Abstract

Learning from imperfect data becomes an issue in many industrial applications after the research community has made profound progress in supervised learning from perfectly annotated datasets. The purpose of the Learning from Imperfect Data (LID) workshop is to inspire and facilitate the research in developing novel approaches that would harness the imperfect data and improve the data-efficiency during training. A massive amount of user-generated data nowadays available on multiple internet services. How to leverage those and improve the machine learning models is a high impact problem. We organize the challenges in conjunction with the workshop. The goal of these challenges is to find the state-of-the-art approaches in the weakly supervised learning setting for object detection, semantic segmentation, and scene parsing. There are three tracks in the challenge, i.e., weakly supervised semantic segmentation (Track 1), weakly supervised scene parsing (Track 2), and weakly supervised object localization (Track 3). In Track 1, based on ILSVRC DET [12], we provide pixel-level annotations of 15K images from 200 categories for evaluation. In Track 2, we provide point-based annotations for the training set of ADE20K [73]. In Track 3, based on ILSVRC CLS-LOC [12], we provide pixel-level annotations of 44,271 images for evaluation [71]. Besides, we further introduce a new evaluation metric proposed by [71], i.e., IoU curve, to measure the quality of the generated object localization maps. This technical report summarizes the highlights from the challenge. The challenge submission server and the leaderboard will continue to open for the researchers who are interested in it. More details regarding the challenge and the benchmarks are available at https://lidchallenge.github.io.

1. Introduction

Weakly supervised learning refers to various studies that attempt to address the challenging image recognition tasks by learning from weak or imperfect supervision. Supervised learning methods, including Deep Convolutional Neural Networks (DCNNs), have significantly improved the performance in many problems in the field of computer vision, thanks to the rise of large-scale annotated data set and the advance in computing hardware. However, these supervised learning approaches are notorious “data-hungry”, which makes them are sometimes not practical in many real-world industrial applications. We are often facing the problem that we are not able to acquire enough amount of perfect annotations (e.g., object bounding boxes, and pixel-wise masks) for reliable training models. To address this problem, many efforts in so-called weakly supervised learning approaches have been made to improve the DC-NNs training to deviate from traditional paths of supervised learning using imperfect data. For instance, various approaches have proposed new loss functions or novel training schemes. Weakly supervised learning is a popular research direction in Computer Vision and Machine Learning communities. Many research works have been devoted to related topics, leading to the rapid growth of related publications in the top-tier conferences and journals such as CVPR, ICCV, ECCV, NeurIPS, TIP, IJCV, and TPAMI.

This year, we provide additional annotations for existing benchmarks to enable the weakly-supervised training or evaluation and introduce three challenge tracks to advance the research of weakly-supervised semantic segmentation [1, 2, 6, 7, 13–17, 20, 22–25, 27, 28, 30, 32, 35–38, 40–42, 44–46, 48–57, 59–61, 63, 66, 67, 74], weakly supervised scene parsing using point supervision [39] and weakly supervised object localization [3–5, 9–11, 18, 19, 21, 26, 29, 31, 33, 34, 43, 47, 58, 62, 64, 65, 68–72, 75], respectively. More details are given in the next section.

We organize this workshop to investigate principle ways of building industry level AI systems relying on learning from imperfect data. We hope this workshop will attract attention and discussions from both industry and academic people and ease the future research of weakly supervised learning for computer vision.
2. The LID Challenge

2.1. Datasets

ILSVRC-LID-200 is used in Track 1, aiming to perform object semantic segmentation using image-level annotations as supervision. This dataset is built upon the object detection track of ImageNet Large Scale Visual Recognition Competition (ILSVRC) [12], which totally includes 456,567 training images from 200 categories. By parsing the provided XML files given by [12], 349,310 images with object(s) from the 200 categories are left. To facilitate the pixel-level evaluation, we provide pixel-level annotations for 15K images, including 5,000 and 10,000 for validation and testing, respectively. Following previous practices, the mean Intersection-Over-Union (IoU) score over 200 categories is employed as the key evaluation metric.

ADE20K-LID is used in Track 2, aiming to learn to perform scene parsing using points-based annotation as supervision. This dataset is built upon the ADE20K dataset [73]. There are 20,210 images in the training set, 2,000 images in the validation set, and 3,000 images in the testing set. We provide the additional point-based annotations on the training set. In particular, this point-based weakly-supervised setting is firstly provided by [39]. Following [39], we consider 150 meaningful categories and generate the pixel annotation for each independent instance (or region) in each training image. The performances are evaluated by pixel-wise accuracy and mean IoU, which is consistent with the evaluation metrics of the standard ADE20K [73].

