Self Semi Supervised Neural Architecture Search for Semantic Segmentation

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Abstract

In this paper, we propose a Neural Architecture Search strategy based on self supervision and semi-supervised learning for the task of semantic segmentation. Our approach builds an optimized neural network (NN) model for this task by jointly solving a jigsaw pretext task discovered with self-supervised learning over unlabeled training data, and, exploiting the structure of the unlabeled data with semi-supervised learning. The search of the architecture of the NN model is performed by dynamic routing using a gradient descent algorithm. Experiments on the Cityscapes and PASCAL VOC 2012 datasets demonstrate that the discovered neural network is more efficient than a state-of-the-art hand-crafted NN model with four times less floating operations.

1 Introduction

Semantic segmentation entails in assigning a specific class to each pixel in an image with the overall aim of discovering objects. It is a key task in the field of computer vision, and has a wide range of applications, including autonomous driving [5], medical research [52], facial recognition [40] and person reidentification [57]. In comparison to other computer vision tasks, the equivalent of this pixel-level label is a difficult and time-consuming effort.

The key challenges here are taking into account the context of objects inside images [39], and, learning with a small set of annotated data together with a large set of unlabeled data. To address these issues, different approaches have been proposed. For automatically taking into account the context, various approaches have been proposed under the self-supervised framework, which consists in exploiting the underlying data structure in order to gain supervision for
an auxiliary task and learn a model by resolving both the auxiliary and the semantic segmentation problems simultaneously. For the problem of learning with partially labeled training data, or semi-supervised learning, existing approaches mostly assign pseudo-labels to unlabeled training data in order to augment the labeled training set using an auxiliary loss; under various perturbations such as images augmentations [22], features [46] or network [29] perturbations; for enforcing the consistency of predictions.

Although both self-supervised and semi-supervised approaches take advantage of data structure from different perspectives, they have never been studied together. Furthermore, hand-crafted NN architectures are used in the bulk of semantic segmentation research. Some recent works have proposed neural architecture search (NAS) for the design of a more flexible network that automatically adapt to the size of the input images [34]. These NAS approaches, on the other hand, were developed with full supervision.

In this work, we present a way to bridge between these three worlds. Our approach is based on self supervision and semi-supervised learning for semantic segmentation. It combines information from the labeled training data with the resolution of a jigsaw pretext task discovered through self-supervised learning, and the search for regularities over the current model output over the labeled and unlabeled training data; in order to create an optimized neural network (NN) model for this task. Dynamic routing with a gradient descent technique is used to seek for the architecture of the NN model.

We evaluate our approach with different settings where the model architecture is obtained by NAS when exploiting the context with either self-supervision or semi-supervised learning. For the latter, we employ two different semi-supervised techniques and show that learning with partially labeled data may not always lead to an efficient model. The performance of the architecture search is shown on known semantic segmentation benchmarks under different partition set-ups and are further compared to a state-of-the-art hand-crafted architecture. We show that when searching for regularities on the outputs of the neural networks while concurrently addressing the pretext task, the proposed model achieves the best results compared to its other variants and a state-of-the-art hand-crafted NN with 4 times less floating-point operations (FLOPs).

The rest of the paper is organized as follows. Section 2 presents an overview of the related work. Section 3 provides details about the semi-supervised techniques used in our framework. Section 4, exhibits our approach, and finally, in Section 5 we present experimental results obtained with our approach on Cityscapes and PASCAL VOC 2012 benchmarks. Finally, in Section 6 we analyze the study’s findings and provide some suggestions for further research.
2 Related Works

2.1 Semantic segmentation

Semantic segmentation consists in classifying each pixel of an image into a class, where each class represents an object or a portion of the image [36]. This task is part of the scene understanding concept, which is much more complex than image classification, as it requires apprehending the whole context of an image. To comprehend a scene, each piece of visual data must be assigned to an entity while taking into account the spatial information.

Recent research on this topic has largely relied on Neural-Networks, as these models have been shown to outperform other techniques in scene analysis [37].

Hand-crafted architectures, designed by experts in the field, are the most popular way to create specific NN models for semantic segmentation. In this category, a wide range of architectures requiring high computational resources exist, including U-Net [52], Conv-Deconv [21] or FCN [37]. However, [59] have shown that, by dissociating context information from the spatial information, it is possible to achieve highly efficient models with lighter architectures.

