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Personality Traits of Students of Helping and Non-Helping Professions:
Case-Based Reasoning Approach

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ABSTRACT

Personality traits are very important in choosing future profession because most professions require certain skills that are related to certain personality traits. The aim of our research was to determine which personality traits contribute the most to the distinction between the students of different professions, e.g. helping and non-helping professions. On a sample of 356 students, of which 216 study helping professions, Big Five Plus Two (BF+2) personality inventory was applied. For obtained data, the classification accuracies were tested with different combinations of 184 items and 18 subtraits of the BF+2 using Case based reasoning classifier. Results showed that the best accuracy had the set of all 18 subtraits and this set outperformed the classification of every combination of subtraits or items.

KEYWORDS

Case-Based Reasoning, Classification, Helping and Non-Helping Professions, Personality Traits

INTRODUCTION

Personality traits are very important when choosing one's future profession. Previously studies showed that personality traits are significant correlates of career maturity (Coertese & Schepers, 2004) as of career decision-making (Somayeh, Abdolhamid, & Gholamreza, 2012).

In order to be successfully, most professions require certain skills that are related to certain personality traits. This means that success in a given profession depends on the compatibility of personality traits of worker and requirements of the profession itself. If there is an adequate synergy between the two, professional objectives can be achieved more easily and with greater success. Furthermore, individuals are more satisfied and perform better when engaged in occupations that match their interests (*Carpenter, Bauer, & Erdogan, 2010*).

The importance of personality traits is perhaps most prominent in helping professions, i.e. those professions that entail working with people, primarily for the purpose of providing assistance, support and encouragement of various aspects of others' welfare. In this study, we want to test differences in personality traits between helping and non-helping professions.

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The aim of this study is to empirically check, in what extent the personality traits and subtraits contribute to the differences between professions. We will use data from personality inventory which was performed on 356 students from the University of Novi Sad. With such data, the classification accuracies were tested with different combinations of items and subtraits. Case based reasoning classifier is used, since this methodology is appropriate for domains where the dependencies between parameters are not known in advance. Additionally, several feature-selection methods are applied in order to select an optimal subset of items/subtraits.

The rest of the paper is organized as follows. Next section brings description of some related works. The main aim of this study is briefly presented in section 3. Section 4 is devoted to the methodology and experimental setup including used data set and instrument. Achieved results are discussed in section 5. Last section brings final conclusions.

RELATED WORK

As we mentioned, the purpose of this study is to determine difference in personality traits between helping and non-helping professions. Previous studies (Hussain, Abbas, Shahzad, & Bukhari, 2012; Záškodná, 2010; Zvenko, 2013) have shown that those who work in helping professions show characteristics that are desirable in social communication, such as kindness and generosity in negotiations, but also altruism, empathy, trustworthiness and care for other peoples' needs. In addition to these characteristics, also important but to a lesser extent are characteristics related to attitude towards work, such as organization, persistence, goal-oriented behavior, inclination towards risk avoidance, and control of undesirable behaviours. In dominant personality trait models such as Five Factor Model and Big Five, these and other similar characteristics capture the agreeableness and consciousness traits. For the remaining three traits of the model (neuroticism, extraversion and openness), there is no agreement whether they contribute to a distinction between helping and non-helping professions. The characteristics that are part of these personality traits pertain to the tendency towards negative or positive emotions and affects, emotional stability, activity and intellectual curiosity (Goldberg, 1990, 1993).

From the standpoint of other personality model, such is Holland Personality Theory of Career Choice, results showed that there is significant relationship between personality types and career choice of students (Kimongo Kemboi, Kindiki, & Misigo, 2016). Moreover, there is congruency between investigative personality type and investigative career choice (which could be related to non-helping professions), as between social personality type and social career choice (which could be related to helping professions).

There is one interesting approach which was proposed by Martínez, Castro, Licea, Rodríguez-Díaz, and Salas (2013). Instead of dimensional approach, authors proposed person-centered approach by using Fuzzy Subtractive Clustering to define Big Five clusters on engineering students i.e. non-helping professions. In comparison to some other methods, like adaptive neuro-fuzzy inference system, proposed clustering method gave better insight into relationship between personality traits and choosing a career. Authors conclude that based on this method, students have better opportunity to choose a career and match their personality type with it.

