Incorporating emotion and personality-based analysis in user-centered modelling

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Abstract Understanding user behaviour under varying conditions, scenarios and journeys is fundamental to the improvement of the user-experience for a given system. Predictive models of user reactions and responses can aid in the design of more intuitive and usable systems. The 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 significant 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 systems, recommender systems, e-commerce applications and knowledge management systems [24]. Furthermore, understanding user behaviour during system events

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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 [1, 2, 13, 15]. A wide range of pervasive and often publicly available datasets encompassing digital footprints, such as social media activity, can be used to infer personality [10, 16]. Big social data offers the potential for new insights into human behaviour and development of robust models capable of describing individuals and societies [5]. 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 building upon previous work in psycholinguistic science (the study of the psychological and neurobiological factors that enable humans to acquire, use, comprehend and produce language) 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 [22]. 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 [7]. The *Linguistic Inquiry and Word Count* (LIWC) psycholinguistics dictionary [21, 25] 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.

2 Personality Insight

Numerous studies have suggested key words and phrases can signal underlying tendencies and that this can form the basis of identifying certain aspects of personality [9, 17, 18, 22]. Scherer [23] introduced a valuable classification with the following distinctions between emotions, moods, interpersonal stances, attitudes and personality traits.

By observing the occurrences of words that related to these five categories, we can conclude to certain degrees about the holder's psychological state. For instance, we have sentiment analysis or opinion mining at one end of the spectrum, by utilising open-source software such as *SentiWordNet*; at the other end of the spectrum we have Mairesse et al. [11] highlighting the use of features from psycholinguistic databases such as *LIWC* [21] to create a range of statistical models for each of the Five Factor personality traits. This "Big Five" model, focuses on five dimensions, namely: *Agreeableness*, *Conscientiousness*, *Extraversion*, *Neuroticism* and *Openness*e [12, 20]. It should be noted that while researchers have continued to work with the Five Factors model, there are well known limitations [3, 6, 19] that are often overlooked; however, over the past 50 years the Five Factor model has become a standard in psychology [11], developing a large body of research for comparison.

The IBM Watson Tone Analyzer[1] is a cloud-based framework to infer emotions from a given text; it uses linguistic analysis to detect three types of tones from written text: emotions, social tendencies, and writing style. Emotions identified include *Anger*, *Fear*, *Joy*, *Sadness* and *Disgust*; identified social tendencies include the Big Five personality traits (as described above); identified writing styles include *Confident*, *Analytical* and *Tentative*. To derive emotion scores from text, IBM Watson Tone Analyzer uses a stacked generalisation-based ensemble framework to achieve greater predictive accuracy [4]. Features such as n-grams (unigrams, bigrams and trigrams), punctuation, emoticons, curse words, greeting words (such as "*hello*", "*hi*" and "*thanks*") and sentiment polarity are fed into machine learning algorithms to classify emotion categories [8]. LIWC is used to find psychologically meaningful word categories from word usage in writing.

IBM Watson Personality Insights[2] provides a deeper understanding of people's personality characteristics, needs, and values to drive personalisation. It extracts and analyses a spectrum of personality attributes to help discover actionable insights about people and entities; the service outputs personality characteristics that are divided into three dimensions: the Big Five, *Values* and *Needs*. While some services are contextually specific depending on the domain model and content, Personality Insights usually only requires a minimum of 3500+ words of any text.

3 Data Analysis & Feature Extraction

3.1 Overview of the Data

Our dataset comes from an online portal for a European Union (EU) 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.

[1] http://www.ibm.com/watson/developercloud/tone-analyzer.html
[2] http://www.ibm.com/watson/developercloud/personality-insights.html

Google Analytics is 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. Figure 1 provides am example plot of web traffic from Google Analytics over one day, clearly showing the drop at 20:00 where the system had been identified as in the *Failure* state.

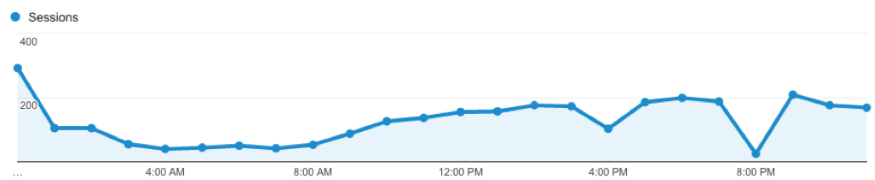

Fig. 1 Google Analytics profile shows behaviour of the system over a 24 hour period (timeline during the day vs. number of active sessions)

All interactions had been collected and grouped by server status, then sent to the IBM Watson Tone Analyzer to generate the emotion social tone scores, to provide an overview of the system behaviour and users interaction with Facebook at the same time. Figure 2 shows the relationship between the server behaviour and emotions of the users; in the system, *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.

