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Changing Faces: Identifying Complex Behavioural Profiles

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Abstract There has been significant interest in the identification and profiling of insider threats, attracting high-profile policy focus and strategic research funding from governments and funding bodies. Recent examples attracting worldwide attention include the cases of Chelsea Manning, Edward Snowden and the US authorities. The challenges with profiling an individual across a range of activities is that their data footprint will legitimately vary significantly based on time and/or location. The insider threat problem is thus a specific instance of the more general problem of profiling complex behaviours. In this paper, we discuss our preliminary research models relating to profiling complex behaviours and present a set of experiments related to changing roles as viewed through large-scale social network datasets, such as Twitter. We employ psycholinguistic metrics in this work, considering changing roles from the standpoint of a trait-based personality theory. We also present further representations, including an alternative psychological theory (not trait-based), and established techniques for crime modelling, spatio-temporal and graph/network, to investigate within a wider reasoning framework.

1 Introduction

The motivation for this preliminary research is a long-standing interest in determining personality and behaviour from digital data and especially profiling insider threats, a situation where granted access is used illegitimately, often in situations where it is known that actions are scrutinised closely (such as by machine learning algorithms). How best then to develop a profile of an individual (we do not consider group behavior in this paper) so that criminal behavior, which is assumed to be different in some way to normal operating behaviour, can be detected. The data footprint will vary significantly based on either time, location or role, as the individual legitimately passes through their range of activities; for instance, an operator accessing a computer terminal at one location in the morning and another in the afternoon. Likewise, the data footprint will change according to shifting emotional states; for instance, the same operator working at a single terminal differently on different days, one day performing the 'harder' tasks first, and another day, the 'easier' tasks first. Thus, we have the general problem of profiling complex behaviours.

From collaborations with several UK police forces and crime prevention partnerships, we have seen a wide range of data and problems, with the need to develop models with predictive or classification power, embedded in decision support systems, namely: gun gangs, terrorism networks, retail crime gangs, volume crime, fraud and sex offences. Each problem collected different data, and therefore different techniques were more appropriate to model the criminal behaviour.

Recent research suggests that it may be possible to identify personality traits through textual analysis, that is, analysis of the style and nature of an individuals written expression. A person's identity or personality is reflected in everything they do, including website design [1] and textual communication on the Internet more generally. The growth of social networking websites has put an enormous amount of such written expressions into the public domain for the first time, and investigators have presented frameworks for forensic treatment of this data [2]. Included in our study, we present an unreported set of experiments related to changing roles as viewed through Twitter social media data.

Attempts to characterise personality typologies, include McAdams' intuitively appealing model [3] with the three levels of (*i*) traits, (*ii*) mental concerns and strategies (intermediate knowing), and (*iii*) life story (intimate level). Gosling [4] describes the trait level as painting a portrait in broad brushstrokes but which leaves out much of the finer detail. An example of a trait model is the Big Five or Five Factors (as used in our study), namely: extraversion, emotional stability, agreeableness to other people, conscientiousness and openness to experience [5,6]. There are many ways to be extraverted for instance, and what are these traits able to tell us about a person's values, beliefs, goals and roles; these are the next level of knowing someone. Having worked through the traits and personal concerns of McAdams first two levels, you strike the bedrock of personality – identity. McAdams describes this third level as "*an inner story of the self that integrates the reconstructed past, perceived present, and anticipated future to provide a life with unity, purpose, and meaning.*"

For many operational purposes McAdams' lower level of traits can often be sufficient, and certainly, because of its extensive use, it provides a way of comparing research; over the last 50 years the Five Factor model has become a standard in psychology [7], developing a large body of research for comparison.

2 Geospatial, Network and Modus Operandi Data

Working with burglary data from West Midlands Police [8,9,10] in the UK, several new methods were developed, including the composite of geographical range and network connections as shown in Figure 1. Each 'square' is an offender, associated by co-defendant (arrested together) links to other offenders. The map for each offender shows their geographic range of offending. Each offender also had a list of property stolen against each of their crimes, and modus operandi (see Table 1), upon which it was possible to develop predictive models.

