A Framework for Interaction-driven User Modeling of Mobile News Reading Behaviour

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ABSTRACT

The news you read is, of course, a highly individual choice and one for which substantial and successful news recommendation techniques have been developed. But as well as *what* news you choose to read, the *way* you choose and read that news is also known to be highly individual. We propose a framework for extending the user profile of news readers with features of these interactions. The extensions are dynamic through monitoring an individual's reading and browsing activity. They include factors learned from the user's interaction log but also factors inferred from category level definitions contained in the framework. We report a study in which users' interactions logs with a news app are used to generate user profiles that are verified with self-reported questionnaire data about reading habits. We discuss the implications of our user modeling approach in news personalisation for both recommendation and user interface personalisation for news apps.

CCS CONCEPTS

• **Human-centered computing** → *HCI theory, concepts and models*; • **Computing methodologies** → *Machine learning*;

KEYWORDS

User Modeling; Personalisation; News Reading Behaviour;

1 INTRODUCTION

Smartphones and tablets might well be the epitome of personal computing but their personalisation has distinct limits. Personalisation occurs in the services users access, for example, news services can learn about a user's news interests and make recommendations of stories they might want to read. Personalisation also occurs in the customisations and adaptations made by users, for example, news apps give users choices in the display of preferred topics and in how content will be displayed (e.g., the optional interactive story carousel feature in the BBC news app), but also with the risk that users might never customize the interface themselves [32]. Mobile platforms in general do not learn about the user from their use of the device and they do not attempt to adapt to the users habits and preferences. In user interface research, adaptation has been a longstanding interest [7], although the desirability of adaptivity ('automatic adaptation') in user interfaces has been sometimes questioned [15, 35] and contrasted with the consistency and predictability of generic but customisable interfaces. A common focus for research on user interface adaptivity has been the re-ordering of frequently visited items within menu systems to quicken visual search and selection. This work has been able to provide clear evidence of the value of adaptivity for users and their preference for it [18, 19].

In the domain of news reading, a rich and relevant domain in which to explore adaptivity in user interfaces, progress in personalising the choice of news content has not been matched by progress in personalising the way that content is accessed and read. News apps such as Flipboard, BuzzFeed, Feedly, News360, Pulse, web-based news portals such Google News and Yahoo News, and research prototypes (WebClipping2 [9], Buzzer [34], SmartMedia [24], LumiNews [29], PEN [20], Focal [21]) frequently do adapt to users individual news interests through content recommendation services and many allow user customization of news feeds [4]. But their user interfaces do not adapt to how individual users characteristically select and read the news, as opposed to what news they are interested in reading. For example, the frequency and time spent reading news will vary considerably between people, as will their patterns of navigating news headlines and reading articles. This means that different users would likely be better served by different interfaces, for example, a user who likes to review all the headlines before choosing an article to read would be best served by a summary presentation of all headlines and a way of marking them as a reading list of articles. It might be expected that news app interfaces would benefit from personalization to the same extent as the news content it provides access to. Moreover, the growing number of news apps available on Google's and Apple's marketplaces and the plethora of news portals justify users' need for news consumption, but also creates the need for that access to be adaptive and personalised which is yet an open question to news services.

In this paper, we argue that news services need to extend beyond news content recommendation to include interaction and consumption habits that reflect the user interface of the news service. We propose a framework that illustrates a user

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model acquisition by extending user profiles of news readers with features of their interaction habits and preferences. Our approach utilises both data-driven acquisition and prior knowledge from category definitions of news reader types that are contained in the framework. Unlike previous attempts in modeling news reading behaviour, our method includes dynamic monitoring of a users reading activity including how she browses news headlines and how many scrolls she uses to read a story. We demonstrate our framework in a study in which interaction logs from 47 users were used to generate user profiles. We build a user profile consisting of six factors that reflect the user's news reading interaction behaviour and we explore different methods for the acquisition including inferences, transformation functions and a supervised learning method. We discuss the implications of our user modeling approach in news personalised systems and suggest initial ideas that could be used to drive user interface personalisation in news services.

