A Multi-Step Approach to Knowledge Integration Using Graph-Based Relational Learning Method: A Case of Developing A New Technology

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ABSTRACT

Fuzzy cognitive maps (FCMs) are a flexible and powerful soft computing technique for modeling and simulating systems. FCMs can successfully depict knowledge and human experience, introducing concepts to represent the essential elements and the cause and effect relationships among the concepts to model the behavior of any system. In this paper, the process of gathering and integrating knowledge from experts in form of fuzzy cognitive maps is enhanced with a graph-based learning method in order to the improve effectiveness of the final digraph.

Keywords: Fuzzy cognitive map, Knowledge integration, Graph-based learning, Diagraph

INTRODUCTION

In tackling complex real world problems, decision makers commonly seek to find and integrate different experts' knowledge and experiences about the problem situation. This multi-expert approach is applied to different fields of management from construction (Lin et al, 2008), health and clinical practice (Greenhalgh et al, 2008) and Financial management (Sun et al., 2007) to facility location selection (Chou et al, 2008).

FCMs were originally developed by Kosko (1986, 1988, 1992, 1997), and since then successfully applied to numerous domains, such as engineering, medicine, control, and political affairs. Their popularity stems from the simplicity and transparency of the underlying model. FCMs constitute an attractive knowledge-based methodology, combining the robust properties of fuzzy logic and neural networks. FCMs represent causal knowledge as a signed directed graph with feedback and provide an intuitive framework which incorporates the experts' knowledge. At the same time FCMs are hindered by necessity of involving domain experts to develop the model. Since human experts are subjective and can handle only relatively simple networks (maps), there is an urgent need to develop methods for automated generation of FCM models.

In order to construct an FCM, usually a group of experts are asked to determine the key factors and their relationship in a brain storm meeting. They discuss different aspects of the system under investigation and determine the structure and interconnections of the system with fuzzy conditional statements. Each expert might draw his own FCM which can be different from the others. With use of the assigned weights by all experts and the degrees of similarity between concepts, a constructed FCM is then built (Khan et al., 2004; Stach et al., 2005; Schneider et al., 1996; Rodriguez-Repiso et al., 2007). In some situations, when similarity of concepts does not necessarily mean the causality between them, FCM cannot be constructed using this method.

This paper focuses on the development of a new method based on using experts' knowledge for constructing an augmented FCM. This method uses a graph-based relational learning algorithm for finding the relational patterns in each FCM and drawing the unique substructures of them. This substructure helps us understand the basic cognitive structure of the system. Finally a substructure of the most frequent patterns in each FCM is produced which is the constructed FCM of all experts.

FUZZY COGNITIVE MAPS

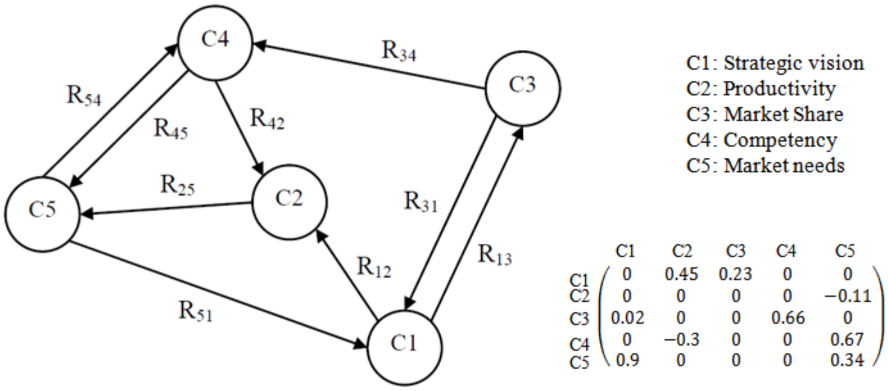
Cognitive maps are digraphs and have their historical origins in graph theory, which started with Euler in 1736 (Biggs et al., 1976). In digraphs, each relation or connection between variables or nodes has a direction (Harary et al., 1965). Axelrod (1976) was the first to use digraphs to show causal relationships among variables as defined and described by experts, rather than by the researcher himself. He called these digraphs cognitive maps. Different successful studies showed cognitive mapping is effective in complex problem situations. (Bauer, 1975; Bougon et al., 1977; Brown, 1992; Carley and Palmquist, 1992; Cossette and Audet, 1992; Hart, 1977; Klein and Cooper, 1982; Malone, 1975; Montazemi and Conrath, 1986; Nakamura et al, 1982; Rappaport, 1979; Roberts, 1973).

Fuzzy Cognitive Maps (FCMs) are graphical representation including nodes determining the most relevant factors of a complex system and links between these nodes determining the relationships between those factors (Rodriguez-Repiso, 2005). FCM is a modeling methodology for complex systems, which is originated from the joining of fuzzy logic and neural networks. FCMs describe the behaviour of a complex mostly dynamic system in terms of concepts that represent an entity, a state, a variable, or a characteristic of the system (Xirogiannis & Glykas, 2004).

