Learn transferable features for semantic image segmentation in the presence of label noise

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Abstract

The ABSTRACT HERE

1 Introduction

Why noisy labels?:This paragraph should discuss the difficulties for collecting perfect segmentation annotations on a large scale
The recent success of deep neural networks benefits from the availability of large-scale supervised datasets such as ILSVRC[23]. However, collecting a dataset for semantic image segmentation on a large scale can be expensive and time-consuming, especially when error-free labels are required. Enormous efforts have been made to create the "gold standard" annotations for the current benchmark segmentation datasets[6, 19, 15]. [1] These datasets allow the deep neural network models for semantic segmentation [16, 28] to develop assuming the perfect segmentation ground truth exists, where perfect means that all the instances were annotated, no non-target object was misannotated, and no instance was misclassified. However, it is natural for human beings to make mistakes due to the lack of expertise, the inherent ambiguity of tasks or unconscious bias. Strong supervision is required to correct the mistakes, including double-checking the annotations over and over again and ensembling opinions from multiple annotators. In some cases, for example in the medical imaging, the "gold standard" itself can be ambiguous and cause disagreement among different annotators. Also, there are some freely available labels, which may or may not be accurate, for specific problems. For example, one can use digital maps, like OpenStreetMap, to annotate aerial images, but such segmentation annotations constructed from maps suffer from the incomplete annotation as well as registration problems.[18] This motivates us to explore how to learn from these noisy annotations.

Why representation?: This paragraph should discuss the idea of noise-robust representation
Deep convolutional neural networks (DCNN) based models often contain two principal components: a stack of convolutional layers to extract hierarchical features and a few task-specific layers to fit the training objectives. Both parts are important to achieve good performance because they are trained jointly in an end-to-end manner via back propagation. The convolutional features were proved "transferable" to a new dataset[27] or even to a different task[8]. The state-of-art DCNN based semantic image segmentation models relies on transferring the pre-trained convolutional filters as well.[16] A typical method to pre-train the convolutional filters is to train a classification model with the large-scale ILSVRC dataset [23] However, this method constrains the semantic image segmentation models to have the same CNN architecture as the image classification models. The CNN design for semantic image segmentation does not neces-

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[1] M: Do we actually have a reference for that? Or other proof?
J: I think the preparation methods described in these papers can be supportive. Microsoft COCO even mentioned the total working hours in the paper.

sarily follow the design of image classification architectures. The segmentation models need both global and local information to predict the category and give a fine segmentation, whereas the classification models care less about local information for object localization. For instance, the presence of the max-pooling layers enable the following convolutional filters to have larger receptive fields but, at the same time, reduce the resolution of the features. Additional upsampling layers can recover the shape of the output segmentation but cannot fully recover the information thrown away. This first-pooling-and-then-upsampling pipeline can result in coarse segmentation output [2] with non-shape boundaries and blob-like shapes. [2] Alternatively, one can also extract convolutional features with semantic segmentation tasks. But it is more difficult to collect well-annotated dataset for semantic image segmentation than for object recognition. A large number of annotated images are of great value to train sufficiently generalized representation and avoid overfitting, given the "data-hungry" nature of DCNNs. [3] Allowing the existence noisy annotations could help significantly increase the number of annotated images and the number of training samples could compensate the impact of annotation errors. We will further discuss this in the related works.

This paragraph should summarize the main ideas.

The different levels of the hierarchical features in DCNNs are believed to play different roles in extracting information from the images. The low-level features process the local information within small neighborhood and the high-level features ensemble information from lower-level features to extract abstract information. The high-level features were found significantly dependent on the exact categories compared to the low-level features which show extraordinary category independence.[27] Previous studies[24, 20] have shown that training with noisy labels can lead to significantly higher classification errors than training with clean labels if the total number of training samples are fixed. It is nevertheless unclear how the annotation errors would influence the learned multiple level

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[2] M: Also for this claim, I think we need a reference or something like that. Or other proof indeed... In addition, I wonder whether we can explain why this may be the case? J: Yes, I can refer to a paragraph in the intro of CRFasRNN and enrich the discussion a bit.

[3] M: For the rest a bit vague... what do we really mean by suffer? Maybe this becomes clear later in the intro...? J: Refrased.

features. We made a hypothesis that annotation errors do not necessarily lead to a "bad representation" because the "generality" of low-level features may contribute to a robustness to the errors when we transfer the learned features to a new dataset with new categories.

