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Guest Editorial

# New perspectives on Causal Networks: the first CaNew workshop

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## 1. Preamble

We are pleased to introduce a selection of the papers presented at the 1998 workshop on ‘Causal Networks from Inference to Data Mining’, CaNew ’98, [59]. This workshop was initiated from the feeling, shared by the organizers and co-chairs, that the field of Bayesian and, in general, Causal Networks deserved special attention from the international research community. We had a growing feeling that several areas had been neglected in research or deserved more attention. The common background of the editors and co-chairs being in Machine Learning, we felt that some ideas that had been long been in use in Machine Learning had not been applied to Causal Networks. However, we also felt that other aspects dealing with the knowledge representation aspects of the Causal Network formalism were also of interest, namely, the construction of networks that used different uncertainty formalisms, new inference methods and the relationship between the classical interpretation of Causal Network and the new ones. The rest of the Workshop Programme Committee members had a similar feeling about that and we tried to convey this by introducing in the workshop title both ends of the Causal Networks research spectrum: from inference to Data Mining. We comment in more detail in Section 3 the opportunities that, from our point of view, lay hidden between both.

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In this spirit a call for papers was made and over 20 contributions coming from six different countries were received. Each paper was submitted to three different referees which kept high the necessary quality standards for the meeting. From all the contributions, finally seven passed through the referees scrutiny and were discussed at the meeting which took place during the Sixth Iberoamerican Conference on Artificial Intelligence, IBERAMIA '98 [7], held in Lisbon in November 1998. We thought that some of the papers deserved wider publication and we were very happy when the editor of the *International Journal of Appoximate Reasoning* agreed on the idea of this Special Issue on Causal Networks. Workshop authors were invited to extend their presentations and submit their modified contributions to the referees of the journal, which followed this journal review procedures. The papers in this issue are the result of the new work by authors, greatly enhanced by the journal referees comments, criticisms and suggestions.

For those readers not familiar with this, for us, exciting research field we give some feedback in Section 2.

## 2. Introduction: why causal networks deserve new attention

Reasoning in terms of cause and effect is an strategy that arises in many tasks [10]. For example, diagnosis is usually defined as the task of finding the causes (illnesses) from the observed effects (symptoms) [42,43]. Similarly, prediction can be understood as the description of a future plausible situation where observed effects will be in accordance with the known causal structure of the phenomenon being studied. Causal models are a summary of the knowledge about a phenomenon expressed in terms of causation. Many areas of the applied sciences (Econometry, Biomedics, Engineering, etc.) have used such a term to refer to models that yield explanations, allow for prediction and facilitate planning and decision making. For a thorough discussion of the concepts underlying causation such as how causation is established or if it can be established only from observation or which are the necessary requisites for a theory to be called 'causal' in general, what 'causal association' means and why 'causal order' is important see [16], and restricted to the social sciences [69]. For a discussion of these aspects in Statistics see [70].

There are many references to 'causal models' causal association, etc., in the AI literature. Interest in causation arises, for example, in commonsense reasoning [37] and automated diagnosis, [12,13,32]. There are also references in qualitative reasoning and modeling [19,75]. Posterior developments such as second generation expert systems posit also the use of a causal model of the domain as meta-level for expert systems [8,72]. The need for diagnosis appears also in engineered devices, which resulted in the motion of 'mythical causality' [15,17] and theories of causal order [34–36,54]. Several other attempts at defining the causality principle and causal reasoning have been contributed by other workers related to AI, most notably those dealing with default and non-monotonic reasoning [11,24–26,40,44,66–68].

All these methods have different semantics for the causality relation. Presently, however, the most agreed upon concept of causation used in AI stems from the work of Judea Pearl in Bayesian Belief Networks [6,41,45,46,48] that has been taken as a reference for the interpretation of causal relations. The underlying formalism has correlates in Decision Theory and in Planning [31]. It can be understood as a hybrid model (involving qualitative and quantitative aspects) of causality inspired from several sources, mainly statistical ideas on causality as correlation but also by ideas about probabilistic causation [56,73].