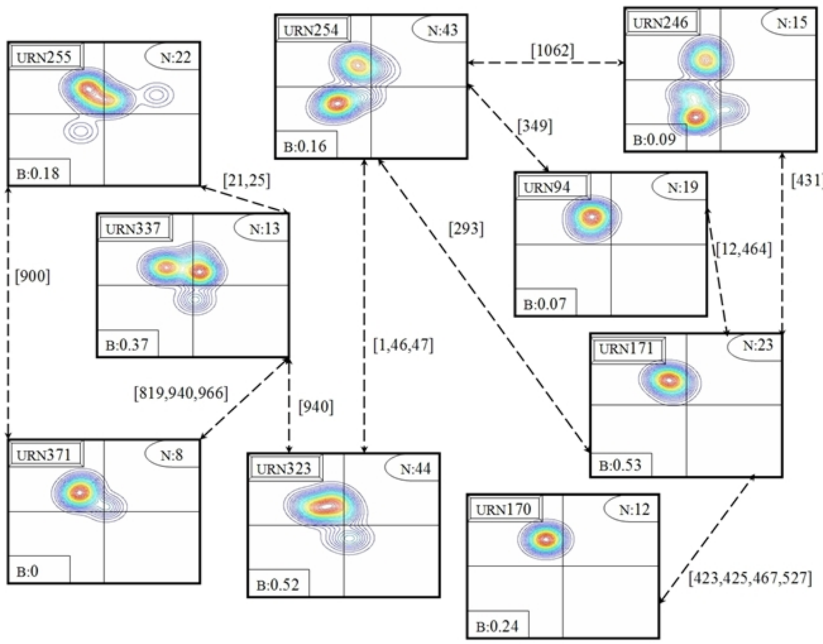

Figure 1: **Geographical networks.** Each box is an offender, displaying their codefendent links, and geographical range of offending.

The modus operandi data was routinely gathered by scenes of crime officers (SOCOs), and contained a range of 'styles' of burgling, using force or craft and so on [11]. A crucial recommendation to West Midlands Police was that the SOCOs would record richer data that could more adequately distinguish between obviously different crime locations and perpetrators, in order to infer behaviours and traits.

Ewart & Oatley [11] compared models that used just spatio-temporal data (including correlated walk analysis) against modus operandi, and a combination of both. The combined models performed best. Figure 2 shows a geographical plot with triples of [*offender home address, location, victim home address*] for a range of crime types, including woundings, murder, manslaughter, kidnapping and firearms offences. Representing the data in this way, we are able (as in the previous geographical network) to see offending characteristics such as criminal range, and relationships between crime types.

It is clear when looking at crime histories of certain gang members in Greater Manchester, UK, that they committed specific types of crimes, for instance it was unlikely for a career burglar to escalate the severity of their crimes to murder. There were predictors evident of future crimes: the future gun users often including in their histories lack of empathy (evidenced by abduction, rape) and failure to accept responsibility for own actions (aggression against police), and

LOCATION OF ENTRY	1. Wall 2. Adjoining Property 3. Below, 4. Front 5. Rear 6. Side7. Roof 8. Window 9. Door 10. Above
ENTRY METHODS AND BEHAVIOUR	1. Smash 2. Cut 3. Cutting equipment 4. Duplicate Key 5. Drill 6.Force 7. Remove Glass 8. Ram 9. Insecure door/window 10. Climbed
TYPE OF DWELLING	1. Old 2. Terrace 3. Maisonette 4. Bungalow 5. Semi-detached 6. Town House 7. Flat
SEARCH BEHAVIOUR	1. Untidy Search 2. Downstairs Only 3. Many Rooms 4. Upstairs Only 5. Tidy Search 6. Search All Rooms
LOCATION OF EXIT	1. Wall 2. Adjoining Property 3. Below 4. Front 5. Rear 6. Side 7. Roof 8. Window 9. Door 10. Exit Same as Entry
ALARM/PHONE	1. Cut Phone 2. Tamper with Alarm 3. Alarm Activated
BOGUS OFFICIAL CRIME	1. Social Services 2. Bogus Official (type unknown) 3. Council 4. DSS 5. Home Help 6. Gardener 7. Other 8. Water

Table 1: Burglary from dwelling house – modus operandi features.

so on. It was clear there were different 'types' of criminal identified within the data.

