Weakly Supervised Semantic Segmentation for Social Images

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Abstract

We tackle the problem of weakly supervised semantic segmentation for social images, whose labels are provided by Internet users. This is an extremely difficult task because the labels are not pixel-level but image-level and usually imprecise/incomplete. In this paper, we present a joint conditional random field model leveraging various contextual relations to address this issue. More specifically, we utilize feature representation generated by convolutional neural network and latent semantic concept model as well as label correlations captured by visual contextual cues and label co-occurrence statistics to handle the noisy annotations. Experimental results on two challenging image datasets PASCAL VOC2007 and SIFT-flow show that our method outperforms state-of-the-art weakly supervised approaches and even achieves accuracy comparable with fully supervised methods.

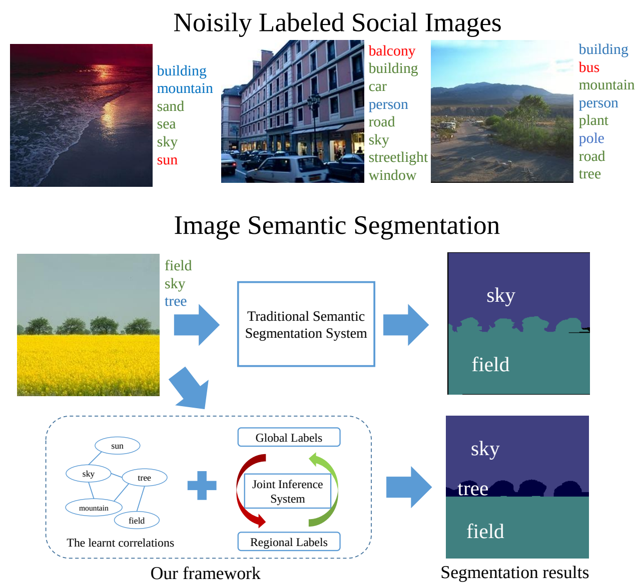


Figure 1. Given a set of social images and their associated labels where label may be precise (green), incorrect (red) or missing (blue), we learn a model that segments and recognizes visual concept in images. Best viewed in color.

1. Introduction

Semantic segmentation, *i.e.*, parsing image into several semantic regions, assigns each pixel (or superpixel) to one of the predefined semantic categories. Most state-of-the-art approaches heavily rely on a sufficiently huge amount of annotated samples in training. However, there are no enough labeled samples for this task because pixel-level (or superpixel-level) annotation is time-consuming and labor-intensive. Recent works have begun to address the semantic segmentation problem in the weakly supervised settings, where each training image is annotated by image-level labels but no pixel-level annotation is given [23, 24, 25, 26, 29, 30, 31]. The existing weakly supervised semantic segmentation methods are based on an unrealistic assumption that image-level labels are provided by professional annotators, and thus are correct and complete.

With the prevalence of photo sharing websites and collaborative image tagging system, such as Flickr, a large number of social images with user provided labels are available from the Internet. These labels are usually image-level; moreover, the quality of labels is not satisfactory: they are often imprecise and incomplete! Figure 1 illustrates a set of representative social images and its associated labels. We can observe that only limited labels accurately describe the visual content of the image, while other labels are imprecise. Moreover, some important labels, which are highly associated with the image, are missing. It is challenging but attractive to learn an effective semantic segmentation model from such social images.

In this paper, we present a weakly supervised method that, for the first time, overcomes the challenge posed by noisy annotations. The proposed method learns a joint conditional random field (CRF) model from weakly labeled social images by sufficiently leveraging various contexts, *e.g.*, the associations between high-level semantic concepts and low-level visual appearance, inter-label correlations, spatial neighborhood cues, and the label consistency between image-level and pixel-level. More specifically, we extract global features for the whole image and local features for the superpixels in multiple scales by convolutional neural network (CNN) and latent semantic concept model (LSC). Then we capture the inter-label correlations by visual contextual cues as well as label co-occurrence statistics. The label consistency between image-level and pixel-level is finally achieved by iterative refinement in a flip-flop manner.

To illustrate both robustness and effectiveness of our method, we demonstrate experimental results on two challenging datasets, PASCAL VOC 2007 and SIFT-flow datasets, which are representative of the hardness of annotation noise occurred in social images. Our method outperforms previous state-of-the-art approaches on standard datasets, demonstrating that the image-level annotation, especially potential relationships, is more efficiently utilized by our method.

