

# Visual Insights from Personal Lifelogs

## Insight at the NTCIR-12 Lifelog LIT Task

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### ABSTRACT

In this paper we describe the Insight Centre for Data Analytics participation in the LIT sub-task of the Lifelog task at NTCIR-12. We present the interactive lifelog visualisation tool that we developed specifically for this task, which allowed us to interrogate the dataset to create insights for six LIT topics.

### Categories and Subject Descriptors

CCS [Human-centered computing]: Visualization Visualization techniques

### General Terms

Lifelog, Visualisation, Infographic

## 1. INTRODUCTION

Lifelogging has received increasing research attention of late and is rapidly becoming a mainstream research topic, however there has been little emphasis on how to visualise and communicate lifelog data to the individual. It is our view that lifelogging has enormous potential as an application of data analytics to enhance the life experience of the individual [6] across many dimensions. Hence, it is very important that consideration be given to how an individual accesses their lifelog. In this paper we present two contributions, firstly we describe a lifelog interrogation tool called the 'Lifelog Insight Tool' which has been developed to allow for the fast and efficient interrogation of large lifelog archives, and used at the NTCIR-12 Lifelog task [4]. Secondly we discuss our approach for addressing six of the ten LIT topics and present some of the associated visualisations of the lifelog insights.

## 2. BACKGROUND AND RELATED WORK

The idea that an individual will gather large lifelogs of personal data in a passive manner has been proposed since the Memex concept of Bush in 1946 [1], which proposed a theoretical pulleys and levers system based on the technology of the time. Many decades later, the MyLifeBits work from Microsoft [3] proposed an interrogation system based on database indexing of multimodal lifelog data. In this work, we extend both of these by developing a software tool to support lifelog interrogation to address the Reflection application of human memory, as suggested in [9].

Previous approaches to visualisation of lifelog data typically included video playback interfaces and storyboard in-

terfaces [6]. There were some novel visualisations developed, such as the 'Colour of Life' display wall interface, described by Kelly et al [8], which represents entire weeks of lifelog images as a large touchscreen colour-map, or the Annual Reports by Nicholas Felton [2] in which manually gathered lifelog data is converted into a book of semantically meaningful infographics on a yearly basis. Inspired by Felton's work, we have developed a software interrogation tool that supports easy interrogation of lifelogs to create highly visual infographics that address LIT topics.

## 3. THE LIFELOG INSIGHT TOOL

An initial analysis of the lifelog data for the NTCIR-12 Lifelog task [5] suggested that an interrogation tool was needed to support fast and efficient reviewing of the dataset. Hence we developed a lifelog interrogation tool that allowed an individual (the searcher) to explore the dataset by the occurrence of visual concepts as detected by the CAFFE CNN-based visual concept detector [7] that was included with the test collection.

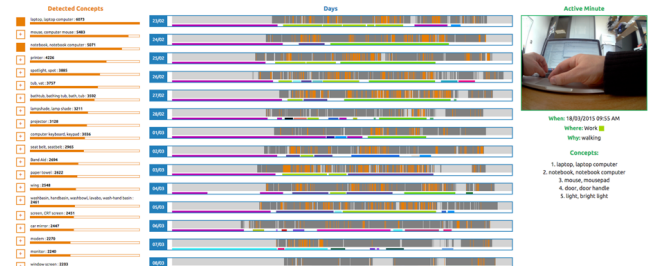


Figure 1: The LIT Main Interface View

The interface to visualise lifelog data is divided into three distinct sections. Each of the sections from left to right focuses on a more granular aspect of the lifelog data. The first (and leftmost) section of the dashboard summarises the automatically detected lifelog concepts that are related to the data and ranks them in an ordered list from most common to least common (see Fig. 2). The numbers next to each concept correspond to the number of images where that concept was detected. Each concept in the list can be clicked on to toggle an active state which will then highlight corresponding visualisations in the dashboard.

The second section, which is in the centre of the dashboard, displays a high-level overview of each day of lifelog data. A day contains 1,440 individual segments representing each minute of that day (see fig. 3), from 00:00 to 23:59.

