Application of the Formal Concept Analysis in Evaluation of Results of ANEWS Questionnaire and Physical Activity of the Czech Regional Centers*

Jiří Zacpal[1], Erik Sigmund[1], Josef Mitáš[2], Vladimír Sklenář[2]

[1] Dept. Computer Science, Palacky University, Olomouc
Tomkova 40, CZ-779 00 Olomouc, Czech Republic
{vladimir.sklenar,jiri.zacpal}@upol.cz
[2] Centre for Kinanthropology Research, Palacky University, Olomouc
tr. Miru 115, CZ-771 11 Olomouc, Czech Republic
{erik.sigmund,josef.mitas}@upol.cz

Abstract. Formal concept analysis is a method of exploratory data analysis that aims at the extraction of natural clusters from object-attribute data tables. The clusters, called formal concepts, can be similar to human-perceived concepts in a traditional sense and can be partially ordered by a subconcept-superconcept hierarchy. The hierarchical structure of formal concepts (so-called concept lattice) represents structured information obtained automatically from the input data table. The goal of this paper is to describe a method of evaluation of ANEWS questionnaire by Formal concept analysis. We describe a method adjustment of questionnaire by scaling to classical formal context. After that we separate some attributes to groups and make so-called "aggregate atributes". This way we make modified formal context and calculate formal concept lattice. We define term "characteristic function" for every concept. This is function, which for given extent or intent return a real number, which characterized this concept and is important for evaluation. Our method is illustrated on ANEWS questionnaire and measured steps in randomized sample of 15-65 years-old inhabitants of the Czech regional centers.

1 Introduction and problem setting

Questionnaires are being used in many areas of human activities. The aim is to reveal patterns of behavior and various kinds of dependencies among variables being surveyed. Descriptive statistics and statistical hypotheses testing are among the tools traditionally used for evaluation of questionnaires. A practical disadvantage of the traditional statistical approaches is the need to formulate

* Supported by grant No. 1ET101370417 of GA AV ČR, by grant No. 201/05/0079 of the Czech Science Foundation, by institutional support, research plan MSM 6198959214, and by grant No. 6198959221 'Physical activity and inactivity of inhabitants of the Czech Republic in the context of behavioral changes' of the MSM.

© Radim Belohlavek, Sergei O. Kuznetsov (Eds.): CLA 2008, pp. 97–108,
ISBN 978–80–244–2111–7, Palacký University, Olomouc, 2008.

hypotheses to be tested. Without any prior structured view on the data contained in the questionnaires, formulation of relevant hypotheses is a difficult task. Another disadvantage of traditional statistical approaches is the limitation regarding what statistics can tell about data and how statistical summaries can be understood by experts in the field of inquiry who are not experts in statistics.

This paper presents results on evaluation of ANEWS questionnaire and physical activity of the czech regional centers. The paper is a continuation of previous studies regarding the IPAQ questionnaire, see [5]. At the beginning of our study, there was a need for an alternative means of evaluation of questionnaires formulated by experts (domain experts) from the Faculty of Physical Culture of the Palacky University, Olomouc, who are involved in a world-wide project of monitoring physical activities in today's population. The experts struggled with classical statistical techniques and were looking for alternative methods of evaluation of the questionnaires. It turned out that basic methods of formal concept analysis (FCA) [10] are quite useful for the domain experts. Putting briefly, a concept lattice and its parts provide the experts with an easy-to-understand hierarchical view on the data.

In terms of FCA, the basic idea is the following. The objects are the individuals (or their groups) being surveyed in the questionnaires, the attributes correspond to the variables being monitored by the questionnaires. The corresponding concept lattice or its parts reveals to the domain expert the groups in dependence on the attributes and the expert can see various dependencies between attributes, how large the groups are etc. Therefore, the concept lattice provides the expert with a first insight into the data. Such an insight is crucial. Very often, this insight is what the expert needs to see. Furthermore, based on this insight, the expert can pursue more detailed inquiries including those based on classical statistical techniques.

Recent study focuses on considering groups of individuals as objects. The present study is based on the idea that some questions are closely related. It's useful to group those attributes which resulted from scaling of the questions into one attribute. Thus we would obtain a more comprehensive view of the questionnaire. This idea made us create so-called "aggregate attributes".

