Intelligent patent analysis through the use of a neural network: experiment of multi-viewpoint analysis with the MultiSOM model

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Abstract

The main area of this paper concerns the neural methods for mapping scientific and technical information (articles, patents) and for assisting a user in carrying out the complex process of analysing large quantities of such information.

In the procedure of information analysis, like in the domain of patent analysis, the complexity of the studied topics and the accuracy of the question to be answered may often lead the analyst to partition his reasoning into viewpoints. Most of the classical information analysis tools can only manage an analysis of the studied domain in a global way. The information analysis tool that will be considered in our study is the MultiSOM tool whose core model represents a significant extension of the classical Kohonen SOM neural model. The MultiSOM neural-based tool introduces the concepts of viewpoints and dynamics into the information analysis with its multi-maps displays and its inter-map communication process. The dynamic information exchange between maps can be exploited by an analyst in order to perform cooperative deduction between several different analyzes that have been performed on the same data.

The paper demonstrates the efficiency of a viewpoint-oriented-analysis as compared to a global analysis in the domain of patents. Both objective and subjective quality criteria are taken into account for quality evaluation.

The experimental context of the paper is constituted by a patent database of 1000 patents related to oil engineering. The patents structure and the patents field semantics are firstly exploited in order to generate different viewpoints corresponding to different areas of interest for the analysts. In the experiment the selected viewpoints correspond to uses, advantages, patentees, and titles subfields of the patents. The indexing vocabulary of each viewpoint is automatically extracted of its related textual contents in the patents through a full text analysis. The resulting vocabulary is then used to rebuild patents descriptions regarding each viewpoint. These descriptions are finally classified through the unsupervised MultiSOM algorithm resulting in as much different maps as viewpoints. A fifth "global viewpoint" which represent the combination of all the specific ones is also considered in order to perform our comparison between a global classification mechanism and a pure viewpoint-oriented classification mechanism.

1. Introduction

The digital maps are not only tools of visualization. They also represent an analysis tool. Appropriate display of class points can give the analyst an insight that it is impossible to get from reading tables of output or simple summary statistics. For some tasks, appropriate visualization is the only tool needed to solve a problem or confirm a hypothesis, even though we do not usually think of maps as a kind of analysis, as for patent analysis. There is many ways to create digital maps. The one we consider here is based on Artificial Neural Networks (ANNs). ANNs are a useful class of models consisting of layers of nodes. The power of ANNs is derived from their learning capability defined as a change in the weight matrix

(W), which represents the strength of the links among nodes. Moreover, both their relationships with multivariate data analysis and their non-linear capabilities represent added-values for classing and mapping. The Kohonen self-organizing map (SOM) model is a specific kind of ANN which implements in only one step the tasks of classing and mapping a data set. In the SOM case, the learning is competitive and unsupervised and the approach gives central attention to spatial order in the classing of data. The purpose is to compress information by forming reduced representations of the most relevant features, without loss of information about their interrelationships. The main advantages of the SOM model are its robustness and its very good illustrative power. Conversely, the fact that original model he his only able to deal with one classification of the data at a time might be considered as a serious bottleneck for exploiting it for fine mining tasks.

In this article we shall be dealing with an innovation that was firstly introduced for the information retrieval purposes [13]. It has also been successfully tested for multimedia mining and browsing tasks, exploiting both the multi-map concept and the synergy between images and text on the same maps [14]. It is the multi-map extension of the Kohonen SOM algorithm. This will be from now signified by the name of MultiSOM. As we shall notice, the MultiSOM introduces the concepts of viewpoints and dynamics into the information analysis concept with its multi-map displays and its inter-map communication process. The dynamic information exchange between maps can be exploited by an analyst in order to perform cooperative deduction between several different analyzes that have been performed on the same data. The principal intent of this article is to propose the MultiSOM model as an ANN implementation of the information analysis concept.

We will mainly focuses on the study of the contribution of the viewpoint's oriented data analysis proposed by the MultiSOM model as compared to the global analysis proposed by the other models. An attempt will be made to define a protocol and to design a platform for this comparison. As soon as the MultiSOM model can be used either in a global way or in a viewpoint-oriented way, it will be used as the reference model for our comparison. The section 2 of the article presents the Kohonen self-organizing maps (SOM) and their main applications in mapping of science and technology. Sections 3 deals with MultiSOM, the multi-map innovation of the SOM algorithm. The context of the experiment on the oil engineering patents and the preprocessing of these latter will be described in the section 4. The Section 5 describes the protocol of comparison which has been set up along with its results. The conclusions are finally exposed.

2. The self-organizing map (SOM)

The basic principle of the SOM is that our knowledge organization at higher levels is created during learning by algorithms that promote self-organization in an spatial order (see [5],[6],[7],[8],[9],[10],[11],[12],[28]). Thus, the architecture form of the SOM network is based on the understanding that the representation of data features might assume the form of a self-organizing feature map that is geometrically organized as a grid or lattice. In the pure form, the SOM defines an "elastic net" of points (parameter, reference, or codebook vectors) that are fitted to the input data space to approximate its density function in an ordered way. The algorithm takes thus a set of N-dimensional objects as input and maps them onto nodes of a two-dimensional grid, resulting in an orderly feature map [9]. A layer of two-dimensional array of competitive output nodes is used to form the feature map. The lattice type of array can be defined to be square, rectangular, hexagonal, or even irregular. Every input is connected to every output node via a variable connection weight. It is the self-organizing property. The SOM belongs to the category of the unsupervised competitive learning networks [4],[11],[13]. It is called competitive learning because there is a set of nodes that compete with one another to become active. To this category belongs also the adaptive resonance theory (ART) model of Grossberg and Carpenter, as well as the self-organizing maps discussed in this paper. In the SOM, the competitive learning means also that a number of nodes is comparing the same input data with their internal parameters, and the node with the best match (say, "winner") is then

tuning itself to that input, in addition the best matching node activates its topographical neighbors in the network to take part in tuning to the same input. More a node is distant from the winning node the learning is weaker. It is also called unsupervised learning because no information concerning the correct classes is provided to the network during its training. Like any unsupervised clustering method, the SOM can be used to find classes in the input data, and to identify an unknown data vector with one of the classes. Moreover, the SOM represents the results of its classing process in an ordered two-dimensional space (R^2). A mapping from a high-dimensional data space R^n onto a two dimensional lattice of nodes is thus defined. Such a mapping can effectively be used to visualize metric ordering relations of input data. As Kohonen [9] says: "The main applications of the SOM are in the visualization of complex data in a two dimensional display, and creation of abstractions like in many classing techniques."