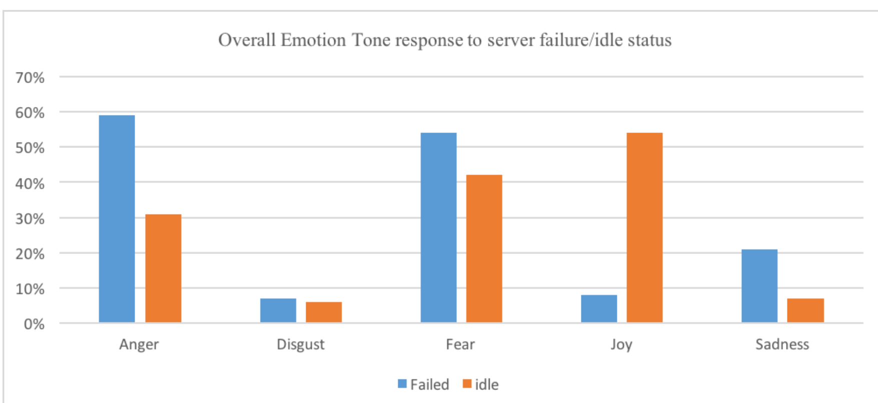

Fig. 2 Overall emotion tone response to server failure/idle status

We identified the user's personality based on analysis of their Facebook interactions (by collecting all comments from user), again by using the IBM Watson Personality Insights tool. However, a number of users in the dataset had completed the Big Five questionnaire (n=44); in these instances, 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 will allow building of a neural network multilayer perception using the potential key elements with higher correlations.

The previous overview encourages further investigation to understand the relationship between user's behaviour and complex computer system behaviours. The data collected from the social media interactions have been grouped by users and using the 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 has been grouped by user's comments and server status (*Failure*, *Idle*) to identify social emotion tone for each user. Table 1 shows a sample of data used in this analysis, with each row representing a unique user, and each column represents the Big Five traits, social emotion tones and server status.

Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism	anger	disgust	fear	joy	sadness	Server Status
0.528	0.523	0.537	0.653	0.511	0.217821	0.793375	0.501131	0.031477	0.284936	Failure
0.252	0.063	0.037	0.266	0.989	0.542857	0.084615	0.178302	0.224453	0.264283	Failure
0.817	0.571	0.157	0.012	0.401	0.162798	0.166694	0.213870	0.410916	0.220049	Failure
0.197	0.130	0.180	0.419	0.990	0.468938	0.259794	0.350803	0.037265	0.636412	Failure
0.155	0.079	0.081	0.226	0.975	0.539162	0.219993	0.431932	0.011625	0.642158	Failure
0.158	0.281	0.332	0.510	0.869	0.419015	0.162022	0.213941	0.066892	0.686369	Failure
0.817	0.571	0.157	0.012	0.401	0.041602	0.026298	0.141606	0.651962	0.106500	Failure
0.058	0.038	0.147	0.375	0.989	0.449222	0.057946	0.181654	0.158412	0.547968	Idle
0.178	0.138	0.800	0.564	0.828	0.207497	0.096643	0.093218	0.769316	0.162241	Idle
0.105	0.463	0.792	0.704	0.041	0.134487	0.257145	0.195858	0.181699	0.509379	Idle
0.589	0.479	0.147	0.339	0.828	0.360527	0.240875	0.321188	0.117492	0.212762	Idle
0.338	0.235	0.104	0.304	0.869	0.164107	0.015058	0.230148	0.629562	0.356028	Idle
0.204	0.203	0.480	0.329	0.892	0.625891	0.193692	0.242459	0.153679	0.166561	Idle
0.689	0.968	0.805	0.465	0.029	0.246246	0.080353	0.123761	0.807537	0.135646	Idle
0.093	0.175	0.642	0.563	0.875	0.279503	0.045658	0.207278	0.088724	0.505607	Idle
0.277	0.296	0.276	0.332	0.892	0.499199	0.143897	0.269725	0.188664	0.285462	Idle
0.055	0.095	0.783	0.699	0.935	0.450997	0.153940	0.263070	0.350778	0.116282	Idle

Table 1 Example data snapshot used in the analysis

3.2 Statistical Analysis

As part of modelling the user's responsive behaviour, one of the approaches to build a conceptual framework model is to apply linear regression to investigate the relationship between the Big Five personality dimensions and the emotion tones features.

