**$n$-CPS: Generalising Cross Pseudo Supervision to $n$ networks for Semi-Supervised Semantic Segmentation**

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**Abstract**

We present $n$-CPS – a generalisation of the recent state-of-the-art cross pseudo supervision (CPS) approach for the task of semi-supervised semantic segmentation. In $n$-CPS, there are $n$ simultaneously trained subnetworks that learn from each other through one-hot encoding perturbation and consistency regularisation. We also show that ensembling techniques applied to subnetwork outputs can significantly improve the performance. To the best of our knowledge, $n$-CPS paired with CutMix outperforms CPS and sets the new state-of-the-art for Pascal VOC 2012 with (1/16, 1/8, 1/4, and 1/2 supervised regimes) and Cityscapes (1/16 supervised). The code is available on GitHub$^1$.

1 Introduction

An intense research effort can be observed in data- and label-efficient machine learning. The latter can be tackled using the semi-supervised learning task. Semantic segmentation can significantly benefit from semi-supervised methods due to the relatively high cost of labelling every pixel. Among numerous techniques, consistency regularisation is proven to improve performance in such settings. The recent cross pseudo supervision (abbreviated as CPS) approach [Chen et al., 2021] has set the new state-of-the-art in the task of semi-supervised semantic segmentation. It simultaneously trains two networks, which are penalised for discrepancies between them. This consistency regularisation mechanism is enriched with a specific one-hot encoding data perturbation. This paper proposes a generalised cross pseudo supervision approach, which can handle more than two networks in the data augmentation process. Our contribution is two-fold:

- we generalise the CPS to handle more than two networks in the training process,
- we propose an ensemble learning inspired approach to evaluation, which treats these networks as a blend of weak learners and acts as a strong one.

$^1$The code will be released after the publication. For reviewers, it is available as supplementary material.

Figure 1: Our method ($n$-CPS-sv, $n = 3$) on the Pascal VOC 2012 dataset, compared to the state-of-the-art CPS [Chen et al., 2021]. R50 and R101 denote ResNet-50 and ResNet-101 respectively.
To the best of our knowledge, n-CPS paired with CutMix [Yun et al., 2019] outperforms CPS and sets the new state-of-the-art for Pascal VOC 2012 for 1/16, 1/8, 1/4, and 1/2 supervised regimes and Cityscapes for 1/16 supervised data. Figure 1 presents results for the Pascal VOC 2012 dataset.

The paper is structured as follows. In the Section 2, we present n-CPS, the proposed method. The results of evaluation are presented Section 3 – the experiment setup in Section 3.1, comparison with the state-of-the art in Section 3.2, and ablation studies in Section 3.3. Section 4 offers a comprehensive literature review of the literature on the topic. The paper is concluded with a short summary in Section 5.

2 Method

This section describes the proposed method. Firstly, we present plain n-CPS. Then, we introduce a variant paired with the CutMix algorithm. Finally, we present ensemble learning techniques, which increases the evaluation performance.

n-CPS. The proposed method generalises the cross pseudo supervision (CPS) approach for semi-supervised segmentation. Similarly to CPS, a key feature of n-CPS is consistency regularisation between the output of one network and the output of another one perturbed with pixel-wise one-hot encoding. This perturbation (denoted as max hereafter) sets 1 for the class with the highest probability and 0 for the others. However, instead of using two networks (with the same architecture but initialised differently), n can be used in n-CPS (setting n to 2 results in the original CPS approach).

Let Dl and DU denote labelled and unlabelled training data sets respectively, both containing images of size W × H. The n-CPS architecture consists of a set of n networks f, each with the same architecture but initialised with different set of parameters from Θ = {θ1, θ2, ..., θn}. The output of the j-th network f(x; θj) on the i-th pixel of the image x is represented by pij. The supervised loss is calculated in a standard way:

\[ \mathcal{L}_L = \frac{1}{|D_l|} \sum_{x \in D_l} \frac{1}{W \times H} \sum_{i=1}^{W} \sum_{j=1}^{H} l(p_{ij}, y_i^l), \]

where l is the loss function (we used the standard cross-entropy loss). The ground truth for the labelled data is marked as y_i^l. For the CPS loss for labelled and unlabelled data, we use the following definitions respectively:

\[ \mathcal{L}_{CPS}^L = \frac{1}{|D_l|} \sum_{x \in D_l} \frac{1}{W \times H} \sum_{i=1}^{W} \sum_{j=1}^{H} \sum_{k=1}^{n} l(p_{ij}, y_{ik}), \]

\[ \mathcal{L}_{CPS}^U = \frac{1}{|D_U|} \sum_{x \in D_U} \frac{1}{W \times H} \sum_{i=1}^{W} \sum_{j=1}^{H} \sum_{k=1}^{n} l(p_{ij}, y_{ik}). \]

