# 2019-08-13

* **Zero-shot learning**

1. **Domain-Specific Embedding Network for Zero-Shot Recognition**

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**Abstract**: Zero-Shot Learning (ZSL) seeks to recognize a sample from either seen or unseen domain by projecting the image data and semantic labels into a joint embedding space. However, most existing methods directly adapt a well-trained projection from one domain to another, thereby ignoring the serious bias problem caused by domain differences. To address this issue, we propose a novel Domain-Specific Embedding Network (DSEN) that can apply specific projections to different domains for unbiased embedding, as well as several domain constraints. In contrast to previous methods, the DSEN decomposes the domain-shared projection function into one domain invariant and two domain-specific sub-functions to explore the similarities and differences between two domains. To prevent the two specific projections from breaking the semantic relationship, a semantic reconstruction constraint is proposed by applying the same decoder function to them in a cycle consistency way. Furthermore, a domain division constraint is developed to directly penalize the margin between real and pseudo image features in respective seen and unseen domains, which can enlarge the inter-domain difference of visual features. Extensive experiments on four public benchmarks demonstrate the effectiveness of DSEN with an average of **9.2%** improvement in terms of harmonic mean.

**Paper: Paper:** [**https://arxiv.org/pdf/1908.04174.pdf**](https://arxiv.org/pdf/1908.04174.pdf)

**Code:** [**https://github.com/mboboGO/DSEN-for-GZSL**](https://github.com/mboboGO/DSEN-for-GZSL)

* **Pooling method**

1. **LIP: Local Importance-based Pooling**

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Comments: Accepted by ICCV 2019

**Abstract**: Spatial downsampling layers are favored in convolutional neural networks (CNNs) to downscale feature maps for larger receptive fields and less memory consumption. However, for discriminative tasks, there are possibilities that these layers lose the discriminative details due to improper pooling strategies, which could hinder the learning process and eventually result in suboptimal models. In this paper, we present a unified framework over the existing downsampling layers (e.g., average pooling, max pooling, and strided convolution) from a local importance perspective. In this framework, we analyze the problems of these widely-used pooling layers and figure out the criteria for designing an effective downsampling layer. According to this analysis, we propose a conceptually simple, general, and effective pooling layer based on local importance modeling, termed as Local Importance-based Pooling (LIP). LIP can automatically enhance discriminative features during the downsampling procedure by learning adaptive importance weights based on inputs in an end-to-end manner. Experiment results show that LIP consistently yields notable gains with different depths and different architectures on ImageNet classification. In the challenging MS COCO dataset, detectors with our LIP-ResNets as backbones obtain a consistent improvement (≥ 1.4%) over plain ResNets, and especially achieve state-of-the-art performance in detecting small objects.1

**Paper:** [**https://arxiv.org/pdf/1908.04156.pdf**](https://arxiv.org/pdf/1908.04156.pdf)

**Code:** [**https://github.com/sebgao/LIP**](https://github.com/sebgao/LIP)

* **BacthNorm**

1. **Instance Enhancement Batch Normalization: an Adaptive Regulator of Batch Noise**

Senwei Liang1∗ , Zhongzhan Huang2∗ , Mingfu Liang3 , Haizhao Yang1,4

**Abstract**: Batch Normalization (BN) normalizes the features of an input image via statistics of a batch of images and this batch information is considered as batch noise that will be brought to the features of an instance by BN. We offer a point of view that self-attention mechanism can help regulate the batch noise by enhancing instance-specific information. Based on this view, we propose combining BN with a self-attention mechanism to adjust the batch noise and give an attention-based version of BN called Instance Enhancement Batch Normalization (IEBN) which recalibrates channel information by a simple linear transformation. IEBN outperforms BN with a light parameter increment in various visual tasks universally for different network structures and benchmark data sets. Besides, even if under the attack of synthetic noise, IEBN can still stabilize network training with good generalization.

**Code: https://github.com/gbup-group/IEBN**

**Paper:** [**https://arxiv.org/pdf/1908.04008.pdf**](https://arxiv.org/pdf/1908.04008.pdf)

* **Real-Time Instance Segmentation**

1. **Explicit Shape Encoding for Real-Time Instance Segmentation**

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Comments: to appear in ICCV2019

**Abstract**: In this paper, we propose a novel top-down instance segmentation framework based on explicit shape encoding, named ESE-Seg. It largely reduces the computational consumption of the instance segmentation by explicitly decoding the multiple object shapes with tensor operations, thus performs the instance segmentation at almost the same speed as the object detection. ESE-Seg is based on a novel shape signature Inner-center Radius (IR), Chebyshev polynomial fitting and the strong modern object detectors. ESE-Seg with YOLOv3 outperforms the Mask R-CNN on Pascal VOC 2012 at mAP@0.5 while 7 times faster.