This paper makes two contributions to user modeling and user interface personalisation. First, it proposes a framework for extending the user profiles for news readers by incorporating facts about their reading habits and preferences, extending beyond their profile of news content interests. Second, it examines alternative approaches to the acquisition of this extended user profile and discusses how it can be exploited in a personalised news app.

2 RELATED WORK

2.1 The News Domain

A relevant and rich domain for investigating personalisation and developing personalised systems is the domain of news. Reading the news has been transformed by digital news gateways and mobile platforms. Prominent news providers including CNN, BBC, Guardian and others are now giving increased priority to their digital news services. The proliferation and recent technological advancements of smartphones, in conjunction with their indispensable roles in peoples everyday lives, have established smartphones as a prominent channel for news consumption [12]. Recent reports [11, 27] place news as the second most popular activity on smartphones after accessing social media, yet provision of a personalised service in this domain is under developed.

News reading is a highly individual activity with marked differences in peoples' preferences of news content, but also in the way they browse, choose and read news stories. Grzeschik et al. [23] reported individual differences in reading activity, which were influenced strongly by the nature of the text rather by the reading devices. A distinctive 'screen-based' mode of reading news is apparent [31] characterised by 'more time spent on browsing and scanning, keyword spotting, one-time reading, non-linear reading, and reading more selectively, while less time is spent on in-depth reading, and concentrated reading'. Evidently, the nature of today's smartphones that are able to deliver news anywhere and anytime perfectly justifies this new reading behaviour.

2.2 Adaptive Presentation and Navigation

A cornerstone of our work is the adaptive hypermedia area. Brusilovsky [5] defines an adaptive hypermedia system as the one that "builds a model of the goals, preferences and knowledge of each individual user, and use this model throughout the interaction with the user, in order to adapt to the needs of that user". Adaptive presentation and navigation support are two techniques, often, utilised by adaptive systems. The former consists of text and multimedia adaptation, whereas the latter includes hiding, sorting, annotation, direct guidance, and hypertext map adaptation. Although adaptive hypermedia research flourished along with the explosion of the WWW, these ideas yet have applicability to date. In the news domain, the content adaptation has been explored for years and researchers have proposed successful recommendation engines to adapt news content. While news services are now able to help people find news of interest [4] and get fresh content that is relevant to them and to their current context, the future of mobile news is still taking shape. The plethora of news apps on marketplaces already provide personalised experience to mobile news readers, but we believe that the personalised news access needs to broaden its score, to further include not only what content users access but also how they access and interact with that content.

2.3 Modeling User's Behaviour

User profiles, often, contain user's related information such as user's interests, knowledge, background and skills, goals, tasks [6]. User interests can be anything from a specific web page to a hobbie-related topic, classified either as short-term or long-term interest. For example, a user attends an opera once a year (short-term) or a user's favorite music genre is jazz (long-term). Modeling user's news interests has been demonstrated in various research prototypes. The NewsDude [3], learns user's interests in daily news by classifying recent events as short-term interests and general news preferences as long-term. Another system [24] utilised articles views and preview time, clicks on news categories and information from Facebook and Twitter as implicit signals of user's interest in particular articles. Further, Carreira et al. [9] utilised total reading time, total number of the article's lines, number of lines read by the user and an approximation of user's average line reading time to classify news articles. User's knowledge and skills mainly capture domain related information (e.g. experts, intermediate, novices). User's background may include work experience, profession or education, among others. For example, an adaptive healthcare information system [10] delivers personalised information based on user's literacy and medical background. Finally, user's goals and tasks represent the user's objective or simply what the user aims to achieve in the system, which may vary across application domains.

