

Class-Agnostic Segmentation Loss and Its Application to Salient Object Detection and Segmentation

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Objectives

We design a loss function which trains the network to clusters pixels of similar appearance together in a weakly-supervised manner, without the need of class-labels. Our loss function forces the descriptors to have low variance on regions/objects, at the same time the descriptor learns to discriminate between different regions.

Introduction

- We present a novel loss function, called class-agnostic segmentation (CAS) loss.
- With CAS loss the class descriptors are learned during training of the network.
- We don't require to define the label of a class a-priori, rather the CAS loss clusters regions with similar appearance together in a weakly-supervised manner.

Data	Training Data				Testing			
	Image	Ground Truth	Image	Ground Truth	Image	Ground Truth	CE	CAS
HFD								
LFD								

Figure 1: Motivational Example: Traditional segmentation/detection methods work well in HFD setting (high-fidelity training data, where class labels are available and accurate) but fail completely in LFD setting (low-fidelity training data, where class labels are either not available or incorrect).

Class-Agnostic Segmentation (CAS) Loss

$$CAS = \frac{\sum_{i=1}^N \int_{r_i} \alpha ||\mathbf{s}(x) - \hat{\mathbf{s}}(r_i)||_2^2 dx}{|r_i|} - \frac{\sum_{i=1}^N \sum_{\substack{j=1 \\ i \neq j}}^N (1 - \alpha) ||\hat{\mathbf{s}}(r_i) - \hat{\mathbf{s}}(r_j)||_2^2}{\text{Discriminator}}$$

- The uniformer term of the loss function reduces variance of the learned descriptor on the regions (segments) - **Intra-class variance**
- The discriminator term increases distance between the learned descriptors for different regions - **Inter-class variance**
- Properties of the CAS loss are sparsity, boundedness and robustness to class-imbalance.

Experiments

We apply our CAS loss function to salient object detection, in two settings of low and high-fidelity training data on **seven** salient object detection datasets. In order to show the utility of the loss function across different domains we then also test on texture and segmentation.





























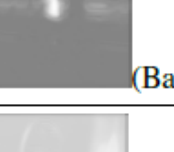
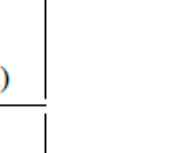
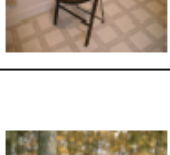







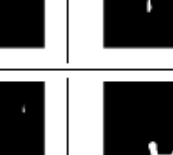




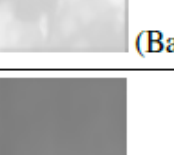
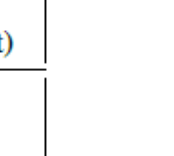














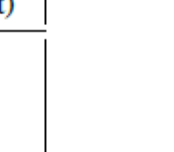















Image	Ground Truth	ResNet-pre-CAS	ResNet-m-CAS	ResNet-d-CAS	ResNet-m-CE	ResNet-d-CE	ResNet-CAS	ResNet-CE	ResNet-CACE	BAS-Net [31]	PoolNet [22]	CPSNet [42]	PFAN [43]	Low-fidelity trained sota	
		High-fidelity trained Our Models						Low-fidelity trained Our Models			State-of-the-art				
															(PFAN)
															(BasNet)
															(BasNet)
															(PoolNet)
															(PFAN)

Figure 3: Visual Results for High-fidelity and Low-fidelity Data Training, and Comparison with State-of-the-art methods

Results

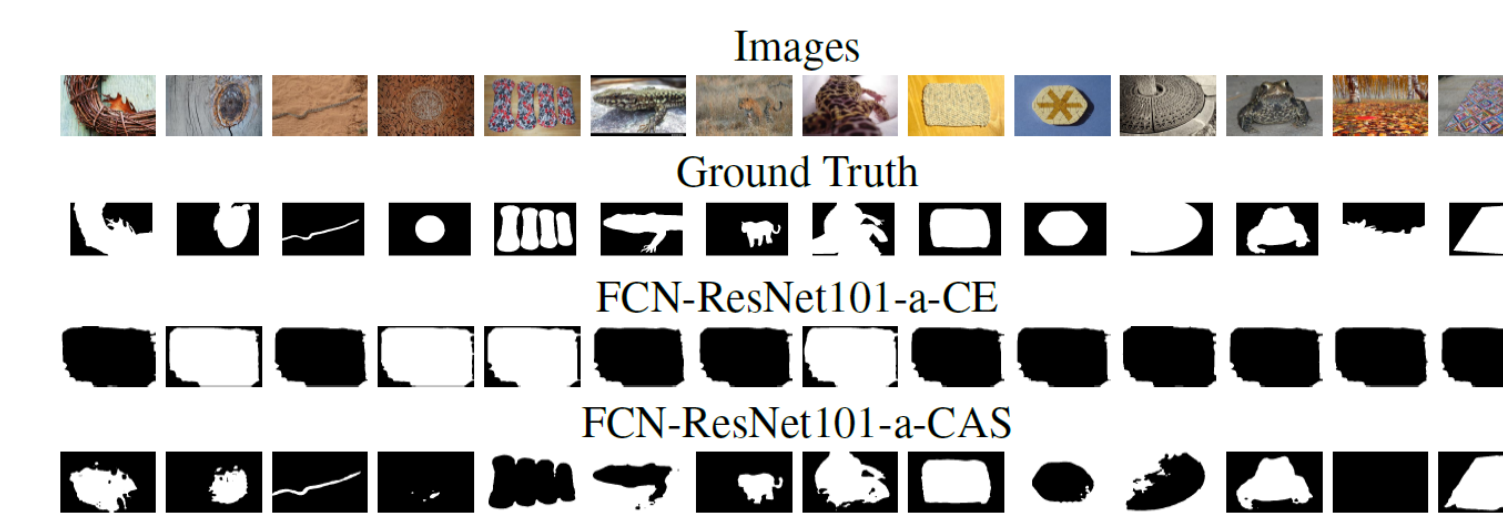


Figure 2: Visual results for texture segmentation experiments

- For low-fidelity training data (incorrect class label) class-agnostic segmentation loss outperforms the state-of-the-art methods on salient object detection datasets by staggering margins of around **50%**.
- For high-fidelity training data (correct class labels) class-agnostic segmentation models perform as good as the state-of-the-art approaches while beating the state-of-the-art methods on most datasets.
- On texture segmentation and general segmentation class-agnostic segmentation loss outperforms competing losses by huge margins.

Discussion

The current approaches for segmentation and detection, which conventionally use cross-entropy loss or a variant of cross entropy loss, have the following drawbacks:

- 1 For large datasets, data annotation will be performed by a huge pool of moderately trained annotators and there will inevitably be errors in label of objects (since these labels are arbitrary and do not correspond to any fundamental notion of appearance).
- 2 The number of classes that one can sample is limited and consequently can not be generalised to the infinite number of classes that exist in real life scenes.
- 3 The loss functions used are agnostic to the notion of class appearance and simply learn to group similarly labelled objects together.

Our CAS loss is independent of the class label and learns to perform unsupervised clustering of the learned descriptors to obtain class labels. Whereas, conventional cross-entropy (CE) based methods completely fail in LFD setting since they are reliant on class label.

Code, Paper and Contact Information

- Code available at https://github.com/sofmonk/class_agnostic_loss_saliency
- Extended version of this paper available at <https://arxiv.org/abs/2010.14793>
- Email: angira.sharma@cs.ox.ac.uk