FCMs have been applied in simulation (Fu, 1991), the physiology of appetite (Taber and Siegel, 1987), modeling of organizational strategies (Paradice, 1992), political developments (Taber, 1991), support for strategic problem formulation and decision analysis (Eden & Ackermann, 1993), electrical circuits (Styblinski and Meyer, 1988), knowledge bases construction (Silva, 1995), virtual world of animals (Dickerson and Kosko, 1994), managerial problems diagnosis (Carrico & Guimaraes, 1997), organizational behavior and job satisfaction (Craiger et al., 1996), failure modes effects analysis (Pelaez & Bowles, 1995), requirements analysis (Montazemi & Conrath, 1986), systems requirements specification (Downing & Fickas, 1992), urban design support (Xirogiannis, Stefanou, & Glykas, 2004), relationship management in airline services (Kang, Sangjae, & Choi, 2004) and web-mining inference amplification (Lee, Kim, Chung, & Kwon, 2002).

The FCM Representation

In Figure 1, a simple FCM (graph) representation is illustrated which has five generic nodes (C1 to C5) and the weighted arcs (edges) showing the relationships between concepts. In this simple fuzzy cognitive map, the relation between two nodes is determined by taking a value in interval [-1, 1]. While -1 corresponds to the strongest negative, +1 corresponds to strongest positive one. The other values express different levels of influence. This model can be presented by a square matrix called an adjacency matrix (Ad).



$$\begin{array}{c|ccccc} & C1 & C2 & C3 & C4 & C5 \\ \hline C1 & 0 & 0.45 & 0.23 & 0 & 0 \\ C2 & 0 & 0 & 0 & 0 & -0.11 \\ C3 & 0.02 & 0 & 0 & 0.66 & 0 \\ C4 & 0 & -0.3 & 0 & 0 & 0.67 \\ C5 & 0.9 & 0 & 0 & 0 & 0.34 \end{array}$$

Figure 1 - Representing a simple Fuzzy Cognitive Map

MINING OF FREQUENT PATTERNS FROM GRAPHS

Graph data mining aims to discover interesting and/or useful patterns that are hidden in a given set of graphs and to use them as explicit knowledge. Graph-based modeling has emerged as a powerful abstraction capable of capturing in a single and unified framework many of the relational, spatial, topological, and other characteristics that are present in a variety of datasets and application areas. (Kuramochi et al., 2005) A number of researchers have developed data mining algorithms that work with graphs in many different fields such as link analysis (Jensen and Goldberg, 1998; Kleinberg et al., 1999; Kleinberg, 1999; Palmer et al., 2002), semantic web (Berendt et al., 2002), behavioral modeling (Wasserman et al., 1994; Mooney et al., 2004), VLSI reverse engineering (Yoshida and Motoda, 1995).

There are two distinct problem formulations for graphs frequent pattern mining, (1) graph-transaction setting and (2) the single-graph setting. Graph-transaction setting uses a set of relatively small graphs (called transactions) as input, whereas in the single-graph setting the input data is a single large graph. The different input datasets affect the way that the frequency of the various patterns is determined. Graph-transaction setting determines the frequency of a pattern by the number of graph transactions that the pattern occurs in, regardless of how many times a pattern occurs in a particular transaction. On the other hand, in the single-graph setting, the frequency of a pattern is determined by the number of its occurrences in the single graph.

In recent years, many efficient algorithms have been developed to find patterns in the graph-transaction setting (Borgelt and Berthold, 2002; Yan and Han, 2002; Inokuchi et al., 2003; Hong et al., 2003; Yan and Han, 2003; Huan et al., 2003; Kuramochi and Karypis, 2004). These algorithms are complete in the sense that they are guaranteed to discover all frequent subgraphs and were shown to be scalable to large graph datasets. Existing algorithms that are guaranteed to find all frequent patterns are (Ghazizadeh and Chawathe, 2002; Vanetik et al., 2002) and algorithms that are heuristic, such as GBI (Yoshida et al., 1994) and SUBDUE (Holder et al., 1994) which can use powerful measures such as information entropy, gini-index and description length to figure out important graph structures (Yoshida and Motoda, 1995; Cook and Holder, 1994).