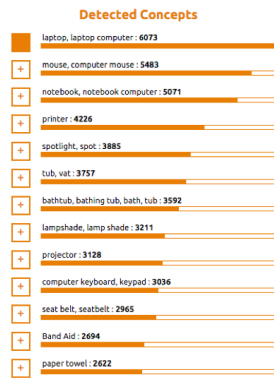


Figure 2: The Concept List

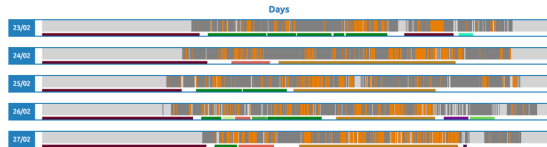


Figure 3: Each day in 1,440 segments

In their default state each minute is represented by a single vertical line of grey colour. However, if an image was captured during that minute, it is represented by a darker shade of grey. The minutes highlighted in orange correspond to the occurrence of visual concepts selected by the user. Directly beneath each day is a related visualisation element that represents locations as colours on the day timeline. If the user hovers their cursor over a selected minute of interest, a tooltip is displayed conveying that current time and location (see Fig. 4).

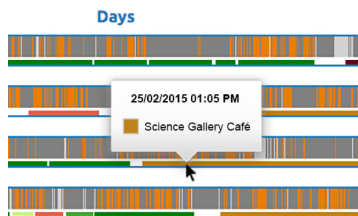


Figure 4: Illustrating the use of Additional Metadata

The third and rightmost section of the dashboard is interacted with by clicking on an individual minute the user wants to further analyse. Upon selection, the third (rightmost) section updates with any known metadata specific to that minute (see Fig. 5).

If the minute contains an image, it is displayed to the user here at a reduced resolution. This in turn can be clicked on if the full resolution needs to be examined by the user. Beneath the image is a list of all available metadata associated with the minute. In this particular dataset a minute can contain a time, location, an activity and the top five most highly scored lifelog concepts that were detected in the image.

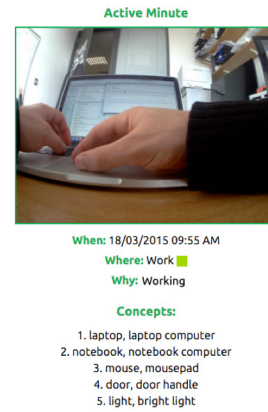


Figure 5: Metadata Miew of a Single Minute

## 4. DATA ANALYSIS USING THE LIT TOOL

The Lifelog Insight Task (LIT) aims to explore knowledge mining and novel visualisation of lifelogs. The LIT task utilised three users' lifelog data referred as User 1, User 2 and User 3. There are 10 topics distributed with the LIT task. Since the LIT task was not evaluated in the traditional sense, we took the liberty to merge some topics that we felt could provide added value when merged. We felt that three of the topics are related ('Eating Habit' is related to 'Coffee Addict' and 'Social Drinker'), so we merged these to create one new insight called 'Diet Monitoring'. Similarly we felt that the 'Green Spaces' and 'Meetings' topics were strongly related to the lifestyle of users so we included 'Green Spaces' as a part of an 'Exercise Routine' insight and the 'Meetings' topic was sufficiently related to the 'Social Interactions' concept, so we produced the 'Healthy Lifestyle' insight merging these. Hence, we considered six insight topics in this report, as follows: (1) Early Morning Commute, (2) Public Transport, (3) Healthy Lifestyle, (4) Diet Monitoring, (5) Digital Screens, and (6) Regularity of Lifestyle.

The general process employed was to explore the lifelog data manually using the insights tool previously described, looking out for the occurrence of concepts that we identified as being potentially relevant to the topics. The minute was our standard unit of analysis. The occurrence of such concepts is explored and aggregated, leading to insights into each topic, which is then converted into a visual infographic-based representation. We summarise the approach for each of the topics separately and we present two infographics.

### 4.1 Early Morning Commute

The Early Morning Commute task provides insights on the methods and duration that each user spends commuting to work or study. In early morning commuting the lifelog data of User 1 and User 2 is measured across three dimensions i.e. Methods (Car, Walking, Bus, Cycling, Airplane), Duration (Start time and End time) and Activity (Work or University) (see Table 1).

### 4.2 Public Transport

Public Transport provides insights into the use of public transport by each user. We identified users taking many forms, such as bus, taxi/passenger car, train, airplane, metro and boat, along with the duration of use. In this initial work,

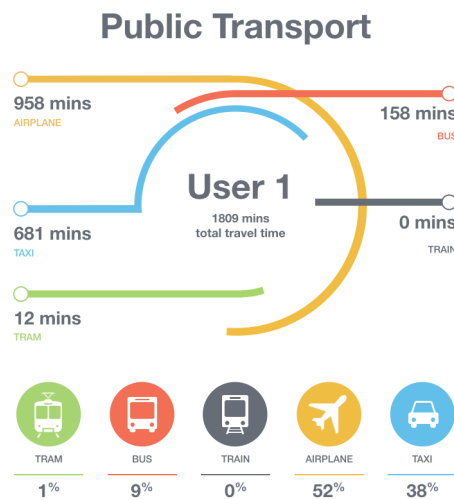
Users	Car	Walking	Bus	Cycling	Airplane
U1	458m	123m	101m	0m	69m
U2	0m	243m	0m	67m	0m

**Table 1: Commuting Comparison between Users 1&2**

this was done by a manual observation of the visual data, but it is reasonable to assume that an automated analysis could be developed to make this accurate and efficient. The findings are summarised in the below table and in Figure 6 as an infographic.

