Using FCA for Seeking Relevant Information Sources

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Abstract. In this paper, we present using formal concept analysis (FCA) for seeking relevant informational sources from many textual resources. The method is based on explications of an atomic concept formalized as constructions of Transparent Intensional Logic (TIL). In this paper we assume, that all explications have been already done and just shown how FCA can be used as a background of text source recommendation.

1 Introduction

This paper deals with another technique which is possible to use for selecting possibly interesting text sources from a given set of text documents. Whole process is based on applying theory of machine learning and concept explication. Because we needed formalise the sentences in natural languages to some formal language, we decided to use strong system of Transparent intensional logic [1].

In prior papers [2], [3] we introduced methods for selecting relevant text sources. All methods are based o machine learning introduced in [4] and concept explication introduced in [5].

In this paper we also use previous results published in [4] and [5] but the theory of FCA is used for searching other possible relevant text sources. As a comparison with other methods we will present our results by same explications presented in [2] where we use association rules for source recommendation.

In chapter 2 we briefly mention the problem of concept explication which is important for next data processing. In chapter 3 we introduce the theory of Formal concept analysis and *relevant ordering*. Chapter 4 shows the particular example how to apply our method.

2 Explication of an atomic concept

Since we are dealing with natural language processing, we use TIL as our background theory. TIL allows us to formalize salient semantic features of natural language in a fine-grained way. For more details see [1].

By combining TIL and machine learning, we explicate atomic concepts for the purpose of understanding them and for retrieval of additional useful

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information. *Carnapian explication*[1] is a process of refinement of an ambiguous or vague expression. The expression, to be refined, is called an *explicandum*; its refinement, obtained by the explication, is called an *explicatum*. For example, a simple expression such as a dog (explicandum) can be refined as "*Dog is adomesticated carnivore*" (explicatum). In terms of TIL, the explicandum is an atomic concept, i.e. an atomic closed construction. The explicatum is a molecular construction defining the explicandum. We also say that the molecular concept is an ontological definition of the object falling under the atomic concept.

For example:

$$^0Dog =_{df} \lambda w \lambda t \lambda x\, [[^0Domesticated\ \ ^0Carnivore]_{wt}\, x]$$

Types: $Domesticated/((o\iota)_{wt}(o\iota)_{wt}); Dog, Carnivore/(o\iota)_{wt}; x \to \iota$

Such explication such as one above we obtained by an algorithm we introduced in [2]. The algorithm exploits symbolic method of supervised machine learning adjusted to natural language processing.The input of the algorithm are sentences in natural language mentioning the expression to be explicated formalised as TIL constructions.

The algorithm, based on Patrick Winston's work [7], iteratively builds the explicatum using the constructions marked as positive or negative examples. With positive examples, we refine the explicatum by inserting new constituents into molecular the construction or we generalize the expliactum so it can adequately define the explicandum. With negative exmples, we specialize the explicatum by inserting new constituents in negated way. By those constituents we differentiate the expliacum of our expression from similar expression's explicatum.

3 FCA and relevant ordering

Formal Conceptual Analysis[2] (FCA) was introduced in 1980s by group lead by Rudolf Wille and became a popular technique within the information retrieval field. FCA has been applied in many disciplines such as software engineering, machine learning, knowledge discovery and ontology construction. Informally, FCA studies how objects can be hierarchically grouped together with their mutual common attributes.

Definition 1. *Let (G, M, I) be a formal context, then $\beta(G, M, I) = \{(O, A)|O \subseteq G, A \subseteq M, A^{\downarrow} = O, O^{\uparrow} = A\}$ is a set of all formal concepts of context (G, M, I) where $I \subseteq G \times M, O^{\uparrow} = \{a|\forall o \in O, (o, a) \in I\}, A^{\downarrow} = \{o|\forall a \in A, (o, a) \in I\}$. $A^{\downarrow}$ is called* ***extent*** *of formal concept (O,A) and $O^{\uparrow}$ is called* ***intent*** *of formal concept (O, A).*

Definition 2. ***Significant objects*** *of object **e** in $\beta(G, M, I)$ is set $SO(e) = \bigcup_{i=1}^{n} O_i^e$, where O^e is extent of a concept $(O, A) \neq (G, B), e \in O, B \subseteq M$. Namely, significant objects of object **e** is union of all extents where the object **e** is as an element.*

[1] See [6]

[2] More in [8].

