Validation of a Cognitive Map

Definition of Quality Criteria to Detect Contradictions in a Cognitive Map

Aymeric Le Dorze, Laurent Garcia, David Genest and Stéphane Loiseau
Laboratoire d'Étude et de Recherche en Informatique d'Angers, Université d'Angers,
2 Boulevard Lavoisier, 49045, Angers Cedex 01, France

Keywords: Cognitive Map, Validation, Quality Criterion, Verification, Test.

Abstract: A cognitive map is a knowledge representation model. Knowledge is represented as a graph where nodes represent concepts and arcs represent influences between these concepts. Each influence has a value that quantifies it. Despite the fact that a cognitive map is quite simple to build, some influence values may contradict each other. This paper provides some quality criteria in order to validate a cognitive map. There are two kinds of quality criteria. The verification validates a cognitive map by computing its internal coherency. The test validates a map from a set of constraints provided by the designer. These criteria indicate if a map does or does not contain contradictions. We also propose a way to adapt these criteria according to the possible values that an influence can take.

1 INTRODUCTION

Cognitive maps (Tolman, 1948) are popular models to help people to make a decision. They provide an easy visual communication medium for humans to perform an analysis of a complex system. They have been used in many fields, such as biology (Tolman, 1948), sociology (Poignonec, 2006), ecology (Celik et al., 2005) or politics (Levi and Tetlock, 1980). They are also studied in the field of Artificial Intelligence (Wellman, 1994), in order to improve the model. Cognitive maps represent an *influence network* as a graph where a *concept* labels a node with a text and an *influence* labels an arc with an *influence value* that qualifies this influence. This influence value belongs to a predefined set called the *value set* which can be composed of symbolic values, such as $\{+,-\}$ (Axelrod, 1976), $\{none, some, much, a\ lot\}$ (Dickerson and Bart, 1994; Zhou et al., 2003), or an interval of numeric values, such as $[-1,1]$ (Kosko, 1986; Satur and Liu, 1999). Thanks to these values, the global influence of any concept of the map on any other one can be evaluated by computing the *propagated influence*. To do so, we compute, the *propagated influence on each path between the two concepts* by combining the values of the influences. Then, we aggregate the propagated influences on every path between the two concepts.

A cognitive map is generally built by one designer or by a group of designers during a brainstorming session. It is often difficult for a designer to build a cognitive map and to ensure its quality. Indeed, the computation of the propagated influence of a concept on an other one may sometimes give an ambiguous value that represents a contradiction. With some value sets, such a value does not exist. However, a concept may still influence another concept in some way on one path and in another way on a different path. A designer may want to know if the map he is building contains such contradictions. The *validation* of a cognitive map helps to detect these contradictions.

There exist several kinks of works that study the validation of knowledge bases. Most of these works such as (Ginsberg, 1988) and (Dibie-Barthélemy et al., 2001) define some properties, called *quality criteria*, that the knowledge base system should respect in order to preserve its quality and reliability. Validation is often split into two different areas: verification and test (Ayel and Laurent, 1991). *Verification* is based on a quality criterion that does not require external information: it is based on the internal coherency of the knowledge base only. *Test* is based on a quality criterion that requires external information, often called *constraints*, integrity constraints, test case, or, more generally, *specification*.

This paper proposes different kinds of quality criteria in order to validate a cognitive map. To our knowledge, no paper has been published on the subject. There exist some works (Christiansen, 2011) that

Le Dorze A., Garcia L., Genest D. and Loiseau S.
Validation of a Cognitive Map - Definition of Quality Criteria to Detect Contradictions in a Cognitive Map.
DOI: 10.5220/0004757103200327
In *Proceedings of the 6th International Conference on Agents and Artificial Intelligence* (ICAART-2014), pages 320-327
ISBN: 978-989-758-015-4
Copyright © 2014 SCITEPRESS (Science and Technology Publications, Lda.)

tried to detect contradictions in a cognitive map, but they were not formally defined and were not based on the notion of quality criterion. The contradictions detected by the quality criteria have two different purposes. On the one hand, they tell the designers of a map that this map contains an error that should be corrected and which part of the map contains that error. One the other hand, they provide to the potential users of the map the parts of the map that are controversial. These parts of the map might be typically discussed in a brainstorming session.

In order to verify a cognitive map, this paper introduces the *non-ambiguity criterion*. A cognitive map is *non-ambiguous* if, for any pair of concepts of the map, the propagated influence on every path between the two concepts equals the propagated influence between the two concepts.

