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# Using Concept Lattice for Visual Navigation Assistance and Attribute Selection

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**Abstract.** The increasing size of structured data that are digitally available emphasizes the crucial need for more suitable representation tools than the traditional textual list of results. A suitable visual representation should both reflect the database's structure for navigation purpose and allow performing visual analytical tasks for knowledge extraction purpose. In this paper we present a visual navigation method that uses a Galois lattice to represent the database's structure. Our method takes advantage of this structure to provide a progressive and coherent navigation in the database. Two views are jointly presented. The first one represents the overall structure of the database while in the second one more precise views are successively given during the navigation process. Moreover, beyond the navigation task, we aim to propose a visual assistance for more analytical tasks. We show how this representation, combined with data analysis techniques, can be used both for navigation and attribute selection while keeping users' mental map.

**Key words:** Formal Concept Analysis, Information Visualization

## 1 Introduction

The size of digitally available indexed document sets increases every day. However, associated exploring tools are often based on the same traditional model: users send their query and are then answered back with huge lists of results. There is a crucial need for more suitable representation tools where the semantics of the documents are better exploited and may be used as a guideline during navigation through the database. Formal concept analysis (FCA) helps to form conceptual structures from data. Such structures may be used to visualize inherent properties in data sets and to dynamically explore a collection of documents. Indeed the associated mathematical formalization is useful not only to organize the database but also to infer some of the reasoning during the information retrieval process. We aim to propose a visual assistance for more analytical tasks. We show how this representation, combined with data analysis techniques, can be used both for navigation and attribute selection while keeping users' mental map. This paper presents a method that combines FCA and Information visualization techniques to assist visual navigation in large collections.

The following section will present the context of our research. The state of the art is presented in section 4, particularly concerning information retrieval using FCA and visualization techniques to explore large databases. Section 5 develops our method that combines FCA and visualization tools to assist users for browsing a large collection. Section 6 deals with our proposal for visual attribute selection method. The last section concludes with some of the limits to and perspectives of our approach.

## 2 Context and Problem Setting

Searching for technical solutions to improve innovation within big companies, I-Nova, our industrial partner, develops collaborative platforms to internally share some parts of the company’s knowledge. The major problem consists in visualizing and browsing a large collection of indexed documents. The current platform makes use of a classical search engine which lists retrieved indexed documents (patents, here) corresponding to a certain set of keywords. Two main problems arise: human operators cannot have an overall view of the whole collection and they cannot evaluate changes in the result sets when adding or removing a keyword, because a new list is displayed for each new query. These drawbacks are particularly semantically noisy for the browsing process. We may note here that this problem is the same as the one encountered by people using web search engines like Google.

Much research has been done to graphically represent indexed document sets in general [19], of which several aim to represent patent databases. In MultiSOM [13], the keywords are divided into subsets corresponding to different aspects of the indexation (costs, techniques, etc.) and a self-organized map is computed one by one for each subset, presenting different points of view on the database. When focusing on a specific item of the collection on one particular map, the user can switch to another map presenting the position of the item in the collection with respect to another aspect. This solution solves the problem of providing an overall view of the collection. However users have lost the ability of selecting a subset of patents through a set of keywords and they have no information about why one patent is close to another in the overall view.

Because on the one hand browsing an overall view may be unsuitable for focusing on a particular keyword and on the other hand displaying local results without any overall information causes users to get lost, we present in this paper a method that assists users’ navigation from overall to local views. The idea is to “sum up” the collection by coherent local views corresponding to subsets of patents/keywords. These views are ordered as a lattice, defining possible navigation paths that will be suggested to users. The views’ lattice is actually a concept lattice [10]. Using FCA and concept lattice for information retrieval is not new [8] but in these approaches, contents of nodes, i.e. local view, are still displayed as a list of results, retaining all the above mentioned problems. Studies on visualization exploration process have been done but mainly in the medical or scientific imagery domain, focusing more on optical transitions between vi-

sualizations [2] than on semantic aspects of the information that is displayed. Before going further towards the solution that we propose, let us give some basic FCA definitions.