Recently, [11, 41], have studied how Neural Architecture Search (NAS) can be applied to the decoder in order to improve the performance for semantic segmentation. However, different from the proposed study, these techniques rely on a fully supervised learning framework.

2.2 Self-supervised Learning

Self-supervised learning entails automatically generating some sort of supervisory signal from the unlabeled data in order to achieve a task [28]. The auxiliary or pretext tasks extracted automatically are generally designed in such a way that solving them requires the learning of useful features. The majority of the new approaches are built on the concept of contrast (i.e. contrastive learning), with a learning procedure that uses network representations of images to learn strong and useful features [26, 9, 24]. In addition, there are other approaches where the goal is to colorize the image [60]; or to fill in missing parts of the image [48] or even to predict the direction of rotation of an image [23].

For the task of classification, some of the first papers have proposed full image-based methods, that is, without patches [23, 18]. Different from that, more recent approaches have proposed patch-based methods. These methods were devised to estimate the relative positions of two non-overlapping patches in a 3×3 grid [17]. Other approaches, generalizing this concept, involve using the entire grid and attempting to solve a jigsaw by anticipating the permutation used to shuffle it [42].

Recently, some research have proposed NAS in a self-supervision setting [35], in which an architecture is discovered using a pretext task and then transferred to a supervised learning context. In this paper, we propose determining the NN architecture for semantic segmentation utilizing two forms of context information: solving a pretext task identified by self-supervision and exploiting the
data structure through semi-supervised learning.

2.3 Semi-supervised Learning

Semi-supervised learning refers to the process of learning a prediction function from both labeled and unlabeled training examples. In this situation, labeled examples are supposed to be few, whereas unlabeled training data are available in abundance. Unlabeled samples include useful information about the prediction problem at hand, which are exploited jointly with the labeled training examples to produce a more efficient prediction function than if just the latter were used for learning [10, 3].

Semi-supervised learning has a long history, and has been studied in a variety of domains and tasks [10, 56, 62]. More recently, semi-supervised learning has gained popularity in the deep learning community, and has shown, in some cases, comparable results to the state-of-the-art of purely supervised methods [32, 38, 55]. Most popular approaches to deep semi-supervised learning [45] include for example generative models, consistency regularization, entropy minimization, or proxy-label methods.

Semi-supervised learning methods, exploiting generative model based approaches, have been performed using e.g. variational autoencoders [30, 1] or generative adversarial networks [43, 16]. These approaches aim to combine information from the joint distribution \( p(x, y) \) of labeled data and the density distribution \( p(x) \) of unlabeled data.

Neural network approaches based on consistency regularization add an auxiliary loss computed over unlabeled samples. This loss computes the divergence between predictions made on unlabeled perturbed data points. Among the first works using this approach, the use of Ladder Networks with additional noisy encoder, encoder and decoder was proposed [50], where they used a consistency regularization loss to denoise representations at each layer. Better results were then obtained by smoothing these predictions, e.g. using Temporal Ensembling [32], Mean Teacher [55], or Virtual Adversarial Training [38]. More recent results were improved with fast-SWA [1], using cyclic learning rates and measuring discrepancy with a set of predictions from multiple checkpoints. Similar to consistency training, which enforces consistent predictions under perturbations, pushing away the decision boundary toward low density regions, entropy minimization accomplish the same goal by increasing the prediction confidence on unlabeled data [44].

Proxy-label methods iteratively assign pseudo-labels to high-confident unlabeled examples and include these pseudo-labeled examples in the learning process. These pseudo labels can either be produced by Self-training [58], that is by the model itself, or by multi-view training, using for example the Co-training framework [49]. Finally, hybrid, or holistic methods such as MixMatch [7], ReMixMatch [6], or FixMatch [54] unified different approaches, combining for example consistency regularization and pseudo-labeling as in FixMatch. More recently, another example of holistic approach, using Cross Pseudo supervision [14] on the task of semantic segmentation, have shown state-of-the-art results.
The majority of the cited methods employ a fixed architecture as their backbone; however, our approach uses information from both partially labeled data and context information, extracted by self-supervised learning, to automatically explore a specific and more flexible architecture for semantic segmentation. Moreover, the obtained model does not require to be retrained, as both, the architecture and its parameters, are learned simultaneously.