In order to test a cognitive map, this paper introduces the *coherency criterion*. To test if a cognitive map is coherent, a *specification* that the map has to check is introduced. A specification is a set of constraints. A *constraint* is a triple made of a source concept, a target concept and a value that represents an expected influence value between the two concepts. However, some constraints may be applicable to many concepts at once and defining a constraint for each pair of these concepts may be tedious. To avoid such an operation, the idea is to use a *taxonomy* of concepts that regroups some concepts into bigger ones such that the most specific concepts of the taxonomy are the concepts of the cognitive map. Thus, the concepts of the constraints belong to the taxonomy. Thanks to this taxonomy and the cognitive map, we are able to compute the *taxonomic influence* between two concepts of the taxonomy according to the propagated influences between the concepts that specializes these two concepts. The idea of the coherency criterion is then to check if the taxonomic influence between the two concepts of a constraint equals the value provided by the same constraint.

In this article, we present in section 2 the classical cognitive map model and how to compute the propagated influence of a concept on another one for the value set $\{+,-\}$. In section 3, we define some verification criteria, including non-ambiguity. In section 4, we define some test criteria, including coherency. We also define the notions of specification and taxonomic influence. To explain intuitively what represent these quality criteria, first we limit ourselves to cognitive maps defined on the value set $\{+,-\}$ since this is the simplest value set. Then, we show how to adapt these criteria to other value sets in section 5 and especially the value set $[-1;1]$.

2 COGNITIVE MAPS

Cognitive maps are a knowledge representation model that represents as a graph influences between concepts. An influence is a causal relation between two concepts labelled with a value. It expresses how a concept influences another one regardless of the other concepts. This value belongs to a predefined set, called the *value set*.

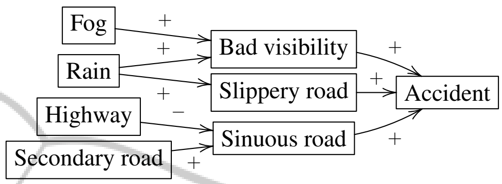

Figure 1: *CM1*, a cognitive map defined on the value set $\{+,-\}$.

Example 1. *The cognitive map shown on figure 1 represents influences between concepts tied to the road traffic. This map is defined on the value set $\{+,-\}$. If we consider the influence between* Rain *and* Bad visibility*, it means that the fact that it rains positively influences the fact that the visibility is bad. On the contrary, if we consider the influence between* Highway *and* Sinuous road*, the fact that we are on a highway negatively influences the fact that the road is sinuous.*

Thanks to the influence values, the global influence of a concept on another one can be computed. For the moment, we focus only on the value set $\{+,-\}$ and we present thus the propagated influence defined by R. Axelrod (Axelrod, 1976). It is composed of three steps.

The first step is to list the different paths that link the first concept to the second one. Since a cognitive map may be cyclic, there is potentially an infinite number of paths between the two concepts. Therefore, the computation is limited to the most meaningful paths only, which are the paths that does not contain any cycle. We call such a path a *minimal path*.

The second step is to compute the influence value that any of these minimal paths brings to the second concept. This influence value is called the *propagated influence on a path* and is denoted by $I\mathcal{P}$. To do that, we use the operator $\wedge$ defined by Axelrod. This operator is close to a multiplication, but for the values $+$ and $-$. That means that the propagated influence on a path is $+$ if the number of negative influence values on this path is even or $-$ otherwise.

Finally, the third step is to aggregate the propagated influences on every minimal path that links the first concept to the second one with an average. To do that, the propagated influence I is defined by Axelrod with the operator $\vee$. If the propagated influence on every path is $+$ (resp. $-$), then the propagated influence is also $+$ (resp. $-$). If at least one path has not the same value as the other paths, then the propagated influence is ambiguous, denoted by the value ?. If there is no path between the two concepts, then the propagated influence is 0.

Example 2. *In CM1, we want to compute the propagated influence of* Rain *on* Accident*.*

1. *there are two minimal paths between* Rain *and* Accident*:* $p_1 = \{Rain \rightarrow Bad\ visibility \rightarrow Accident\ \}$ *and* $p_2 = \{Rain \rightarrow Slippery\ road \rightarrow Accident\}$*;*
2. *the propagated influences on* p_1 *and* p_2 *are:* $I\mathcal{P}(p_1) = + \wedge + = +$ *and* $I\mathcal{P}(p_2) = + \wedge + = +$*;*
3. *the propagated influence of* Rain *on* Accident *is so:* $I(\mathrm{Rain}, \mathrm{Accident}) = I\mathcal{P}(p_1) \vee I\mathcal{P}(p_2) = + \vee + = +$.

We can conclude that the rain positively influences the risk of an accident.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

3 VERIFICATION

To verify a cognitive map, two quality criteria are proposed. The first one, the cleanliness, can be seen as a sub-case of the non-ambiguity and is presented in section 3.1. The second one, the non-ambiguity, is presented in section 3.2.