Users	Tram	Bus	Train	Airplane	Taxi
U1	12min	158mins	0mins	958mins	681mins
U2	0mins	55mins	138mins	360mins	50mins
U3	0mins	752mins	0mins	202mins	0mins

**Table 2: The Duration of Public Transport Use**



**Figure 6: Public Transport use of User 1**

### 4.3 Healthy Lifestyle

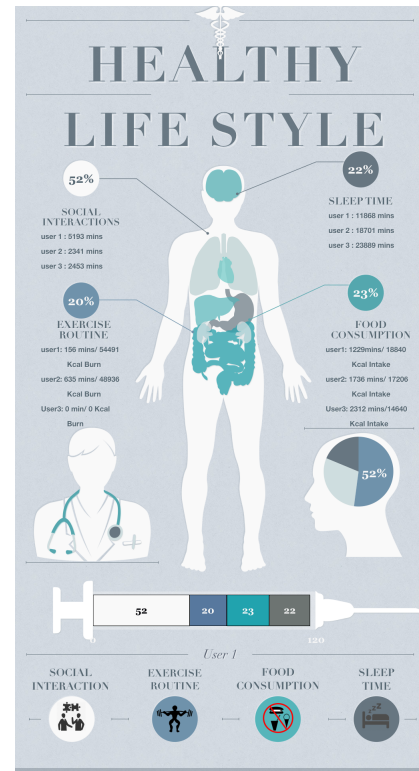
Although there are many aspects to a healthy lifestyle that we could examine, for this topic, the lifelog of all three users was compared across the three dimensions of exercise, eating and social interactions. Exercise was examined in terms of the type of exercise and the duration of exercise. Eating was examined in terms of the type of food, duration of consumption, total coffees per day, total cold drink/beers per day, all based on a partially automated diet analysis. Finally, Social Interactions was examined in terms of the type of interaction, location of the interaction, and duration of interaction. The below table shows a summary of the overall durations of all three aspects of healthy lifestyle per user and Figure 6 shows the resultant infographic.

### 4.4 Diet Monitoring

All food and drink consumed by all three users were found using the LIT tool and analysed to identify (1) the time of the first and last dietary event of every day, (2) the types

Users	Exercise	Eating	Social
U1	2.6h	20.5h	86.5h
U2	10.6h	29h	54h
U3	0h	38.5h	24.4h

**Table 3: Distribution of the types by rank**



**Figure 7: Example of infographic displaying User 1's healthy lifestyle by comparing his lifestyle from other users. Calories are duration-estimated.**

of food consumed or bought, (3) the types of drink consumed and bought, and (4) the duration of consumption event. We identified that breakfast generally occurs between 4am-10am, lunch between 11am-3pm, and dinner between 5pm-12am. We noted that the different users have different dietary habits, as shown in Table 4. For example, user 2 always eats cereal at home, but user 1 eats various different types of breakfast when at home and cake/bread with coffee when in a cafe, while user 3 did not usually eat breakfast. For lunch, both users 1 & 2 eat a conventional restaurant lunch at their place of work, while user 3 usually eats similar meals every day at home. For dinner, user 1 is a social eater, while user 2 eats mostly at home, and user 3 always eats dinner very late, nearly 10pm and mostly eats rice, beans and vegetables. It is difficult to calculate exact quantities of food consumed from the data, so we focus instead on the food occurrence frequency (see Table 4).

We can infer that user 1 has the comparatively better living habit: no alcohol, eating fruits and vegetables with meals, no excessive carbonated drinks and sweets. It is noted that users 1 and 2 drink a significant amount of coffee daily. It is our consideration that user 3 has the least healthy diet, both in terms of foods as well as the times of consumption.

	Type	U1	U2	U3
Food	cereals, bread, rice, pasta	ENT	ED	ED
	vegetables, fruits	ED	SW	ENT
	milk, cheese, meat, fish, eggs	SW	ED	ED
	oil, sweets	N	N	SW
Drink	coffee/tea	ED	ED	SW
	juice	SW	SW	ED
	carbonated beverage	ENT	SW	ED
	beer/wine	N	ENT	SW

**Table 4: Diet consumption frequency of users (\*N = never, ENT = every now and then, SW = sometime during the week, ED = every day)**

## 4.5 Digital Screen

Seeking insights into the use of digital screens by each user, we were interested in how much time each user spent in front of screen and the nature of these interactions. The categories of digital screen we considered were computer, TV, smartphone and tablet, hence we made heavy use of the LIT tool screen and smartphone-related concepts. We considered the time and duration of the screen accesses.