3 Framework and baselines

We assume that we have a labeled training set $D_\ell = \{(x_l, y_l)\}_{1 \leq l \leq m}$ of size $m$, and a possibly much larger set of unlabeled training examples $D_u = \{(x_u)_{m+1 \leq u \leq m+n}\}$ of size $n$. We further consider that $\theta$ represents the set of all network weights.

In our setting, we consider the jigsaw solving pretext task as the self-supervised method. The main motivation here is that performing well on jigsaw puzzles necessitates a thorough comprehension of scenes and objects [42] which is also closely related to semantic segmentation. On the other hand, there is no apparent consensus in the literature on which semi-supervised approach is the most efficient for semantic segmentation. Here we considered the Mean-Teacher and the Co-Teaching approaches, which have been increasingly popular in recent years. Our goal is to investigate their efficacy in the context of semantic segmentation using neural architecture search. Depending on the self-supervised and semi-supervised method, we define $L_{\text{method}}$ as the unsupervised loss related to the considered approach (i.e. $\text{method} \in \{\text{ssl}, \text{ssup}\}$). In all scenarios, the supervised loss $L_s$ is based on an individual loss $\ell_d$ defined as the cross-entropy or the OHEM [53] loss, depending on the dataset.

3.1 Self-supervised regularization

For the self-supervised learning method, a geometric transformation is applied to the inputs for the pretext task, and a label is generated. For each labeled training example, $(x_l, y_l) \in D_\ell$ this transformation on the input $x_l$ acts as an augmentation and the same transformation is applied on $y_l$. For an unlabeled example $x_u \in D_u$, the label produced by the transformation, $y_u$, is used as the ground truth with respect to the pretext task. As proposed in [42], the key idea of the jigsaw pretext task is to learn visual representations for puzzles solving. In practice, this task consists in cutting images in 9 patches from a grid of $3 \times 3$. The patches are then mixed using specified random permutations, and the network is trained to predict the permutation in question in order to solve the problem. The suggested self-supervised learning strategy is depicted in Figure 1. Along with the supervised semantic segmentation problem, one or more distinct pretext tasks can be considered in this framework. In addition, unlike other state-of-the-art approaches, just one network is employed, and the perturbation is applied to the input via geometric transformation.

In our experiments, we followed a similar approach to [8], by training the network in a multitask manner, where a supervised loss ($L_s$) is minimized along
Figure 1: Illustration of the self-supervised learning strategy, \( x_u \) is an unlabeled sample and \((x_l, y_l)\) is a labeled training example. The label \( y_j^{l\text{jig}} \) is the transformed version of \( y_l \), where \( j\text{ig} \) is the id of the applied jigsaw permutation, \((p_l)_1 \leq i \leq m\) are predictions for the supervised semantic segmentation task, \( p_j^{l\text{jig}} \) and \( p_j^{u\text{jig}} \) are the prediction for the pretext task.

a self-supervised loss \( (L_u^{ssl}) \) that acts as a regularizer. In this case, for a given permutation \( j\text{ig} \in \{1, \ldots, k\} \) where \( k \) is the total number of considered permutations; the problem of jigsaw solving can be formulated as a classification task using the produced pretext labels for both labeled \((y_j^{l\text{jig}})_1 \leq i \leq m\) and unlabeled training samples \((y_j^{u\text{jig}})_1 \leq u \leq n\). The self-supervised loss function is in this case, the average cross-entropy loss:

\[
L_u^{ssl} = \frac{1}{k} \sum_{j\text{ig}=1}^{k} \left( \frac{1}{m} \sum_{D_l} \ell_{ce}(p_j^{l\text{jig}}, y_j^{l\text{jig}}) + \frac{1}{n} \sum_{D_u} \ell_{ce}(p_j^{u\text{jig}}, y_j^{u\text{jig}}) \right)
\]

where \( \ell_{ce}(.) \) is the individual cross-entropy loss function. In all of ours experiments, we used a fixed set of \( k = 100 \) permutations, as in [42]. For the supervised loss, we consider the average cross-entropy for the supervised semantic segmentation task over the labeled training set:

\[
L_s = \frac{1}{m} \sum_{D_l} \ell_{d}(p_l, y_l),
\]

3.2 Semi-supervised Mean Teacher method

The mean-teacher method was developed for semi-supervised classification [55] under the self-training paradigm [2]. The approach has lately been adapted to semi-supervised semantic segmentation [22].

