Bipartite Conditional Random Fields for Panoptic Segmentation

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Abstract

We tackle the panoptic segmentation problem with a conditional random field (CRF) model. Panoptic segmentation involves assigning a semantic label and an instance label to each pixel of a given image. At each pixel, the semantic label and the instance label should be compatible. Furthermore, a good panoptic segmentation should have a number of other desirable properties such as the spatial and color consistency of the labeling (similar looking neighboring pixels should have the same semantic label and the instance label). To tackle this problem, we propose a CRF model, named Bipartite CRF or BCRF, with two types of random variables for semantic and instance labels. In this formulation, various energies are defined within and across the two types of random variables to encourage a consistent panoptic segmentation. We propose a mean-field-based efficient inference algorithm for solving the CRF and empirically show its convergence properties. This algorithm is fully differentiable, and therefore, BCRF inference can be included as a trainable module in a deep network. In the experimental evaluation, we quantitatively and qualitatively show that the BCRF yields superior panoptic segmentation results in practice.

1. Introduction

Panoptic segmentation of images is a problem that has received considerable attention in computer vision recently. It combines two well-known computer vision tasks: semantic segmentation and instance segmentation. Panoptic segmentation differentiates between two types of semantic labels: stuff labels and thing labels. Stuff classes are semantic classes of shapeless regions of similar texture or material such as grass, sky, and road. Thing classes are semantic classes of countable objects such as people, animals, and vehicles [19]. The goal of panoptic segmentation is to assign a semantic label and an instance label for each pixel in the image. Clearly, the concept of instances is valid only for thing classes. Therefore, the instance label of a pixel labeled with a stuff semantic class is neglected.

Although semantic segmentation and instance segmentation are apparently very related problems, in the current state of the art methods in computer vision, they are solved in substantially different ways. The semantic segmentation problem is usually solved with a fully convolutional network architecture such as FCN [36] or DeepLab [5], whereas the instance segmentation problem is solved using an object detector based method such as Mask-RCNN [14]. Each of these architectures have their own strengths and weaknesses. For example, fully-convolutional network based semantic segmentation methods have a wide field of view, specially when used with dilated convolutions [44], and therefore can make semantic segmentation predictions with global information about the image. In contrast, region proposal based networks, such as Mask-RCNN, focus on specific regions of interest during the later stages of the network and make predictions using strong local features available within a given region of interest. It is natural to think of a systematic way of combining the complementary strengths of these two different approaches.

We propose a Conditional Random Field (CRF) based framework for panoptic segmentation. Our framework, named Bipartite Conditional Random Fields (BCRF), takes inputs from both a semantic segmentation module and an instance segmentation module, and uses additional prior ideas about a good panoptic segmentation. It then performs probabilistic inference on a graphical model to obtain the best panoptic label assignment given the semantic segmentation classifier, the instance segmentation classifier, and the image itself. Our framework provides a heuristic-free, probabilistic method to combine semantic segmentation results and instance segmentation results - yielding a panoptic segmentation with consistent labeling across the whole image. We formulate our bipartite CRF using different energy functions to encourage the spatial, appearance and semantic
The Bipartite CRF proposed in this paper can be used to combine the predictions of a semantic segmentation model and an instance segmentation model to obtain a consistent panoptic segmentation.

Importantly, we show that our proposed BCRF inference is fully differentiable with respect to the various parameters used within the CRF and also the semantic segmentation and instance segmentation classifier inputs. Therefore, the BCRF module can be used as a first-class citizen of a deep neural network to perform panoptic segmentation. A deep network equipped with the BCRF module is capable of structured prediction of consistent panoptic labels and is end-to-end trainable. We show an example application of this framework and demonstrate that superior results can be used by probabilistic combination of a semantic segmentation classifier and an instance segmentation classifier in the BCRF framework.

2. Related Work

The task of semantic segmentation has historically captured much attention [37, 27, 33, 10] with multiple innovations emerging as a direct result [32, 4, 8]. With the popularity of deep convolutional feature extractors, multiple recent works have focused on multi-scale feature extraction [46, 8, 44, 45] and end-to-end structured predictions [47, 5, 6, 1, 31, 7] to better solve this task. While the former allows networks to capture objects of all scales, the latter allows better granularity in outputs. Further, the wider field of view in these networks, especially since the introduction of dilated convolutions [44, 45], provides better contextual understanding that directly benefits the task of semantic segmentation. This greater awareness of global information is a key uniqueness of most recent works. Also note how multiple approaches based on structured predictions [47, 31, 1, 26] have been highly successful in the task of semantic segmentation.