Users	Computer	TV	Smartphone	Tablet
U1	134h, 54m	12h, 52m	26h, 46m	0m
U2	118h, 34m	0h, 35m	21h, 58m	0m
U3	55h, 43m	32h, 13m	45h, 40m	10m

**Table 5: Digital Screen Usage**

Generally, all users use a computer for work, smartphone for communication and reading, and a TV for watching TV shows and football. User 1 and user 2 spend more time in the front of computer than user 3, who likes to spend his time with the TV and smartphone. There are many inferences that could be made by such data, especially so when combining it with the outcome of the dietary analysis.

## 4.6 Regularity

Regularity, also known as rhythmicity, refers to the repeating nature of a user’s many life activities. While there are many dimensions which can be employed to explore regularity in lifestyle, we focus on the repetitive nature of a set of common daily activities. In terms of lifestyle regularity, some people lead a highly regular and predictable daily lifestyle (user 1), whereas others lead a chaotic and unpredictable lifestyle, with most people comfortable in between these two extremes. In order to understand what is a quantifiable measure of daily routine regularity, we employed the ‘Social Rhythm Metric’-SRM[5] measure. The SRM is used to record ‘when’ and ‘with whom’ a set of common lifestyle activities take place on a daily basis. We identified nine common activities that the users engaged in. The typical day of user 1 is shown in Table 6, along with the typical variance in the times of that user. This is calculated over data that did not include exceptional days, such as international travel. It can be seen that that user has a very regular lifestyle.

## 5. CONCLUSIONS

At NTCIR-12, Insight@DCU took part in the LIT sub-task of the Lifelog task. In this paper, we describe our activities for the LIT sub-task. Firstly we describe the LIT

Event	Typical Time	Typical Location
Camera on	06:30 $\pm$ 2.6%	home
Watch TV news	06:38 $\pm$ 2.1%	home
Physical exercise	06:50 $\pm$ 0.7%	home
Breakfast	07:10 $\pm$ 0.2%	home
Go outside	07:40 $\pm$ 1%	N/A
Start work	08:05 $\pm$ 2%	DCU
Lunch	13:52 $\pm$ 7%	Restaurant
Dinner	18:12 $\pm$ 5.3%	home
Turn off camera	22:16 $\pm$ 2.1%	home

**Table 6: The typical day of User 1**

tool which provides an interface to explore and examine the lifelog. This allowed for the efficient interrogation of the large dataset across multiple dimensions, including location, time, activity and visual concepts. Secondly, we described some of the data analysis outcomes for six of the LIT tasks and present the results of two of these as a set of infographics. This is a subset of the full suite of infographics that we developed for the LIT task.

## 6. ACKNOWLEDGMENTS

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## 7. REFERENCES

- [1] V. Bush. As we may think. *The Atlantic Monthly*, 176(1):101–108, Jul 1945.
- [2] N. Felton. Annual Reports. <http://feltron.com/>, 2016. [Online; accessed 01-May-2016].
- [3] J. Gemmell, G. Bell, and R. Lueder. MyLifeBits: a personal database for everything. *Communications of the ACM*, 49(1):88–95, 2006.
- [4] C. Gurrin, H. Joho, F. Hopfgartner, R. Albatat, and L. Zhou. Overview of ntcir-12 lifelog task. In *Proceedings of NTCIR-12, Tokyo, Japan*, 2016.
- [5] C. Gurrin, H. Joho, F. Hopfgartner, L. Zhou, and R. Albatat. Overview of NTCIR-12 lifelog task. In *In Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval, Pisa, Italy, July 17-21*, 2016.
- [6] C. Gurrin, A. F. Smeaton, and A. R. Doherty. Lifelogging: Personal big data. *Foundations and Trends in Information Retrieval*, 8(1):1–125, 2014.
- [7] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the ACM International Conference on Multimedia*, pages 675–678. ACM, 2014.
- [8] P. Kelly, A. R. Doherty, A. F. Smeaton, C. Gurrin, and N. E. O’Connor. The colour of life: novel visualisations of population lifestyles. In *MM ’10 Proceedings of the international conference on Multimedia*. ACM, 2010.
- [9] A. J. Sellen and S. Whittaker. Beyond total capture: A constructive critique of lifelogging. *Commun. ACM*, 53(5):70–77, May 2010.