The modeling mechanism is considered indispensable for any adaptive system. Adaptive systems often rely on effective user models wherein "unobservable information about a user is inferred from observable information from that user" [16]. Unobservable information may include any user's related

Figure 1: A conceptual diagram of a user profile for personalised news access. (left) A user profile that consists of user's news interests (e.g. article preference) (right) A user profile that consists of user's news reading interactions (e.g. reading style)

information, as previously explained. Observable information is collected either explicitly through direct user intervention and/or implicitly through monitoring user activity [22, 38]; the latter being often preferred by users. User models vary in the methods used for inferring unobservable information from the observable. A large body of research has focused on modeling users directly from their actions with specific user interface elements, clickstream behaviour [39], usage patterns [14] and others, often without any prior knowledge about users. More sophisticated methods of user modelling involve supervised learning techniques for inferring preferences from interaction data [4, 26] specifically on desktop environments but also in the mobile environment in relation to search engines [2], web page navigation [9], and using function usage histories to refine menu displays [17]. By contrast, a less widely used paradigm has focused on the use of stereotypes [28] or ontologies [36] to which a given user may belong. The central focus in this latter approach is that prior knowledge about users can be used and users are treated as entities with particular characteristics. For example, some user models infer group level user stereotypes or categories, particularly in relation to natural dialogues [8], accessible systems for users with disabilities [37], and museum visitors [30].

In our user modeling approach to news reading, we propose to extend the user profile with facts about an individual user's habits and preferences relating to how they access and read the news. This extended user profile would enable tailored adaptive presentation and navigation support in news apps that extends beyond news content recommendation.

3 OUR FRAMEWORK

A domain-specific user profile for personalised news access will contain facts about a user's news interests (i.e. what news content they prefer to read) and facts about their news reading interaction patterns (i.e. how to access and interact with that content) (Figure 1). While many successful techniques for news recommendation (i.e. content-based, collaborative filtering or hybrid) have been developed, techniques for modelling users news reading interaction patterns have not been developed. By incorporating user modeling of news reading interaction patterns as part of their personalisation engines, as well as the news content, news services would be able to adapt the user interface to the individual user.

Our prior research work [13] has identified three news reader types, discriminated by interaction factors arising in the users news reading interaction behaviour. The framework characterizes the hierarchical relationship of these abstracted factors with data that can be captured from logging the user's interactions. Building on our previous work, we propose a hierarchical framework that would enable the analysis of mobile-sensing data in order to build a user profile.

Our user modeling approach aims to build a user profile that consists of the six factors that reflect a user's news reading interaction behaviour. As might be seen, the factors of Frequency, Reading Time and Time of Day can be directly computed from users usage with the news app without the need of a learning process. For example, one can track the sessions of opening/closing the app and compute whether a user is a frequent news reader or not. However, the factors of reading style, browsing strategy and location/context are more high-level behaviours and more complicated constructs to determine. We explain in Section 4 the different approaches in inferring, computing and learning these factors. The factors are defined as follows:

- *Frequency*: How often users read the news(many times a day, once a day or occasionally)
- *Reading Time*: The daily time spent on reading the news(0-5 minutes, 5-10 minutes, or 10+ minutes)
- *Time of Day*: The period in the day when the user usually reads the news (morning, afternoon or evening)
- *Reading Style*: How people read a selected news article (i.e. detailed reading, skimming or scanning)
- *Browsing Strategy*: How people browse headlines and select news stories (i.e. scan headlines in a particular section, navigate through all sections)
- *Location/Context*: Where people read the news (at home, at work, public)

The framework characterises the raw interaction data collected from users' interactions with a news app (Figure 3) and the layers of abstraction over those data that constitute the user model, achieved by both bottom up and top down processes. A similar layered hierarchical framework has been proposed by Mohr [33] to support the monitoring of the mental health of at-risk people from their low level interactions with their mobile phones. The framework is fundamental in our approach, as it enriches low-level interactions with high-level constructs of news reading behaviour.

