QCM: A QP-Based Concept Map System

Morteza Dehghani and Ken Forbus

Qualitative Reasoning Group, Northwestern University
2133 Sheridan Road, Evanston, IL 60201 USA
{morteza, forbus}@northwestern.edu

Abstract

Qualitative representations have proven to be useful formalisms for capturing human mental models. As a result, qualitative modeling could become an important tool for cognitive science. Specifically, an environment in which qualitative representations can be used to explore mental models and different type of reasoning and simulations can be performed on these models can be a useful tool for cognitive scientists. In this paper, we introduce the Qualitative Concept Map system, designed for cognitive scientists, for building and simulating qualitative and Bayesian models using qualitative process theory and Bayesian inference.

Introduction

Qualitative representations capture the intuitive, causal aspects of many human mental models (Forbus & Gentner 1997). This includes aspects of modeling not handled by traditional formalisms, such as conditions of applicability and other types of modeling knowledge. Qualitative modeling could become an important tool for cognitive science, by providing formal languages for expressing human mental models. The qualitative reasoning community has explored a wide range of representations and techniques, pursuing its goal to capture the breadth of qualitative reasoning, ranging from the person in the street to the expertise of scientists (Forbus et al. 2004). A unified platform in which cognitive scientists can apply qualitative representations, explore mental models and be able to integrate these models with other forms of reasoning, can become a useful tool for cognitive scientists.

In this paper, we present the Qualitative Concept Map system (QCM) which provides a cognitive scientist friendly environment that allows modelers to explore qualitative models, incorporate them into probabilistic models and output them in formats usable in other forms of reasoning (e.g. analogical reasoning). An earlier version of this system was used to build models of transcript data (Dehghani, Unsworth, Lovett, & Forbus, 2007). These models were exported as predicated calculus statements which were used via analogical generalization to classify the models based on the culture and level of expertise of the participants. Since then, we have expanded the model in several ways. First, we integrated our qualitative simulator (Gizmo), to provide a complementary first-principles simulation engine. Second, we added a probabilistic reasoning mode. Finally, we enhanced the user interface functionality to provide easier access to reasoning features.

We first introduce our system, discuss its different features and describe some real-world cognitive science examples modeled in it. Next, we describe the qualitative mode of the system and Gizmo. We then describe the probabilistic mode and how information available in the qualitative mode can be integrated into the probabilistic mode. We close by discussing related and future work.

Qualitative Concept Map System

QCM is the first modeling tool which has been specifically designed for cognitive scientists. It provides a unified reasoning platform in which mental models can be constructed and analyzed using Qualitative Process theory (Forbus, 1984) and Bayesian Networks (Pearl 1988). QCM is connected to Gizmo, a full implementation of QP theory, for providing qualitative simulations, including envisionment. QCM also uses a Bayesian inference algorithm for calculating probabilities of evidence and posterior probabilities.

QCM uses a concept map interface (Novak & Gowin, 1984). For example, Figure 1 shows how QCM can be used to model the effects of fear on different properties of the self, and effects of external processes on these properties, as described in Jami ‘al Sa’adat (The Collector of Felicities) (al-Naraqi, 18th Century), an Islamic book of ethics written in the 18th century. QCM automatically checks for any modeling errors which violate the laws of QP theory and probability theory, providing detailed error messages. QCM can import and export models via GraphML (Brandes, Eiglsperger, Herman, Himsolt, & Marshall, 2001), allowing graphs drawn in QCM to be easily viewed in other graph drawing programs. This facilitates collaboration between modelers. More importantly, for cognitive simulation purposes, models can be exported as predicate calculus statements. This enables QCM models to be used in a variety of types of reasoning, such as analogical reasoning.