ILSVRC is used in Track 3, aiming to make the classification networks be equipped with the ability of object localization. This dataset is built upon the image classification/localization track of ImageNet Large Scale Visual Recognition Competition (ILSVRC), which includes 1.2 million training images from 1000 categories. Different from previous works to evaluate the performance in an indirect way, i.e. bounding box, we annotate pixel-level masks of 44,271 images (validation/testing: 23,151/21,120) to facilitate the evaluation to be performed in a direct way. These annotations are provided by [71], where a new evaluation metric, i.e., IoU-Threshold curve, is also introduced. Particularly, the IoU-Threshold curve is obtained by calculating IoU scores with the masks binarized with a wide range of thresholds from 0 to 255. The best IoU score, i.e., Peak-IoU, is used as the key evaluation metric for the comparison. Please refer to [71] for more details of the annotation masks and the new evaluation metric.

2.2. Rules and Descriptions

Rules This year, we issue two strict rules for all the teams

• For training, only the images provided in the training set are permitted. Competitors can use the classification models pre-trained on the training set of ILSVRC CLS-LOC to initialize the parameters. However, they CANNOT leverage any datasets with pixel-level annotations. In particular, for Track 1 and Track 3, only the image-level annotations of training images can be leveraged for supervision, and the bounding-box annotations are NOT permitted.

• We encourage competitors to design elegant and effective models competing for all the tracks rather than ensembling multiple models. Therefore, we restrict the parameter size of the inference model(s) should be LESS than 150M (slightly more than two DeepLab V3+ [8] models using ResNet-101 as the backbone). The competitors ranked in the Top 3 are required to submit the inference code for verification.

Timeline The challenge started on Mar 22, 2020, and ended on June 8, 2020. Each participant was allowed a maximum of 5 submissions for the testing split of each track.

Participating Teams We received submissions from 15 teams in total. In particular, the teams from the Computer Vision Lab at ETH Zurich, Tsinghua University, the Vision & Learning Lab at Seoul National University achieve the 1st place in Track 1, Track 2, and Track 3, respectively.

2.3. Results and Methods

Tables 1, 2, 3 show the leaderboard results of Track 1, Track 2 and Track 3, respectively. Particularly, the team from ETH Zurich significantly outperforms others by a large margin in the Track 1. In the Track 3, the top 3 teams achieve similar Peak-IoU scores from 61.48 to 63.08. Furthermore, we demonstrate the comparison of IoU-Threshold curves of 5 teams for Track 3 in Figure 1.
The comparison of IoU-Threshold curves of different teams for Track 3.

Figure 1.

An overview of the proposed approach by the team of CVL at ETH Zurich.

Figure 2.

2.3.1 CVL at ETH Zurich Team
(Won the 1st place of Track 1)

The proposed approach adopts cross-image semantic relations for comprehensive object pattern mining. Two neural co-attentions are incorporated into the classifier to complement capture cross-image semantic similarities and differences. In particular, the classifier is equipped with a differentiable co-attention mechanism that addresses semantic homogeneity and difference understanding across training image pairs. More specifically, two kinds of co-attentions are learned in the classifier. The former one aims to capture cross-image common semantics, which enables the classifier to better ground the common semantic labels over the co-attentive regions. The latter, called contrastive co-attention, focuses on the rest, unshared semantics, which helps the classifier better separate semantic patterns of different objects. These two co-attentions work in a cooperative and complimentary manner, together making the classifier understand object patterns more comprehensively. Another advantage is that the co-attention-based classifier learning paradigm brings an efficient data augmentation strategy due to the use of training image pairs. An overview of the proposed approach is shown in Figure 2.

2.3.2 The Machine Learning Lab at Ukrainian Catholic University Team
(Won the 3rd place of Track 1)

The approach proposed by this team consists of three consecutive steps. The first two steps extract high-quality pseudo masks from image-level annotated data, which are then used to train a segmentation model on the third step. The presented approach also addresses two problems in the data: class imbalance and missing labels. All these three steps make the proposed approach be capable of segmenting various classes and complex objects using only image-level annotations as supervision. The results produced from different steps are shown in Figure 3.

