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Using Language and Affective Profiles to Investigate Differences between Individuals

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Abstract

The affective profiles model (i.e., four possible profiles based on the combination of people's high/low positive/negative affect) has led to a great number of studies on individual differences during the past ten years. Nevertheless, only a handful of these studies have investigated actual behavior. Here we put forward two ways for analyzing online behavior (i.e., Facebook status updates) using data published elsewhere. We used the affective profiles model as the framework to investigate individual differences in the words people use when they write on Facebook and the semantic content of their status updates. We suggest that the use of computerized methods to quantify and analyze text need to be used in order to move the affective profiles model into the era of big text data.

Introduction

Presenting affect as being composed of two systems, each one of them categorized as high and low, leads to four different combinations beyond a two-system approach [1]. In this line of thinking, Archer et al. have theorized on four possible affective profiles based on the combination of people's affectivity levels: self-fulfilling (high positive affect, low negative affect); high affective (high positive affect, high negative affect); low affective (low positive affect, low negative affect); and self-destructive (low positive affect, high negative affect). For the past ten years, the affective profiles model has led to a great number of studies (Figure 1) that have investigated individual differences in ill-being and well-being [2]. Nevertheless, most of these studies have used self-reports, that is, only a handful of studies have investigated actual behavior among individuals with different profiles. In this context, individuals' activities on the Internet (e.g., connecting to others, expressing preferences, status updates) provide excellent observable data for studying human behavior [3,4]. However, the amount of text data is hard to handle using common qualitative methods.

In recent years, the advancement of computerized techniques has facilitated handling big text corpus. Here we put forward two ways of analyzing big text corpus using data published elsewhere. Importantly, the affective profiles model can be used as the framework for this type of analysis, that is, as a model to organize text data.

Method

Participants (N=304) were recruited through Amazon's Mechanical Turk (https://www.mturk.com/mturk/welcome) and asked to provide the 15 latest status updates from their own Facebook account. Affectivity was measured using the Emotional Well-Being Scales [5]. All analyses were carried out using Semantic Excel, which is a web-based software developed by S. Sikström. This software is specifically developed to create and analyze quantified representations of text (www.semanticexcel.com).

Results and Discussion

As the first part of the analyses, we simply compared the frequency of the words in the participants' status updates, for each affective profile, to the word frequency in the Google n-grams database (Figure 2a). This database (http://ngrams.googlelabs.com) comprises probably the largest amount of Terabytes of text data available to the public in different languages (for recent description of the Google n-gram database see Lin et al. [6]). We also compared the words in status updates of participants with one profile to those in the rest of the status updates in the dataset at hand (Figure 2b). Figure 2a and 2b show the results of these analyses, in which the font sizes of the words in the word clouds are proportional to the square root of the chi-square value associated with these frequencies. The 100 words with the largest chi-squared values are plotted. These results suggest that the participants with different affective profiles generated different status updates, as illustrated by the different words in each word cloud (Figure 2a and 2b). These differences were not only in relation to all words found in natural language (i.e., Google n-grams) but also between participants with a specific profile and the rest of the participants.

The second method used here for quantitatively analyze texts was the Latent Semantic Analysis (LSA) algorithm [7]. This method involves applying an algorithm to create semantic representations of the various semantic based contents. In short, the LSA-algorithm assumes that words that occur close to each other in text can be used as a source of information; which is used to create multi-dimensional semantic representations. That is, the context that words occur in normally consists of a meaning that more often than not corresponds to the meaning of the word [7-9]. As a result, the content can be represented as a vector in a multi-dimensional semantic space. In turn, the semantic representations of single words can be used to summarize larger text by adding the representations, and normalizing the length of the vectors to