Along with the emergence of highly accurate object detection works [35, 30], instance specific semantic segmentation started gaining significant attention. Early approaches use structured prediction based methodologies [43, 11], some often involving CRFs [15, 38]. With the advent of deep learning based approaches, instance segmentation methodologies have mostly taken the form of two-stage proposal based approaches [9, 39, 13, 25]. These methods were superseded by Mask R-CNN [14], laying the foundation for most current state-of-the-art instance segmentation approaches. Mask R-CNN builds off a conceptually simple extension of Faster R-CNN [35] obtained by adding a sep-
arate object mask prediction branch in parallel to the existing ones, capturing information local to each instance. This key contrasting feature is common even in later works built off Mask R-CNN [29]. Another similar recent work by Arnab et al. [3] moves in a slightly new direction by using a CRF to obtain instance segmentation outputs from a semantic segmentation using bounding box (from an object detection network) and instance shape cues. Our work differs from this in three significant ways: presence of pixel-wise cross potentials, using instance mask cues from a region-based network, and the ability to explicitly learn and model relationships between classes.

Since its formal introduction by Kirillov et al. [19], the task of panoptic segmentation has gained popularity, with multiple works attempting to transform existing network architectures to tackle this task [28, 42, 12, 24, 34, 41]. A key feature common among most of these works is fusing the logit outputs of existing semantic and instance segmentation networks to obtain a panoptic segmentation using some unique approach. The work of Arnab et al. [3] which emerged prior to this, may also be considered as an initial step in this direction. The work by Kirillov et al. [17] explores extending a feature pyramid network [18] based Mask R-CNN [14] to output semantic segmentation as well, followed by heuristic based fusion to produce a panoptic output. Another similar approach is seen in the work by Xiong et al. [41] where the outputs are combined using a simple resizing and addition of semantic and instance logits alongside a method to output additional unknown labels for difficult pixels. Our work differs from these approaches with the inclusion of a CRF based layer for combining the two semantic and instance heads.

Conditional Random Fields (CRFs) are known as excellent models for structured prediction tasks such as semantic segmentation. Early works that used CRFs for semantic image segmentation includes [15, 38]. Most of these early methods of CRFs for semantic segmentation used 4-connected or 8-connected locally connected graphs. In [21], the authors proposed an efficient mean field based inference algorithm to solve fully connected CRFs with Gaussian edge potentials. The authors of [47] later showed that this CRF inference algorithm can be formulated as a Recurrent Neural Network (RNN). This module, known as CRF-RNN, was plugged into a fully convolutional network to obtain the state-of-the-art in semantic image segmentation at the time. Similar trainable CRF models have been used in works such as [2], for semantic segmentation with higher-order potentials and, [3] for instance segmentation. In [23], where the problem of panoptic segmentation with weak and semi supervision was addressed, the authors used a CRF for refining instance segmentation labels. However, it worked on homogeneous instance labels only and therefore was similar in spirit to previous fully connected CRFs.

In our work, we propose a bipartite CRF operating on the semantic segmentation task and the instance segmentation task simultaneously. This CRF has energies within semantic segmentation labels, energies within instance segmentation labels, and also energies across semantic and instance segmentation labels. To the best of our knowledge, this is the first time a bipartite CRF with cross connections between semantic and instance labels has been proposed in the context of pixel-wise labeling.

3. Background: Conditional Random Fields

Conditional Random Fields (CRFs) are a class of statistical modeling method used for structured prediction. A CRF, used in the context of pixel-wise label prediction, models pixel labels as random variables that form a Markov Random Field (MRF) when conditioned upon the image. CRFs have primarily been used in computer vision for semantic image segmentation. In this setting, CRFs encourage the desirable properties of a good segmentation, such as the spatial consistency (e.g. spatially neighboring pixels should have the same label) and color consistency (e.g. a semantic segmentation boundary should correspond to a edge in the image) through various energy functions used in the formulation. A CRF formulation usually has energy terms arising from an imperfect classifier (sometimes known as the unary energy) and energy terms encouraging the consistency properties of the segmentation (sometimes known as the pairwise energy). Some semantic CRF models also include higher order energy terms to encourage higher order consistency properties such as consistency of the labeling within super-pixels [2].