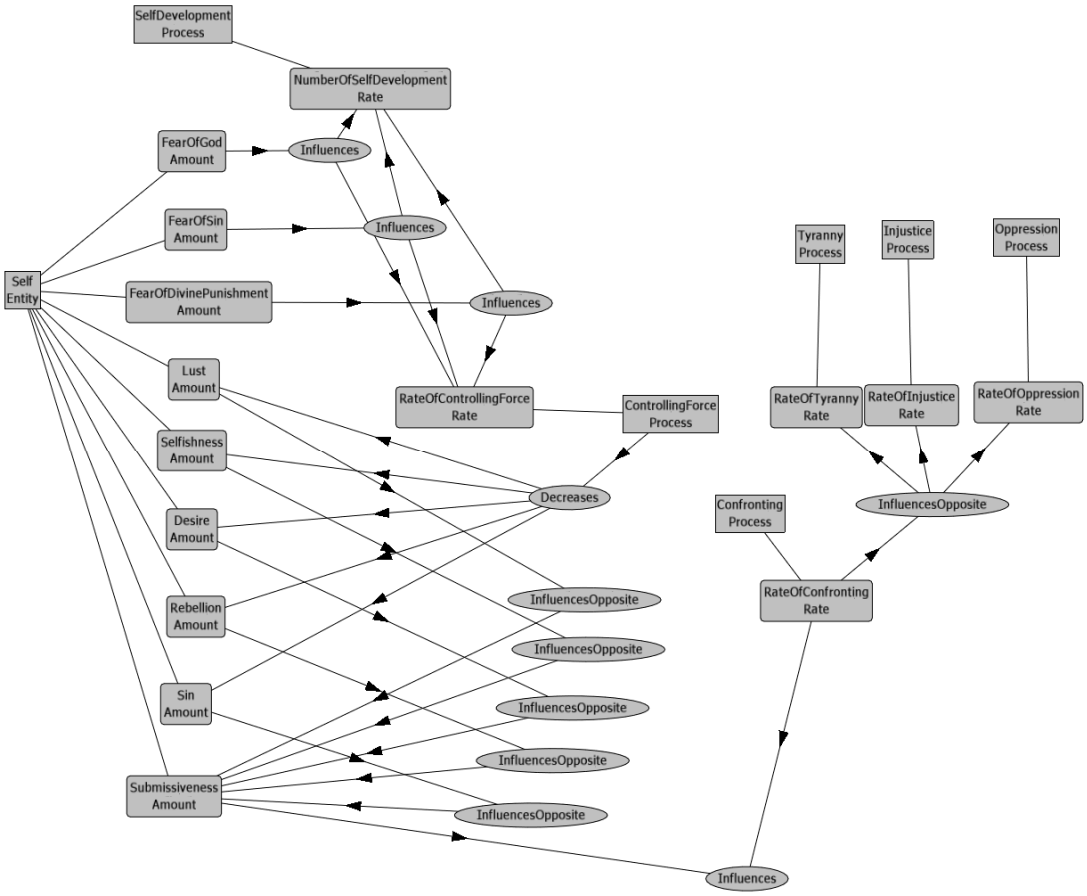

Figure 1: The Effects of Fear on Different Properties of the Self

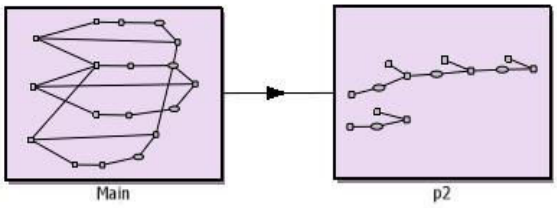

Figure 2: The Meta-Pane

QCM utilizes multiple panes to represent distinct qualitative states. This is important for capturing changes over time. For example, often modelers need to discuss immediate effects of a change followed by long-term effects of a change. The meta-pane (Figure 2) allows modelers to see all the states at once. Modelers can easily extend the vocabulary of specific processes and quantities used in the models, to expedite model creation.

QCM has been used for modeling a variety of different phenomena, from abstract models of religious beliefs to concrete qualitative reasoning scenarios. Figure 3 illustrates one pane from a model for the Bears Disappearing scenario modeled from transcript data gathered by psychologists from a native American group (Dehghani et al. 2007). Figure 4 shows the initial state of a heat transfer scenario and figure 6 is an example of Bayesian reasoning in QCM.

