PREVIEW

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Electronics and Computer Science

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Designing an Efficient Mobile Interface for Capturing Rationale Behind Peer-Produced Recommendations

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Abstract

Using mobiles to find information online can be a demanding task: the daunting quantity of unrelated or inaccurate information swamps genuinely useful information, making it difficult to find helpful information in situations where the mobile phone is not the primary focus or where time is short. This project investigates a method of forming recommendations from peer-produced information for the purpose of serendipitous discovery or decision support.

As such, this project contributes two sets of findings. The first pertains to a probe study where, through the role-play of participants, we establish what people recommend and why. This allows the forming of a structure for storing the rationale behind a recommendation as metadata. The second relates to the design of a mobile interface, *Groovy*, for the capturing of rational as structured metadata; namely, how effectively it captures rationale and how it performs compared to existing interfaces. Through a field study of this interface in a photo-tagging game, we consider how such a tool could impact on people's every-day activities in practice.

Acknowledgments

To the best of my knowledge, this project report does not contain any material written by others. This project has been conducted by myself, with assistance from my supervisors, researchers and friends, who I acknowledge below. Research and work that has influenced this project have been acknowledged and referenced throughout this report.

I would like to thank dr mc schraefel and Dr. Max Van Kleek for their support in this project and motivating me throughout.

I thank Dexter Lowe, Jim Skinner and Bahman Asadi for kindly advising me in producing this LaTeX document. I also thank Richard Gomer for discussing his thoughts on the user interface design with me.

Finally, I'd like to express my appreciation for those who took some time to participate in the two studies.

Contents

1 Introduction

With vast quantities of information available via the web, finding relevant information among the irrelevant "noise" can be time-consuming and laborious. In situations where people want information at hand quickly, and without effort, such as when their primary focus is elsewhere, or when they must make a decision in a short space of time, current information systems may be too slow or hard to use. This demonstrates the need for a tool that would allow the generation of recommendations – peer-produced information paired with information about the context it is useful in – to be provided to people who would find them useful in the aid of serendipitous discovery and decision support.

Seeking information online using mobile devices can be slow and difficult. Minimal contextual information means that information on, for example, which cake to purchase in a bakery would require a lot of effort to find. An individual may give up or simply not attempt to find such information as it presents the daunting task of sifting through largely irrelevant data (Beale 2007).

Studies have shown that the ability for a person to make effective decisions may be dramatically improved when they are provided with relevant information that indicates the effect of a decision (Melone et al. 1993). For example, the shopping website *Amazon.com* offers customer reviews of products, consisting of a star rating and text description of good and bad features of the product. Whilst browsing products, shoppers are able to see the average star rating below each item, and once clicked on, the textual reviews. As discussed in (Lee 2009), the effect of positive reviews positively affects the *Purchasing Intention* of customers, with the quality and quantity of arguments increasing this effect. The provision of these accounts of other customers' real experiences at purchase time indicates to a shopper whether the product would give them a positive or negative experience, and thus they can make a decision that will be unlikely to negatively affect them, demonstrating the positive effect that such decision aids can have on even routine purchases.

Furthermore, the availability of online tools that allow browsing of products using certain criteria, such as faceted browsing, allowing a user to specify the desired features and price of a product, has also affected the behaviour of customers (Kamis & Davern 2004). Websites such as Yelp are able to recommend places to eat based on a user's preferences. More recently, the positive effect of adding certainty to a customer's purchase decision has motivated a number of recommendation algorithms to be applied to e-commerce websites (Schafer et al. 2001). Amazon.com recommends customers items based on the profile of the customer and the qualities of the item, and the conversion rates have been demonstrated as being in considerable excess of products that are not targeted (such as through banner advertisements) (Linden et al. 2003).

This report will consider how peer-produced information might be repurposed as recommendations by capturing the rationale – why someone has shared it. Such recommendations could then be targeted towards users for the purposes of, for example, supporting people's routine decisions, or serendipitous discovery. Using mobile devices to ask for this rationale allows the capture of contextual infromation, such as location, providing further information about who might be interested – e.g., people nearby.

This project will involve an iterative user-centred design investigation of an application for mobile devices that allows the generation of recommendations quickly and easily, focusing on two major design questions:

1. *What information is required to describe rationale?*: How can the rationale be encoded as structured metadata, such that it may be reused to form recommendations?

2. *How can rationale be captured in a pervasive way?*: How can it be made easy to use, and fun, such that people will want to do it?

This report will first give an overview of the problems that will be addressed and the challenges involved, followed by a discussion of related projects and studies and the contributions to research. Two major tasks involved in this project will then be discussed, with the methodology and findings detailed. First, in order to understand what information would be required to elicit recommendations, a prestudy was carried out, where 15 participants were asked to upload photos and describe why others might like them.

This was a cultural probe (Gaver et al. 1999) that gathered information on what people experience on a day to day basis. Following one week of uploading photos, the participants were asked why they uploaded these photos. This allowed us to establish the rationale behind their submissions. From this, we were able to extract types of information that were consistent across many of the recommendations. These "dimensions" included what the photo depicted, how much the participant likes it and when and where it might be useful. The results of this study we used to write an academic paper for submission to DIS2012[1].

Following this, we designed Groovy, a mobile gestural interface for the capturing of rationale in the form of dimensions. A field study of this interface was conducted, in which 21 participants were asked to encode the rationale for recommending particular photos. We present these findings and give an insight into how such a tool could impact people's everyday activities.

[1]ACM conference on Designing Interactive Systems 2012, deadline 20th January 2012 – `http://dis2012.org/`

2 Motivation

Current information systems are limited in their capturing of information useful for the repurposing of data as recommendations (Beale 2007). Peer-produced information has a number of limitations, forming challenges in establishing this contextual information. Specifically, data may lack the following qualities, making it difficult to understand:

1. *Structure*: Information captured as text or photos, for example, is difficult for machines to understand;

2. *Consistency*: Users may have different understandings of what they should submit, leading to inconsistent information that is difficult to use;

3. *Accuracy*: Peer-produced content may be incorrect or inaccurate, providing others with false or misleading information.

This section highlights the challenges and the motivations behind this project.

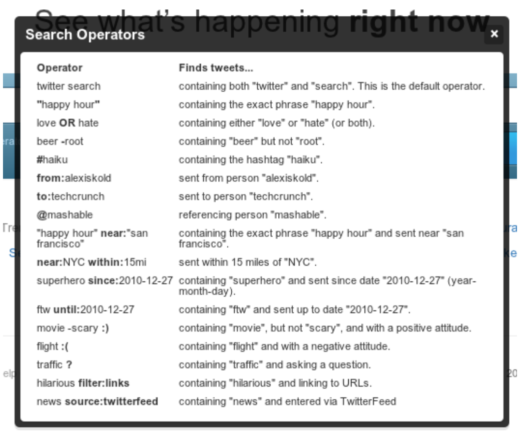
2.1 Challenges in accessing information

Some search mechanisms on sites with peer-produced information, such as Twitter[2] and Quora[3] (Figure 1), assist users in finding information by analysing the content and context. While full-text searching still takes place, using contextual data allows search results specific to what is relevant to them; e.g., a user may only be interested in products available geographically near them, or events that happened in the last hour. Some services, such as Trendsmap[4] (Figure 2), use this contextual data to visualise the information.

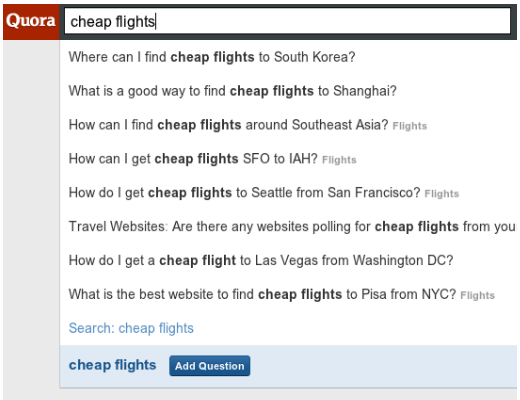
However, these search mechanisms present limitations. While tweets do capture certain contextual data – such as hashtags, users, time and location – they are otherwise only able to be filtered via full-text searching. With the subject of the information unclear, searching for a particular topic will often result in a lot of "noise" (information that is irrelevant, incorrect, poorly framed, or badly-informed). Sifting through this information may be time-consuming and require effort (Beale 2007).

In situations where a time-critical decision must be made, or where a person is conducting some other attention-intensive primary activity, searching through the noise "on-the-go" takes too long and requires too much effort. In particular, studies of mobile information needs (Sohn et al. 2008) revealed that most information needs while driving or walking goes unresolved because the necessary resources can't be consulted in a suitable way – e.g., quickly, without using hands.

[2] `https://twitter.com/`
[3] `http://www.quora.com/`
[4] http://trendsmap.com/



(a) Twitter offers a number of search operators, allowing users to see tweets with specific content or context.



(b) Quora's search offers suggestions for answers based on the appearance of the phrase within the question title.

