Graphical Models Wrap-Up

Machine Learning
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Why Graphical Models?

A modular language for describing probability distributions
Why Graphical Models?
Vision Problems

Low-level vision  High-level vision

Restoration

Segmentation

Depth estimation

Recognition

Summary

We have presented three algorithmic techniques for speeding up the belief propagation approach for solving low level vision problems formulated in terms of Markov random fields. The main focus of the paper is on the max-product formulation of belief propagation, and the corresponding energy minimization problem in terms of costs that are proportional to negative log probabilities. We also show how similar techniques apply to the sum-product formulation of belief propagation. The use of our techniques yields results of comparable accuracy to other algorithms but hundreds of times faster. In the case of stereo we quantified this accuracy using the Middlebury benchmark. The method is quite straightforward to implement and in many cases should remove the need to choose between fast local methods that have relatively low accuracy, and slow global methods that have high accuracy.

The first of the three techniques reduces the time necessary to computing a message update from $O(k^2)$ to $O(k)$, where $k$ is the number of possible labels for each pixel. For the max-product formulation this technique is applicable to problems where the discontinuity cost for neighboring labels is a truncated linear or truncated quadratic function. The method is not an approximation, it uses an efficient algorithm to produce exact results as the brute force quadratic time method. For sum-product a similar technique yields an $O(k \log k)$ runtime with all but one of the techniques. In each case the running time of the algorithm is controlled by varying the number of message update iterations. We see that each speedup technique provides an important speedup even when the number of labels is small (16 disparities for the Tsukuba images).

Table 1 shows evaluation results of our stereo algorithm on the Middlebury stereo benchmark [9]. These results were obtained using the parameters described above. Overall our method per-
Drill, Baby, Drill!

Yes, We Can!
dependencies defined by relationships in data
Promises of Graphical Models

• General-purpose, declarative representation of distributions
• Improve models and algorithms independently
• Analysis of algorithms using graph theory
  • general domain-agnostic analyses
Challenges

• Graphical model language too rich, too general

• Inference and learning are NP-Hard in general

• Lots of open questions about quality of approximation algorithms

• small pockets of known families of models and algorithms that admit guaranteed approximations (or bounds)