### 3 Formal Concept Analysis Background

In this section we briefly recall FCA basic definitions from [1][10]. A formal context is a triple  $(G, M, I)$  where  $G$  is a set of objects,  $M$  a set of attributes and  $I$  is a binary relation between the objects and the attributes, i.e.  $I \subseteq G \times M$ . For a set  $O \subseteq G$  of objects and a set  $A \subseteq M$  of attributes, we define the set of attributes common to the objects in  $O$ , by  $f : 2^G \rightarrow 2^M$   $f(X) = \{a \in A | \forall o \in X, (o, a) \in I\}$ , the set of objects which have all attributes in  $A$ , by:  $g : 2^M \rightarrow 2^G$   $g(Y) = \{o \in O | \forall a \in Y, (o, a) \in I\}$ . The pair  $(f, g)$  is a Galois connection between  $(2^G, \subseteq)$  and  $(2^M, \subseteq)$ . A formal concept of the context  $(G, M, I)$  is pair  $(O, A)$  with  $O \subseteq G$ ,  $A \subseteq M$  and  $A = f(O)$  and  $O = g(A)$ .  $A$  is called the *intent* and  $O$  the *extent* of the concept  $(A, O)$ . Let  $L$  be the set of concepts of  $(G, M, I)$  and let  $\leq_L$  be a partial order defined as follows:  $(A1, O1) \leq_L (A2, O2) \iff (A1, O1) \leq_L (A2, O2) \iff A1 \subseteq A2 \iff O2 \subseteq O1$ . The pair  $(L, \leq_L)$  is called the Galois lattice or Concept lattice of  $(G, M, I)$ . The simplified extent of a concept  $(O, A)$  is the set of objects which belong to  $O$  and do not belong to any lower concept. In other words, the simplified extent denotes objects that do not have any other attributes than those in  $A$ . In the following we denote indifferently objects as documents or patents and attributes as terms or keywords.

### 4 State of the Art

Searching for a solution to assist the navigation through a large database, we focus particularly on two aspects in the following state of the art: applications that use FCA techniques for information retrieval and visualization techniques that may be used to graphically parse large sets of data.

#### 4.1 Formal Concept Analysis for Information Retrieval

The powerful classification skills of Formal Concept Analysis have found many applications for information retrieval. Some of them have been listed in [16]. Since the early works of [11] on an information retrieval system based on document/term lattices, a lot of research leading to significant results has been done. In [5], Carpineto and Romano argue that, in addition to their classification behaviors for information retrieval tasks, concept lattices can also support an integration of querying and browsing by allowing users to navigate into search results. Nowadays several industrial FCA-based applications like Credo [5] or Mail-Sleuth [9] are available. Mail-Sleuth is an e-mail management system providing classification and query tools based on FCA. This tool allows users to navigate into data and intervene in the term classification by displaying concept lattices. Upstream research has studied the understandability of a lattice

representation by novice users [9]. Image-Sleuth [8] proposes an interactive FCA-based image retrieval system in which subjacent lattices are hidden. Users do not interact with an explicit representation of a lattice. They navigate from one concept to another by adding or removing terms suggested by the system. This ensures a progressive navigation into the lattice.

## 4.2 Visualization Techniques to Browse Large Databases

Graphical solutions for visualizing a mass of abstract information have been studied for several decades, leading to the emergence of the information visualization domain [3]. Even with the use of a visual representation, the navigation into a large collection may not be obvious. Schneiderman has defined a visualization information paradigm called “focus + context” which recommends to first provide an overall view, then to let the user identify an area of interest (focus) and finally to display locally contextual information (context) [17]. Starting from an overall view helps users to maintain a unique mental map but they still have to achieve the focus task on their own.

In the particular case of document visualization, [3] defines two categories of solutions: on the one hand visualizations of the inner structure of a document (WebBook [4]) and on the other hand visualizations of a document collection, e.g. DocCube [14]. The work presented in this paper belongs to this second category which can also be divided into two parts depending on how the structure of the collection is managed. Some tools show this structure by representing clusters of documents (e.g. Grokker) using tiling based visualization techniques such as TreeMaps [12]. Some other tools do not show the collection’s structure and represent the collection by a set of points into two or three dimensions dispatched according to a semantic distance usually based on indexed vectors (e.g. DocCube).

The choice between these two strategies depends on the users’ needs. Showing the structure allows a more progressive navigation through clusters but reduces the probability of visual insight which the observation of similarity distances may offer. We have tried to benefit from both solutions by using the first one for the overall view and the second one for local views (see section 5).

## 4.3 Knowledge Maps and Multidimensional Scaling

The tests and validations of our approach are done through an agent oriented software environment that we developed. MOLAGE (for Molecular Agents) allows visual manipulation of entities using several visual functionalities (zoom, fisheye, semantic lenses, filtering, etc.). Each entity may be typed and described by several attributes (descriptors). The collection of those entities may represent a multimedia database, e.g. music titles described by moods, textual documents characterized by a keywords’ vector, pictures that are classified according to their subject, etc.

Considering the set of descriptors, each entity is characterized in a  $m$  dimensions’

space. The collection is projected onto a 2 dimensional plane using a MultiDimensional Scaling projection (MDS - [15]). The method consists in minimizing a 'stress' function between  $n$  points (originally described in an  $m$ -dimensional space) after those points have been projected onto a space with fewer than  $m$  dimensions. The minimization is performed through the compression or extension of the (Euclidian) distances between the points in the smaller dimension [2]. This type of MDS approach is known as Force Directed Placement or Spring Embedding Algorithm.