The main contributions of this paper are summarized as follows:

- We propose a weakly supervised semantic segmentation model for social images, where only image-level labels are available for training, or even worse, the annotations can be imprecise or incomplete.
- We design a joint learning framework to sufficiently leverage various contexts including feature-label association, inter-label correlation, and spatial neighborhood cues.
- We explore an effective strategy that jointly captures label co-occurrence statistics as well as visual contextual cues to model the label correlations.

2. Related Work

Being such a fundamental problem in computer vision community, numerous methods have been proposed for the semantic segmentation task in the fully supervised settings. Shotton *et al*. [18] formulate semantic segmentation as a CRF model over image pixels incorporating shape-texture color, location and edge cues in a single unified model. This model is further extended in series papers [10, 12, 13]. For instance, Kohli *et al*. utilize the higher order potentials [10] as a soft decision to ensure that pixels constituting a particular segment have the same semantic concept. Ladicky *et al.* extend the higher order potentials to hierarchical structure in [12] by using multiple segmentations and further integrate label co-occurrence statistics in [13]. However, these methods heavily rely on pixel-level annotations during the training stage.

Comparison with fully supervised semantic segmentation, there has been little work in the weakly supervised settings due to the fact that it is more challenging than the fully supervised task. Verbeek and Triggs [23] make the first attempt to learn a semantic segmentation model from image-level tagged data. They leverage several appearance descriptors to learn the latent aspect model via probabilistic Latent Semantic Analysis (pLSA) [8]. Furthermore, the spanning tree structure and Markov Fields are integrated with the aspect model in order to take the spatial information into consideration. In [24], Vezhnevets and Buhmann cast the weakly supervised task as a multi-instance multi-task learning problem with the framework of Semantic Texton Forest (STF) [17]. Based on [24], Vezhnevets *et al*. [25, 26] integrate the latent correlations among the superpixels belong to different images which share the same labels into CRF. Xu *et al*. [29] simplify the previous complicated framework by a graphical model that encodes the presence/absence of a class as well as the assignments of semantic labels to superpixels.

However, all these approaches are based on the assumption that the initial image-level labels are clean and complete. It is not a practical requirement in many real-world applications. Although sharing similarities with both fully supervised and weakly supervised semantic segmentation, an significant and novel difficulty we address in this paper is the issue of noisy annotations (*e.g*., labels can be incorrect and incomplete), which makes the task more challenging and intractable. To tackle this problem, we investigate label correlations, which are neglected by previous weakly supervised methods [23, 24, 25, 26, 29], based on not only label co-occurrence statistics but also the visual contextual cues.

Besides, we take latent semantic concept model generated by an unsupervised method as a mid-level representation of superpixels, while other methods (*e.g*., [25, 29]) only use the appearance model as a low-level representation, to narrow down the gap between semantic space and feature space, in the meantime, to make the whole framework more stable under the noisy condition. Unlike previous weakly supervised methods (*e.g*., [26, 29]), we also utilize multiple scale segmentations trying to avoid the weakness of choice of segmentation which cannot cover all the quantization level of objects.

3. The Proposed Model

Suppose that each image I is associated with a label vector $\boldsymbol{y} = [y_1, ..., y_L]$, where L is the number of categories, and $y_i = 1$ indicates that the i-th category is present in this image, otherwise $y_i = 0$. In the training set, $\boldsymbol{y}$ is given; however, it may be incorrect or incomplete. In the test set, $\boldsymbol{y}$ is unknown. For each image, we employ the existing multi-scale segmentation algorithm and get a set of superpixels $\{x_p\}_{p=1}^{M}$ over multiple image quantizations. Here, M is the total number of superpixels in image I. The label of superpixel x_p is denoted as $h_p \in \{1, 2, ..., L\}$, and the labels of all superpixels for image I are $\boldsymbol{h} = [h_1, ..., h_M]$, which are not provided for training.

Our goal is to infer the most suitable semantic label for each superpixel in an image and the adjacent superpixels sharing the same semantic label are fused as the whole one. In order to achieve this, we build a conditional random field (CRF) on the image-level label variables $\boldsymbol{y}$ and the superpixel-level label variables $\boldsymbol{h}$. We connect each superpixel variables to its neighbors to encode a local smoothness constraint. Specifically, let $\mathcal{N}$ denote the neighborhood system among the superpixels, we define an energy function E with five types of potential as follows:

$$\begin{aligned} E(\boldsymbol{y}, \boldsymbol{h}, I) = &\sum_{i=1}^{L} \varphi_i(y_i, I) + \sum_{1 \le i,j \le L} \varphi_{ij}(y_i, y_j) \\ &+ \sum_{p=1}^{M} \psi_p(h_p, x_p) + \sum_{(p,q) \in \mathcal{N}} \psi_{pq}(h_p, h_q) \\ &+ \tau(\boldsymbol{y}, \boldsymbol{h}) \end{aligned} \tag{1}$$

where φ_i and ψ_p encode the unary potentials of image-level and superpixel-level constraints respectively, φ_{ij} encodes inter-label correlation, and ψ_{pq} are the spatial context constraints for each superpixel, both φ_{ij} ψ_{pq} is the pairwise potentials, and $\tau(\boldsymbol{y}, \boldsymbol{h})$ ensures the consistency between global and regional labels. The posterior distribution $P(\boldsymbol{y}, \boldsymbol{h}|I)$ of the CRF can be written as $P(\boldsymbol{y}, \boldsymbol{h}|I) = \frac{1}{Z(I)} \exp\{-E(\boldsymbol{y}, \boldsymbol{h}, I)\}$, where $Z(I)$ is the normalizing constant. Thus, the most probable labeling configuration $\boldsymbol{y}^\star, \boldsymbol{h}^\star$ of the random field can be defined as $\boldsymbol{y}^\star, \boldsymbol{h}^\star = \arg\min_{\boldsymbol{y},\boldsymbol{h}} E(\boldsymbol{y}, \boldsymbol{h}, I)$. The details of each potential will be described in the following sections, and a graphical representation of the energy function is illustrated in Figure **??**.

3.1. Unary Potential

Image-Level Potential We model input image by two aspects: On the one hand, we utilize convolutional neural network (CNN) to represent the appearance model of each image, especially the first fully-connected layer containing 4096 neurons of a 19-layers model [19]. On the other hand, for latent semantic concept model, we model the CNN representation as a finite mixture of latent semantic concepts by probabilistic latent semantic analysis (pLSA) [20], which can recover visual models of semantic labels in a completely unsupervised manner. Similar to [28], we regard fully-connected layer as input considering each neuron as a visual word w_i and each image as a document d_j, then the occurrence frequency of image on w_i is the i-th dimension of d_j. In addition, there is a hidden semantic topic variable t_k associated with all the visual words. We treat each topic t_k as a latent semantic concept. The pLSA optimizes the joint probability $P(w_i, d_j, t_k)$. Marginalizing over the latent concept t_k determines the conditional probability $P(w_i|t_k)$:

$$P(w_i|d_j) = \sum_{k=1}^{K} P(t_k|d_j) P(w_i|t_k) \tag{2}$$

where $P(t_k|d_j)$ is the probability of latent semantic concept t_k occurring in image j. Formally, we formulate image-level feature as I by concatenating the appearance feature d_j and latent semantic concept distribution $P(\boldsymbol{t}|d_j)$, and define the i-th image-level label presence potential φ_i as follows:

$$\varphi_i(y_i, I) = -\log f_i(I) \tag{3}$$

where $f_i(I)$ is the linear support vector machine score function associated with label i.

Superpixel-Level Potential Similar with image-level potential, we both consider the appearance model and latent semantic concept model in order to narrow down the gap between low-level feature space and high-level semantic space, in the meantime, to reduce the negative impact of inaccurate image-level labels. Formally, we encode the unary potential of superpixel-level as follows:

$$\begin{aligned} \psi_p(h_p, x_p) = -\log\big\{&w_1 \phi_a(h_p, a_p, \theta_a) \\ &+ w_2 \phi_c(h_p, c_p, \theta_c)\big\} \end{aligned} \tag{4}$$

where a_p, c_p are the appearance feature and latent semantic concept distribution vectors extracted from the superpixels, θ_a, θ_c donate the parameters with respect to appearance model and latent semantic concept model, w_1, w_2 are the weighting coefficients for the unary terms. We define the appearance model $\phi_a(h_p, a_p, \theta_a)$ and latent semantic concept model $\phi_c(h_p, c_p, \theta_c)$ measuring how well the local appearance a_p and latent semantic concept c_p matches the semantic label h_p. The details of learning θ_a and θ_c will be illustrated in Section 3.3.

3.2. Pairwise Potential

Label Correlation We model inter-label co-occurrence by constructing inter-label correlation matrix which characterizing the interaction between semantic concepts and helps to model the relationship among feature space of superpixels. Due to the unknown semantic annotation of superpixels, learning these latent information is an unsupervised learning problem. Moreover, the context contain some useful latent information which can be learned for semantic label noise reduction.

