Incorporating Emotion and Personality-Based Analysis in User-Centered Modelling

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Abstract Understanding complex user behaviour under various conditions, scenarios and journeys is fundamental to improving the user-experience for a given system. Predictive models of user reactions, responses – and in particular, emotions – can aid in the design of more intuitive and usable systems. Building on this theme, the preliminary research presented in this paper correlates events and interactions in an online social network against user behaviour, focusing on personality traits. Emotional context and tone is analysed and modelled based on varying types of sentiments that users express in their language using the IBM Watson Developer Cloud tools. The data collected in this study thus provides further evidence towards supporting the hypothesis that analysing and modelling emotions, sentiments and personality traits provides valuable insight into improving the user experience of complex social computer systems.

1 Introduction

As computer systems and applications have become more widespread and complex, with increasing demands and expectations of ever-more intuitive human-computer interactions, research in modelling, understanding and predicting user behaviour demands has become a priority across a number of domains. In these application domains, it is useful to obtain knowledge about user profiles or models of software applications, including intelligent agents, adaptive systems, intelligent tutoring

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systems, recommender systems, e-commerce applications and knowledge management systems [12]. Furthermore, understanding user behaviour during system events leads to a better informed predictive model capability, allowing the construction of more intuitive interfaces and an improved user experience. This work can be applied across a range of socio-technical systems, impacting upon both personal and business computing.

We are particularly interested in the relationship between digital footprint and behaviour and personality [6, 8]. A wide range of pervasive and often publicly available datasets encompassing digital footprints, such as social media activity, can be used to infer personality [5, 9] and development of robust models capable of describing individuals and societies [3]. Social media has been used in varying computer system approaches; in the past this has mainly been the textual information contained in blogs, status posts and photo comments [1, 2], but there is also a wealth of information in the other ways of interacting with online artefacts. From sharing and gathering of information and data, to catering for marketing and business needs; it is now widely used as technical support for computer system platforms.

The work presented in this paper is builds upon previous work in psycholinguistic science and aims to provide further insight into how the words and constructs we use in our daily life and online interactions reflect our personalities and our underlying emotions. As part of this active research field, it is widely accepted that written text reflects more than the words and syntactic constructs, but also conveys emotion and personality traits [10]. As part of our work, the IBM Watson Tone Analyzer (part of the IBM Watson Developer Cloud toolchain) has been used to identify emotion tones in the textual interactions in an online system, building on previous work in this area that shows a strong correlation between the word choice and personality, emotions, attitude and cognitive processes, providing further evidence that it is possible to profile and potentially predict users identity [4]. The *Linguistic Inquiry and Word Count* (LIWC) psycholinguistics dictionary [11, 13] is used to find psychologically meaningful word categories from word usage in writing; the work presented here provides a modelling and analysis framework, as well as associated toolchain, for further application to larger datasets to support the research goal of improving user-centered modelling.

The rest of the paper is structured as follows: in Sections 2 and 3 we present our data, the statistical analysis and identify the key elements of our model; in Section 4 we summarise the main contributions of this paper, as well as making clear recommendations for future research.

2 Data Analysis & Feature Extraction

Our dataset comes from an online portal for a European Union international scholarship mobility hosted at a UK university. The dataset was generated from interactions between users and a complex online information system, namely the online portal for submitting applications. The whole dataset consists of users (N=391), interactions and comments (N=1390) as responses to system status and reporting their experience with using the system. Google Analytics has been used to track user behaviour and web statistics (such as impressions); this data from has been used to identify the server's status and categorised the status as two stages: *Idle*, where the system had a higher number of active sessions; and marked as *Failure*, where the system had a lower number of sessions engaged. Interactions were first grouped by server status, then sent to the IBM Watson Tone Analyzer to generate emotion social tone scores. In what follows *Failure* status shows a significant difference in overall *Anger* in different status; furthermore, the *Joy* parameter shows a significant difference with the system in *Idle* and *Failure* status. However *Fear* and *Sadness* parameters is almost the same, even with the system in *Idle* status.