We detailed the MOLAGE environment and its use for navigating through a massive music collection in [6]. In this particular application, the musical landscape is used to semi-automatically index new music records just by "drag and drop" of a new entity on the map. It is also used to automatically build musical playlists. However some drawbacks were still present, in particular the lack of assistance for the visual navigation through the map. That is why we proposed to give some semantics to the map and to assist the building of this map in [7]. In the following, we broaden this visual assistance by proposing a method for browsing large databases.

## 5 A Visual Database Browsing Method

Within large databases, it is often possible to distinguish several layers that may be considered separately. Our idea is to keep the human operator's mental map as stable as possible and to give him or her some hints when he or she switches from one view to another one.

### 5.1 Problem Decomposition

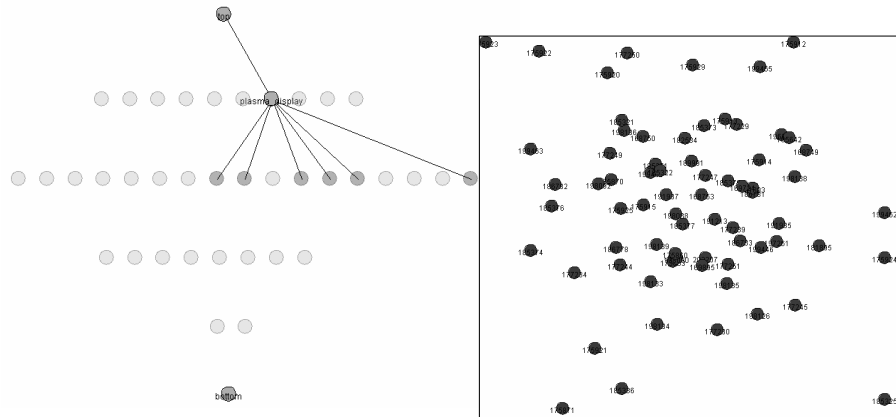
Our approach aims to provide adapted visualizations for different abstraction layers. Information visualization techniques aim to assist the user in a visual inference task. It is very hard to reach a compromise between a strongly analytic strategy displaying results of classification methods on data and a visualization representing more faithfully all raw data. The first approach may be clearer for users but may introduce a bias in their interpretation and preclude insight by hiding unexpected information. The second approach faces the dimensionality problem of visualizing too much information at the same time. Our work proposes to satisfy both approaches by finding a compromise.

We assume that Schneiderman's overview, i.e. the overall view corresponding to the higher abstraction layer, has to emphasize the structure of the document collection because that is where the source of insight may reside at this level. This overview should be used as a kind of GPS for the further navigation into different local views. For the lower abstraction level, i.e. Schneiderman's context views, the aim is to display concrete relations between local data using the most intuitive visualization techniques. In the following we will briefly describe the overall view and then local views. A more detailed presentation can be found in [26].

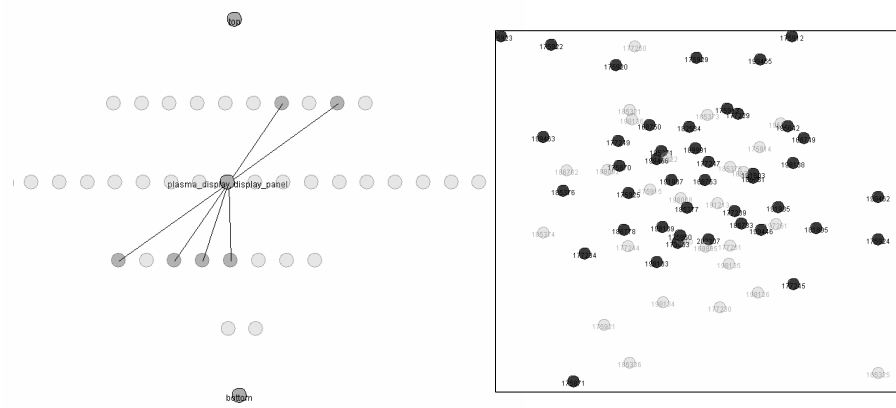
## 5.2 Lattice-based Overview

The concept lattice computed from the document/term (patent/keyword, for us) matrix will be used both as a support for navigation across the collection (as used in Image-Sleuth), and as a visual overview emphasizing its structure. Its related Hasse diagram [18] is displayed using force direct placement techniques (see section 4.2).