It is also important to remark that Pearl's Bayesian Networks are not the only graphical network formalisms that have a causal semantics. Other graphical representations tied with causality and which have some degree of equivalence with Pearl's networks are: statistical association graphs [50], path models [76], Heckerman's modification of influence diagrams [30] and Spirtes causal schemas [29]. *Abductive Causal Networks*, first proposed by Peng and Reggia [52,53] for example is also a graph representation for causal links in diagnosis domains. Similarly, in Statistics, causality is the key concept of a whole area devoted to graphical models [3,38,39,74].

Although these models are quiet different in their underlying assumptions about causation and causality, there are some common features to all that allow us to approximate a working definition.

*Causal Network*: A Causal Network is a graph where nodes represent variables and links stand for causal associations. Links can be directed or undirected and may be weighted by a factor or combination of factors expressing the strength of causal association.

This is the most general definition. Table 1 expresses the possible combinations and the actual formalisms.

In general in all these models the fundamental dimensions of any causation theory, i.e., causal association and causal precedence are established by means of non-temporal criteria. Precedence is identified by means of structural properties of the constructed graphs. In fact, what happens is that graphs are built in such a way as to ensure that nodes appearing in 'higher' positions are causally prior to nodes appearing in lower levels of the graph.

*Decomposable Graph Models* are the expression of Bayesian non-parametric methods for extracting statistical models from data. From the point of view of graph structure and dependency properties they can be assimilated to Markov Networks. As such, they express association in terms of conditional dependence among clusters of variables. It is difficult to say how causal order is established. No previous assumption about the role of the variables in the model is made, so they can be used to extract causal knowledge from observational data, see [74] for an extensive treatment of their properties.

Table 1
A classification of causal graph models

| Type of graph | Causal association | Causal order | Type of link |
|---|---|---|---|
| Bayesian Belief Network | Conditional dependence | Order in graph | Directed |
| Decomposable Graphical Models | Correlation | Not used | Undirected |
| Stochastic Causal Theories | Correlation | Order in graph | Directed |
| Path Models | Regression coeffs. | Order in paths | Directed and undirected |
| Pearl's Causal Theories | Conditional dependence and functional relationships | Order in graph | Directed |
| Causal Decision Networks | Conditional dependence and unresponsiveness | Order in graph | Directed |
| Cooper BBN | Constraints on conditional independence | Order in graph | Directed |

*Path Models* [76] are special representations for multiple linear regression models. Given the regression model

$$r_{XY} = \beta_1 + \beta_2 X_2 X_1 + \beta_3 X_3 X_1,$$
$$r_{XY} = \beta_1 X_2 X_1 + \beta_2 + \beta_3 X_3 X_2,$$
$$r_{XY} = \beta_1 X_3 X1 + \beta_2 X_3 X_2 + \beta_3,$$

where $\beta_i$ is a standardized partial coefficient. $\beta_i$ can be interpreted as how much $Y$ changes when $X_i$ is changed one unit. Causal association strength is expressed by means of the value of the regression coefficient, i.e., by the strength of correlation between variables. There are several ways of establishing causal order.

*Stochastic Causal Theories*, due to Spirtes et al. [29,71] establish causal associations by imposing constraints on the correlations between variables. They are applicable to observational data.

*Cooper's Modification of Bayesian Belief Networks* [9] imposed additional constraints to previously detected conditional dependence between variables in order to qualify them as causal. They are specially geared to be used with observational data and hidden variables.

*Decision Networks* establish a previous separation of variables into observation variables and utility variables and the causal association is derived in terms of how observations may influence the final utility of a decision.

*Pearl's Causal Theories* [21,22,47,49–51] main merit lies in that they can be used for establishing conditions on how causal effects can be ascertained using only observational data. They correspond to linear structural equation models, which are models widely used in social and statistical sciences where some linear combination of variables are used to explain the behavior of a given one. It would seem that this would require extensive a priori knowledge of the domain in order to extract such a model. Pearl's work shows that this is not so: information from observational data can be enough.