The SOM algorithm is presented in details in ([2],[9],[12],[13],[19]). It consists of two basic procedures: (1) selecting a winning node and (2) updating weights of the winning node and its neighboring nodes. This preliminary learning phase is not straightforward process [9]. It necessitates several different learning steps, single map evaluations, and comparisons between a lot of generated maps in order to find at least a reliable map, at most an optimal one [13],[32].

Let $x(t) = \{x_1(t), x_2(t),\ldots, x_N(t)\}$ be the input vector selected at time t, and $W_k(t) = \{W_{k1}(t), W_{k2}(t),\ldots, W_{kN}(t)\}$ the weights for node k at time t. The smallest of the Euclidean distances $\|x(t) - W_k(t)\|$ can be made to define the winning node s:

$$\|x(t) - W_s(t)\| = \min \|x(t) - W_k(t)\|$$

After the winning node s thus selected, the weights of s and the weights of the nodes in a defined neighborhood (for example all nodes within a square or a cycle around the winning node) are adjusted so that similar input patterns are more likely to select this node again. This is achieved through the following computation:

$$W_{ki}(t+1) = W_{ki}(t) + \alpha(t) \times h(t) \times [X_i(t) - W_{ki}(t)],$$

$$\text{for } 1 \le i \le N$$

where $\alpha(t)$ is a gain term ($0 \le \alpha(t) \le 1$) that decreases in time and converges to 0, and $h(t)$ is the neighborhood function.

Once the SOM algorithm is achieved, the data can be set to the nodes of the map. For each input data vector, the winning node is selected according to the algorithm first step presented above, and the data are affected to this selected node.

In the quantitative studies of science, the Kohonen self-organizing maps have been successfully used for mapping scientific journal networks [2], and also author co-citation data [33]. Maps have been also successfully used for several other applications in the general area of data analysis like for classifying meeting output [30], for classing socio-economic data [32] and for documentary database contents mapping and browsing [13],14]. Kaski et al. have implemented a specific adaptation of SOM, named WEBSOM, for the analysis of important document collections [6]. WEBSOM main characteristic is to include strategies for reducing the dimension of the entry data descriptions by using random projection techniques applied on word histograms extracted from the document contents. WEBSOM method has been tested for patents abstract analysis [7]. Nevertheless, as this method only manages such an analysis in a global way, it can only provide the analyst with general overview of the topics covered by the patents along with their interactions. A more exhaustive description of all the SOM applications might be found in [32].

After the map building, the main characteristics of the classes resulting from the topographical classification process have to be highlighted to the analyst in order to provide him an overview (i.e. a global summary) of the analysis results. This task is difficult because the profiles of the obtained classes are mostly complex weighted combination of indexes extracted from the data. We have previously observed that single extraction strategy like the one proposed by [17] could cause shortcomings or mistakes in the interpretation of the database contents. The first set of solutions we proposed for solving this problem, like class labeling and zoning strategies or generalization mechanisms, are presented in [14]. Figure 3 of

section 4 presents a map resulting from these processes.

In all the following sections, we will consider that the classification process deals with electronic documents associated with their description in the form of index vectors. Classes will be represented by node vectors or class profile; each component of the vectors being the coordinate of a document index element (keyword). The list of the input data, which are the documents affected to the node, will represent the "class members" profile. The conceptual mean of the classes will be below called a *topic*. This semantic information is supplied by the classified keywords and documents.

3. The MultiSOM model

The communication between self-organizing maps that has been first introduced in the context of an information retrieval model [10], represents a major amelioration of the basic Kohonen SOM model. From a practical point of view, the multi-map display introduces in the information analysis the use of *viewpoints*. Each different viewpoint is achieved in the form of map. Each map is a spatial order in which the information is represented into nodes (classes) and spatial areas (group of classes). The multi-map enables a user to highlight semantic relationships between different topics belonging to different viewpoints. Each map represents a particular viewpoint. Figure 4 of section 4 illustrates it.

3.1 The viewpoint paradigm

The viewpoint building principle consists in separating the description space of the documents into different subspaces corresponding to different keyword subsets. The set of V all possible viewpoints issued from the description space D of a document set can be defined as:

$$V = \{v_1, v_2, \ldots, v_n\}, v_i \in P(D), \text{with } \bigcup_{i=1}^{n} v_i = D$$

where each v_i represents a viewpoint and $P(D)$ represents the set of the parts of the description space of the documents D; the union of the different viewpoints constitutes the description space of the documents.

The viewpoint subsets issued from V may be overlapping ones. Moreover, they may also fit into the structure of the document when they correspond to different vocabulary subsets associated to different documents subfields, if any. Other viewpoints may be also manually extracted from an overall document description space. At last, the viewpoint model is flexible enough to tolerate document descriptions belonging to different media, as soon as these descriptions can be implemented by description vectors (for ex. an image can be simultaneously described both by a keyword vector and by color histogram vector).

The inter-map communication mechanism, which is described hereafter, takes directly benefit of the above described viewpoint model in order to overcome the low quality problem inherent to a global classification approach while conserving a overall view on the interaction between the data.

3.2 Inter-map communication mechanism

In MultiSOM, this inter-map communication is based on the use of the data that have been projected onto the maps as intermediary nodes or activity transmitters between maps. The intercommunication process between maps operates in three successive steps. Figure 1 shows graphically the three steps of this intercommunication mechanism.

At the step 1, the original activity is directly set up by the user on the node or on the logical areas of a source map through decisions represented by different scalable modalities (full acceptance, moderated acceptance, moderated rejection, full rejection) directly associated to nodes activity levels. This procedure can be interpreted as the user's choices to highlight (positively or negatively) different topics representing his centers of interest relatively to the viewpoint associated to the source map. The original activity could also be indirectly set up by the projection of a user's query on the nodes of a source map. The effect of this process will then be to highlight the topics that are more or less related to that query. The activity transmission protocol, which corresponds to the steps 2 and 3 of the inter-map communication mechanism, is extensively described in [24].

To perform in the best conditions, the inter-map communication process obviously necessitates that a significant part of the data should play that roles between the maps. This last condition could be easily verified if each vector used for the map generation indexes a significant part of the bibliographic database.