Definition 3. *Let $SO(e)$ is a set of significant objects of an object* $\mathbf{e}$*, let $\gamma(e)$ is a set of concepts (O, A) where $e \in O$,i.e.: $\gamma(e) = \{(O^e, (O^e)^{\uparrow}) | (O^e, (O^e)^{\uparrow}) \neq (G, B), B \subseteq M, (O^e, (O^e)^{\uparrow}) \in \beta(G, M, I)\}$, then* $\boldsymbol{a} \sqsubseteq \boldsymbol{b}$ *is in* ***relevant ordering***[3] *iff $max(|(O^a)^{\uparrow}|) \leq max(|(O^b)^{\uparrow}|), a, b, \in SO(e), (O^a, (O^a)^{\uparrow}), (O^b, (O^b)^{\uparrow}) \in \gamma(e)$.*

Example: Let have a formal context described by the following Table 1.

Table 1. Formal context

O/A	a_0	a_1	a_2	a_3
o_0	1	1	0	0
o_1	0	1	1	0
o_2	0	0	1	1

The set of all *formal concepts* $\beta(G, M, I) = \{C_0, C_1, C_2, C_3, C_4, C_5, C_6, \}$, where $C_0 = (\{o_0, o_1, o_2\}, \emptyset), C_1 = (\{o_0, o_1\}, \{a_1\}), C_2 = (\{o_0\}, \{a_0, a_1\}), C_3 = (\{o_1, o_2\}, \{a_2\}), C_4 = (\{o_1\}, \{a_1, a_2\}), C_5 = (\{o_2\}, \{a_2, a_3\}), C_6 = (\emptyset, \{a_0, a_1, a_2, a_3\})$

Get the set of *significant objects* of object o_2**,** $SO(o_2)$:

1. Find set $\gamma(o_2) \rightarrow \gamma(o_2) = \{(\{o_1, o_2\}, \{a_2\}), (\{o_2\}, \{a_2, a_3\})\}$
2. Find all *extents* O_i from $\beta(G, M, I)$ where $O_i \neq G$ and $o_2 \in O_i \rightarrow O_1^{o_2} = \{o_2\}, O_2^{o_2} = \{o_1, o_2\}$
3. Create the union of all extents found in step 2 $\rightarrow SO(o_2) = \{o_1, o_2\}$

Find *relevant ordering* of $SO(o_2)$

1. For all $x \in SO(o_2)$ calculate max of $|(O^x)^{\uparrow}|$, where $((O^x), (O^x)^{\uparrow}) \in \gamma(o_2) \rightarrow max(|(O^{o_1})^{\uparrow}|) = 1, max(|(O^{o_2})^{\uparrow}|) = 2$
2. Order $SO(o_2)$ by definition 3 $\rightarrow o_1 \sqsubseteq o_2$

Table 2. Relevant object ordering

Exp.	Intent	DF	RT
o_2	$\{a_2, a_3\}$	$\{\}$	-
o_1	$\{a_2\}$	$\{a_3\}$	-

In our table the column DF represents the difference from the selected object (first row in table - o_2). The column RT will represent the document which is represented by the particular object in column Exp.

Remark: In our study, every object represents one explication of a particular natural language concept. From that point of view, the set of all constituents (row in a table) represents *intent* of a particular formal concept. There exist a formal concept $(\{e\}, \{e\}^{\uparrow})$ for each explication e.

