Discovering Latent Classes for Semi-Supervised Semantic Segmentation

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Abstract

High annotation costs are a major bottle neck for the training of semantic segmentation systems. Therefore, methods working with less annotation effort are of special interest. This paper studies the problem of semi-supervised semantic segmentation. This means that only a small subset of the training images is annotated while the other training images do not contain any annotation. In order to leverage the information present in the unlabeled images, we propose to learn a second task that is related to semantic segmentation but easier. On labeled images, we learn latent classes consistent with semantic classes so that the variety of semantic classes assigned to a latent class is as low as possible. On unlabeled images, we predict a probability map for latent classes and use it as a supervision signal to learn semantic segmentation. The latent classes as well as the semantic classes are simultaneously predicted by a two branch network. In our experiments on Pascal VOC and Cityscapes we show that the latent classes learned this way have an intuitive meaning and that the proposed method achieves state of the art results for semi-supervised semantic segmentation.

1. Introduction

In recent years, deep convolutional neural networks (DCNNs) have achieved astonishing performance for the task of the semantic segmentation. However, to achieve good results, DCNN-based methods require an enormous amount of high-quality annotated training data, acquiring which takes a lot of effort and time. This problem is especially acute for the task of semantic segmentation, due to the need of per-pixel labels for every training image. To mitigate the annotation expenses, Hung et al. [14] proposed a semi-supervised algorithm that employs images without annotation during training. On labeled data, the authors train a discriminator network which distinguishes segmentation predictions and ground truth annotations. On unlabeled data, they use the discriminator to obtain two kinds of supervision signals. First, they use the adversarial loss to enforce realism in the predictions. And second, they use the discriminator to locate regions of sufficient realism in the prediction. These regions are then annotated by the semantic class with highest probability. The network for semantic segmentation is then trained on the labeled images and the estimated regions of the unlabeled images. Although the ap-
proach reported impressive results for semi-supervised segmentation, it does not leverage the entire information which is present in the unlabeled images since it discards large parts of the images.

In this work, we propose an approach for semi-supervised semantic segmentation that does not discard any information. Our key observation is that the difficulty of semantic segmentation depends on the definition of the semantic classes. This means that the task can be simplified if some classes are grouped together or if the classes are defined in a different way, which is more consistent with the similarity of the instances in the feature space. We therefore do not focus on regions where the semantic classes can be detected with high confidence, but we propose to learn latent classes that can be reliably inferred for the entire unlabeled training images as illustrated in Figure 1.

Our network consists of two branches and is trained on labeled and unlabeled images jointly in an end-to-end fashion as illustrated in Figure 2. While the semantic branch learns to infer the given semantic classes, the latent branch learns the most helpful latent classes for semi-supervised learning by itself. While the number of latent classes can differ from the number of semantic classes, we use the conditional entropy to enforce the consistency between latent classes and semantic classes. This means that we aim to minimize the variety of semantic classes that are assigned to a latent class. While the conditional entropy is used to learn the latent classes, we use a second loss that ensures that the inferred semantic classes on the unlabeled images are consistent with the inferred latent classes. Using this loss, we use the latent classes as additional supervision for the semantic branch.

We demonstrate that our model achieves state of the art results on PASCAL VOC 2012 [8] and Cityscapes [6]. Moreover, our proposed branched architecture of the segmentation network results in increased interpretability of the results. We show that the latent classes predicted by the latent branch correspond to super-categories of semantic classes as illustrated in Figure 1. Additionally, we show that the learned latent classes are superior to manually defined super-categories.

2. Related work

Expensive acquisition of pixel wise annotated image ground truth was recognized as a major bottle neck for the training of deep semantic segmentation models. Consequently, the community sought ways to reduce amount of annotated images while loosing as less performance as possible.

Weakly supervised semantic segmentation methods learn to segment images from cheaper image annotations, i.e. pixel wise labels are exchanged for cheaper annotations for all the images in the training set. The proposed types of annotations include bounding boxes [30, 16, 24, 40], scribbles [26, 41, 42] or human annotated keypoints were used in [2].

Image level class tags have attracted a special attention. A minority of works in this area first detect potential object regions and then identify the object class using the class tags [31, 33, 9].