The advantage of taking groups and the relative frequencies instead of individuals and original attributes is conciseness of the description provided by the resulting concept lattice which is what the experts asked for. The disadvantage, as with any other method which involves aggregation and summarization, is loss of information. We present our method, experimental results, as well as a brief description of the software tool we used.

2 Questionnaire adjustment

Each questionnaire consists of questions to which the respondents choose an answer from a multiple choice. From the perspective of FCA the group of respondents can be understood as a set of objects and individual questions as attributes. The respondents answers then create binary relation between the set of objects and the attributes. The answers do not have to be necessarily bi-valent (yes-no). Multiple-value type of answers (age, number of steps,) can appear here. Due to this, a suitable scale needs to be applied to transfer the multiple-value type of answers into bivalent forms. The result of this process is a context $\langle X, Y, I\rangle$, where X is the set of objects – respondents, Y is the set of attributes – adjusted answers from the questionnaire and I is the binary relation between X and Y, where $(x, y) \in I$ means that respondent x answered yes to question y.

Another adjustment of the questionnaire is based on the idea that some questions are closely related. For example question: "The streets in my neighborhood do not have many cul-de-sacs (dead-end streets)" is closely related with question: "The distance between intersections in my neighborhood is usually short (100 yards or less; the length of a football field or less)", because the questions are related to conditions for walking. Was it not more useful than to group those attributes which resulted from scaling of the questions into one attribute? Thus we would obtain a more comprehensive view of the questionnaire. This idea made us create so-called "aggregate attributes".

Firstly, an expert needs to decide which questions can be grouped into an "aggregate attributes". Then, we replace all the attributes which were formed through scaling with "aggregate attributes" using the following procedure. We calculate the weighted mean of individual attributes and we scale this mean.

Formally: There is number n of questions in the questionnaire which we want to cluster into the "aggregate attributes". Through scaling of these questions $\sum_{i=1}^{n} m_i$ of attributes was created, where m_i is the number of attributes which was formed through scaling of i-question. The weighted mean for the object x, is calculated according to the formula:

$$v(x) = \sum_{i=1}^{n} \sigma_i \sum_{j=1}^{m_i} \omega_{ij} I(x, a_{ij})$$

where

σ_i is weight of question i

ω_{ij} is weight of attribute j which was formed through scaling of question i

a_{ij} is attribute which was formed through scaling of question i, $j \in m_i$

I is binary relation between X and Y_1, which is the original set of attributes from which we remove all the attributes which we have grouped into aggregate attributes and then we add the aggregate attributes into it.

Value $v(x) \in \langle 0, 1\rangle$. We create 5 aggregate attributes according to these rules:

$\langle x$,NAME-very low$\rangle \in I_1$ iff $v(x) \in \langle 0, 0.2\rangle$

$\langle x$,NAME-low$\rangle \in I_1$ iff $v(x) \in (0.2, 0.4\rangle$

$\langle x$,NAME-moderate$\rangle \in I_1$ iff $v(x) \in (0.4, 0.6\rangle$

$\langle x$,NAME-high$\rangle \in I_1$ iff $v(x) \in (0.6, 0.8\rangle$

$\langle x$,NAME-very high$\rangle \in I_1$ iff $v(x) \in (0.8, 1\rangle$,

where NAME is the name of the group of attributes which we grouped. Using these aggregate attributes, we replace all the grouped attributes. This way a formal context $\langle X, Y_1, I_1 \rangle$ is created, where Y_1 is the original set of attributes from which we remove all the attributes which we have grouped into aggregate attributes and then we add the aggregate attributes into it. $\langle x, y \rangle \in I_1$ if y is not aggregate attribute and for aggregate attributes the above rules are applied.

Example 1. For better understanding we provide an example. There are questions (G1-G3) in the questionnaire which concern Streets in my neighborhood. The expert states the values in individual weights: $\sigma_{G1} = 0.4$, $\sigma_{G2} = 0.4$ and $\sigma_{G3} = 0.2$ To all questions, the respondents could choose these answers: 1 - strongly disagree, 2 - somewhat disagree, 3 - somewhat agree, 4 - strongly agree. The value of weights is stated in Tab. 1. They created 5 "aggregate attributes": Street-very low, Street-low, Street-moderate, Street-high, Street-very high (the classification of streets depending on their suitability for walking). If respondent x answers the questions this way: G1 - 3, G2 - 1, G3 - 2, will be $v(x) = 0.4 \cdot 0.75 + 0.4 \cdot 0.5 + 0.2 \cdot 0{,}5 = 0.6$ and then $\langle x,\text{Street-moderate}\rangle \in I_1$.