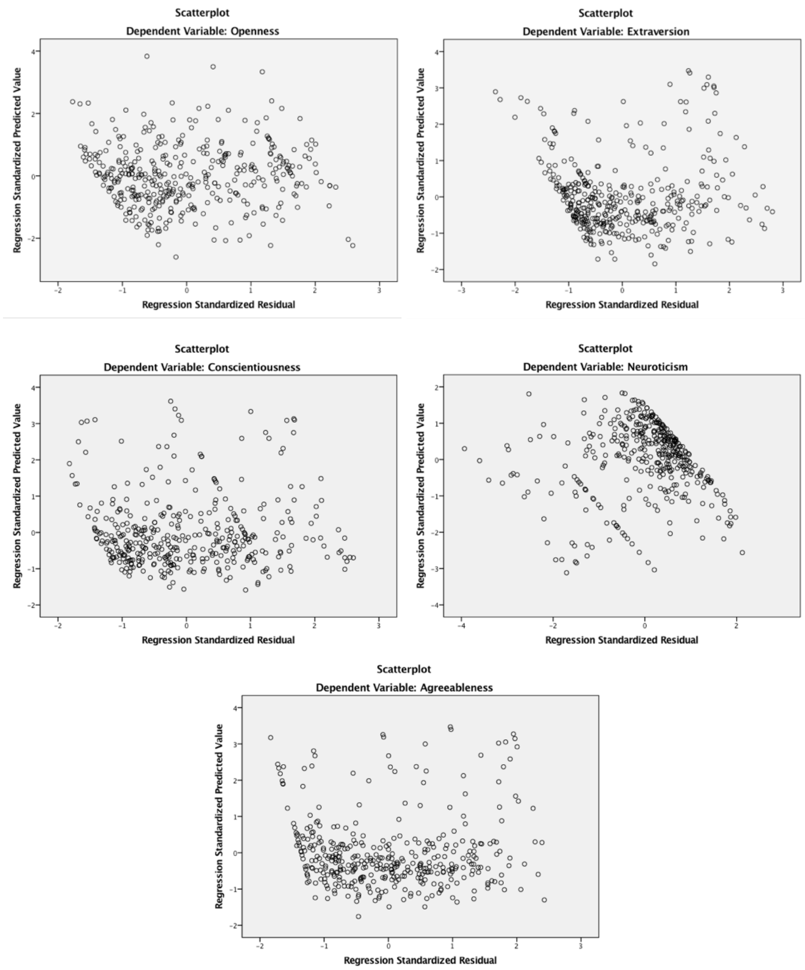

Fig. 3 Scatterplots of Big Five dimension (dependent variables) and social emotion tones (independent variables)

	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

Table 2 Linear regression coefficients

The linear regression (see Table 2 and Figure 3) does not show significant correlations between the Big Five dimensions and the social emotion tones; however, certain correlations can be highlighted and used as key elements for the model at this stage. The correlation of *Openness* and *Disgust*, is 0.479; the correlation of *Extraversion* and *Joy* is 0.446 with p-value of zero. *Conscientiousness* and *Joy* with 0.436 correlation 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; however, it is noticed that *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 you can see in Table 3, 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.

	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

Table 3 Pearson correlations

3.3 Key Elements of the Model

According to the output of the statistical analysis presented in Table 2 (linear regression) and Table 3 (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 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.

Correctly classified instances:	43 (*75.44%*)
Incorrectly classified instances:	14 (*24.56%*)
Kappa statistic:	0.5295
Mean absolute error:	0.3432
Root mean squared error:	0.4246
Total number of instances:	57

Table 4 Re-evaluation output of proposed 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*). As shown in Table 4, 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. 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

This paper presents preliminary results from a larger ongoing theme of research to profile online/digital behaviour [13, 15], which could provide the conceptual framework to improve user experience and computer system architecture design. Social media is now not only being used 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. Such social networks provide substantial textual and interaction datasets for analysis, providing further insight into personality traits and social emotion tones.

We are also interested in profiling complex behaviours and psychopathies using social network analysis, particularly for crime informatics [14]. 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 [16].

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 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 case. Furthermore the available of high-quality, low-cost and adaptable tools provided by the IBM Watson Developer Cloud (e.g. IBM Watson Tone Analyzer and IBM Watson Personality Insights tools), provide significant further opportunities to integrate linguistic analysis into this research domain. The outcome of the model produced during this work provides the following recommendations for future research to further incorporate emotion and personality-based analysis in user-centered modelling:

- Expanding the dataset by gathering more data from similar types of interactions, as well as technical queries;
- Annotate and categorise the dataset by gender to investigate the relationship between gender and emotion raised by the user in different computer system statuses;
- Explore 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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