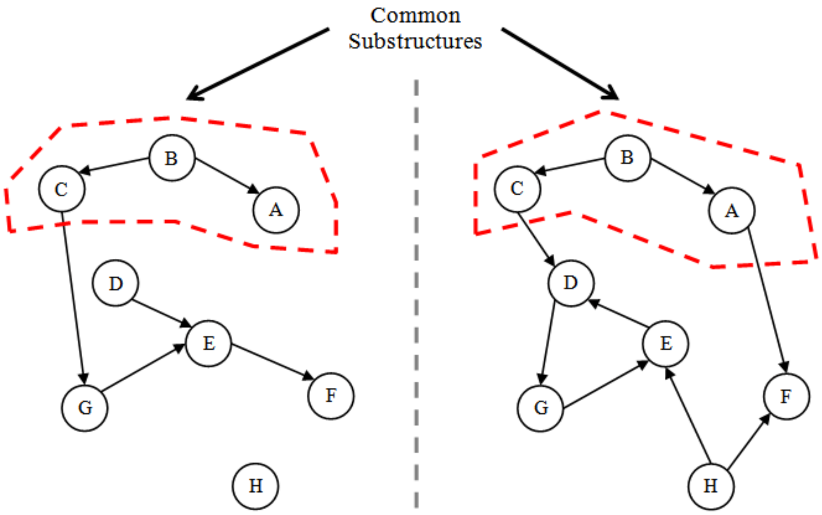


Figure 2 - Subdue discovers common substructures within multiple graphs

Graph-based relational learning is focused on finding novel and meaningful, but not necessarily most frequent, substructures in a graph representation of data. Using SUBDUE as a graph-based relational learning system (Holder et al., 1994) we can discover interesting, useful approximate substructure patterns in structural data which is based on minimum description length (MDL) (Rissanen, 1989) principle and optional background knowledge. SUBDUE not only discovers patterns which abstract instances of the patterns by compression, but also provides better understanding of the data (Cook and Holder, 1994). Using background knowledge given as predefined substructures can guide graph-based relational learning to find more meaningful substructures. SUBDUE has been applied to a variety of areas such as Chemical Toxicity, MolecularBiology, Security and Web Search.

Subdue uses a variant of beam search for its main search algorithm which is depicted in Figure 3 and summarized in Figure 2. It grows a single node incrementally by expanding a node in it. At each expansion it searches for the best total description length: the description length of a pattern and the description length of the graph set with all the instances of the pattern condensed into single nodes. SUBDUE performs approximate matching to allow slight variations of substructures, thus supporting the discovery of approximate substructures.

```
SUBDUE(Graph,BeamWidth,MaxBest,MaxSubSize,Limit)
     ParentList = Null;
     ChildList = Null;
     BestList = Null;
     ProcessedSubs = 0;
     Create a substructure from each unique vertex label
          and its single-vertex instances;
     Insert the resulting substructures in ParentList;
     while ProcessedSubs ≤ Limit
          and ParentList not empty
     do
          while ParentList is not empty
          do
               Parent = RemoveHead(ParentList);
               Extend each instance of Parent in all possible
               ways;
               Group the extended instances into Child
               substructures;
          for each Child
          do
               if SizeOf(Child) less than MaxSubSize
```

```
                    then
                    Evaluate Child;
                    Insert Child in ChildList in order by value;
                    if BeamWidth < Length(ChildList)
                    then
                         Destroy substructure at end of ChildList;
               Increment ProcessedSubs;
               Insert Parent in BestList in order by value;
               if MaxBest < Length(BestList)
               then
                    Destroy substructure at end of BestList;
               Switch ParentList and ChildList;
     return BestList;
```

Figure 3 - SUBDUE's discovery algorithm

SUBDUE's search is guided by the MDL principle given in Eq. (1), where $DL(S)$ is the description length of the substructure being evaluated, $DL(G \setminus S)$ is the description length of the graph as compressed by the substructure, and $DL(G)$ is the description length of the original graph. In this technique, the best substructure is the one that minimizes compression ratio:

$$Compression = \frac{DL(S) + DL(G \setminus S)}{DL(G)} \tag{1}$$

MULTI-STEP FCM LEARNING METHOD

The proposed multi-step FCM learning approach includes the following steps:

(1) Drawing of fuzzy cognitive maps for each expert,
(2) Coding the fuzzy cognitive maps into adjacency matrices,
(3) Categorizing the weights of relationship and labeling the arcs accordingly,
(4) Preparing the FCMs for being used by SUBDUE algorithm,
(5) Running and collecting the results of learning algorithm,
(6) Translating the results to an FCM,
(7) Checking the validation of the FCM with experts.

These steps are illustrated with a real world problem situation case study on using VOIP (Voice over IP) technology instead of satellite telephones in offshore industry.

ILLUSTRATION OF THE FCM METHOD

Background

Iranian Offshore Engineering and Construction Company (IOEC) is the first Iranian general contractor in the oil and gas industry, specializing in offshore engineering, procurement, construction, pipe coating, pipe laying, and installation of jackets, TopSites, etc. IOEC designs, procures, builds, installs and services a complete range of offshore surface and partial subsurface infrastructure for the offshore oil and gas industry. With more than 400 employees operating wherever there is offshore oil and gas activity. IOEC is one of the largest truly integrated offshore and subsea pipeline companies in the Middle East.

IOEC has successfully expanded its offshore services providing projects with full marine fleet support for pipe laying, installation, hook-up, and commissioning. Today as a Holding Company, IOEC is planning to extend its oil, gas and petrochemical activities to onshore and offshore, upstream as well as downstream activities and operations. IOEC owns over $600 million in assets including fabrication yards, concrete weight coating plant (CWC), pipe laying vessels, various lifting vessels, barges and other relevant equipment .

In the recent years IOEC has been growing considerably. This philosophy set out in this section has been developed to help IOEC maintain its position as a general contractor in the offshore oil and gas industry and to help to attain its aim of becoming "the contractor of choice across the range of products and services that they offer."

In IOEC, telecommunication project started in June 2001 with the scope of telecom building utilities, detail engineering, supply equipment/material, construction and installation, testing, commission and training. Different communication systems were developed such as VHF radio system, paging radio system, marine radio system, and satellite communication. Voice over IP technology is regarded as essential for economic communications between the company’s vessels, offices in Iran and abroad. Different aspects of developing this new technology was captured by five experts and therefore five FCMs were drawn.