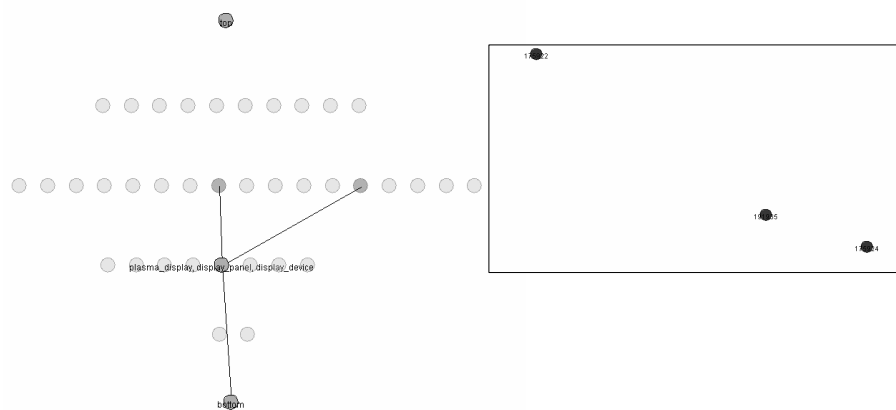
All edges may not be represented as in Fig. 1 (left) to avoid visual overloading. We use a visual device called “topological lenses” [7] to show edges of the selected node and to emphasize nodes reached by these edges. For instance, on Fig. 1, selected node’s intent is *plasmadisplay*. Relied concepts and their intents are emphasized. Since an overview supporting navigation is now provided to users, we will present in the following how a local view associated with a lattice concept is visualized. Beside the overview, a local view is simultaneously displayed which represents the objects contained in the extent of the node that has been selected by the user on the overall view. Hence, an interaction user-case consists in the following steps. First users select a node on the overview (Fig. 1 left), the local view is then updated to display the node’s extent (Fig. 1 right). Secondly users goes deeper in the lattice by selecting a child node of the previous one in the over view (Fig. 2 left), the local view is updated and objects that belong to the previous node’s extent but not to the current node disappear (Fig. 2 right). Fig. 2 illustrates the navigation process. The overall view is a Hasse diagram with nodes represented by circles. The selected node is *plasmadisplay*. The local view is a square containing a dense cluster of nodes, each labeled with a number (e.g., 1.0.1, 1.0.2, etc.).



**Fig. 1.** The selection of a concept on the overall view (*left hand side*) displays patents contained in the concept’s extent (*right hand side*) and suggests navigation paths by emphasizing new concepts on the overall view.

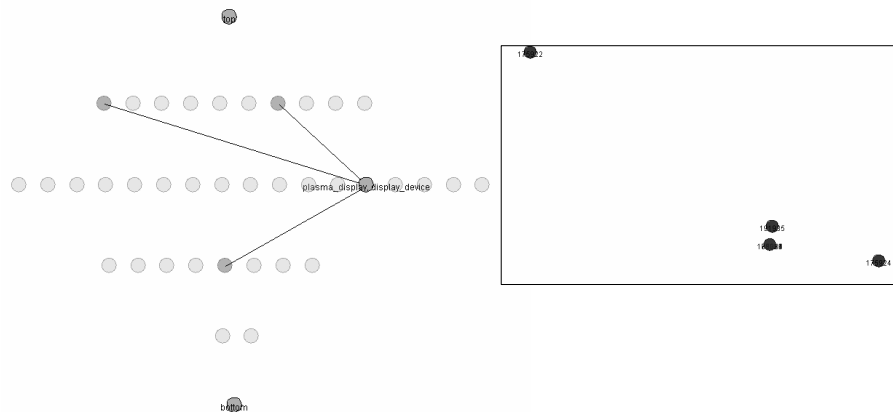


**Fig. 2.** The selection of a concept on the overall view (*left hand side*) displays patents contained in the concept's extent (*right hand side*) and suggests navigation paths by emphasizing new concepts on the overall view.



**Fig. 3.** The selection of a concept on the overall view (*left hand side*) displays patents contained in the concept's extent (*right hand side*) and suggests navigation paths by emphasizing new concepts on the overall view.





**Fig. 4.** The selection of a concept on the overall view (*left hand side*) displays patents contained in the concept’s extent (*right hand side*) and suggests navigation paths by emphasizing new concepts on the overall view.