**Paper:** [**https://arxiv.org/pdf/1908.04067.pdf**](https://arxiv.org/pdf/1908.04067.pdf)

**Code: https://github.com/WenqiangX/ese seg**

* **Distillation**

1. **UM-Adapt: Unsupervised Multi-Task Adaptation Using Adversarial Cross-Task Distillation**

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Comments: Oral Paper in ICCV 2019

**Abstract**: Aiming towards human-level generalization, there is a need to explore adaptable representation learning methods with greater transferability. Most existing approaches independently address task-transferability and cross-domain adaptation, resulting in limited generalization. In this paper, we propose UM-Adapt - a unified framework to effectively perform unsupervised domain adaptation for spatially-structured prediction tasks, simultaneously maintaining a balanced performance across individual tasks in a multi-task setting. To realize this, we propose two novel regularization strategies; a) Contour-based content regularization (CCR) and b) exploitation of inter-task coherency using a cross-task distillation module. Furthermore, avoiding a conventional ad-hoc domain discriminator, we re-utilize the cross-task distillation loss as output of an energy function to adversarially minimize the input domain discrepancy. Through extensive experiments, we demonstrate superior generalizability of the learned representation simultaneously for multiple tasks under domain-shifts from synthetic to natural environments. UM-Adapt yields state-ofthe-art transfer learning results on ImageNet classification and comparable performance on PASCAL VOC 2007 detection task, even with a smaller backbone-net. Moreover, the resulting semi-supervised framework outperforms the current fully-supervised multi-task learning state-of-the-art on both NYUD and Cityscapes dataset.

**Paper:** [**https://arxiv.org/pdf/1908.03884.pdf**](https://arxiv.org/pdf/1908.03884.pdf)

* **Loss function**

1. **IoU Loss for 2D/3D Object Detection**

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Comments: Accepted by international conference on 3d vision 2019

**Abstract**: In 2D/3D object detection task, Intersection-over-Union (IoU) has been widely employed as an evaluation metric to evaluate the performance of different detectors in the testing stage. However, during the training stage, the common distance loss (e.g., L1 or L2) is often adopted as the loss function to minimize the discrepency between the predicted and ground truth Bounding Box (Bbox). To eliminate the performance gap between training and testing, the IoU loss has been introduced for 2D object detection in [1] and [2]. Unfortunately, all these approaches only work for axis-aligned 2D Bboxes, which cannot be applied for more general object detection task with rotated Bboxes. To resolve this issue, we investigate the IoU computation for two rotated Bboxes first and then implement a unified framework, IoU loss layer for both 2D and 3D object detection tasks. By integrating the implemented IoU loss into several state-of-the-art 3D object detectors, consistent improvements have been achieved for both bird-eye-view 2D detection and point cloud 3D detection on the public KITTI [3] benchmark.

**Paper:** [**https://arxiv.org/pdf/1908.03851.pdf**](https://arxiv.org/pdf/1908.03851.pdf)

* **NAS**

1. **AutoGAN: Neural Architecture Search for Generative Adversarial Networks**

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Comments: accepted by ICCV 2019

**Abstract:** Neural architecture search (NAS) has witnessed prevailing success in image classification and (very recently) segmentation tasks. In this paper, we present the first preliminary study on introducing the NAS algorithm to generative adversarial networks (GANs), dubbed AutoGAN. The marriage of NAS and GANs faces its unique challenges. We define the search space for the generator architectural variations and use an RNN controller to guide the search, with parameter sharing and dynamic-resetting to accelerate the process. Inception score is adopted as the reward, and a multi-level search strategy is introduced to perform NAS in a progressive way. Experiments validate the effectiveness of AutoGAN on the task of unconditional image generation. Specifically, our discovered architectures achieve highly competitive performance compared to current stateof-the-art hand-crafted GANs, e.g., setting new state-of-theart FID scores of 12.42 on CIFAR-10, and 31.01 on STL-10, respectively. We also conclude with a discussion of the current limitations and future potential of AutoGAN.

**Paper:** [**https://arxiv.org/pdf/1908.03835.pdf**](https://arxiv.org/pdf/1908.03835.pdf)

**Code:** [**https://github.com/TAMU-VITA/AutoGAN**](https://github.com/TAMU-VITA/AutoGAN)**.**

* **Report**

1. **Recent Advances in Deep Learning for Object Detection**

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**Abstract**: Object detection is a fundamental visual recognition problem in computer vision and has been widely studied in the past decades. Visual object detection aims to find objects of certain target classes with precise localization in a given image and assign each object instance a corresponding class label. Due to the tremendous successes of deep learning based image classification, object detection techniques using deep learning have been actively studied in recent years. In this paper, we give a comprehensive survey of recent advances in visual object detection with deep learning. By reviewing a large body of recent related work in literature, we systematically analyze the existing object detection frameworks and organize the survey into three major parts: (i) detection components, (ii) learning strategies, and (iii) applications & benchmarks. In the survey, we cover a variety of factors affecting the detection performance in detail, such as detector architectures, feature learning, proposal generation, sampling strategies, etc. Finally, we discuss several future directions to facilitate and spur future research for visual object detection with deep learning.