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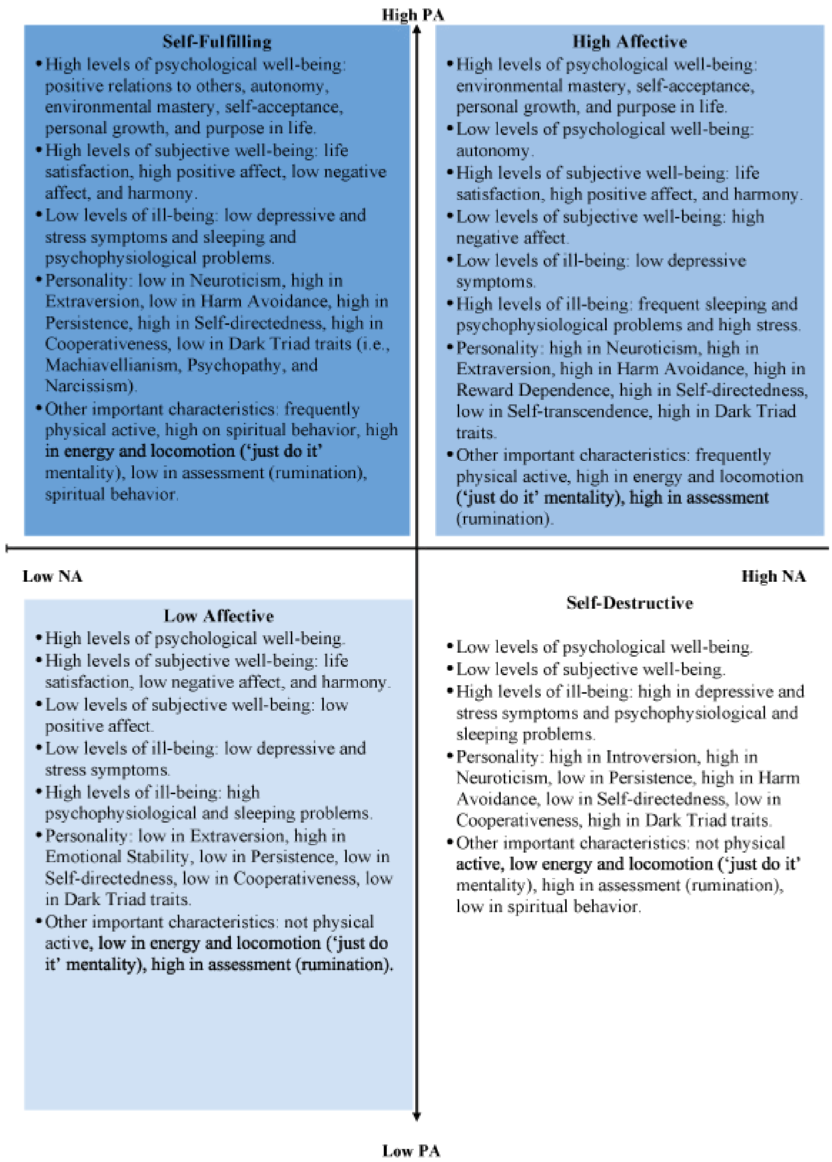

Figure 1: Summary of the results using the affective profiles model during the past decade. Most of these results are based on survey studies with a few exceptions using behavioral data.

one. The similarity between semantic representations can be measured by the cosines of the angle between the vectors, which is mathematically equivalent to multiplying each dimension with each other and adding the resulting products. This similarity measure can then be used in standard statistical procedures such as correlations, regressions, t-tests, analysis of variance, etcetera [10-14]. Here we conducted a semantic difference test to examine whether sets of Facebook status updates significantly differed between participants with distinct affective profiles (Table 1). In these tests, after a semantic representation of the status updates for each profile is created, a difference is calculated by subtracting one profile's semantic representation from the one that is under comparison using a 10%-leave-out method. This difference is used to measure the semantic distance of each text (when that text is left out in the 10%-leave-out procedure) in each profile to be compared. A standard t-test was finally used to investigate the difference between semantic distances. As seen in Table 1, the content in Facebook status updates written by individuals with a low affective profile differed to the content in Facebook status updates written by individuals with any of the other profiles [15-17].

Conclusion and Final Remarks

All in all, the model put forward by Archer et al. has served as a good framework for understanding the way people's affective system regulates behavior. We suggest that the use of computerized methods to quantify and analyze text need to be used in order to move the affective profiles model into the era of big text data.

A third method for analyzing text, is the use of words with predefined sets of psycholinguistic characteristics (i.e., word-norms)

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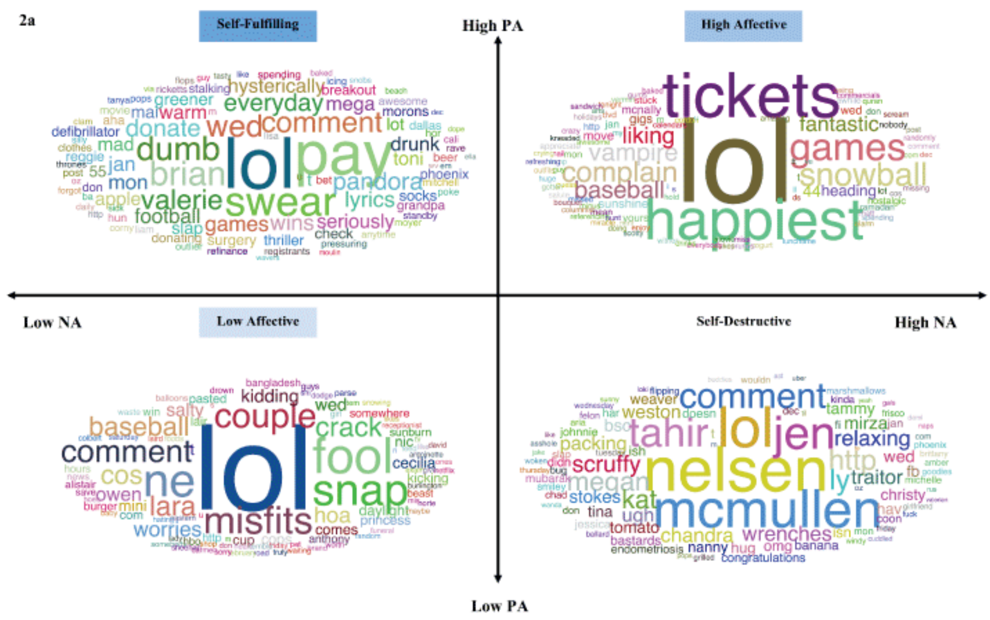