## 3. New proposals for research

It is clear from the preceding paragraphs, or at least we want to extract that idea, that graphical causal representations admit not only different views but that their implicit oneness deserves further research in several aspects. Some hints on them can be found in [28,61].

From our current understanding of the field, the following topics have received less attention than deserved but, still, seem to be challenging areas in causal network research:

1. Causality criteria other than conditional independence and its representation. See [1,54,76].
2. Formal relationships and properties of the different causal network formalisms, as studied in [11,62–65].
3. Study of different reasoning mechanisms on networks guided by causality as in [10] or [4].
4. Causal concepts and relationships in uncertainty formalisms other than probability, as in [18].
5. New ways of looking at the process of learning causal networks from data, either by resorting to formalisms other than probability [23,57] or by conceptualizing the learning process closer to the methods of Machine Learning than to the ones from the Statistical Modeling community (for example getting into account prior knowledge in a more expressive way than priors on distributions or devising incremental methods [20,55]). See [58] for a survey of current methods.
6. Scaling up methods for learning to respond to the challenges of real Data Mining applications with high dimensionality [5].
7. Practical applications.

These opportunities were the reasons that drove us to organize 'CaNew '98, International Workshop on Causal Networks' in the framework of IBERAMIA, the Sixth Iberoamerican Conference on Artificial Intelligence [7].

## 4. The CaNew '98 Workshop

We tried to make evident the main goals of this workshop in its motto 'From inference to Data Mining'. One important topic for us was the formal aspects of the causal graph formalism, specifically the complexity problems encountered in present reasoning schemas. On the other end of the topic arc we thought that innovative methods for learning should also have a representation in the workshop.

As we said above, we received more than 20 contributions from six countries. Topics of these papers ranged from Statistical classification methods based on graphical structures to the philosophical underpinnings of causality and its graphical representation. From these papers, seven were selected for presentation in the workshop. Finally, for this special issue of the International Journal of Approximate Reasoning, the five papers that we comment in the following were accepted.

### 4.1. The selected papers

De Campos and Huete in *A new Approach for Learning Belief Networks using Independence Criteria* propose new methods that resort to the independence properties of causal networks to guide the learning process. This is a departure from typical methods based on distributional properties of the networks estimated or the traditional constraint-based methods devised by Geiger and Pearl [27]. They built on previous work on the area of studying conditional independence properties and of devising learning methods from them [14,33].

The problem of using prior knowledge in guiding the learning process for Bayesian Network models is addressed by Castelo and Siebes in *Priors on Network Structures. Biasing the search for Bayesian Networks*. They set their efforts in a Bayesian updating framework and pinpoint the strengths and difficulties of that approach. We think that their proposal departs from other typical ways of incorporating prior knowledge to Causal Network learning methods as, for example the ones proposed by Buntine [2].

Using properties of conditional independence, expressed in a local way is used by Fay and Jaffray as a means for improving some reasoning schemas in *A Justification of Local Conditioning in Bayesian Networks*.

A high-level way of specifying a different graphical formalism with underlying causal interpretation is proposed, discussed and explained by Lacruz, Lasala and Lekuona in *Graphical Dynamic Linear Models: Specification use and Graphical Transformations*. This paper departs from the traditional identification of Causal Networks with Bayesian Belief Networks but stresses the importance of graphical representations of causality and offers new ways for specifying and manipulating such structures.

Finally, our own work in treating prior knowledge in the learning of a non-standard causal network formalism is presented in *Prior Knowledge for Learning Networks in Non-Probabilistic Settings*. There, we extend previous results [60] by trying to use some forms of prior knowledge in the learning method.

## 5. Next steps

All in all the selected papers address part of the topics we already isolated as interesting. The discussions ensuing in the workshop as well as the new contributions of authors and the comments from referees have illustrated the interest of having a new look at those causal representations. We thank both the organizers of IBERAMIA '98, and the editors of the International Journal of Approximate Reasoning for providing such good environments for discussion and publication. The referees both for the workshop and for this issue did a great work and all of us learnt from their remarks. We feel that this first effort deserves a continuation and it will, probably, have one in an international setting.

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