We identified the user's personality based on analysis of their Facebook interactions, namely by collecting all comments from the users, again using the IBM Watson Personality Insights tool. However, a number of users in the dataset had completed the Big Five questionnaire (N=44); for these users, their Big Five scores have been used instead. The second stage involved grouping the comments based on server status and segmenting these interactions by user; this allowed us to investigate the impact of server status in the emotion of the user and investigate the Big Five dimension as a constant parameter. By investigating the relationship between personality trait dimensions and the social emotion tones, we are able to find the highest correlation to identify the key elements of the potential model by applying linear regression and Pearson correlation. This allowed building of a neural network multilayer perception using the potential key elements with higher correlations.

The data collected from the social media interactions was grouped by users and via IBM Watson Personality Insights, we were able to identify the Big Five personality traits for each user. Using the IBM Watson Tone Analyzer, the data was grouped by user's comments and server status (*Failure*, *Idle*) to identify the social emotion tone for each user.

3 Statistical Analysis and Key Elements of Model

As part of modelling the users' responses and behaviour, in order to build a conceptual framework model, we applied linear regression to investigate the relationship between the Big Five personality dimensions and the emotion tones.

Linear regressions (presented in Table 1 and Figure 1) do not show significant correlations between the Big Five dimensions and the social emotion tones. There are, however correlations that can be used as key elements for the model; namely the correlation of *Openness* and *Disgust* (0.479), *Extraversion* and *Joy* (0.446 with p-value of 0), *Conscientiousness* and *Joy* (0.436),and *Disgust* with 0.255.*Agreeableness*, does not appear to have a high impact in the social emotion parameters, with the highest correlation being 0.188 with *Joy*, which can be overlooked as a useful factor in the model. *Neuroticism* and *Disgust* is -0.363, *Joy* is -0.487 and p-value is zero is both cases; and *Sadness* with 0.233. All correlation values are $<$0.5.

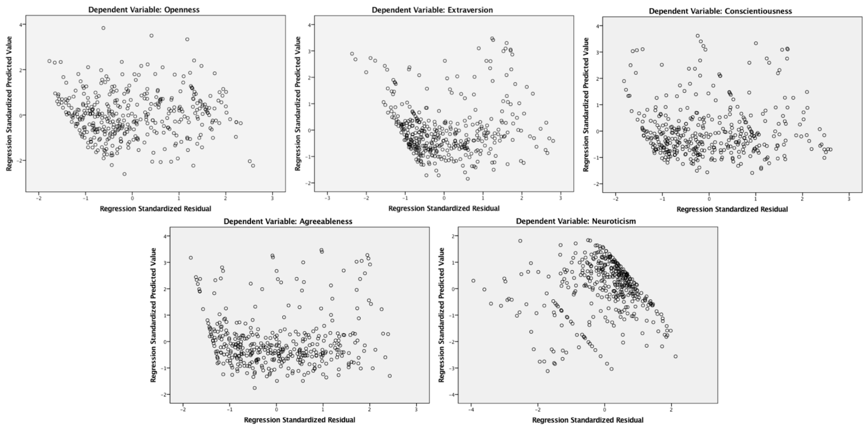

Fig. 1 Scatterplots of the Big Five dimension (dependent variables) and social emotion tones (independent variables)

Table 1 Linear regression coefficients

	Openness			Extraversion			Conscientiousness			Agreeableness			Neuroticism		
	B	t	Sig	B	t	Sig	B	t	Sig	B	t	Sig	B	t	Sig
(constant)	0.356	3.282	0.001	0.162	1.642	0.101	0.16	1.623	0.105	0.297	2.831	0.005	0.828	9.934	0
anger	-0.063	-0.735	0.463	0.064	0.831	0.406	0.124	1.592	0.112	0.024	0.293	0.769	0.116	1.767	0.078
disgust	0.478	4.354	0	0.114	1.142	0.253	0.255	2.551	0.011	-0.061	-0.574	0.566	-0.363	-4.303	0
fear	0.065	0.534	0.594	0.172	1.549	0.122	0.04	0.356	0.722	0.093	0.783	0.434	-0.023	-0.241	0.81
joy	0.066	0.561	0.575	0.446	4.179	0	0.436	4.058	0	0.188	1.652	0.099	-0.487	-5.39	0
sadness	-0.226	-2.118	0.035	-0.185	-1.906	0.057	-0.03	-0.313	0.754	0.014	0.132	0.895	0.233	2.841	0.005

However, *Agreeableness* does not have a linear relationship with any of the social emotion tones. Furthermore, the social emotion tones that have a potential linear relationship are *Disgust*, *Joy* and *Sadness*, since the three tones have a correlation between >0.3 and <0.5.