The framework consists of four layers (Figure 2). Layer 1 consists of low-level values related with sensors data and news reading interactions (e.g. GPS coordinates, scroll positions). Layer 2 defines functions for extraction and aggregation of

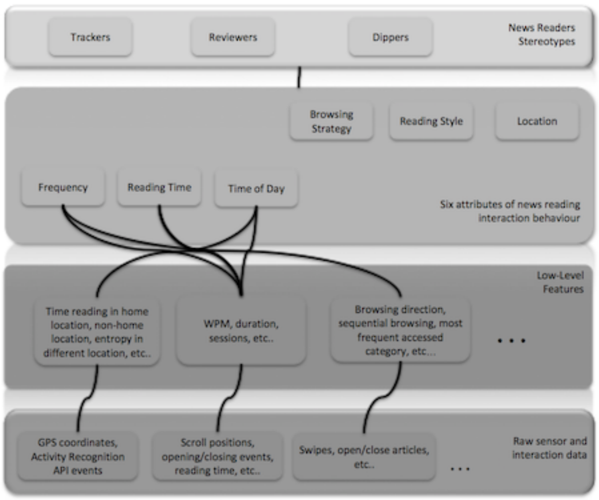

Figure 2: Mobile-sensing framework for analysing news reading behaviour

raw data into low-level features. By doing so, we extract meaningful information from the raw data (e.g. daily reading sessions, swipes directions). Layer 3 defines transformation functions of low-level features into the six factors of news reading interaction behaviour. Layer 4 integrates a News Reader Typology into the framework [13]. The framework defines the layers in relation to users' patterns of news consumption rather than the news content they consume.

3.1 Layer 1: Raw interaction data

Layer 1 defines the raw sensor data and low-level news reading interaction data collected using our prototype news app. The app logged different interactions made while reading articles, browsing to choose articles and context related data through the devices sensors. For example, a number of low-level events related with scroll positions that can determine how the user read an article, the trajectory of swipes and navigation behaviour for choosing articles to read. The app also utilised location services of the device as well as the Google's Activity Recognition API that allowed us to capture whether the phone was still or moving while reading.

3.2 Layer 2: Low-level features

Layer 2 of the hierarchical framework adds information to the low-level behaviourial and sensor data. It defines functions for extraction and aggregation of raw data into low-level features. For example, the different articles read on a day are aggregated into a low-level feature of number of daily articles read. The feature engineering is structured around three categories of features; the Reading, the Navigation and the Context related features.

3.2.1 Feature Extraction. The low-level features were chosen with the aim of revealing all aspects of news reading behaviour according with the six factors. All the features were aggregated on a daily level as well as intra-daily features were computed, dividing a day into three periods (Morning: 4-11 TW1, Afternoon: 12-19 TW2 and Evening: 20-3 TW3). A Boolean value was also extracted that indicates whether a date falls into weekend or not. Combining all features (including the Boolean value of isWeekend), a set of 103 features was extracted.

3.2.2 Reading Features. Reading features refer to data related with how users perform the reading task. We computed unique reading sessions, number of unique articles read, articles that were read more than once, reading duration, number of articles that scroll was used, number of articles that were read in whole (computed using scroll reached the end of the window), spikes in reading that could be an indication whether they followed a constant reading fast scroll up and down vs. constant ascending scrolling, and words per minute in terms of how much of the article exposed to the user divided by how much time required to read it (min, max, mean, median and std were computed for these features). For all reading features we computed one value for their overall daily behaviour as well as three more values for the intra-daily behaviour, which resulted in 30 reading features.

3.2.3 Navigation Features. Navigation features refer to data related with how users navigated and chose news stories to read. We computed unique navigation sessions, total news categories browsed, number of news categories that all headlines were browsed (we use number of swipes of direction in order to find whether a user browsed all headlines of a particular category), number of non-sequential and sequential navigation (i.e. the trajectory of user's browsing across categories - e.g. a. [1, 3, 7, 2, 4]→non-sequential or b. [1, 4, 8 or 9, 7, 2]→sequential numbers indicate the category id), number of swipes left, number of swipes right, total number of swipes, time spent in browsing headlines, most frequent news story reached across categories. The final navigation features set including the overall daily and intra-daily values resulting in 40 features.

3.2.4 Context Features. Context features refer to data related mainly with users' location while they were accessing the news. We treated location as sensitive user's data, thus we further preprocessed all location related data. All locations were obfuscated with unique identifiers (UUID) and a new identifier was generated if two locations were more than 10m away. By doing so, we ensure that users' location data will not be exposed to the researcher who performed the analysis. Further, data preprocessing consisted of determining a possible Home location for each individual. To compute the home location, we took the two most frequently appearing identifiers in TW1 and TW3 (in this case 5am-9am for TW1 and 10pm-4am for TW3) for each user session, under the assumption that people are more likely to be at their homes during those time intervals. Then, the most frequent identifier of the two was marked as home and subsequently all of a user's entries were marked as home or non-home locations.