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In the next section, we summarized the related works for deep learning with noisy labels. In Section 3 we formulate the annotation errors into three categroies: misannotation, misclassification and incomplete annotation. We tested our hypothesis in Section 4, studying whether the misannotation and misclassification had an impact on learning "transferable" features. In Section 5 we connected training with inexaustive annotations to Positive and Unlabeled Learning.

2 Related work

Transfer Learning The first-layer features in the modern CNNs are often observed converged to either Gabor filters or color blobs, regardless the exact learning objectives and the training dataset. These first-layer features are then often described as *general*. By contrast, the last-layer features significantly depend on the learning objective and dataset and they are denoted *specific*. Yosinski et.al.[27] studied the features in the intermediate layers, transiting from general to specific by measuring how much the tranformed pre-trained features boost the fine-tuning performance on a new dataset, i.e. the "transferability" of the features. They found features from several bottom layers, not only the first layer, were "transferable" to a new dataset, meaning that they were not specific for a particular category but were shared across categories. This discovery led to our hypothesis that the general features can be more robust to annotation errors, either object misannotation or instance misclassidication, than the specific features. We used the same measure as Yosinki et.al. did to quantitatively measure the "transferability" of the features and reported the robustness to instance misannotation and instance misclassification for the learned representation.

Unsupervised pre-training Apart from supervised pre-training, one can also obtain the pre-trained features in an unsupervised or a semi-supervised way. The most

common method is to train a generative model with either *auto-encoder* variants or *deep beilief network*. Vincent et al.[25] trained multiple levels of representation robust to the corrupted inputs with stacked denoising auto-encoders. Masci et al.[17] presented a stacked convolutional auto-encoder unsupervised pre-training for hierarchical feature extraction. Hinton et al.[11] proposed a greedy learning algorithm to train *deep belief nets* one layer at a time to train hierarchical features. Lee et al.[12] presented a *convolutional deep belief network*, to learn hierachical convolutional representations. A few studies[5, 4, 1] highlighted the advantage of unsupervised pre-training compared to the random initialization, connecting unsupervised pre-training to a norm of regularization and a method that help disentangle the sample variations. However, better random initialization strategies, for example, xavier initialization[9] and its variants, have shortened the gap between unsupervised pre-training and random initialization. Using unsupervised pre-training or not now becomes a tradeoff between the time and resources invested and the performance gain. Unsupervised deep representation learning is in general not comparable to supervised representation learning especially when large scale dataset is available. A proper method to learn features in the presence of label noise should at least outperform unsupervised pre-training because noisy information is still better than no information.

Deep Learning with Noisy Labels   A few studies[24, 20] investigated the impact of label noise on classification performance with convolutional neural networks assuming the labels were randomly transited from one to another given the probabilities fall in a transition matrix. They found a significant decrease in classification performance along with the increase of false label proportion when the total number of examples is fixed. They then proposed methods to handle this label noise at random (NAR)[7] situation by either introducing a linear noise layer on top of the output layer[24] or correcting the loss functions with an estimation of the noise transition matrix[20]. Xiao et al.[26] integrated a probabilistic graphic model to an end-to-end deep learning system to train predicting class labels, either correct or wrong, as well as to correct the wrong labels. Reed & Lee[21] proposed an empirical way of taking into account the *perceptual consistency* for

large-scale object recognition and detection when incomplete and noisy labels exist by introducing a bootstrapping modification to the negative log-likelihood, in either a "Hard" or a "soft" favor.

Noise robustness In contrast to the works above, Rolnick et al.[22] argued that deep neural networks can learn robustly from the noisy dataset as long as an appropriate hyper parameters choice was made. They studied instead of replacing the correct labels with noisy labels but diluting correct labels with noisy labels to support their argument. They then concluded sufficiently large training set is of more importance than lower the level of noise. This work is closely related to our work in Section 4, except that we focus on the label noise robustness regarding the feature "transferability" instead of the classification performance. Additionally, most of these studies focus on the classification problems, whereas our work inclined more to the semantic segmentation problem.

Positive and Unlabeled Learning   If we consider the in-exhaustive annotation issue only, i.e., only a proportion of the target instances were annotated, the problem becomes similar to a so-called *positive and unlabelled learning* (PU learning) setup[14]. In the positive and unlabeled learning setup, the training dataset has two sets of examples: the *positive (P) set*, contained only positive examples, and the *unlabeled (U) set*, contained a mix of positive or negative examples. If we categorize the pixels into either *foreground pixels* or *background pixels*, the correctly annotated instances form the positive set, and the unannotated instances are mixed with the background pixels, forming an unlabeled set. The previous studies about PU learning mainly focus on the binary classification for linear-separable problems[3, 13], whereas we showed in Section 5 that it is possible to train deep neural networks for multiple classes with only "positive" and unlabeled examples.