## 6 Using Concept Lattice for Attribute Selection

This section aims to provide a visual answer to the following question: “*I have identified a set of instances of particular interest in the database. I would like to find its location in the database structure and which attributes have the ability to put these instances together*”. Databases have increased not only in size but also in complexity. [20] reports that while as of 1997 only few papers in the attribute selection community were dealing with domains described by more than 40 attributes, most papers were exploring domains with hundreds to tens of thousands of features five years later. Consequently a preprocess called attribute selection is often needed in order to reduce dimensionality before starting data analysis techniques. It consists in selecting attributes that are relevant according to the future data mining task. Beyond the technical purpose of reducing dimensionality for data mining processes, attribute selection constitutes an interesting process as itself. When used to select attributes that are relevant according to a classification task, its results give information about which attributes can be used to separate or describe classes. Detailed reviews of attribute selection techniques can be found in [20] and [21]. In particular, IGLUE [25] is an instance-based learning system that uses Galois lattices to perform attribute selection. All techniques share the following skeleton which sums up the process in four key steps, namely *subset generation*, *subset evaluation*, *stopping criterion*, and *result validation*. First an attribute subset is generated according to a certain search strategy, the second step evaluates the subset’s relevance and consequently selects or discards the subset, then if the stopping criterion is not satisfied a new subset is generated and the process is repeated. Finally the selected best subset needs to be validated by prior knowledge. Attribute selection is used for many data mining tasks, we will focus on its application for classification.

Our attribute selection process is supervised. It means that the objects' membership to the considered class is known *a priori*. This prior knowledge may come from an additional class attribute or from an additional numerical attribute with a threshold value. These additional attributes do not belong to the formal context, and thus are not involved in the lattice computation, because we assume that attributes used to build the lattice reflect the persistent database structure, while class membership attributes are related to a particular exploitation of the database. Objects are partitioned into two classes with respect to an additional class attribute, positive (objects that belong to the class) and negative objects and we propose to use the database's lattice to perform attribute selection. The search strategy consists in browsing the Galois lattice using breadth-first traversal from top to bottom, the generated subset being the current node's intent. The intent is evaluated considering the value for Shannon's entropy on the current node's extent. The entropy will be minimal if all objects in the extent belong to the same class. If entropy is below a given threshold and most of the objects in extent positive, the intent is selected. The stopping criterion is satisfied when all nodes have been evaluated. Finally, selected intents are emphasized on the lattice's representation, creating navigation paths in the lattice.

### 6.1 Subset Generation

Considering a context with  $n$  attributes, there exist  $2^n$  candidate subsets. An exhaustive search is therefore computationally prohibitive. In order to reduce the search space, two main strategies have been designed: complete and sequential search. Complete search strategies, such as *branch and bound*, ensures that all optimal subsets will be explored. The space search is still in  $O(2^n)$  but in practice fewer subsets are explored. Concerning sequential search strategies, mostly based on the greedy hill climbing approach, they explore a search space in  $O(n^2)$  or less but completeness is not guaranteed. Randomness may be introduced in sequential approaches in order to avoid local optima. Since our main goal is to maintain users' mental map and thus to use the same visual structure, the lattice, for both navigation and display of attribute selection results, we use the lattice as the search space. The explored subsets are the nodes' intents. The number of explored subsets is then the size of the lattice, i.e.  $O(2^{\min(|A|, |O|)})$ . In practice the size of the lattice is smaller since only attribute subsets that are meaningful according to the two closure operators lead to the creation of a node.

### 6.2 Subset Evaluation

Shannon entropy [22] is used to evaluate the relevance of a node's intent. It measures the ability of the intent to discriminate the positive with the negative objects that appear in the node's extent. Note that this evaluation does not take into account the number of objects in the extent. Therefore nodes containing very few objects may be selected. Formally, considering a node  $(A_1, O_1)$  its associated

entropy is computed as follows:

$$H(A_1, O_1) = - \left( \frac{|O_1^+|}{|O_1|} \cdot \log_2 \left( \frac{|O_1^+|}{|O_1|} \right) + \frac{|O_1^-|}{|O_1|} \cdot \log_2 \left( \frac{|O_1^-|}{|O_1|} \right) \right)$$

where  $|O_1^+|$  (resp.  $|O_1^-|$ ) is the number of positive (resp. negative) objects in the extent. A null entropy occurs when objects in the extent are either all positive or all negative. Since the goal is to select attributes according to the class, i.e. according to positive attributes, a node is said optimal if its entropy is below a given threshold  $\alpha$  and if positive objects represent more than half of the extent, formally:  $(A_1, O_1)$  is optimal if  $H(A_1, O_1) \leq \alpha$  and  $\frac{|O_1^+|}{|O_1|} > \frac{1}{2}$ . In the following example, we set  $\alpha = 0$ . Note that if  $H(A_1, O_1) = 0$  then  $\frac{|O_1^+|}{|O_1|} > \frac{1}{2} \Leftrightarrow O_1^- = \emptyset$ .