This time the loss is calculated with y_{ik}, which is the one-hot encoded output of the k-th network on the unlabelled data. Finally, the overall loss \( \mathcal{L} \) is defined as:

\[ \mathcal{L} = \mathcal{L}_L + \lambda (\mathcal{L}_{CPS}^L + \mathcal{L}_{CPS}^U), \]

where \( \lambda \) is the weight of CPS loss. Figure 2 depicts calculating the CPS loss.

Details are presented in Algorithm 1. In each batch, we select images from the labelled and unlabelled data set, which are denoted as \( x^L, x^U \) respectively. Then, we perform the forward passes on all the data using all the networks separately. The n-CPS model consists of \( n \) networks, and the output of each network is the pixel-wise probability of each class. The i-th one is represented by \( f(\cdot; \theta_i) \). Then, we perform the cross pseudo supervision for each unique pair of networks \( \binom{n}{2} \) times. The one-hot encoded outputs of the l-th and r-th networks are denoted as \( Y_l \) and \( Y_r \). In this case, max is a pixel-wise maximum function that selects each pixel’s maximum value from the two masked images. It is calculated without passing the gradient (denoted as \( \mathcal{X} \) in the algorithm). The CPS loss is performed both on the labelled and unlabelled data. Then, we calculate the standard supervised loss for each network. The overall loss consists of the standard labelled loss \( \mathcal{L}_L \) and the CPS losses \( \mathcal{L}_{CPS}^L \) and \( \mathcal{L}_{CPS}^U \) (for labelled and unlabelled data weighted by \( \lambda \) and normalised by the factor of \( \frac{1}{n} \)). While n-CPS needs \( \binom{n}{2} \) CPS loss calculations per batch, the most computationally expensive forward calls are hit only 2n times per batch, which effectively makes the time complexity of the algorithm linear in \( n \).

n-CPS with CutMix. We also used the CutMix augmentation algorithm [Yun et al., 2019] adapted to semantic segmentation [French et al., 2019], as it was proven to be very effective in the original CPS approach [Chen et al., 2021]. Algorithm 2 presents our method. In each batch, we select images from the labelled and unlabelled data set, and we randomly select a binary mask M. Regarding the data, \( x^L, x^U, x^m \) represent the labelled, unlabelled and mixed data respectively. Notice that there are two different sets of unlabelled data, \( x^L_U \) and \( x^U_U \). They both are used to generate the mixed data \( x^m \), which is the result of the CutMix applied with

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**Algorithm 1 n-CPS**

```python
1: for each batch do
  2: \( \mathcal{L} \leftarrow 0, \mathcal{L}_L \leftarrow 0, \mathcal{L}_{CPS}^L \leftarrow 0, \mathcal{L}_{CPS}^U \leftarrow 0 \)
  3: \( x^L, x^U, Y^* \leftarrow \text{dataloader}.\text{iter()} \)
  4: for \( i = 1, \ldots, n \) do
  5: \( P_l^i \leftarrow f(x^L; \theta_i) \)
  6: \( P_u^i \leftarrow f(x^U; \theta_i) \)
  7: end for
  8: for \( (l, r) \in \binom{n}{2} \) do
  9: \( Y_l^U \leftarrow \max(P_l^i), Y_r^U \leftarrow \max(P_r^i) \) // \( \mathcal{X} \)
  10: \( Y_l^U \leftarrow \max(P_l^i), Y_r^U \leftarrow \max(P_r^i) \) // \( Y^* \)
  11: \( \mathcal{L}_{CPS}^L \leftarrow \mathcal{L}_{CPS}^L + \mathcal{L}_{CPS}(P_l^i, Y_r^U) + \mathcal{L}_{CPS}(P_r^i, Y_l^U) \)
  12: \( \mathcal{L}_{CPS}^U \leftarrow \mathcal{L}_{CPS}^U + \mathcal{L}_{CPS}(P_l^i, Y_r^U) + \mathcal{L}_{CPS}(P_r^i, Y_l^U) \)
  13: end for
  14: for \( i = 1, \ldots, n \) do
  15: \( \mathcal{L}_L \leftarrow \mathcal{L}_L + \lambda \sum_{k=1}^{n} l(p_{ij}, y_{ik}) \)
  16: end for
  17: \( \mathcal{L} \leftarrow \mathcal{L}_L + \frac{1}{n} \mathcal{L}_{CPS}^L + \mathcal{L}_{CPS}^U \)
  18: \( \mathcal{L}.\text{backward()} \)
end for
```

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batch-wise mask \( M \). The mask is the same size as the image and is randomly generated to satisfy CutMix constraints.