3   Problem Formulation

Briefly formulate the problem.

Semantic Segmentation tasks can be considered as per-pixel classification problem. Each of the pixels is assigned a label of either 0, indicating a background pixel,

or $k \in 1, \ldots, K$ denoting a foreground pixel corresponding to an instance from one of the K categories. The aforementioned errors can be interpreted by the pixel label flipping: *misannotation* is label flipped from 0 to k, *inexaustive annotation* flipped from k to 0, and *misclassification* flipped from i to j, where $i, j, k \in 1, \ldots, K$. The misannotated instances are assumed to be visually distinguishable against the background and have natural semantic meaning. All the label flips have one instance as the minimum fliping unit.

Instance Misannotation and Instance Misclassification One hypothesis made in this work is that the *misannotated and misclassified* instances can still provide information for training multi-scaled features that are *transferable*[27] to the other datasets and categories. Supposing a dog toy is wrongly annotated as a dog, given that the "dog" is one of the target categories while the "toy" is not, the error would introduce bias into the last layer but not necessarily into the first convolutional layers. The high-level features were found more dependent on a particular category, i.e. more *specific*, than the low-level features, whereas the low-level features were found less category-dependent, i.e. more *general*. [27] We wanted to explore whether the "generality" of low-level features contributes to the annotation error robustness when we transfer the learned features to a new dataset with new categories. That leads us to the following research question:

1. How do misannotation and misclassification of instances influence the "transferability" of the learned features respectively?

We experimented, in Section 4, how transferable the learned features are in two special cases for the two types of annotation error:

instance misannotation all instances from the non-target categories are misannotated as instance from the target category

instance misclassification the classes for all the instances are completely randomly assigned

[4] The *transferability* of the features can be evaluated by how much they can boost the performance of training a

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Initial Representation	mean IU (aerospace, bicycle, bird, boat, bottle)	mean IU (bus, car, cat, chair, cow)	mean IU (dining table, dog, horse, motorbike, person)	mean IU (potted plant, sheep, sofa, train, TV)
ImageNetModel	0.42 ± 0.01	0.51 ± 0.01	0.49 ± 0.01	0.47 ± 0.01
SingleCategory	0.42 ± 0.01	0.51 ± 0.01	0.49 ± 0.01	0.47 ± 0.01
PixelObjectness	0.30 ± 0.02	0.35 ± 0.01	0.29 ± 0.02	0.35 ± 0.03
CompleteCategory	0.29 ± 0.01	0.36 ± 0.01	0.29 ± 0.01	0.37 ± 0.01
RandomCategory	0.29 ± 0.01	0.33 ± 0.03	0.26 ± 0.01	0.28 ± 0.01
FromScratch	0.29 ± 0.01	0.29 ± 0.03	0.27 ± 0.01	0.30 ± 0.02

Table 1: Performances of FCN with Alexnet trained to segment 5 categories from the PASCAL VOC2011 dataset with different representation initializations. *Complete-Category* is the model pre-trained to segment the other 15 categories from the PASCAL VOC2011 dataset; The *PixelObjectness* model was pre-trained to distinguish the instance against the background; The *RandomCategory* model was pre-trained to segment instances with randomly assigned categories from 1 to 15.

new dataset. [27] *TODO One sentence summarizes the results.*

Inexaustive annotating

The exhaustive annotations can introduce bias to both the decoding layer and the encoding layers because they negatively contribute to the activations in all the layers. [5] The inexhaustive annotations need to be properly handled given the prior knowledge modeling the missing pattern of the annotations. Given that we believe any annotated instance provide information, all the foreground pixels that correspond to the annotated instances become reliable and the background pixels may contain both the true background pixels and object pixels unannotated. That satisfies a Positive and Unlabeled learning setup where the training dataset contains only the positive examples and unlabeled examples that are the mixed of the positive samples and negative samples.

4 Pre-train features by learning "objectness"

5 Positive and Unlabeled Learning

One sentence summary of Positive and Unlabeled Learning

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[4]M: So, to what extent is this the actual research question that you would like to answer? J: I think this section answers your question now.