This approach is based on consistency regularization that constraints a model to have the same output for a given input. The underlying model is made of two neural networks of the same structure, one denoted as student, \( f(\theta) \), and the other called teacher, \( f(\overline{\theta}) \), where \( \overline{\theta} \) denote the exponential moving average
(i.e. EMA) of the parameters of the student, and are iteratively computed as:
\[ \tilde{\theta}_{t+1} = \alpha \theta_t + (1 - \alpha) \theta_t, \]
with \( \alpha \) a hyperparameter used to control the dependency between the two networks. In this method, only the student is trained using the labeled training set and the predictions of the teacher. Let \( (p^t_l)_1 \leq l \leq m \) and \( (p^t_l)_1 \leq l \leq m \) be the outputs predicted by the student and teacher networks on labeled examples; and, \( (p^s_u)_1 \leq u \leq n \) and \( (p^t_u)_1 \leq u \leq n \) predictions of both networks on unlabeled samples. The consistency regularization is achieved by restricting the distribution outputs of both networks to be as close to each other as possible on labeled and unlabeled samples provided as inputs to both models; and that by minimizing the following unlabeled loss by the student:
\[ L^{sup-mt}_u = \frac{1}{m} \sum_{l \in D_l} \ell_{MSE}(p^t_l, p^s_l) + \frac{1}{n} \sum_{u \in D_u} \ell_{MSE}(p^t_u, p^s_u) \]
where \( \ell_{MSE} \) is the Mean-Square Error summed up over all pixels and classes.

The supervised loss of the student is based on the teacher outputs and the ground truth of the labeled training examples:
\[ L_s = \frac{1}{m} \sum_{l \in D_l} \ell_d(p^t_l, y_l), \]

Figure 2 illustrates this strategy. At the beginning, both networks have the same initial weights. At each iteration, the parameters of the student are first

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Figure 2: Illustration of mean teacher process. \( p^t_l, p^s_l \) and \( p^t_u, p^s_u \) are predictions for labeled and unlabeled samples, by the student and the teacher, respectively. The EMA arrow stand for exponential moving average of weights from the student to the teacher.
updated by minimizing both the supervised and unsupervised losses; then the parameters of the teacher are updated by EMA (2). Following [22], we fixed $\alpha$ to 0.99 in our experiments.

3.3 Semi-supervised co-teaching method

This method is based on self-training [2] and it is well-known in the deep learning community, and it has been widely used in different problems, including semantic segmentation [14]. Similarly to the mean teacher approach, co-teaching uses two networks of the same architecture (e.g. $f(\theta_a)$, $f(\theta_b)$). However, differently from the previous approach, here the two networks update their weights and are independently trained. The main idea is that each network can learn from the other one. Formally, given an unlabeled input $x_u$, each network, i.e. $f(\theta_a)$ and $f(\theta_b)$, predicts an output $p_a^u$ and $p_b^u$. Then by one-hot encoding, these outputs are transformed to pseudo-labels: $\tilde{y}_a^u$ and $\tilde{y}_b^u$; which serve as ground truth for the other network, and the definition of a cross-pseudo supervision loss over the unlabeled data:

$$L_{cps}^u = \frac{1}{n} \sum_{D_u} (\ell_{ce}(p_a^u, \tilde{y}_b^u) + \ell_{ce}(p_b^u, \tilde{y}_a^u)), \quad (5)$$

Similarly to $L_{cps}^u$, a cross-pseudo supervision loss $L_{cps}^l$ can be defined on the examples in $D_l$ and the unsupervised loss is defined as the sum of these two

![Figure 3: Illustration of the co-teaching workflow, where $x_u$ is an unlabeled sample, $(x_l, y_l)$ is a pair of labeled samples. The terms $p_l^a, p_l^b$ and $p_u^b, p_u^a$ are predictions for labeled and unlabeled samples of the Model A and B respectively. $\tilde{y}_l^a, \tilde{y}_l^b, \tilde{y}_u^a, \tilde{y}_u^b$ are the associated pseudo-labels obtained with one-hot encoding.](image)
losses:

\[ L_{sup}^{ct} = L_{sup}^{ps} + L_{sup}^{ps} \]  \hspace{1cm} (6)

The supervised loss that is used for the training of both networks is defined as:

\[ L_s = \frac{1}{m} \sum_{d_l} (\ell_d(p^a_l, y_l) + \ell_d(p^b_l, y_l)) \]  \hspace{1cm} (7)

Figure 3 illustrates the whole process of co-teaching. In our setup both models, \( f(\theta_a) \) and \( f(\theta_b) \), are dynamic, and their weights are found independently one from the other.

