Augmented Semi-Supervised Learning for Salient Object Detection with Edge Computing

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***Abstract*—Salient object detection (SOD) from raw sensor images in the edge networks can effectively speed up the decision-making process in the complex environments, because it simulates the mechanism of human attention to identify salient objects from images. The success of supervised deep learning approaches have been widely proved SOD field. However, the imbalanced and limited training data at each edge device pose a huge challenge for us to deploy deep learning methods in the edge computing environments. In this article, we propose a cloud-edge distributed augmented semi-supervised learning architecture for SOD over the edge networks. The framework consists of two components: the base classification networks are employed in different edge nodes, and the reverse augmented network is employed in cloud. First, the base classification networks are trained with data from edge nodes while the reverse augmented network is trained with the whole data. Then, we concatenate each base classification network with reverse augmented network, thus the latter network can help the training of former network. Finally, we integrate the outputs of all base classification network to generate the pseudo-labels, which are used for semi-supervised learning of the augment network. We demonstrated a convincing performance of our semi-supervised learning framework on four bench-marked data-sets. These results show that our augmented semi-supervised learning framework can outperform other optimization strategies on deep learning for the edge computing.**

***Index Terms*—Edge computing, Salient object detection, Semi-supervised learning**

I. Introduction

Salient object detection from raw sensor images collected from edge networks aims to segment the most informative parts from complex environments. It is an essential step for a wide range of application include visual tracking, visual question answering, and person re-identification, and has attracted a lot of attention [1], [2]. Recently, deep learning has become an important tool for salient object detection (SOD) from complex and massive data since its powerful ability of hierarchical feature mining and representation. Deep learning is also deployed to the scenario of edge computing environments with promising early results. A commonly deployment paradigm is the cloud-edge distributed structure. For example, the method in [3] employs low-level layers of deep neural network in the edge nodes while high-level layers in the cloud. Thus it make use of deep feature extraction, and also alleviate network traffic via uploading reduced intermediate data generated by edge nodes rather than original raw data.

However, existing cloud-edge distributed deep leaning frameworks in [4] may suffer from the imbalanced and limited training data in different edge devices. Most of them directly deploy deep learning algorithms to edge networks, thus their accuracy and generalization performance heavily dependent on the balanced and sufficient training data. However, it is challenging to obtain the balanced and sufficient training data in the real edge computing environment. First, it is difficult to collect balanced data from different edge devices. For example, if a sensor device is deployed in the market, it can collect a lot of images of people due to a large number of customers. Conversely, if a sensor device is deployed in the remote areas, we can only collect limited images of people. Imbalanced data of different senor devices may reduce the generalization of the employed deep models. Second, it is difficult to obtain enough labeled data. Even though many raw data can be obtained from the devices, it is time-consuming and expensive to label them. Therefore, it is desirable for edge computing to develop a cloud-edge distributed deep learning framework without requiring a large number of balanced training data.

In this article, we propose an augmented semi-supervised learning cloud-edge framework for SOD with edge computing.The framework has a special designed cloud-edge structure to address the imbalance and limited training data problem: the base classification networks are deployed in edge devices for SOD from the raw images, the reverse augmented network is deployed in the cloud, which can act as a regularization to the base classification networks via reconstructing images from predicted SOD map. In particular, the reverse augmented network is trained with whole data, thus it can act as a teacher who further improve the base classification networks. To exploit the unlabeled images, we first generate pseudo-labels via integrating the predicted results of all base classification networks. Then those pseudo-labels are also used for the training of the reverse augmented network. Our framework leverages the benefits of both cloud-edge paradigm and deep learning. A large number of computing tasks on global data are performed by the reverse augmented network on the cloud. Only a small amount of local data is processed in edge nodes by base classification network. At the same time,

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the collaboration among deep models on the cloud and the edge nodes guarantees the promising performance in edge computing environments.