Figure 1: Using contents or context of information to assist users in finding things that they want

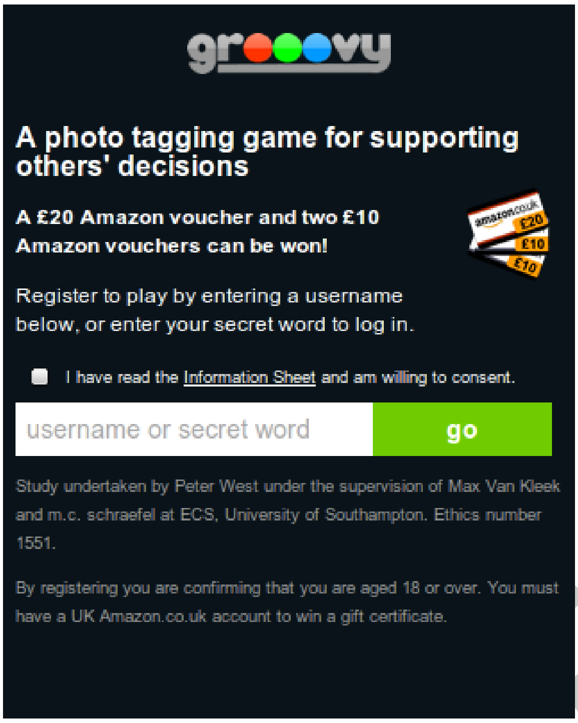
2.2 Challenges in capture

In order to form recommendations from peer-produced information, as much useful contextual data as possible should be captured, allowing people to search for information based on their "needs" and context. This presents two major challenges:

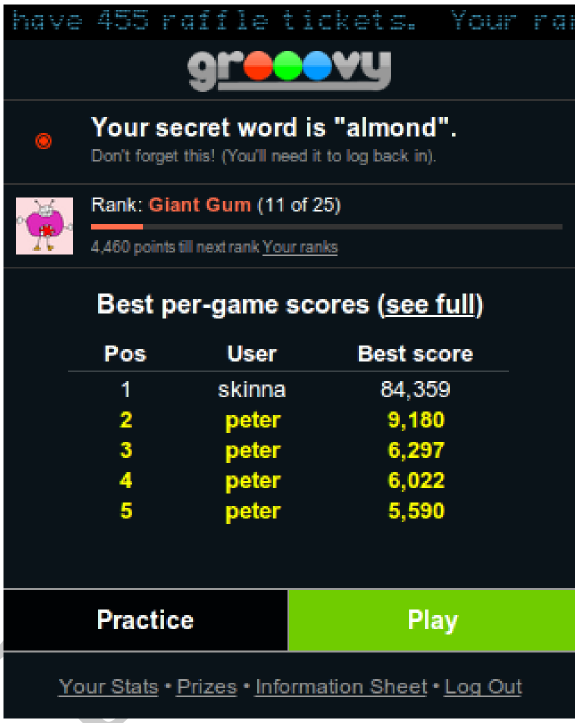
1. *Encouraging capture*: Persuading people to make recommendations about anything. Many experiences are not recognized as "interesting", due to their familiarity (similarity to past experiences), or the perception that such experiences are trivial and not important (Juliusson et al. 2005);

2. *Interface design*: Designing a way to allow people to make recommendations quickly and easily, while capturing contextual information.

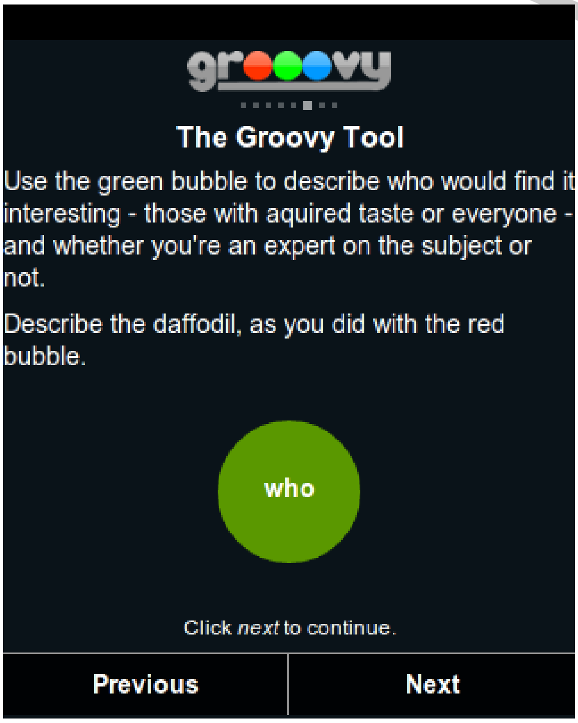
With the widespread availability of mobile phones, and their capabilities to support geo-location and high-responsiveness, mobile phones may present a pervasive solution to encouraging capture. Pertaining to user interface design, current capture techniques, such via text and menus, may not be as fast as gestural interfaces for mobile users.