Once an appropriate energy function is formed, the optimal labeling is found as the labeling that minimizes the CRF energy (or equivalently, maximizes the probability). This is known as the inference of the CRF. The exact inference of a CRF with dense pairwise connections is intractable and hence approximate inference methods such as mean field variational inference has to be utilized to solve the CRF in reasonable time [21]. For a detailed treatment of CRFs, the reader is referred to [20].

4. Bipartite CRFs

We propose a CRF formulation with bipartite random variables to capture interactions between semantic labels and instance labels. Inference of this CRF gives the jointly most probable semantic and instance segmentation (and therefore, the panoptic segmentation) for a given image.

For each pixel $i$, define a pair of discrete random variables $(X_i, Z_i)$ to denote its semantic label and the instance label, respectively. For each $i$, $X_i$ can take values in $\mathcal{L} = \{l_1, l_2, \ldots, l_L\}$, where each $l_j$ is a semantic label and $L$ is the number of semantic labels (includes both stuff and thing...
Algorithm 1 Inference on Bipartite CRF

1: $Q_i(l) := \text{softmax}_l(-\phi_i(l))$ and $R_i(t) := \text{softmax}_t(-\psi_i(t))$  \hspace{1cm} \triangleright \text{Initialization}
2: \textbf{while} not converged \textbf{do}
3: \hspace{1cm} $Q'_i(l) := \phi_i(l)$  \hspace{1cm} \triangleright \text{Update due to the first term}
4: \hspace{1cm} $Q'_i(l) := \sum_{l' \in L} \left( \mu(l, l') \sum_{j \neq i} \text{Sim}_\phi(i, j) Q_j(l') \right)$  \hspace{1cm} \triangleright \text{Update due to the second term}
5: \hspace{1cm} $R'_i(t) := \psi_i(t)$  \hspace{1cm} \triangleright \text{Update due to the third term}
6: \hspace{1cm} $R'_i(t) := \sum_{t' \in T} \left( [t \neq t'] \sum_{j \neq i} \text{Sim}_\psi(i, j) R_j(t') \right)$  \hspace{1cm} \triangleright \text{Update due to the fourth term}
7: \hspace{1cm} $Q'_i(l) := \sum_{t \in T} \left( f(l, \text{class}(t)) R_i(t) \right)$  \hspace{1cm} \triangleright \text{Updates due to the fifth term}
8: \hspace{1cm} $R'_i(t) := \sum_{l \in L} \left( f(l, \text{class}(t)) Q_i(l) \right)$
9: \hspace{1cm} $Q'_i(l) := \sum_{t \in T} \left( f(l, \text{class}(t)) \sum_{j \neq i} \text{Sim}_\Omega(i, j) R_j(t') \right)$  \hspace{1cm} \triangleright \text{Updates due to the sixth term}
10: \hspace{1cm} $R'_i(t) := \sum_{l \in L} \left( f(l, \text{class}(t)) \sum_{j \neq i} \text{Sim}_\Omega(i, j) Q_j(l') \right)$
11: \hspace{1cm} $Q_i(l) := \text{softmax}_l \left( Q'_i(l) \right)$ and $R_i(t) := \text{softmax}_t \left( R'_i(t) \right)$  \hspace{1cm} \triangleright \text{Normalization}
12: \textbf{end while}

Let $X = [X_1, X_2, \ldots, X_N]$ and $Z = [Z_1, Z_2, \ldots, Z_N]$, where $N$ is the number of the pixels in the image. A joint assignment $(x, z)$ to these two random vectors $(X, Z)$ gives a unique semantic label and an instance label to each pixel $i$, and therefore represents a panoptic segmentation of the image. Note that, $x \in L^N$ and $z \in T^N$. In this work, we discuss the probability of such assignments and formulate the probability distribution function so that the “good” panoptic segmentation will have a high probability. We then perform inference on this formulation to find the assignment that maximizes the probability to obtain the best panoptic segmentation.