3.1 Cleanliness

For this criterion, we only consider the pairs of concepts that are linked by a direct influence in a cognitive map. A pair of concepts is said *clean* iff the propagated influence of the first concept of the pair on the second one equals the value labelling the influence between the two concepts. Such a criterion means that a direct influence between two concepts is supposed to represent the propagated influence of a concept on the other one.

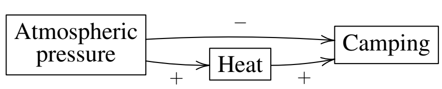

Figure 2: An unclean pair of concepts.

Example 3. *On the simple cognitive map of figure 2, the atmospheric pressure is avoided by campers. However, the atmospheric pressure generates heat, and heat pleases campers.*

Let us consider the pair of concepts (Atmospheric pressure*,* Camping)*. We compute* $I(\mathrm{Atmospheric\ pressure}, \mathrm{Camping}) = - \vee (+ \wedge +) =$?. *This value is different from the value of the influence between* Atmospheric pressure *and* Camping*, which is* $-$*. Therefore, the pair of concepts* (Atmospheric pressure*,* Camping) *is not clean.*

More generally, a cognitive map is *clean* iff every pair of concepts of the map linked by an influence is clean.

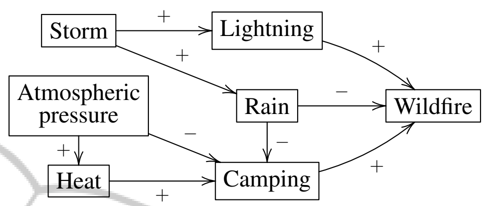

Figure 3: The cognitive map *CM2*.

Example 4. *The cognitive map CM2 (figure 3) represents the influences of many concepts on the risk that a wildfire occurs. On this map, the pair* (Rain*,* Wildfire) *is clean. However, as already shown in example 3, the pair* (Atmospheric pressure*,* Camping) *is not clean. Therefore, the map CM2 is not clean.*

Note that we cannot apply the cleanliness criterion on the pair (Storm*,* Wildfire) *as these concepts are not directly linked by an influence. Therefore, this pair is neither clean nor unclean.*

3.2 Non-ambiguity

The cleanliness criterion only focuses on the concepts that are directly linked by an influence. The non-ambiguity criterion is based on the cleanliness but is focused on any pair of concepts of the map.

A pair of concepts is said *non-ambiguous* iff the propagated influence on every minimal path that links the first concept of the pair to the second one equals the propagated influence of the first concept on the second one. Such a criterion means that this influence must be in agreement with the propagated influence regardless of how the first concept influences the second one.

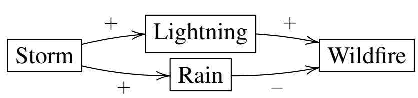

Figure 4: An ambiguous pair of concepts.

Example 5. *On the simple cognitive map of figure 4, on the one hand, a storm lights wildfires by generating lightnings. On the other hand, a storm extinguishes wildfires by triggering rain.*

Let us consider the pair of concepts (Storm*,* Wildfire)*. We compute:*

$$I\mathcal{P}(Storm \rightarrow Lightning \rightarrow Wildfire) = +$$
$$I\mathcal{P}(Storm \rightarrow Rain \rightarrow Wildfire) = -$$

This gives us a propagated influence of $I(\mathrm{Storm}, \mathrm{Wildfire}) = ?$. *Since this value is different from the propagated influences on the two paths linking the two concepts, we conclude that the pair of concepts* (Storm, Wildfire) *is ambiguous.*

Given these definitions of the cleanliness and the non-ambiguity criteria, it is easy to show that any non-ambiguous pair of concepts linked by an influence is also clean. More generally, a cognitive map is *non-ambiguous* iff every pair of concepts of the map is non-ambiguous. It is also easy to show that a non-ambiguous cognitive map is also clean.

Example 6. *On the map* CM2 *(figure 3), we have already shown in example 5 that the pair* (Storm, Wildfire) *is ambiguous. Moreover, as we already know that the pair* (Atmospheric pressure, Camping) *is unclean, we can conclude that it is also ambiguous. Therefore, the map* CM2 *is ambiguous.*

4 TEST

A test criterion needs external information to validate a model. In our case, this external information is a set of constraints called a specification. A constraint is an expected influence value between two concepts. We explain what is a specification and a constraint in section 4.1. Then, we define two test criteria. First, in section 4.2, the coherency checks that the influence value computed in the map equals the value specified by the constraint. Then, in section 4.3, the compatibility adds some flexibility to the coherency criterion.