Previous linear regression analysis suggested that the following Big Five dimensions: *Openness*, *Extraversion*, *Conscientiousness* and *Neuroticism* have the highest correlation with the social emotion tones: *Joy*, *Sadness* and *Disgust*. For further analysis, the Pearson correlation for the same dataset has been performed to compare the output with the linear regression correlations. As noted in Table 2, there is no significant correlation in both; however, in the Pearson correlation, *Neuroticism* has the highest correlation values across emotion tones, especially *Anger*, *Joy* and *Sadness*. *Joy* does have a correlation with all Big Five dimensions except for *Agreeableness* which agrees with the previous analysis. However, *Disgust* does not have a strong correlation with any of the Big Five dimensions, which deviates from the previous analysis.

According to the output of the statistical analysis presented in Table 1 (linear regression) and Table 2 (Pearson correlation), the Big Five dimension identified as the key elements from the personality traits are: *Openness*, *Extraversion*, *Conscientiousness* and *Neuroticism*. The statistical analysis agrees that *Agreeableness* does

Table 2 Pearson correlations

	Anger	Disgust	Fear	Joy	Sadness
Openness	-0.098	0.231	0.043	0.035	-0.151
Conscientiousness	-0.111	-0.001	-0.113	0.267	-0.19
Extraversion	-0.175	-0.077	-0.071	0.349	-0.291
Agreeableness	-0.068	-0.089	-0.027	0.14	-0.069
Neuroticism	0.375	-0.037	0.153	-0.488	0.379

not have a significant correlation across any of the social emotion tones. The social emotion tones to be used as key input elements for the proposed model are *Joy*, *Sadness*, *Anger* and *Disgust*; although the *Anger* tone did not show any significant correlation in linear regression analysis, the value of the Pearson correlation coefficient is between 0.3 and 0.5 which can be used as input for the model.

The dataset used to build this model is based upon a number of users (N=391), eight inputs (*Openness*, *Extraversion*, *Conscientiousness*, *Neuroticism*, *Joy*, *Sadness*, *Anger* and *Disgust*) and the class/output variable as the server status (where No: System *Failure* and Yes: System *Idle*). The total number of the instances for the testing set is 57; the output of the model shows a 75.44% corrected predicted instances and 24.56% incorrectly classified instances (kappa statistic: 0.5295; mean absolute error: 0.3432; RMS error: 0.4246). As this has been performed on a small subset of the overall larger project dataset, the output data is encouraging and provides the infrastructure for further analysis and research to exploit the full dataset.

4 Conclusions and Future Work

In this paper, preliminary results from a larger ongoing theme of research to profile online/digital behaviour have been presented[2]; the objective is to build a conceptual framework to improve user experience and computer system architecture design. The research also concerns applicability in interested in profiling complex behaviours and psychopathies using social network analysis, particularly for crime informatics [7]. Previous work in this space analysed the document uploading behaviour (such as motivation letters, and social media interactions) of the applicants of the international scholarship mobility portal; by examining the upload footprint for the users we were able to determine several classes of behaviour [9].

Social media is used, not only as a content and sharing platform, but also as a platform for technical support for various of online applications and services. This paper demonstrates the analysis of one such online application that has used Facebook as technical support platform for the users. We have produced a model that can predict server status based on personality traits and social emotion tones, by investigating the linear regression and Pearson correlation to identify the key elements to

[2] See original extended paper: http://arxiv.org/abs/1608.03061

be used as input for the neural network to build this model (*Openness*, *Extraversion*, *Conscientiousness*, *Neuroticism*, *Joy*, *Sadness*, *Anger* and *Disgust*). The produced model shows a good potential start for further data analysis, with 75% accuracy in predication based on 57 test cases. Furthermore the available of high-quality, low-cost and adaptable tools provided by the IBM Watson Developer Cloud, provide significant further opportunities to integrate linguistic analysis into this research domain. The model produced from this work provides a number of recommendations for future research to further incorporate emotion and personality-based analysis in user-centered modelling. In particular, expanding the dataset by gathering more data from similar types of interactions, as well as technical queries; annotating and categorising the dataset by gender to investigate the relationship between gender and emotion raised by the user in different computer system statuses; as well as exploring different computer events not only limited to *Idle* and *Failure*, but including more complex events e.g. account hacked, system speed, unexpected error and unsaved data.

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