The probability of a panoptic segmentation $(x, z)$, given the image $I$, can be modeled as a Gibbs distribution of the following form:

$$
\Pr(X = x, Z = z | I) = \frac{1}{Z(I)} \exp(-E(x, z | I)),
$$

where $Z(I) = \sum_{(x, z)} \exp(-E(x, z | I))$, is a normalization constant, sometimes known as the partition function. The term $E(x, z | I)$ is known as the energy of the configuration $(x, z)$. Hereafter, we drop the conditioning on $I$ in the notation for brevity. The energy of our bipartite CRF is defined as follows:

$$
E(x, z) = \sum_i \phi(x_i) + \sum_{i < j} \Phi(x_i, x_j) + \sum_i \psi(z_i) + \sum_{i < j} \Psi(z_i, z_j) + \sum_i \omega(x_i, z_i) + \sum_{i < j} \Omega(x_i, z_j),
$$

where $x_i$ and $z_i$ are the elements of the vectors $x$ and $z$, respectively. The meaning of each term will be described in detail below. Note that, since a “good” panoptic segmentation should have a high probability, it should have a low energy. Various terms in Eq. (2) should therefore encourage a good panoptic segmentation by penalizing disagreements with our prior knowledge about a consistent panoptic segmentation.

### 4.1. Semantic Component of the CRF

In the following, we discuss the first two terms of the energy function in Eq. (2). The first term encourages the semantic segmentation result to be consistent with the initial classifier.

$$
\phi(X_i = x_i) = - \log(Pr_0(X_i = x_i)),
$$

where $Pr_0(\cdot)$ is the classifier probability score for the semantic segmentation.

The second term in Eq. (2) encourages the smoothness of the semantic labeling:

$$
\Phi(X_i = x_i, X_j = x_j) = \mu(x_i, x_j) \text{Sim}_\phi(i, j),
$$

where $\mu : L \times L \rightarrow \mathbb{R}$ is the label compatibility function, and $\text{Sim}_\phi(i, j)$ is a similarity measure between the pixels.
\(i\) and \(j\). This term penalizes assigning different labels to a pair of pixels that are “similar”. Following \[21\], we use a mixture of Gaussians as the similarity measure. Therefore,

\[
\text{Sim}_\Phi(i, j) = \sum_m \omega_{\Phi,m} \exp\left(-\frac{\|f_i^{(m)} - f_j^{(m)}\|^2}{2\sigma_{\Phi,m}^2}\right) \tag{5}
\]

where \(f_i\) is a feature vector for pixel \(i\) containing information such as its spatial location and bilateral features (RGB + spatial coordinates). We use the same spatial and bilateral features used in \[21\].

### 4.2. Instance Component of the CRF

For the instance classification, we also assume the existence of an initial classifier, such as Mask R-CNN, that provides a confidence score for each instance at each pixel. Note that Mask R-CNN provides fixed-size instance segmentation predictions with respect to the bounding boxes of the detections. However, these predictions can be easily mapped to the full image by using bilinear interpolation and trivial coordinate transforms.

In the following, we use \(z_i \in \{\text{inst}_0, \text{inst}_1, \ldots, \text{inst}_N\}_{\text{inst}}\), where \(N_{\text{inst}}\) is the number of instances detected in the image. The label \(\text{inst}_0\) is reserved for the special case where the pixel does not belong to an instance, i.e., it belongs to a stuff class.

Similar to the semantic segmentation case, the third term in Eq. (2) encourages the panoptic segmentation to be consistent with the instance classifier probabilities \(\text{Pr}_0\):

\[
\psi(Z_i = z_i) = -\log(\text{Pr}_0(z_i)). \tag{6}
\]

The fourth term in Eq. (2) encourages instance label consistency across the whole image by penalizing assigning different instance labels to similar pixels:

\[
\Psi(Z_i = z_i, Z_j = z_j) = [z_i \neq z_j] \text{Sim}_\Psi(i, j). \tag{7}
\]

The compatibility transform in this case is fixed to be \([z_i \neq z_j]\), where \([\cdot]\) is the Iverson bracket. The similarity measure \(\text{Sim}_\Psi\) has a similar form to Eq. (5).

### 4.3. Cross Potentials in the CRF

An important contribution of this paper is the introduction of cross potentials between the semantic segmentation and instance segmentation. The semantic segmentation and the instance segmentation are highly related problems and therefore the solutions should agree: the semantic label at any pixel has to be compatible with the instance label at that pixel. For example, if the instance labeling says that the pixel \(i\) belongs to an instance of a person class, the semantic label at pixel \(i\) should also have the person label. If the initial classifier results for the instance segmentation and the semantic segmentation do not agree, one of them should correct itself depending on the interactions of other terms in the CRF.