Here we consider two aspects to construct inter-label matrix. On the one hand, we measure the co-occurrence of concepts pair (i, j) based on statistics by $[1 - (1 - P(i|j))(1 - P(j|i))]$, where $P(i|j)$ is the empirical probability of concept i occurring under the condition that concept j has occurred. On the other hand, we determine the inter-label correlation via discriminative regions overlap of concepts pair. The discriminative region of concept indicates the most informative sub-windows of each image within a multi-class classification framework. The basic idea is to analyze the variation of classification score when artificially blackout different regions of the image. We observe that blackout a discriminative sub-window causes a massive confusion for one-vs-one classifier, especially in cluster condition. This produces a set of sub-windows, which are deemed likely to contain the discriminative region for specific semantic label, from initial segmentation of each image. After localizing discriminative area, we can easily construct the inter-label correlation matrix by using both the available image-level label and region-level overlap (as illustrated in Figure **??**). More concretely, we define the label correlation potential ψ_R as follows:

$$\varphi_{ij}(y_i, y_j) = y_i y_j R(i,j)[1-(1-P(i|j))(1-P(j|i))] \quad (5)$$

where $R(i,j)$, scaled to $[0,1]$, is calculated from the overlapping area of discriminative regions between category i and j.

Hierarchical Model and Spatial Constraints Considering the weakness of the single choice of segmentation, we utilize multiple segmentations to disambiguate low-level segmentation cues. We divide the superpixels into different quantization level according to the particular segmentation scale we chose. Then we include the inter-level energy cost ϕ_{inter} to investigate the most suitable segmentation scale each object belongs to. Besides, we integrate the intra-level energy cost ϕ_{intra}, which could discourage superpixel-level noise, to smooth the object boundaries. Let the two neighboring superpixels (inter-level or intra-level) be x_p and x_q (*i.e.*, $(p,q) \in \mathcal{N}$), we define the pairwise potential ψ_{pq} as follows,

$$\psi_{pq}(h_p, h_q) = \begin{cases} \phi_{inter}(h_p, h_q) & \text{if } |l_p - l_q| = 1, \\ \phi_{intra}(h_p, h_q) & \text{if } l_p = l_q, \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

where l_p indicates the quantization level that the superpixel x_p belongs to. The inter-level energy cost ϕ_{inter} is defined as:

$$\phi_{inter}(h_p, h_q) = \gamma \cdot O(x_p, x_q) \cdot \mathbf{1}(h_p \neq h_q) \quad (7)$$

where $O(x_p, x_q)$ refers to the intersection (overlapping area) of two superpixels, $\mathbf{1}(\cdot)$ is the indicator function and γ is the weighting coefficient. This formulation is based on the higher order constraints [10, 12] that superpixels lying within the same clique are more likely to take the same label. And the intra-level energy cost ϕ_{intra} is defined as:

$$\phi_{intra}(h_p, h_q) = S(x_p, x_q) \cdot (1 - R(h_p, h_q)) \quad (8)$$

where $S(x_p, x_q) \in [0,1]$ measures the visual similarity between superpixel x_p and x_q, $R(h_p, h_q) \in [0,1]$ is an inter-concept correlation between label h_p and h_q. Hence, we pay a high cost for the similar superpixels if they were assigned different labels and for the superpixels which were assigned an irrelevant label to the context.

Label Consistency We require that the superpixel labels be consistent with the image labels: if any superpixel x_p takes the label i, then image label indicator $y_i = 1$; otherwise $y_i = 0$. Such constraints can be encode by the following potential:

$$\tau(\boldsymbol{y}, \boldsymbol{h}) = C \sum_{i,p} \mathbf{1}(y_i = 0 \wedge h_p = i) \quad (9)$$

where $\mathbf{1}(\cdot)$ is the indicator function and C is a positive constant that penalizes any inconsistency between the image-level and superpixel-level labels. It is worth noting that such label consistency potential is a soft constraint. Thus, we can further simultaneously refine superpxiel label and image label via an iterative process.

3.3. Learning Parameters

Due to the fact that pixel-level labels are not available during the training stage, we cannot use cross-validation [10] to learn the weights for each potential. Inspired by [25], we scale the pairwise potentials so as to make them comparable with unary potentials instead of using cross-validation procedure. After selecting the weights of each potential, we can learn the parameters of appearance model θ_a and latent semantic concept model θ_c via an alternating optimization [25]: 1) fix $\boldsymbol{h}$ and learn θ_a, θ_c; 2) fix θ_a, θ_c and infer $\boldsymbol{h}$. The first step corresponds to a continues optimization problem, hence the optimal appearance parameters θ_a and latent semantic concept parameters θ_c can be found efficiently via the existing supervised methods (*e.g.*, [18]). The second step is a discrete optimization problem and we provide the details in Section 3.4.