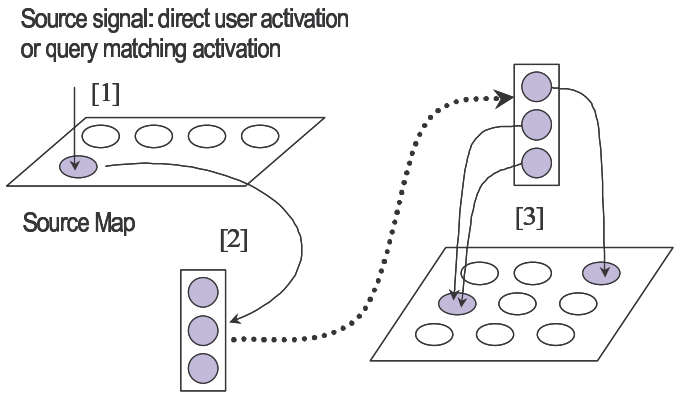


Figure 1: Inter-map communication mechanism. This figure represents the main steps of the inter-map communication mechanism. [1] The activity is set up directly by the user or by a query formulation on one or several nodes of one or several source map. [2] The activity is transmitted to the data nodes associated to the activated class nodes of the source map. [3] The activity is transmitted through the data nodes to other maps to which these data are associated. Positive as well as negative activity could be managed in the same process. Note that the data are in this case indexed document.

4. Application

In the two preceding sections we have introduced MultiSOM after having previously presented the SOM algorithm. In this section, we shall then use a real example, to make some of the notions more concrete. We argue that visualization into form of a set of maps represents an important added-value for analysis in the technology watching tasks, as well as in science watch, and in knowledge discovery in databases. Our example is a set of 1000 patents about oil engineering technology recorded during the year 1999.

4.1 The analysis phase

The role of the MultiSOM application has been firstly planed by the domain expert in order to get answers to such various kinds of questions on the patents that:

1: "Which are the relationships between the patentees?"

2: "Which are the advantages of the different oils?",

3: "Does a patentee works on a specific engineering technology, for which advantage and for which use?",

4: "Which is the technology that is used by a given patentee without being used by another one?",

5: "Which are the main advantages of a specific oil component and do this advantages have been mentioned in all the patents using this component?".

An analysis carried out on all the possible types of question led the expert to define different viewpoints on the patents that could be associated to different closed semantic domains appearing in these questions. One of the main aim of the expert was to be able to use each viewpoints separately in order to get answers to domain closed questions (like questions 1,2) while maintaining the possibility of a multi-viewpoint communication in order to get answers to multi-domain questions (like questions 3,4,5) that might also contain negation (like question 4). The specific viewpoints which have

been highlighted by the expert from the set of possible questions are:

1: Patentees,

2: Title (often contains information on the specific components used in the patent),

3: Use,

4: Advantages.

A fifth "global viewpoint" which represent the combination of all the specific ones is also considered in order to perform our comparison between a global classification mechanism, of the WEBSOM type, and a pure viewpoint-oriented classification mechanism, of the MultiSOM type.

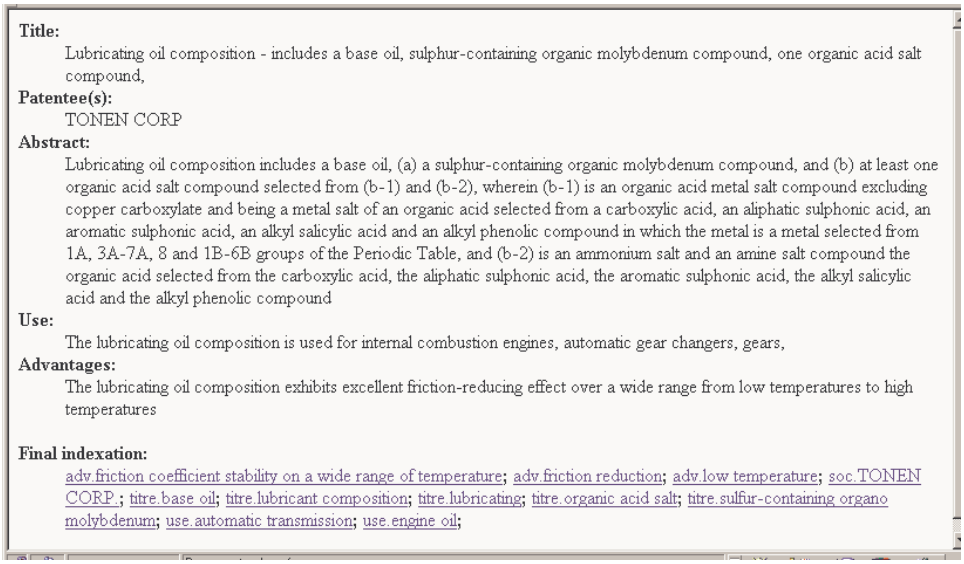
4.2 The technical realization

The role of this phase consists in mapping the four specific viewpoints highlighted by the domain expert in the preceding phase in four different maps. A preliminary task consists in obtaining the index set (i.e. the vocabulary set) associated to each viewpoint from the full text of the patents. This task has been itself divided into three elementary steps. At the step 1, the structure of the patent abstracts is parsed in order to extract the subfields corresponding to the **Use** and to the **Advantages** viewpoints[1]. At the step 2, the rough index set of each subfield is constructed by the use of a basic computer-based indexing tool [4]. This tool extracts terms and noun phrases from the subfield content according to a normalized terminology and its syntactical variations. It eliminates as well usual language templates. At the step 3, the normalization of the rough index set associated to each viewpoint is performed by the domain expert in order to obtain the final index sets. The normalization of the **Title**, **Use** and **Advantages** subfields consists in choosing a single representative among the terms or noun phrases which represent the same concept (for ex., "oil fabrication" and "oil engineering" noun phrases will be both assimilated to the single "oil engineering" noun phrase). The normalization of the **Patentees** viewpoint is operated in the same way considering that the same firm can appear with different names in the set of published patents. After the construction of the final index sets, the patents are re-indexed separately for each viewpoint thanks to these sets. Figure 2 presents a patent abstract including its generated multi-index.