The first cross potential term (the fifth term in Eq. (2)), encourages instance label and the semantic label at a given pixel to agree:

\[
\omega(X_i = x_i, Z_i = z_i) = f(x_i, \text{class}(z_i)). \tag{8}
\]

Here, \(\text{class}(z_i)\) is the class label of the instance \(z_i\) with \(\text{inst}_0\) mapped to a special class null. Note that, for all valid instances, the class label can be obtained from the instance classifier (e.g. Mask R-CNN). The function \(f(\cdot, \cdot) : (\mathcal{L}, \mathcal{L}_{\text{things}} \cup \{\text{null}\}) \rightarrow \mathbb{R}_0^+\), captures the cost of incompatibility and is defined as follows:

\[
f(x_i, \text{class}(z_i)) = \begin{cases} 0, & \text{if } x_i = \text{class}(z_i) \\ 0, & \text{if } x_i \in \mathcal{L}_{\text{stuff}} \text{ and } \text{class}(z_i) = \text{null} \\ \eta(x_i, \text{class}(z_i)), & \text{otherwise.} \end{cases} \tag{9}
\]

The above function covers three cases: 1) If the semantic label and the class label of the instance label match, there will be no penalty for such assignment since there is no incompatibility in this case. 2) If the semantic segmentation assigns a stuff label and the instance segmentation assigns \(\text{inst}_0\) label, there will be no penalty in that case either. 3) If the semantic label and the instance label mismatch, there will be a penalty with the magnitude decided by the function \(\eta(\cdot, \cdot) : \mathcal{L}_{\text{things}} \cup \{\text{null}\} \times \mathcal{L}_{\text{things}} \cup \{\text{null}\} \rightarrow \mathbb{R}^+\). This function is learned from data as described in Section 5.

The last term in Eq. (2), encourages the consistency of semantic label and the instance label among similar looking pixels and has the form:

\[
\Omega(X_i = x_i, Z_j = z_j) = f(x_i, \text{class}(z_j)) \text{Sim}_\Omega(i, j), \tag{10}
\]

where each symbol has the meaning described above.

### 5. Inference and Parameter Optimization

The best panoptic segmentation given the model described in Section 4 is the assignment \((x, z)\) that maximizes the probability in Eq. (1). However, since the graphical model used in BCRF has dense connections between the pixels, the exact inference is infeasible. We therefore use an approximate parallel mean field inference algorithm following \[21\].

In this setting, the joint probability distribution is approximated by the product of marginal distributions:

\[
\text{Pr}(X = x, Z = z) \approx \prod_i Q_i(x_i) R_i(z_i), \tag{11}
\]

where \(Q_i(x_i) = \text{Pr}(X_i = x_i)\) and \(R_i(z_i) = \text{Pr}(Z_i = z_i)\) are the marginal distributions. Out of all the distributions
Table 1: Pascal VOC dataset. Panoptic segmentation results on the Pascal VOC validation set.

| Method       | PQ   | SQ   | RQ   |
|--------------|------|------|------|
| Without BCRF | 70.50| 88.65| 78.83|
| With BCRF    | 71.76| 89.63| 79.33|

that can be written down in this factorized form, the closest distribution to the original joint distribution is found by minimizing the KL divergence \[20, 21\]. For our BCRF formulation, this results in the iterative algorithm detailed in Algorithm 1.

To make our model flexible, we deliberately include a number of parameters in the BCRF model, which we automatically learn from the training data. More specifically, the BCRF model has the following parameters:

1. Weight multipliers for different energy terms: each term in Eq. (2) is multiplied with a weight parameter, which decides the relative strength of the term. This parameterization helps learn the optimal combination of different energies in the CRF. For example, if the initial semantic segmentation model has better accuracy than the instance segmentation model, the \(\phi\) unary energy might be weighted more than the \(\psi\) unary energy.

2. Parameters for similarity functions: Each similarity function \(\text{Sim}_X(i, j)\) of the form shown in Eq. (4) has its own parameters. These learn the relative strength of spatial and appearance consistency of the panoptic segmentation.

3. Label compatibility matrices: The two functions \(\mu(\ldots)\) and \(\eta(\ldots)\) are initialized to have a zero cost for a pair identical labels and a fixed cost for any combination of two different labels. They are then given the freedom to automatically learn the relative penalty strengths for different label combinations.