In the following steps, to augment all experts' knowledge, a graph learning method is used.

Step 1: Drawing Of Fuzzy Cognitive Maps for Experts

Experts develop FCMs or mental models manually based on their knowledge in related area. At first, they identify key domain aspects or concepts (Table 1). Secondly, each expert identifies the causal relationships among these concepts and thirdly estimates causal relationships strengths. This achieved digraph (FCM) shows not only the components and their relationships but also the strengths (Figure 4).

Table 1

Main concepts in the field of new technology development which is identified by all experts

Node	Concept
A	Complexity of new technology
B	Integration risk
C	Technology development performance
D	Actual testing results
E	Discrepancy
F	Target testing results
G	Redevelopment
H	Technology development risk
I	Technology maturity
J	Training
K	Technology development
L	Technology development management
M	Testing Effort
N	Actual Costs
O	Cost Overrun
P	Funding
Q	Funding Stability

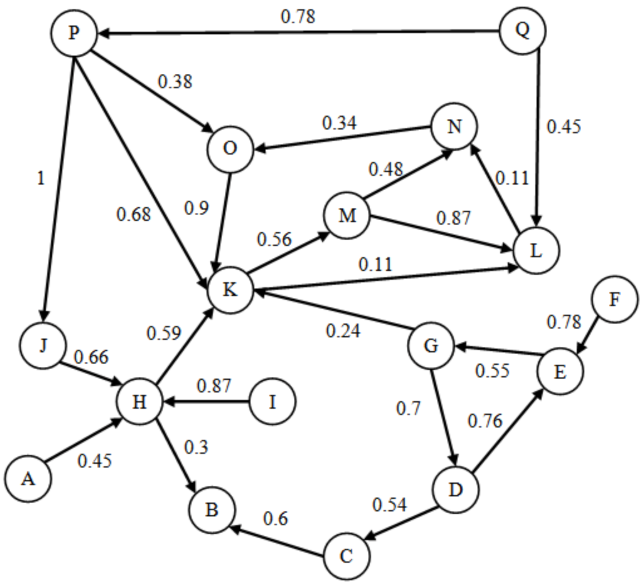


Figure 4 - A fuzzy cognitive map describing the technology development aspects which is drawn by one expert (FCM 01)

All these five FCMs have the same concepts (which were agreed by all five experts) but different relationships and weights. In the next step FCMs are coded into their adjacency matrices.

Step 2: Coding the Fuzzy Cognitive Maps into Adjacency Matrices

Collecting every five fuzzy cognitive maps, FCMs are coded into weight matrices (adjacency matrices) as shown in Table 2.

Table 2

The adjacency matrix for FCM 01

concepts	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
A		0	0	0	0	0	0	0.45	0	0	0	0	0	0	0	0	0
B	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0.6		0	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0.54		0.76	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	0		0	0.55	0	0	0	0	0	0	0	0	0	0
F	0	0	0	0	0.78		0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0.7	0	0		0	0	0	0.24	0	0	0	0	0	0
H	0	0.3	0	0	0	0	0		0	0	0.59	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0.87		0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0.66	0		0	0	0	0	0	0	0

K	0	0	0	0	0	0	0	0	0	0		0.11	0.56	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	0		0	0.11	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0.87		0.48	0	0	0
M	0	0		0	0	0	0	0	0	0	0	0	0		0.34	0	0
O	0	0	0	0	0	0	0	0	0	0	0.9	0	0	0		0	0
P	0	0	0	0	0	0	0	0	0	1	0.68	0	0	0	0.38		0
Q	0	0	0	0	0	0	0	0	0	0	0	0.45	0	0	0	0.78	

Step 3: Categorizing the Weights Of Relationship

In order to categorize the weights of relationships, a 3-point Likert scale which is one of the best known rating scales (poor, average, high) was used (Likert, 1932). The idea is to define a label for each arc. For example the relationship between C and B is 0.6 which according to Table 3 is a medium strength relationship.

Table 3

Likert labels for relationships

Likert label	Weight Interval
Poor (P)	[0, 0.24]
Medium (M)	[0.25, 0.74]
High (H)	[0.75, 1]

Using Table 3, a labeled FCM is produced (Figure 5).