4 SELENE: Self sEmi-supervised LEarning with NEural Architecture Search

This section presents our self-supervised semi-supervised learning approach for semantic segmentation based on Neural Architecture Search, that we call SELENE.

4.1 SELENE learning scheme

Our learning problem for semantic segmentation is to jointly find an optimized architecture of a neural network and its parameters, \( \theta \), that minimize the weighted sum of a supervised loss, \( L_s \); and two unsupervised losses defined from self-supervision, \( L_{ssl} \), and semi-supervised learning \( L_{ssup} \):

\[ L_{total} = \lambda_0 L_s + \lambda_1 L_{ssl} + \lambda_2 L_{ssup} \]  \hspace{1cm} (8)

This idea is based on the premise that for the difficult task of scene analysis, which is highly dependent on context, it is required to use a specific model to leverage low and high-level information from the data. The low-level information here are the associations between the pixels of an image and their classes, which are present in the labeled training set. The high-level information is recovered from the unlabeled training data by first resolving the auxiliary jigsaw pretext task using self-supervised learning and then using semi-supervised learning to exploit the structure of the unlabeled data. The pseudocode of SELENE is depicted in Algorithm 1. The neural architecture search is performed using the Dynamic Routing approach presented in the next section. First, the routing path is arbitrarily set, and model weights are initialized using imageNet pre-trained weights and Kaiming initialization (Section 5.2). At each epoch \( e \), defined as the largest size between the labeled and the unlabeled training sets, two batches of data; \( B_l \) and \( B_u \); are randomly extracted from these two sets. Unlabeled losses; \( L_{ssl} \) and \( L_{ssup} \), are then set using the self-supervised regularization and the semi-supervised method with the current neural network’s predictions as presented in Section 3. A new routing path and weights are then found by minimizing the total loss, \( L_{total} \) (8).
Algorithm 1: Pseudo-code of SELENE

**Input:** \( \mathcal{D}_u, \mathcal{D}_\ell, E: \) epochs, \( M: \) method, \( \lambda_0, \lambda_1, \lambda_2: \) losses weights

1. \( N \leftarrow \max(|\mathcal{D}_u|, |\mathcal{D}_\ell|) \)
   
   /* The Dynamic routing structure (Sect. 4.2) is used to set up the initial architecture. */

2. \( f_\theta \leftarrow \text{DR\_structure()} \)
   
   /* Initialization of the weights */

3. \( f_{\theta_0} \leftarrow \text{init()} \)

4. for \( e \in \text{range}(0, E) \) do

5.   for \( i \in \text{range}(0, N) \) do

6.     \( t \leftarrow i + e \)
   
   /* Get batch of labeled samples */

7.     \( \mathcal{B}_\ell \leftarrow \mathcal{D}_\ell \)
   
   /* Get batch of unlabeled samples */

8.     \( \mathcal{B}_u \leftarrow \mathcal{D}_u \)

9.     \( \mathcal{L}_{ssl}, \mathcal{L}_{sup} \leftarrow M(\mathcal{B}_l, \mathcal{B}_u, f_{\theta_0}) \)

10. \( \mathcal{L}_{\text{total}} \leftarrow \lambda_0 L_s + \lambda_1 L_{ssl} + \lambda_2 L_{sup} \)

11. \( f_{\theta_{t+1}} \leftarrow \text{DR\_optimize}(f_{\theta_t}, \mathcal{L}_{\text{total}}) \)

end

**Output:** \( f_\theta^\ast: \) Network with trained weights after \( E \) epochs

4.2 Architecture Search with Dynamic Routing

Dynamic networks have exhibited superiority in network capacity and greater performance with budgeted resource use, by fitting the model’s architecture to the input data. Among different approaches, dynamic routing [34], on which we base our routing algorithm, has the advantage of allowing the transfer of weights from a prior training, that has become more essential in terms of time savings.