However the majority of approaches use class activation maps (CAMs) [48] to initially locate the classes of interest. Pinheiro et al. [32, 39] pioneered in this area and a huge number of improvements followed [18, 44, 13, 45, 12, 1, 29, 4, 36, 46, 43, 3, 42, 10]. A few works leveraged additional data available on the Internet, for example [11, 15, 21] use videos. While the works mentioned above mainly focus on refining the localisation cues obtained from the CAM, recently the task of improving the CAM itself received attention [23, 20, 21].

Some of the works mentioned above consider a setup where a part of the images had pixel wise annotations. They were used to train in a fully supervised setup, while the weakly supervised method was applied to the remaining images with cheap annotations. Papandreou et al. [30] was a pioneering work in applying deep learning to this area. It is an expectation maximization based approach, modelling the pixel level labels as hidden variables and the image labels or bounding boxes as the visible ones. Lee et al. [20] introduce a sophisticated dropout method to obtain better class activation maps on unlabeled images. Earlier, Li et al. [23] improved the CAMs by automatically erasing the most discriminative parts of an object. Wei et al. [46] examine what improvement in CAMs can be achieved by dilated convolution engineering. Different to previous approaches, Zilong et al. [13] do not improve the CAM but focus on refining high confidence regions obtained from the CAM by deep seeded region growing.

The setting without any supervision cues on unlabeled images was so far only addressed by [14]. They use a discriminator network to supervise the predictions on unlabeled data. Additionally, the discriminator indicates the regions with high segmentation confidence, which the authors then incorporate into their custom loss. This work is the one most related to ours, since we use the same supervision setting. The idea to learn an easier auxiliary task as an intermediate step was exploited in the area of domain adaptation for semantic segmentation [47, 7, 19, 38, 25]. However, to our knowledge, we are the first to use simpler auxiliary tasks as an intermediate step in semi supervised semantic segmentation.

The idea to discover clusters in data with latent classes to facilitate learning was already used in object detection [34, 49], joint object detection and pose estimation [22] and weakly supervised video segmentation [35]. However apart from addressing a different vision task, these approaches
discover subcategories of classes while we look for suitable super categories.

3. Method

An overview of our method is given in Figure 2. Our proposed model is a two branch network. While the semantic branch serves to solve the final task, the purpose of the latent branch is to learn latent classes consistent with semantic classes. We consider latent classes consistent with semantic classes, if the variety of possible semantic classes given a latent class is as low as possible. Essentially, the latent branch learns to subdivide the semantic classes into super categories as fine grained as possible. While the fraction of annotated data is not sufficient to solve the task of semantic segmentation well, it is still enough to learn the prediction of latent classes reasonably well, since this is easier. Thus, the predictions of the latent branch can then serve as a supervision signal for the latent branch on unlabeled data.

The branches share a common backbone which can be any network for visual inference. In our case we use a single scale Deeplab Resnet [5] model up to the last feature layer. The last feature map serves as input to two parallel convolutional layers. One of the is the latent branch, the other the semantic branch, their output are the latent class segmentation prediction and the semantic class segmentation prediction respectively. For further details on our architecture, see Section 4.1.

On labeled data we use the cross entropy loss \( L_{ce} \) to supervise the semantic branch and the latent loss \( L_{latent} \) to supervise the latent branch. On unlabeled data, we measure the consistency of the latent and semantic branch using a consistency loss \( L_{cons} \). For labeled as well as unlabeled data, we refine the predictions of the semantic branch with a discriminator network which is trained to distinguish ground truth segmentation maps from predictions.

We elaborate our method in more detail below.

3.1. Training on labeled data

The latent classes \( l \in L \) have to provide as much information about semantic classes \( c \in C \) as possible. Consequently, we want to enforce a consistent assignment of semantic classes to latent classes and reduce the variety of semantic classes assigned to a latent class. To this end, we use the conditional entropy of semantic classes given the latent class as a loss term to train the latent branch:

\[
L_{latent} = - \sum_{l \in L} \sum_{c \in C} P_l(l,c) \log(P_b(c|l))
\]

The index \( b \) denotes that the probability is calculated batch wise. We first estimate the joint probability:

\[
P_b(c,l) = \frac{1}{NHW} \sum_{n,h,w} S_l(n,h,w,l) Y_n^{(h,w,c)}
\]

where \( H \) is image height, \( W \) is the image width, \( N \) is the number images in the batch, \( X_n \in \mathbb{R}^{H \times W \times 3} \) is the image, \( S_l \) is the predicted probability of the latent classes and \( Y_n \in \mathbb{R}^{H \times W \times |C|} \) is the ground truth for semantic classes. From this, we obtain \( P(c|l) \)

\[
p(c|l) = \frac{p(c,l)}{\sum_c p(c,l)}
\]

Obtaining the conditional entropy from multiple batches is in principle desirable but requires the storage of feature maps from multiple batches. Therefore we compute it per batch.