(a) log in screen

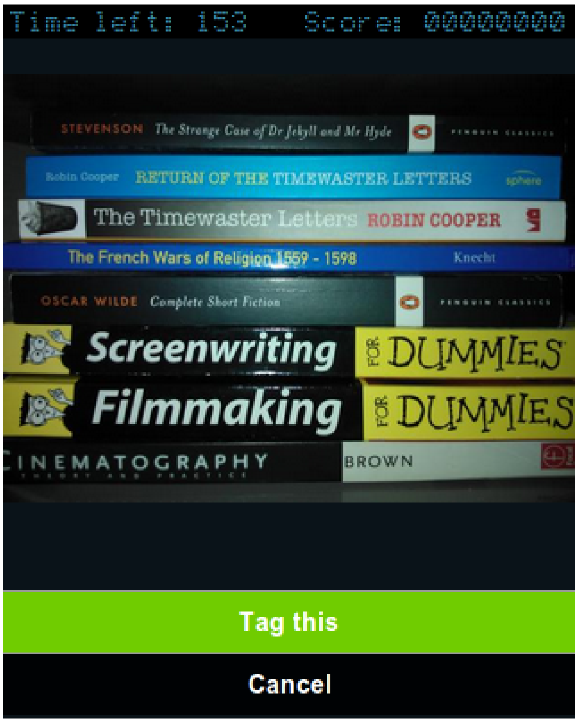


(b) main screen, visible once logged in

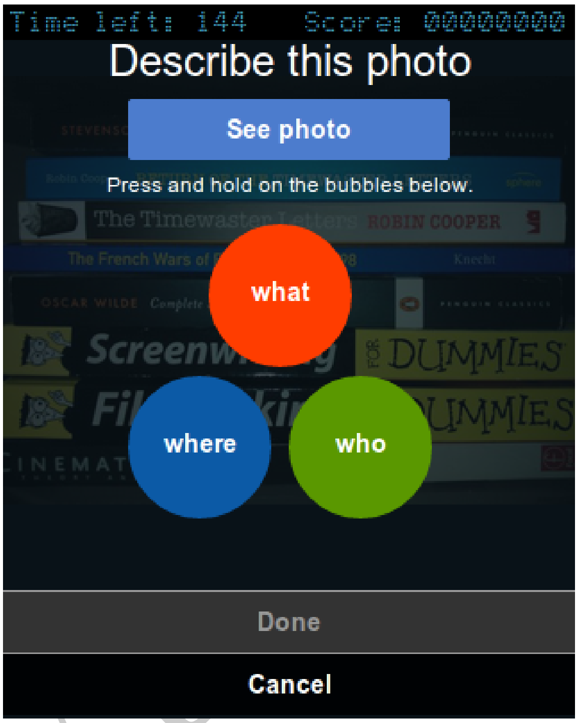


(c) practice mode, showing tutorial on the green Groovy bubble

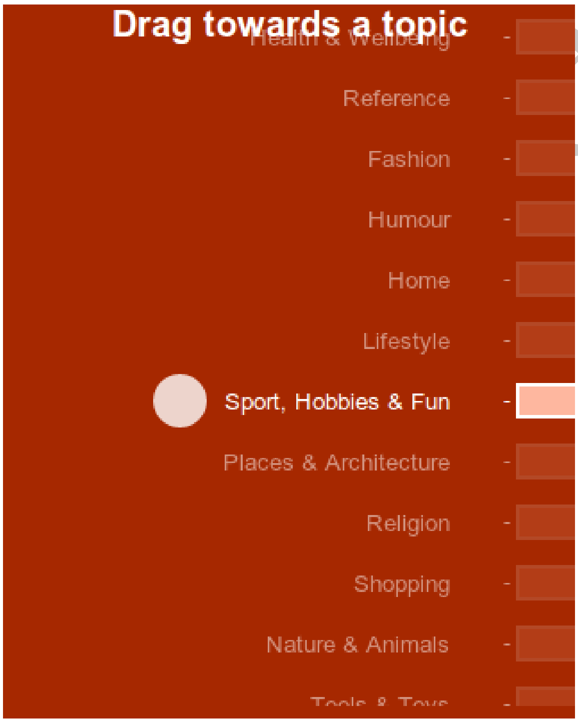
(d) in-game, showing photo thumbnails



(e) previewing a photo

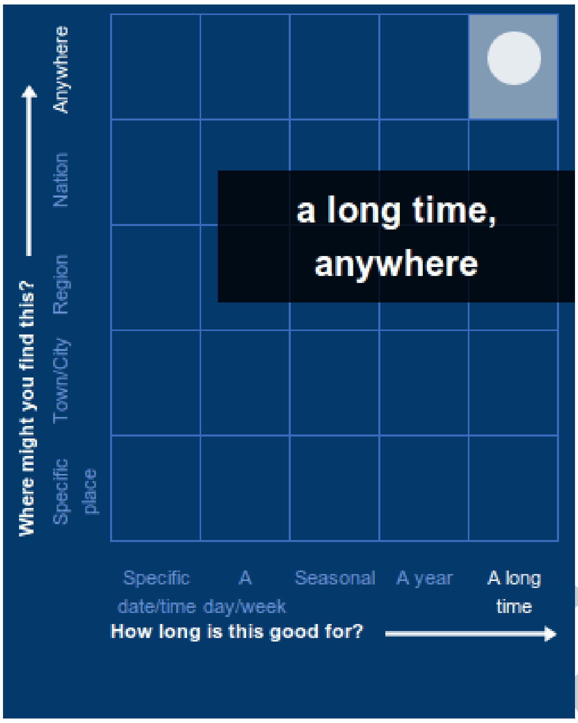


(f) the Groovy interface

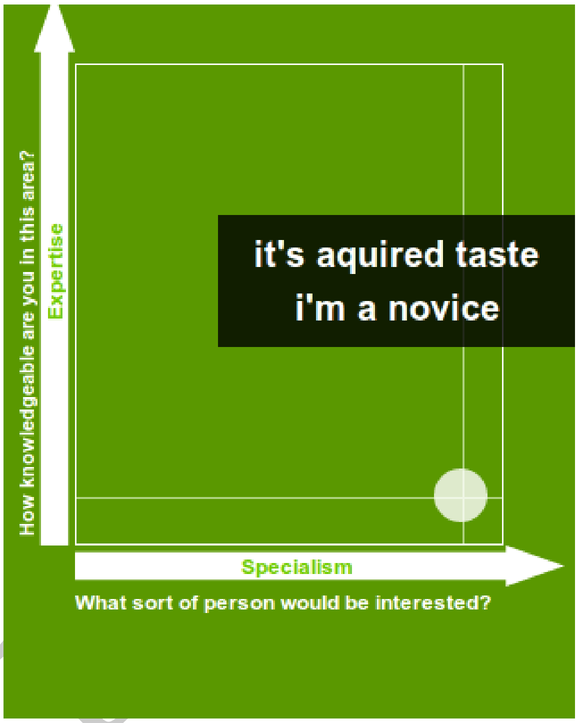


(g) inside the red bubble

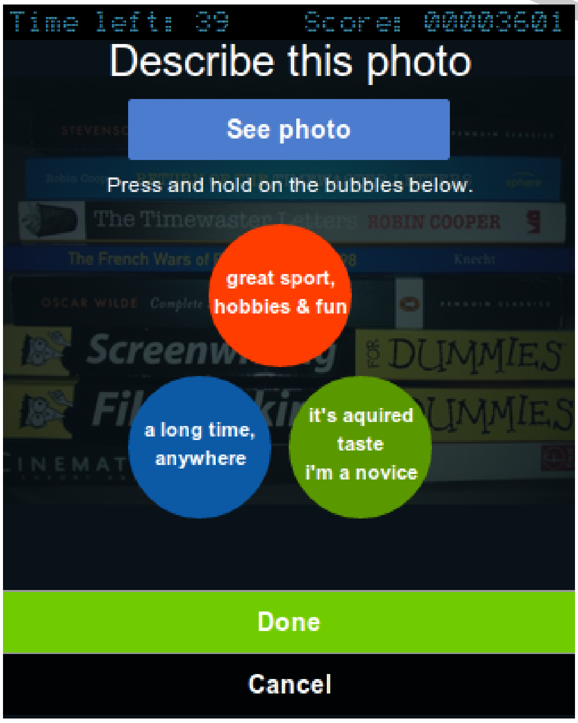
(h) moving one's finger towards the right scrolls in the valence sliders



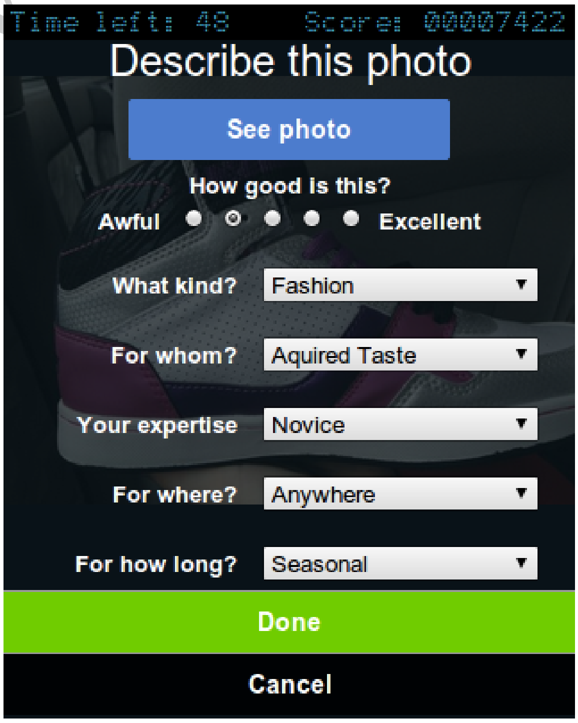
(i) inside the blue bubble



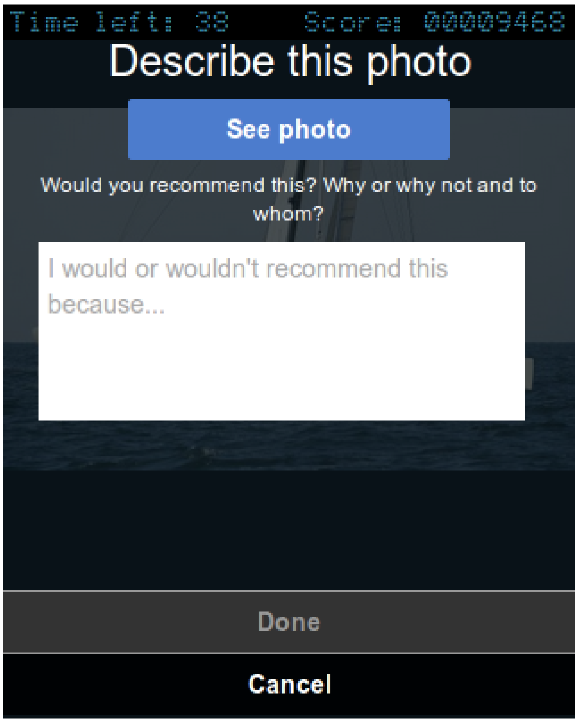
(j) inside the green bubble



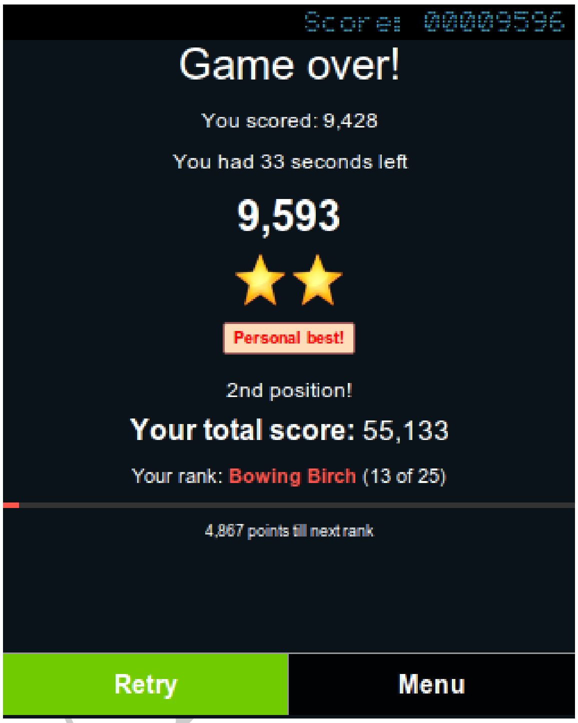
(k) once specified, each bubble contains text to describe what it is set to