However, it can be assumed that a better insight into the differences between helping and non-helping professions could be achieved through analysis of specific personality traits, so-called subtraits, that are, in fact, part of the basic personality traits. Therefore, this study is focused in that direction, aimed to explore on which hierarchical level of personality the prediction of helping or non-helping professions is better.

Besides that, we can emphasise and conclude that majority of authors in this area usually uses standard statistical methods and rarely tries to apply some of wide range of artificial intelligence (AI) techniques to process data sets. AI methods generally can obtain more reliable and more quality processing data and accordingly higher quality results. In this study, we use Case-Based Reasoning -

CBR (Aamodt & Plaza, 1994; Budimac & Kurbalija, 2001). One of the main differences between this and other existing approaches is that CBR a very trustworthy AI technique that offers high-quality processing of data and more reliable results.

MAIN AIM OF THE STUDY

The aim of this study is to determine which personality subtraits contribute the most to the distinction between the students of helping and non-helping professions, by applying innovative approach in this domain i.e. case-based reasoning approach. In this study, personality inventory Big Five Plus Two (BF+2: Smederevac, Mitrović, & Čolović, 2010) was used as a reference frame to study personality traits. BF+2 contains 184 items which form 18 subtraits, which in turn form seven basic personality traits. Five of seven basic traits are the same as in the Big Five model, while the additional two are related to self-evaluation. The significance of additional dimensions is in registering the indicators of maladaptive behaviour (Smederevac et al., 2010), which may be indicative when differentiating between those who working in helping from those who working in non-helping professions. In this study, we want to test whether all items or all subtraits are necessary for the classification process, and eventually to select some subset of items/subtraits with significant classification accuracy. Moreover, we want to test on which hierarchical level of personality the prediction of helping or non-helping professions is better.

METHODOLOGY AND EXPERIMENTAL SETUP

Participants in Experiment

Participants (356) were students from the University of Novi Sad, of which 216 (179 females) study helping professions and 140 (45 females) study non-helping professions. Helping professions include disciplines such as medicine, special education and rehabilitation, psychology and pedagogy, whereas non-helping professions include disciplines such as electrical and mechanical engineering and architecture. As could be expected, females are more often in helping professions, compared to males ($\chi^2_{(1)} = 93.69$, $p < .001$).

Instrument

Big Five Plus Two Inventory (BF+2: Smederevac et al., 2010) measures seven basic personality traits, each contains of two or three subtraits which resulted in 18 subtraits in total. More precisely, Neuroticism contains subtraits anxiety, depression and negative affect; Extraversion includes warmth, positive affect and sociability; Conscientiousness includes self-discipline, persistence and cautiousness; Aggressiveness includes anger, disagreeableness and tough-mindedness; Openness contains intellect and novelty seeking; Positive valence includes superiority and positive self-concept, and Negative valence consists of two facets - manipulative style and negative self-concept. BF+2 contains 184 items with 5-point Likert scale for responding. In this study, items scores as average scores of subtraits are used.

Characteristics of Classification

The used classifier is based on Case-Based Reasoning technology - CBR (Aamodt & Plaza, 1994; Budimac & Kurbalija, 2001). CBR is considered as a problem-solving technology (or technique) where the new problems are solved by adapting solutions that worked for similar problems in the past. This approach is extremely suitable for less examined domains – for domains where rules and connections between parameters are not known, that applies for domain used in this research. By our knowledge, application of this approach is very innovative and new in this area.

The main phases of the CBR activities (Aamodt & Plaza,1994) are described in the CBR-cycle (Figure 1). In the retrieve phase, the most similar case (or *k* most similar cases) to the problem case, is retrieved, while in the reuse phase some modifications to the retrieved case is done in order to provide better solution to the problem (case adaptation). As the CBR only suggests solutions, there may be a need for a correctness proof or an external validation, so that system will stay consistent in regard to environment. That is the task of the phase revise. In the retain phase the knowledge, learned from this problem, is integrated in the system by modifying some knowledge containers.

