Social Representation Networks

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***Abstract*—The present study aimed to find patterns in free word associations. Associations were gathered from two nationally comprehensive samples in Hungary (N1 = 505; N2 = 505) to the cue "migrant". We demonstrated that network analysis based on co-occurrences reveals distinct clusters based on attitudes and emotions.**

Keywords-social representation; natural language processing; free word association

I. INTRODUCTION

Our social environment provides access to a large amount of information on social phenomena. This information is accumulated and shared via communication. In social psychology, the collection of opinions shared by a social group regarding a social object is called a social representation [1]. Social representation studies frequently apply free associations [2]. However, the data-driven grouping of associations reflecting psychologically meaningful dimensions is a challenge to social psychology. Furthermore, opinions have a dynamic nature [3] and they can also polarize into multiple views [4].

In Section 2, we describe the procedure and the methods. In Section 3, we summarize our results. In Section 4, we discuss results and limitations. In Section 5, we point out prospects for future work.

II. METHODS AND PROCEDURE

We gathered multiple response free associations from two nationally comprehensive samples in Hungary (N1 = 505; N2 = 505) and the cue was the word 'migrant' (currently a highly sensitive societal issue in Europe). Each respondent had to associate five words. We also applied a psychological measure to assess respondents' attitudes toward migrants (validated Hungarian version [5] of the Social Distance (SD) scale [6]). We constructed networks from these associations for both samples separately. Nodes were the different associations. Edge weights were defined based on co-occurrences in individual responses. To find psychologically-relevant dimensions behind individual opinions, we used module detection (Louvain algorithm [7] and consensus partitioning [8]). We validated the modular structure with the help of the SD scale. Independent sample t-tests were applied with Bonferroni correction.

III. RESULTS

The two most frequent associations are displayed in Table I. and Table II. for Sample 1 and Sample 2, respectively.

TABLE I.

	Associations	*Z-score*
Module 1	war	3.99
	refugee	3.94
Module 2	immigrant	3.58
	stranger	2.70
Module 3	terrorism	4.52
	Islam	1.16
Module 4	violence	4.91
	fear	3.70

TABLE II.

	Associations	*Z-score*
Module 1	refugee	5.36
	war	3.46
Module 2	immigrant	4.14
	Islam	1.74
Module 3	terrorism	5.53
	violence	4.49

In case of Sample 1, respondents assigned to the Module 1 showed the lowest SD score. ($M = 3.9$, $SD = 2.2$). Respondents assigned to Module 2 reported higher level of SD score ($M = 4.6$, $SD = 2.2$). Respondents assigned to the Module 3 reported even higher level of SD score ($M = 5.2$, $SD = 2.1$). Respondents assigned to Module 4 showed the highest SD score ($M = 6$, $SD = 1.6$). Module 1 showed significantly lower score than Module 2 ($t(481) = -3.4$, $p = .02$), Module 3 ($t(484) = -6.4$, $p < .001$) and Module 4 ($t(600) = -13.3$, $p < .001$.) Module 2 had significantly lower d SD score than Module 3 ($t(403)=-2.6$, $p<.001$) and Module 4 ($t(519) = -7.8$, $p < .001$.) Module 3 had significantly lower SD score than Module 4 ($t(522) = -4.9$, $p < .001$).

In case of Sample 2 respondents assigned to Module 1 showed the lowest SD score (M = 4.4, SD = 2.2). Respondents assigned to Module 2 (M = 5.1, SD = 2). Respondents assigned to Module 3 showed the highest SD score (M = 6.2, SD = 1.5). Module 1 had significantly lower SD score than Module 2 ($t(597) = -4$, $p < 0.001$) and Module 3 ($t(717) = -12.4$, $p < .001$). Module 3 had significantly lower SD score than Module 4 ($t(602) = -6.9$, $p < 0.001$).

IV. DISCUSSION

Our results indicate that module detection in association networks yields a psychologically meaningful mapping of the rich symbolic context behind attitudes in a structured way. The modules reflected distinct attitudes toward asylum seekers based on pairwise statistical comparisons of attitude scores between respondents who were affiliated with different modules.

Our networks can be seen as a subtype of large-scale semantic networks [9]–[11] map constant lexical relations among words of a language. As opposed to these models, our study focuses on a single social object which generates polarized opinions. Furthermore, opinions in social issues fluctuate over time [3]. They can be significantly reshaped by events (e.g., war, terrorism or economic changes). Such changes can be observed in our social representation networks. For example, the association "terrorism" is one of the most frequent associations in both samples, which is in line with previous results on the stability of frequent components [1]. However, it appeared in completely different contexts in the two samples. In the first sample, it had a stereotypical connection to Arab/Islam-related concepts (this associative relation had already been found before the current migration-related events by other researchers as well [12]). In the second sample, its frequency increased and it had stronger relations to other associations indicating threat, violence and crime. A possible explanation can be that in the time-interval between the two data gatherings, a significant terror attack happened in Nice in July, 2016 and this event could be perceived as result of the increased number of migrants after the Syrian war. A future study could investigate how social representations are updated according to changes in the environment.

A limitation is that multiple response free associations are sparse datasets. As a consequence of sparsity, we have to be careful with interpretations based on a single connection in our networks and rely more on the modules which are derived from multiple connections. Another limitation is that the method was demonstrated regarding only one social object.

V. CONCLUSION

Our research can provide an empirical basis for constructing knowledge graphs to analyze texts in political, social and ideological domains. Modules constructed from individual word usage patterns indicated significantly different attitudes toward migrants. Human respondents provide more relevant associations than corpus-based association extraction [13]. The downside is that collecting associations from human respondents is tedious, the datasets can be sparse and they expire. However, combining human associations with extracted associations yields a promising performance [13]. This implies that associations can be used as representative signals to build more comprehensive databases for text comprehending in a given domain. For example, our empirically-validated word clustering can be extended with web-mining and natural language processing techniques.

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