The context features list consisted of unique context sessions, time reading at home and non-home location daily, ratio of time reading at home over non-home location, total movements while reading, entropy at non- home location (as a measure of the temporal dispersion of locations), entropy of different locations visited while reading throughout the day. Again, the final context features list including daily and intra-daily values resulted in 32 features.

3.3 Layer 3: High-level six factors

Having introduced the mechanisms to transform the raw sensor data and users' interactions into low-level features, Layer 3 defines functions that can transform the low-level features into the six factors that describe news reading behaviour. As previously explained the factors of Frequency, Reading Time and Time of Day can be directly computed from low-level features, whereas the factors of Reading Style, Browsing Strategy and Location/Context are more complicated but we defined transformation functions for this set of factors, as one of the approaches we examined make use of them.

3.3.1 Transformation Functions to compute Frequency, Reading Time and Time of Day. 'Frequency': We aggregate the number of reading sessions on a daily basis to determine the frequency of reading. For example, if two or more reading sessions appear on the log of one particular day then we mark it as 'many times a day'.

'Reading Time': We compute the average daily reading time low-level feature and accordingly we mark it as 0-5 minutes, 5- 10 minutes or 10+ minutes.

'Time of Day': We compute the time spent in reading in the three time windows (TW1, TW2, TW3) and then we assign accordingly the output as 'Morning', 'Afternoon', and 'Evening' using the highest value among the three time windows.

3.3.2 Transformation Functions to compute Browsing Strategy, Reading Style and Location/Context. The functions defined for these factors make assumptions and rely on heuristics. These factors are more complex behavioural constructs to simply capture from combining low-level features, but it was explored. We discuss an alternative learning approach (4.2.6) in which we trained a classifier to learn these factors.

'Reading Style': We estimate words per minute (wpm), which is an indication of the pace the reading was performed. We calculate the proportion of the article that is exposed to the user by using scroll positions. This approximates the number of words viewed by dividing the max scroll position reached by total size of the document and multiplied by the number of words. Then, the wpm is computed by dividing the approximate number of words viewed by the reading duration. Finally, the possible output values for reading style are 'detailed reading' if the wpm is up to 230, 'scanning' if it is greater than 700 and 'skimming' if it is in between.

'Browsing Strategy': We use low-level features such as the number of different categories of headlines browsed and the number of times headlines were browsed in a day as well as the total number of headlines categories browsed. We compute two ratios: (a) categories in which all headlines were browsed over different sessions which indicates whether a user has a preferred category, and (b) unique categories browsed over unique navigation sessions which indicates whether a user accesses most of the categories available. Given the nine news categories present in the news app we set a threshold for particular category browsing as 1 and for browsing through all categories as 6. Given the two ratios and the thresholds then a rule-based algorithm produces three possible outputs (a) 'both', meaning that the user on different occasions either only reads articles in a selected category or categories, and at other times chooses to view articles in all categories, (b) 'particular', meaning that the user navigates only in particular categories, and (c) 'all', meaning that the user navigates most of the cases through all categories.

'Location': A rule-based algorithm is used to determine whether the user is reading the news at home or in a non-home location. A location where the user spends more time than any other specific location is designated as home. The inference is modified by the time at which the news is read making the assumption that most people are at work in the second time window. We use entropy of location to describe the variability in different locations, meaning that if the user has a high entropy they are more likely to be in a public setting, while low entropy indicates a work environment.

3.4 Layer 4: News Reader Types

Layer 4 integrates the News Reader Typology from our previous work into the framework. It is used by one of the approaches we take to building the user profile through making inferences about the high-level behaviourial factors as an alternative to computing them directly from the low-level features.