We can summarize the main contributions of this work here:

- We first introduce the cloud-edge distributed augmented semi-supervised deep learning-based SOD into edge computing environments. The proposed method can perform well without requiring a large amount of balanced training data. Therefore, it is more suitable for the real edge computing environment.
- We propose a reverse augmented network to cope with imbalanced data problem. The reverse network is deployed in cloud, and also trained on global data. Then, it act a further supervision to regular the learning of base classification networks deployed in edge nodes.
- We propose a pseudo-label generation strategy to address the limited training data problem. We leverage the diversity of the classification networks deployed in edge nodes to generate different results. Then, we integrate those results to obtain a final pseudo-label via the ensemble method.

II. A RELOOK ON STATE-OF-THE ART

We review the supervised deep learning-based methods for SOD followed by the semi-supervised deep learning methods. In the end, we discuss the deep learning for edge computing.

A. Deep learning-based SOD

Supervised deep learning-based methods have been widely examined in SOD field since its competitive performance on SOD task. These methods can accurately and automatically segment salient objects via training a deep neural network from massive data. Due to its powerful ability for multi-level and multi-scale features mining and representation, convolutional neural network (CNN) takes the advantage of the coarse shape information and fine boundary information. For instance, Wang et al. [5] employ a DNN-L network for local feature extraction and a DNN-G network for global search. [6] first employ a CNN to extract local features for each superpixel, and then a the standard VGGNet to capture high-level features. In the end, the salient object region is predict a two-layers regression network from both high- and low-context features. Li et al. [7] propose a multi-inputs framework. They first decompose the image into different patches followed by extract multi-scale features from these patches using different parts of the whole networks. The obtained features from different patches are finally concatenated for SOD. However, the above discussed works rely heavily on CNN based multi-level and multi-scale feature extraction and classification networks. Such a learning framework does not fully utilize advanced semantic information. In addition, spatial information of those features failed to be passed to the last layers of the whole network, which lead to the loss of global information. To cope with above issues caused by fully connected layers, the fully convolutional network (FCN) is employed to consider pixel-level operations. [8] designs two sub-branches in the whole network: a segment-wise spatial pooling stream (SPS) and a pixel-level fully convolutional stream (FCS). Then the outputs of these two sub-branches are fused for final SOD. The work in [9] takes the advantages of both pyramidal feature extraction and hierarchical data collection. A pyramidal neural network is employed to obtain thin-to-coarse feature representation for salient objects, and the hierarchical data collection is employed to obtain within-semantic knowledge and cross-semantic knowledge between Different categories of data. In addition, many sample but efficient techniques i.e. pre-training, fine-tuning, deeply supervision and versatile architectures are also combined into deep SOD models. However, the state-of-art supervised learning method heavily rely on a great number of balanced labels for training. The difficulties of collecting such data in edge computing environments require more advanced deep learning paradigm, such as semi-supervised deep learning.

B. Semi-supervised deep learning

Semi-supervised deep learning aims to achieve reliable results with limited labeled data. A common method is deep representation learning, which can map the raw data to a low dimension space in both unsupervised and semi-supervised way. Recently, unsupervised adversarial training has attracted the attention from researchers since its ability for modeling the data distribution. Adversarial training based methods can be divided into two main categories. First, one category that focuses on data synthesis, or unpaired domains translation. The another category focuses the scene with limited labeled data. In this case, the adversarial training is used to map the generate features into one common space. To further exploit the unlabeled data, co-training of multi-deep nets is proposed in classification and segmentation tasks. For instance, the method in [10] employ three different deep network to predicted pseudo-labels, which are then edited for model training. Semi-supervised learning is adopted in many applications with strong generalization performance, however, it is not well developed in edge computing environment.

C. Deep learning in edge computing

Due to the outstanding performance of deep learning in many practical applications like computer vision and natural language processing, there is a great impetus to apply it to edge computing. In fact, many works [11], [12], [13] have been done on how to make better use of deep learning in edge computing environments. There are three common deployment paradigms of deep learning: the edge only, the cloud only and cloud-edge distributed. In practical application, the first two paradigms have obvious shortcomings. On the one hand, the *edge-only* paradigm requires a large amount of computational resources to perform a deep learning algorithm in edge nodes, on the other hand, the *cloud-only* paradigm depends on the communication bandwidth between the edge nodes and the cloud. The cloud-edge distributed paradigm [14] is more advanced, which has real-time response and requires less computing resource in edge nodes. However, all three paradigm assume that there are balance and sufficient training data, which are difficult to obtain in practice. In contrast,