2.3.3 Tsinghua&Intel Team
(Won the 1st place of Track 2)

The team reveals two critical issues existing in the current state-of-the-art method [39]: 1) it relies upon softmax outputs, or say logits. It is known that logits can be overconfident upon the wrong prediction; 2) harvesting pseudo labels using logits would introduce thresholds, and it is very time-consuming to tune thresholds for modern deep networks. Some observations are shown in Figure 4.

To tackle these issues, the proposed approach builds upon uncertainty measures instead of logits and is free of threshold tuning, which is motivated by a large-scale analysis of the distribution of uncertainty measures using strong models and challenging databases. This analysis leads to the discovery of a statistical phenomenon called uncertainty mixture. Inspired by this discovery, this team proposes to decompose the distribution of uncertainty measures with a Gamma mixture model, leading to a principled method to
harvest reliable pseudo labels. Beyond that, the team assumes the uncertainty measures for labeled points are always drawn from a particular component. This amounts to a regularized Gamma mixture model. They provide a thorough theoretical analysis of this model, showing that it can be solved with an EM-style algorithm with a convergence guarantee.

### 2.3.4 Vision&Learning Lab at Seoul National University
(Won the 1st and 2nd places for Track 3 and Track 1)

This team demonstrates the popular class activation maps [72] suffers from three fundamental issues: (i) the bias of GAP to assign a higher weight to a channel with a small activation area, (ii) negatively weighted activations inside the object regions, and (iii) instability from the use of the maximum value of a class activation map as a thresholding reference. They collectively cause the problem that the localization prediction to be highly limited to the small region of an object. The proposed approach incorporates three simple but robust techniques that alleviate the regarding problems, including thresholded average pooling, negative weight clamping, and percentile as a thresholding standard. More details can be found in Figure 5.

### 2.3.5 Mepro at Beijing Jiaotong University Team
(Won the 2nd place of Track 3)

The proposed method achieves localization on any convolutional layer of a classification model by exploiting two kinds of gradients, called the Dual-Gradients Localization (DGL) framework. DGL framework is developed based on two branches: 1) Pixel-level Class Selection, leveraging gradients of target class to identify the correlation ratio of pixels to the target class within any convolutional feature maps, and 2) Class-aware Enhanced Map, utilizing gradients of the classification loss function to mine entire target object regions, which would not damage classification performance. The proposed architecture is shown in Figure 6.

To acquire the integral object regions, gradients of classification loss function are used to enhance the information of the specific class on any convolutional layer. DGL framework demonstrates that any convolutional layer of the classification model has the localization ability, and some layers have better performance than the last convolutional layer in an offline manner.

### 2.3.6 PCA Lab at Nanjing University of Science and Technology Team
(Won the 3rd place of Track 3)

The proposed model is composed of two auto-encoders, as shown in Figure 7. In the first auto-encoder, a classifier is trained with the global average pooling by using image-level annotations as supervision. The learned classifier is further applied to obtain Class Activation Maps (CAMs) according to [72]. Then, the team uses the binary images generated by CAMs as pseudo-pixel-level annotations to conduct binary classification. After the first decoder, a bilinear upsampling operation is further applied to get the binary image with the same size as the raw image.

In the second auto-encoder, the team aims to recover the binary image to the raw image to obtain the refined binary output image. The output binary image of the first decoder is used as the input of the second encoder. The binary image
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The proposed model is composed of two encoders. In the first part, we train level annotations. Followed by the first decoder, we use bilinear upsampling to get the binary image with the same size of the input of auto-encoders. In the second part, we expect to re-cover the input of global average pooling in the first encoder under the supervision of weight and sum the convs to get class activation maps. Then we use binary images generated by CAMs as pseudo level annotations. We transfer front and background images in all layers into binary images with a threshold, add front and background binary images together, and then fuse the binary images generated by all layers into binary images with a threshold, add front and background. The front part and the background part are operated in different channels of a layer independently and then are fused to the final prediction image. To be specific, they transfer front and background images in all layers into binary images with a threshold, add front and background binary images together, and then fuse the binary images generated by all layers. As a result, we may get the refined binary output images, which are used as pseudo annotations for the next iteration. The above process iterates until convergence.

2.3.7 Beijing Normal University (Won the 5th place of Track 3)

This team simply apply the approach proposed in [10] to compete the Track 3.

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