The semantic branch \( S_c \) is optimized with the cross entropy loss.

\[
L_{ce} = - \sum_{l,w,n} \sum_{c \in C} Y_n^{(h,w,c)} \log(S_c(X_n)^{(h,w,c)})
\]

To enforce realism in the semantic predictions, we additionally apply an adversarial loss:

\[
L_{adv} = - \sum_{h,w,n} \log(D(S_c(X_n))^{(h,w)})
\]

Details on our discriminator network are given in Section 3.3 In summary, on labeled data, our loss comprises three weighted loss terms:

\[
L_{labeled} = L_{ce} + \lambda_{latent} L_{latent} + \lambda_{bl} L_{adv}
\]

3.2. Training on unlabeled data

Figure 3 illustrates our key idea on unlabeled data. To leverage the supervision signal from the latent branch on unlabeled data, we first map the prediction of the semantic branch \( S_{l,c} \) to a probability distribution of latent classes \( S_{l,c} \).

\[
S_{l,c}(X_n)^{(h,w,l)} = \sum_{c \in C} P(l|c) S_c(X_n)^{(h,w,c)}
\]

We estimate \( P(l|c) \) from the predictions of the latent branch on labeled data. We keep track of how often semantic and latent classes co-occur with an exponentially moving average:

\[
M_{c,l}^{i} = (1-\alpha) M_{c,l}^{(i-1)} + \alpha \sum_{h,w,n} Y_n^{(h,w,c)} S_l(X_n)^{(h,w,l)}
\]

where \( i \) denotes the number of the batch. The initialization is \( M_{c,l}^{0} = 0 \). The parameter \( 0 < \alpha < 1 \) controls how fast we update the average. We set \( \alpha \) to the batch size divided by the number of images in the data set. Using the acquired co-occurrence matrix \( M \), \( P(l|c) \) is estimated as:

\[
P(l|c) = \frac{M_{c,l}}{\sum_{k \in L} M_{c,k}}
\]
Figure 2. Overview of the proposed method. Black arrows indicate usage of labeled data, orange arrows the usage of unlabeled data. Solid arrows indicate that the gradient is back propagated. The semantic branch predicts the pixel wise class labels and the latent branch predicts latent classes. On labeled data, the semantic branch is supervised with a cross entropy loss $L_{ce}$, and the latent branch learns latent classes that are consistent with semantic classes using the latent loss $L_{latent}$. On unlabeled data, the output of the latent branch serves as a supervision signal for the semantic branch ($L_{cons}$). Additionally, on labeled as well as unlabeled data, the semantic branch receives adversarial feedback $L_{adv}$ from a discriminator network distinguishing predicted and ground truth segmentations.

Our proposed consistency loss function is the mean cross-entropy between the latent variable maps predicted by the latent branch $S_l$ and the ones constructed based on the prediction of the semantic branch $S_{lc}$.

$$L_{cons} = -\frac{1}{NHW} \sum_{n,h,w,l \in L} S_l(X_n)^{(h,w,l)} \cdot \log(S_{lc}^l(X_n)^{(h,w,l)})$$  \hspace{1cm} (10)

The minimization of this loss forces the semantic branch to predict classes which are assigned to highly probable latent classes. We back propagate the gradient of this loss only to the latent branch.

For the unlabeled data the loss function is the sum of the adversarial loss and the consistency loss.

$$L_{unlabeled} = \lambda_{ulbl adv} L_{adv} + \lambda_{cons} L_{cons}$$ \hspace{1cm} (11)

The adversarial term is the same as for the labeled data in (5).

Figure 3. To compute the consistency loss on the unlabeled data, we first map the semantic class predictions $S_c(X_n)$ to latent class predictions $S_{lc}(X_n)$ (7) with help of the estimated distribution $P(l|c)$ (9). Then we compute the cross entropy loss with $S_{lc}(X_n)$ serving as the predictions and the output of the latent branch $S_l$ as the labels.