QP Modeling

QP theory as a representation language for physical phenomena includes:

- Continuous parameters (quantities)
- Causal relationships between them (influences)
- Mechanisms underlying physical causality (physical processes)

Systems and phenomena are modeled via sets of entities with continuous parameters, whose relationships are expressed using a causal, qualitative mathematics, where processes provide an explicit notion of mechanism. In QP

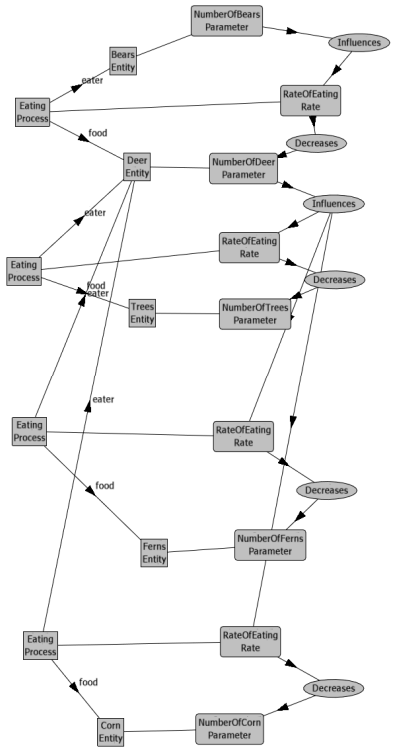

Figure 3: The Bears Disappearing Scenario Modeled from Transcript Data

theory direct influences are modeled using I+ (≡ *Increases*) and I- (≡ *Decreases*) which indicate an integral connection between two parameters, i.e., heat flow decreases the heat of its source and increases the heat of its destination. Indirect influences are modeled by $\propto_{Q+}$ (≡ *Influences*) and $\propto_{Q-}$ (≡ *InfluencesOpposite*) which indicate functional dependence between two parameters, i.e., the heat of something determines its temperature. Gizmo Mk2 is a full

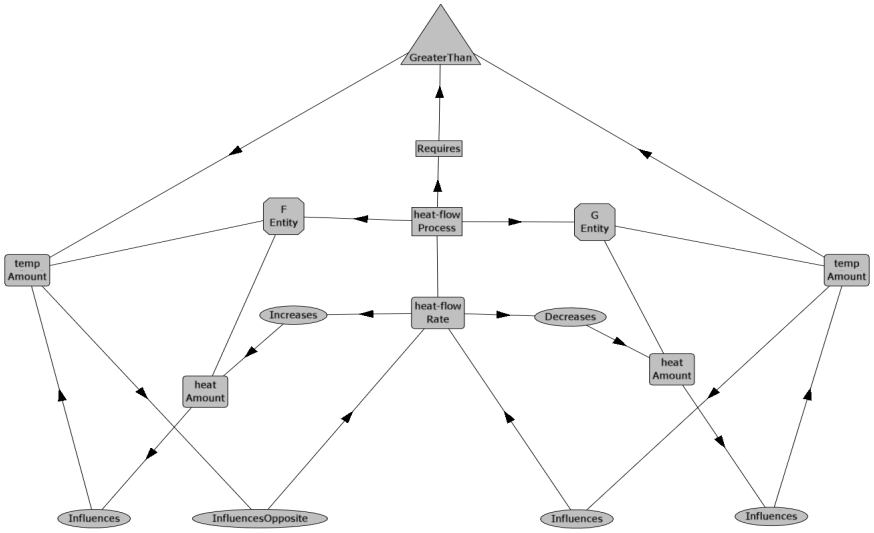

Figure 4: Heat-Transfer Scenario

```
;;; Quantity Functions
(defquantityfunction Rate (?thing))
(defquantityfunction heat-flow-rate (?Rate))
(defquantityfunction heat (?Amount))
(defquantityfunction Amount (?thing))
(defquantityfunction temp (?Amount))

;;; Entities
(defentity G-type
  :quantities   ((heat :type Amount)
                 (temp :type Amount))
  :consequences ((qprop (temp G-type)
                        (heat G-type)))
  :documentation "finite-thermal-physob")

(defentity F-type
  :quantities   ((heat :type Amount)
                 (temp :type Amount))
  :consequences ((qprop (temp F-type)
                        (heat F-type)))
  :documentation "finite-thermal-physob")

;;; Processes
(defprocess heat-flow
 :participants ((the-G :type G-type)
                (the-F :type F-type))
 :conditions   ((> (temp the-G) (temp the-F)))
 :quantities   ((heat-flow-rate :type Rate))
 :consequences ((i- (heat the-G) heat-flow-rate)
                (i+ (heat the-F) heat-flow-rate)
                (qprop (heat-flow-rate heat-flow)
                       (temp the-G))
                (qprop- (heat-flow-rate heat-flow)
                        (temp the-F))))
```

Figure 1: Domain Theory generated from the Heat-Transfer Scenario

implementation of QP theory and works as the qualitative reasoning engine of QCM. Gizmo has been designed to be lightweight and incremental to be used as a module in larger systems. The user has tight control over the process of qualitative simulation in Gizmo. Algorithms for both total and attainable envisioning are included as well.