In our approach, the routing space (or structure) noted \( f_\theta \), is defined as a 4-level network with \( L \) layers composed of cells (Figure 4). Each level in this structure represents a stride rate, where the size of the input is successively reduced by descending in the network. The strides rates are thus \( 1/4 \) for the highest level and \( 1/32 \) for the deepest one. Depending on whether the level is greater or lower, the image ratio is then lowered or raised by \( 2 \). The path through the levels is performed by a convolution with a kernel size of \( 1 \), while the size is reduced, the convolution increases the number of feature map by \( 2 \).

For the initialization of the dynamic structure, we set a fixed 3-layer block 'STEM' (green cell in Figure 4), used to reduce the resolution of the input to \( 1/4 \). Note that in this block, separated convolution are used. At the end, we find a simple decoder (red cells in Figure 4), which go from bottom to top of the levels. This decoder is just a composition of convolution and upsampling operations in order to add the features of each level. Once added, the features
Figure 4: Illustration of the dynamic routing structure. This structure is composed of a part called 'STEM', the green cell, and a decoder, the red cells. The blue cells part is the encoder, each cell contains two operations a **Separable convolution 3x3** and an **Identity**.

go through a last classification layer. Concerning the cells aspect (blue cells in Figure 4), each cell is made up of two operations, which are here a separable convolution with a kernel of 3 and an identity operation. The choice of the identity operation will result in the creation of a skip-connection. The choice of the path in this structure, the choice of the cell operations and the parameters of each operation are all optimized using the gradient descent algorithm.

5 Experiments

We ran a series of experiments to study how the combination of self-supervised and semi-supervised learning with NAS can help to take advantage of unlabeled training data to construct an efficient NN for semantic segmentation.

5.1 Datasets

**Pascal VOC 2012** The Pascal VOC dataset [19], which contains 20 object classes and one background category, is a widely used dataset in object semantic segmentation. The original dataset contains almost 13000 images, including 1464 images for training, 1449 for validation, and 1456 for testing as standard splits. We employ the augmented version provided by [25] as a standard base for our work, raising the total number of usable images for training to 10582.

**Cityscapes** The Cityscapes dataset [15] is frequently utilized, mostly in the context of analyzing urban scenes. The collection contains 5000 finely annotated images, each with a per-pixel label from one of 19 semantic classes. There are 2975 images for training, 500 for validation, and 1525 for testing in the splits provided, with each image having a resolution of 1024x2048. Following other studies, we solely use the training and validation sets in our experiments.
There is also a part known as coarse, which contains 20,000 images with coarse annotations; not used in our experiments.

5.2 Experimental setup

For both datasets, similar data augmentation to [14, 34] have been used. Random scaling, followed by random horizontal flipping, and random square cropping have been applied as augmentation. The scaling factor was taking values in \( \{0.5, 0.75, 1, 1.25, 1.5, 2.0\} \), and the crop size ranges from 800 for Cityscapes and 512 for Pascal VOC, with padding, and an ignored value if necessary. We set the hyperparameter of the supervised loss in (8); \( \lambda_0 = 1 \) in all of our experiments.

To investigate the effects of semi-supervised and self-supervised settings on the learning of parameters, we respectively set the corresponding hyperparameters; \( \lambda_1 \) and \( \lambda_2 \); in (8) to 0. These scenarios will be presented in the next section. We deploy an extra classifier for the pretext task in the self-supervised experiments. Accordingly, the dynamic routing output is taken in the other direction (from top to bottom in Figure 4). Then, before the fully connected layer, we apply global average pooling to the features.

Concerning technical aspects, SELENE is implemented using PyTorch [47] library, and trained using Nvidia GPUs. The encoder of the network (i.e. blue dots in Figure 4) is initialized by the ImageNet pre-trained weights, provided by [34], while the others weights (i.e. red and green dots in Figure 4) are initialized using Kaiming initialization [27]. For parameter updates, we used a standard mini-batch SGD with momentum of 0.9, with an initial learning rate of 0.02. In addition, we adopt a polynomial learning rate decay with a power of 0.9. The training batch size is 8 for Cityscapes and 16 for Pascal VOC. Concerning the dynamic routing structure, we follow [34] and set \( L = 16 \).

Finally, results are reported on the full validation set for each dataset (500 for Cityscapes, 1449 for Pascal VOC) using the standard mean Intersection-over-Union (mIoU) metric [51]. In all of our experiments, we use single scale testing with no augmentation.