4.1 Specification

A *constraint* is a triple made of two concepts and one value. A constraint expresses an expected influence value between two concepts. Thus, the first concept of the constraint is the *cause* of the influence and the second one is the *effect*. We use a taxonomy to express constraints applicable to many concepts. A *taxonomy* of concepts associates as set of concepts to a simple inheritance partial order $<$. Thus, a taxonomy can be represented as a set of rooted trees.

Example 7. *The taxonomy of concepts T1 (figure 5) orders some concepts.*

With the ontological cognitive map model (Chauvin et al., 2009), a cognitive map is associated to an ontology in order to compute the ontological influence between two concepts. As this notion of ontology is equivalent to our notion of taxonomy, we reuse

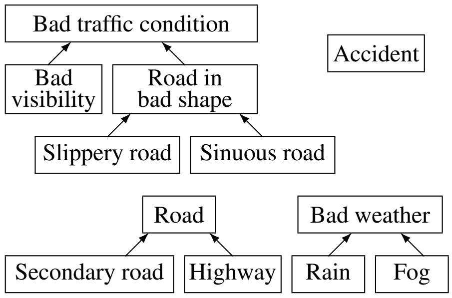

Figure 5: A taxonomy of concepts *T1*.

the ontological influence to define our taxonomic influence. To do so, the concepts of the map need to be the least concepts of the taxonomy. Thus, each concept of the taxonomy represents one or many concepts of the map. We call the set of concepts that a concept of the taxonomy represents its *elementary concepts*.

Example 8. *The taxonomy T1 (example 7) generalises the concepts of the cognitive map* CM1 *(example 1). Thus, the concepts of* CM1 *are the least concepts of T1. We can associate T1 to* CM1 *in order to compute a taxonomic influence. The elementary concepts of* Bad traffic condition *are* Bad visibility, Sinuous road *and* Slippery road. *The elementary concept of* Rain *is just* Rain *itself.*

The taxonomic influence I_T between two concepts is computed by aggregating the propagated influences between every pair made of an elementary concept of the first concept and an elementary concept of the second one. To aggregate these propagated influences, we use the $\odot$ operator presented in figure 6. The value $\oplus$ means "positive or null". The value $\ominus$ means "negative or null".

$\odot$	$+$	$\oplus$	0	$\ominus$	$-$	$?$
$+$	$+$	$\oplus$	$\oplus$	$?$	$?$	$?$
$\oplus$	$\oplus$	$\oplus$	$\oplus$	$?$	$?$	$?$
0	$\oplus$	$\oplus$	0	$\ominus$	$\ominus$	$?$
$\ominus$	$?$	$?$	$\ominus$	$\ominus$	$\ominus$	$?$
$-$	$?$	$?$	$\ominus$	$\ominus$	$-$	$?$
$?$	$?$	$?$	$?$	$?$	$?$	$?$

Figure 6: The $\odot$ operator.

Example 9. *We consider the concepts* Bad weather *and* Bad traffic condition *of T1. The taxonomic influence of* Bad weather *on* Bad traffic condition *relatively to CM1 is:*

$$I_T(\mathit{Bad\ weather}, \mathit{Bad\ traffic\ condition}) = \odot \left\{ \begin{array}{l} I(\mathit{Fog}, \mathit{Bad\ visibility}) \\ I(\mathit{Fog}, \mathit{Slippery\ road}) \\ I(\mathit{Fog}, \mathit{Sinuous\ road}) \\ I(\mathit{Rain}, \mathit{Bad\ visibility}) \\ I(\mathit{Rain}, \mathit{Slippery\ road}) \\ I(\mathit{Rain}, \mathit{Sinuous\ road}) \end{array} \right\} = \odot \left\{ \begin{array}{c} + \\ 0 \\ 0 \\ + \\ + \\ 0 \end{array} \right\} = \oplus$$

SCIENCE AND TECHNOLOGY PUBLICATIONS

The idea of the constraint is to verify that the taxonomic influence between the concepts of the constraint is in agreement with the value of the constraint. Thus, this value must belong to $\{+,\oplus,0,\ominus,-,?\}$.

A specification of constraints is a set of constraints defined on a taxonomy such that the concepts of any constraint belongs to the taxonomy.

Example 10. *Let us consider the following three constraints:*
$s_1 = \langle \textit{Bad traffic condition}, \textit{Accident}, + \rangle$
$s_2 = \langle \textit{Bad weather}, \textit{Bad traffic condition}, + \rangle$
$s_3 = \langle \textit{Road}, \textit{Sinuous road}, - \rangle$
Their concepts all belong to T1 and their values to $\{+,\oplus,0,\ominus,-,?\}$. *Thus, we can build the specifications* $S_1 = \{s_1\}$, $S_2 = \{s_1, s_2\}$ *and* $S_3 = \{s_1, s_2, s_3\}$.