In order to provide support for novice modelers, the domain theory and the scenario of the model are automatically extracted from the graph and sent to Gizmo. This is extraction is performed by going over all the nodes in the graph and, for each node, determining the type of node it is (e.g. Entity, Process, Quantity). Based on this information, QCM automatically obtains the required information for that type of node from the graph and sends the information to Gizmo. The domain theory extracted for the heat-transfer model of Figure 4 is presented in Figure 5. If the system determines that the model is missing some required information, a detailed error message is presented to the modeler.

The automatic extraction of the domain theory and the scenario file is, we believe, a major boon to novice modelers. While many of the ideas of qualitative modeling come naturally to scientists, outside of computer science, experience in writing logically quantified formulae is rare. Modelers need motivation, and being able to get results without having to first write a general domain theory helps reduce the entry barrier. As their models become more complex, the automatically produced models can become a starting point for writing standard QP theory domain models.

Bayesian Modeling

Agents continually update their beliefs using different

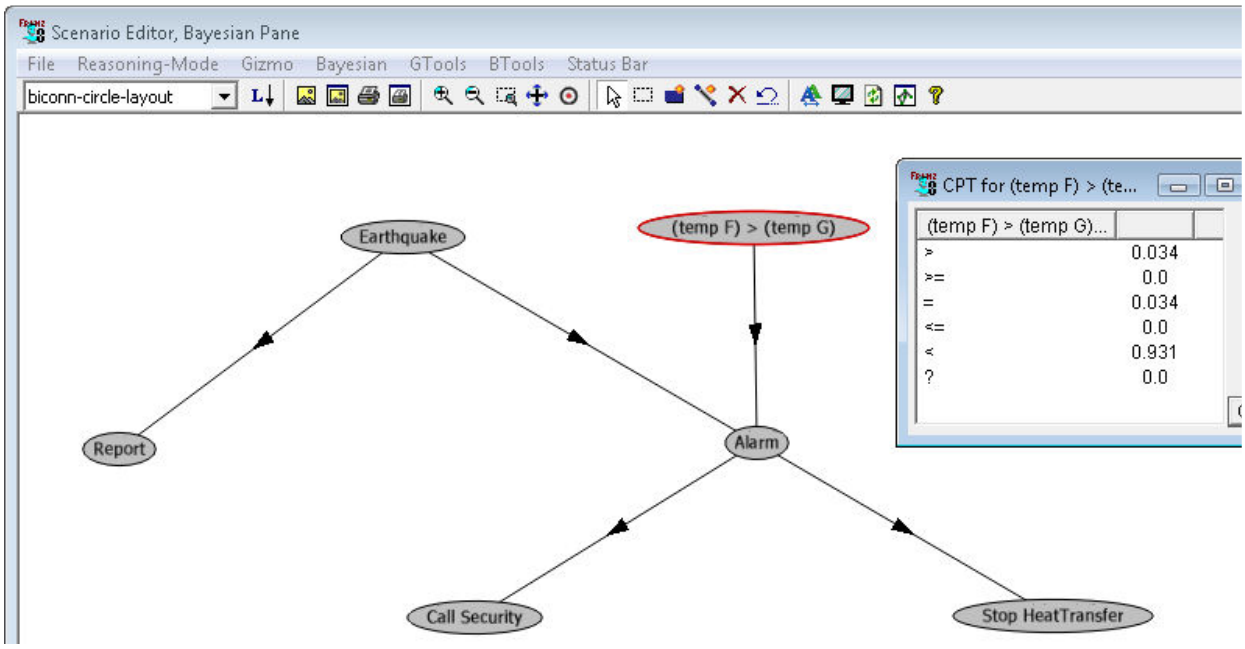

Figure 6: A Bayesian Network

types of new information. These updates affect their causal beliefs about the uncertainties in the world. In order to model this process, we need a rich causal representation and a method for capturing and updating uncertain beliefs about the world. QP theory provides us with a high level of expressiveness needed to capture many intuitive, causal aspects of human cognition. One can use the QP framework to reason about relations between things and the effect of these relations on the state of the world. However, QP theory does not provide the mechanism necessary for capturing probabilities. Bayesian networks (Pearl, 1988) are the most widely used approach for probabilistic reasoning. This formalism provides a succinct representation for probabilities, where conditional probabilities can be represented and reasoned with in an efficient manner. Providing an interface in which both QP and Bayesian formalisms can be used in parallel can potentially be helpful for cognitive scientists.