The following task consists in building the maps representing the different viewpoints, using the map algorithm described in section 2. Before these step, a classical ***IDF-Normalization*** step [27] is applied to the index vectors associated to the patents in order to reduce the influence of the most widespread terms of the indexes. For each specific viewpoint a map of 10x10 nodes (classes) is finally generated. Two global maps representing global unsupervised classifications, of the ***WEBSOM*** type [7], of the patents are also constructed. The index sets of these maps represent the union of the index sets of all the specific viewpoints. They only differ one to another by the number of their classes. The first one (**GlobMin**) is constrained to have the same number of classes as the viewpoint maps (i.e. 100 classes). The second one (**GlobMax**) is constrained to have to sum of the number of classes of all the viewpoint maps (i.e. it becomes a 20x20 map comprising 400 classes). The table 1 summarizes the results of the patent indexation and the map building. A single viewpoint map resulting from the map building process is presented at the figure 4. Some remarks must be made concerning the results shown in table 1. (1) The index count of the **Title** field is significantly higher than the other ones. An analysis of the indexes shows that the information contained in the patent titles is both sparser, of higher diversity, and more precise than the ones contained in the **Use** and **Advantages** fields. Thanks to the expert opinion, the high level of generality of the **Use** and **Advantages** fields, which consequently led to poorer generated indexes, could be explained as an obvious strategy of the Patentees for indirectly protecting their patents. (2) The number of final patentees (i.e. 32) has been significantly reduced by the expert as compared to the one initially generated by the computer-based indexing tool. The main part of this reduction is not due to variations in patentee names. It is related to the fact that the prior goal of the study was to consider the main companies and their relationships. Thus, the patentees corresponding to small companies have been grouped into a same

[1] The **Patentees** and **Title** subfields are directly represented in the original patent structure and therefore do not necessitate any extraction.

general index: “Divers”. (3) On the **Patentees** map, the number of classes is close to the final number of retained patentees. Most of these patentees will then be associated to separate classes on the **Patentees** map. (4) Only 62% of the patents have an **Advantages** field and 75% a **Use** field. Consequently, some of the patents will not be indexed for the all the expected viewpoints. The role of the mechanism of communication between viewpoints (see next section) will then be to generate indirect evaluation of the contents of these patents on their missing viewpoints through their associations with other patents.



Title:
Lubricating oil composition - includes a base oil, sulphur-containing organic molybdenum compound, one organic acid salt compound,

Patentee(s):
TONEN CORP

Abstract:
Lubricating oil composition includes a base oil, (a) a sulphur-containing organic molybdenum compound, and (b) at least one organic acid salt compound selected from (b-1) and (b-2), wherein (b-1) is an organic acid metal salt compound excluding copper carboxylate and being a metal salt of an organic acid selected from a carboxylic acid, an aliphatic sulphonic acid, an aromatic sulphonic acid, an alkyl salicylic acid and an alkyl phenolic compound in which the metal is a metal selected from 1A, 3A-7A, 8 and 1B-6B groups of the Periodic Table, and (b-2) is an ammonium salt and an amine salt compound the organic acid selected from the carboxylic acid, the aliphatic sulphonic acid, the aromatic sulphonic acid, the alkyl salicylic acid and the alkyl phenolic compound

Use:
The lubricating oil composition is used for internal combustion engines, automatic gear changers, gears,

Advantages:
The lubricating oil composition exhibits excellent friction-reducing effect over a wide range from low temperatures to high temperatures

Final indexation:
adv.friction coefficient stability on a wide range of temperature; adv.friction reduction; adv.low temperature; soc.TONEN CORP.; titre.base oil; titre.lubricant composition; titre.lubricating; titre.organic acid salt; titre.sulfur-containing organo molybdenum; use.automatic transmission; use.engine oil;

Figure 2: Example of a patent abstract with its generated multi-index. The multi-index that has been generated for the above patent abstract corresponds to the “**Final indexation**” field. The terms of the generated multi-index are prefixed by the name of the viewpoint to which they are associated: “adv.” for the **Advantages** viewpoint, “titre.” for the **Title** viewpoint, “use.” for the **Use** viewpoint, “soc.” for the **Patentees** viewpoint.

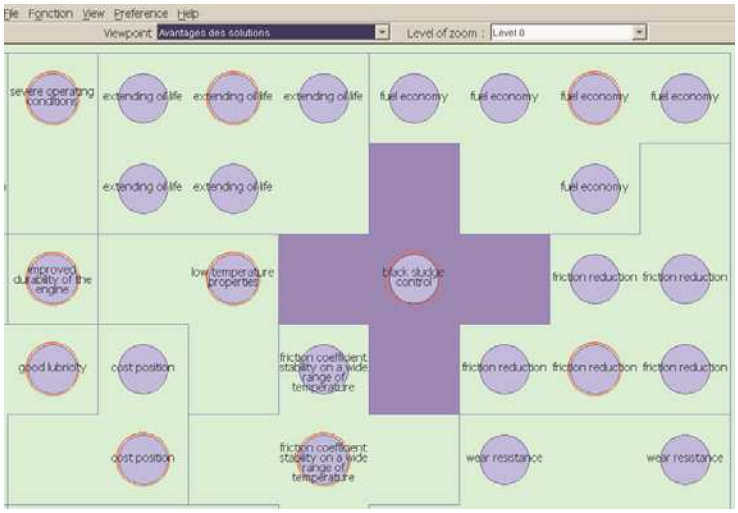


Figure 3: Example of a generated map. Partial view of a topographic map of 10 x 10 nodes. The map is initially organized as a square 2D grid of nodes. The viewpoint chosen for the showed map is the "**Advantages**" viewpoint. The names of the classes illustrate the topics (considering the chosen viewpoint) that have been highlighted by the

learning. After the learning, the nodes related to the same topics have been grouped into coherent areas thanks to the topographic properties of the map. The number of nodes of each area can then be considered as a good indicator of the topic weight in the database. Topics or areas near one to another represent related notions. For example, the "**extending oil live**" area shares some of its borders with the "**black sludge control**" area on the map. The proximity of these two areas illustrates the fact that oil duration strongly depends of maintaining a low level of sludge in it. The surrounding circles represent the centers of gravity of the areas.

	Patentees	Title	Use	Advantages	GlobMin *(WEBSOM)*	GlobMax *(WEBSOM)*
Number of indexed documents (NID)	1000	1000	745	624	1000	1000
Number of rough indexes generated (NRI)	73	605	252	231	1395	1395
Number of final indexes (NFI)	32	589	234	207	1075	1075
Numbers of map classes with members (/100)	28	55	57	61	89	238

Table 1: Summary of the results of patent indexation and map building. Note that the NRI (resp. NFI) of the "global viewpoint" are less than the sum of the NRIs (resp. NFIs) of all the specific viewpoints (i.e. 1089) because there are similar indexes occurring in different viewpoints.