4 BUILDING A USER PROFILE

The framework characterizes the abstraction of an extended user profile from a user's interactions with a news reading app. The extended user profile consists of a set of interaction factors that are particular to an individual user. We now report a study which demonstrates the application of the framework to generate user profiles for people reading the news with a news app. The study involved users using a news app created for the purpose and capable of reporting data about the users interactive behaviours such as swipes, scrolls and taps.

4.1 Data Collection with Habito News

Habito News (Figure 3) is a news app we developed to explore news reading interactions [13]. It mimics the BBC news app in terms of the organisation and presentation of headlines and the layout of news stories; live news is fed from the BBC news API and presents the news in row of thumbnails (nine news categories and nine news articles in each category). The app was implemented on the Android platform, deployed through the Google Play store and installed by 47 users on

Figure 3: Our prototype news app, Habito News. (a) Login page (b) Built-in consent form (c) Survey related with the six factors (d) News headlines menu (e) News article presentation

their own smartphones. Apart from delivering news stories, the app is capable of logging the low-level data explained in Layer 1 of the framework.

4.1.1 Participants. Mainly recruited through university and social-network posts, but also as the app was listed on Google Play it was practically accessible to everyone. Participants who were recruited through university entered a draw for a £50 Amazon voucher, whereas anyone else who directly downloaded the app did not receive any compensation for their participation. The inclusion criteria consisted of (a) participants own an Android device with OS greater than 4.3 and (b) use Habito News as the their primary news reading application for a period of 2-weeks. To ensure that participants used our app as their primary source, we logged the apps running in the background (while Habito News was open), but also applying filters for the News&Magazines category to ensure privacy, as we did not want to obtain any other information about users running apps.

4.1.2 Procedure. Upon download, users signed up with Habito News. Before providing any data, users had to agree to a built-in consent form disclosing the type of data that was being monitored as well as providing information related with the setup of the study. The registration process consisted of two steps with data gathered using explicit methods through a built-in form and a questionnaire. Participants provided demographic information such as their age, gender and date of birth through a built-in form. They also answered six questions about their news reading behaviour. We use this source of information to validate the models that predict the high-level behaviourial constructs of news reading interaction behaviour. The six questions along with the potential responses (users chose one answer for each question) are (Figure 3(c)):

(1) How often do you read news on your mobile device? [a. Many times b. Once c. Occasionally]
(2) How much time a day do you spend reading news on your mobile device? [a. 0-5 min b. 5-10 min c. 10+ min]
(3) How do you look for stories of interest? [a. All b. Particular c. Both]
(4) How do you read a news story? [a. Detailed b. Skimming c. Scanning]
(5) Where do you often read news? [a. Home b. Work c. Public Transport]
(6) What time of the day do you usually read news? [a. Morning b. Afternoon c.Evening]

4.2 Modeling the six factors

The interaction factors of Frequency, Reading Time and Time of Day were computed directly from the low-level features using the transformation functions provided in layer 2 of the framework. To model the interaction factors of Reading Style, Browsing Strategy and Location/Context we explored three approaches, (a) inferences from the News Reader Typology, (b) using the transformation functions and (c) supervised machine learning method.

4.2.1 Ground-truth information. To evaluate the approaches we used participants' answers to the questions they were asked at initial registration about their news reading habits and preferences. Specifically, their answers to the three questions about how they browsed headlines, how they read articles and where they read the news were used as the ground truth against which the different approaches would be assessed. Table 1 shows the distribution of the answers for each question related with the three factors. We set the baseline model for each factor as the majority class in their distribution. For example, the factor of Reading Style has a distribution of detailed reading 27.3%, skimming 31.3% and scanning 41.4%; baseline model is set to the 'scanning class' distribution. A similar approach was followed for the other factors. Therefore, we would expect our models to outperform the baseline models.