### 6.3 Example

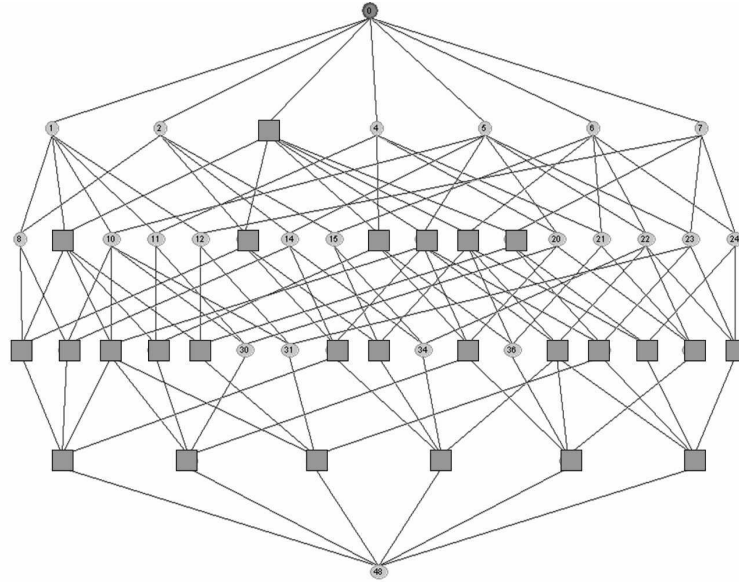
This section illustrates the attribute selection process on a small example taken from UCI Repository [24]. The lenses data set [23] contains 24 instances and four nominal attributes. An instance is a patient profile described by the four attributes *age*, *spectacle prescription*, *astigmatism*, and *tear-drop rate*, i.e. factors that have to be taken into account in the choice of a type of contact lenses for a particular patient

A fifth attribute, *decision*, gives for each profile the recommended type of lenses: *hard*, *soft*, or *none*, dividing patient profiles into three classes. The scenario applied on this example consists in identifying which of the four medical factors are associated with the decision to contraindicate contact lenses. A nominal scale is applied in order to discretize the four attributes. The resulting formal context has seven binary attributes, namely *age:young*, *age:pre-presbyopic*, *age:presbyopic*, *prescription:myope*, *prescription:hypermetrope*, *astigmatism*, and *tear-drop:reduced*. We assume that these binary attributes reflect the persistent structure of the database and the associated Galois lattice, computed using GALICIA, has 50 nodes. Positive objects are those which have the value *none* for the additional attribute *decision*, negative ones are the others. Figure 5 shows the resulting lattice where square nodes denote optimal nodes with null entropy. During the breadth-first traversal, the first optimal node found is the third node on the first level. Its intent is  $A_1 = \{tear - drop : reduced\}$  and its extent  $O_1$  contains 12 positive objects and no negative one. Its associated entropy is then:

$$H(A_1, O_1) = - \left( \frac{12}{12} \cdot \log_2 \left( \frac{12}{12} \right) + \frac{0}{12} \cdot \log_2 \left( \frac{0}{12} \right) \right) = 0$$

assuming that  $\log_2 0 = 0$  by applying L'Hôpital's rule. The fact that the node  $(A_1, O_1)$  is optimal can be interpreted as: "only positive objects own  $A_1$ ". In the present case it means that "only positive objects own  $\{tear - drop : reduced\}$ ", or in other words  $\forall o \in O, \{tear - drop : reduced\} \in f(o) \Rightarrow o \in O^+$ . If  $O^+ - O_1 = \emptyset$ , i.e. if all positive objects belong to the optimal node's extent, the converse is also satisfied.

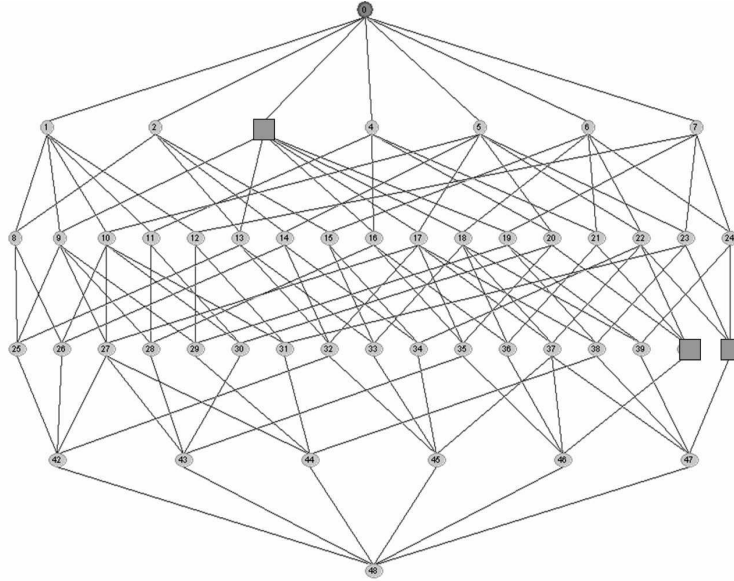
An interesting point is that, thanks to the Galois lattice structure, all the child nodes of an optimal node are also optimal. Hence, considering two concepts  $(A_2, O_2) \leq_L (A_1, O_1)$ , if  $(A_1, O_1)$  is optimal then  $O_1 \subseteq O^+$ . Since  $O_2 \subseteq O_1$  thanks to  $\leq_L$  we have  $O_2 \subseteq O^+$ . When an optimal node is found, this result allows to discard all its child nodes from the search space.