3.4. Joint Inference with Alternating Procedure

Given an image I, our task is to assign each pixel a predefined semantic label. We achieve this as an energy minimization problem (1), in which our inference algorithm searches for optimal configuration of image-level label $\boldsymbol{y}^\star$ and superpixel-level label $\boldsymbol{h}^\star$. To efficiently minimize the energy function, we solve it in the following two alternating optimization steps:

$$\begin{aligned} \boldsymbol{y}^* = \arg\min_{\boldsymbol{y}} \sum_i \varphi_i(y_i, I) + \frac{1}{2}\tau(\boldsymbol{y}, \boldsymbol{h}^*) \\ + \sum_{1 \leq i,j \leq L} \varphi_{ij}(y_i, y_j), \end{aligned} \quad (10)$$

$$\begin{aligned} \boldsymbol{h}^* = \arg\min_{\boldsymbol{h}} \sum_p \psi_p(h_p, x_p) + \frac{1}{2}\tau(\boldsymbol{y}^*, \boldsymbol{h}) \\ + \sum_{(p,q) \in \mathcal{N}} \psi_{pq}(h_p, h_q). \end{aligned} \quad (11)$$

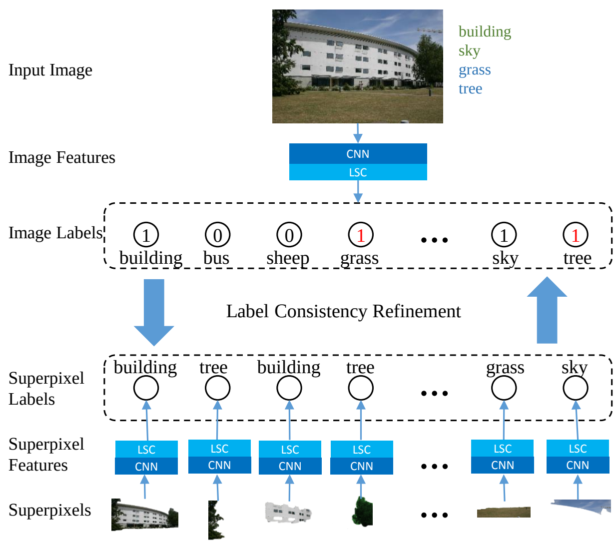


Figure 2. Illustration of our joint inference system. We simultaneously optimize the image-level label as well as superpixel-level label in a unified model so as to obtain the most suitable label configurations.

As a standard binary CRF problem, the first subproblem in Equation (10) has an explicit solution which utilizes min-cut/max-flow algorithms (*e.g.*, the Dinic algorithm [3]) to obtain the global optimal label configuration. And the second subproblem in Equation (11) reduces to an energy minimization for a multi-class CRF. Although finding the global optimum for this energy function has been proved to be a NP-hard problem, there are various approximate methods for fast inference, such as approximate maximum a posteriori (MAP) methods (*e.g.*, graph-cuts [2]). In this paper, we adopt move making approach [2] that finds the optimal α-expansion [2, 11] by converting the problems into binary labeling problems which can be solved efficiently using graph cuts techniques. The energy obtain by α-expansion has been proved to be within a known factor of the global optimum [2]. Considering the two alternate optimization steps together, we summarize our joint inference system in Algorithm 1.

4. Experiments

In this section, we evaluate the effectiveness of our proposed approach for weakly supervised semantic segmentation for social images based on two sets of experiments. The first set of experiments compares our approach with state-of-the-art algorithms on two standard datasets. The second set of experiments verifies the robustness of our approach under the noisy condition, in the meantime, evaluates the individual components that contribute to noisy reduction.

Algorithm 1 Energy Minimization Inference

Input: a image I and its representation of superpixels $\{x_p\}$
Output: the image-level label variables $\boldsymbol{y}$ and the superpixel-level label variables $\boldsymbol{h}$

Construct the graphical model according to the energy function (1).
Initialize $\boldsymbol{y}$ and $\boldsymbol{h}$ with the highest unary potential according to Equation (3) and (4), respectively.
for iteration $t = 1$ to T **do**
    fix $\boldsymbol{y}$, optimize $\boldsymbol{h}$ via Equation (11)
    fix $\boldsymbol{h}$, refine $\boldsymbol{y}$ via Equation (10)
end for
Return the final configuration $\boldsymbol{y}$ and $\boldsymbol{h}$.