[3] Classical concept ordering is defined as: $(O, A) \sqsubseteq (O_1, A_1)$ iff $A \subseteq A_1$

4 Demonstration on example

As an example of recommending relevant information sources based on FCA, we use the same data we used in [2]. In our example we used text sources dealing with a concept *wild cat*. We obtained 8 explicates of the concept from different textual sources ($s_1, ..., s_8$). That means that each explication describes the concept of *being a wild cat* from other point of view. Those explications are following:

$$e_1 = ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['\leq ['Weight_{wt}\ x]\ '11] \wedge ['\geq ['Weight_{wt}\ x]\ '1.2]]['Wild\ 'Cat]] \wedge ['Req\ 'Mammal\ ['Wild\ 'Cat]] \wedge ['Req\ 'Has\text{-}fur\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['\leq [['Average\ 'Body\text{-}Length]\ x]\ '80] \wedge ['\geq [['Average\ 'Body\text{-}Length]\ x]\ '47]]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['= [['Average\ 'Skull\text{-}Size]\ x]\ '41.25]]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['= [['Average\ 'Height]\ x]\ '37,6]]['Wild\ 'Cat]]$$

$$e_2 = ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['Live\text{-}in_{wt}\ [\lambda w \lambda t \lambda y[[['Mixed\ 'Forrest]_{wt}\ y] \vee [['Deciduous\ 'Forrest]_{wt}\ y]]]]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['\geq ['Territory\text{-}Size_{wt}\ x]\ '50]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['Ter\text{-}Marking_{wt}\ x\ 'Clawing] \vee ['Ter\text{-}Marking_{wt}\ x\ 'Urinating] \vee ['Ter\text{-}Marking_{wt}\ x\ 'Leaves\text{-}Droppings]]['Wild\ 'Cat]]$$

$$e_3 = ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['\leq ['In\text{-}Heat\text{-}Periodwt\ x]\ '8] \wedge ['\geq ['In\text{-}Heat\text{-}Periodwt\ x]\ '2]]\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['Seek_{wt}\ x\ 'Mate\ ['Loud\ 'Meow]]\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['= ['Pregnancy\text{-}Periodwt\ x]\ '65]\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['\leq ['Litter\text{-}Size_{wt}\ x]\ '4] \wedge ['\geq ['Litter\text{-}Size_{wt}\ x]\ '3]]\ ['Wild\ 'Cat]]$$

$$e_4 = ['Req\ 'Mammal\ ['Wild\ 'Cat]] \wedge ['Req\ 'Has\text{-}fur\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['= [['Average\ 'Skull\text{-}Size]\ x]\ '41.25]]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['Ter\text{-}Marking_{wt}\ x\ 'Clawing] \vee ['Ter\text{-}Marking_{wt}\ x\ 'Urinating] \vee ['Ter\text{-}Marking_{wt}\ x\ 'Leaves\text{-}Droppings]]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['= ['Pregnancy\text{-}Periodwt\ x]\ '65]\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['\leq ['Litter\text{-}Size_{wt}\ x]\ '4]\ ['Wild\ 'Cat]]$$

$$e_5 = ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['\geq [['Average\ 'Body\text{-}Length]\ x]\ '47]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['Ter\text{-}Marking_{wt}\ x\ 'Clawing] \vee ['Ter\text{-}Marking_{wt}\ x\ 'Urinating] \vee ['Ter\text{-}Marking_{wt}\ x\ 'Leaves\text{-}Droppings]]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['= ['Pregnancy\text{-}Periodwt\ x]\ '65]\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['\leq ['Litter\text{-}Size_{wt}\ x]\ '4]\ ['Wild\ 'Cat]]$$

$$e_6 = ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['\geq [['Average\ 'Body\text{-}Length]\ x]\ '47]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x[['Ter\text{-}Marking_{wt}\ x\ 'Clawing] \vee ['Ter\text{-}Marking_{wt}\ x\ 'Urinating] \vee ['Ter\text{-}Marking_{wt}\ x\ 'Leaves\text{-}Droppings]]['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['Seek_{wt}\ x\ 'Mate\ ['Loud\ 'Meow]]\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['\leq ['Litter\text{-}Size_{wt}\ x]\ '4]\ ['Wild\ 'Cat]]$$

$$e_7 = ['Req\ 'Mammal\ ['Wild\ 'Cat]] \wedge ['Req\ 'Has\text{-}fur\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['\leq ['Weight_{wt}\ x]\ '11]\ ['Wild\ 'Cat]] \wedge ['Typ\text{-}p\ \lambda w \lambda t\ \lambda x['Live\text{-}in_{wt}\ [\lambda w \lambda t \lambda y[[['Mixed\ 'Forrest]_{wt}\ y] \vee$$