Table 1. Weights ω_{ij} from example 1.

questions	answers			
	1	2	3	4
G1 - absence of cul-de-sac (dead-end streets)	0.25	0.5	0.75	1
G2 - short distance between intersections	0.25	0.5	0.75	1
G3 - alternative routes for getting from place to place	0.25	0.5	0.75	1

Typically, such a formal context contains many objects and a manageable number of attributes. The corresponding concept lattice is too large for an expert to comprehend. In addition, the expert might not be interested in the formal concepts from this concept lattice. Rather, the expert might want to consider aggregates of the individual respondents as objects in the formal context with the aggregates defined by having the same attributes on a set S of attributes specified by an expert, such as those regarding age, sex, etc., with S being a subset of the set Y of all attributes. Attributes from S will be called characteristic attributes.

The aggregates we consider are equivalence classes of individual respondents. For respondents $x_1, x_2 \in X$, put

$$x_1 \equiv_S x_2 \text{ if and only if } \{x_1\}^{\uparrow} \cap S = \{x_2\}^{\uparrow} \cap S.$$

Clearly, $\equiv_S$ is an equivalence relation on X and $x_1 \equiv_S x_2$ means that x_1 and x_2 have the same attributes from S, i.e. are indistinguishable by the attributes from S. We call the classes $[x]_{\equiv_S}$ of $\equiv_S$ aggregate objects and denote, furthermore,

– by X_1 the set of all classes of $\equiv_S$, i.e. $X_1 = X/\equiv_S$, by Y_2 the set of those attributes from Y_1 not included in S, i.e. $Y_2 = Y_1 - S$.

Now, for each class $[x]_{\equiv_S}$ from X_1 and each attribute $y \in Y_2$, we consider the relative frequency of objects in having attribute y and denote it by $I_2([x]_{\equiv_S}, y)$ or simply by $I_2(x, y)$. That is, we put

$$I_2(x, y) = \frac{|\{x_1 \in [x]_{\equiv_S} : x_1 \text{ has } y\}|}{|[x]_{\equiv_S}|}$$

We can consider I_2 a fuzzy relation which will indeed be the case in this study. Namely, we will consider a particular concept lattice associated to $\langle X_1, Y_2, I_2 \rangle$, called a lattice of crisply generated fuzzy concepts. For technical reasons, we round the degrees assigned by I_1 to those from the scale $\{0, 0.01, \ldots, 0.99, 1\}$.

More details on this method are described in the article [5].

3 Characteristic concept function

With Formal Concept Analysis we can find concepts whose intent include attributes interesting for our way of evaluation. Extents of these concepts contain some number of respondents. Often we are not interesting in attributes of individual respondent. Only values that characterize all respondents in the concept extent as a whole are interesting for concept evaluation. Arithmetic mean of the value with more than two-valued attribute is possible example of such value. We will use the term "characteristic function" for function that returns such value for given extent.

4 Questionnaire analysis

The ANEWS questionnaire (Neighborhood Environment Walkability Scale - Abbreviated) includes 54 questions in total. They were answered by 662 respondents. Using the method described above, we created 8 aggregate attributes, from which we created 40 attributes using scaling (8x5). Next to these attributes, the context involves other attributes of demographic data: gender (2 attributes), BMI (4), age (5), smoking (2), driver (2), orgPA (4), Steps5bigger2 (2) - attribute indicated, whether the respondents shows more steps during week than at weekend, Steps (4) - see Tab. 2.

Table 2. Scale for value Steps

attribute	steps per week
Steps-low	less then 5 999
Steps-moderate	6 000-9 999
Steps-high	10 000-13 999
Steps-very high	more than 14 000

Thus we obtained a formal context which includes 662 objects and 65 attributes. For another adjustment of formal context, aggregate objects are applied. We used Sex-male, Sex-female and steps (Steps-low, Steps-moderate, Steps-high a Steps-very high) as characteristic attributes. The obtained formal fuzzy context includes 8 objects and 59 attributes. Using it, we created corresponding fuzzy conceptual lattice. When studying the lattice, we tried to examine what influence the environment (characterized by aggregate attributes) has on the number of steps in respondents. We studied males and females separately. The Tab. 3 shows the corresponding concepts for male and Tab. 4 for female. We state only the aggregate attributes in the levels of very high (VH) and high (H). It is possible to compare also the other levels (moderate, low a very low), but we were interested mainly in the positive influence of the environment on steps.