Similar type modus operandi and the geographic and temporal data was available for retail crime gangs in the north-east of England [12]. Retail crime is defined as specifically stealing from retail outlets or shops. We were interested in the most useful way of characterising a network or gang – was it perhaps on the basis of its membership (i.e. its stability, number, type: family or not) or do gangs differ on the basis of their geographical range and modi operandi, for instance falling into groups such a 'local', 'travelling' or not. We explored this by analysing line connectivity and node connectivity over time for particular gangs and the concepts of fragmentation, density, transitivity and core/periphery structures (see Borgatti et al. [13]). Certainly it was intimated from intelligence that within the data there were specialist and highly organised gangs, for instance gangs from eastern Europe specialising in purse theft, or a Malaysian gang targeting cheque fraud, or others favouring mobile phone theft.

3 Personality Theories

3.1 Detection (covertly) of personality type through game playing

A set rules of nine rules, representing the nine types of the Enneagram personality typolology [14], was embedded in a game with various 'states' through which

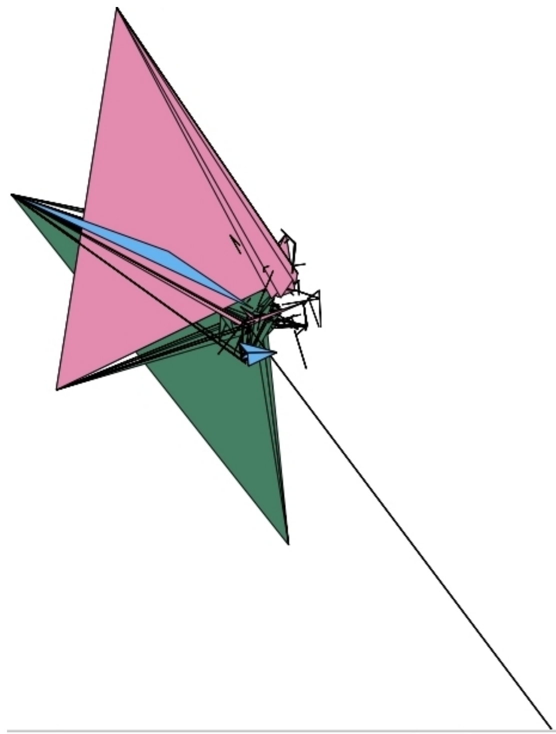

Figure 2: **Offender-Victim-Offence triples.** Legend: woundings (light blue), murder (purple), manslaughter (dark blue), kidnapping (green), firearms offences (brown).

a user could navigate [15]; see Figure 3. States in an 'everyday life game' might include: '*Getting ready for work*', '*Taking an evening meal*', '*Walking through a park*' and so on. States are linked according to real life, so you can pass from '*Taking breakfast*' to '*Travelling to work*', but not from the former to '*Taking an evening meal*'. Questions are asked of the user at each 'state', the answers to which are known to indicate evidence of a certain personality type. For instance, rules for Types 2 and 5 are presented in Listings 1 and 2. Importantly, the player is unaware that the game is slowly determining their personality type (hence the name SNEAK). SNEAK actively searches for the nearest useful 'states' that can quickly lead to a classification, and plots a course towards them. As each state follows coherently from the previous, SNEAK presents the new states to the player, and the player is unaware of the unfolding analysis.

This system was a rapidly developed prototype, to investigate the extent of domain knowledge required to achieve a realistic classification. Commenting on the system, an experienced Enneagram practitioner said of Rule 1 that it was representative of the type but that "*...it could also possibly be a type2Giver. 'sensingPerfection' is too high a concept, probably something that the person is*