5.3 Experimental results

In this section, we present the experimental results obtained by SELENE under various settings. For all the experiments, we use the same partitions as proposed in [14].

5.3.1 Self-supervised regularization

We begin by examining the obtained gain by performing the jigsaw pretext problem discovered by self-supervised learning (Section 3.1) simultaneously with the pixel classification task for semantic segmentation. In this scenario, the corresponding hyperparameter of self-supervised learning in (8); \( \lambda_1 \) was set to 0.1; and; we disabled the effect of semi-supervised learning by setting the hyperparameter \( \lambda_2 \) to 0. The corresponding model is denoted by \( \text{SELENE}_{\lambda=0} \) and
it is compared to the fully supervised setting, in which no self-supervised nor semi-supervised learning is utilized. In the following, $\text{SELENE}_{\lambda_1=0}$, stands for the fully supervised model. Table 1 summarizes results obtained for different fraction of the labeled training set on PASCAL VOC. The highest performance rates are indicated in boldface. It turns out that the pretext task effectively adds information to semantic segmentation, although the benefits are limited. This could be due to the fact that images are cut using a $3 \times 3$ grid for puzzle solving, and the resolution of the jigsaw problem may introduce noise into the pixel classification, particularly where puzzle pieces are cut.

| Fraction of the labeled training set | $\frac{1}{16}$ | $\frac{1}{8}$ | $\frac{1}{4}$ | $\frac{1}{2}$ |
|--------------------------------------|---------------|---------------|---------------|---------------|
| $\text{SELENE}_{\lambda_1=0}$       | 53.33         | 59.45         | 65.21         | 69.02         |
| $\text{SELENE}_{\lambda_2=0}$       | 53.80         | 60.33         | 65.25         | 69.27         |

Table 1: mIoU of $\text{SELENE}_{\lambda_1=0}$ and $\text{SELENE}_{\lambda_2=0}$ obtained on validation set of PASCAL VOC for different fractions of the labeled training set.

### 5.3.2 Semi-supervised learning

We now investigate the effect of semi-supervised learning alone by setting $\lambda_1$ to 0. The resulting model is referred to as $\text{SELENE}_{\lambda_1=0}$ in the following. By setting $\lambda_1$ to 0, we hence disable the associated geometric transformation. As semi-supervised techniques, we employed Mean Teacher (Section 3.2) and Co-teaching (Section 3.3) techniques with the aim of analyzing the outcome of their underlying assumption in the behavior of $\text{SELENE}$. For the Mean teacher method, the hyperparameter $\lambda_2$ (8) was empirically set to 100; and in the case of
Table 2: mIoU of $\text{SELENE}_{\lambda=0}$ and DeeplabV3+ [14] obtained on Cityscapes validation set, using different fractions of the labeled training set with Mean-teacher (top) and co-training (down) approaches. Best results are shown in bold.

| Fraction of the labeled training set | $\frac{1}{16}$ | $\frac{1}{8}$ | $\frac{1}{4}$ | $\frac{1}{2}$ |
|-------------------------------------|----------------|----------------|----------------|----------------|
| **Mean teacher**                    |                |                |                |                |
| $\text{SELENE}_{\lambda=0}$        | 67.54          | 72.60          | 75.28          | 77.74          |
| DeeplabV3+                          | 66.14          | 72.03          | 74.47          | 77.43          |
| **Co-teaching**                     |                |                |                |                |
| $\text{SELENE}_{\lambda=0}$        | 68.30          | 73.10          | 75.58          | 78.30          |
| DeeplabV3+                          | 69.79          | 74.39          | 76.85          | 78.64          |

Table 3: mIoU of $\text{SELENE}_{\lambda=0}$ and DeeplabV3+ obtained on Pascal VOC validation set. Best results are shown in bold.

| Fraction of the labeled training set | $\frac{1}{16}$ | $\frac{1}{8}$ | $\frac{1}{4}$ | $\frac{1}{2}$ |
|-------------------------------------|----------------|----------------|----------------|----------------|
| **Mean teacher**                    |                |                |                |                |
| $\text{SELENE}_{\lambda=0}$        | 65.05          | 68.64          | 72.19          | 73.95          |
| DeeplabV3+                          | 64.72          | 68.12          | 71.41          | 72.97          |
| **Co-teaching**                     |                |                |                |                |
| $\text{SELENE}_{\lambda=0}$        | 60.67          | 64.02          | 69.91          | 71.23          |
| DeeplabV3+                          | 64.13          | 69.52          | 71.77          | 74.11          |