6. BCRF in a Deep Network

In this section, we discuss how BCRF can be used in a deep network. In [47], authors showed that, in the semantic segmentation setting, mean field inference of a CRF with Gaussian pairwise potentials can be formulated as a Recurrent Neural Network (RNN). Since our BCRF also uses an iterative mean field algorithm of similar nature, it is readily adaptable into the RNN based inference described in [47]. Therefore, BCRF can be a first-class citizen of a deep network performing panoptic segmentation. Importantly, this formulation allows automatic optimization of the BCRF parameters described in Section 5, using backpropagation and a gradient descent algorithm such as stochastic gradient descent (SGD). This is a major advantage since it allows us to increase the number of parameters used in BCRF, and hence increase its flexibility, without adding to the burden of manual parameter optimization.

In the current state-of-the-art methods, semantic segmentation and instance segmentation are solved with different network architectures with complimentary strengths. The BCRF formulation given a systematic way of combining these strengths in a probabilistic framework. Such an example usage of BCRF is shown in Figure 1. The CNN feature extractor here can be a common backbone network such as ResNet-101 or ResNeXt. The semantic segmentation branch is usually a fully convolutional network that is capable of seeing a wide field of view, whereas the instance segmentation branch is a region-proposal based network such as Mask R-CNN. The semantic segmentation branch’s output is taken as the \(\phi\) unary potential input to the BCRF, and instance segmentation branch’s output as the \(\psi\) unary potentials. In addition, the raw image is also fed into the BCRF to derive the similarity functions \(\text{Sim}_X(\ldots)\) using the pixel locations and the RGB values.

During the training of the network, in the forward pass, BCRF inference is performed using Algorithm 1. A suitable loss function for panoptic segmentation can then be used at the output of the network. In the backward pass, differentials with respect to the loss function will be passed into the BCRF inference to optimize various parameters used in the BCRF model. Importantly, during the backward pass, after BCRF inference, the error differentials can be passed on to the semantic branch and the instance branch both to optimize their parameters, and subsequently, the feature extractor CNN’s parameters. Therefore, the whole network, including the BCRF component, can be jointly trained.
Table 2: COCO dataset. Panoptic segmentation results on the COCO validation set.

| Category | PQ W/O BCRF | PQ BCRF | SQ W/O BCRF | SQ BCRF | RQ W/O BCRF | RQ BCRF | Classes |
|----------|-------------|---------|-------------|---------|-------------|---------|---------|
| All      | 41.4        | 41.7    | 78.3        | 79.1    | 50.8        | 51.1    | 133     |
| Things   | 47.4        | 47.4    | 80.4        | 80.4    | 57.3        | 57.3    | 80      |
| Stuff    | 32.5        | 33.2    | 75.1        | 77.1    | 40.9        | 41.6    | 53      |

Table 3: Pascal VOC dataset. Detailed class-wise panoptic segmentation results on the Pascal VOC validation set comparing results without BCRF vs with BCRF on a standard network.

| Class      | PQ W/O BCRF | PQ BCRF | SQ W/O BCRF | SQ BCRF | RQ W/O BCRF | RQ BCRF |
|------------|-------------|---------|-------------|---------|-------------|---------|
| Background | 90.8        | 92.33   | 93.39       | 94.69   | 97.22       | 97.51   |
| Aeroplane  | 78.55       | 80.37   | 88.57       | 92.6    | 88.68       | 86.79   |
| Bicycle    | 29.78       | 31.71   | 67.36       | 68.46   | 44.21       | 46.32   |
| Bird       | 84.98       | 85.09   | 93.05       | 93.24   | 91.32       | 91.25   |
| Boat       | 65.83       | 66.21   | 85.33       | 86.48   | 77.14       | 76.56   |
| Bottle     | 67.44       | 64.05   | 92.05       | 90.68   | 73.26       | 70.63   |
| Bus        | 82.68       | 82.58   | 94.56       | 95.46   | 87.44       | 86.51   |
| Car        | 72.22       | 70.93   | 93.69       | 91.7    | 77.08       | 77.35   |
| Cat        | 77.41       | 83.4    | 91.24       | 93.73   | 84.85       | 88.97   |
| Chair      | 43.3        | 41.79   | 82.5        | 82.64   | 52.49       | 50.57   |
| Cow        | 76.91       | 80.42   | 92.81       | 93.95   | 82.87       | 85.6    |
| Diningtable| 51.33       | 51.8    | 80.81       | 82.88   | 63.51       | 62.5    |
| Dog        | 76.63       | 81.59   | 90.5        | 93.29   | 84.67       | 87.46   |
| Horse      | 76.86       | 81.4    | 89.38       | 91.11   | 86          | 89.34   |
| Motorbike  | 78.07       | 80.21   | 87.5        | 89.89   | 89.23       | 89.23   |
| Person     | 76.33       | 77      | 89.75       | 89.73   | 85.05       | 85.81   |
| Pottedplant| 58.98       | 60.62   | 85.41       | 85.32   | 69.06       | 71.05   |
| Sheep      | 74.29       | 74      | 93.86       | 93.48   | 79.15       | 79.15   |
| Sofa       | 60.37       | 62.12   | 88.47       | 89.5    | 68.24       | 69.41   |
| Train      | 78.52       | 80.05   | 88.7        | 90.43   | 88.52       | 88.52   |
| T V monitor| 79.23       | 79.34   | 92.8        | 92.93   | 85.38       | 85.38   |
| Mean Value | **70.5**    | **71.76** | **88.65**   | **89.63** | **78.83**   | **79.33** |