4.2.2 Preparing the datasets for the analysis. A common problem when dealing with mobile-sensing data is missing values. Despite the fact that Habito News was designed in such a way as to minimise this problem, our dataset suffered from missing values. For example, it prompted the user to enable location services in order not to miss context related values. However, nothing could have been done for the other two categories of data as we did not want to intervene and force people to read under given instructions but rather we let them perform it on their own pace and when they had the need to read the news. Therefore, there are cases in our dataset where values for some categories are missing (e.g. navigation is missing due to the user read a few articles without performing any browsing). Such cases were dropped from the final dataset used for the analysis. Apart from missing values, further data pruning was carried out in order to eliminate users with one-day usage (Figure 4). In particular the 47 users initial dataset reduced down to 33 users. We treated this set of users as outliers as their behaviour could have added noise to the data due to these users have downloaded the app and then after a day's usage opted-out. Therefore, the final dataset consisted of 198 daily datapoints and a 103 features space.

4.2.3 Inferences from the News Reader Typology. Given the computed factors of the Frequency, Reading Time and Time of Day, we derived the other three factors from the typology based on the characteristics of the stereotypical profiles. To derive Reading Style we used frequency and reading time, we used frequency for Browsing Strategy and we used frequency and time of day for Location/Context. For example, the typology defines skimming as the reading style of a news reader type who reads the news many times a day. It defines 'looking for particular section' as a browsing strategy of a news reader who reads the news occasionally. Similar definitions are provided in the original News Reader Typology, which can be retrieved in [13]. Table 2 shows the accuracy in inferring the three behaviourial factors.

4.2.4 Using the transformation functions. The second approach we explored, made use of the transformation functions that are defined in layer 2 of the framework to compute the factors of reading style, browsing strategy and location/context. It is important to mention the assumptions and heuristics that used to create those functions. For example, we used words per minute as an indication of the pace while reading, which in turn used to distinguish detailed reading from skimming and from scanning. At first glance it may seem straightforward, but the factor of reading style might be more complicated and depend on other variables than simply on words per minute.

4.2.5 Performance of rule-based approaches. We used a Cosine Similarity function in which we transformed the output of the derived (4.2.3) and computed (4.2.4) behaviourial factors into binary vectors and compared them with binary vectors of the ground truth. Table 2 shows the accuracy in computing the three behaviourial factors. The accuracies were below the baseline models except for the reading style that was computed using the function provided by the framework. For the location/context factor both algorithms completely failed. A possible explanation for that is the fact that these behaviourial factors might depend on different variables that the rule-based approaches failed to capture, and thus we examine a learning method in the next section.

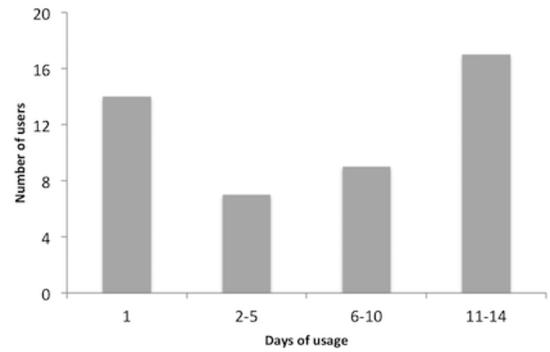

Figure 4: Habito News usage for the 2-week trial

Factor	Values	Distribution
Reading Style	detailed	27.28%
	skimming	31.30%
	detailed	41.42%
Browsing Strategy	particular	28.79%
	all	49.49%
	both	21.72%
Location/Context	home	80.81%
	public	19.19%

Table 1: Distribution of the ground truth information for each factor

4.2.6 Supervised learning method. Given that the results produced by the rule-based approaches did not outperform the baseline models for each factor, in the third approach we examined the use of a supervised machine learning method with the low-level feaures set as input, allowing the algorithm to learn and detect any hidden structure and associations between the low-level behaviourial features and the high-level factors.

We trained three Random Forest (RF) classifiers, one for each individual factor. The choice of RF was reinforced by the fairly small dataset used to train the algorithm, as it is recognised for its accuracy and its ability to deal with small sample sizes. We tuned each individual RF classifier with 500 estimators (trees) and due to the imbalanced datasets we used a balanced class weight mode that automatically adjusts

Factor	Inferences	Functions	RF
Reading Style	36.36%	52.02%	60.00%
Browsing Strategy	42.42%	24.74%	54.73%
Location/Context	45.95%	36.86%	82.10%

Table 2: Accuracies of inferring, computing and learning the three behaviourial factors

the weights inversely proportional to the classes distributions. To avoid overfitting of the algorithms, we ran a k-fold (k=10) validation by leaving one instance out. Table 2 shows the performance in learning the three behaviourial factors.