Aggression
NPI. Arrested Sunday [DATE] at TK Maxx, Ncle City Centre. Stole clothing valued at £150. Arrested [DATE] at M&S, Newcastle, for £20 theft. DOESN'T LIKE BEING ARRESTED!! MAY RESIST VIOLENTLY.
Modus operandi (what is stolen, from where and how)
Thefts from TKMaxx v £90, Eisenegger, v £64 and Sports Connection v £62, all committed [DATE].
Prolific. 31 Shopthefts recorded since [DATE]. Brief eg's - 240899 Kwik Save,Wallsend, £41 / 130599 Superdrug Ncle, £34 / [CODE] HMV Ncle £49 / [CODE] Disney Store Ncle £15 / [CODE] M&S Ncle £144
Arrested with [PERSON] on [DATE]Theft from HMV,Ncle,val £25, Method – One detags items,passes to other to conceal. Prev Shopthefts '99 - Fenwick [DATE]val £22 & [DATE] val £5, Superdrug [DATE] val £16, Boots v £17 , Bodyshop £5
Sighting by [STAFF], Bhs, Ncle at 1705hrs [DATE]. Suspected attempt Refund Fraud on trousers., val. £25.
At the close of a day's thieving/refunding he collects unused cheques and cash proceeds of fraudulent refunds, having probably allowed deductions for his cohorts' commission. Well organised. Seen in Curry's red Corsa [NUMBERPLATE].
Her last two thefts qualify Tams for a mention in this Target File. On [DATE] She stole clothing from two Newcastle stores - River Island, Eldon Sq (val.stolen £174) and Etams, (val.stolen £230) she has used foil lined bags in the past.
Drug addict, [PERSON] is out daily stealing to feed his habit, and usually steals DURACELL batteries which he can sell on for cash. He has used baskets in Stores/Supermarkets and wanders around with Duracell batteries hidden under a few groceries
Big value clothing theives using big foil lined bags. Make sure you are aware of them because they are very active and very good at their job.
Known associates and gang affiliations
Experienced shopthief and longstanding member of the [GANG], she has recently been arrested together with [PERSON] and [PERSON] (her Partner) on [DATE] for the usual BULK CLOTHING THEFT val.£684, from Littlewoods, Metro Centre.
Thefts from Fenwick and C&A [DATE] with [PERSON], [PERSON], [PERSON], and [PERSON]. VAL £474
Prolific Shopthief in company with partner [PERSON] IDO XXX, in Washington, Metrocentre and other Tyneside areas.

Table 2: Examples of intelligence related to retail crime.

not normally conscious of.", and of Rule 5, that it was again representative, "*but it is generally an easily recognisable type anyway, at least, by themselves.*"

The rules were simple, the states were contrived and of a limited number, in order that every response from every type was able to be coded. This is a long way from automatically diagnosing someone's personality type through user interaction. Indeed, even for a human, administering a personality interview is notoriously difficult; for instance, the standard PCL-R assessment procedure for psychopathy [16] requires a semi-structured interview and a review of available file and collateral information. The purposes of the interview include providing a sample of the individual's interpersonal style, and allowing the user to compare and evaluate the consistency of statements and responses, both within the interview and between the interview and the collateral/file information [16]. Plutchick and Conte [17] confirm this difficulty: "*A simple change in test instructions e.g. 'how do you feel now?' vs. 'how do you usually feel?' generally changes a mood measure into a personality trait measure.*". Without significant structure it is hard to know what is being assessed.

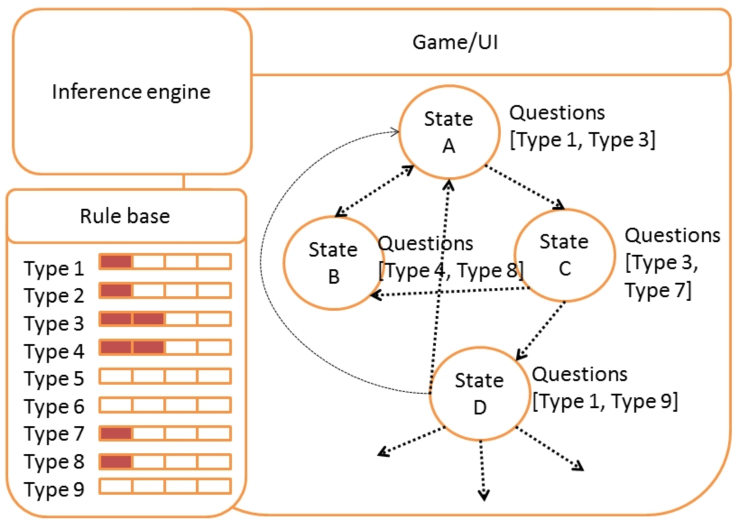

Figure 3: **SNEAK architecture.** The rules/classifications are partially instantiated. SNEAK will direct the user to a question that will differentiate between the two most likely current classifications (Type 3 and 4).