The main problem in implementing almost every CBR system is to find a good similarity measure – the measure that can tell in what extent the two cases are similar. An appropriate structure called Case Retrieval Net - CRN (Lenz, Bartsh-Sporl, Burkhard, & Wess, 1998) was developed to compute similarity measure on the basis of the importance of all attributes. A part of CRN is shown on Figure 2. In this net, there exists a node for each value of each attribute (information entity node) and for each solution (case node). The nodes are connected with two types of weighted arcs: acceptance and relevance arcs. The new problem is solved by spreading activation process from activated information entity nodes to the other information entity nodes, and then to the case nodes. The case node which accumulates the majority of activation is the suggested solution.

All mentioned concepts of CBR together with CRN memory structure are implemented in system Case Based Generator (CaBaGe: Kurbalija & Ivanovic, 2005). The CaBaGe system can be easily used in classification process by representing desired classes of cases as case nodes in CRN. The system is used in such a way in this study.

Figure 1. The CBR-cycle after Aamodt and Plaza (1994)

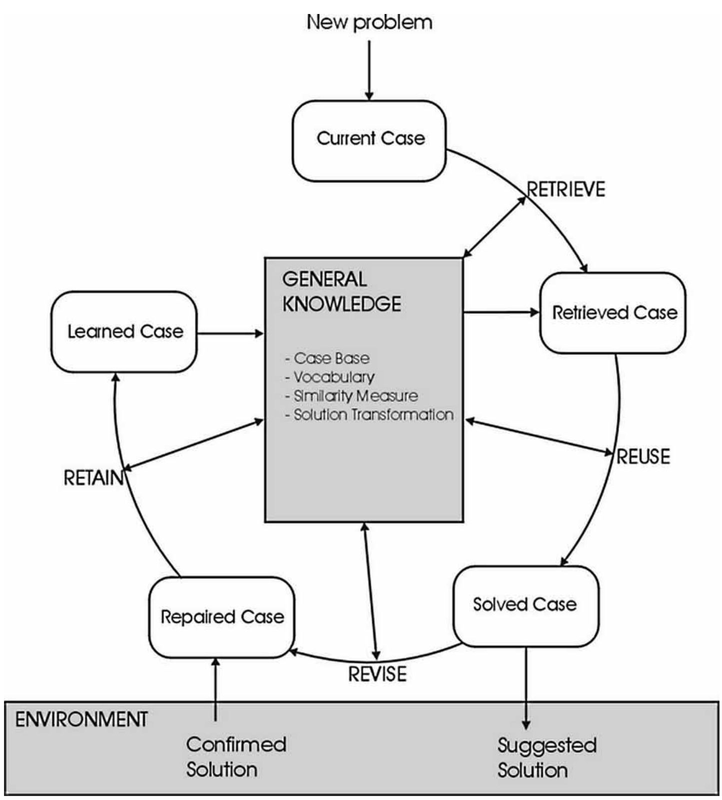
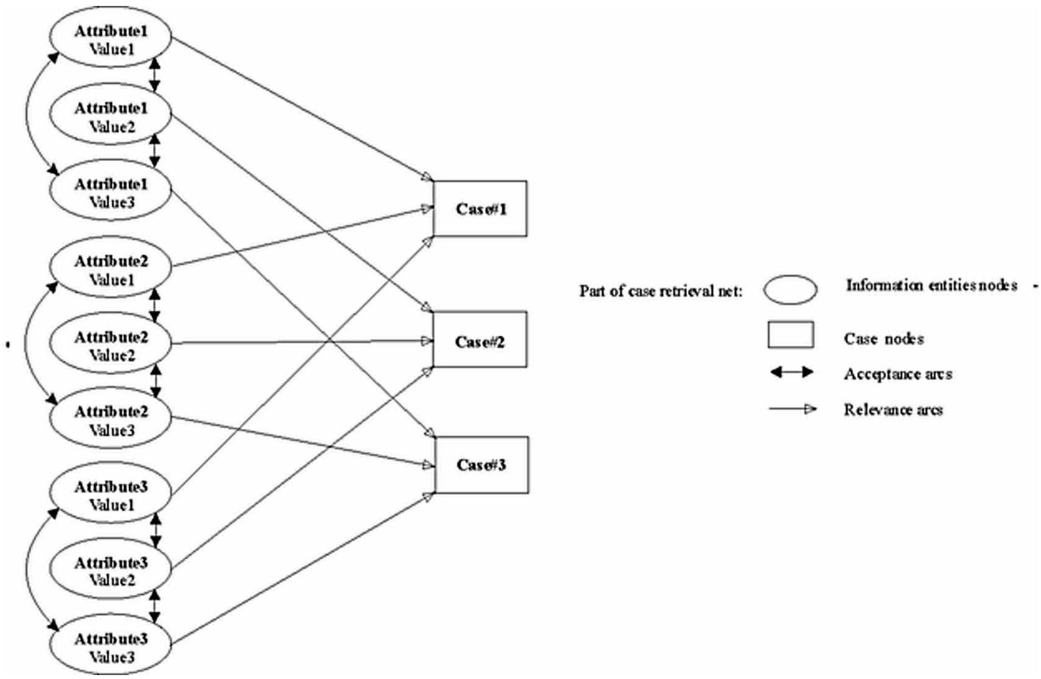