3.3. Discriminator network

Our discriminator network $D$ is a fully-convolutional network [28] with 5 layers and leaky-RELU as nonlinearity. It takes label probability maps as input (either from the segmentation network or ground-truth maps) and outputs spatial confidence maps. Each pixel of the output represents the confidence of the discriminator whether the corresponding pixel in a semantic label map was sampled from the ground-truth map or the segmentation prediction. The out-
put of the discriminator network is used to encourage the semantic branch of the segmentation network to produce more ground-truth-like predictions. We train the discriminator network with the help of the spatial cross-entropy loss using both labeled and unlabeled data:

\[
L_D = -\sum_{h,w} (1 - y_n) \log(1 - D(S_c(X_n))^{h,w}) + y_n \log(D(Y_n)^{h,w})
\]

(12)

where \(y_n = 0\) if a sample is drawn from the segmentation network, and \(y_n = 1\) if it is a ground-truth map. By minimizing such a loss, the discriminator learns to distinguish between the generated and the true label probability maps.

4. Experiments

In this section, we present our implementation details, compare our method with the current state of the art, conduct ablation studies and analyze our method in more detail experimentally.

4.1. Implementation details

We implemented our proposed method using the PyTorch framework. For a fair comparison with the current state of the art method [14], we choose the same backbone architecture and keep the same hyper parameters where appropriate.

Being more specific, as our segmentation network we take a single scale ResNet-based DeepLab-v2 [5] architecture that is pre-trained on the ImageNet [37] and MSCOCO [27]. We branch the proposed network at the last layer by applying Atrous Spatial Pyramid Pooling (ASPP) [5] two times to produce two sets of predictions. Finally, we use bilinear upsampling to make the predictions match the initial image size.

For the discriminator network, we use a fully-convolutional network, which contains 5 convolutional layers with kernels of the sizes \(4 \times 4\) and 64, 128, 256, 512, 1 channels, applied with a stride equal to 2. Each convolutional layer, except for the last one, is followed by a LeakyReLU with the leakage coefficient equal to 0.2.

The optimization of the segmentation network is performed using SGD with momentum equal to 0.9 and the learning rate decay of \(10^{-4}\). The learning rate, that is initially equal to \(2.5 \times 10^{-4}\), is decreased with polynomial decay with the power of 0.9. For the discriminator, we employ the Adam optimizer [17], where the initial learning rate is equal to \(10^{-4}\) and that follows the same decay schedule as introduced for the segmentation network.

As for the hyper-parameters of our model, four of them correspond to the factors of the individual loss terms in the final loss functions: \(\lambda_{lb,adv}, \lambda_{ulb,adv}, \lambda_{latent}\) and \(\lambda_{cons}\). We train our final model with \(\lambda_{lb,adv}\) and \(\lambda_{ulb,adv}\) equal to 0.01 and 0.001 respectively, while hyper-parameters \(\lambda_{latent}\) and \(\lambda_{cons}\) are set to 1.0 and 0.1. Another hyper-parameter that we experimented with in our work is the number of latent classes. By default we use 20 latent classes.

At each iteration, we alternately apply the previously described training scheme on the batch of the randomly sampled labeled and unlabeled data. To ensure robustness of the evaluation procedure, we report results averaged over 5 random seeds that control the sampling procedure. We add the consistency loss term only after 5000 iterations since the latent branch needs to learn some useful latent classes first.

We conducted experiments on two data sets for semantic segmentation: Pascal VOC 2012 [8] and Cityscapes [6].

The Pascal VOC 2012 data set contains images with objects from 20 foreground classes and one background class. There are 10528 training and 1449 validation images in total. During the training procedure the images are cropped with crop size equal to \(321 \times 321\) and undergo random scaling and horizontal mirroring. We train our model for 20k iterations with a batch size of 10. The testing of the resulting model is carried out on the validation set.

The Cityscapes data set comprises images extracted from 50 driving scene videos. It contains 2975, 500 and 1525 images in the training, validation and test set, respectively, with annotated objects from 19 categories. During training, we preprocess the images by performing cropping operations with crop size equal to \(505 \times 505\) and also additionally apply random scaling and horizontal mirroring. On the Cityscapes data set our model is trained for 40k iterations with batches of size 2. We report the results of testing the resulting model on the validation set.

As evaluation metric, on both data sets we report mean-intersection-over-union (mIoU).

4.2. Comparison with the state of the art

We follow the semi-supervised learning protocol that was proposed in [14]. This means that 1/8, 1/4 or 1/2 of the training images are annotated and the other images are without any annotations. Note that we also use the same architecture: A single scale ResNet-based DeepLab net.