Table 3. Degree of some attributes in concepts, which extents consist of aggregate objects SexMale an Steps-low, Steps-moderate, Steps-high, Steps-very high. Aggregate objects: L - Steps-low, M - Steps-moderate, H - Steps-high, VH - Steps-very high.

attribute	extent		
	L,M,H,VH	VH	L
BuildingsFlat-very high	0	0.01	0
BuildingsFlat-high	0.18	0.18	0.23
BuildingsHouse-very high	0	0.06	0
BuildingsHouse-high	0.34	0.42	0.46
Distance-very high	0.01	0.01	0.08
Distance-high	0.15	0.26	0.15
Neighbourhood-very high	0.08	0.14	0.08
Neighbourhood-high	0.23	0.28	0.23
Safety-very high	0.38	0.53	0.53
Safety-high	0.39	0.39	0.46
Service-very high	0.38	0.53	0.38
Servie-high	0.35	0.39	0.46
Street-very high	0.38	0.57	0.38
Street-high	0.26	0.26	0.46
Walking-very high	0.15	0.24	0.15
Walking-high	0.43	0.45	0.76

The levels of correspondence express minimal number of respondents in percentage, which show the given attribute. Based on the comparison of the concepts, we can see that great difference between respondents who show high number of steps (VH) and low number of steps (L) on a day, are apparent mainly in the Street-very high attribute. It is apparent that the type of street is closely associated with the number of steps. Due to this we focused on the aggregate attribute Street. We formed a formal context of attributes which were parts of the aggregate attribute Street. These attributes are formed from questions ClosedStreet (The streets in my neighborhood do not have many cul-de-sacs (dead-end streets)), ShortDistance (The distance between intersections in my neighborhood is usually short (100 yards or less; the length of a football field or

Table 4. Degree of some attributes in concepts, which extents consist of aggregate objects SexFemale an Steps-low, Steps-moderate, Steps-high, Steps-very high. Aggregate objects: L - Steps-low, M - Steps-moderate, H - Steps-high, VH - Steps-very high.

attribute	extent		
	L,M,H,VH	VH	L
BuildingsFlat-very high	0	0	0
BuildingsFlat-high	0.10	0.19	0.10
BuildingsHouse-very high	0	0.05	0
BuildingsHouse-high	0.34	0.34	0.52
Distance-very high	0.03	0.03	0.10
Distance-high	0.21	0.26	0.21
Neighbourhood-very high	0.05	0.09	0.05
Neighbourhood-high	0.10	0.33	0.10
Safety-very high	0.44	0.47	0.52
Safety-high	0.34	0.45	0.36
Service-very high	0.47	0.57	0.47
Servie-high	0.30	0.30	0.42
Street-very high	0.34	0.48	0.36
Street-high	0.33	0.35	0.42
Walking-very high	0.21	0.21	0.26
Walking-high	0.41	0.56	0.57

less) and MoreWays (There are many alternative routes for getting to one place in my neighborhood. (I don't have to go the same way every time). Each question can be answered in values 1 to 4. Using scaling we obtained a context which was formed by 662 objects (respondents) and 36 (25 - demographic attributes, 12 - attributes of environment) attributes. We used the method of aggregate objects. As characteristic attributes, we used gender (Sex-male, Sex-female) and steps (Steps-low, Steps-moderate, Steps-high a Steps-very high). A formal fuzzy context was thus created which included 6 objects and 33 attributes. We formed a corresponding fuzzy conceptual lattice. Examining the lattice we were trying to identify whether any question from the aggregate attribute Street has greater influence on the number of steps in respondents. We studied males (Tab. 5) and females (Tab. 6) separately.

The levels of correspondence express minimal number of respondents in percentage, which show the given attribute. Based on the comparison of the concepts, we can see that great difference between respondents who show high number of steps (VH) and low number of steps (L) on a day, are apparent mainly in the MoreWays attribute (here we are interested primarily in the value 4 of the answer – strongly agree). It is apparent that the variety of walking routes, when I do not have to take just a one way, are attractive and motivating for walking and cycling.