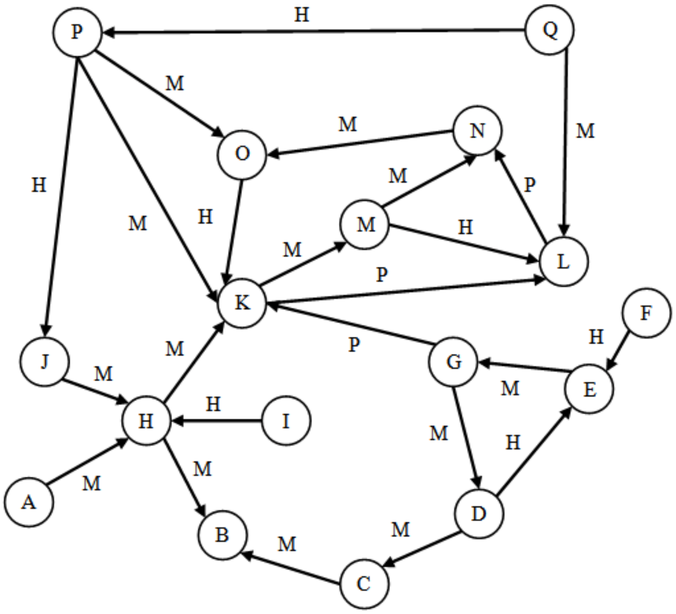


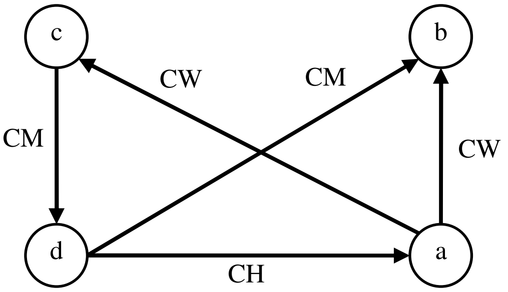
Figure 5 - Labeled FCM 01 using a 3-point Likert scale

Step 4: Preparing the FCMs

Before using SUBDUE as a graph-based learning method, FCMs should be transformed to the appropriate codes. Subdue algorithm uses this codes to analyze the graphs. For example consider the following graph coding (Figure 6).

Sample codes which are used by SUBDUE

```
v 1 a
v 2 b
v 3 c
v 4 d
d 1 2 causality_weak (CW)
d 1 3 causality_weak (CW)
d 3 4 causality_medium (CM)
d 4 2 causality_medium (CM)
d 4 1 causality_high (CH)
```



```
Legend:
"v" means vertex and "d" mean a directed relationships
```

Figure 6 - SUBDUE graph coding samples

The first line of code means that the graph has a vertex (node) which labeled "a" and second also means that the next vertex is labeled "b" and so on. Line five means that the graph has a directed relationship which is labeled "causality_weak". This relationship means poor causality between two vertexes (nodes or concepts) "a" and "b". Figure 7 shows the code representation of first FCM in form of SUBDUE algorithm syntax.

```
% This is FCM 01 (Code Comments)
v 1 A                d 3 2 M
v 2 B                d 4 3 M
v 3 C                d 4 5 H
v 4 D                d 7 4 M
v 4 E                d 5 7 M
v 4 F                d 6 5 H
v 4 G                d 9 8 H
v 4 H                d 10 8 M
v 4 I                d 7 11 P
v 4 J                d 11 12 P
v 4 K                d 11 13 M
v 4 L                d 12 14 P
v 4 M                d 15 11 H
v 4 N                d 16 10 H
v 4 O                d 16 11 M
v 4 P                d 16 15 M
v 4 Q                d 17 16 H
d 1 8 M              d 14 15 M
d 8 2 M              d 13 14 M
d 8 11 M             d 13 12 H
                     d 17 12 M
```

Figure 7 - FCM 01 code representation

Step 5 and 6: Drawing the Final FCM

In this step the SUBDUE algorithm is used with a computer package and finally a FCM is produced as shown in Figure 8.

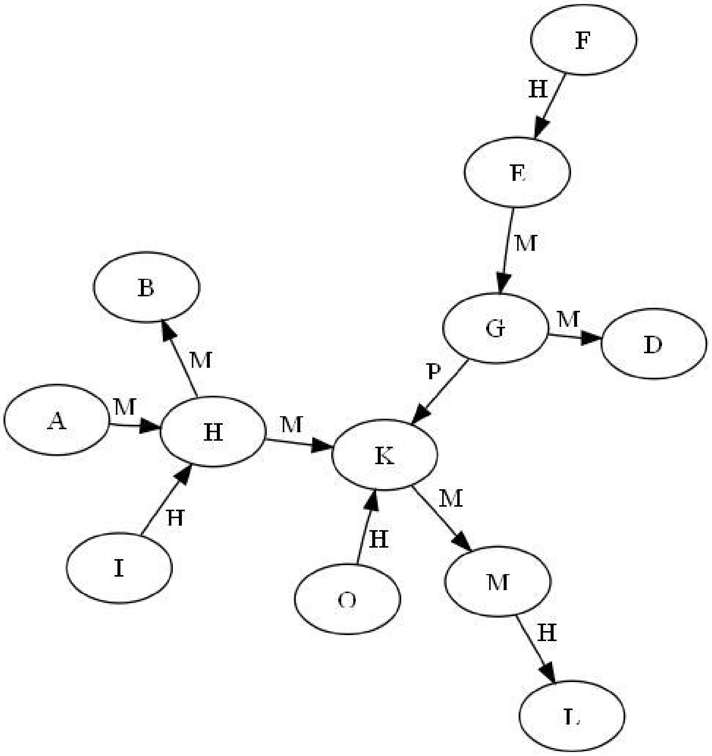


Figure 8 - Final FCM which is automatically produced via SUBDUE

Step 7: Validating the Final FCM

Once the resulted FCM is constructed automatically, it should be validated with one or a group of relevant experts to show valid causal relationships of a system. After this process of validation, the final FCM is drawn as shown in Figure 9.

