageNet, the training time overhead introduced by DenseCL is less than 1%.

4.4. Discussions on DenseCL

To further study how DenseCL works, in this section, we visualize the learned dense correspondence in DenseCL. The issue of chicken-and-egg during the training is also discussed.

**Dense correspondence visualization.** We visualize the dense correspondence from two aspects: comparison of the final correspondence extracted from different pre-training methods, i.e., MoCo-v2 vs. DenseCL, and the comparison of different training status, i.e., from the random initialization to well trained DenseCL. Given two views of the same image, we use the pre-trained backbone to extract the features $F_1$ and $F_2$. For each feature vector in $F_1$, we find the
corresponding feature vector in $F_2$ which has the highest cosine similarity. The match is kept if the same match holds from $F_2$ to $F_1$. Each match is assigned an averaged similarity. In Figure 4, we visualize the high-similarity matches (i.e., similarity $\geq 0.9$). As shown, DenseCL extracts many more high-similarity matches than its baseline. It is in accordance with our intention that the local features extracted from the two views of the same image should be similar.

Figure 5 shows how the correspondence changes over training time. The randomly initialized model extracts some random noisy matches. The matches get more accurate as the training time increases.

**Chicken-and-egg issue.** In our pilot experiments, we observe that the training loss does not converge if we set $\lambda$ to 1.0, i.e., removing the global contrastive learning, and only applying the dense contrastive learning. It may be because at the beginning of the training, the randomly initialized model is not able to generate correct correspondence across views. It is thus a chicken-and-egg issue that good features will not be learned if incorrect correspondence is extracted, and the correct correspondence will not be available if the features are not sufficiently good. As shown in Figure 5, most of the matches are incorrect with the random initialization. The core solution is to provide a guide when training starts, to break the deadlock. We introduce three different solutions to tackle this problem. 1) To initialize the model with the weights of a pre-trained model; 2) To set a warm-up period at the beginning during which the $\lambda$ is set to 0; 3) To set $\lambda \in (0, 1)$ during the whole training. They all solve this issue well. The second one is reported in Table 4, with $\lambda$ being changed from 0 to 1.0 after the first 10k iterations. We adopt the last one as the default setting for its simplicity.

5. Conclusion

In this work we have developed a simple and effective self-supervised learning framework DenseCL, which is designed and optimized for dense prediction tasks. A new contrastive learning paradigm is proposed to perform dense pairwise contrastive learning at the level of pixels (or local features). Our method largely closes the gap between self-supervised pre-training and dense prediction tasks, and shows significant improvements in a variety of tasks and datasets, including PASCAL VOC object detection, COCO object detection, COCO instance segmentation, PASCAL VOC semantic segmentation and Cityscapes semantic segmentation. We expect the proposed effective and efficient self-supervised pre-training techniques could be applied to larger-scale data to fully realize its potential, as well as hoping that DenseCL pre-trained models would completely replace the supervised pre-trained models in many of those dense prediction tasks in computer vision.

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