Then, we perform the forward passes on all the data using all the networks separately, similarly to \( n \)-CPS. Cross pseudo supervision for each unique pair of networks is performed slightly differently regarding one-hot encoding vectors. They are obtained by combining images in a CutMix-like approach and applying the maximum function. The overall loss consists of the standard labelled loss \( \mathcal{L}_L \) and the CPS loss \( \mathcal{L}_{CPS}^U \) weighted by \( \lambda \) and normalised by the factor of \( \frac{1}{n-1} \). Similarly to the original CPS with CutMix augmentation, the CPS loss is not calculated on supervised data and therefore \( \mathcal{L}_{CPS}^L \) is not calculated. Once again, forward calls are linear in \( n \) and setting \( n = 2 \) results in the original CPS+CutMix approach.

**Algorithm 2 \( n \)-CPS+CutMix**

```python
1: for each batch do
2: \( \mathcal{L} \leftarrow 0, \quad \mathcal{L}_L \leftarrow 0, \quad \mathcal{L}_{CPS}^U \leftarrow 0 \)
3: \( x_L, x_I, x_U, M, Y^* \leftarrow \text{dataloader.iter()}) \)
4: \( x^m \leftarrow \text{CutMix}(x_U, x_U, M) \)
5: for \( i = 1, \ldots, n \) do
6: \( Y_i \leftarrow \text{max}(P_{i1} \odot (1 - M) + P_{i2} \odot M) \) // \( \forall \)
7: \( Y_r \leftarrow \text{max}(P_{r1} \odot (1 - M) + P_{r2} \odot M) \) // \( \forall \)
8: \( \mathcal{L}_{CPS}^U \leftarrow \mathcal{L}_{CPS}^U + \mathcal{L}_{CPS}(Y_i, Y_r) + \mathcal{L}_{CPS}(P_r, Y_l) \)
9: end for
10: for \( (l, r) \in \binom{n}{2} \) do
11: \( \mathcal{L}_L \leftarrow \mathcal{L}_L + \mathcal{L}_L(P_{l1} \odot Y^*) \)
12: end for
13: \( \mathcal{L} \leftarrow \mathcal{L}_L + \lambda \frac{\mathcal{L}_{CPS}^U}{(n-1)} \)
14: \( \text{backward()} \)
15: end for
```

**Ensemble learning techniques.** In the language of ensemble learning, an ensemble is a set of weak learners (models trained independently), which together forms a strong model. During the \( n \)-CPS training process, there are \( n \) networks trained separately. In the original approach, the evaluation used only the results of the first network and discarded the other ones. While this approach alone was proven to generate state-of-the-art results, our empirical results show that including all the information from the trained networks is beneficial for performance. In the original CPS paper, the experiment showed that even in the last steps of learning, approximately 5\% of pixels are labelled differently by the trained networks.

Therefore, we use the results of all the networks. It can be realised by taking the pixel-wise softmax of the output of each network and then combining the results in several ways. In this paper, we test two of them: max confidence (denoted as \( mc \)) and soft voting (\( sv \)). In the max confidence approach, we choose the result with the highest score. In other words, for each pixel, we choose the class from the most confident network. In the PyTorch-like notation, that max confidence voting is defined as: \( \text{softmax}(y, \text{dim}=2).\text{max(dim=0)} \), where the concatenated output of all networks \( y \) is of shape \((n, b, c, w, h)\) representing consecutively number of the networks, batch size, number of classes, width and height. The soft voting approach is similar, but instead of choosing the class with the highest score, we sum the probabilities of all the networks. This is proportional to the weighted mean of the output of all networks. In the PyTorch-like notation that would translate to \( \text{softmax}(y, \text{dim}=2).\text{sum(dim=0)} \).

3 Evaluation

This section describes the evaluation of the proposed approach. First, we present the setup of our experiments and the training details. We evaluate \( n \)-CPS on PASCAL VOC 2012 and Cityscapes datasets. Ablation studies are also performed.