Figure 2. Part of case retrieval net



Feature Selection

To explore weather all 184 items or 18 subtraits of BF+2 make better distinction between two professions, we applied feature selection techniques in order to select minimum set of items/subtraits which give reasonable classification accuracy and thus improve the performance of classifier.

Feature selection techniques are set of data mining techniques which select a subset of relevant features in order to give better or at least the same results as original set of features in some model construction (Han & Kamber, 2006). The utilisation of feature selection techniques could improve the resulting model in several aspects: simplification of model, gain in performance and reduction of overfitting.

All feature selection techniques could be divided in two major groups: filter and wrapper methods. Filter methods analyze intrinsic properties of data ignoring the classifier. These methods usually rank the features according to some criteria, and select the desired number of features with highest scores. Filter methods have extremely short computation times, but tend to select redundant variables because they do not consider the relationships between variables. On the other hand, wrapper methods take into the considerations the interactions of features. They select the optimal subset of features for a particular classifier. In ideal case, all possible subsets of features should be evaluated but this is computationally impracticable. Therefore, some metaheuristics methods are applied. In this study, we have used two filter methods: Correlation Based Selection (CBS: Hall, 1998) and Relief algorithm (Kira & Rendell, 1992). Additionally, wrapper method based on best-first-search algorithm was used (Russell & Norvig, 1995).

RESULTS AND DISCUSSION

In the first phase of experiment we performed 2-class classification accuracy analysis for CBR classifier with all 184 items. The classification accuracy was 0.6057. In addition, we performed wrapper based feature selection algorithm in order to select a smaller set of features with possibly better accuracy. The method selected 12 items whose combination resulted in 0.7383 classification accuracy.

Although, the classification accuracy was significantly improved and the number of items dramatically reduced, the calculation time of wrapper method was more than 8 days (on Intel i7 processor @ 3.40GHZ with 12GB RAM). In order to reduce this calculation time, we performed a more convenient feature selection methodology: first, a fixed number of items was selected using filter methods (in this case: 150, 120, 100, 80, 60, 40, 30, 20 and 10), and then on selected items a wrapper method was used to select an optimal subset of items. The results for Relief and CBS methods, together with the calculation times are given in Table 1 and Table 2, respectively.