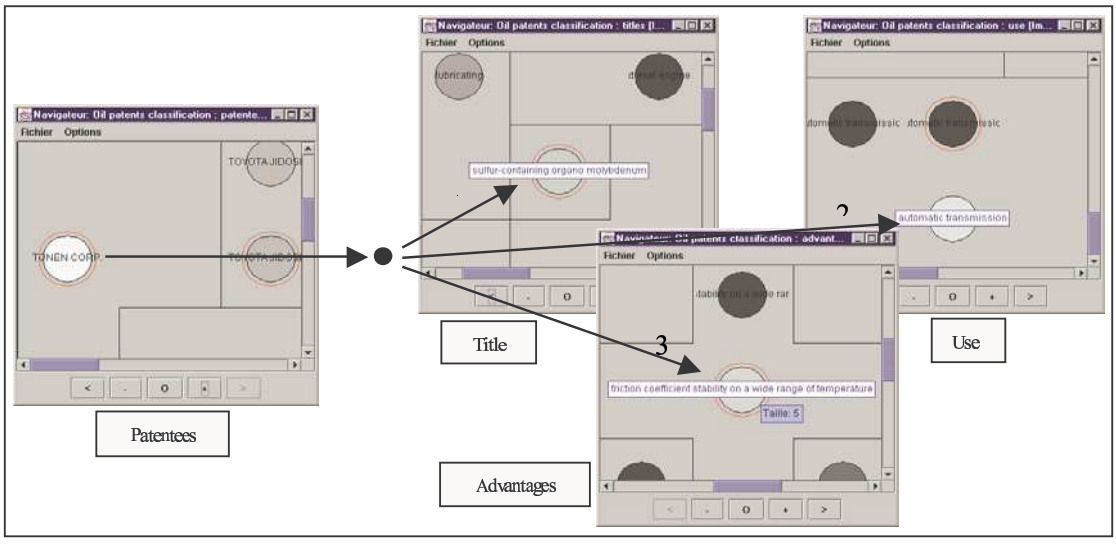


Figure 4: Example of exploitation of the inter-map communication mechanism. The analyst decision to activate the area corresponding to the TONEN CORP. company on the **Patentees** map and to propagate the activity to the thematic maps associated to the **Use**, **Advantages** and **Title** viewpoints corresponds to a "viewpoints crossing query" whose explicit formulation might look like: "I want to know which are the specific areas of competence (concerning oil use, oil composition and expected advantages) of the TONEN CORP. company, if there are. The MultiSOM application let him interactively find that TONEN CORP. company is a specialist of the lubrication of the automatic transmissions [arrow n°2 on the map] and that it adopted for this kind of lubrication sulfur-containing organo-molybdenum compound [arrow n°1] whose main advantages are to provide oil with a friction coefficient that is stable on a wide range of temperature [arrow n°3]. In this case, an inverted propagation from the target topics should be also used to verify that these topics only belong to TONEN CORP. areas of competence. The whiter is the color of a node representing a map class (topic), the higher is its resulting activity.

4.3 Inter-map communication for analysis

In comparison with the standard mapping methods, as such as principal component analysis, multidimensional scaling or WEBSOM global SOM analysis, the advantage of the multi-map displays is the inter-map communication mechanism that MultiSOM environment provides to user. Each map is representing a viewpoint. Each viewpoint is representing a subject category. The inter-map communication mechanism assisted the user to cross information between the different viewpoints. In both cases, the responses of the system are given both through activity profiles on the maps and through patents examples associated to the most active class representatives of these maps. The estimation of the quality of thematic deduction is achieved through an evaluation of the activity focalization on the target maps (see [13]). The figure 4 illustrates a thematic deduction between the four different viewpoints of the study.

5. Evaluation

The advantages of the MultiSOM method seem obvious to the expert of the domain: the original multiple viewpoints classification approach of MultiSOM tends to reduce the noise which is inevitably generated in an overall classification approach while increasing the flexibility and the granularity of the analyses. Moreover, with a global classification method, like WEBSOM, important relationships between some subtopics are hidden in the class profiles and therefore very difficult to precisely characterize. The expert found more than 35 of such important relationships by the use of the MultiSOM method. A simple example is given by the comparison of the figure 3 and the figure 5. Other examples of more elaborated topic relationships that can be only obtained by the MultiSOM inter-map communication mechanism are given in the annex of the paper. Finally, the expert argued that the possibility of interactively activating, positively or negatively, the classes on the maps represents a great help for tuning very precisely an analysis process. Nevertheless, expert empirical evaluation remains insufficient to objectively compare global approach to viewpoint-oriented approach. For this last purpose, we propose new objective classification quality estimators for both evaluating and optimising the results of the classification and of the mapping methods, especially when they are applied in the domain of documentary databases. These estimators are described in the next section.

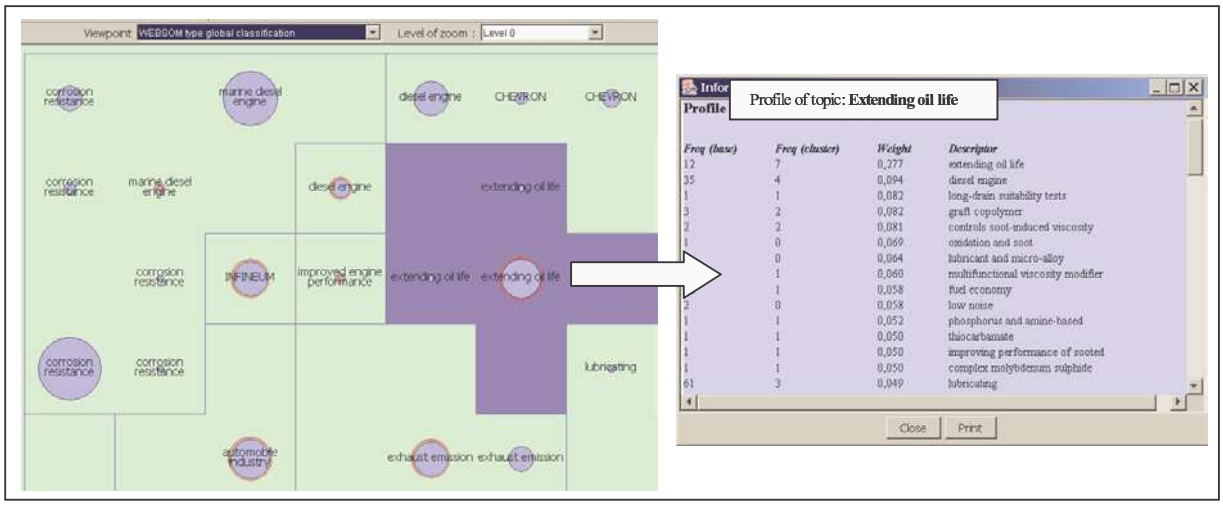


Figure 5: Results of a WEBSOM-like global mapping of 10x10 nodes (GlobMin). The left part of the figure represents the WEBSOM-like mapping (i.e. without viewpoint management) of the content of the patent abstracts. The right part of the map represents the description (i.e. profile) of the "**extending oil life**" WEBSOM global topic. Even if a strong relationship between "**extending oil life**" and "**black sludge control**" topics has been highlighted by

the MultiSOM viewpoint-oriented classification (see map of figure 3), this relationship has been lost by the WEBSOM-like classification due to the noise of the global classification (this relationship do not appear, neither in the above map, nor in the "**extending oil life**" topic profile).