Co-teaching, $\lambda_2$ was set to 5 for Cityscapes and in a range between 0.5 to 1.5 for Pascal VOC. Tables 2 and 3 show the results for different fractions of the labeled training sets of the Cityscapes and Pascal VOC datasets, respectively. For comparison, we report the performance of DeepLabV3+ [13] based on ResNet-50, which employs a hand-crafted encoder-decoder structure. On both datasets, $\text{SELENE}_{\lambda=0}$ performs better than DeeplabV3+ with the Mean Teacher strategy for all fractions of the labeled training set. We believe that this is because, with the Co-Training approach, the noise introduced when each of the classifiers assigns pseudo-labels to unlabeled examples has a snowball effect, reinforcing the predictions of the models in these errors and leading to an erroneous final model. Some approaches considered noise-label modelling jointly with the prediction function [31]. On the other hand, Mean Teacher is based on the consistency regularization with the only constraint that the outputs of the student and the teacher networks on the same unlabeled examples should be as close as possible. In this case, there is no label-noise propagation and, with this approach, $\text{SELENE}$
| Fraction of the labeled training set | $\frac{1}{16}$ | $\frac{1}{8}$ | $\frac{1}{4}$ | $\frac{1}{2}$ |
|-------------------------------------|----------------|--------------|--------------|--------------|
| SELENEM$_1$ = $\lambda_2 = 0$      | 53.33          | 59.45        | 65.21        | 69.02        |
| SELENEM$_2$ = $\lambda_2 = 0$      | 53.80          | 60.33        | 65.25        | 69.27        |
| SELENEM$_1$ = $\lambda_1 = 0$      | 65.05          | 68.64        | 72.19        | 73.95        |
| SELENE                            | **65.32**      | **68.96**    | **72.49**    | **74.47**    |

Table 4: mIoU of SELENE and its variants obtained on the validation set of PASCAL VOC.

is able to leverage the lack of label information by exploiting more efficiently the structure of the data using the unlabeled training set. These results are consistent with those of Figure 5 which depicts the evolution of mIoU with respect to the percentage of labeled training set for the training of DeepLabV3+ [13], and SELENE$_{\lambda_1 = 0}$ on Pascal VOC and Cityscapes using the Co-Teaching technique.

![Figure 6](image_url)

Figure 6: Comparison in terms of FLOPs(G) between SELENE and DeeplabV3+ on Pascal VOC and Cityscapes datasets.
5.3.3 Self-supervised and Semi-supervised learning

Finally, in Table 4 we compare the performance of SELENE with self-supervised and semi-supervised learning using the Mean-Teacher technique to its other versions discussed above on the Pascal VOC dataset. The pretext task has also here a limited benefit on semi-supervised learning, comforting the idea that, while complementing, puzzle solving and pixel classification are not totally correlated. In Figure 6, we compare DeeplabV3+ and SELENE with the co-teaching approach in terms of floating-point operations. It comes out that SELENE use up to 4 times less floating-point operations with respect to this measure than the neural-network with the hand-crafted architecture.

6 Summary & Outlook

In this study, we proposed a self-supervised semi-supervised learning approach with Neural Architecture Search for semantic segmentation. We showed on Pascal VOC and Cityscapes datasets that by jointly solving a jigsaw pretext task discovered using self-learning over unlabeled training data and leveraging the structure of the unlabeled data with Co-Teaching, our approach finds an efficient neural network model for this task. Concerning the limitations of our study, we can include the fact that we study only a single self-supervised task, which could not relate the full potential of the self-supervised regularization. Another point, could be the proposed framework is sensitive to the choice of techniques used, which are not all equally efficient, as well as the number of data point used which in some cases can pose performance problems. This work opens up new perspectives, including the hyperparameters tuning with some dedicated techniques [20][33]. Moreover, we found that combining self-supervised and semi-supervised learning is promising, and that alternative self-supervised learning strategies, such as rotation [23] or the more recent contrastive technique [26, 9] should be investigated for semantic segmentation. Another point could also be the potential improvement of the decoder by using a spatial pooling module (e.g. PSP[61], ASPP[12]), as in [34].

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