**Fig. 5.** Galois Lattice computed from the contact-lenses database binary context. Square nodes are optimal and their intents form the resulting selected attribute subsets with respect to the *no lenses* class.

#### 6.4 Results Interpretation and Association Rules

The resulting lattice answers the original question: “*where are my instances of interest in the database structure and what are the related relevant attributes?*”. Users can see at first sight how considered instances are dispatched with respect to the database structure representation used for navigation. Related attribute subsets are the emphasized nodes’ intents. Optimal nodes can also be interpreted as association rules between their intent and the class membership. These rules have a maximal confidence since all objects in optimal nodes are positive. Their support is the number of objects in the extent. Note that thanks to the lattice based representation, users can identify optimal nodes with best supports with respect to their relative position. Hence, considering two optimal nodes  $(A_2, O_2) \leq_L (A_1, O_1)$  and their related rules  $c_2 : A_2 \rightarrow class$  and  $c_1 : A_1 \rightarrow class$ ,



**Fig. 6.** Galois Lattice computed from the contact-lenses database binary context. Square nodes are optimal and their intents form the resulting selected attribute subsets with respect to the *no lenses* class.

then  $support(c2) \leq support(c1)$  since  $|O_2| \leq |O_1|$ . Also note that  $c_2$  is redundant compared to  $c_1$  since  $A_2 \subseteq A_1$ .

Since child nodes of an optimal node are also optimal, when an optimal node appears in the first levels like in the present example, the resulting lattice may be overcrowded by redundant square nodes. It is not visually easy to separate these redundant nodes from those that are not children of a higher optimal node. For this reason we propose to emphasize optimal nodes that are not children of an optimal node (see Fig. 6). Only three optimal nodes remain: one node on the first level which intent is  $\{tear-drop:reduced\}$  and two nodes on the third level which respective intents are  $\{age:pre-presbyopic, astigmatism, prescription:hypermetrope\}$  and  $\{age:presbyopic, astigmatism, prescription:hypermetrope\}$ . These two last nodes were hidden among child nodes of the first one in Fig. 5. Finally, the attribute selection process visually provides to users the following results: the patient profiles for which contact lenses are contraindicated are either those who have a reduced tear-drop rate or those whose have one of the two particular attributes combination listed above.

## 7 Conclusion

This paper has presented a method for visual navigation in databases combining classification behaviors of FCA to produce overviews and intuitive visualization techniques when focusing on local views. Our method uses a Galois lattice to

represent the database's structure. Our goal was to preserve an unique overall representation of the database which could be suitable both for users that want to perform free exploration without knowing precisely what they want or how to get it, and for users that want to extract information according to a specific subset of the database. Research presented in this paper only deals with assisting users in their navigation or in interpreting results of an attribute selection process, and it does not actually infer information that present techniques would not be able to infer. This is a proper problem of information visualization. Indeed, noticing Robert Spence's definitions "*to visualize is to form a mental model or mental image of something. Visualization is a human cognitive activity, not something that a computer does*", our goal is not to produce formal results from raw data because data analysis techniques such as FCA succeed without any visualization need. We try to explore new techniques to provide bootstraps for the cognitive activity of users.