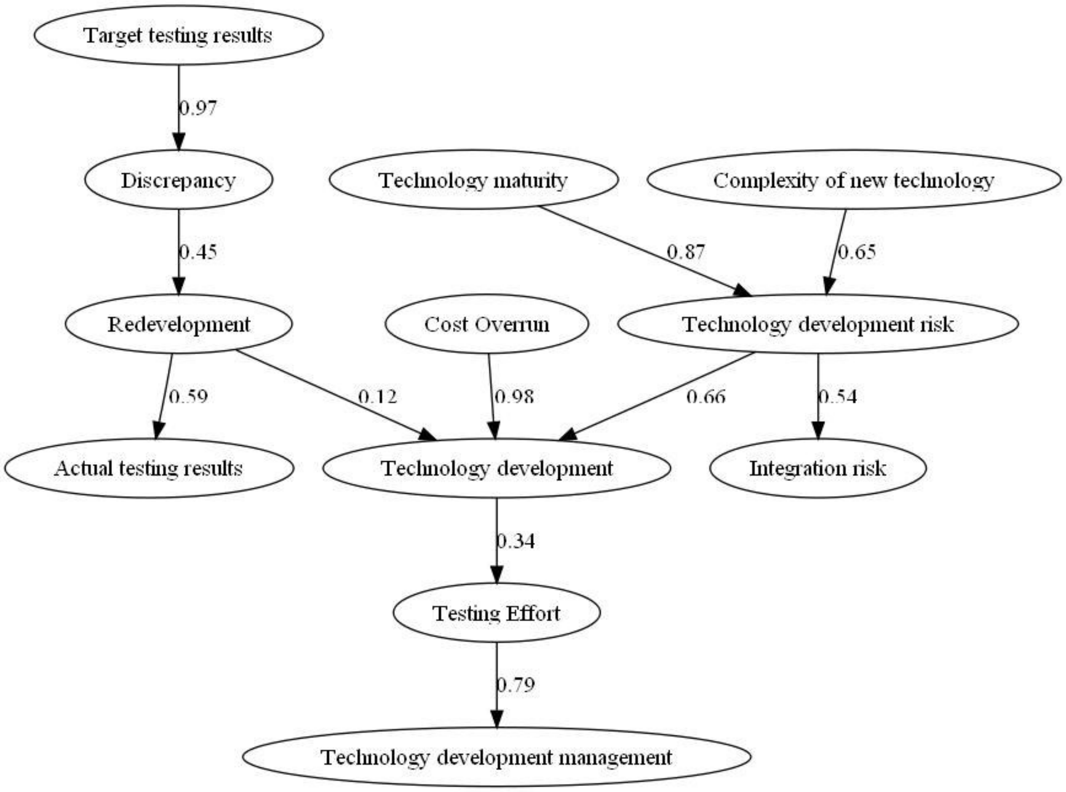


Figure 9 – Final FCM for developing new telecommunication technology in offshore industry

CONCLUSION

The critical process of gathering and integrating knowledge from experts in form of fuzzy cognitive maps is enhanced with a graph-based learning method in order to the improve effectiveness of the final digraph. A fuzzy model which represents the system in a form that corresponds closely to the way it is perceived by humans is developed to show the dynamic complex causal relationships for developing a new technology in offshore industry. The model can be easily altered to incorporate new phenomena for example by changing the graph datamining method.

REFERENCES

Axelrod, R. (1976) Structure of Decision: The Cognitive Maps of Political Elites, Princeton University Press, Princeton, NJ

Bauer, V. (1975) Simulation, evaluation and conflict analysis in urban planning. In: Baldwin, M.M. (Ed.), Portraits of Complexity, Applications of Systems Methodologies to Societal Problems. Battelle Institute, Columbus, OH, pp. 179–192

Biggs, N.L., Lloyd E.K., Wilson R.J., (1976) Graph Theory: 1736–1936. Clarendon Press, Oxford

Bougon, M., Weick, K., Binkhorst, D., (1977) Cognition in organizations: an analysis of the Utrecht Jazz Orchestra. Admin. Sci. Quart. 22, 606–639

Borgelt, C. and Berthold, M.R. (2002) Mining molecular fragments: Finding relevant substructures of molecules. In Proc. of 2002 IEEE International Conference on Data Mining (ICDM), pp. 51–58

Brown, S.M. (1992) Cognitive mapping and repertory grids for qualitative survey research: some comparative observations. J. Manage. Stud. 29, 287–307

Cook, D.J. and Holder, L.B. (1994) 'Substructure Discovery Using Minimum Description Length and Background Knowledge', Journal of Artificial Intelligence Research, Vol. 1, pp. 231–255

Cook, D. J. and Holder, L. B. (1994) Substructure discovery using minimum description length and background knowledge. Journal of Artificial Intelligence Research, 1:231–255

Craiger, J.P., Weiss, R.J., Goodman, D.F., Butler, A.A., (1996) Simulating organizational behavior with fuzzy cognitive maps. Int. J. Comput. Intel. Org. 1, 120–133