3.1 Experiment setup

**Datasets.** The datasets used in this experiment are the same as in the original CPS paper [Chen et al., 2021] – PAS-
CAL VOC 2012 [Everingham et al., 2010] and Cityscapes [Cordts et al., 2016]. The PASCAL VOC 2012 contains 21 classes (including the background class). Regarding Cityscapes, it comprises 30 classes. We also follow GCT [Ke et al., 2020] protocols regarding the ratio of supervised-to-unsupervised images in the dataset (1/16, 1/8, 1/4, 1/2). The sampling scheme is taken from the CPS paper [Chen et al., 2021] to provide a fair comparison with other methods. Both datasets are evaluated using the standard mean intersection over union (mIoU) metric in % over val sets (1,456 images in PASCAL VOC 2012 and 500 in Cityscapes).

**Training details.** We use the same training setup as in the original CPS paper [Chen et al., 2021]. We extend the original PyTorch codebase with our n-CPS approach, although training details (such as augmentations or hyperparameters) stays the same. This means that we use DeepLabv3+ [Chen et al., 2018] as our network with ResNet-50/101 backbones [He et al., 2016] paired with mini-batch SGD with momentum (0.9) and weight decay (0.0005). We also use the poly learning rate policy, in which the initial learning rate is multiplied by $(1 - \frac{\text{iter}}{\text{step}})^{0.9}$. For Pascal VOC, both supervised and CPS loss is computed using standard cross-entropy loss. Regarding Cityscapes, OHEM loss [Shrivastava et al., 2016] is used for supervised loss and cross-entropy loss for CPS loss. VOC models were trained on 4×V100 GPUs, whereas Cityscapes models on 8×V100 GPUs.

### 3.2 Results

We report mIoU results from the network with the highest-scoring step (not necessarily the last one). These results use $n = 3$ as the number of networks and MC and SV ensembling techniques. The training regime is taken from the CPS paper, and it consists of different supervision ratios (1/16, 1/8, 1/4, 1/2) trained for 32/34/40/60 and 128/137/160/240 steps for Pascal VOC and Cityscapes, respectively. We report the best test results during the evaluation (not necessarily the result from the last step).

**Pascal VOC 2012.** The first part of Table 1 presents the results on the Pascal VOC dataset compared to other recent methods (the non-our results are taken from the CPS paper [Chen et al., 2021]). For different supervision regimes (1/16, 1/8, 1/4, 1/2), the version without CutMix outperforms the mIoU results reported in the original CPS paper (previous state-of-the-art) by $+0.15/+0.49/+1.57/+1.16$ percentage points for ResNet-50 and $+1.33+/+0.75/+1.06/+1.38$ pp for ResNet-101. Regarding the version with CutMix algorithm, the n-CPS approach is better than CPS by $+0.05/+0.54/+0.95/+0.50$ pp for ResNet-50 and $+1.38/+1.55/+1.29/+1.62$ pp for ResNet-101. Mean confidence and soft voting ensembles behave similarly, and usually, the difference is slight (not more significant than ±0.1 mIoU). Interestingly, for ResNet-50, the version without CutMix outperforms the version with CutMix. This effect is not observed with ResNet-101.

**Cityscapes.** The second part of Table 1 presents the results on the Cityscapes dataset compared with other recent methods. Similarly, the non-our results are taken from the CPS paper [Chen et al., 2021]. We do not report results for the ResNet-101 backbone network due to the unavailability of the appropriate hardware (8×V100 GPUs were not enough in terms of RAM). On ResNet-50 and without CutMix, n-CPS achieved $−0.01/+0.49−0.11/+0.65$ pp change of mIoU compared to CPS. With CutMix on, our approach outperforms the current state of the art by $+1.61/+1.00/+0.58/+0.43$ pp. Even without testing our approach on ResNet-101, the n-CPS on ResNet-50 outperforms CPS on ResNet-101 on 1/16 supervision (+1.36 mIoU). Interestingly, the model based on ResNet-50 with the CutMix algorithm showed a slightly worse performance 1/2 supervision than the model without it. This behaviour is consistent with the PASCAL VOC 2012 results.

### 3.3 Ablations

This section presents the ablation experiments on the Pascal VOC 2012 dataset. We try to assess the importance of generalising CPS by controlling the number of networks $n$. Then, we address the influence of the max confidence ensembling technique without cross-pseudo supervision. Finally, we study how the choice of ensembling technique influences the performance.