QCM provides a framework in which the agent's knowledge about the causal structure of the world can be captured using the QP formalism, while the agent's uncertain knowledge and expectations about the outcomes of his/her actions can be captured by subjective probabilities and represented by a Bayesian Network. Modelers can switch the mode of reasoning from QP to Bayesian and make probabilistic models. This feature allows cognitive scientists to take advantage of different types of reasoning available in both formalisms. In the Bayesian mode, modelers can perform exact inference on the network and calculate the probabilities using Recursive Conditioning (RC) (Darwiche, 2001). RC is an any-space algorithm which works by recursively partitioning the network into smaller networks using conditioning and solving each subnetwork as an independent problem. Networks created in the Bayesian mode are saved in the Hugin format, which is the standard format for many data mining and machine learning programs. This again helps modelers who use QCM collaborate more easily with other scientists using other modeling programs.

Determining a Priori Probabilities using Qualitative Simulations

One of the main obstacles in probabilistic reasoning is finding the a priori probabilities of variables in the model. One approach to overcome this obstacle is to use qualitative simulations. QCM uses the information available in the QP mode to calculate a priori probabilities of quantities used in the qualitative model. In this framework, the probability distribution is defined over a set of possible worlds determined by the constraints of the qualitative model. If the modeler chooses to include a qualitative parameter, such as a quantity or a derivative, as a node in the probabilistic model, QCM can determine the probabilistic distribution of the values of that parameter by model counting. The idea is to calculate the degree of belief in that statement over all the possible worlds determined by qualitative envisionment. For example, if `(temp F) > (temp G)` relationship from the heat-transfer scenario of Figure 4 needs to be included as a node in the model, QCM performs an attainable envisionment determining in how many possible worlds `(temp F)` β `(temp F)` where β={<,<=,=,>=,>,?} hold to be true. Based on this measure a probability value can be assigned to `(temp F) > (temp G)` (see Figure 6 for an example of a Bayesian network which uses this relationship). In other words, we are saying that under the current constraints in *n* of *m* possible worlds `(temp F) > (temp G)`, therefore the probability of `(temp F) > (temp G)` is *n*/*m*. We believe this method can provide a robust way of calculating a priori probabilities for physical phenomena for which we can define a QP model for.

Related Work

QCM is a successor to VModel (Forbus et al. 2001). VModel was developed to help middle-school students learn science. Like QCM, it uses a subset of QP theory to provide strong semantics. However, VModel was limited to single-state reasoning, whereas QCM can be used to model continuous causal phenomena with multiple states. Similar differences hold with Betty's Brain (Biswas et al 2001), which provides a domain-specific concept map environment that students can use in learning stream ecology.

The closest other qualitative modeling tools are MOBUM (Machado & Bredeweg, 2001) and VISIGARP (Bouwer & Bredeweg 2001) which have lead to Garp3 (Bredweg et al 2006, Bredweg et al 2007). Like QCM, these environments are aimed at researchers, but their focus is on constructing models for qualitative simulation, including generic, first-principles domain theories. QCM focuses instead on helping capture concrete, situation-specific qualitative explanations of phenomena. Thus, it provides a useful tool for scientists working with interview data.

Different approaches for qualitative Bayesian inference have been proposed. These methods include: qualitative probabilistic networks (Wellman 1990), qualitative certainty networks (Parsons and Mamdani 1993) and a method which incorporates order of magnitude reasoning in qualitative probabilistic networks (Parsons 1995). Keppens (2007a, 2007b) employs some of these methods for qualitative Bayesian evidential reasoning in the domain of crime investigation. QCM integrates information available from qualitative simulations in probabilistic networks, whereas other approaches mostly use qualitative techniques in performing inference on Bayesian networks.