$[[{}^{\prime}Deciduous\ {}^{\prime}Forrest]_{wt}\ y]]]][{}^{\prime}Wild\ {}^{\prime}Cat]] \wedge [Typ\text{-}p\ \lambda w \lambda t\ \lambda x[[{}^{\prime}Ter\text{-}Marking_{wt}\ x\ {}^{\prime}Clawing] \vee [{}^{\prime}Ter\text{-}Marking_{wt}\ x\ {}^{\prime}Urinating] \vee [{}^{\prime}Ter\text{-}Marking_{wt}\ x\ {}^{\prime}Leaves\text{-}Droppings]][{}^{\prime}Wild\ {}^{\prime}Cat]] \wedge [Typ\text{-}p\ \lambda w \lambda t\ \lambda x[{}^{\prime}Seek_{wt}\ x\ {}^{\prime}Mate\ [{}^{\prime}Loud\ {}^{\prime}Meow]]\ [{}^{\prime}Wild\ {}^{\prime}Cat]] \wedge [Typ\text{-}p\ \lambda w \lambda t\ \lambda x[{}^{\prime}= [{}^{\prime}Pregnancy\text{-}Periodwt\ x]\ {}^{\prime}65]\ [{}^{\prime}Wild\ {}^{\prime}Cat]]$

$e_8 = [Typ\text{-}p\ \lambda w \lambda t\ \lambda x[{}^{\prime}\geq [[{}^{\prime}Average\ {}^{\prime}Body\text{-}Length]\ x]\ {}^{\prime}47]\ [{}^{\prime}Wild\ {}^{\prime}Cat]] \wedge [\lambda w \lambda t \lambda x[{}^{\prime}\geq [{}^{\prime}Territory\text{-}Size_{wt}\ x]\ {}^{\prime}50][{}^{\prime}Wild\ {}^{\prime}Cat]] \wedge [Typ\text{-}p\ \lambda w \lambda t\ \lambda x[{}^{\prime}\leq [{}^{\prime}Litter\text{-}Size_{wt}\ x]\ {}^{\prime}4]\ [{}^{\prime}Wild\ {}^{\prime}Cat]]$

After obtaining all explications the user selects one of them which is the most relevant from his point of view. In our case e_1. The whole process of recommendation starts after the explication selection.

From explications mentioned above, we make an incidence matrix written in Table 3.

Each row represents one explication and each column represents particular property. The value 1 represent that the explication contains the property, value 0 represents that the explication doesn't have the property.

The $e_1, ..., e_8$ are identifiers of the explications.

Table 3. Formal context of explications

O/A	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
$\mathbf{e_1}$	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
$\mathbf{e_2}$	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
$\mathbf{e_3}$	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
$\mathbf{e_4}$	1	1	0	0	0	0	1	0	0	0	1	0	0	0	1	1	0
$\mathbf{e_5}$	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	1	0
$\mathbf{e_6}$	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	1	0
$\mathbf{e_7}$	1	1	1	0	0	0	0	0	1	0	1	0	0	1	1	0	0
$\mathbf{e_8}$	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0

The columns' numbers in Table 3 represent the following attributes:

1. ${}^{\prime}Mammal$
2. ${}^{\prime}Has-fur$
3. $\lambda w \lambda t \lambda x[{}^{\prime}\leq [{}^{\prime}Weight_{wt}\ x]\ {}^{\prime}11]$
4. $\lambda w \lambda t \lambda x[{}^{\prime}\geq [{}^{\prime}Weight_{wt}\ x]\ {}^{\prime}1.2]$
5. $\lambda w \lambda t \lambda x[{}^{\prime}\geq [[{}^{\prime}Average\ {}^{\prime}Body\text{-}Length]\ x]\ {}^{\prime}47]$
6. $\lambda w \lambda t \lambda x[{}^{\prime}\leq [[{}^{\prime}Average\ {}^{\prime}Body\text{-}Length]\ x]\ {}^{\prime}80]$
7. $\lambda w \lambda t \lambda x[{}^{\prime}= [[{}^{\prime}Average\ {}^{\prime}Skull\text{-}Size]\ x]\ {}^{\prime}41.25]$
8. $\lambda w \lambda t \lambda x[{}^{\prime}= [[{}^{\prime}Average\ {}^{\prime}Skull\text{-}Height]\ x]\ {}^{\prime}37.6]$
9. $\lambda w \lambda t \lambda x [{}^{\prime}Live\text{-}in_{wt}\ [\lambda w \lambda t \lambda y[[[{}^{\prime}Mixed\ {}^{\prime}Forrest]_{wt}\ y] \vee [[{}^{\prime}Deciduous\ {}^{\prime}Forrest]_{wt}\ y]]]]$
10. $\lambda w \lambda t \lambda x[{}^{\prime}\geq [{}^{\prime}Territory\text{-}Size_{wt}\ x]\ {}^{\prime}50]$
11. $\lambda w \lambda t \lambda x[[{}^{\prime}Ter\text{-}Marking_{wt}\ x\ {}^{\prime}Clawing] \vee [{}^{\prime}Ter\text{-}Marking_{wt}\ x\ {}^{\prime}Urinating] \vee [{}^{\prime}Ter\text{-}Marking_{wt}\ x\ {}^{\prime}Leaves\text{-}Droppings]]$
12. $\lambda w \lambda t \lambda x[{}^{\prime}\leq [{}^{\prime}In\text{-}Heat\text{-}Periodwt\ x]\ {}^{\prime}8]$
13. $\lambda w \lambda t \lambda x[{}^{\prime}\geq [{}^{\prime}In\text{-}Heat\text{-}Periodwt\ x]\ {}^{\prime}2]$
14. $\lambda w \lambda t \lambda x[{}^{\prime}Seek_{wt}\ x\ {}^{\prime}Mate\ [{}^{\prime}Loud\ {}^{\prime}Meow]]$
15. $\lambda w \lambda t \lambda x[{}^{\prime}= [{}^{\prime}Pregnancy\text{-}Periodwt\ x]\ {}^{\prime}65]$
16. $\lambda w \lambda t \lambda x[{}^{\prime}\leq [{}^{\prime}Litter\text{-}Size_{wt}\ x]\ {}^{\prime}4]$
17. $\lambda w \lambda t \lambda x[{}^{\prime}\geq [{}^{\prime}Litter\text{-}Size_{wt}\ x]\ {}^{\prime}3]$

From Table 3, we obtained following concepts by using FCA:

0. $(\{e_1, e_2, e_3, e_4, e_5, e_6, e_7, e_8\}, \emptyset)$
1. $(\{e_1, e_4, e_7\}, \{1, 2\})$
2. $(\{e_1, e_4\}, \{1, 2, 7\})$
3. $(\{e_1, e_5, e_6, e_8\}, \{5\})$
4. $(\{e_1, e_7\}, \{1, 2, 3\})$
5. $(\{e_1\}, \{1, 2, 3, 4, 5, 6, 7, 8\})$
6. $(\{e_2, e_4, e_5, e_6, e_7\}, \{11\})$
7. $(\{e_2, e_7\}, \{9, 11\})$
8. $(\{e_2, e_8\}, \{10\})$
9. $(\{e_2\}, \{9, 10, 11\})$
10. $(\{e_3, e_4, e_5, e_6, e_8\}, \{16\})$
11. $(\{e_3, e_4, e_5, e_7\}, \{15\})$
12. $(\{e_3, e_4, e_5\}, \{15, 16\})$
13. $(\{e_3, e_6, e_7\}, \{14\})$
14. $(\{e_3, e_6\}, \{14, 16\})$
15. $(\{e_3, e_7\}, \{14, 15\})$
16. $(\{e_3\}, \{12, 13, 14, 15, 16, 17\})$
17. $(\{e_4, e_5, e_6\}, \{11, 16\})$
18. $(\{e_4, e_5, e_7\}, \{11, 15\})$
19. $(\{e_4, e_5\}, \{11, 15, 16\})$
20. $(\{e_4, e_7\}, \{1, 2, 11, 15\})$
21. $(\{e_4\}, \{1, 2, 7, 11, 15, 16\})$
22. $(\{e_5, e_6, e_8\}, \{5, 16\})$
23. $(\{e_5, e_6\}, \{5, 11, 16\})$
24. $(\{e_5\}, \{5, 11, 15, 16\})$
25. $(\{e_6, e_7\}, \{11, 14\})$
26. $(\{e_6\}, \{5, 11, 14, 16\})$
27. $(\{e_7\}, \{1, 2, 3, 9, 11, 14, 15\})$
28. $(\{e_8\}, \{5, 10, 16\})$
29. $(\emptyset, \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17\})$