5.1 Evaluation procedure

When anyone aims at comparing classification methods, he will be faced with the problem of choice of reliable classification quality measures. The classical evaluation measures for the quality of a classification are based on the intra-class inertia and the inter-class inertia [16][17][25]. Thanks to these two measures, a classification is considered as good if it possesses low intra-class inertia as compared to its inter-class inertia. However, in the case of a Kohonen classification, as well as for many other numerical classification methods, these measures are often strongly biased, mainly because the intrinsic dimensions of the classes profiles (number of non-zero components in the profiles) are not of the same order of magnitude than the intrinsic dimensions of the data profiles[2]. It is especially true in the documentary domain where the number of indexes in the documents is extremely low as compared to the dimension of their overall description space.

A promising way we have found in order to more precisely highlight the main characteristics of the classes of the map and to validate the thematic deductions between the maps consists in coupling the MultiSOM model with a symbolic model using Galois lattice conceptual classification of the patents regarding the same viewpoints as the one used for the map building. This approach is extensively described in [31]. A Galois lattice model could also be considered as a pure natural elementary classifier. Indeed, it groups the data by directly considering their intrinsic properties (i.e. without any preliminary construction of class profiles). Hence, one might derive from its behavior news class quality evaluation factors which can be substituted to the measures of inertia for validating the intrinsic properties of the numerical classes. For the sake of user-orientation, our measures will be based in a parallel way on the recall and precision criteria which are extensively used from evaluating the result quality of information retrieval (IR) systems. In IR [29], the **Recall** ***R*** represents the ratio between the number of relevant documents which have been returned by an IR system for a given query and the total number of relevant documents which should have been found in the documentary database. The **Precision** ***P*** represents the ratio between the number of relevant documents which have been returned by an IR system for a given query and the total number of documents returned for the said query. **Recall** and **Precision** generally behave in an antagonist way: as **Recall** increases, **Precision** decreases, and conversely. The ***F*** function has thus been proposed in order to highlight the best compromise between these two values [35]. It is given by:

$$F = \frac{2(R * P)}{R + P} \qquad \text{(Eq. 1)}$$

Based on the same principles, the **Recall** and **Precision** measures which we introduce hereafter evaluate the quality of a classification method by measuring the relevance of its resulting class content[3] in terms of shared properties. In our further descriptions, the class content is supposed to be represented by documents and the indexes (i.e. the properties) of the documents are supposed to be weighted by values within the range $[0,1]$.

Let us consider a set of classes C resulting from a classification method applied on a set of documents D, the **Recall** measure is expressed as:

$$R = \frac{1}{|\overline{C}|}\sum_{c\in\overline{C}}\frac{1}{S_c}\sum_{p\in S_c}\frac{|c_p^*|}{|C_p^*|}\ ,\quad P = \frac{1}{|\overline{C}|}\sum_{c\in\overline{C}}\frac{1}{S_c}\sum_{p\in S_c}\frac{|c_p^*|}{|c|}$$

where S_c is the set of properties which are peculiar to the class c that is described as:

$$S_c = \left\{ p \in d, d \in c \;\middle|\; \overline{W}_c^p = Max_{c' \in C}\left(\overline{W}_{c'}^p\right) \right\}$$

where $\overline{C}$ represents the peculiar set of classes

[2] In the SOM method, a second bias is generated by the class construction process that tends to maintain the topographic properties of the map by enhancing the similarities between neighboring classes.

[3] The content of a class is represented by the subset of original data that have been associated to it by the classification process.

extracted from the classes of C, which verifies:

$$\overline{C} = \{c \in C \,|\, S_c \neq \varnothing\}$$

and:

$$\overline{W}_c^p = \frac{\sum_{d \in c} W_d^p}{\sum_{c' \in C} \sum_{d \in c'} W_d^p}$$

where W_x^p represents the weight of the property p for element x.

Similarly to IR, the **F-measure** (described by Eq. 1) could be used to combine **Recall** and **Precision** results. Moreover, we have demonstrated in [16] that if both values of **Recall** and **Precision** reach the unity value, the peculiar set of class $\overline{C}$ represents a Galois lattice. Therefore, the combination of this two measures enables to evaluate to what extent a numerical classification model can be assimilated to a Galois lattice natural classifier. The stability of our **Quality** criteria has also been demonstrated in [16].

5.2 Evaluation results

	Patentees	Title	Use	Advantages	Average F *(MSOM)*	GlobMin *(WEBSOM)*	GlobMax *(WEBSOM)*
R	0,94	0,89	0,78	0,77		0,87	0,84
P	0,92	0,40	0,63	0,60		0,48	0,65
F	0,93	0,55	0,70	0,67	0,71	0,61	0,68

Table 2: Summary of the results of Quality, Recall and Precision evaluation: The nearer the different values are from 1, the better are the classification results. The F value provides a synthesis of the results of R and P.

The examination of the **Quality** measures of the table 2 gives more reliable and stable results because these measures are both independent of the classification method and of the size of the description space. It highlights the overall superiority of the viewpoint-oriented approach as compared with a global approach with the same number of class (**GlobMin**). As the number of classes is strongly increased in the global approach (**GlobMax**), its quality is simultaneously increased, but the advantage of the viewpoint-oriented approach remains obvious in the average (higher Average F-value on all viewpoints than F-value of **GlobMax**), with a more reasonable number of classes per maps from a user point of view. The specific case of the **Title** classification should be discussed here. The bad quality of this classification is both due to the index sparseness of this field[4] and to an inappropriate number of classes, relatively to the size of its associated description space. An interesting strategy would then be to make use of the quality factor $\boldsymbol{Q}$ in order to find the optimal number of classes for this classification. An unbalance between **Recall** and **Precision** (in the favour of **Recall**) can be observed in the case of the worse classifications (**GlobMin** and **Titles**). Such an unbalance means that documents with different properties sets are grouped in the same classes, leading conjointly to the risk of confusion in the interpretation of the content of the classes by the user.

The quality analysis clearly shows that the viewpoint-oriented approach enhance the quality of interpretation of a classification by both reducing the number of class to be consulted by the user on each viewpoint and providing him with more coherent and exhaustive classes in terms of content.