**Importance of $n$-CPS.** To assess the importance of $n$-CPS, we run a series of experiments on the PASCAL VOC 2012 dataset with different values. The results are reported in Table 2 in terms of the mIoU under different supervision regimes. We report the results of the original CPS [Chen et al., 2021], as well as the results of our implementation ($n$-CPS, where $n \in \{2, 3\}$). All networks were trained on DeepLabv3+ with ResNet-50/101 as a backbone and using $\lambda = 1.5$. Most importantly, we did not use any ensembling techniques here. Note that while the original CPS is equivalent to ours reproduced with 2-CPS, these results are slightly different due to randomness. Nevertheless, one can observe that evaluating only the first network $f_1$ (as in the original CPS paper), which is not necessarily the best performing one, does not show the immediate advantage of using $n$-CPS (except ResNet-101 without CutMix).

**Importance of ensemble networks.** The previous paragraph showed that the choice of increased $n$ does not improve the performance alone. However, in Section 3.2 we have already shown that the method combined with proper ensembling technique yields state-of-the-art results. To isolate the effect of ensembling, we performed a series of experiments with $\lambda$ set to zero. This disabled cross-pseudo supervision loss from the learning process and effectively turned the task to standard supervised ensemble learning. Table 3 presents the results of this ablation study. As it turns out, for 2-CPS, ensembling resulted in +1.57 pp to mIoU, while ensembling and CPS ($\lambda = 1.5$) provided another +2.78 pp for 1/16 supervised data. The trend is consistent in different supervision regimes, though it diminishes with larger shares of supervised
Table 1: Comparison of the semi-supervised segmentation methods (mIoU under different supervision regimes, DeepLabv3+).

|                  | ResNet-50 | ResNet-101 |
|------------------|-----------|------------|
|                  | 1/16      | 1/8        | 1/4        | 1/2      | 1/16      | 1/8        | 1/4        | 1/2      |
| **Pascal VOC 2012** |           |            |            |          |           |            |            |          |
| MT [Tarvainen and Valpola, 2017] | 66.77     | 70.78      | 73.22      | 75.41    | 70.59     | 73.20      | 76.62      | 77.61    |
| CCT [Ouali et al., 2020] | 65.22     | 70.87      | 73.43      | 74.75    | 67.94     | 73.00      | 76.17      | 77.56    |
| CutMix-Seg [French et al., 2019] | 68.90     | 70.70      | 72.46      | 74.49    | 72.56     | 72.69      | 74.25      | 75.89    |
| GCT [Ke et al., 2020] | 64.05     | 70.47      | 73.45      | 75.20    | 69.77     | 73.30      | 75.25      | 77.14    |
| CPS [Chen et al., 2021] | 68.21     | 73.20      | 74.24      | 75.91    | 72.18     | 75.83      | 77.55      | 78.64    |
| CPS+CutMix [Chen et al., 2021] | 71.98     | 73.67      | 74.90      | 76.15    | 74.48     | 76.44      | 77.68      | 78.64    |
| 3-CPS-mc (ours) | 68.36     | 73.45      | 75.75      | 77.00    | 73.51     | 76.46      | 78.59      | 79.90    |
| 3-CPS-sv (ours) | 68.28     | 73.69      | 75.81      | 77.07    | 73.25     | 76.58      | 78.61      | 80.02    |
| 3-CPS-mc+CutMix (ours) | 72.03     | 73.67      | 74.18      | 75.85    | 75.80     | 77.96      | 78.97      | 80.06    |
| 3-CPS-sv+CutMix (ours) | 71.97     | 74.21      | 75.83      | 77.06    | 77.99     | 78.95      | 80.26      |          |
| **Cityscapes** |           |            |            |          |           |            |            |          |
| MT [Tarvainen and Valpola, 2017] | 66.14     | 72.03      | 74.47      | 77.43    | 68.08     | 73.71      | 76.53      | 78.59    |
| CCT [Ouali et al., 2020] | 66.35     | 72.46      | 75.68      | 76.78    | 69.64     | 74.48      | 76.35      | 78.29    |
| GCT [Ke et al., 2020] | 65.81     | 71.33      | 75.30      | 77.09    | 66.90     | 72.96      | 76.45      | 78.58    |
| CPS [Chen et al., 2021] | 69.79     | 74.39      | 76.85      | 78.64    | 70.50     | 75.71      | 77.41      | 80.08    |
| CPS+CutMix [Chen et al., 2021] | 74.47     | 76.61      | 77.83      | 78.77    | 74.72     | 77.62      | 79.21      | 80.21    |
| 3-CPS-mc (ours) | 69.78     | 74.80      | 76.74      | 79.29    | –        | –          | –          | –        |
| 3-CPS-sv (ours) | 69.76     | 74.88      | 76.74      | 79.27    | –        | –          | –          | –        |
| 3-CPS-mc+CutMix (ours) | 76.06     | 77.58      | 78.36      | 79.15    | –        | –          | –          | –        |
| 3-CPS-sv+CutMix (ours) | 76.08     | 77.61      | 78.41      | 79.2    | –        | –          | –          | –        |