[5]J: This argument need evidence too, or experiment/discussions in details in Section 5
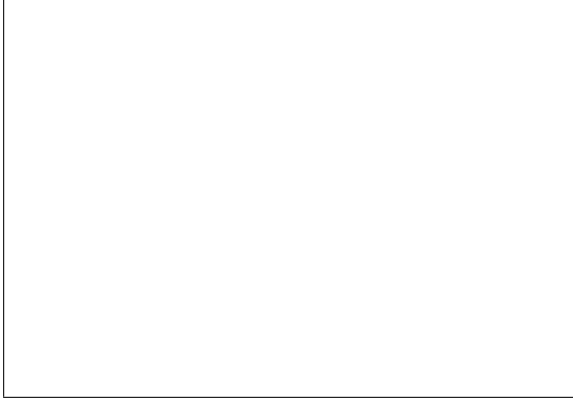
Figure 1: Visualization of first-layer features from different pre-trained models.
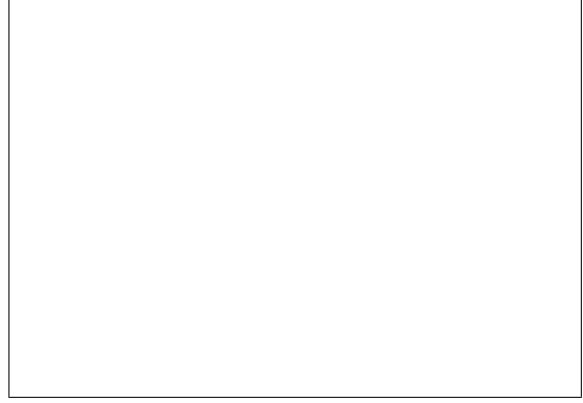

Figure 2: Varying the number of categories while pre-training the representation and the pre-trained weights were fine-tuned to segment 5 categories from the PASCAL VOC2011 dataset.

Annotation	Loss	acc.	prec.	rec.	F_1
Complete	CrossEntropyU.	0.87 ± 0.01	0.88 ± 0.01	0.82 ± 0.01	0.85 ± 0.01
50%(P+N)	CrossEntropyU.	0.83 ± 0.01	0.84 ± 0.01	0.78 ± 0.01	0.80 ± 0.01
50%P+U	CrossEntropyU.	0.64 ± 0.04	0.93 ± 0.08	0.34 ± 0.02	0.44 ± 0.06
50%P+U	WeightedU.	0.78 ± 0.01	0.75 ± 0.01	0.75 ± 0.01	0.76 ± 0.01
50%P+U	ExponentialU.	0.82 ± 0.01	0.86 ± 0.01	0.73 ± 0.01	0.78 ± 0.01
50%P+U	BootstrapHard	0.74	0.81	0.60	0.67
50%P+U	DropoutReg.				

Table 2: Image classification with positive examples partially annotated. The complete dataset contains images from CIFAR10 as the **positive** (P) set and images from CIFAR110 as the **negative** (N) set. The unannotated positive examples from P set construct the **unlabeled** (U) set together with the N set.

Formulation *This part should explain the Positive and Unlabeled Learning setup with mathematical representation when necessary.*

Weighted Logistic Regression *This part should discuss the linear model for observing positive conditioning on true positive and its relationship to changing the class weight.*

Exponential Loss for unlabeled examples *This part should explain why the exponential loss could perform better than the cross-entropy loss, potentially with a figure of 2D Gaussians.* The "soft" bootstrapping loss in [21] is actually equivalent to a softmax regression with *minimum entropy regularization*[10] which was originally proposed for semi-supervised learning. Minimum entropy regularization encourages the model to have a high confidence in predicting labels.

This paragraph should explain why fade-in was introduced to avoid all-positive inital prediction

This part should explain the influence of the imbalanced problem and how to overcome.

