Image Segmentation using Conditional Random Fields
[CSE 471] Statistical Methods in AI

Santosh K (201150883), Sudheer T (201550851), Srikanth M (20163014)

Abstract

Given a image containing object(s), the task is to segment the image based on objects and label each segmented object. In this project, we plan to replicate the work done in [2], where in the authors perform multi-class image segmentation using conditional random fields. Further, they use 'global features for image classification' as a complementary information along with the local features to obtain better segmentation. In the current project, our primary focus is on understanding and implementing conditional random fields (CRFs) for the task of object based image segmentation.

1 Markov random fields

Markov random fields (MRFs) are generative models, which can be used to model the joint distribution of the data (features) $\mathbf{X}$ and the labels (multi-class) $\mathbf{Y}$, i.e., $P(\mathbf{X}, \mathbf{Y})$. Once we obtain the joint distribution, we can easily obtain the conditional distributions $P(\mathbf{Y} \mid \mathbf{X})$ and $P(\mathbf{X} \mid \mathbf{Y})$, but it often difficult to model the joint distribution, especially when the random variables are continuous and dependent on each other.

MRFs can also be used in unsupervised scenario, just to model the distribution of features $\mathbf{X}$. It is important to note that the features (color and, texture based) are highly correlated (dependent on) with each other, and hence we need random fields to model such data. The factorization of the joint distribution of such data (features) can expressed with the help of *potential functions*, $\varphi_C(\mathbf{x}_c)$ [1].

$$p(\mathbf{x}) = \frac{1}{Z} \prod_C \varphi(\mathbf{x}_C), \tag{1}$$

where each potential function $\varphi(\mathbf{x}_C)$ represents a maximal clique in the graph defined by the random field, and Z is called as partition function which acts as a normalization constant.

2 Conditional random fields

Conditional random fields model only the probability distribution over target labels (in our case) given the data i.e., $P(\mathbf{Y} \mid \mathbf{X})$. This is primarily useful, when we have labeled data and our task is only prediction, i.e., given a test feature vector $\mathbf{X}_t$, we would like to obtain the distribution (posterior probability) over the target labels, $P(\mathbf{Y} \mid \mathbf{X}_t)$.

CRFs do not model the data (the factorization of the data does not matter), and so they are less complex than MRFs. This also makes CRFs limited on to the prediction task.

3 Approach

We follow the approach as described in [2] and the steps are briefly described as follows:

1. Initially, apply an unsupervised segmentation technique to partition the complete image into number of patches on multiple scale levels. Each scale level gives different granularity in terms of color, and each patch represents a set of neighboring pixels. Initially we use simple k-means to as the clustering technique.

2. For each patch on each level, obtain color, texture and SIFT (scale invariant feature transform) features. These features are dependent on each other.

3. From all patch features, compute a global feature vector.
4. Train SVMs to predict the class label for each path and also for the complete image.
5. Build a CRF to model the dependencies between obtained patch labels, given the feature vectors.
6. Applying a threshold on the posteriors of the labels gives the final segmentation.

4 Project plan and milestones

1. Sep 24, 2016: Implementation the pipeline as described in Section 3, with primary focus on CRF and using existing libraries for feature extraction and SVM.
2. Oct 31, 2016: Depending on the progress and obtained results, we also plan to implement the MRFs for unsupervised image segmentation.

References

[1] Christopher M. Bishop. *Pattern Recognition and Machine Learning.* Springer-Verlag New York, Inc., 2006.

[2] Nils Plath, Marc Toussaint, and Shinichi Nakajima. Multi-class image segmentation using conditional random fields and global classification. In *Proceedings of the 26th Annual International Conference on Machine Learning*, ICML '09, pages 817–824, New York, NY, USA, 2009. ACM.