Listing 1: Rule for Type 1 Perfectionist

```
Rule1:if
 (Person isa avoidAnger,A) and
 (Person isa postponePleasure,B) and
 (Person isa tryToBeGood,C) and
 (Person isa sensingPerfection,D)
 then
 (Person isa type1Perfectionist,E).
```

Listing 2: Rule for Type 5 Observer

```
Rule5:if
 (Person isa needTimeToReflect,A) and
 (Person isa drainedByCommittment,B)
     and
 (Person isa greedyForKnowledge,C)
     and
 (Person isa
     detachesAttentionToImpartiallyObserve,D)
 then
 (Person isa type5Observer,E).
```

3.2 Detection of personality traits through textual analysis of social network data

Advances in psychology research have suggested it may be possible to classify personality through usage of textual analysis of social networking sites rather than the traditional approaches such as interviews or survey self-completion. Studies in the USA have suggested certain key words and phrases can signal underlying tendencies and that this can form the basis of identifying certain aspects of personality [18]. Extrapolating forward suggests that by investigation of an individual's online comments it maybe possible to identify individuals personality traits. Initial evidence in support of this hypothesis was demonstrated in 2012 by a study which analysed Twitter data for signs of psychotic behaviour in respondents [19].

There have been many studies relating to personality and language using the Five Factor model of personality [20,21,22,23]. However, the Five Factor model has known limits [24,25,26]: it has been criticised for its limited scope, methodology and the absence of an underlying theory, and attempts to replicate the Five Factor model in other countries with local dictionaries have succeeded in some countries but not in others [27,28]. Additionally, while Costa and McCrae [5] claim that their Five Factor model "represents basic dimensions of personality", psychologists have identified important trait models, for instance Cattell's 16 Personality Factors [29] and Eysenck's biologically based theory [30]. However, as discussed previously, this model has a significant body of research, which provides useful context for studies.

We have used a top-down dictionary approach [22], as opposed to a bottom-up method, such as collection of words and n-grams. We use two standard psycholinguistic dictionaries: LIWC [1] and MRC [2], and the equations based upon these features, for the Five Factors, based upon the work of Mairesse et al. [7]. MRC category `K_F_NSAMP` is the Kucera-Francis number of samples (from the Brown Corpus analysis), LIWC categories `UNIQUE`, `ABBREVIATIONS` and `PRONOUN` are the number of unique words, abbreviations and pronouns respectively, and `HEARING` is a count of words such as 'heard', 'listen', 'sound'. An example equation is presented in Listing 3.

Listing 3: Equation relating to extraversion psychological trait, based on MRC and LIWC psycholinguistic features.

```
Extraversion =
    -0.0379 * MRC.K_F_NSAMP +  -0.0803 * LIWC.UNIQUE +
        -0.6074 *  LIWC.ABBREVIATIONS +   0.1445 *
        LIWC.PRONOUN +  -0.3941 * LIWC.HEARING + 17.1407;
```

[1] Linguistic Inquiry and Word Count. Pennebaker and King [20] discuss the individual differences in linguistic styles, and developed the LIWC tool to try and measure these. Their text analysis software calculates the degree to which people use different categories of word, determining the degree any text uses positive or negative emotions, self-references, causal words, and 70 other language dimensions.

[2] The MRC Psycholinguistic Database is a machine-usable dictionary containing 150,837 words with up to 26 linguistic and psycholinguistic attributes for each – psychological measures are recorded for only about 2500 words. This data was empirically derived, which differs from the human judgment of psychological categories that created the LIWC.

The data that we have used for this study is from Twitter, and specifically looks at a person's retweet count. This tag is an unofficial way to provide attribution to the original publisher. If a person wishes to share a tweet from someone else (irrespective of whether they agree or disagree with it), it is possible to re-tweet it and share it on their own Twitter timeline. The retweet count provides the number of times that the tweet has been re-tweeted.

Therefore, a retweet count of zero means the tweet is authored by the user, whereas a value greater than zero means that someone else authored the tweet, although the user has shared the content. A count of zero indicates the user's own words and sentiments, a count greater than zero indicates other's words. Of course we can make further categories, for instance a count of 1 will indicate people being directly followed, and much larger counts will indicate very popular sentiments, and so on. However for this study, we consider only these two categories. In this way, for a single user, we have two different chunks of text, aggregated self-authored tweets and aggregated followed tweets. We perform our Five Factor analysis on these, giving two sets of Five Factor results for each user. In future work we will use multi-dimensional scaling to work out an algorithmic difference between users; however for this study we have selected Chernoff faces [31] for the visual representation. The Five Factors are displayed as five features on a stylised face. Figure 4 shows the Chernoff face representation of the Five Factors (using the R language with the *aplpack* library). A specific facial feature represents each one of the factors. Additionally the height of face (extraversion) has an additional impact also on the colour of the face, the width of eyes influences the eye colour, the width of hair affects the colour of the hair, and the width of nose effects the colour of nose.