## References

1. Barbut, M., Monjardet, B.: *Ordre et Classification: Algèbre et Combinatoire*. Hachette, Paris (1970)
2. Buja, A. and Swayne, D.F.: Visualization Methodology for Multidimensional Scaling. In *Journal of Classification* vol. 19, n 1 (2002) 7-43
3. Card, S. K., Mackinlay, J. D. and Shneiderman, B.: *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann Publishers (1999)
4. Card S. K., Hong L., Mackinlay J. D., Chi E. H.: *3Book: a scalable 3D virtual book*, CHI'04 extended abstracts on Human factors in computing systems, Vienna, Austria, ACM Press, (2004)
5. Carpineto, C., Romano, G.: Exploiting the Potential of Concept Lattices for Information Retrieval with CREDO. In: *Journal of Universal Computing*, vol. 10, n8 (2004) 985-1013
6. Crampes, M., Ranwez, S., Velickovski, F., Mooney, C., Mille, N.: An integrated visual approach for music indexing and dynamic playlist composition, 13th Annual Multimedia Computing and Networking (MMCN'06), San Jose, CA, US. (2006)
7. Crampes, M., Ranwez, S., Villerd, J., Velickovski, F., Mooney, C., Emery, A., Mille, N.: Concept Maps for Designing Adaptive Knowledge Maps. In *Concept Maps, A Special Issue of Information Visualization*, vol. 5, n 3, Guest Editors: S.-O. Tergan, T. Keller and R. Burkhard, Palgrave - Macmillan, (2006)
8. Ducrou, J., Vormbrock, B., Eklund, P.: FCA-based Browsing and Searching of a Collection of Images. In: *Proceedings of the 14th International Conference on Conceptual Structures*. LNAI 4068, Springer Verlag (2006) 203-214
9. Eklund, P., Ducrou, J., Brawn, P.: Concept Lattices for Information Visualization: Can Novices Read Line Diagrams? In: P. Eklund (Ed.), *Concept Lattices: Second International Conference on Formal Concept Analysis*, LNCS 2961. Berlin: Springer, (2004) 14-27
10. Ganter, B., Wille, R.: *Formal Concept Analysis: Mathematical Foundations*. Springer, Berlin (1999)
11. Godin, R., Gecsei, J., Pichet, C.: Design of Browsing Interface for Information Retrieval. In N. J. Belkin, C. J. van Rijsbergen (Eds.), *Proc.SIGIR '89*, (1989) 32-39

12. Johnson, B., Schneiderman, B.: Tree-Maps: a Space-Filling Approach to the Visualization of Hierarchical Information Structures. In Proceedings of the Second IEEE Conference on Visualization, IEEE Computer Society Press, Los Alamitos, CA (1991) 284-291
13. Lamirel, J., Al Shehabi, S.: MultiSOM: A Multiview Neural Model for Accurately Analyzing and Mining Complex Data. In: Proceedings of the Fourth international Conference on Coordinated and Multiple Views in Exploratory Visualization, IEEE Computer Society, Washington, DC (2006) 42-54
14. Mothe J., Chrisment C., Dousset B., Alaux J.: DocCube: Multi-Dimensional Visualisation and Exploration of Large Document Sets, Journal of the American Society for Information Science and Technology, JASIST, Special topic section: web retrieval and mining, vol. 7, (2003) 650-659
15. Platt, J.C.: FastMap, MetricMap, and Landmark MDS are all Nystrom Algorithms. 10th International Workshop on Artificial Intelligence and Statistics (2005) 261-268
16. Priss, U.: Formal Concept Analysis in Information Science. In: Annual Review of Information Science and Technology, vol. 40. American Society for Information Science, Washington, DC (2006) 521-543
17. Schneiderman, B.: The Eyes have it: a Task by Data Type Taxonomy for Information Visualizations. In: Proceedings of the IEEE Symposium on Visual Languages. (1996) 336-343
18. Tollis I.G.: Graph drawing and information visualization, ACM Computing Surveys., vol. 28, n 4, (1996)
19. Tricot, C., Roche, C., Foveau, C.E., Reguigui, S.: Cartographie Smantique de Fonds Numriques Scientifiques et Techniques. In: Document Numrique, vol. 9, n 2, (2006) 13-36
20. Guyon, I., Elisseeff, A.: An Introduction to Variable and Feature Selection. Journal of Machine Learning Research 3, 1157-1182 (2003)
21. Liu, H., Yu, L.: Towards Integrating Feature Slection Algorithms for Classification and Clustering. IEEE Transactions on Knowledge and Data Engineering 17, 491-502 (2005)
22. Shannon, C.E.: A Mathematical Theory of Communication. Bell System Technical Journal 27, 379-423 623-656 (1948)
23. Cendrowska, J.: PRISM: An Algorithm for Inducing Modular Rules. International Journal of Man-Machine Studies 27, 349-370 (1987)
24. UC Irvine Machine Learning Repository, <http://archive.ics.uci.edu/ml/>
25. Nguifo, E.M., Njiwoua, P., IGLUE: A lattice-based constructive induction system. Intelligent Data Analysis 5, 73-91 (2001)
26. Villerd, J., Ranwez S., Crampes M., Carteret, D.: Using Concept Lattices for Visual Navigation Assistance in Large Databases: Application to a Patent Database. In: Fifth International Conference on Concept Lattices and Their Applications, pp. 88-99. (2007)