**Paper:** [**https://arxiv.org/pdf/1908.03673.pdf**](https://arxiv.org/pdf/1908.03673.pdf)

# 2019-08-14

* **Detection & NAS**

1. **Matrix Nets: A New Deep Architecture for Object Detection**

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**Abstract**: We present Matrix Nets (xNets), a new deep architecture for object detection. xNets map objects with different sizes and aspect ratios into layers where the sizes and the aspect ratios of the objects within their layers are nearly uniform. Hence, xNets provide a scale and aspect ratio aware architecture. We leverage xNets to enhance key-points based object detection. Our architecture achieves mAP of 47.8 on MS COCO, which is higher than any other single-shot detector while using half the number of parameters and training 3x faster than the next best architecture.

**Paper:** [**https://arxiv.org/pdf/1908.04646.pdf**](https://arxiv.org/pdf/1908.04646.pdf)

* **Multi-task**

1. **Feature Partitioning for Efficient Multi-Task Architectures**

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**Abstract:** Multi-task learning holds the promise of less data, parameters, and time than training of separate models. We propose a method to automatically search over multi-task architectures while taking resource constraints into consideration. We propose a search space that compactly represents different parameter sharing strategies. This provides more effective coverage and sampling of the space of multi-task architectures. We also present a method for quick evaluation of different architectures by using feature distillation. Together these contributions allow us to quickly optimize for efficient multi-task models. We benchmark on Visual Decathlon, demonstrating that we can automatically search for and identify multi-task architectures that effectively make trade-offs between task resource requirements while achieving a high level of final performance.

**Paper:** [**https://arxiv.org/pdf/1908.04339.pdf**](https://arxiv.org/pdf/1908.04339.pdf)

**Pruning & Quantization**

1. **Effective Training of Convolutional Neural Networks with Low-bitwidth Weights and Activations**

Bohan Zhuang, Jing Liu, Mingkui Tan, Lingqiao Liu, Ian Reid, Chunhua Shen

**Abstract**: This paper tackles the problem of training a deep convolutional neural network of both low-bitwidth weights and activations. Optimizing a low-precision network is very challenging due to the non-differentiability of the quantizer, which may result in substantial accuracy loss. To address this, we propose three practical approaches, including (i) progressive quantization; (ii) stochastic precision; and (iii) joint knowledge distillation to improve the network training. First, for progressive quantization, we propose two schemes to progressively find good local minima. Specifically, we propose to first optimize a net with quantized weights and subsequently quantize activations. This is in contrast to the traditional methods which optimize them simultaneously. Furthermore, we propose a second progressive quantization scheme which gradually decreases the bit-width from high-precision to low-precision during training. Second, to alleviate the excessive training burden due to the multi-round training stages, we further propose a one-stage stochastic precision strategy to randomly sample and quantize sub-networks while keeping other parts in full-precision. Finally, we adopt a novel learning scheme to jointly train a full-precision model alongside the low-precision one. By doing so, the full-precision model provides hints to guide the low-precision model training and significantly improves the performance of the low-precision network. Extensive experiments on various datasets (e.g., CIFAR-100, ImageNet) show the effectiveness of the proposed methods.

**Paper:** [**https://arxiv.org/pdf/1908.04680.pdf**](https://arxiv.org/pdf/1908.04680.pdf)

1. **Adversarial Neural Pruning**

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**Abstract**: It is well known that neural networks are susceptible to adversarial perturbations and are also computationally and memory intensive which makes it difficult to deploy them in real-world applications where security and computation are constrained. In this work, we aim to obtain both robust and sparse networks that are applicable to such scenarios, based on the intuition that latent features have a varying degree of susceptibility to adversarial perturbations. Specifically, we define vulnerability at the latent feature space and then propose a Bayesian framework to prioritize features based on their contribution to both the original and adversarial loss, to prune vulnerable features and preserve the robust ones. Through quantitative evaluation and qualitative analysis of the perturbation to latent features, we show that our sparsification method is a defense mechanism against adversarial attacks and the robustness indeed comes from our model’s ability to prune vulnerable latent features that are more susceptible to adversarial perturbations

**Paper:** [**https://arxiv.org/pdf/1908.04355.pdf**](https://arxiv.org/pdf/1908.04355.pdf)