4.1. Experimental Setup

We utilize a linear maximum margin classifier leveraging both convolutional neural network feature and latent semantic concepts distribution in order to construct $\varphi_i(y_i, \boldsymbol{I})$ for label completion. In particular, we extract a 4296 dimensional global feature vector for each image by concatenating appearance feature and latent semantic concept distribution. The 4296 dimensional feature vector includes: the second to last layer of convolutional neural network [19] pre-trained on ImageNet [16], as the 4096-dimensional appearance feature, and topic distribution learned from pLSA [8], as the 200-dimensional latent semantic concept distribution. We use the publicly available implementation *Caffe* [9] to compute the CNN features, and a one-vs-one linear support vector machine [5] per class for initial forecast for image-level annotations.

Then, we employ the Multiscale Combinatorial Grouping System [1] to obtain the multi-scale superpixel representation of each image. Concretely, we use three segmentation scales to generate about 10, 30, 50 superpixels per image respectively. We represent each superpixel by its appearance feature and latent semantic concept distribution, which are extracted in the same way as the global features.

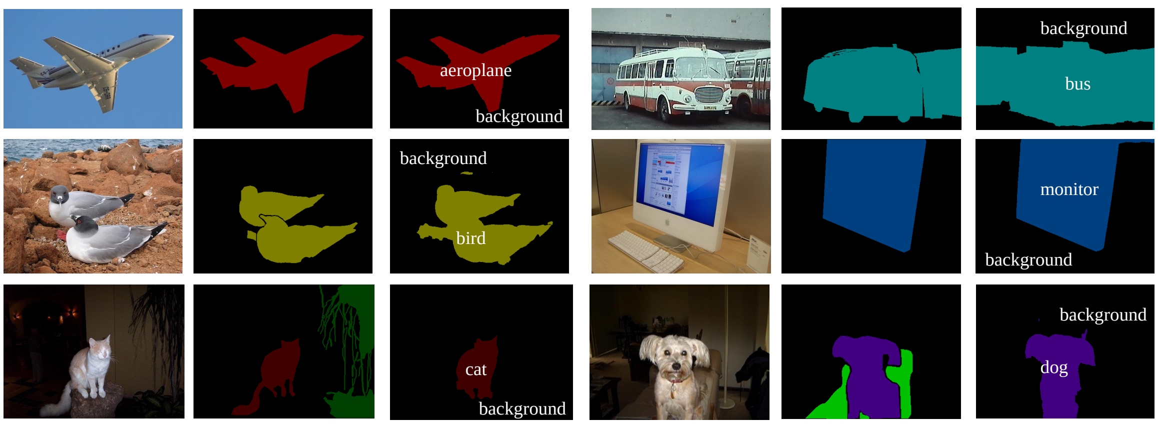
4.2. Comparison with State-of-the-art

In this experiment, we compare our approach with the existing state-of-the-art weakly supervised semantic segmentation methods as well as fully supervised semantic segmentation algorithms on two challenging datasets: PASCAL VOC 2007 [4] and SIFT-flow [15].

PASCAL VOC 2007 This dataset was used for the PASCAL Visual Object Category segmentation contest 2007. It is especially challenging for the presence of background clutter, illumination effect and occlusions. It contains 5011 training images, and 4952 test images. Within the training set, for a subset of 422 images which are suitable for evaluation of the segmentation task, the object in these images are

	Methods	average	background	aeroplane	bicycle	bird	boat	bottle	bus	car	cat	chair	cow	diningtable	dog	horse	motorbike	person	pottedplant	sheep	sofa	train	tv/monitor
Fully Supervised	Brookes	9	78	6	0	0	0	0	9	5	10	1	2	11	0	6	6	29	2	2	0	11	0
	INRIA [7]	24	3	1	45	34	16	20	0	68	58	11	0	44	8	1	2	59	37	0	6	19	63
	MPI [14]	28	3	30	31	10	41	7	8	73	56	37	11	19	2	15	24	67	26	9	3	5	55
	TKK [27]	30	23	19	21	5	16	3	1	78	1	3	1	23	69	44	42	0	65	30	35	89	71
	UoCTTI [6]	21	3	24	53	0	2	16	49	33	1	6	10	0	0	3	21	60	11	0	26	72	58
Weakly Supervised	Zhang *et al.* [30]	24	–	48	20	26	25	3	7	23	13	38	19	15	39	17	18	25	47	9	41	17	33
	Ours	27	66	26	15	61	12	15	51	30	38	6	29	19	25	29	26	19	12	18	4	28	28

Table 1. Quantitative analysis of VOC2007 results [4], intersection vs. union measure, define as $\frac{TP}{TP+FN+FP}$, in comparison with state-of-the-art methods. The results of fully supervised methods are taken from [4].