Importance of the ensemble learning method. We also investigate how the choice of ensemble technique influences the performance during the whole training process. Apart from the best results reported in Table 1, we also control it in a full training procedure. To do so, we trained n-CPS ($n = 3, \lambda = 1.5$) with the 1/8 supervised regime with ResNet-50 on the Pascal VOC dataset and control evaluation results for different types of ensemble techniques presented in Section 2: no ensembling (i.e. only the first network is evaluated), max confidence and soft voting. Figure 3 shows the results of the ablation study. The highest mIoU scores were 73.85 for soft voting and 73.71 for max confidence. In this case, soft voting was better than max confidence by 0.11 mIoU points on average. Soft voting was also better on the majority of learning steps. Notice that these results are slightly different than the results reported in Table 1, as they were collected in a separate run.

4 Related Work

This section briefly describes other work in the areas of semantic segmentation and semi-supervised learning.

Semantic segmentation. Semantic segmentation is a fundamental problem in computer vision, which consider assigning labels to each pixel in an image. Modern deep neural networks successfully adapted to this problem, with...
Contrastive learning is built around learning representations and semi-supervised learning. Recently, an intense interest due to the high cost of labelling. The goal of semi-supervised learning is to learn a model on a dataset, for which the labels are known on a certain percentage of the data. Semi-supervised learning combines semantic segmentation and semi-supervised learning. Recently, an intense effort can be observed in developing two families of techniques: contrastive learning and consistency regularisation. Contrastive learning is built around learning representations which are close for the samples of the same class and far otherwise. Consistency regularisation assumes that the same samples should yield the same labels under different – often heavy – augmentations and perturbations. The disagreement between models is later used for the training. Apart from CPS [Chen et al., 2021], there are several architectures dedicated to semi-supervised learning. A somewhat similar approach is cross-consistency training (CCT) [Ouali et al., 2020] or GCT [Ke et al., 2020], which uses cross-confidence consistency for feature perturbation. Mean teacher [Tarvainen and Valpola, 2017] considers a setting in which two models (student and teacher) are trained on the same dataset but using different augmentations. The student model is trained in a standard way, while the teacher model is an exponential moving average of student models from previous steps. The latter is also responsible for generating pseudo labels. The Mean Teacher framework combined with CutMix [Yun et al., 2019] was used for semi-supervised segmentation in CutMix-Seg [French et al., 2019]. In Dynamic Mutual Training (abbreviated as DMT) [Feng et al., 2020], two neural networks are trained using a dynamically re-weighted loss function. The authors of DMT leverage the disagreement between the models, which indicates a possible error and lowers the loss value. ReCo (an abbreviation from Regional Contrast) [Liu et al., 2021] is a pixel-level contrastive learning framework, which incorporates memory-efficient sampling strategies. The framework proved to be very effective in few-supervision scenarios, reaching 50% mIoU on Cityscapes while requiring only 20 labelled images.

### 5 Summary

In this paper, we presented n-CPS – a generalisation of the consistency regularisation framework CPS. We also proposed to utilise all the learned subnetworks for evaluation purposes using the ensemble learning techniques. Evaluation of our approach on the Pascal VOC dataset showed that it sets the new state-of-the-art in its category. Future work should address the evaluation of the behaviour of models with n ≥ 4. An unavoidable limitation of such a study stems from the large number of parameters involved in the models. In practical settings, this means relatively large GPU memory requirements. Moreover, further work should consider the evaluation of ResNet-101 on the Cityscapes dataset, as the results on ResNet-50 are promising.

### CRediT author statement

**Dominik Filipiak** (80% of the work): Conceptualisation, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Writing – Original Draft, Writing – Review & Editing, Visualization, Project Administration. **Piotr Tempczyk** (10% of the work): Conceptualisation, Funding Acquisition, Supervision, Writing – Review & Editing. **Marek Cygan** (10% of the work): Conceptualisation, Supervision, Resources, Writing – Review & Editing.
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