Figure 2a: Users' status updates compared to general word frequency in Google n-grams organized on the basis of Facebook users' type of affective profile (i.e., self-destructive, low affective, high affective, and self-fulfilling).

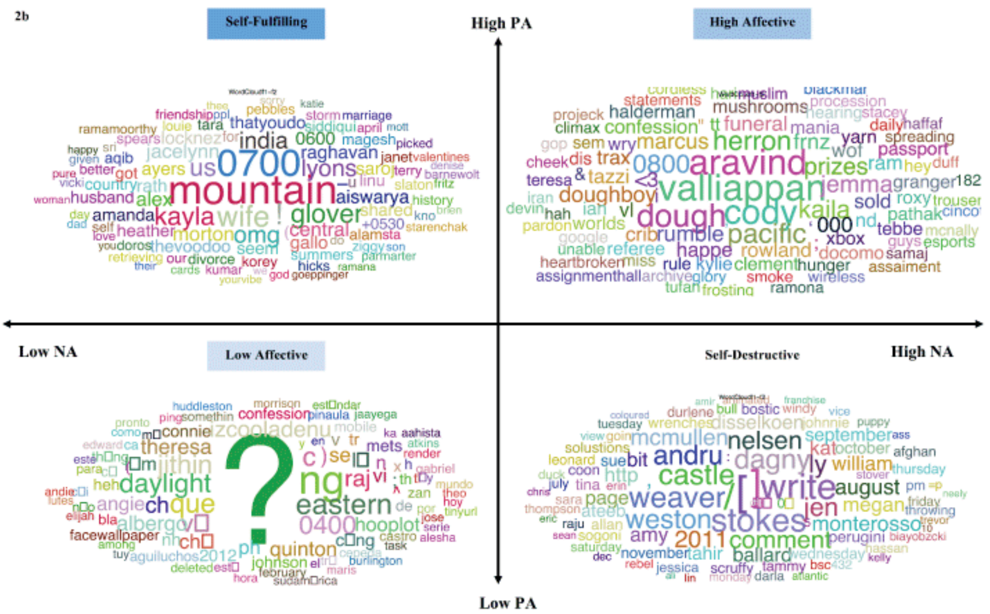

Figure 2b: Word clouds of Facebook status updates. Word clouds showing words that differed in occurrence between Facebook users' status updates with each specific affective profile and the rest of the Facebook users' status updates in the same data set.

to further examine differences between sets of narratives (e.g., status updates) [16]. These word-norms are created by asking an independent sample of participants to generate words they associate to hypothesis-relevant key words, such as, "happiness" if the researcher is interested in knowing if people with distinct profiles differ between each other in how happy participants are on the basis of their status updates. One way or the other, the use of language-based measures of behavior in conjunction with person-centered models, such as the affective profiles model, might help to the understanding of how human beings behave and why do they behave in certain, specific and sometimes unpredictable ways.

	Self-destructive (n = 113)	Low Affective (n = 40)	High Affective (n = 33)	Self-fulfilling (n = 118)
Self-destructive	-			
Low Affective	0.38**	-		
High Affective	-0.06ns	0.46**	-	
Self-fulfilling	-0.20ns	0.49***	-0.10ns	-

Table 1: Effect sizes showing semantic differences in status updates between individuals with distinct affective profiles. **Note**: ***p*** <.01; ****p* < .001; ns: not significant

"Language is surely too small a vessel to contain these emotions of mind and body that have somehow awakened a response in the spirit." By Marguerite Radclyffe Hall

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Conflict of Interest

Dr. Danilo Garcia is the Director of the Blekinge Center of Competence, which is the Blekinge County Council's research and development unit. The Center works on innovations in public health and practice through interdisciplinary scientific research, person-centered methods, community projects, and the dissemination of knowledge in order to increase the quality of life of the habitants of the county of Blekinge, Sweden. He is also an Associate Professor at the University of Gothenburg and together with Professor Trevor Archer and Associate Professor Max Rapp Ricciardi, the leading researcher of the Network for Empowerment and Well-Being. Erik Lindskär is a research assistant at the Blekinge Center of Competence and a member of the Network for Empowerment and Well-Being. The data used here was used in an earlier study published elsewhere, see [12].

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