Integrating Probabilistic Reasoning into a Symbolic Diagrammatic Reasoner

Joseph L. Bokor and Ronald W. Ferguson

College of Computing, Georgia Institute of Technology
Atlanta, GA 30332 USA
{jlbokor, rwf}@cc.gatech.edu

Abstract

A key part of diagram understanding is the problem of glyph recognition. Glyph recognition is hard, because a glyph may be drawn in many different ways and with varying levels of precision. A diagrammatic reasoner must be able to recognize such glyphs. This paper presents a new glyph recognition mechanism that combines a probabilistic representation with an existing symbolic diagrammatic reasoner. This reasoner, GeoRep, recognizes glyphs using a visual domain theory supported by a logic-based truth-maintenance system (LTMS). Here we extend GeoRep's LTMS to include nodes that encapsulate naïve Bayes classifiers. The result is a reasoner that can leverage the benefits of both symbolic truth maintenance and probabilistic networks.

Introduction

Diagrams are important to a wide variety of tasks that include problem solving, communication, and collaboration (Glasgow, Narayanan, and Chandresekaran, 1995). These tasks are frequently aided by a diagram's ability to capture and convey many spatial relations at a glance.

In most diagrammatic reasoners, the first step is to combine the initial visual primitives into visual symbols or *glyphs*. Glyphs, especially when drawn quickly, however, are often imprecisely drawn. For example, Figure 1 shows four glyphs that are all easily interpreted as a NAND-gate, even though three are drawn imprecisely.

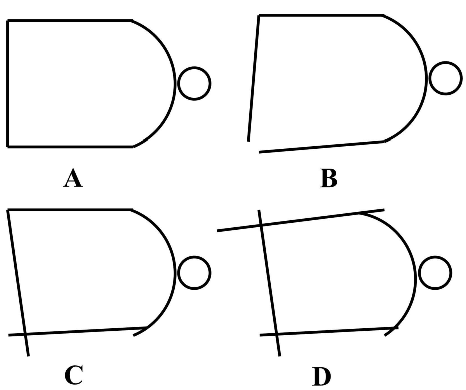

Figure 1: A is a precisely drawn NAND-gate glyph. B, C, and D are examples of imprecisely drawn glyphs.

Importantly, the imprecision in each glyph cannot be corrected by assuming tolerance values. GeoRep can recognize constituent relations in glyphs when they are within tolerance values, but if even one crucial relation exceeds the tolerance values (as in Figure 1C and 1D), it fails to recognize the glyph.

To more robustly recognize glyphs, we need a new method for recognition. This paper discusses the integration of a new probabilistic mechanism into a diagrammatic reasoner. The mechanism encapsulates naïve Bayes classifiers in nodes in a logic-based truth maintenance system (LTMS). The Bayes classifiers capture the imprecision and uncertainty inherent in drawn diagrams. The encapsulation of Bayes classifiers in the existing LTMS allows the flexibility of probabilistic reasoning with the efficiency of a symbolic reasoner.

Implementation

GeoRep is a diagrammatic reasoner that takes as input vector graphics files and outputs a predicate calculus representation of the diagram (Ferguson and Forbus, 2000; Ferguson et al., 2003). GeoRep creates this representation using a two-stage architecture. The first stage creates a dependency network of low-level visual relations. The second stage uses the dependency network and a rule-based visual domain theory to produce a description of the diagram.

We have created a new glyph recognition mechanism by encapsulating naïve Bayes classifiers into LTMS nodes created by GeoRep's rules. The classifiers are created during the rule firing process and stored directly in LTMS nodes. Communication is enabled between the classifier and the LTMS in order to maintain the proper truth value for a glyph interpretation.

Integration into the Rule System

We now look at how rules in the visual domain theory create nodes within the LTMS. For each glyph recognition rule, its set of preconditions captures the visual element types and the minimal set of spatial relations needed to attempt further glyph recognition.