Cossette, P., Audet, M. (1992) Mapping of an idiosyncratic schema. J. Manage. Stud. 29, 325–347

Carley, K., Palmquist, M. (1992) Extracting, representing, and analyzing mental models. Social Forces 70, 601–636

Carrico, L., & Guimaraes, N. (1997) Facilitating analysis and diagnosis in organisations. Lectures in Computer Science, 131–144

Cho, S., Chang, H., and Shen, C (2008) A fuzzy simple additive weighting system under group decision-making for facility location selection with objective/subjective attributes. European Journal of Operational Research, Volume 189, Issue 1, 16 August 2008, Pages 132-145

Downing, K., & Fickas, S. (1992) Conceptual modelling, databases, and CASE: An integrated view of information system development. New York: John Wiley.

Dickerson J.A., Kosko B. (1994) Fuzzy virtual worlds, Artif.Intel. Expert 7, 25–31

Eden, C., & Ackermann, F. (1993) Evaluating strategy—Its role within the context of strategic control. Journal of Operational Research Society, 44

Fu, L. (1991) CAUSIM: A rule-based causal simulation system. Simulation, 56(4)

Greenhalgh J, Flynn R, Long A.F., Tyson S (2008) Tacit and encoded knowledge in the use of standardised outcome measures in multidisciplinary team decision making: A case study of in-patient neurorehabilitation. Social Science & Medicine, Volume 67, Issue 1, July 2008, Pages 183-194

Ghazizadeh, S. and Chawathe, S. (2002) SEuS: Structure extraction using summaries. In Proc. of the 5th International Conference on Discovery Science, pp. 71–85

Holder, L.B., Cook, D.J., and Djoko, S. (1994) Substructure discovery in the SUBDUE system. In Proc. of the AAAI Workshop on Knowledge Discovery in Databases, pp. 169–180

Hong, M., Zhou, H.,Wang,W., and Shi, B. (2003) An efficient algorithm of frequent connected subgraph extraction. In Proc. of the 7th Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD-03), Springer-Verlag, Vol. 2637, pp. 40–51

Huan, J., Wang, W., and Prins, J. (2003) Efficient mining of frequent subgraph in the presence of isomophism. In Proc. of 2003 IEEE International Conference on Data Mining (ICDM'03), pp. 549–552

Hart, J.A., (1977) Cognitive maps of three Latin American policy makers. World Politics 30, 115–140

Harary F., Norman R.Z., Cartwright D. (1965) Structural Models: An Introduction to the Theory of Directed Graphs. John Wiley & Sons, New York

Inokuchi, A.,Washio, T., & Motoda, H. (2003). Complete mining of frequent patterns from graphs: Mining graph data. Machine Learning, 50 (3) : 321–354

Jensen, D. and Goldberg, H. (Eds.). (1998) Artificial Intelligence and Link Analysis Papers from the 1998 Fall Symposium. AAAI Press.

Kosko, B. (1988) Hidden patterns in combined and adaptive knowledge networks, Internet. J.Approx. Reason. 2, 377–393.

Kosko, B. Fuzzy cognitive maps, Internat. J. Man-Mach. Studies 24 (1986) 65–75.

Kosko B., Neural Networks and Fuzzy Systems, Prentice-Hall, Englewood Cliffs, NJ, 1992.

Kosko, B. Fuzzy Engineering, Prentice-Hall, Englewood Cliffs, NJ, 1997

Khan, M., Quaddus M (2004) Group decision support using fuzzy cognitive maps for causal reasoning, Group Decision Negotiation J. 13 (5) 463–480

Klein, J.H., Cooper, D.F., (1982) Cognitive maps of decision-makers in a complex game. J. Operation. Res. Soc. 33, 63–71

Kang, I., Sangjae, L., & Choi, J. (2004) Using fuzzy cognitive map for the relationship management in airline service. Expert Systems with Applications, 26, 545–555

Kuramochi, M., Karypis, G. (2005) Finding Frequent Patterns in a Large Sparse Graph. Data Mining and Knowledge Discovery, DOI: 10.1007/s10618-005-0003-9

Kleinberg, J.M. (1999) Authoritative sources in a hyperlinked environment. Journal of the ACM (JACM), 46(5):604–632

Kleinberg, J.M., Kumar, R., Raghavan, P., Rajagopalan, S., and Tomkins, A.S. (1999) The Web as a graph: Measurements, models and methods. Lecture Notes in Computer Science, 1627:1–17

Kuramochi, M. and Karypis, G. (2004) An efficient algorithm for discovering frequent subgraphs. IEEE Transactions on Knowledge and Data Engineering, 16(9):1038–1051

Lin Y, Lee P, Chang T, Ting H (2008) Multi-attribute group decision making model under the condition of uncertain information. Automation in Construction, Volume 17, Issue 6, August 2008, Pages 792-797

Likert, R. (1932) A technique for the measurement of attitudes, Archives of Psychology 140, pp. 5–53

Lee, K. C., Kim, J. S., Chung, N. H., & Kwon, S. J. (2002) Fuzzy cognitive map approach to webmining inference amplification. Expert Systems with Applications, 22, 197–211