Another possibility of the questionnaire analysis is using so-called characteristic function of the concept. In this case, we define it as arithmetic mean of number of steps for respondents – objects, for 7 days in the extent of the concept.

Table 5. Degree of some attributes in concepts, which extents consist of aggregate objects SexMale an Steps-low, Steps-moderate, Steps-high, Steps-very high. Aggregate objects: L - Steps-low, M - Steps-moderate, H - Steps-high, VH - Steps-very high.

attribute	extent		
	L,M,H,VH	VH	L
ClosedStreets-1	0.03	0.06	0.08
ClosedStreets-2	0.10	0.10	0.15
ClosedStreets-3	0.28	0.28	0.46
ClosedStreets-4	0.31	0.54	0.31
MoreWays-1	0	0.03	0
MoreWays-2	0.09	0.09	0.15
MoreWays-3	0.38	0.38	0.62
MoreWays-4	0.23	0.49	0.23
ShortCross-1	0.09	0.10	0.08
ShortCross-2	0.21	0.22	0.23
ShortCross-3	0.35	0.40	0.54
ShortCross-4	0.15	0.27	0.15

Table 6. Degree of some attributes in concepts, which extents consist of aggregate objects SexMale an Steps-low, Steps-moderate, Steps-high, Steps-very high. Aggregate objects: L - Steps-low, M - Steps-moderate, H - Steps-high, VH - Steps-very high

attribute	extent		
	L,M,H,VH	VH	L
ClosedStreets-1	0.05	0.09	0.11
ClosedStreets-2	0.13	0.15	0.21
ClosedStreets-3	0.27	0.29	0.32
ClosedStreets-4	0.37	0.47	0.37
MoreWays-1	0.03	0.03	0.05
MoreWays-2	0.10	0.10	0.21
MoreWays-3	0.42	0.40	0.42
MoreWays-4	0.32	0.46	0.32
ShortCross-1	0.10	0.13	0.11
ShortCross-2	0.16	0.18	0.16
ShortCross-3	0.33	0.40	0.37
ShortCross-4	0.23	0.27	0.37

We used a formal context with aggregate attributes. We wanted to examine what influence service availability has on the value of characteristic function (aggregated attribute Service-very high, Service-high, Service-moderate, Service-low and Service-very low). The values of the characteristic function for individual concepts are shown in Tab. 7.

Table 7. Value of characteristic concept function

intent	avarage of steps	number of objects
Sex-male	12198	278
Sex-male, Distance-very high	8934	8
Sex-male, Distance-high	13226	60
Sex-male, Distance-moderate	12193	138
Sex-male, Distance-low	11707	69
Sex-male, Distance-very low	11871	3
Sex-female	11907	384
Sex-female, Distance-very high	10574	21
Sex-female, Distance-high	12019	110
Sex-female, Distance-moderate	12318	180
Sex-female, Distance-low	11095	69
Sex-female, Distance-very low	11408	4

Using this type of analysis, we can replace the classification of steps according to clear limits set in advance (Tab. 2) with one more concrete value. Along with the value of the arithmetic mean, we have to consider the number of objects to which the arithmetic mean is related (Tab. 5). Tab. 5 shows that in groups of men, it is apparent that longer distance to services (Distance-moderate, Distance-high and Distance-very high) is closely associated with higher number of steps per day. In women, the difference is not so apparent. Services (shops, restaurants, offices, banks, etc.) are an important part of everyday life, therefore further distance from the place of living does not impede women and men in accessing them.

5 Software tool

We used a software tool which is developed in the Department of Computer Science at Palacky University, Olomouc, to create the fuzzy contexts and to browse the corresponding fuzzy concept lattice. This software tool supports the whole process of the processing and evaluation of IPAQ questionnaire. The basic overview of functions that are supported and their succession is shown in Fig. 1.

The processing of the questionnaire consists of the following steps.