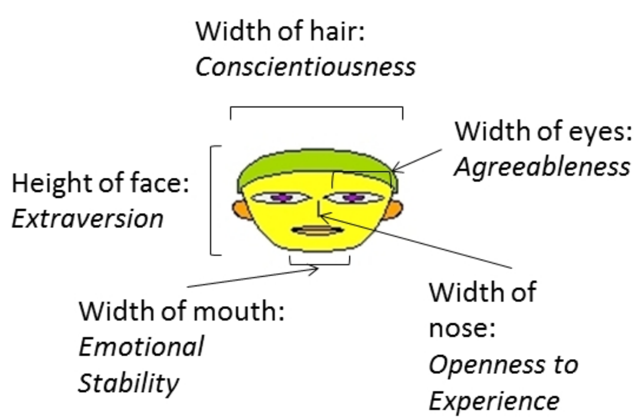

Figure 4: **"Mean" Chernoff face labelled with dimensions.**

The sample used undergraduate students (n=47) that engaged with a study (to be reported) looking at the correlation between social media profiles (Twitter, Facebook, LinkedIn) and personality typology and affect questionnaires: 44-item Big-Five Inventory, 12-item Dark Triad inventory, 30-item Trait Emotional Intelligence Questionnaire (Short Form), 144-item Riso-Hudson Enneagram Type Indicator Version 2.5 and 48-item Eysenck Personality Questionnaire–revised (Short Scale). We have only presented eight profiles in Figure 5, deliberately choosing profiles that present significant differences between the self-authored and other-authored faces.

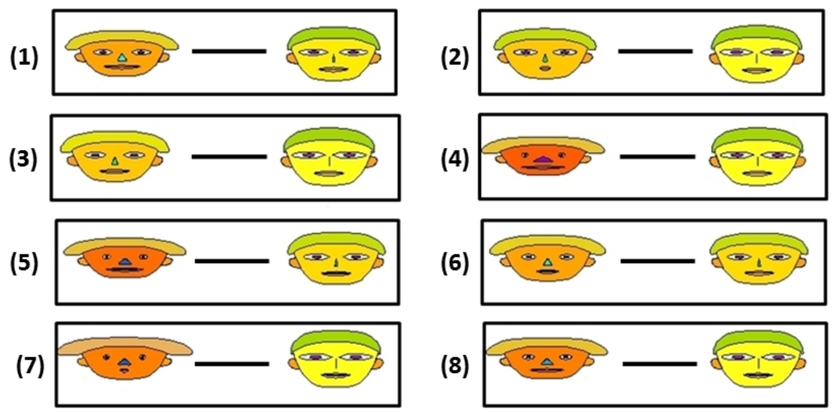

Figure 5: **Pairs of behaviour for a user.** Left image of each pair is self-authored, i.e. self-image, and right image is other-authored but liked.

4 Conclusions

While we have to be cautious about what we deduce in relation to criminal profiling [32,33], there is no doubt it is possible to determine certain traits of operational value from structured analysis of data from crime investigations. This will be equally true of data aggregated from other sources. Different data lends itself to different forms of analysis. In some circumstances traits and affects can be revealed, in others perhaps even the beliefs, opinions, or notions of identity (McAdams' top and middle levels).

This paper has presented a wide range of operational data and modelling techniques. These have differed with respect to the degree of knowledge inherent in the data itself, the sophistication of the modelling technique and the difficulty of the operational inference. The geospatial and network data (and their standard modelling techniques) are sufficient to characterise certain features of operational usefulness (matching crimes in an area, identifying possible accomplices, determining local versus travelling criminals), but barely reaching McAdams' trait level. Modus operandi data contains greater potential for psychological modelling, for instance whether someone is careful, risk averse, capable of violence, possessing a degree of craft, all indicating traits. The rule-based personality game illustrated the need for a heavily indexed and tightly constrained knowledge to detect personality features best described as McAdams' middle and even highest level. Finally the textual data from Twitter was sufficient to apply psycholinguistic techniques (although we are not able in this paper to consider the limitations of the approach), revealing personality trait knowledge (McAdams' lowest level). The technique (and future use of multi-dimensional scaling) shows how different high level profiles for an individual can be computed and visualised.

It is hoped that with additional knowledge sources, and solutions from the converging fields of psychology and personality, mindfulness and psychoanalysis, with computer-based models (for instance, using belief-desire-intention (BDI) agents and life-logging) that this field will develop significantly in the future.

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