We report the results on Pascal VOC 2012 and Cityscapes in Table 1 and Table 2 respectively and plot them in Figure 4 and Figure 5. We outperform the previous state of the art on both data sets for all annotated data shares. The improvement is especially pronounced if we look at the performance gap between the respective semi supervised method trained with 1/8 of the data being annotated and training the method on a fully annotated train set. For the method of [14], the relative performance as compared to the fully supervised setup on Pascal VOC 2012 is 92.8% while for ours it is 95.1%. On Cityscapes, the relative performance for [14] is 86.9% while for ours it is 95.5%. Some qualitative results are shown in Figure 8 and Figure 9.
Table 1. Comparison to the state of the art on Pascal VOC. Both methods use the same single scale ResNet-based Deeplab architecture. We report the mean IoU and the relative performance compared to fully supervised learning.

| method          | fraction of annotated images | mIoU         |
|-----------------|-----------------------------|--------------|
|                 | 1/8 | 1/4 | 1/2 | full |
| [14]            | 69.5% | 72.1% | 73.8% | 74.9% |
| proposed        | 71.3% | 72.4% | 73.9% | 75.0% |

| method          | relative performance          |              |
|-----------------|-------------------------------|--------------|
|                 |                               |              |
| [14]            | 92.8% | 96.3% | 98.5% | 100.0% |
| proposed        | 95.1% | 96.5% | 98.5% | 100.0% |

Table 2. Comparison to the state of the art on Cityscapes. Both methods use the same single scale ResNet-based Deeplab architecture. We report the mean IoU and the relative performance compared to fully supervised learning. Note that despite [14] gives better numbers in the fully supervised setting, our method performs better on all fractions of annotated images due to a far smaller relative gap between the performance on a partially annotated training set and a fully supervised setup.

| method          | fraction of annotated images | mIoU         |
|-----------------|-----------------------------|--------------|
|                 | 1/8 | 1/4 | 1/2 | full |
| [14]            | 58.8% | 62.3% | 65.7% | 67.7% |
| proposed        | 63.3% | 65.4% | 66.1% | 66.3% |

| method          | relative performance          |              |
|-----------------|-------------------------------|--------------|
|                 |                               |              |
| [14]            | 86.9% | 92.0% | 97.0% | 100.0% |
| proposed        | 95.5% | 98.6% | 99.7% | 100.0% |

Figure 4. Comparison between our method and the current state of the art [14] on Pascal VOC. We plot the performance for training with different fractions of annotated data. Note that the performance gap between training on 1/8 of the annotations being available and a fully annotated train set is significantly smaller in our case.

4.3. Ablation experiments

In our ablation experiments, we first isolate the contribution of the latent classes as well as the adversarial signal. Then we examine what the latent classes are learning and show that they truly form meaningful super categories of the semantic classes. Finally we show that the same performance can not be achieved with human defined super categories.

4.3.1 Analyzing the components

Our baseline is training the semantic branch on 1/8 of the data using the cross entropy loss only. To isolate the effect of latent classes, we add the latent and semantic loss to this baseline. As can be seen from Table 3, the performance grows by 3.2% from 64.1% to 67.3%. Adding the adversarial loss on labeled data as well as unlabeled data gives an additional improvement of 4.0% which yields us the final performance of 71.3%. Figure 8 shows the effect of the additional supervision signals. On Pascal VOC, there is a dominant background class. The latent variables help to discover foreground objects which otherwise would be assigned to the background class. Grouping semantic categories into latent classes alleviates the class imbalance. The adversarial signal further refines the predictions.

4.3.2 Interpretation of latent classes

We evaluate the performance for different number of latent classes. We do it for 2, 4, 6, 10, 20 and 50 latent classes on Pascal VOC with 1/8 of the data being labeled. The results
The distribution is pretty sparse, essentially the latent classes form super categories of Pascal classes with similar appearance. Some of the 20 latent classes are idle while all 10 latent classes get used.