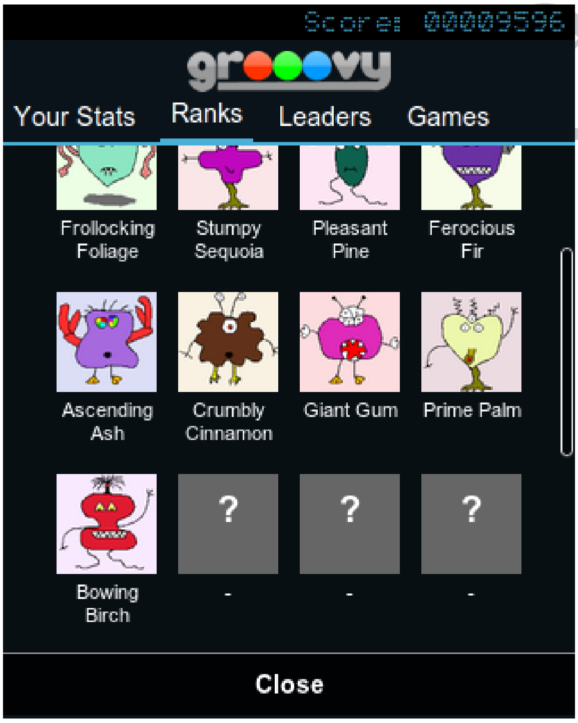
(l) Menu interface



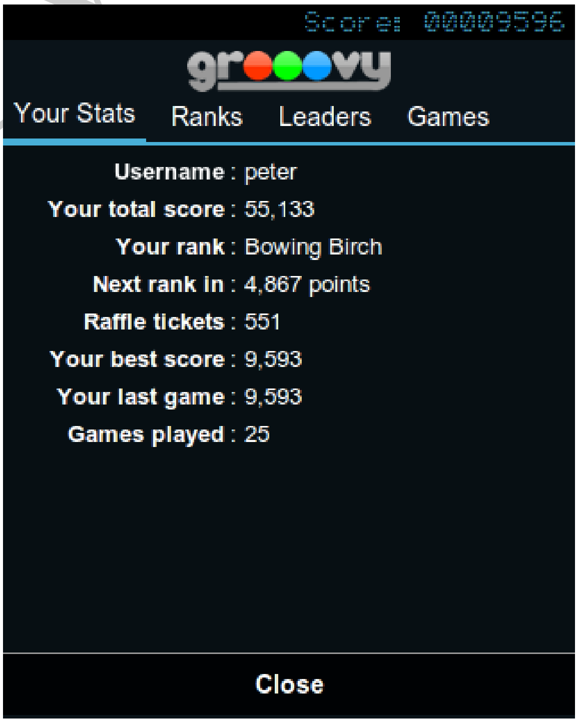
(m) Text interface



(n) end-game screen



(o) rank screen



(p) user statistics screen

factors include the user's ability to use the phone's keyboard and variations in the mobiles used (e.g., those with hardware keyboards or predictive text might be expected to be faster than those without);

2. *The photo*: Figure 13a demonstrates that, for some photos, the text tag is, on average, faster to complete than Groovy, suggesting that some photos may be difficult to describe using Groovy;

3. *The user*: Figure 13b demonstrates that some users are faster at the Text that Groovy, perhaps because they have a tendency to enter short Text tags, which do not contain the dimensions that Groovy tags do, or their familiarity with text input.

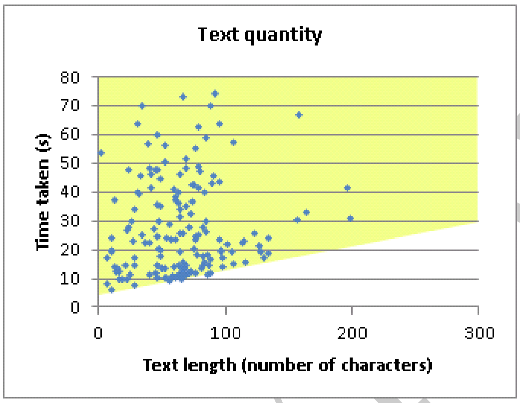
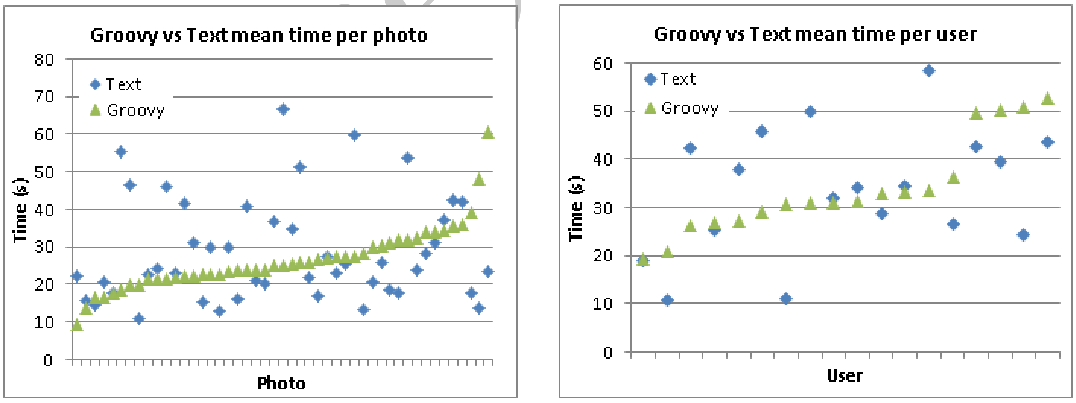


Figure 12: Time taken vs. text length. Highlighted area indicates where further data points would be expected to appear based on the fastest data points.



(a) per photo (only shows photos with at least one Menu and one Groovy tag)

(b) per user (only shows users who completed at least one Menu and one Groovy tag)

Figure 13: Mean time for Groovy and Menu tags to be completed under different circumstances

In order to further analyse data captured by the Text interface, it is useful to get a metric of the quantity of information collected. The Menu and Groovy interfaces both capture information as structured metadata – information about each dimension is stored separately and in a readily available form for filtering. Conversely, text captured is natural language – information about dimensions would have to be extracted in order to repurpose the tag as structured metadata. Therefore, in order to establish what dimensions were captured, a researcher applied grounded theory (Glaser & Strauss 1967) to each Text tag to establish what dimensions it described. The following are example tags that were collected and analysed:

> "Laptop with peg"

This indicates the topic "peg", but does not indicate a person's preference towards it (valence), who it would be interesting to (niche), the expertise of the user or where and when it may be found (locationality and temporality). (Scores 1.)

> "This is coffee. I do not like coffee, so I would not recommend it"

Indicates topic, and a negative user preference. It also reveals that the user must have tried it ("I do not like coffee"), so the user experience can be inferred. Niche, location and time are not indicated. (Scores 3.)

> "Ice-cream is tasty. I would recommend it to everyone."

Indicates topic, a positive user preference, demonstration of expertise ("is tasty") and specifies a niche ("everyone"). (Scores 4.)

> "Colourful vanilla icecream cone. Tasty and refreshing in the summer"

Indicates topic, positive user preference and expertise. Additionally, it is specified that it is good in the summer, indicating temporality. (Scores 4.)

> "Some people playing football. Good any time of year and happens in many places."

Indicates topic, user preference ("good"), but does not say why, so not experience, temporality ("any time of year") and locationality ("many places"). (Scores 4.)

Dividing the time taken by the number of dimensions gives a "time per dimension", revealing a mean of 2.67 dimensions per Text tag (10.12s per dimension). Figure 14 shows that a person who writes more tends to specify more dimensions.

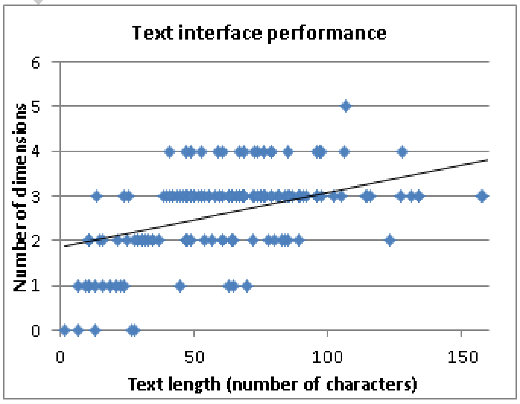


Figure 14: Number of dimensions entered vs. text length.

8.2 Menu interface

Figure 15 illustrates the number of dimensions entered, showing that typically a user will specify all of the dimensions.

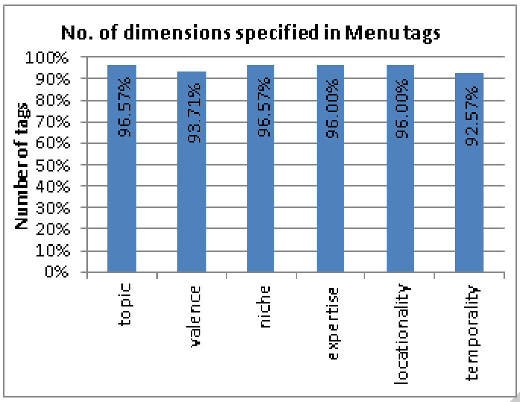


Figure 15: Number of times each menu item was specified

8.3 Groovy interface

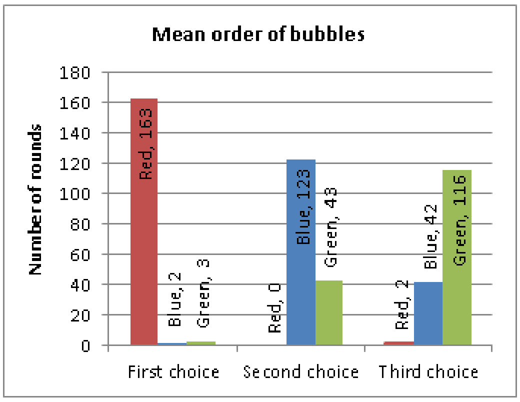
Figure 16 illustrates the order in which users chose the bubbles – with red chosen first 163 out of 168 times, blue chosen second 123 times out of 166 and green chosen third 116 times out of 160. The following can be observed from this:

1. Red was nearly always chosen first, suggesting that users will read top down. This may suggest that cultural traits affect how people use the interface. This could also pertain to colour preference: red stands out amongst the blue and green, and may appear to be more urgent.

2. Blue was more much more likely to be chosen second than green, suggesting that users, in general, will be more likely to read from left to right. Interestingly, the blue is "less bright" than the green, which may be why some users pick green first. This might suggest that the willingness to follow left to right is stronger than following brightness of colour.

