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Complex system tacit knowledge extraction through a formal method

Mickaël Wijnberg, mickaël.wajnberg@telecomnancy.net; Mario Lezoche, mario.lezoche@univ-lorraine.fr; Blondin Alexandre Massé, blondin_masse.alexandre@uqam.ca; Petko Valtchev, valtchev.petko@uqam.ca; Hervé Panetto, herve.panetto@univ-lorraine.fr;

A complex system, integrates multiple sub-systems. (Carney, Fisher, & Place, 2005) Each sub-system contains some form of domain knowledge but the main difference that can be seen between a complex system and a set of simple system is that the knowledge the complex system presents is larger than the sum of the knowledge that each sub-system contains (Billaud, Daclin, & Chapurlat, 2015). In both cases, each sub-system is made of elements that are exploitable together, but two different sub-systems have information that can't be used in concert. Therefore, the tacit knowledge, the knowledge contained in the interaction between the sub-system, is usually harder to extract than the knowledge contained in the sub-systems. (Yahia, Lezoche, Aubry, & Panetto, 2011).

In “simple cases”, the sub-system can be presented as a formal context, a cross-table of objects and their attributes, and the links between the diverse sub-systems can be represented as relational context, a cross-table containing the objects of two sub-systems, and modeling if two objects are in relation. In this paper, we aim to present the process to extract knowledge from such a model of complex system. We will show how to apply it to a use case of real data from the neurology domain.

The technique

A formal context (a sub-system) can be presented as a cross-table like the one in Figure 1. It lists a set of cars and their characteristics, a simple cross means that the specific car presents the characteristic. Through a technique called Formal Concept Analysis (Wille, 1992) (Szathmari, et al., 2014) (Ganter & Wille, 2012) (Carpineto & Romano, 2004), that presents all the possible clusters from such a context, a lattice of the clusters (called concepts) is generated. For any node (a cluster) you can extract knowledge through the dependency between the attributes and the objects. In each node, as in Figure 2a, all the objects present every attribute, and no other object in the table presents all the attributes of the concept. The node gives us the information that TWINGO and FIAT 500 are all compact and cheap, and that no other car in the table is both compact and cheap.

CARS	electrical (elec.)	powerful (pow.)	compact (comp.)	cheap (ch.)
TWINGO			×	×
TESLA 3	×	×		
ZOÉ	×		×	
FIAT 500		×	×	×

Figure 1 – Table of concepts and properties

The lattice can also be presented in a compressed form (each attribute or object is presented only once but can be deduced from the shape of the lattice) as in Figure 2b

For each node, knowledge from relation on attributes can be extracted: the attributes of the compressed node imply the other attributes in its extended version. Node 4 gives that if a car is cheap, then it is compact. These two aspects present how to extract knowledge from a formal context, in other words a simple system.

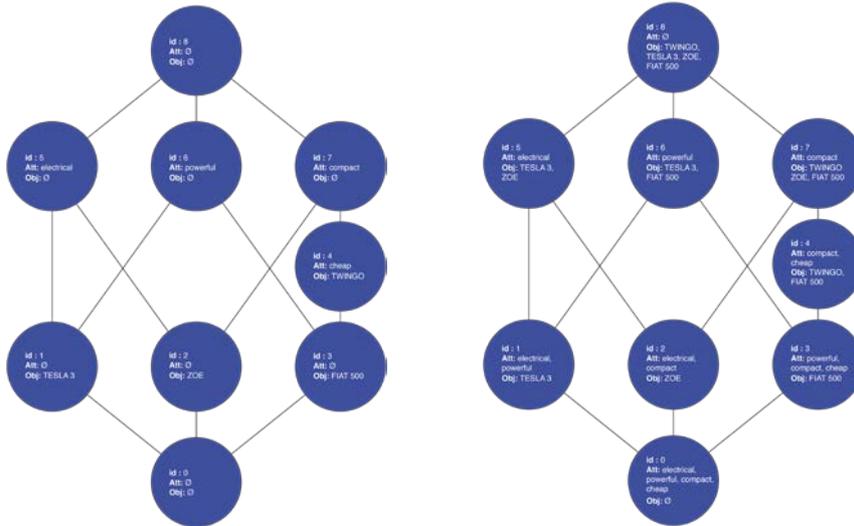


Figure 2 – a) Concept Lattice in normal shape – b) Concept Lattice in compressed shape

In the case of a complex system, we will be presented with multiple formal contexts and relations between these contexts. The formal concept analysis can handle each formal context separately but it is not designed to take care of the relations between them. An extension to the paradigm is proposed: the Relational Concept Analysis (RCA). (Rouane-Hacene, 2007) (Rouane-Hacene, 2013). We grant the previous example with a second formal context that can be found in the Figure 3. The formal concept analysis will design the following lattice.