In the same table we report the number of effective latent classes. We consider a latent class \( l \) to be effectively used at threshold \( t \), if \( P(l|c) \) for some semantic class \( c \). We report this number for \( t = 0.1 \) and \( t = 0.9 \). The number of effective latent classes differs only slightly for these 2 thresholds. This shows that a latent class typically either constitutes a super category of at least one semantic class or is not used at all. The number of effective classes saturates at 14 for 20 and 50 available latent classes. To see if a semantic class is typically mapped to a single latent class, we plot \( P(l|c) \) for inference on Pascal VOC as well as on Cityscapes and show the results in Figures 6 and 7, respectively. Indeed, the mapping from semantic classes to latent classes is very sparse. Typically, for each semantic class \( c \), there is one dominant latent class \( l \), i.e., \( P(l|c) > t \). If the number of latent classes increases to 20, some of the latent classes are not used. Qualitatively, the latent branch groups the semantic classes into super categories based on similar appearance. For example on Cityscapes for 20 latent classes, the super categories are (pole+traffic light+traffic sign), (person+rider+motorcycle+bicycle), (wall+fence), (truck+bus+train).

### 4.3.3 Justification of latent variables

Since the latent classes typically learn super categories of the semantic classes, the question rises if the same effect can be achieved with manually defined super categories. In this experiment, the latent classes are replaced with 10 super categories (we report the assignment to the super categories in the supplementary material). For labeled data, the latent branch is trained to predict these super categories using the cross entropy loss. For unlabeled data, everything remains the same as for the proposed method. We report the results in Table 5. The performance using the super categories is only 69.0% which is significantly below the proposed method for 10 latent variables.

Another approach would be to learn all semantic classes instead of the latent classes or super categories in the latent branch. This gives 68.5%, which is also far worse than the proposed method.

Finally, we compare our method to an approach where the two branches both predict semantic classes and are trained in a symmetric way. Being more specific, on labeled data they are trained with a cross entropy loss as well as the adversarial loss. On unlabeled data, we apply an adversarial loss.
ial loss to both of them and use $KL(S_1|S_2) + KL(S_2|S_1)$ as a consistency loss. This approach performs better giving 69.1%, but this is still clearly inferior to our proposed method. Overall, this shows the necessity to learn the latent classes in a data driven way.

### 5. Conclusion

In this work we addressed the task of semi supervised semantic segmentation, where a small fraction of the data set is labeled in a pixel wise manner, while most images not have any type of labels for the images. Our key contribution is a two branch segmentation architecture, which uses latent classes learned in a data driven way on labeled data to supervise the semantic segmentation branch on unlabeled data. We experimentally prove that the latent classes learned in this way have an interpretable meaning. Combined with an adversarial learning scheme, our method achieves new state of the art results on Pascal VOC as well as on Cityscapes.

| justification of latent classes | method | number lat. cls. | performance |
|----------------------------------|--------|------------------|-------------|
| manual                           | 10     | 69.0%            |
| learned                          | 10     | 70.7%            |
| semantic classes                 | 21     | 68.5%            |
| semantic classes KL              | 21     | 69.1%            |
| learned                          | 20     | 71.3%            |

Table 5. Instead of learning latent classes in a data driven way, we evaluate three baseline approaches. 1) 10 manually defined super categories. 2) Learning the semantic classes itself in the latent branch. 3) (KL symmetry) training two identical semantic branches with cross entropy on labeled data, adversarial feedback and KL consistency on labeled data. The comparison shows the superiority of latent classes.
References

[1] Jiwoon Ahn and Suha Kwak. Learning pixel-level semantic affinity with image-level supervision for weakly supervised semantic segmentation. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4981–4990, 2018. 2

[2] Amy Bearman, Olga Russakovsky, Vittorio Ferrari, and Li Fei-Fei. What’s the point: Semantic segmentation with point supervision. *European Conference on Computer Vision (ECCV)*, pages 549–565, 2016. 2

[3] Rania Briq, Michael Moeller, and Juergen Gall. Convolutional simplex projection network for weakly supervised semantic segmentation. *British Machine Vision Conference (BMVC)*, 2018. 2

[4] Arslan Chaudhry, Puneet Dokania, and Philip HS Torr. Discovering Class-Specific Pixels for Weakly-Supervised Semantic Segmentation. *British Machine Vision Conference (BMVC)*, 2017. 2

[5] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Dengxin Dai, Christos Sakaridis, Simon Hecker, and Luc Van Gool. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(4):834–848, 2018. 3, 5

[6] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigor Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. 2, 5

[7] Dengxin Dai, Christos Sakaridis, Simon Hecker, and Luc Van Gool. Curriculum model adaptation with synthetic and real data for semantic foggy scene understanding. *International Journal of Computer Vision (IJCV)*, 111(1):98–136, 2014. 2, 5