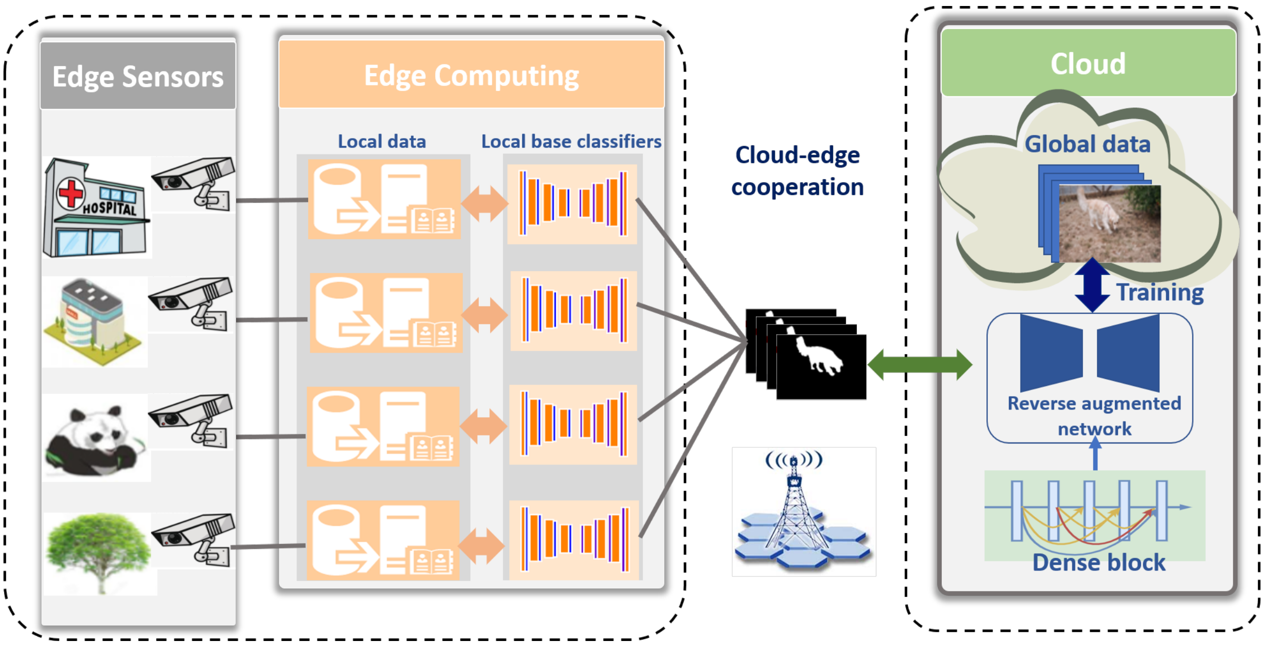

Fig. 1. The cloud-edge distributed paradigm of our framework. The base classification networks are deployed in edge nodes, each of which can only 'watch' the local images. The reverse augmented network is deployed in cloud, which can 'watch' whole images.

our proposed augmented semi-supervised learning can take advantages of cloud-edge distributed paradigm. By leveraging the cooperation between the cloud and the edge nodes, our method can achieve more stable performance without sufficient training data.

III. The Framework for Augmented Semi-Supervised Learning

A. An overview of the framework

As illustrated in Fig. 1, the base classification networks are deployed in different edge nodes. A reverse augmented network is deployed in the cloud. The learning process in cloud-edge can be divided into following three steps. First, the base classification networks are initialized based on the local training data, and the reverse augmented network is initialized based on the whole training data. Then, we alternately concatenate each base classification network with the reverse augmented network, thus the latter network can help the learning of the former network. Finally, we integrate the outputs of the classification networks to generate pseudo-labels, which are then used for semi-supervised leaning of the reverse augmented network.

B. Initialization

To better present our framework, we first give some basic descriptions. For the edge computing environment, we are given a labeled dataset and an unlabeled dataset. Those data are collected from the all edge nodes. Note that each edge node has its own lebeled and unlabeled sub-dataset).