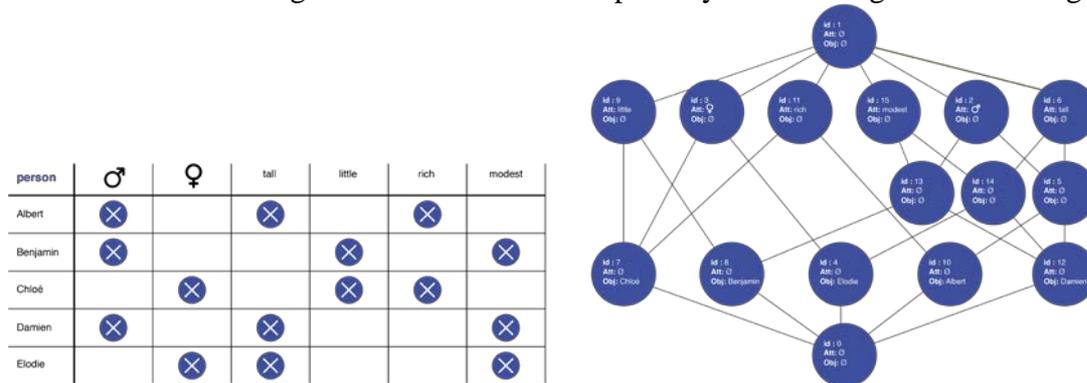


Figure 3 – A new context: a) Table representation – b) Concept Lattice representation

Added to that, the system is provided with a relation table, the one found in the Figure 4.

BUY	TWINGO	TESLA 3	ZOÉ	FIAT 500
Albert		⊗		
Benjamin	⊗			
Chloé		⊗		⊗
Damien			⊗	
Elodie			⊗	

Figure 4 – Relations between the two contexts

The scientific question is how to use that information to extract knowledge? RCA uses the relation table to enrich each lattice through the information contained in the other one. The

main principle is linking the objects from the two tables and iterate the procedure until all the concepts are taken in account. If we have a context A with its lattice A and a context B with its lattice B plus the relation table linking objects of A to objects of B, an iteration is made from A to B then from B to A. In the iteration from A to B one column is added to the context A for each node in lattice B, the cross in the column depends on the operation applied to the relational context. It gives enriched contexts such as the one in Figure 5. Then since the contexts have been updated, the lattice needs to be updated too and it processes again until a fixed point is reached (its existence is guaranteed). Each lattice now contains more

person	♂	♀	tall	little	rich	modest	00 : boy E	01 : boy E	02 : boy E	03 : boy E	04 : boy E	05 : boy E	06 : boy E	07 : boy E	08 : boy E
Albert	×		×		×			×				×	×		×
Benjamin	×			×		×					×			×	×
Chloé		×		×	×			×		×	×	×	×	×	×
Damien	×		×			×		×				×		×	×
Elodie		×	×			×		×				×		×	×

Figure 5 – Enriched Context

information. This information deals with the other context by using the same rules extraction process than in a lattice generated through formal concept analysis. New knowledge is discovered such as tall people buy electric cars, knowledge that couldn't have been found with the separate exploitation of the two formal contexts. We now want to illustrate a use case of the method in a real data application.

Use case from Neurology domain

The use case we have chosen to bring validation on the method comes from neurology. The brain conveys information through electric signal, which can be evaluated towards an Electroencephalography (EEG), a clinical examination that consists in getting the electrical signal with captors put on the head. This examination induces an excellent time precision but is not perfectly accurate for the spatial information. When a part of the brain (called cortical area) gets activated and emits electrical signal, this area receives oxygen through blood, and this oxygenated blood has a different magnetism that can be tracked through functional magnetic resonance imaging (fMRI). This clinical examination, contrary to electroencephalography is spatially accurate, but because the blood flow is slow compared to