Malone, D.W., (1975) An introduction to the application of interpretive structural modeling. In: Baldwin, M.M. (Ed.), Portraits of Complexity: Applications of Systems Methodologies to Societal Problems, Battelle Institute, Columbus, OH, pp. 119–126

Montazemi, A.R., Conrath, D.W., (1986) The use of cognitive mapping for information requirements analysis. MIS Quart. 10, 45–55

Montazemi, A., & Conrath, D. (1986) The use of cognitive mapping for information requirements analysis. MIS Quarterly(March), 1986

Mooney, R.J.,Melville, P., Tang, L.R., Shavlik, J., Castro Dutra, I. de, Page, D. et al. (2004) Relational data mining with inductive logic programming for link discovery. In AAAI Press/The MIT Press, pp. 239–255

Nakamura, K., Iwai, S., Sawaragi, T., (1982) Decision support using causation knowledge base. IEEE Trans. Syst., Man, Cybernet. SMC 12, 765–777

Pelaez, C., & Bowles, J. (1995) Applying fuzzy cognitive maps knowledge representation to failure models effects analysis. IEEE Annual Reliability and Maintainability Symposium.

Palmer, C.R., Gibbons, P.B., and Faloutsos, C. (2002) ANF: A fast and scalable tool for data mining in massive graphs. In Proc. of the 8th ACM SIGKDD Internal Conference on Knowlege Discovery and Data Mining (KDD-2002) Edmonton, AB, Canada, pp. 81–90 Berendt, B., Hotho, A., and Stumme, G. 2002. Towards semantic web mining. In International Semantic Web Conference (ISWC), pp. 264–278

Paradice, D. (1992) SIMON: An object-oriented information system for coordinating strategies and operations. IEEE Transactions on Systems, Man, and Cybernetics, 22(3)

Rodriguez-Repiso L, Setchi R, Salmeron J (2007) Modelling IT projects success with Fuzzy Cognitive Maps. Expert Systems with Applications 32 543–559

Rodriguez-Repiso, L. (2005). Indicators of Success for IT Projects. Case Study. MSc Systems Engineering with IT Applications. Cardiff University

Rappaport, R.A., (1979) Ecology, Meaning, and Religion. North Atlantic Books, Richmond, CA.

Roberts, F.S., (1973) Building and analyzing an energy demand signed digraph. Environ. Plann. 5, 199–221.

Rissanen, J. (1989) Stochastic Complexity in Statistical Inquiry. World Scientific, Singapore.

Sun, J., Li H (2007) Financial distress early warning based on group decision making. Computers & Operations Research, In Press, Corrected Proof, Available online 21 November 2007

Stach., W, Kurgan, L., Pedrycz W, Reformat M (2005) Genetic learning of fuzzy cognitive maps. Fuzzy Sets and Systems, Volume 153, Issue 3, 1 August 2005, Pages 371-401

Schneider, M., Shnaider b E, Kandel A, Chew G (1998) Automatic construction of FCMs. Fuzzy Sets and Systems 93 161-172

Styblinski, M.A. & Meyer B.D. (1988) Fuzzy cognitive maps, signal flow graphs, and qualitative circuit analysis, Proc. 2nd IEEE Internat. Conf. on Neural Networks (ICNN-87) Vol II 549-556

Silva, C. (1995) Fuzzy cognitive maps over possible worlds. In 4th IEEE international conference on fuzzy systems, Japan

Taber, R. and Siegel M. (1987) Estimation of expert weights with fuzzy cognitive maps, Proc. 1st 1EEE lnternat. Conf. on Neural Networks (ICNN" 87), Vol. II 319-325

Taber, R. (1991) Knowledge processing with fuzzy cognitive maps, Expert Systems Appl. 2, 83-87

Vanetik, N., Gudes, E., and Shimony, S.E. (2002) Computing frequent graph patterns from semistructured data. In Proc. of 2002 IEEE International Conference on Data Mining (ICDM), pp. 458–465

Wasserman, S., Faust, K., and Iacobucci, D. (1994) Social network analysis : Methods and applications. Cambridge University Press.

Xirogiannis, G., & Glykas, M. (2004) Fuzzy cognitive maps in business analysis and performance-driven change. IEEE Transactions on Engineering Management, 51(3), 334–351

Yoshida, K. and Motoda, H. (1995) CLIP: Concept learning from inference patterns. Artificial Intelligence, 75(1):63–92

Yan, X. and Han, J. (2002) gSpan: Graph-based substructure pattern mining. In Proc. of 2002 IEEE International Conference on Data Mining (ICDM), pp. 721–724

Yan, X. and Han, J. (2003) CloseGraph: Mining closed frequent graph patterns. In Proc. of the 9th ACMSIGKDD International Conference on Knowledge Discovery and Data Mining (KDD-2003), pp. 286–295

Yoshida, K., Motoda, H., and Indurkhya, N. (1994) Graph-based induction as a unified learning framework. Journal of Applied Intelligence, 4:297–328

Yoshida, K. and Motoda, H. (1995) ‘Clip: Concept Learning from Inference Pattern’, Artificial Intelligence, Vol. 75, no. 1, pp. 63–92