3. The first bubble was completed more times than the second bubble, but not considerably so, indicating that users are willing to use at least two bubbles in a round. The third bubble is slightly less, but again, not by a considerable amount, suggesting that the majority of users are willing to use all three bubbles in a single round (supported by Figure 17, illustrating that all bubbles are nearly always completed).

Research has shown that the use of interfaces is affected by cultural traits of a person – such as reading from left to right (Shen et al. 2006). Furthermore, colour preferences of people have been studied, indicating the perception of a colour can be influenced by brightness and saturation and its connotation to the real world (Crozier 1996). These may be factors in the choices that people make in the Groovy interface.



(a) *Number of times bubbles were chosen for first, second and third choice*

(b) *Arrows indicate a typical user's progression through the bubbles*

Figure 16: The order in which users chose the bubbles

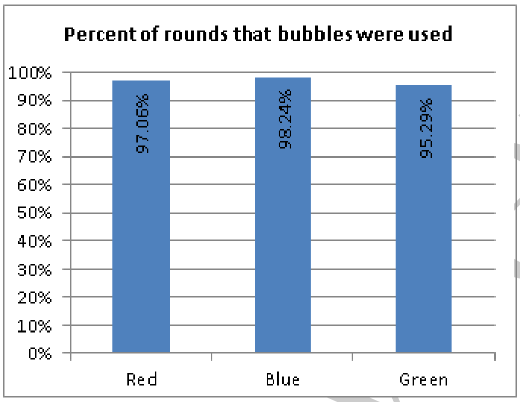
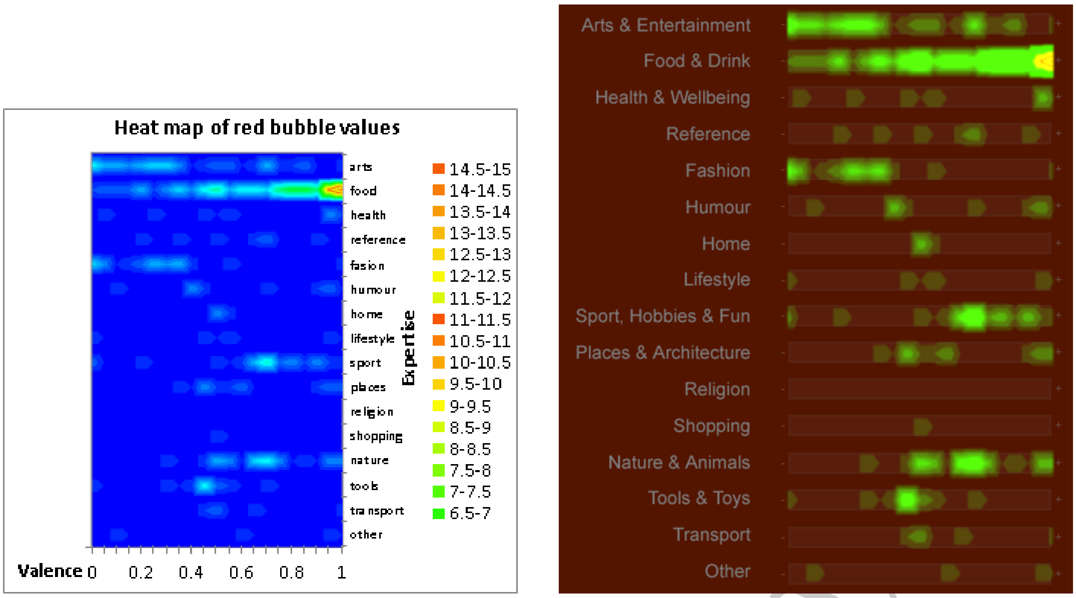


Figure 17: Percentage of rounds that each bubble was used

The values selected for the red bubble are illustrated in Figure 18 in the form of a heatmap. It is clear from this that the most common topic selected is food, with generally a positive attitude. Other trends include "Poor arts", "Poor fashion", "Good sport" and "Good nature".

Values that were selected for the blue bubble are illustrated in Figure 19. In general, the most common choices appear to be the most extreme – i.e., top left, top right, bottom right or bottom left. Note also that this may have been affected by the initial position of a user's finger. Some may have lifted this finger too soon and selected this area.

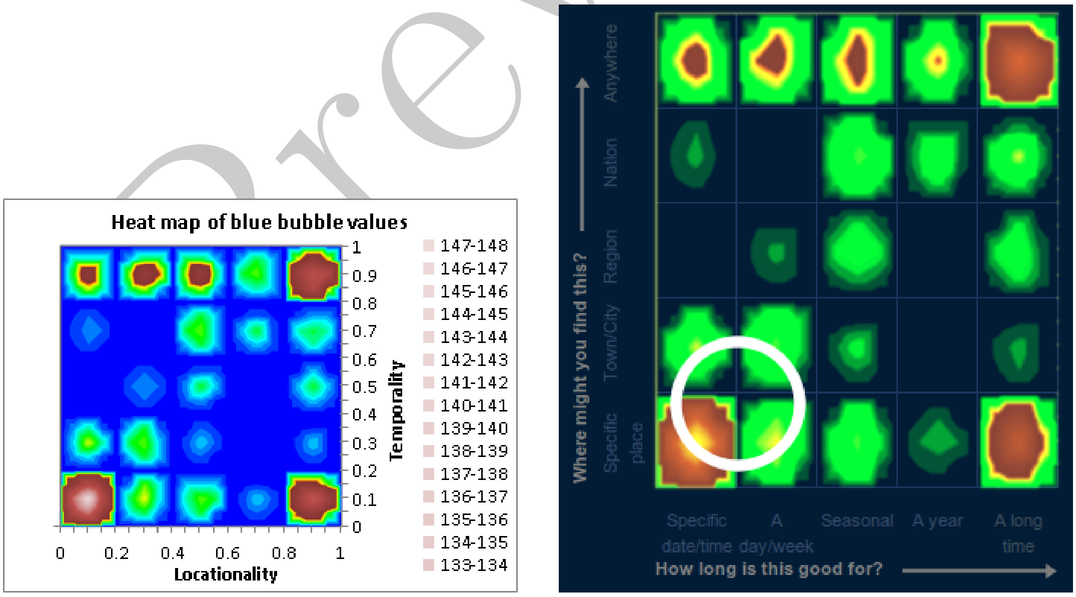
Figure 20 illustrates the values collected using the green interface, with a bivariate, multimodal distribution evident (values tend towards centre of the four "quadrants"). It shows that users have a tendency to pick more extreme values, perhaps due to being unaware that the axes are continuous scales (instead they presume it is formed of quadrants due to the four forms of feedback). The large quantity of values in the bottom right correlates to the initial finger placement, suggesting that many users may have released their finger instead of first specifying the values.



(a) *values as a heatmap*

(b) *interface with heatmap overlayed. Note that when this interface is used, the bars are in fact not visible until scrolled to the right, and the topics below "Places & Architecture" are not visible until scrolled down.*

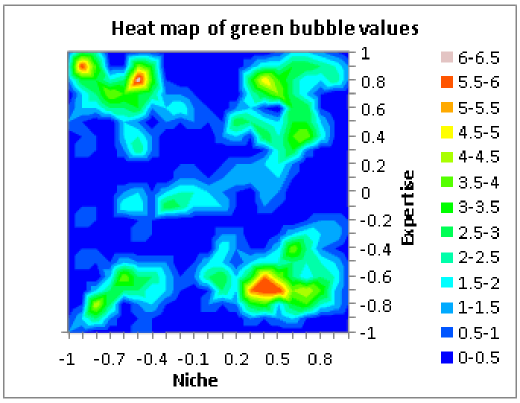
Figure 18: Red bubble heatmaps demonstrating what values were most popular and how this maps onto where they touched on the interface



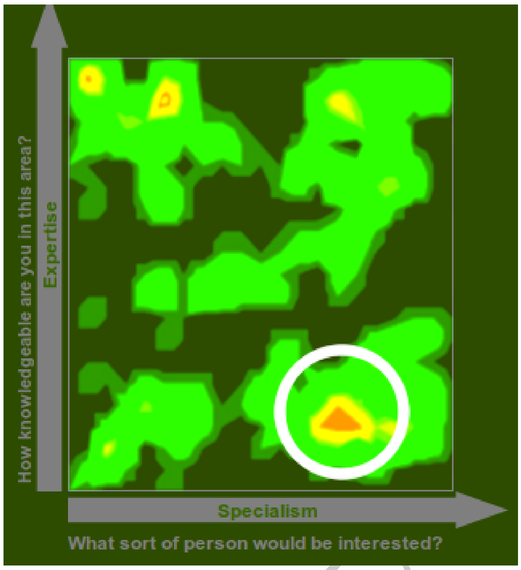
(a) *values as a heatmap*

(b) *interface with heatmap overlayed. Circle indicates where the finger will be positioned initially.*

Figure 19: Blue bubble heatmaps demonstrating what values were most popular and how this maps onto where they touched on the interface



(a) values as a heatmap

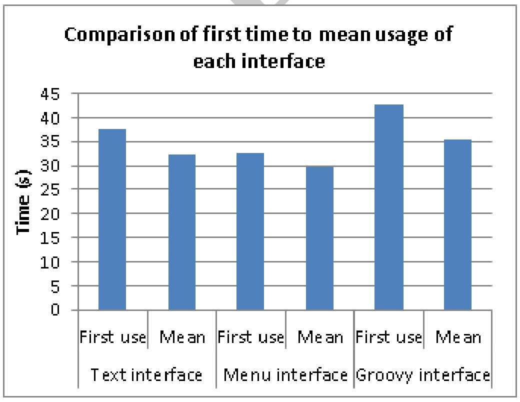


(b) interface with heatmap overlayed. Circle indicates where the finger will be positioned initially.