5.3 Optimisation of classification results

The quality criteria that have been presented in

[4] This can be "a posteriori" confirmed by the inertia results for this viewpoint.

the latter section can also be used for optimizing the number of classes for each viewpoint map. The goal of this process is to provide the analyst with an optimal quality of interpretation for each individual map associated to a specific viewpoint. For that purpose, different maps are generated from 6x6 to 24*24 nodes (classes) for each viewpoint. The principle of our algorithm of classification optimisation, which is described in [16], is to search for a **break-even point** (i.e. intersection point) between **Recall** and **Precision**. The map whose quality criteria stand the nearest from the break-even point is considered as the optimal one. The figure subjectively illustrates the difference of accuracy that can be obtained in the analysis by optimizing the map size for a given viewpoint. As it is shown in the figure 6, high quality maps are usually characterized by more precise topic labels and smaller average size of their logical areas.

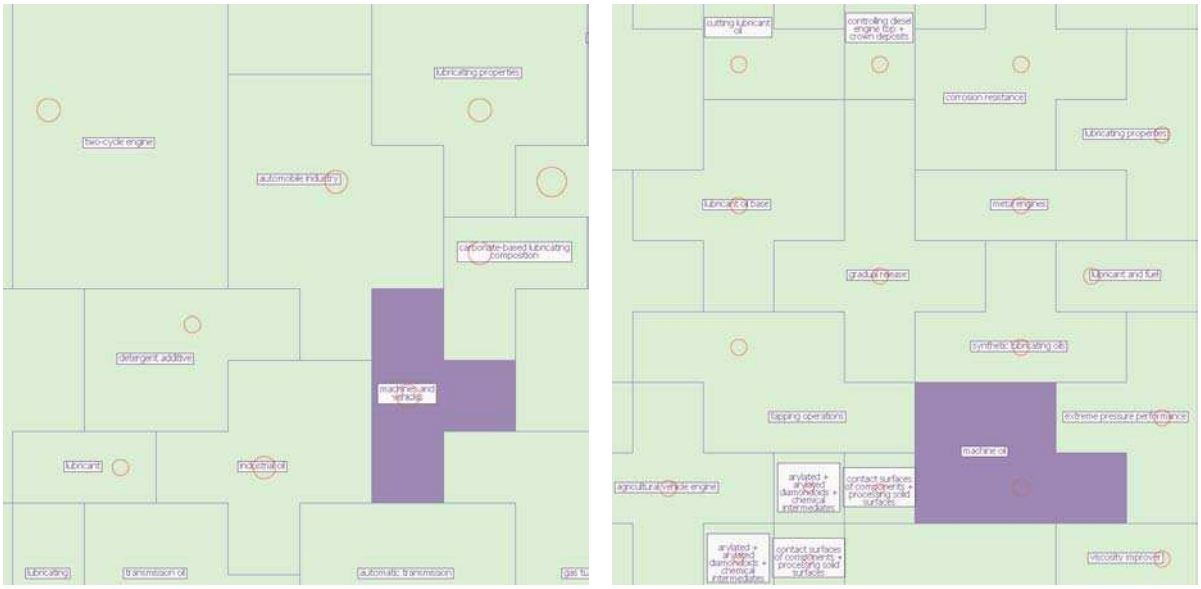


Figure 6: **Comparison between a 11x11 "Use viewpoint" thematic map and a 16x16 "Use viewpoint" thematic map through map extracts:** the 11x11 map extract is presented at the left, the 16x16 map extract is presented at the right. On the figure, the focus is given "**machine oil**" topic. The comparison highlights, as an example, that the logical surrounding of this topic is more precisely defined in the 16x16 map (optimal quality) than in the 11x11 map (lower quality). Moreover, in the 11x11 map, the topic "**machine oil**" has been derived in a more fuzzy scope topic named "**machine and vehicles**".

6. Conclusion

We have presented a new self-organizing multi-map system. We proposed it as a visualization-based system for scientific and technical information analysis, like patents analysis. The model that this multi-map environment provides is certainly not the map but in its original extended version of intercommunication between multiples maps. Each map representing a particular viewpoint extracted from the data. These viewpoints are related either by the problem to be solved, or by the intercommunication mechanism between the maps. We have exposed both the map generation and their intercommunication mechanism. We finally showed how one can evaluate such a viewpoint-oriented approach by comparing it to a global classification approach.

The advantages of the MultiSOM method seem obvious both in terms of objective evaluation, like the one we proposed, and for the domain experts: the original multiple viewpoints classification approach of MultiSOM tends to reduce the noise which is inevitably generated in an overall classification approach while increasing the flexibility and the granularity of the analyses. Moreover, with a global classification method, even if this latter manages overlapping classes, important

relationships between some subtopics are hidden in the class profiles and therefore very difficult to precisely characterize.

Our experiment has also highlighted that our quality evaluation factors that we have proposed can be benefitely used for optimizing the classifications in terms of number of classes, either these classifications are global or they are viewpoint-oriented. This optimization seems to be mandatory when one want to classify documents issued from the Web, where sparseness could usually be a blocking factor.

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ANNEX: EXAMPLE OF DYNAMIC ANALYSIS

Dynamic analysis takes place mainly by using the inter-map communication mechanism which makes it possible to bring to successful conclusion sets of topics deductions between different viewpoints chosen like investigation subfields. This analysis is based on the generation of an initial activity corresponding to the premises of the deductions to check. According to the stage of analysis, this activity can itself be generated several manners by the analyst on one or more source maps. If the activity generation is directly operated by analyst on a map, it corresponds then to a broad set of topics questions. If the activity generation is operated indirectly by projection of a query on a map or by activation of documents group stored beforehand in a document collector, it corresponds then to more targeted questions, which can intervene in one advanced stage of the analysis.

The analyst interest is to highlight the specific areas of competence of the ***Exxon*** *company. On the simulation of analysis we develop on figure 7, we will consider two different viewpoints, the* ***Patentees*** *viewpoint which will represent the source of the analysis and the* ***Title*** *viewpoint which will represent its destination.*

The analyst starts the process of deduction by generating an initial activity on the main ***Exxon*** *topic (i.e. Exxon area gravity center) of the* ***Patentees*** *viewpoint map. To obtain a broad set of potential deductions, he selects the* ***Possibilistic*** *mode of deduction [14]. The activity generated by the inter-map communication mechanism on the* ***Title*** *viewpoint map is focused in two different zones of this map, corresponding to two potential results.*

In the first active zone (1), the analyst makes use of two different naming strategies to facilitate its interpretation, namely, ***a naming strategy based on the profile of the topics*** *(more generic) and a* ***naming strategy based on the profile of the best members (i.e. patents) of the topics*** *(more specific). These operations enable him to highlight that the* ***Exxon*** *company is specialized in a correlative way on topics: "****marine diesel engine****", "****surfactant system****" and "****basic calcium compound****". The expert checks the correlation between these topics by consulting the patents associated to the topic "****surfactant system****" (2). The title of the patents already confirm him the problematic detected by the application. A thorough examination of the contents of the documents will show him than the purpose of use of surfactant containing calcium in addition with the normal formula of oils is to protect the combustion chambers of the marine diesel engines against corrosion due to the absorption of air charged out of salt during their operation. The problem of protection of the marine engines against corrosion is sufficiently important to represent a field of investigation for an oil manufacturer like* ***Exxon.***