4.2 Coherency

A cognitive map is *coherent with a constraint according to a taxonomy* iff the taxonomic influence between the two concepts of the constraint equals the value of the constraint.

Example 11. *We test the coherency of CM1 with the constraints from example 10 according to T1.*
CM1 is coherent with $s_1 = \langle$*Bad traffic condition, Accident,* $+\rangle$ *according to T1. Indeed,* $I_{\mathrm{T}}(\textit{Bad traffic condition}, \textit{Accident}) = +$ *and* $+$ *is the value of* s_1.
However, CM1 is not coherent with $s_2 = \langle$*Bad weather, Bad traffic condition,* $+\rangle$ *according to T1 because* $I_{\mathrm{T}}(\textit{Bad weather}, \textit{Bad traffic condition}) = \oplus \neq +$.
CM1 is not coherent with $s_3 = \langle$*Road, Sinuous road,* $-\rangle$ *according to T1 either because* $I_{\mathrm{T}}(\textit{Road}, \textit{Sinuous road}) = ? \neq -$.

More generally, a cognitive map is *coherent with a specification* according to a taxonomy if it is coherent with every constraint of the specification according to this taxonomy.

Example 12. *We consider the specifications of the example 10.*
CM1 is coherent with $S_1 = \{s_1\}$ *according to T1 because CM1 is coherent with* s_1 *according to T1.*
However, CM1 is not coherent with either $S_2 = \{s_1, s_2\}$ *nor* $S_3 = \{s_1, s_2, s_3\}$ *according to T1 because CM1 is not coherent with* s_2 *according to T1.*

4.3 Compatibility

The coherency criterion is based on a strict equality between two values. The equality may be too strict for some designers. Indeed, if we consider the constraint s_2 from the example 11, the computed taxonomic influence is $\oplus$ whereas the value in the constraint is $+$. Hence, the coherency criterion is not validated. However, as $\oplus$ means "positive or null", one could consider that this value is globally positive. Therefore, since the expected value is positive, one could argue that the criterion should be validated. To do so, we need to extend the coherency criterion by adding some flexibility to it.

That is why we define the compatibility criterion. The idea is to replace the equality by a more flexible relation between two values. We define the notion of *compatible values*. The idea is to list, for any value of $\{+,\oplus,0,\ominus,-,?\}$, the set of values that are close to it.

Each value is trivially compatible with itself. We consider also that each value is compatible with the values that are really close to it. This means that $+$ is compatible with $\oplus$, $\oplus$ is compatible with $+$ and 0, 0 is compatible with $\oplus$ and $\ominus$ and so on... However, the only value compatible with ? is itself. Note that ? is compatible with 0 as ? represents a mix of positive and negative values, and thus includes 0. This notion is represented on figure 7 where a value α_1 is compatible with another value α_2 iff $\alpha_1 \blacktriangleleft \alpha_2$.

$\blacktriangleleft$		α_2					
		$+$	$\oplus$	0	$\ominus$	$-$	?
α_1	$+$	✓	✓	×	×	×	×
	$\oplus$	✓	✓	✓	×	×	×
	0	×	✓	✓	✓	×	×
	$\ominus$	×	×	✓	✓	✓	×
	$-$	×	×	×	✓	✓	×
	?	×	×	✓	×	×	✓

Figure 7: Compatible values.

We define now the compatibility criterion. A cognitive map is *compatible with a constraint according to a taxonomy* iff the taxonomic influence between the two concepts of the constraint is compatible with the value of this constraint.

Example 13. *We test the compatibility of CM1 with the constraints from example 10 according to T1.*
CM1 is compatible with $s_1 = \langle$*Bad traffic condition, Accident,* $+\rangle$ *according to T1 because* $I_{\mathrm{T}}(\textit{Bad traffic condition}, \textit{Accident}) = + \blacktriangleleft +$.
CM1 is now compatible with $s_2 = \langle$*Bad weather, Bad traffic condition,* $+\rangle$ *according to T1 because* $I_{\mathrm{T}}(\textit{Bad weather}, \textit{Bad traffic condition}) = \oplus \blacktriangleleft +$.
However, CM1 is still not compatible with $s_3 = \langle$*Road, Sinuous road,* $-\rangle$ *according to T1 because* $I_{\mathrm{T}}(\textit{Road}, \textit{Sinuous road}) = ? \not\blacktriangleleft -$.

Like the coherency criterion, more generally, a cognitive map is *compatible with a specification* according to a taxonomy if it is compatible with every constraint of the specification according to this taxonomy.