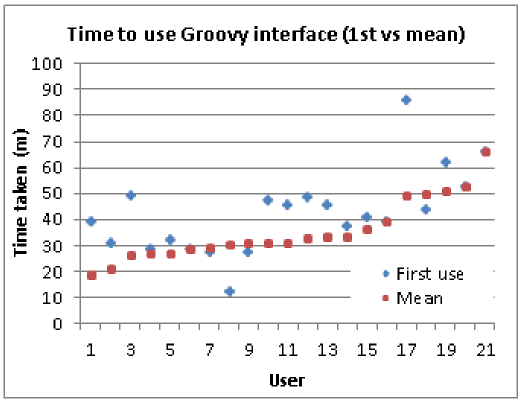
Figure 20: Green bubble heatmaps demonstrating what values were most popular and how this maps onto where they touched on the interface

8.4 Effect of practice: learning curves

Analysis has revealed that the mean first use for each interface takes longer than the mean for all uses (Figure 21a). This supports the argument that users improve in speed with each use of an interface. Figure 21b shows that, for the Groovy interface, most users' first use takes longer than their future choices (illustrated with the mean of all their uses).



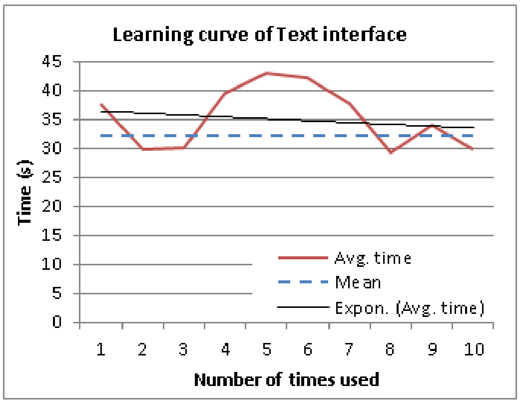
(a) for each interface



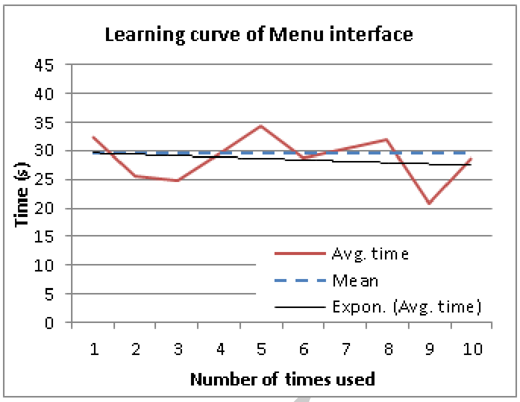
(b) for Groovy per user

Figure 21: First use vs. mean use

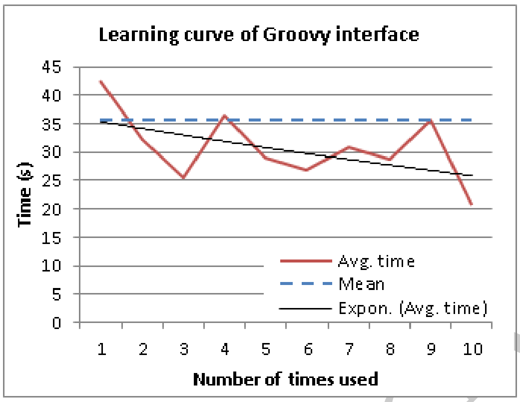
Further analysis reveals that this "learning curve" is evident for all three interfaces (Figure 22), however, it is most evident for the groovy interface, as shown in Figure 22c. The gradient of the curve suggests that users will continue to speed up after the tenth use and surpasses the speed at which the menu could be used at approximately the seventh use (Figure 22e).



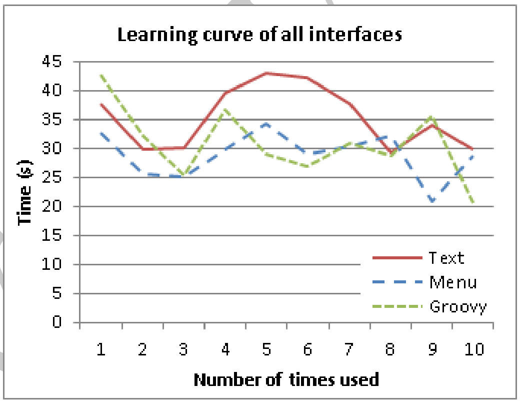
(a) Text interface



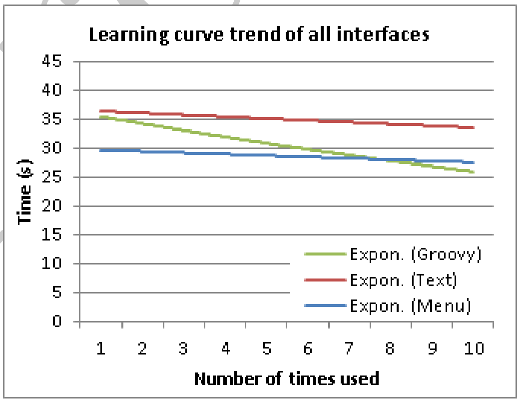
(b) Menu interface



(c) Groovy interface



(d) All interfaces



(e) All interfaces (trend lines)

Figure 22: The average time for the interfaces for the first 10 times they were used, with exponential trend lines illustrating the "learning curve".

It has been observed that, all three interfaces perform consistently faster for the second and third use, accounting for the valley at use 2 and 3 in each graph. This unusual correlation could be explained by an element of the gamification – the time limit. A user might, after realising there is a time limit, be rushed and attempt to complete the interfaces quickly. Once they realise that the time limit is extended per photo, they can afford to take more time.

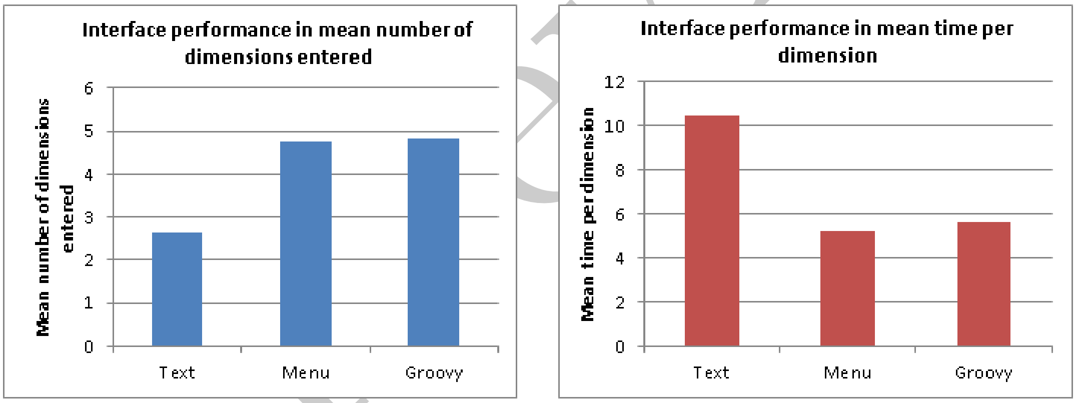
8.5 Comparing the interfaces

Data about the number of dimensions entered for the Groovy and Menu interfaces can be determined from the collected data: for Groovy, this is twice the number of bubbles that have been used (since there are two dimensions per bubble) and for the Menu interface, this is the number of options that have been specified. This yields the results presented in Table 3 (which includes the number of dimensions for Text tags determined through the process discussed in Section 8.1).

Method	Mean number of dimensions entered	Mean time per dimension
Text	2.65	10.45s
Menu	4.74	5.23s
Groovy	4.81	5.67s
Overall	4.07	7.12s

Table 3: Tag quantity for the three input methods.

Figure 23 shows a direct comparison of the three tag types, showing that the Menu and Groovy interfaces encourage a greater number of dimensions to be entered than text and that dimensions are dimensions are specified quicker using Menu and Groovy.



(a) for mean number of dimensions entered *(b) for mean time taken per dimension*

Figure 23: Input interface performance

An independent one-tailed T-Test was performed on the number of dimensions for Menu and Groovy tags in order to establish the significance of the difference, generating $p = 4.66 \times 10^{-29} < 0.05$, indicating a statistical significance. Comparing Text against Groovy, $r^2 = 2.32^{-5}$. Comparing Menu against Groovy $r^2 = 9.32^{-5}$.

Figure 24 illustrates the number of photos tagged with each topic, showing a consistency between the Groovy and Menu interfaces.