*The construction of a query containing the single descriptor "****surfactant system****" (3) on the* ***Title*** *viewpoint will allow the analyst:*

*1. To validate the correlation between "****surfactant system****" and "****marine diesel engine****" topics which will be interpreted by the fact that "****surfactant system****" is only associated with "****marine diesel engine****".*

*2. To check the inverse deduction "****surfactant system → Exxon****" which will insure him that* ***Exxon*** *is the only company whose interest in the conception of "****surfactant system****".*

The result of the projection of the query on the ***Title*** *viewpoint map (4) shows that the generated activity is peculiar to the logical topic area "****marine diesel engine****", which confirms the first assumption. Simultaneously with projection, the documents that are relevant for the query are presented in a Collector (5). The global activation of these documents allows analyst to initiate a new deduction. Then, the result of this latter can be examined on the* ***Patentees*** *map. Like only the main* ***Exxon*** *topic has been activated (6), the second assumption of the analyst is confirmed.*

The second active zone (7) generated by the initial process of deduction will allow the analyst

to observe that the second major field of activity of ***Exxon*** *is the "****biodegradable****" oils. He will be able to also note that these oils are more specifically used for the lubrication of the two-stroke engines ("****two cycle engine****") that reject generally much unburned oil.* ***Probabilistic*** *mode of deduction will allow him to check if the inverse deduction, namely, that* ***Exxon*** *is the only company to be worked on biodegradable oils, can be validated (8). This process will lead the analyst to conclude that "****biodegradable****" oil manufacturing is shared between* ***Exxon*** *and* ***Mobil*** *companies (9), which are the most important oil manufacturers.*

*A complementary use of negative activity setting on the "****two cycle engine****" topic (10) will show more precisely to the analyst that that* ***Mobil*** *company mainly focuses on manufacturing of biodegradable oils for "two stroke engines" and, in a complementary way, that* ***Mobil*** *company only focuses on manufacturing of biodegradable oils for "four stroke engines" (11).*

The simulation of analysis presented here above shows clearly how the analyst can make use of the MultiSOM functionalities in order to highlight all the privileged activity fields of the ***Exxon*** *company starting from a patents database related to engineering of oils. Main functionality is inter-map communication. Multiple naming strategies, generation of queries and collection of intermediate results that have been implemented complementary to inter-map communication also play an important role in the analysis process.*

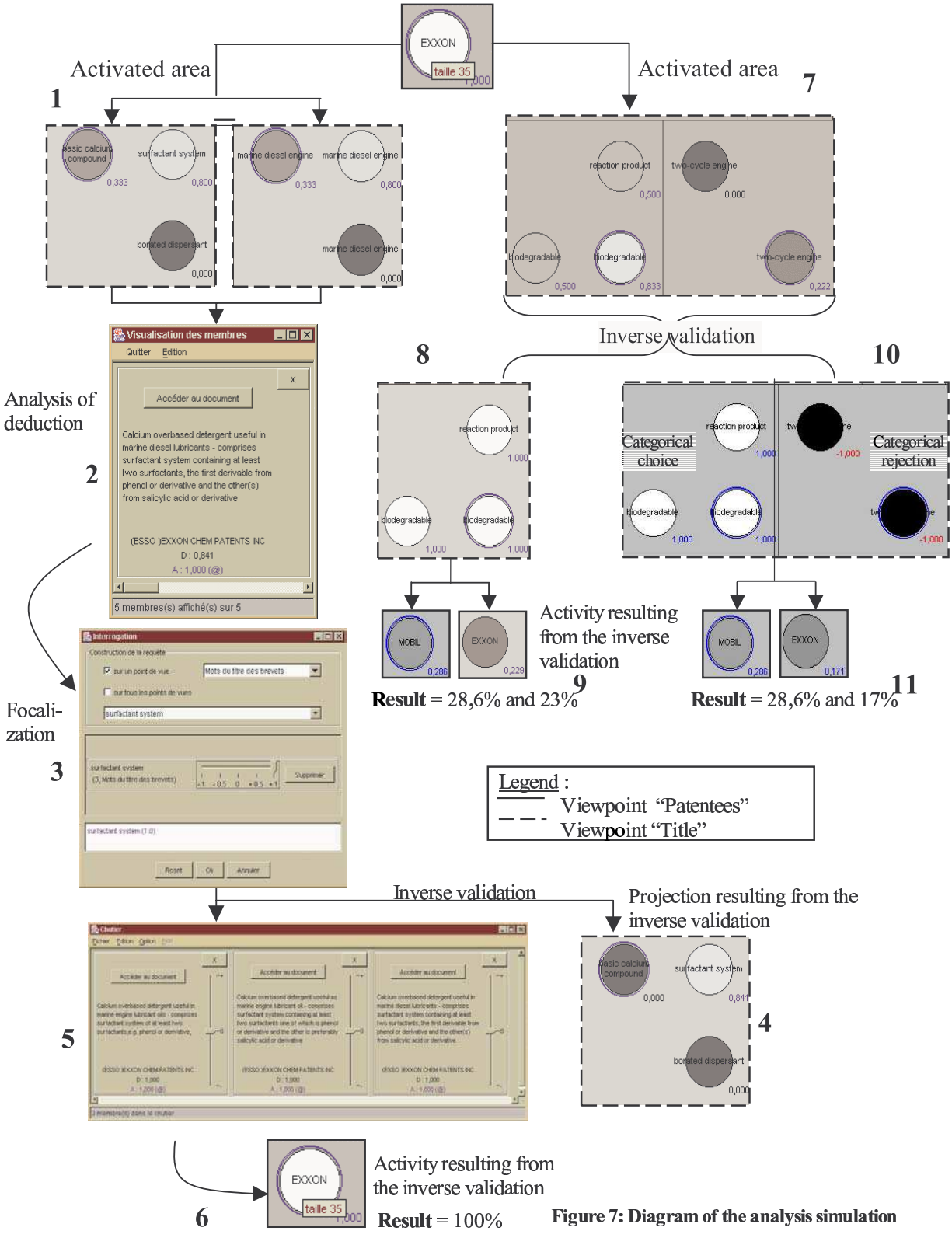

Figure 7: Diagram of the analysis simulation