Original Image | Ground Truth | Our Results | Original Image | Ground Truth | Our Results

Figure 3. Qualitative results on the VOC-2007 data set. Successful segmentations (top 2 rows) and failure cases (bottom).

marked at pixel level; while the objects in the other images only have the bounding boxes indicating the location of the object and rough boundaries. And there are 20 foreground and 1 background classes in this dataset used for the task of classification, detection, and segmentation.

SIFT-flow The SIFT-flow dataset[15] is derived from the LabelMe subset and contains 2688 images of resolution 256x256 pixels, accompanied with a hand labeled segmentation of 33 unique semantic categories. This dataset has been widely adopted for semantic segmentation and it is also very challenging for the reason that there are large number of classes in the dataset and 4.43 labels per image. Besides, the frequency of classes is distributed with a power-law. For fair comparison, we use standard dataset split (2488 images for training and 200 images for testing) provided by [15].

Quantitative and Qualitative Results Comparisons of our performances against other methods (both fully supervised and weakly supervised) are given in Tables 1 and 2. The results on the VOC2007 dataset show that our approach outperforms the other state-of-the-art weakly supervised methods, demonstrating that the image-level annotations are more efficiently utilized by our method. In the meantime, the results conducted by our framework are comparable with the fully supervised method even though we use much less supervised information than these methods. Similar results are obtained on the SIFT-flow dataset, which is more challenging than the previous one. It is worth noting that our method demonstrates a comparable performance in noisy condition as well, more detail will be discussed in the following section.

Figures 3 and 4 show the successful and failed cases of two datasets respectively. In Figure 3, the typical failure is due to the cluttered background which shares high visual similarities with the undetected objects. And in Figure 4, the failure is mainly caused by intra-class variability which remains very challenging in computer vision community.

4.3. Performance under the Noisy Condition

To verify both robustness and effectiveness of our method to noisy annotation condition, we try to reproduce the real-world noise distribution to the initial image-level

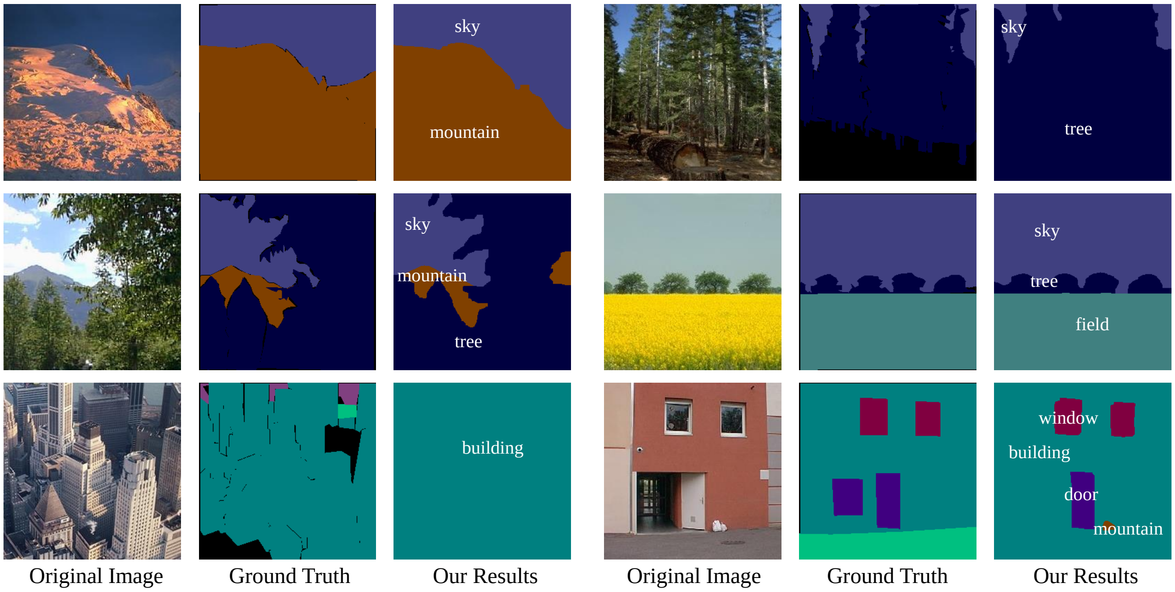


Figure 4. Qualitative results on the SIFT-flow data set. Successful segmentations (top 2 rows) and failure cases (bottom).