6   Results

7   Conclution

References

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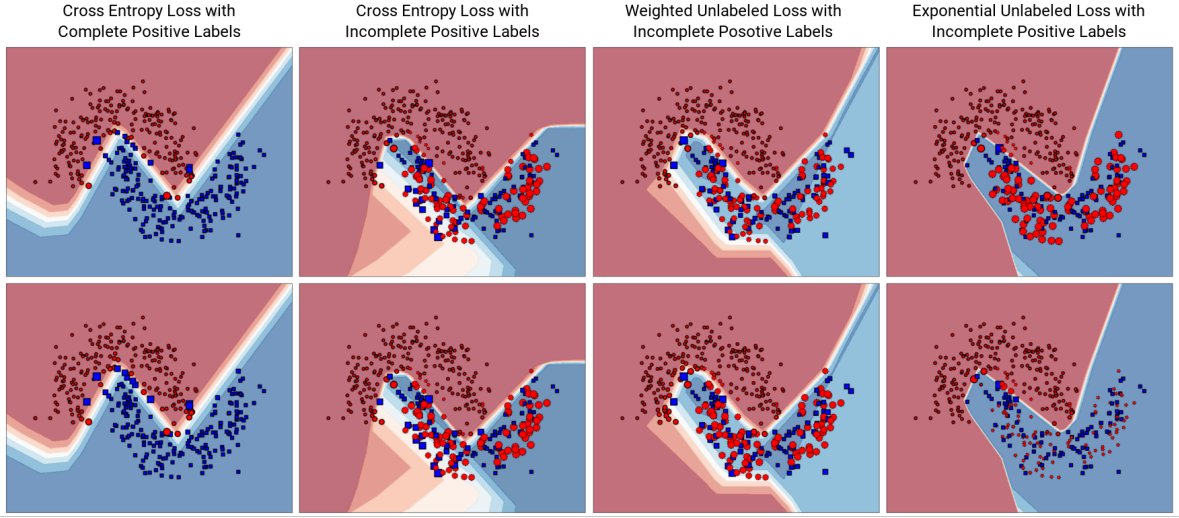
Figure 3: 2D moons dataset with non-linear separable decision boudary. Four hundreds samples per class were drawn randomly from two interleaving half circles with noises added with a minor standard deviation. A **red circle** indicates an example labelled as positive whilst a **blue square** indicates the example has a negative label. The **leftmost** figures have complete positive labels, meaning the positive and negative labels are all correct, whereas, in **the other figures** only half of the positives were correctly labelled and the rest were mixed with the negative samples. The **background colors** represent the probability for the area to be positive given by the classifier trained with the given samples and labels: **red** for high probability areas, **blue** for low probability areas and **white** for the class transition areas, i.e.decision boundaries. The **size of the markers** in the top row denotes the per-class normalized training losses and the **size of the markers** in the bottom row the per-class normalized derivatives w.r.t the output of the last layer for the trained Multilayer Perceptron (MLP) with the different losses.
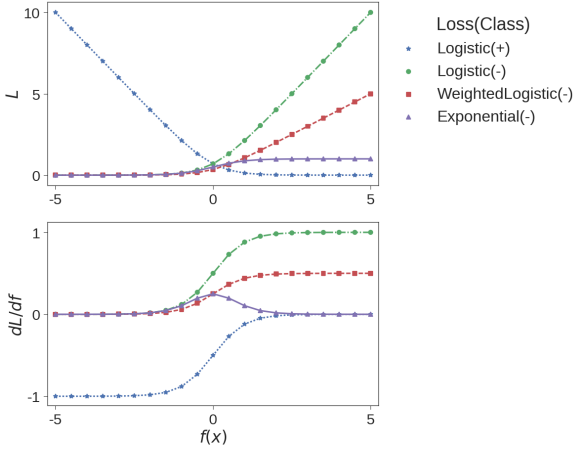
Figure 4: The Logistic Loss, Weighted Logistic Loss, Exponential Loss and their dirivatives with respect to the model output.
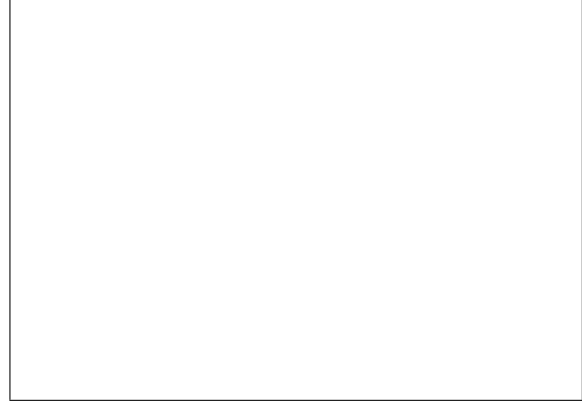

Figure 5: Varying percentage of annotated positives 10%, 20%, 50%, 80% and 100% with images from CIFAR10 as the positives and images from CIFAR110 as the negatives.

Annotation	Loss	pixel acc.	mean acc.	mean IU	f.w. IU
Complete	CrossEnt.U				
50%(P+N)	CrossEnt.U				
50%P+U	CrossEnt.U				
50%P+U	WeightedU				
50%P+U	ExponentialU				
50%P+U	BootstrapHard				
50%P+U	DropoutReg.				

Table 3: Image semantic segmentation with images contain single instance only from the PASCAL VOC2011 segmentation dataset. The complete **positive** (P) set denotes the foreground instances and the **negative** (N) set consists of the background. The unannotated instances from P set construct the **unlabeled** (U) set together with the N set.

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