The learning method produced better results compared to the rule-based approaches, as all three learnt behaviourial factors exceeded the baseline values. The browsing strategy improved by 12.31%, reading style by 23.64% and location/context compared to the inferences approach. Further, the browsing strategy improved by 29.99%, reading style by 7.98% and location/context by 45.24% compared to the accuracies observed using the transformation functions.

Another important insight that can be drawn from the learning method is the features importance, which can be used to inform the heuristics and the design/refinement of the transformation functions or lead to better understanding of the behaviourial factors. For example, the current transformation function of reading style (4.2.4) uses an approximation of the words per minute. Among the 10 most predictive features of the reading style classifier were the different statistics for wpm (max, min, median, std) and daily reading time, which currently the function makes use of, but also navigation related features (e.g. number of swipes, categories browsed) that the heuristics did not to consider.

5 DISCUSSION

In this paper we present a framework for extending user profiles of news readers with attributes of their interaction habits and preferences. Our framework characterises the process of analysing news reading interaction patterns. We demonstrate it with a corpus of interactions logs obtained from a prototype news app in order to build a user profile consisting of six factors. We directly compute the factors of frequency, reading time and time of day from the low-level features, and we explore three approaches for the factors of reading style, browsing strategy and location/context including inferences, computation using heuristics and learning methods.

The rule-based approaches did not yield good performances but the learning method was able to learn and predict the high-level behaviourial factors. The learning method outperformed the baseline models for each factor and improved significantly the accuracies of predicting these factors compared to the rule-based approaches. The results suggest that our method is feasible in principle and with further training and tuning of the algorithms it can be deployable. Our framework has the potential to enrich existing news personalised services, as it captures another aspect of news reading behaviour that reflects users' interaction habits and preferences. The six factors of the extended news reader profile could be matched with preferences for different user interface elements or interactions in order to generate personalised compositional user interfaces. that would aim to enhance user's news reading experience. For example, a user who tracks and follows the news throughout the day could be given access to features such as tagged previously-read articles or stories with updates, as opposed to a casual news reader who is more likely not to benefit from these features. Likewise, a user who likes to read an article underneath a top headline while commuting at work would be better served by a different user interface and interaction than the user who reads the very same article at home. These examples illustrate the application of our user modeling framework in which the six factors of the news reader profile reflect the user interface choice in a personalised news app.

Finally, it is important to highlight some of the limitations of the current work and discuss future directions of this research. First, the relatively small sample size used is of an immediate future work as it might yield better algorithms' performances. Second, the ground truth used to train the models obtained through self-reported questionnaires. Despite the fact that it is a standard technique, it relies on peoples' ability to accurately assess themselves, which can be considered as a limitation. This could be explained by the fact that "humans do not remember experiences in a consistent and linear way, but rather recall events selectively and with various biases" [1, 25]. Alternatively, we could observe users' interaction behaviour in a laboratory setting with video recordings in order to obtain the ground truth information. However, doing so implies that we lose ecological validity of our results, thus we aimed to investigate it in a field study to explore as much as possible users' natural behaviour while reading the news. Further future directions include the generalisation of our framework in order to provide generic methods that can translate news interaction patterns from different news apps and providers other than the BBC. This would enable the integration of our framework in different news layout organisations and interactions, and thus it would enable the generation of extended news reader profiles for news consumption despite the different news apps layouts.

6 CONCLUSIONS

We proposed a framework for extending news reader user profiles with factors from low-level interactions and news reading consumption patterns. We illustrated our framework using users' interaction logs of a news app that used to generate user profiles, which validated with self-reported questionnaire data. We discussed the implications of our user modeling approach in news personalisation for both recommendation and user interface personalisation for news apps.

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