Methods	Supervision	Per-Class (%)
Liu *et al.* [15]	full	24
Tighe *et al.* [21]	full	29.4
Tighe *et al.* [22]	full	39.2
Vezhnevets *et al.* [25]	weak	14
Vezhnevets *et al.* [26]	weak	21
Zhang *et al.* [30]	weak	26
Zhang *et al.* [31]	weak	27.7
Xu *et al.* [29]	weak	27.9
Ours (0% noise)	weak	32.3
Ours (10% noise)	weak	32.8
Ours (25% noise)	weak	32.4
Ours (50% noise)	weak	29.8
Ours (75% noise)	weak	22.3

Table 2. Quantitative results on the SIFT-flow dataset [15], average per-class recall measure, defined as $\frac{TP}{TP+FN}$, in comparison with state-of-the-art methods.

labels for SIFT-flow dataset. More concretely, for a certain image in the dataset, each image-level label might be omitted or replaced by other incorrect labels. Here we suppose the probability of missing label is $p_{missing}$, which controls the missing labels set proportion of the whole label set.

We construct label pair confusion matrix where each entry p_{ij} indicate the probability of labeling category i instead of category j. This matrix is determined by manual observation on the empirical evidence from the collaborative image tagging system. In particular, We utilize Flickr API using queries for predefined semantic concepts and collect the number of incorrect labeling error occurred. After normalization we obtain the representative inter-label confusion probability distribution from statistics of real-world images.

We fix the probability p_{ij}, and set different values of $p_{missing}$ to obtain a set of noisy labeled datasets as shown in Table 3. The level of noise strength is determined by the percent of image with noisy annotations. It can be observed that our method can perform better or comparable results with respect to the state-of-the-art approaches.

Noisily Labeled Images (%)	10	25	50	75
Noisy Labels per Image	1.3	1.4	1.7	2.4
Per-Class Accuracy (%)	32.8	32.4	29.8	22.3
Label Refinement (%)	93.7	93.4	92.3	90.4

Table 3. Extra statistics on noisily labeled SIFT-flow dataset as well as quantitative results on semantic segmentation and label refinement of our approach.

To justify the individual components that contribute to noisy reduction, we conduct a control test as shown in Figure 5. It displays the performance degradation caused by removing these components and demonstrates the indispensability of these conponents in our approach especially under the noisy condition. Moreover, Figure 5 shows that the label correlation significantly reduce the degradation of performance when the total number of noisy labels is within a threshold and the latent semantic concept distribution seems more effective when there are large mount of noisy labels.

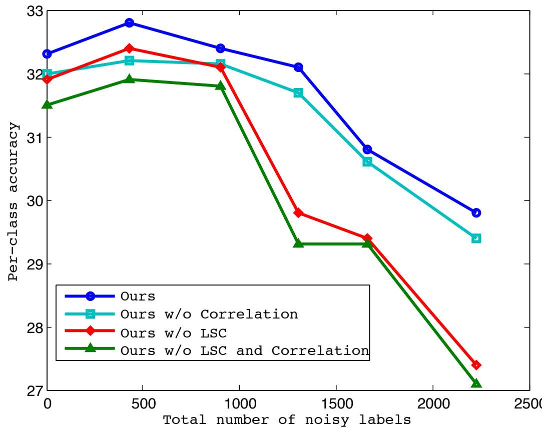


Figure 5. Evaluation of the individual components on noisily labeled SIFT-flow dataset.

5. Conclusions

In this paper, we have investigated the challenging but realistic problem of weakly supervised segmentation for social images. We present a novel approach incorporating various contextual relations into a unified CRF model. We show that our method can put up with noisy images with incorrect or incomplete annotations. To demonstrate both robustness and effectiveness of our method, we perform experiments on two real-world datasets and illustrate improvement over existing weakly supervised semantic segmentation techniques on standard datasets. In the future we will focus on Internet image collections, which are notably larger and remarkably diverse. We can evaluate the proposed method directly over the social image collection with user-provided tag while we need to manual generate the ground truth segmentations for the evaluation.

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