Figure 25 illustrates the number of different topics that photos were tagged with, illustrating that most had only one – all tags for these photos agreed on the topic. Some photos had differing topics specified in the tags, demonstrating that some photos were not easily identifiable as pertaining to a single topic that was provided

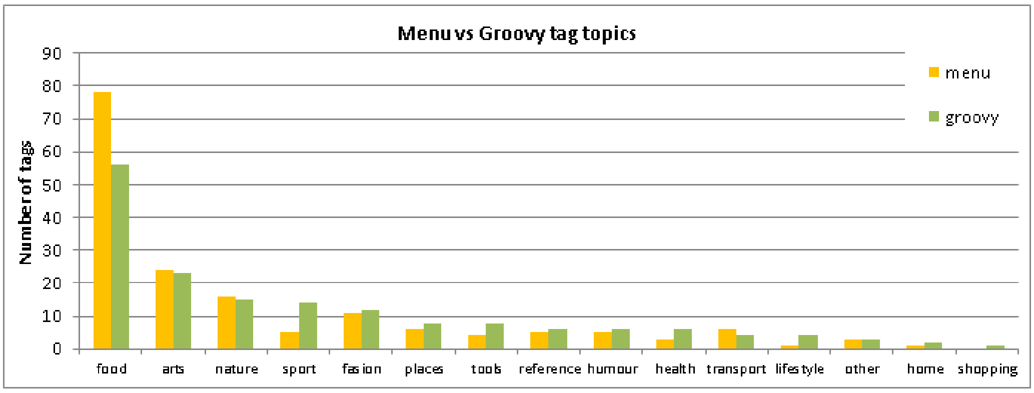


Figure 24: Number of photos tagged as each topic

via this interface. However, this occurred for both Menu and Groovy, demonstrating that the Groovy interface does not add ambiguity or bias.

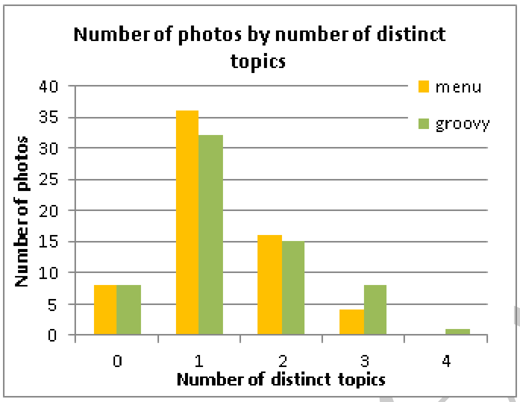


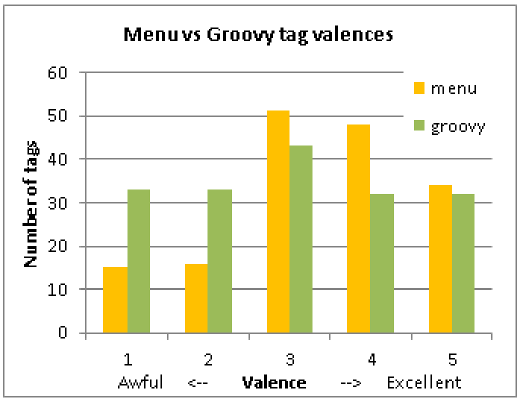
Figure 25: Number of distinct topics photos were tagged as

Figure 26: This photo was tagged with three different topics: arts, other and reference

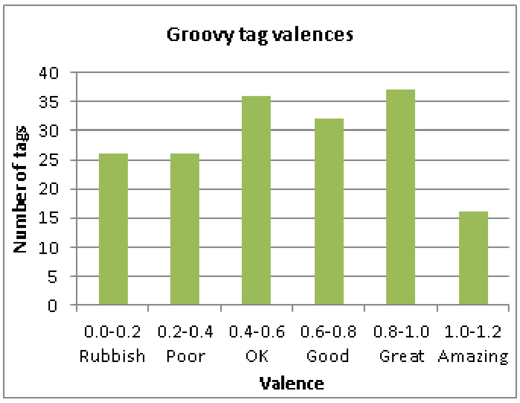
Figure 26 shows the values collected from the Menu and Groovy interfaces. Valences tend to be more frequently around the middle "OK" values. This is more evident on the Menu interface.

For niche and expertise, values tend to the values for the Groovy and Menu are very similar. In Section 8.3, it was thought that the initial placement of the user's finger resulted in a large amount of values in the "novice, acquired taste" areas. However, compared to the Menu tags, the deviation in small. The menu in fact shows a greater number of tags with Novice, showing that the initial finger placement does not bias the captured information.

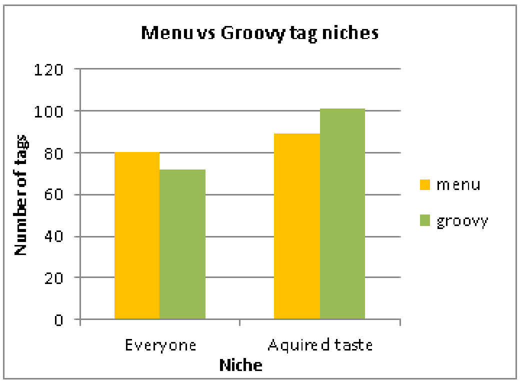
The values for locationality and temporality demonstrate on both interfaces that users felt that extreme values were usually the most appropriate for both Menu and Groovy tags, showing that it is not due to a bias of the Groovy interface.



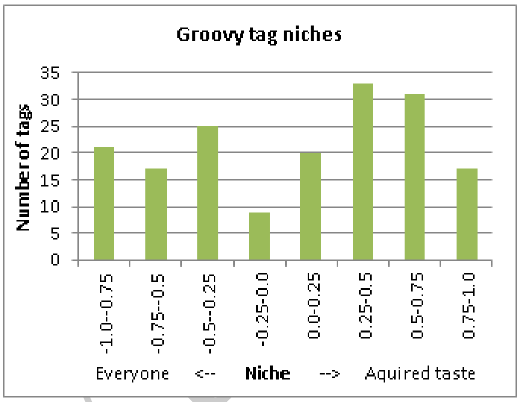
(a) Valence



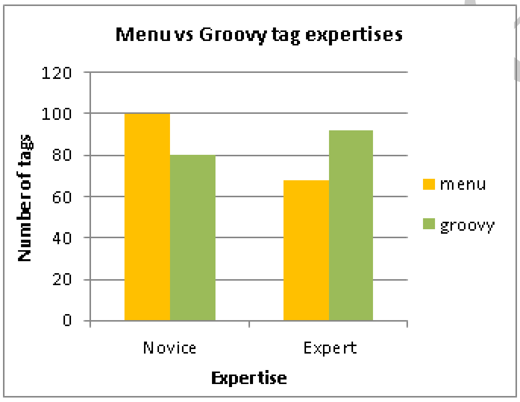
(b) Valence



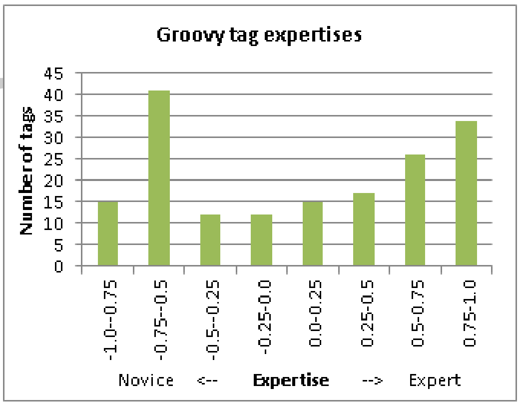
(c) Niche



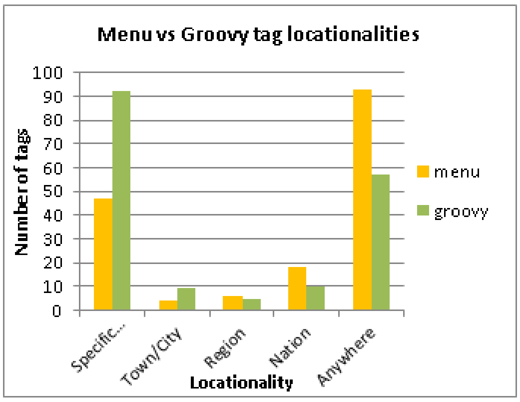
(d) The feedback to the user is "Everyone" for less than 0 and "Aquired taste" for more than 0.



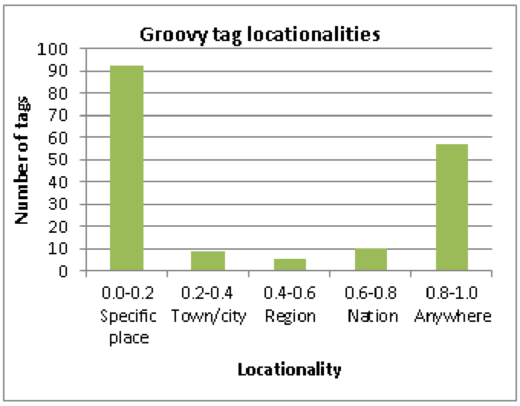
(e) Expertise



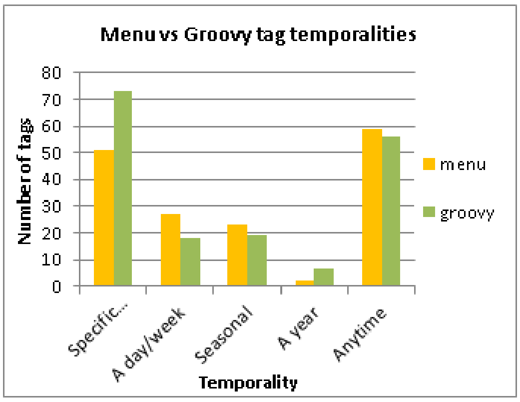
(f) The feedback to the user is "Novice" for less than 0 and "Expert" for more than 0.