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

Example 14. *We consider the specifications of the example 10.*
CM1 is now compatible with $S_1 = \{s_1\}$ *and* $S_2 = \{s_1, s_2\}$ *according to T1 because CM1 is compatible with* s_1 *and* s_2 *according to T1.*
However, CM1 is still not compatible with $S_3 = \{s_1, s_2, s_3\}$ *according to T1 because CM1 is still not compatible with* s_3 *according to T1.*

5 SETTINGS

The quality criteria previously defined are only applicable to cognitive maps defined on $\{+,-\}$. As explained earlier, a cognitive map can be defined on other value sets, such as $[-1;1]$ or $\{none < few < much < a\ lot\}$. Every quality criterion except the compatibility checks the equality of two values. Thus, technically, they can be applied to a cognitive map defined on any other value set than $\{+,-\}$. However, as already explained in the previous section, sometimes an equality may be too strict for a designer. The notion of compatible values is defined to add some flexibility to the coherency criterion. Therefore, the idea is to redefine the notion of compatible values for these other value sets and thus to define new quality criteria that add some flexibility to the already existing criteria, using the notion of compatible values.

Note that we will not redefine the coherency criterion for numeric values as the idea of this criterion is to check that two values are strictly equal. Moreover, adding flexibility to this criterion leads to redefine the compatibility criterion.

In this section, we propose a method to adapt our criteria to the value set $[-1;1]$. We define first how to compute the propagated influence associated to the value set $[-1;1]$ in section 5.1. We define then how to adapt first the cleanliness and the non-ambiguity criteria in section 5.2 and second the compatibility criterion in section 5.3. Finally, we explain briefly how to adapt these criteria to the value set $\{none < few < much < a\ lot\}$ in section 5.4.

5.1 Propagated Influence for $[-1;1]$

We present in this section the propagated influence defined in (Chauvin et al., 2009) for the value set $[-1;1]$. The idea for the computation is very similar to the one for $\{+,-\}$. The only change is how the values are aggregated. The propagated influence on a minimal path is defined as the multiplication of the values of the influences that compose this path. Then, the propagated influence of a concept on another one is defined as the average of the propagated influences on the minimal paths between the two concepts.

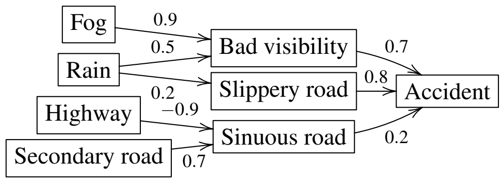

Figure 8: *CM1b*, a cognitive map defined on the value set $[-1;1]$.

Example 15. *The cognitive map CM1b (figure 8) is the cognitive map CM1 (example 1) defined on the value set* $[-1;1]$. *This value set allows to be more expressive on the influence values.*

The propagated influence of Rain on Accident is this time $I(Rain, Accident) = \frac{0.5\times0.7+0.2\times0.8}{2} = 0.255$.

5.2 Cleanliness and Non-ambiguity for $[-1;1]$

To adapt our criteria for the value set $[-1;1]$, we need to redefine the notion of compatible values. The idea is to use a *threshold* that specifies a granted margin of error. This positive numeric value is used to define an interval around a specific value to specify which values are granted. Therefore, we define a tolerance threshold: the higher the threshold, the higher the number of granted values. If the threshold is 0, we find back a strict equality. Thus, a value is said *compatible according to a threshold* with an other one iff their absolute difference is lesser than or equal to this threshold.

Thanks to the notion of compatible values according to a threshold, we are able to define new quality criteria that add flexibility to the old ones. To do that, we simply replace the relation of equality in the old criteria by the notion of compatible values according to a threshold in the new ones.

We say that a pair of concepts is *clean according to a threshold* if the propagated influence of the first concept of the pair on the second is compatible with the value labelling the influence between the two concepts, according to this threshold. We say also that a pair of concepts is *non-ambiguous according to a threshold* if the propagated influence on every minimal path that links the first concept of the pair to the second one is compatible with the propagated influence of the first concept on the second one, according to this threshold. With these definitions, we define trivially what is a clean cognitive map according to a threshold and a non-ambiguous cognitive map according to a threshold. Note that the cleanliness is still a sub-case of the non-ambiguity.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

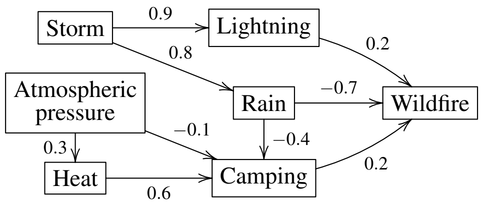

Figure 9: The cognitive map *CM2b*, defined on the value value set $[-1;1]$.

Example 16. *We consider the cognitive map CM2b (figure 9). This map is a more expressive version of CM2 (example 6) defined on the value set* $[-1;1]$.