Conclusions

QCM provides the basic functionality needed for cognitive scientists to build, simulate and explore qualitative mental models. This system has been expanded in several ways since the version used in Dehghani et al. (2007). First, it now uses Gizmo as its qualitative reasoning engine,

offering a full range of qualitative simulation abilities. Second, modelers can now work in a probabilistic mode and use RC to perform exact inference on their models. Third, QCM automatically integrates qualitative information for calculating a priori probabilities of quantities used in the qualitative mode. Fourth, the interface of the system has been enhanced offering easier access to reasoning capabilities. Finally, models can now be exported in different formats facilitating collaboration between modelers. We believe that QCM provides the formalism and the functionality necessary for automatic evaluation of psychological data. Moreover, it can potentially be a helpful tool for teaching undergraduate cognitive science courses.

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References

Biswas, G., Schwartz, D., Bransford, J. & The Teachable Agents Group at Vanderbilt. (2001). Technology Support for Complex Problem Solving: From SAD Environments to AI. In Forbus, K. and Feltovich, P. (eds). *Smart Machines in Education: The coming revolution in educational technology*. AAAI Press.

Brandes, U., Eiglsperger, M., Herman, I., Himsolt, M. and Marshall, M. S. (2001). "GraphML Progress Report: Structural Layer Proposal." *Proceedings of the 9th International Symposium on Graph Drawing (GD-01).* Vienna, Austria.

Bredeweg, B., Bouwer, A., Jellema, J., Bertels, D., Linnebank, F. and Liem, J. (2007). Garp3 - A New Workbench for Qualitative Reasoning and Modelling. *4th International Conference on Knowledge Capture* (K-CAP 2007), D. Sleeman and K. Barker (eds), pages 183-184, Whistler, BC, Canada, October 2007.

Bredeweg, B., Salles, P., Bouwer, A., and Liem, J. (2006). Garp3 – A new Workbench for Qualitative Reasoning and Modelling. *Proceedings of the 20th International Workshop on Qualitative Reasoning*. Hanover, NH.

Bouwer A. and Bredeweg B. (2001): VISIGARP: graphical representation of qualitative simulation models, in: *Artificial Intelligence in Education – AI-ED in the Wired and Wireless Future*, J.D. Moore, G. Luckhardt Redfield and J.L. Johnson, eds, IOS Press/Ohmsha, Osaka, Japan, 2001, pp. 294–305.

Darwiche, A. (2001). "Recursive Conditioning." *Artificial Intelligence* 126, no. 1-2: 5-41.

Dehghani, M., Unsworth, S., Lovett, A., Forbus, K. (2007). Capturing and Categorizing Mental Models of Food Webs using QCM. 21st International Workshop on Qualitative Reasoning (QR). Aberystwyth, U.K.

Forbus, K. (1984). Qualitative Process Theory. Artificial Intelligence, 24, 85-168.

Forbus, K., Carney, K., Harris, R., and Sherin, B. (2001) Modeling Environment for Middle-School Students: a Progress Report. In G. Biswas ed. *Papers from the 2001 Qualitative Reasoning Workshop* Stoughton, WI, The Printing House.

Forbus, K., Carney, K., Sherin, B. and Ureel, L. (2004). Qualitative modeling for middle-school students. *Proceedings of the 18th International Qualitative Reasoning Workshop*, Evanston, Illinois, August.

Forbus, K. and Gentner, D. (1997). Qualitative mental models: Simulations or memories? *Proceedings of the Eleventh International Workshop on Qualitative Reasoning*, Cortona, Italy, June 3-6, pp. 97-104.

Keppens, J. (2007). "On Qualitative Probabilities for Legal Reasoning about Evidence." *Proceedings of the 21st International Workshop on Qualitative Reasoning.*

Keppens, J. (2007). "Towards Qualitative Approaches to Bayesian Evidential Reasoning." *Proceedings of the 11th International Conference on Artificial Intelligence and Law.*

Machado, V. and Bredeweg, B. 2001. Towards Interactive Tools for Constructing Articulate Simulations. *Proceedings of QR01*

Novak J. D., & Gowin D. B. (1984). *Learning How To Learn*. New York: Cambridge University Press.

Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems.* San Francisco: Morgan Kaufmann.

Parsons, S. (1995). "Refining reasoning in qualitative probabilistic networks." *Proceedings of the 11th Conference on Uncertainty in Artificial Intelligence.*

Parsons, S. & E Mamdani, E. (1993). "On reasoning in networks with qualitative uncertainty." *Proceedings of the 9th Conference on Uncertainty in Artificial Intelligence.*

Wellman, M. (1990). "Fundamental concepts of qualitative probabilistic networks." *Artificial Intelligence* 44 (1990): 257-303.