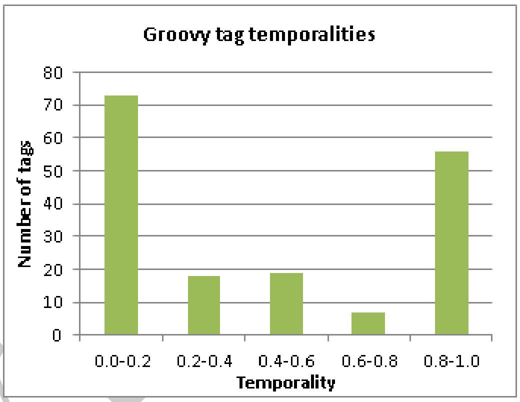
(g) Locationality



(h) Locationality



(i) Temporality



(j) Temporality

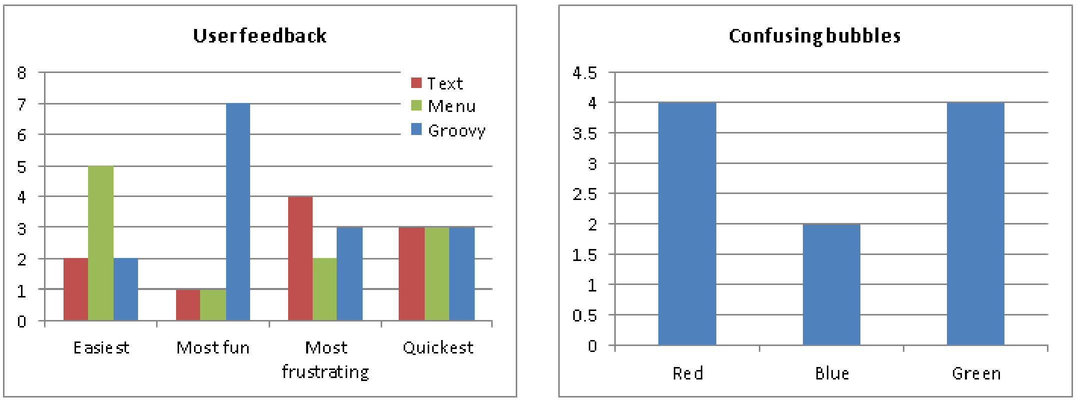
Figure 26: Left graphs illustrate the values collected from the Menu and Groovy interfaces and the total of these. Right graphs show the ranges of the values collected from just the Groovy interface.

8.6 Feedback from surveys

Nine participants were asked to complete a questionnaire after their participation. Figure 27a illustrates which interfaces users found easiest, most fun, most frustrating, and quickest, demonstrating that most found Menu the easiest and Groovy the most fun. Some found that Groovy was the most frustrating.

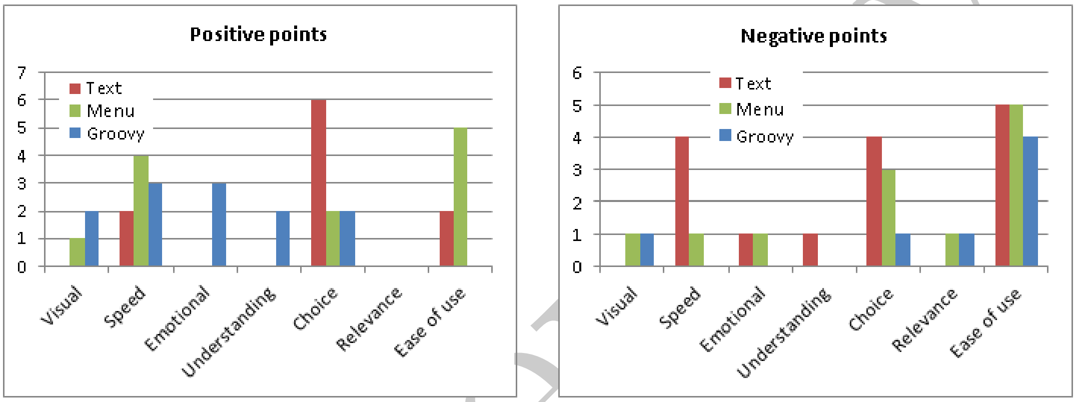
Figure 27b illustrates that many found the Red and Green bubbles confusing, and shows Blue as the least confusing. The feedback pertaining to the red bubble mostly suggested it was too difficult to use – the list of topics was too long, and the requirement to scroll the screen required effort. For the green bubble, there was confusion about whether the available options were 4 discrete values or a continuous scale. Feedback for the blue bubble suggested it was not always relevant to the photo – when asked to tag a beer, one user was confused about whether they should specify how long it would last before it goes off, or how long the invention itself lasts.

Participants were asked to express the positive and negative points of each interface. Grounded theory was applied to these, and the results shown in Figure 28. Figure 28a illustrates that, on an emotional level, users found Groovy most exciting. Figure 28b



(a) *which interfaces users found easiest, most fun, most frustrating, and quickest* (b) *bubbles that users found most confusing*

Figure 27: User responses in the survey



(a) *positive points* (b) *negative points*

Figure 28: User responses in the survey regarding positive and negative points of each interface

demonstrates that many find the choice in Text too open – not enough instruction is given in what they should write. This backs up the hypothesis that some might cancel or leave when confronted with the Text interface

Some users also complained of difficulty using the interfaces due to the placement of their finger or hand. Different areas of the screen are visible, depending on how the phone is being held – sometimes someone's finger or hand obstructs screen, making it difficult to see some areas of the interface.

8.7 Tag quality

In order to establish the quality of the collected information, two volunteers, who were not part of the study, were given a number of tags with their corresponding photo and asked to indicate whether they agreed that the tag was appropriate. They used a part of Groovy for this (Figure 29). The results are presented in Figure 30. A tag is considered good quality if at least half of its dimensions are agreed on.

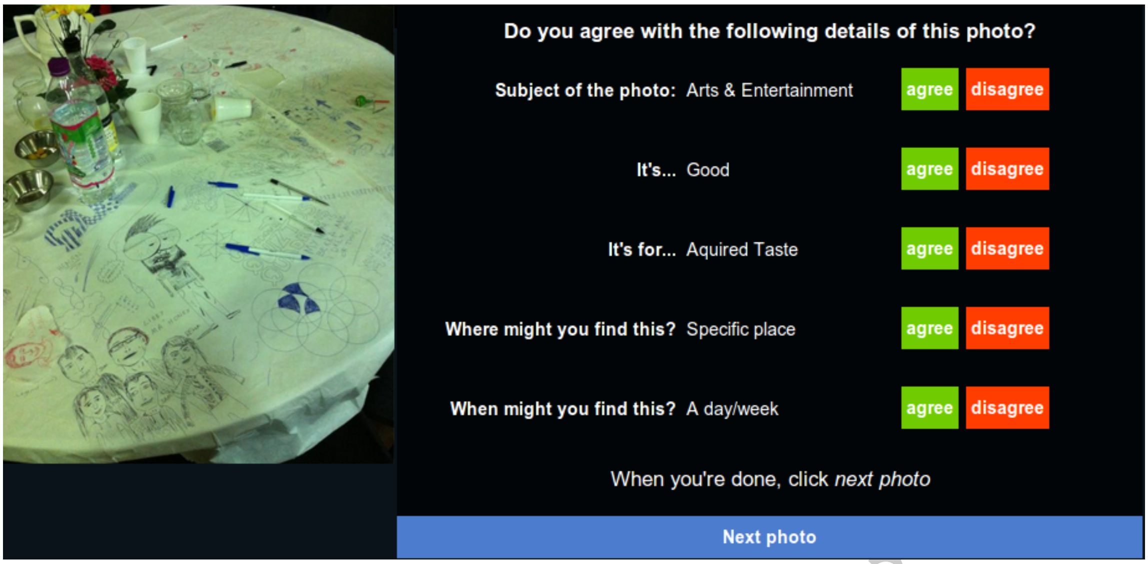


Figure 29: interface that the reviewers used to rate tags

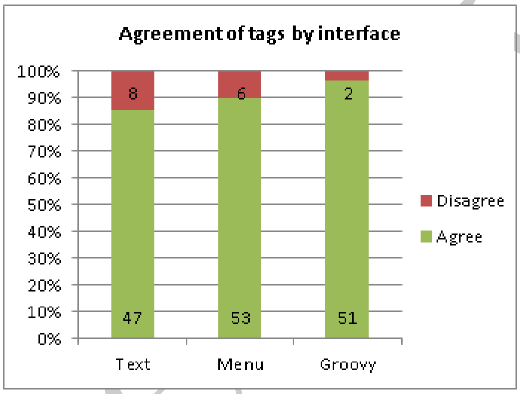


Figure 30: Agreement (where number of agreed dimensions is greater than disagreed dimensions) for each interface

Most tags that have been reviews were agreed with. Text has more tags that were disagreed with than Groovy, indicating the Groovy might be a more reliable method for collecting the data due to its consistency.

Analysis of the agreement with separate dimensions in Menu and Groovy tags reveals that they generally correlate (Figure 31) – where one performs particularly well, so does the other. *Topic* is the more agreed upon dimension and *temporality* the least.

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