7. Experiments

In this section, we first show the convergence of the mean field based inference algorithm for BCRF and then show the usefulness of the BCRF model by evaluating its performance on the Pascal VOC dataset and the COCO dataset.

7.1. Convergence of the Inference

It is difficult to provide a theoretical convergence guarantee for mean field algorithms with parallel updates [40, 20]. We therefore provide empirical evidence to show that the presented mean field inference algorithm for our BCRF with cross potentials converge under normal conditions. To this end, we estimate the KL divergence between the original joint distribution and the factorized distribution (see Eq. (11)), at the end of each iteration in Algorithm 1. Note that this KL divergence can be estimated up to a constant using the method described in [22]. We pick 20 random images from the Pascal VOC validation set and average the KL divergence for each iteration across these images. The resulting plot is shown in Fig. 2. It can be seen that the KL divergence measure, and therefore the inference algorithm, converges within a few iterations. We also note that visual results do not change after about 5 iterations.

7.2. Results on the Pascal VOC Dataset

In this experiment we use the architecture shown in Figure 1 and CNN components similar to the ones used in [41]. More specifically, we use a ResNet-50 with an FPN as the backend, to which we attach a fully convolutional network as the semantic segmentation head and a Mask R-CNN network as the instance segmentation head.

During both training and inference we used 5 mean-field iterations for BCRF. At the output, we calculate the loss function as a summation of two components: the usual pixel-wise categorical cross entropy loss for the semantic component [32] and the loss used in [3] for the instance component. We used full-image training with batch size 1.
and SGD with learning rate 0.0007 and momentum 0.99. In Table 1, we report the summary of the quantitative results. Table 3 shows the class-wise results. Qualitative results are shown in Table 4, where benefits of optimally combining the semantic segmentation classification and instance segmentation classification with BCRF can be seen.

7.3. Results on the COCO Dataset

To further evaluate the usefulness of BCRF without any efforts for end-to-end training, experiments were conducted on the COCO dataset by simply plugging in the BCRF on an existing pre-trained model. We used a combination of publicly available models of [41, 16], which produced a PQ score of 41.4% on the COCO validation set. The parameters of the BCRF were hand-tuned using a small subset of train images. Results obtained from that BCRF model without end-to-end training are listed in Table 2.

Table 4: Visualizations on Pascal VOC. Example images from the Pascal VOC validation set. Columns left to right: original image, semantic output before BCRF, instance output before BCRF, semantic output after BCRF, instance output after BCRF. Each row contains a new image. The standard Pascal VOC color map is used for the semantic segmentation results.
8. Conclusion

We proposed a probabilistic graphical model based framework for panoptic segmentation. Our CRF model with two different kinds of random variable, named Bipartite CRF or BCRF, is capable of optimally combining the predictions from a semantic segmentation model and an instance segmentation model to obtain a good panoptic segmentation. We use different energy functions in our BCRF to encourage the spatial, appearance, and instance-to-semantic consistency of the panoptic segmentation. An iterative mean field algorithm was then used to find the panoptic labeling that approximately maximizes the conditional probability of the labeling given the image. We further showed that the proposed BCRF framework can be used as an embedded module within a deep neural network to obtain superior results in panoptic segmentation.

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