- **Reading data**. IPAQ questionnaire is recorded in the form of an MS Excel file. The columns of this file contain respondents' answers to individual

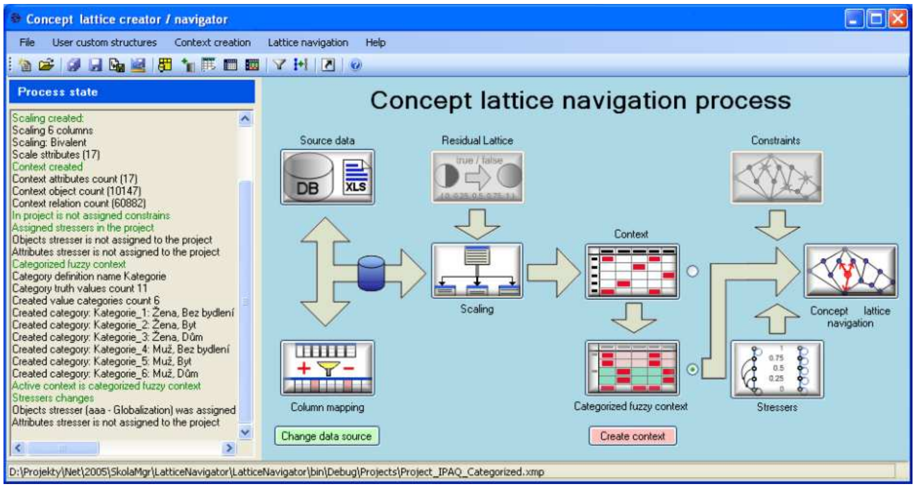

Fig. 1. Base screen of application

questions. The software tool allows to specify which columns are included in the processing.

– **Scaling**. The answers to some questions may be in the form of many-valued attributes. For example, the values in the column Age may be in the interval from 18 to 69. Due to this fact it is necessary to transform the original file to the form in which each column contains only 0 or 1. This process is called conceptual scaling [10]. Our software tool allows one to specify the bivalent attributes and the scale for each column in data source file.
– **Creation of aggregate objects**. The tool allows to interactively specify the set of characteristic attributes. The user also chooses parameters regarding the structure of truth degrees.

A fuzzy context is created after these steps. A user can then explore the associated fuzzy concept lattice and its concepts. Our software tool does not create the whole concept lattice. Instead, it supports an interactive navigation in the concept lattice. It shows the information related to the current concept and its direct neighbors. A user selects next steps by choosing an ancestor or successor of the current concept. He/she can move from a more general concept to a more special concept and vice versa. He/she can also specify the content of the extent or the intent and move to the appropriate concept. We can see the user's screen in Fig. 2.

The navigation in the concept lattice needs the calculation of the current concept and its neighbors only. This calculation is relatively fast and does not depend on the size of the whole concept lattice. Due to this fact the navigation proceeds on-line and the user can modify the course of navigation interactively, based on information gained. The user can also specify additional constraints to be satisfied by formal concepts which are to be presented to him/her.