It is expected that for a smaller number of items selected with filter methods (below 30 items) the wrapper methods cannot achieve high classification accuracies. However, for some intermediate number of selected items (between 60 and 100) very high accuracies can be achieved, in some cases even higher then after wrapper method used on all 184 items. Number of selected items after wrapper method is approximately the same in all cases (between 10 and 20). However, the main improvement of this method lies in the computation times. It is obvious that the computation times are constant

Table 1. Feature selection with relief method

Relief			Wraper		
No. of Items	Accuracy	Time(ms)	Accuracy	Time	Selected Items
150	0.602151	1140	0.724014	6d6h	13
120	0.580645	1140	0.749104	2d22h	14
100	0.562724	1172	0.774194	2d5h	16
80	0.580645	1156	0.745520	2d2h	19
60	0.569892	1109	0.738351	1d2h	17
40	0.544803	1141	0.688172	14h16min	17
30	0.555556	1172	0.641577	2h25min	11
20	0.548387	1313	0.594982	1h17min	10
10	0.430108	1203	0.430108	8min	7

Table 2. Feature selection with CBS method

CBS			Wraper		
No. of Items	Accuracy	Time(ms)	Accuracy	Time	Selected Items
150	0.605734	94	0.752688	6d0h	12
120	0.620071	79	0.738351	3d11h	12
100	0.627240	78	0.745520	3d9h	15
80	0.623655	78	0.741935	1d5h	12
60	0.620071	93	0.770609	1d13h	15
40	0.620071	78	0.752688	16h31min	14
30	0.627240	62	0.756272	6h13min	12
20	0.630824	78	0.706093	1h47min	14
10	0.634408	78	0.691756	1h8min	9

and very short for filter methods. In addition to that, the computation times of wrapper method with reduced number of items are significantly shortened. For example, for 60 items selected with CBS filter method, the wrapper method selected 15 items with classification accuracy (0.770609) better then with original data (0.7383). Moreover, this better result is obtained nearly five times faster.

In order to obtain higher classification accuracies, which mean a higher prediction of helping/non-helping professions, we performed a classification analysis on the 18 subtraits. The classification is also 2-folded: the goal is to guess whether the participant belongs to helping or non-helping profession on the basis of his/her subtraits. The CBR classifier is used as in the previous phase.

The classification accuracy with the full set of subtraits is very high: 0.872521. We also applied the wrapper method on all 18 subtraits and it selected 13 subtraits with worse accuracy of 0.866855. The calculation times are here considerably shorter compared to analysis on items, since the number of subtraits is 10 times lower. Further, we applied both filter methods on initial set of subtraits and selected the following predefined number of subtraits: 15, 12, 10, 8, 6, 4, 3, 2 and 1. The wrapper method is not applied further, since the number of subtraits is reasonably small. The results are given in Table 3.

It is evident that no one combination (filter or wrapper) of selected subtraits can beat the accuracy of a full set of 18 subtraits. Furthermore, the classification with subtraits outperformed the classification of every combination of items. That fact naturally imposes the conclusion that the set of 18 subtraits represents a complete set which is needed for a prediction of profession type, at least for used CBR classifier.

CONCLUSION

The main challenge of our research presented here was to discover which personality subtraits contribute the most to the distinction between the students of helping and non-helping professions. To achieve this, we applied innovative approach in this domain i.e. we used case-based reasoning technique for classification. We performed classification on the level of items and subtraits of BF+2 personality inventory.

The main result is that all 18 subtraits from BF+2 had the best classification accuracy of helping and non-helping professionals (87.25%). This result is not in line with previously studies (Hussain et al., 2012; Kimongo Kemboi et al., 2016; Záškodná, 2010; Zvenko, 2013) in which specific personality traits are isolated as correlates of those two profession's types. It seems that using the CBR classifier lead to cumulative effect of all personality subtraits in contribution to distinction between helping and non-helping professionals. It is possible that CBR classifier is not enough sensitive in applying

Table 3. Feature selection of filter methods on subtraits

No. of Subtraits		Relief	CBS
15		0.849858	0.852691
12		0.830028	0.793201
10		0.813031	0.787535
8		0.779037	0.776204
6		0.733711	0.750708
4		0.711048	0.713881
3		0.671388	0.668555
2		0.441926	0.478754
1		0.059490	0.070822

on personality constructs. Also, the results showed that personality is very complex system and that isolation of several traits is not enough for distinction between those two professions. In the other words, isolation of several subtraits seems too simplified, because all examined personality subtraits have significant role in distinction of professions. It is possible that person-centered approach in opposite to dimensional approach would give different results, which is suggestion for future research.

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