As shown in Fig. 1, we deploy a set of base classification networks for all edge nodes. Those base classification networks can predict salient object from the given images. We also deploy a reverse augmented network in the cloud, which can reconstruct the image from the given salient object maps. A common practice to learn both the base classification networks and the reverse augmented network is the maximum likelihood estimation based on the parameterized conditional distributions. In our framework, each base classification network is trained with the sub-dataset collected from the corresponding edge node. The reverse augmented network is trained with whole labeled data. Therefore, we only use limited computing and memory resources to train the base classification networks in the edge nodes, and much computing resources to train reverse augmented network in the cloud. But there are still two challenges. First, the generalization performance of the base classification networks is inadequate because it can only 'watch' the images of the edge node it deployed. Though the reverse augmented network can 'watch' the images from all the edge nodes, it is expensive to deploy reverse augmented network in each edge node, since it requires a significant amount of storage and computing resources. Second, it is difficult to label all the data collected from sensor devices. How to exploit the unlabeled data to further improve the model is a challenging but interesting problem in edge computing environment. In next two subsections, we will address the mentioned challenges.

C. Augmented learning for edge nodes

Obviously, the base classification networks and the reverse augmented network are reverse processes of each other. We aim to learn base classification networks and reverse augmented network jointly and enable them to complement each other via data consistent. As shown in Fig. 2, we concatenate base classification networks and reverse augmented network, thus that we obtain a new function as follows. The base

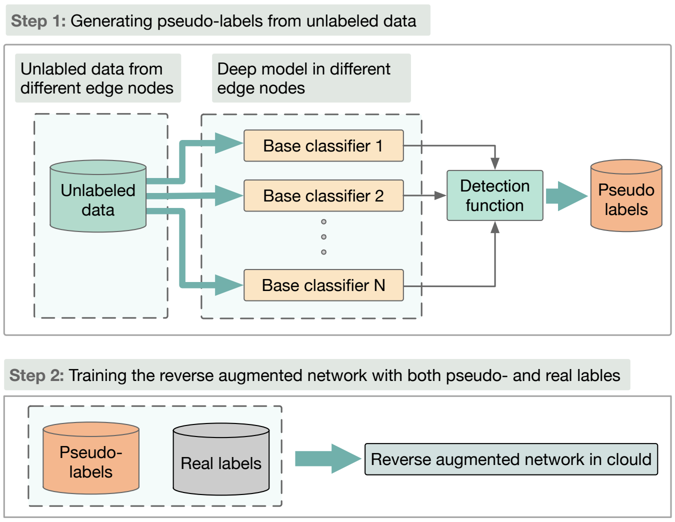

Fig. 2. Semi-supervised learning. Step 1: the pseudo-labels are generated from the base classification networks via ensemble method. Step 2: Both the generated pseudo-labels and real labels are used for the training of the reverse augmented network in cloud.

classification networks first predicts the salient object maps from the observed images, then the reverse augmented network regenerate the images from predicted salient object maps. In our implementation, the function is solved based on reconstruction loss. We argue that if the salient object is accurately predicted by the base classification networks, the the reverse augmented network can also accurately regenerate original image from predicted salient object. In another word, the reverse augmented network acts as a *teacher*, which can further enhance the predicted results of the base classification network. Because the reverse augmented network 'watches' at the whole images from all edge nodes, the joint training of the base classification network and the reverse augmented network would improve the generalization performance of the base classification network. Thus, we call it reverse augmented network. In our framework, we alternately concatenate each base classification network and the reverse augmented network, thus the base classification networks in all edge nodes can be improved by the reverse augmented network.

D. Semi-supervised learning in cloud

The unlabeled data can be exploited to further improve the deep model. In a typical edge computing environment, a large amount of raw image data can be collected from the edge nodes. It is important to use those raw data, which contain more patterns.