Conceptual lattice of obtained formal concepts is visualised in Fig. 1. Dark nodes represent concepts which *extent* contains only *significant objects*. The nodes with bright numbers represent the particular explications.

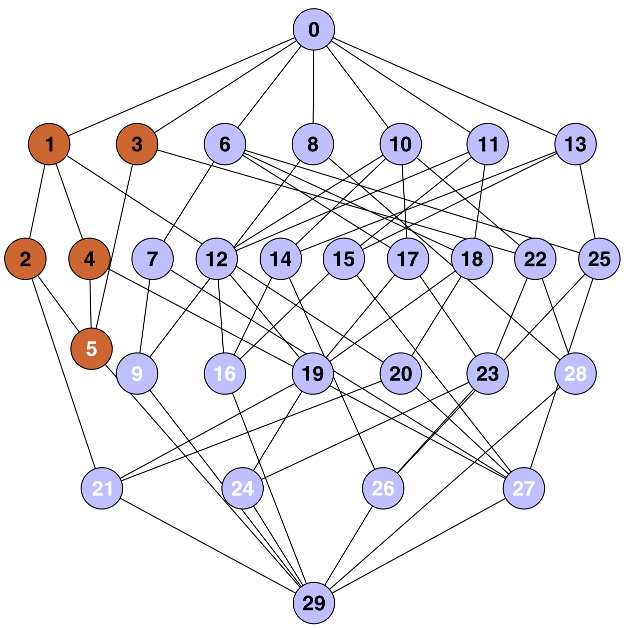

Fig. 1. Lattice of formal concepts

Significant objects of object (explication) e_1 is following set: $SO(e_1) = \{e_1, e_4, e_5, e_6, e_7, e_8\}$. The set of all concepts which have our explication e_1 as a mutual object is the following set:

$$\gamma(e_1) = \{(\{e_1\}, \{1,2,3,4,5,6,7,8\}), (\{e_1, e_4\}, \{1,2,7\}), (\{e_1, e_7\}, \{1,2,3\}), (\{e_1, e_5, e_6, e_8\}, \{5\}), (\{e_1, e_4, e_7\}, \{1,2\}),\}$$

The ordering is represented by following Table 4. The higher the row is the higher priority (relevance) the document (text source) has.

It is clear that the first row represents the document of selected explication (in our case e_1) and the next rows represents documents which has explications obtaining the largest mutual intent with descending tendency.

Table 4. Final text sources' ordering

Exp.	Intent	DF	RT
e_1	{1,2,3,4,5,6,7,8}	{}	$\{s_1\}$
e_4	{1,2,7}	{3,4,5,6,8}	$\{s_4\}$
e_7	{1,2,3}	{4,5,6,7,8}	$\{s_7\}$
e_5	{5}	{1,2,3,4,6,7,8}	$\{s_5\}$
e_6	{5}	{1,2,3,4,6,7,8}	$\{s_6\}$
e_8	{5}	{1,2,3,4,6,7,8}	$\{s_8\}$

Explicitly the relevant text sources ordering is as follows:

$$e_8(s_8) \sqsubseteq e_6(s_6) \sqsubseteq e_5(s_5) \sqsubseteq e_7(s_7) \sqsubseteq e_4(s_4) \sqsubseteq e_1(s_1)$$

5 Conclusion

In this paper, we introduced method which uses the FCA for selecting the most relevant text sources and we introduced *relevant ordering* to order the set of selected explications from the most relevant to the less ones. The goal was to introduce method which could help the user to organize text sources from the most significant therefore the user does not need to go through all documents to get the relevant information.

We are aware of the time consuming method of FCA. In the future we will focus on some modifications which will strongly reduce the time of data post-processing.

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