When these preconditions are met and the rule fires, it adds the glyph interpretation to the TMS dependency network (as in the previous version of GeoRep), but also adds a probabilistic node as a node that conjunctively supports the current rule's interpretation (Figure 2). The node is created with the implicational structure dictated by the rule, allowing the node to be retracted if any of the trigger conditions become false (e.g., if a visual element is deleted from the diagram).

The probabilistic node then maintains the probability of the current interpretation. To do this, it must estimate the supporting probabilities of prior nodes, which represent supporting visual relations. If the visual relation is already in GeoRep's knowledge base, the prior node is considered evidence. If missing, however, a visual test for that relation is called automatically, and if the test is passed, the relation is added to both GeoRep's knowledge base and as classifier evidence. Once the evidence has been collected, the probability of the current interpretation is computed.

Communication between Representation Levels

Probabilistic nodes must communicate dynamically with the LTMS, and do so in two ways (Figure 2).

First, they can change the truth value for the glyph interpretation in the LTMS. The classifier in the probabilistic node generates a probability for the interpretation based on the existing evidence. When this probability reaches a threshold value, the labeling of the LTMS node is changed to *True*. Similarly, if the probability is below the threshold, the LTMS node will be labeled *False*.

The second method of communication is via the evidence collection process. To gather evidence, the naïve Bayes classifier accesses GeoRep's representations to determine whether a particular relation is present. If a relation is not present, a visual test is run directly on the diagram and the results of this visual test may be stored directly into the existing diagram representation.

This represents a more sophisticated implementation of top-down influences than in earlier versions of GeoRep. Previously, rule triggers could make callbacks to visual routines, but the results were only used in the instantiated rule and discarded afterwards. The visual test results were never added into the diagram representation. This new implementation allows the anticipated glyph structure represented by the probabilistic networks to guide further visual processing.

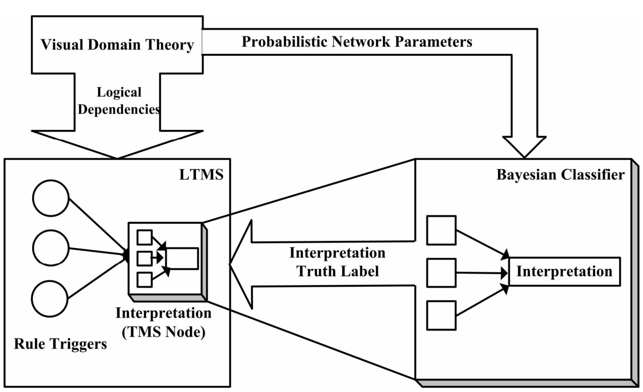

Figure 2: The interactions and communications between the truth maintenance system and the Bayesian networks.

Results and Future Work

Using this probabilistic mechanism with the LTMS, we were able to improve the glyph recognition capabilities of the GeoRep reasoner. The original reasoner is unable to correctly interpret three of the four NAND-gates in Figure 1 (B, C, and D), because the imprecision in the drawn glyphs provided inadequate visual relations to fire visual domain theory rules. However, the new mechanism is capable of recognizing all of the NAND-gate glyphs in the figure.

In addition to more robust glyph recognition, the new mechanism allows further processing of a diagram to occur. Within the visual domain theory, rules are often created that are based not on visual elements, but on glyphs and visual relations between glyphs. When imprecise glyphs are not recognized, the rules based on glyphs do not fire and diagram processing is blocked. The new mechanism overcomes the imprecision, recognizing glyphs even when poorly-drawn and allows the diagram processing to continue using rules that previously would not have been fired.

Although the mechanism increases the diagram understanding capabilities of GeoRep, there is still work to be done. We are working on a better language for describing the Bayes classifiers within rules. We are also investigating integrating the probabilistic calculations directly into the rule triggers, in order to avoid the overhead of creating separate nodes to contain the Bayes classifiers.

References

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