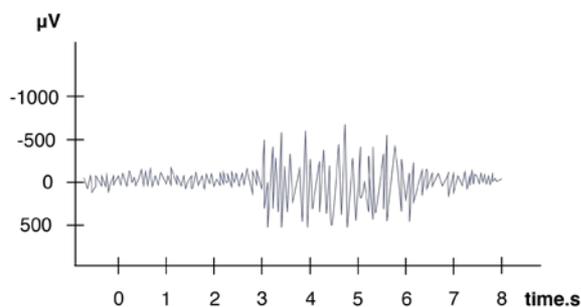


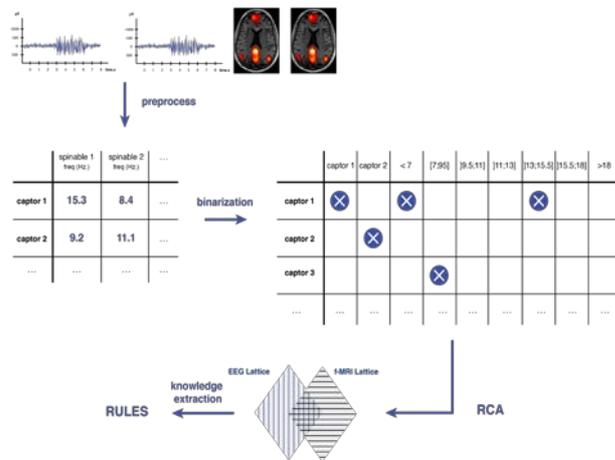
Figure 6 – Sleep Spindle signal

electrical signal, the temporal aspect is not precise. In our study the focus is made on a particular signal the brains emits while one is asleep: the sleep spindle. Through encephalography, it can be seen as a punctual (in the temporal aspect) excitation that occurs periodically within the sleep. The signal has the shape of Figure 6. (Gath & Bar-On, 1983) (Gath & Bar-On, 1980). The hypothesis from the neurologists is that there is a correlation

between the areas that presents the strongest signal from the spindle and the most represented frequencies in it (that can be extracted through a Fourier transformation). Through a process of knowledge extraction via relational concept analysis, we want to exploit the temporal precision of electroencephalography in concert with the functional magnetic resonance imaging spatial precision in order to assert or reject such hypothesis.

The process

Due to the constraints of length, we present as a result the engineering process for knowledge discovery (Figure 7). First are provided the raw data that are preprocessed to extract the signal



values and then digitalized to give relevant cross-tables. One formal context compiles the results of EEG, another one compiles the information for fMRI and relational contexts are made to link the formal contexts. These relations precise which electroencephalogram captor cover which cortical area, and links electric signal to blood oxygenation response. Then a RCA method is applied to generate the lattices before we analyze the associations rules that can be

Figure 7 – Extraction process

extracted. Through this process we aim to discover first relations in the form « If cortical area A presents a sleep spindle with frequencies in the range [r1; r2] then we also have area B that presents a spindle with frequencies in the range [r3; r4] ».

Conclusion

The knowledge extraction method using relational concept analysis has been applied only to a toy example but the results have shown the potential of relational concept analysis as an accurate technique to process interoperability of heterogeneous data.

Bibliography

- Billaud, S., Daclin, N., & Chapurlat, V. (2015). Interoperability as a key concept for the control and evolution of the System of Systems (SoS). *International IFIP Working Conference on Enterprise Interoperability*, (pp. 53-63).
- Carney, D., Fisher, D., & Place, P. R. (2005). Topics in interoperability: System-of-systems evolution.
- Carpineto, C., & Romano, G. (2004). *Concept data analysis: Theory and applications*. John Wiley & Sons.
- Ganter, B., & Wille, R. (2012). *Formal concept analysis: mathematical foundations*. Springer Science & Business Media.
- Gath, I., & Bar-On, E. (1980). Computerized method for scoring of polygraphic sleep recordings. *Computer programs in biomedicine*, 11, 217-223.
- Gath, I., & Bar-On, E. (1983). Classical sleep stages and the spectral content of the EEG signal. *International journal of neuroscience*, 22, 147-155.
- Rouane-Hacene, M., Huchard, M., Napoli, A., & Valtchev, P. (2007). *Extraction de concepts et de relations en analyse relationnelle de concepts (ARC)*. unpublished, ENST, Paris. Retrieved from <http://www.lirmm.fr/huchard/Documents/Papiers/sfc-060907.pdf>
- Rouane-Hacene, M., Huchard, M., Napoli, A., & Valtchev, P. (2013). Relational concept analysis: mining concept lattices from multi-relational data. *Annals of Mathematics and Artificial Intelligence*, 67, 81-108. doi:10.1007/s10472-012-9329-3
- Szathmary, L., Valtchev, P., Napoli, A., Godin, R., Boc, A., & Makarenkov, V. (2014). A fast compound algorithm for mining generators, closed itemsets, and computing links between equivalence classes. *Annals of Mathematics and Artificial Intelligence*, 70, 81-105. doi:10.1007/s10472-013-9372-8
- Wille, R. (1982). Restructuring Lattice Theory: An Approach Based on Hierarchies of Concepts. In I. Rival (Ed.), *Ordered Sets: Proceedings of the NATO Advanced Study Institute held at Banff, Canada, August 28 to September 12, 1981* (pp. 445-470). Dordrecht: Springer Netherlands. doi:10.1007/978-94-009-7798-3_15
- Wille, R. (1992). Concept lattices and conceptual knowledge systems. *Computers & mathematics with applications*, 23, 493-515.
- Yahia, E., Lezoche, M., Aubry, A., & Panetto, H. (2011). Semantics enactment in enterprise information systems. *IFAC Proceedings Volumes*, 44, 13064-13073.