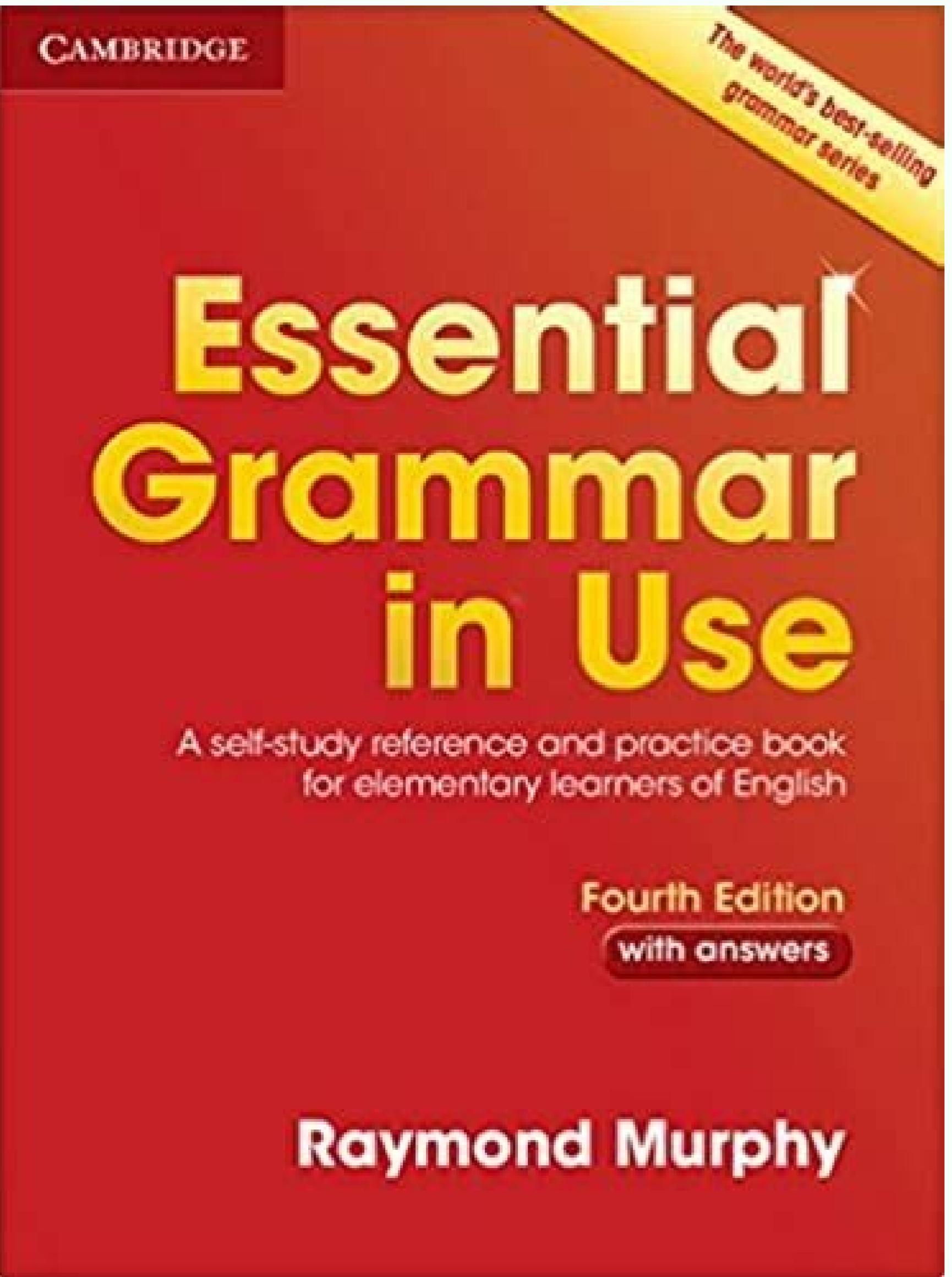


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Learning from Scale-Invariant Examples for Domain Adaptation in Semantic Segmentation

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Abstract. Self-supervised learning approaches for unsupervised domain adaptation (UDA) of semantic segmentation models suffer from challenges of predicting and selecting reasonable good-quality pseudo labels. In this paper, we propose a novel approach of exploiting scale-invariance property of the semantic segmentation model for self-supervised domain adaptation. Our algorithm is based on a reasonable assumption that, in general, regardless of the size of the object and stuff (given context) the semantic labeling should be unchanged. We show that this constraint is violated over the images of the target domain, and hence could be used to transfer labels in-between differently scaled patches. Specifically, we show that semantic segmentation model produces output with high entropy when presented with scaled-up patches of target domain, in comparison to when presented original size images. These scale-invariant examples are extracted from the most confident images of the target domain. Dynamic class specific entropy thresholding mechanism is presented to filter out unreliable pseudo-labels. Furthermore, we also incorporate the focal loss to tackle the problem of class imbalance in self-supervised learning. Extensive experiments have been performed, and results indicate that exploiting the scale-invariant labeling, we outperform existing self-supervised based state-of-the-art domain adaptation methods. Specifically, we achieve 1.3% and 3.8% of lead for GTA5 to Cityscapes and SYNTHA to Cityscapes with VGG16-FC8 baseline network.

1 Introduction

Deep learning based semantic segmentation models [29,3,32,31] have made considerable progress in last few years. Exploiting hierarchical representation, these models report state-of-the-art results over the large datasets. However, these models do not generalize well, when presented with out of domain images, their accuracies drops. This behavior is attributed to the shift between the source domain, one over which model has been trained, and target, over which its being tested. Most of semantic segmentation algorithms are trained in a supervised fashion, requiring pixel-level, labor extensive and costly annotations. Collecting such fine-grain annotations for every scene variation is not feasible. To avoid this pain-striking task, road scene segmentation algorithm use synthetic but photo-realistic datasets, like GTA5 [26], Synthia [21], etc., for training. However, they

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