Inspired by ensemble learning, the deep learning algorithm deployed on the edge nodes are regraded as the base classifier. A key issue for ensemble learning is *how to learn diverse and accurate base classifiers*, thus a strong classifier can be constructed via integrating the outputs of the base classifiers. A commonly adopted approach in the edge computing environment is to use local data collected from different edge nodes to train the diverse and accurate base classifiers. In our case, the goal is not directly utilizing the base classifiers to generate final results in real time, instead, we provide a training strategy to exploit unlabeled based on reverse augmented network. In particular, as illustrated in Step 1 (Fig. 2), we use a decision function to obtain peseudo-labels from a given unlabeled images. Then, we train the reverse augmented network with both pseudo-labels and real labels as shown in Step 2. The decision function in our method is implemented by commonly used average approach.

E. Other details

We adopt FCN-net to fit our base classification networks deployed in edge nodes. The encoder has one convolution layer and three convolution blocks, while the decoder has a symmetric structure. For all convolution layers in our framework, 2D dilated CNN is employed because of its great capability in feature extraction. For the first convolution layer, we use three different sizes convolution kernel (3^2, 5^2, 7^2) to generate hierarchical information for further learning. For the rest of convolution layers in network, the 3^2 convolution kernel is used.

For the reverse augmented network in the cloud, we deployed a more powerful model to learn from a large mount of data. Specifically, the reverse augmented network takes the same structure of the FCN, but the difference is that dense blocks are applied. We employ four dense blocks with 1, 4, 8, and 8 layers for encoder network, while the other four dense blocks with 8, 8, 4, and 1 layers for decoder network. The 3^2 convolution kernel is used for all layers.

We implemented all python codes on one desktop computer with Intel Xeon CPU 5-2650 and 64 GB DDR2 memory. The OS of this desktop computer is the Ubuntu 16.04. We use NVIDIA GTX1080 GPU to run all python codes over Tensorflow. In the end, the random gradient descent is 0.9 momentum in our deep learning model. The initial value of learning rate is set to 0.001.

IV. Performance Evaluation

A. Experiment setup

We perform the proposed framework on four popular public data-sets [15]: VOS, DAVIS, FBMS, and NTT. The SOD data-set consists of 200 videos (64 minutes) with 7,650 uniformly sampled keyframes, which can be divided into 23 subject scenarios. The DAVIS contains 50 high quality videos about human, animal, vehicle, object and action with 3,455 densely annotated frames. The Freiburg-Berkeley Motion Segmentation (FBMS) is collected for motion scenarios. This data-set contains 59 videos with 720 sparsely annotated frames. The NTT data-set is collected from outdoor scenarios, which contains 10 video with individual video has 5-10 s long duration. Three evaluation metrics, such as Precision score, Sensitivity score, and F-measure are considered to measure the performance of our framework.

For one data-set, we deploy a specific base classification for each scenario. For instance, in VOS data-set, we employ 28 base classification networks for 28 scenarios, each of base classification network learned with data from corresponding scenario. The reverse augmented network is deployed in cloud

Fig. 3. Visual comparsion of different SOD methods. The first and second columns are images from different scenes and corresponding ground truth. The remaining columns present the predicted results of different methods, of which the third column is the results of our method.

and learned with data from all 28 scenarios. In DAVIS data-set, five base classification networks are deployed for five scenarios. Then, depending on the the data scale, ten and three base classification networks are deployed for the FBMS and the NTT, respectively. In order to see the effectiveness of the proposed framework with limited labeled data, we perform the experiments with different scales of labeled data on the four data-set.

B. Results and comparison

Fig. 3 illustrates two typical examples from four different scenarios, i.e., zoo, car, people, and airplane. The third column of Fig. 3 demonstrates our proposed framework. We observe the following: the proposed method can accurately detect a) the salient object from complex background as the zoo shown, b) the big salient object as well as the small salient object as the car and people shown respectively, and 3) the complex salient object as airplane shown. The results in all four scenarios show the effectiveness of our method in imbalanced data environment.

In addition, Table I shows the quantitative results in terms of Precision, sensitivity and F-measure. Our method have achieved the promising results on four datasets, i.e., 0.871 (VOS), 0.852 (DAVIS), 0.780 (FBMS) and 0.755 (NTT) for F-measure. Table I depicts the quantitative results of our method when different scale of labeled data are given on the four datasets. It is worth noting that when only 30% of the labeled data is given, our approach still delivers a good performance, i.e. 0.783 (VOS), 0.711 (DAVIS), 0.702 (FBMS) and 0.682(NTT) for F-measure. The results in Table II show the effectiveness of our proposed method in limited data environments.