[8] Mark Everingham, S. M. Ali Eslami, Luc. Van Gool, Christopher K. I. Williams, John Winn, and Andrew Zisserman. The Pascal Visual Object Classes Challenge: A Retrospective. *International Journal of Computer Vision (IJCV)*, 111(1):98–136, 2014. 2, 5

[9] Ruochen Fan, Qibin Hou, Ming-Ming Cheng, Gang Yu, Ralph R. Martin, and Shi-Min Hu. Associating inter-image salient instances for weakly supervised semantic segmentation. *European Conference on Computer Vision (ECCV)*, pages 371–388, 2018. 2

[10] Weifeng Ge, Sibei Yang, and Yizhou Yu. Multi-evidence filtering and fusion for multi-label classification, object detection and semantic segmentation based on weakly supervised learning. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1277–1286, 2018. 2

[11] Seunghoon Hong, Donghun Yeo, Suha Kwak, Honglak Lee, and Bohyung Han. Weakly supervised semantic segmentation using web-crawled videos. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2224–2232, 2017. 2

[12] Qibin Hou, Daniela Massiceti, Puneet Kumar Dokania, Yunchao Wei, Ming-Ming Cheng, and Philip H. S. Torr. Bottom-up top-down cues for weakly-supervised semantic segmentation. Energy Minimization Methods in Computer Vision and Pattern Recognition, pages 263–277, 2018. 2

[13] Zilong Huang, Xinggang Wang, Jiasi Wang, Wenyu Liu, and Jingdong Wang. Weakly-supervised semantic segmentation network with deep seeded region growing. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7014–7023, 2018. 2

[14] W.-C. Hung, Y.-H. Tsai, Y.-T. Liou, Y.-Y. Lin, and M.-H. Yang. Adversarial learning for semi-supervised semantic segmentation. In *Proceedings of the British Machine Vision Conference (BMVC)*, 2018. 1, 2, 5, 6

[15] B. Jin, M. V. O. Segovia, and S. Ssstrunk. Webly supervised semantic segmentation. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1705–1714, 2017. 2

[16] A. Khoreva, R. Benenson, J. Hosang, M. Hein, and B. Schiele. Simple does it: Weakly supervised instance and semantic segmentation. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1665–1674, 2017. 2

[17] Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *ArXiv*, abs/1412.6980, 2014. 5

[18] Alexander Kolesnikov and Christoph H Lampert. Seed, expand and constrain: Three principles for weakly-supervised image segmentation. *European Conference on Computer Vision (ECCV)*, pages 695–711, 2016. 2

[19] Vinod Kumar Kurmi, Vipul Bajaj, K. S. Venkatesh, and Vinay P. Namboodiri. Curriculum based dropout discriminator for domain adaptation. *BMVC*, 2019. 2

[20] Jungbeom Lee, Einji Kim, Sungmin Lee, Jangho Lee, and Sungroh Yoon. Flickenet: Weakly and semi-supervised semantic image segmentation using stochastic inference. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019. 2

[21] Jungbeom Lee, Einji Kim, Sungmin Lee, Jangho Lee, and Sungroh Yoon. Frame-to-frame aggregation of active regions in web videos for weakly supervised semantic segmentation. In *The IEEE International Conference on Computer Vision (ICCV)*, October 2019. 2

[22] Hanxi Li, Xuming He, Nick Barnes, and Wang Mingwen. Learning hough transform with latent structures for joint object detection and pose estimation. pages 116–129, 01 2016. 2

[23] K. Li, Z. Wu, K. Peng, J. Ernst, and Y. Fu. Guided attention inference network. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2019. 2

[24] Qizhu Li, Anurag Arnab, and Philip H.S. Torr. Weakly- and semi-supervised panoptic segmentation. *European Conference on Computer Vision (ECCV)*, pages 106–124, 2018. 2

[25] Qing Lian, Fengmao Lv, Lixin Duan, and Boqing Gong. Constructing self-motivated pyramid curriculums for cross-domain semantic segmentation: A non-adversarial approach. In *The IEEE International Conference on Computer Vision (ICCV)*, October 2019. 2

[26] Di Lin, Jifeng Dai, Jiaya Jia, Kaiming He, and Jian Sun. Scribblesup: Scribble-supervised convolutional networks for
semantic segmentation. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3159–3167, 2016. 2

[27] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *European Conference on Computer Vision (ECCV)*, pages 740–755, 2014. 5

[28] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3431–3440, 2015. 4

[29] S. J. Oh, R. Benenson, A. Khoreva, Z. Akata, M. Fritz, and B. Schiele. Exploiting saliency for object segmentation from image level labels. *IEEE International Conf on Computer Vision and Pattern Recognition (CVPR)*, pages 5038–5047, 2017. 2