We consider a threshold of 0.3. *The pair* (Rain, Wildfire) *is unclean according to this threshold. Indeed,* $I(\text{Rain}, \text{Wildfire}) = -0.39$ *and* $|-0.39 - (-0.7)| = 0.31$, *which is greater than* 0.3.

Note that this time, the pair (Atmospheric pressure, Camping) *is clean according to this threshold. Indeed,* $I(\text{Atmospheric pressure}, \text{Camping}) = |0.04 - (-0.1)| = 0.14$ *and* $0.14 \leq 0.3$. *However, in example 4,* (Rain, Wildfire) *was clean and* (Atmospheric pressure, Camping) *was unclean. This is due to the fact that in example 4, two opposite values (+ and −) necessarily invalidate the criterion whereas with these criteria, only the gap between two values matters.*

With a threshold of 0.3, *the pair* (Storm, Wildfire) *is ambiguous according to this threshold. Indeed,* $I\mathcal{P}(\text{Storm} \rightarrow \text{Rain} \rightarrow \text{Wildfire}) = -0.56$, $I(\text{Storm}, \text{Wildfire}) = -0.148$ *and* $|-0.56 - (-0.148)| = 0.412 > 0.3$.

5.3 Compatibility for $[-1;1]$

Now, we would like the compatibility criterion for the value set $[-1;1]$. Before defining this criterion, we need first to define the taxonomic influence for the value set $[-1;1]$. Again, we base ourselves on the definition of the ontological influence for $[-1;1]$ (Chauvin et al., 2009). To compute this influence, we need first to compute the propagated influences between every pair made of an elementary concept of the first concept and an elementary concept of the second one. The taxonomic influence is then defined as an interval between the minimal and the maximal propagated influences.

Example 17. *We consider the concepts* Bad weather *and* Bad traffic condition *of T1 (example 7). The taxonomic influence of* Bad weather *on* Bad traffic condition *relatively to CM1b (example 15) is:*

$$I(\text{Fog}, \text{Bad visibility}) = 0.9 \quad I(\text{Rain}, \text{Bad visibility}) = 0.5$$
$$I(\text{Fog}, \text{Slippery road}) = 0 \quad I(\text{Rain}, \text{Slippery road}) = 0.2$$
$$I(\text{Fog}, \text{Sinuous road}) = 0 \quad I(\text{Rain}, \text{Sinuous road}) = 0$$
$$I_{\text{T}}(\text{Bad weather}, \text{Bad traffic condition}) = [0;0.9]$$

Given this definition of the taxonomic influence, we cannot use the threshold method for the compatibility criterion. Indeed, this criterion compares a taxonomic influence to a specified value. The value of a taxonomic influence is an interval, which is not a numeric value. Therefore, the threshold method cannot work with such values as it only works with numeric values.

We have thus to define the notion of *compatible intervals*. To do so, we distinguish the interval that represents the taxonomic influence and the interval that represents the value of the constraint. We consider that the interval of the constraint describes all the values accepted for the taxonomic influence to validate the said constraint. The interval of the taxonomic influence describes the possible values for this influence. Thus, we say that the interval of the taxonomic influence and the interval of the constraint are *compatible* iff the interval of the taxonomic influence is included into the interval of the constraint. Therefore, a cognitive map is *compatible with a constraint according to a taxonomy* iff the taxonomic influence between the two concepts of the constraint is included into the value of the constraint.

Given the notion of compatibility with a constraint for the value set $[-1;1]$, the definition of the compatibility with a specification for $[-1;1]$ is trivial.

Example 18. *We test the compatibility of CM1b (example 15) according to T1 (example 7). We define the 3 following constraints, based on the ones from the example 10, defined on the taxonomy T1:*

$s'_1 = \langle \text{Bad traffic condition}, \text{Accident}, [0;1] \rangle$
$s'_2 = \langle \text{Bad weather}, \text{Bad traffic condition}, [0.5;1] \rangle$
$s'_3 = \langle \text{Road}, \text{Sinuous road}, [-1;-0.5] \rangle$

The constraint s'_1 *means that a positive influence is expected. The constraint* s'_2 *means that a strong positive influence is expected. The constraint* s'_3 *means that a strong negative influence is expected.*

CM1b is compatible with s'_1 *according to T1 because* $I_{\text{T}}(\text{Bad traffic condition}, \text{Accident}) = [0.2;0.8]$ *and* $[0.2;0.8] \subseteq [0;1]$.
However, CM1b is not compatible with s'_2 *according to T1 because* $I_{\text{T}}(\text{Bad weather}, \text{Bad traffic condition}) = [0;0.9]$ *and* $[0;0.9] \not\subseteq [0.5;1]$.
CM1b is not compatible with s'_3 *according to T1 either because* $I_{\text{T}}(\text{Road}, \text{Sinuous road}) = [-0.9;0.7]$ *and* $[-0.9;0.7] \not\subseteq [-1;-0.5]$.