We compare our method with several fully-supervised methods, i.e., FCN, CSDW, GF, and SAG [1]. Table. II summarizes the comparison results on the four benchmark datasets. Note that the F-measure score of our method (0.871) is higher than CSDW (0.861) on VOS data-set. From these figures, we can see that our method outperforms the other four methods on all data-sets in terms of the evaluation indices satisfying the validity and accuracy of the method.

C. Take Away Message and Future Research Direction

We designed one reverse augmented network in this paper to improve the performance of the edge nodes, and then to leverage the unlabeled data via an ensemble learning strategy. However, there are still several limitations in our work that need to be overcome: 1) how to generalize the proposed method to more computer vision tasks and 2) how to deploy the proposed method in real application scenarios with minimum cost.

V. Conclusion

In this article, we have proposed cloud-edge distributed augmented semi-supervised learning framework for salient

TABLE I
QUANTITATIVE COMPARISONS (PRECISION, SENSITIVITY, AND F-MEASURE) BETWEEN THE PROPOSED METHOD AND THE COMPARED METHODS ON FOUR BENCHMARKS

Benchmark	Parameter	VOS	DAVIS	FBMS	NTT
FCN	Precision	0.782	0.545	0.580	0.683
	Sensitivity	0.833	0.840	0.748	0.736
	F-measure	0.802	0.663	0.647	0.704
CSDW	Precision	0.870	0.534	0.589	0.690
	Sensitivity	0.848	0.825	0.778	0.750
	F-measure	0.861	0.650	0.665	0.714
GF	Precision	0.633	0.421	0.447	0.450
	Sensitivity	0.801	0.768	0.687	0.598
	F-measure	0.700	0.569	0.543	0.509
SAG	Precision	0.722	0.380	0.401	0.480
	Sensitivity	0.771	0.819	0.756	0.608
	F-measure	0.742	0.719	0.543	0.531
Ours	Precision	0.841	0.856	0.806	0.776
	Sensitivity	0.891	0.846	0.741	0.721
	F-measure	0.871	0.852	0.780	0.755

TABLE II
QUANTITATIVE RESULTS (PRECISION, SENSITIVITY AND F-MEASURE) OF OUR METHOD, WHICH ARE TRAINED WITH DIFFERENT SCALE OF LABELED DATA

Labeled data	Parameter	VOS	DAVIS	FBMS	NTT
20%	Precision	0.730	0.553	0.570	0.603
	Sensitivity	0.762	0.652	0.611	0.624
	F-measure	0.742	0.593	0.587	0.611
40%	Precision	0.759	0.601	0.624	0.688
	Sensitivity	0.822	0.719	0.677	0.690
	F-measure	0.784	0.648	0.645	0.689
60%	Precision	0.804	0.652	0.690	0.746
	Sensitivity	0.861	0.782	0.732	0.751
	F-measure	0.827	0.704	0.707	0.748
80%	Precision	0.828	0.680	0.715	0.773
	Sensitivity	0.884	0.801	0.755	0.775
	F-measure	0.850	0.728	0.731	0.774
100%	Precision	0.841	0.856	0.806	0.776
	Sensitivity	0.891	0.846	0.741	0.721
	F-measure	0.871	0.852	0.780	0.755

object detection. For each edge node, we deploy one scene-specific base classification network for local salient object detection. In the cloud, we deploy one reverse augmented network to reconstruct image from salient object map. Moreover, we proposed two learning strategies to integrate the base classification networks and the reverse augmented network: 1) In order to obtain more stable performance with imbalance data in edge environment, we jointly train the base classification networks and the reverse augmented network via concatenating them, thus the former network can be improved by the former network. 2) In order to further exploit the unlabeled data, we use the diversity of the base classification networks to generate pseudo-labels, which are then used for the training of the reverse augmented network. The extensive experiments demonstrate that effectiveness of our method, as well as its promising results with limited labeled data, and also the superiority to the existing approaches. In the future work, we will study how to extend the proposed method to more computer vision tasks in real edge computing environment.

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