[30] George Papandreou, Liang-Chieh Chen, Kevin P Murphy, and Alan L Yuille. Weakly- and semi-supervised learning of a deep convolutional network for semantic image segmentation. In *International Conference on Computer Vision (ICCV)*, pages 1742–1750, 2015. 2

[31] Deepak Pathak, Philipp Krähenbühl, and Trevor Darrell. Constrained convolutional neural networks for weakly supervised segmentation. In *International Conference on Computer Vision (ICCV)*, pages 1796–1804, 2015. 2

[32] Pedro H. O. Pinheiro and Ronan Collobert. From image-level to pixel-level labeling with convolutional networks. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1713–1721, 2015. 2

[33] Xiaojuan Qi, Zhengzhe Liu, Jianping Shi, Hengshuang Zhao, and Jiaya Jia. Augmented feedback in semantic segmentation under image level supervision. *European Conference on Computer Vision (ECCV)*, pages 90–105, 2016. 2

[34] Nima Razavi, Juergen Gall, Pushmeet Kohli, and Luc Van Gool. Latent hough transform for object detection. pages 312–325, 10 2012. 2

[35] A. Richard, H. Kuehne, and J. Gall. Weakly supervised action learning with rnn based fine-to-coarse modeling. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1273–1282, July 2017. 2

[36] Anirban Roy and Sinisa Todorovic. Combining bottom-up, top-down, and smoothness cues for weakly supervised image segmentation. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7282–7291, 2017. 2

[37] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. 5

[38] Christos Sakaridis, Dengxin Dai, and Luc Van Gool. Guided curriculum model adaptation and uncertainty-aware evaluation for semantic nighttime image segmentation. In *The IEEE International Conference on Computer Vision (ICCV)*, October 2019. 2

[39] Wataru Shimoda and Keiji Yanai. Distinct class-specific saliency maps for weakly supervised semantic segmentation. *European Conference on Computer Vision (ECCV)*, pages 218–234, 2016. 2

[40] Chunfeng Song, Yan Huang, Wanli Ouyang, and Liang Wang. Box-driven class-wise region masking and filling rate guided loss for weakly supervised semantic segmentation. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019. 2

[41] Meng Tang, Abdelaziz Djelouah, Federico Perazzi, Yuri Boykov, and Christopher Schroers. Normalized cut loss for weakly-supervised cnn segmentation. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1818–1827, 2018. 2

[42] Meng Tang, Federico Perazzi, Abdelaziz Djelouah, Ismail Ben Ayed, Christopher Schroers, and Yuri Boykov. On regularized losses for weakly-supervised cnn segmentation. *European Conference on Computer Vision (ECCV)*, pages 524–540, 2018. 2

[43] Xiang Wang, Shaodi You, Xi Li, and Huimin Ma. Weakly-supervised semantic segmentation by iteratively mining common object features. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1354–1362, 2018. 2

[44] Yunchao Wei, Jiashi Feng, Xiaodan Liang, Ming-Ming Cheng, Yao Zhao, and Shuicheng Yan. Object region mining with adversarial erasing: A simple classification to semantic segmentation approach. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 6488–6496, 2017. 2

[45] Yunchao Wei, Xiaodan Liang, Yunpeng Chen, Xiaohui Shen, Ming-Ming Cheng, Jiashi Feng, Yao Zhao, and Shuicheng Yan. Stc: A simple to complex framework for weakly-supervised semantic segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(11):2314–2320, 2017. 2

[46] Yunchao Wei, Huaxin Xiao, Honghui Shi, Zekun Jie, Jiashi Feng, and Thomas S. Huang. Revisiting dilated convolution: A simple approach for weakly- and semi-supervised semantic segmentation. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 7268–7277, 2018. 2

[47] Yang Zhang, Philip David, and Boqing Gong. Curriculum domain adaptation for semantic segmentation of urban scenes. *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 2039–2049, 2017. 2

[48] Bolei Zhou, Aditya Khosla, Agata Lapedriza, Aude Oliva, and Antonio Torralba. Learning deep features for discriminative localization. *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2921–2929, 2016. 2

[49] Xiangxin Zhu, Dragomir Anguelov, and Deva Ramanan. Capturing long-tail distributions of object subcategories. pages 915–922, 09 2014. 2