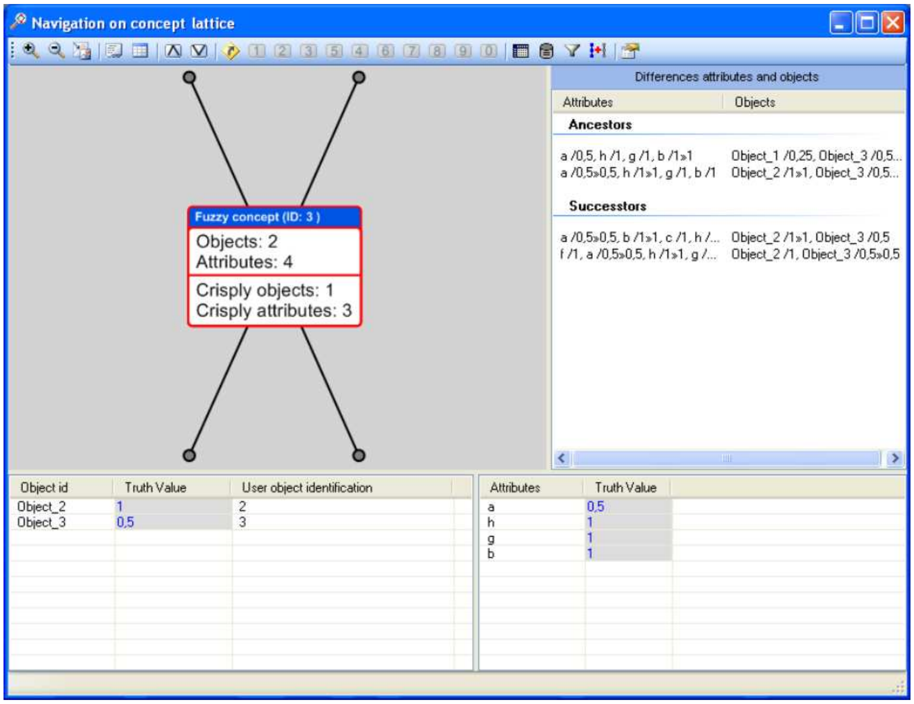

Fig. 2. Navigation in fuzzy concept lattice

6 Conclusions

Our paper described a method of analysis of a questionnaire which comprises number of questions which can be grouped based on their relation in meaning. Such an approach allows for a more global assessment of the data. We have applied this method to the ANEWS questionnaire. We can conclude that environment which is physical activity friendly and stimulating in Czech cities can be on the basis of the data and number of steps per day characterized by availability of services in short distances, walking friendly streets (walkability and cleanness of streets, no cul-de-sacs) and by nice environment in residential areas.

References

1. Bauman, A., Chey, T., Bowles, H., Smith, B., Meron, D., Ainsworth, B., Jones, D. A., Craig, C., Cameron, C., Sjostrom, M., Hagestromer, M., Frome,l K., Mitas, J. *et al.*: *International physical activity prevalence estimates: Results from the International Prevalence Study in 20 Countries*, Medicine and Science in Sports and Excercise (in press).
2. Belohlavek, R.: *Fuzzy Relational Systems: Foundations and Principles*. Kluwer, Academic/Plenum Publishers, New York, 2002.

3. Belohlavek, R.: Concept lattices and order in fuzzy logic. *Annals of Pure and Applied Logic* **128**(1–3)(2004), 277–298.
4. Belohlavek, R., Sklenar, V., Zacpal, J.: Crisply generated fuzzy concepts. ICFCA 2005, Int. Conf. Formal Concept Analysis, *LNAI* 3403, pp. 268–283, Springer-Verlag, Berlin/Heidelberg.
5. Belohlavek, R., Sklenar, V., Zacpal, J., Sigmund, E.: Evaluation of questionnaires supported by formal concept analysis. CLA 2007, Strany: 96–108, University of Montpellier II.
6. Belohlavek, R., Vychodil, V.: Reducing the size of fuzzy concept lattices by hedges. In: FUZZ-IEEE 2005, The IEEE International Conference on Fuzzy Systems, May 22–25, Reno (Nevada, USA), pp. 663–668.
7. Belohlavek, R., Vychodil, V.: What is a fuzzy concept lattice? In: Proc. CLA 2005, 3rd Int. Conference on Concept Lattices and Their Applications, September 7–9, Olomouc, Czech Republic, pp. 34–45.
8. Ben Yahia, S., Jaoua, A.: Discovering knowledge from fuzzy concept lattice. In: Kandel A., Last M., Bunke H. (Ed.): *Data Mining and Computational Intelligence*, pp. 167–190, Physica-Verlag.
9. Carpineto, C., Romano, G.: *Concept Data Analysis. Theory and Applications.* J. Wiley, 2004.
10. Ganter, B., Wille, R.: *Formal Concept Analysis. Mathematical Foundations.* Springer, Berlin, 1999.
11. Hájek, P.: *Metamathematics of Fuzzy Logic.* Kluwer, Dordrecht, 1998.
12. Klir, G. J., Yuan, B.: *Fuzzy Sets and Fuzzy Logic. Theory and Applications.* Prentice-Hall, 1995.
13. Krajči, S.: A generalized concept lattice. *Logic J. of IGPL* **13**, 543–550.
14. Pollandt, S.: *Fuzzy Begriffe.* Springer-Verlag, Berlin/Heidelberg, 1997.
15. Sklenář, V., Zacpal, J., Sigmund, E.: *Evaluation of IPAQ questionnaire by FCA*, CLA 2005, pp. 60–69, ISBN: 80–248–0863–3, Palacky University, Olomouc, 2005.
16. Thomas, J. R., Nelson, J. K., Silverman, S. J.: *Research Methods in Physical Activity.* Human Kinetic, Champaign, 2005.
17. Wille, R.: Restructuring lattice theory: an approach based on hierarchies of concepts. In: I. Rival (Ed.): Ordered Sets, 445–470, Reidel, Dordrecht-Boston, 1982.