5.4 Quality Criteria for $\{none < few < much < a\ lot\}$

The value set $\{none < few < much < a\ lot\}$ is a totally ordered set of values. With such a value set, the propagated influence on a path is usually defined as a min and the propagated influence as a max. Since this value set contains very few values, the notion of compatible values may not be as useful for this value set as for the value set $[-1;1]$. However, we can still list the values that are compatible with a specific value, as we did for the set $\{+,\oplus,0,\ominus,-,?\}$. One easy way to do this is to use the total order between the values. This order can indeed by used to define a *distance* between the values. We can then use again a threshold such that, if the distance between two values is lesser than or equal to this threshold, then these two values are compatible according to this threshold.

6 CONCLUSIONS

We have presented a way to validate cognitive maps by introducing four different kinds of quality criteria for cognitive maps defined on the value set $\{+,-\}$. We have so introduced two kinds of verification criteria, the cleanliness and the non-ambiguity and two kinds of test criteria, the coherency and the compatibility. We have also proposed a way to adapt these criteria to other value sets such as $[-1;1]$.

We have tested our criteria on cognitive maps relative to fishing (Christiansen, 2011). Our criteria detect the contradictions spotted by the authors as well as others contradictions that may be interesting to study. To do so, we developed a software that implements the quality criteria in order to automatically validate a cognitive map (Le Dorze, 2013).

As for now, our approach can only inform a designer that its map does or does not validate a specific quality criterion. It does not tell the user where are the contradictions spotted by the criterion and how to correct them. Our current research are leading on this point.

REFERENCES

Axelrod, R. M. (1976). *Structure of decision: the cognitive maps of political elites*. Princeton, NJ, USA.

Ayel, M. and Laurent, J.-P. (1991). *Validation, verification and test of knowledge-based systems*. John Wiley & Sons, Inc., New York, NY, USA.

Celik, F. D., Ozesmi, U., and Akdogan, A. (2005). Participatory Ecosystem Management Planning at Tuzla Lake (Turkey) Using Fuzzy Cognitive Mapping. *eprint arXiv:q-bio/0510015*.

Chauvin, L., Genest, D., and Loiseau, S. (2009). Ontological Cognitive Map. *International Journal on Artificial Intelligence Tools*, 18(5):697–716.

Christiansen, G. (2011). Modélisation du savoir portée par les acteurs d'un système : application aux pêcheurs à la coquille en rade de Brest. Master's thesis, Agrocampus Ouest, Saint-Brieuc, France.

Dibie-Barthélemy, J., Haemmerlé, O., and Loiseau, S. (2001). Refinement of Conceptual Graphs. In Delugach, H. S. and Stumme, G., editors, *ICCS 2001*, volume 2120 of *Lecture Notes in Computer Science*, pages 216–230. Springer.

Dickerson, J. A. and Bart, K. (1994). Virtual Worlds as Fuzzy Cognitive Maps. *Presence*, 3(2):73–89.

Ginsberg, A. (1988). Knowledge-Base Reduction: A New Approach to Checking knowledge Bases for Inconsistency and Redundancy. In Shrobe, H. E., Mitchell, T. M., and Smith, R. G., editors, *AAAI 1988*, pages 585–589. AAAI Press / The MIT Press.

Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machines Studies*, 24:65–75.

Le Dorze, A. (2013). *Validation, synthèse et paramétrage des cartes cognitives*. PhD thesis, LERIA, Université d'Angers, France.

Levi, A. and Tetlock, P. E. (1980). A Cognitive Analysis of Japan's 1941 Decision for War. *The Journal of Conflict Resolution*, 24(2):195–211.

Poignonec, D. (2006). *Apport de la combinaison cartographie cognitive/ontologie dans la compréhension de la perception du fonctionnement d'un écosystème récifolagonaire de Nouvelle-Calédonie par les acteurs locaux*. PhD thesis, ENSA Rennes, France.

Satur, R. and Liu, Z.-Q. (1999). A Contextual Fuzzy Cognitive Map Framework for Geographic Information Systems. *IEEE Transactions on Fuzzy Systems*, 7(5):481–494.

Tolman, E. C. (1948). Cognitive maps in rats and men. *The Psychological Review*, 55(4):189–208.

Wellman, M. P. (1994). Inference in cognitive maps. *Mathematics and Computers in Simulation*, 36(2):137–148.

Zhou, S., Zhang, J. Y., and Liu, Z.-Q. (2003). Quotient FCMs – A Decomposition Theory for Fuzzy Cognitive Maps. *IEEE Transactions on Fuzzy Systems*, 11(5):593–604.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS