Lifelong User Modeling and Meta-cognitive Scaffolding: Support Self Monitoring of Long Term Goals

Lie Ming Tang and Judy Kay

University Of Sydney
http://chai.it.usyd.edu.au
ltan8012@uni.sydney.edu.au

Abstract. It is becoming increasingly easy to capture lifelong data about a person. This creates the potential for valuable new ways for people to self-monitor diverse aspects their lives. If people are to do this effectively, we need to ensure that relevant aspects of lifelong user models are available to the user, in a form that is meaningful. Beyond this, current research indicates that most people need a meta-cognitive scaffolding to make more effective use of such information. This paper reviews work about such meta-cognitive scaffolding. Then it presents use cases illustrating how this scaffolding can help people achieve long term goals. We use these to identify requirements for the architecture and associated user interfaces for a lifelong user model with scaffolded self monitoring. Our key contribution is the requirements for a system that scaffolds self monitoring of long term goals, based on data stored in a lifelong user model.

Keywords: meta-cognition, scaffolding, self monitoring, lifelong user modeling, goal setting

1 Introduction

Computing devices have rapidly advanced in processing power, mobility and communication. We can now readily collect very detailed personal data, for aspects such as physical activity over long periods of time (e.g., steps per day, over weeks, months and years). It is also easy to store vast and growing amounts of such information. This constitutes a form of lifelong user model. When this is suitably interpreted and relevant sets of information are combined, lifelong user modeling has the potential to help people achieve their long term goals such as healthy weight, increasing physical activity [13] or lifelong learning [18] such as learning a foreign language. Such user models can play a key role in behavioural change [20] and self regulated learning [4].

It is important for people to monitor and reflect on their progress, adjust their actions and behaviour based on real evidence over the long term. Granular and long term data about individuals can be captured in lifelong user models and help accurately measure performance, progress and relate to their long term goals.

The interfaces through which people see their lifelong user models are critical as they encourage trust and credibility [10] in behaviour change applications.

This paper is concerned with helping people make effective use of displays of their lifelong user model and for goal setting. In particular, we take account of research which indicates the need to *scaffold* users in the *meta-cognitive processes* of *self monitoring* and *reflection.* Such scaffolding has been effective in computer based learning [2] and in supporting physical activity [17, 14] They are likely to be key in enabling users to take on the role of end-user programmers, controlling what data are collated in lifelong user models and then interpreting it in terms of 'means' goal intended to enable long term 'end' goal as termed in [5].

Consider a scenario where a hypothetical user, Alice, has an *end goal* to maintain the recommended level of moderate physical activity, at least 30 mins / 5 days a week [13] . She sets *means goals* of: walking twice a week and jogging once a week. If suitable data collection about these activities is available, she can see whether she is achieving each means and end goal. This paper explores the requirements for an interface that can facilitate self monitoring and reflection. We draw on lifelong user modeling [16, 15], meta-cognitive principles of self monitoring [23], reflection [11] and computer based meta-cognitive scaffolding support [4].

The next section reviews key related work. Then we present a set of use cases as a foundation for our identification of requirements for system design and interfaces that scaffold self monitoring for reflection to support long term goals.

2 Related work

This section introduces the three key foundations for our work. The first of these is lifelong user modeling. The second is work on meta-cognition and the need for scaffolding. We then introduce open learner modelling since it draws the earlier two parts together.

Long term user modelling refers to the capture of long term information about the users [16, 15]. This emerging view of a user model diverges from the classical works where a user model was typically tightly integrated into a single application. There are many challenges in lifelong user modelling, (see [15] for a review of these). For this work, the key concern is that the model can hold a large amount of information that has the potential to be valuable for people to monitor their progress towards their long term goals.

Meta-cognition refers to knowledge about one's own knowledge [22]. It includes diverse skills, such as the dozens identified in [4]. For our work, the key skills relate to reflection that is based on long term user models. To achieve long term goals, a person draws on meta-cognitive skills in setting goals, thinking about how realistic they are, monitoring progress [11] and using this to revise goals, recognising that some were achieved, some were not and that some were unrealistic [23]. Effective interpretation of the information, in order to monitor progress is critical. Yet many people do not automatically make good use of information about themselves to self-monitor [3, 21]. However, there is evidence that systems which do scaffold metacognitive skills, such as self monitoring and reflection, can improve these critical skills [2]. Open learner models (OLMs) provide interfaces that enable people to view, and sometimes, to manipulate their user model [6]. For this paper, OLMs provide a body of work on interfaces that externalise a learner model. Some OLMs have tackled the challenge of showing large user models in a cognitive domain, as in VLUM [25] and this enabled learners to assess their progress [15] Another presented a visualisation to support reflection [12] through visualisation of student activity relative to other students.

Ambient displays can provide a form of OLM that is designed to blend into the environment until the user wants to consult it. These may be important for people monitoring long term goals. For example, *Breakaway* [14] was designed to help people remember to achieve their goals to take breaks from long periods of sitting. A small sculpture based on user's chair appears upright if the user had taken breaks and it slouched if the user had been sitting for a while. The CareNet glanceable display on a picture frame [9] showed key information about an elderly person's daily activity. This was a form of OLM for their carer family living elsewhere.

While results are not conclusive due to sample size and technology, using visual abstraction techniques to present information is promising. A study in the open learner model for children [6] represented a child's knowledge state as pictorial abstraction of misconceptions where a tree is healthy or dying the more misconception a child has on a topic. An example of glanceable display is the UbiFit system [8] showing a garden where number of flowers represent different types of activities. There are also studies where social interaction is tested to encourage physical activity [19].

While there has been some work that has tracked use of OLMs over months (e.g., [6]), the challenge of supporting self monitoring and reflection over years and decades is new ground for lifelong user modelling.

3 Use Cases of scaffolded self monitoring based on a lifelong user model

In this section, we describe three use cases related to a hypothetical person 'Alice'. It will present examples of visualisations and discuss potential for customisation and personalisation. It will also identify how we can scaffold self monitoring and reflection to achieve long term goals.

Use Case 1 : To run City2Surf (14 km) in 1 hour and to maintain at least 100 mins of exercise per week
It is recommended for adults to have a minimum of 30 min of moderate-intensity aerobic physical activity 5 times per week [13]. Alice would like to maintain this and also to train for City2Surf which is an annual 14 Km fun run in Sydney. She decides to track running and walking exercises where she uses a pedometer with time recording capability [1] and stopwatch to time her runs.

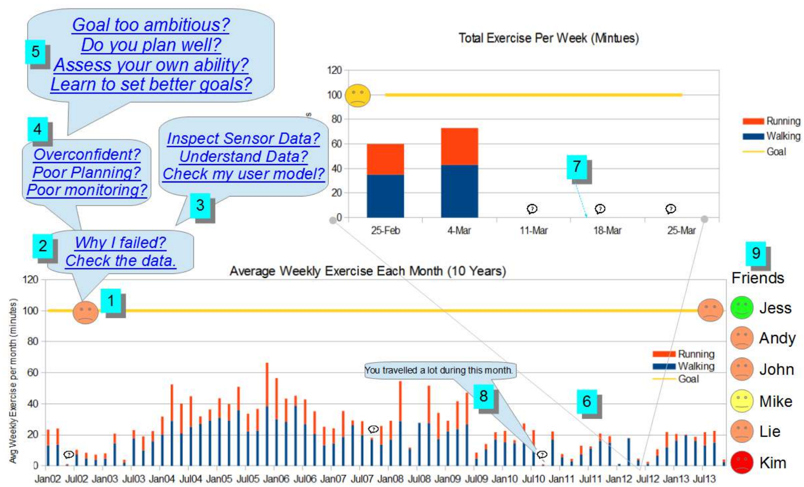

Fig. 1. Graph showing average weekly exercise 2002-2013 Walking & Running and includes some example interface elements.

Figure 1 shows elements that monitor Alice physical activity over time. The Goal line (yellow) represents her end goal of 100 minutes exercise per week and allow her to reflect on her achievement and drill down into a particular month (label 6). The *"smilie"* face is an example of physical abstractions of goal attainment label 1 inspired by [8, 17]. Elements of meta-cognitive scaffolding can be incorporated in labels 2, 3, 4, and 5 where users are asked to reflect on their progress, understanding and meta-cognitive skills. Label 8 illustrates how system represent knowledge about a user e.g., Alice travelled in Jul-10, got injured during Aug-10 which can be incorporated into the user experience to foster reflection in her ability, accuracy of data and goal setting.

Figure 2 shows another view focusing on the goal of running City2Surf 14 km in 1 hour. Alice can deduce that her speed is reducing over last 10 years. This can help her reflect on whether she has set her goals too high or if other factors such as gaining weight and being less active could have contributed. Meta-cognitive scaffolding can help her through encouraging her to reflect on her ability to seek help, plan and set better goals. By showing her data over a long period of 10 years, she is able to see the truth about her declining ability over time and reflect accurately about her abilities.

Use Case 2 : Avoid prolonged periods of sitting to less than 8 hours per day. Prolonged sedentary behaviour is detrimental to long term health [26]. To monitor this, a combination of devices are employed such as fitbit, desktop PC application, lifelog camera or a seat sensor. It is not always straight forward to determine inactivity due to sensing limitation or user preference so data may not

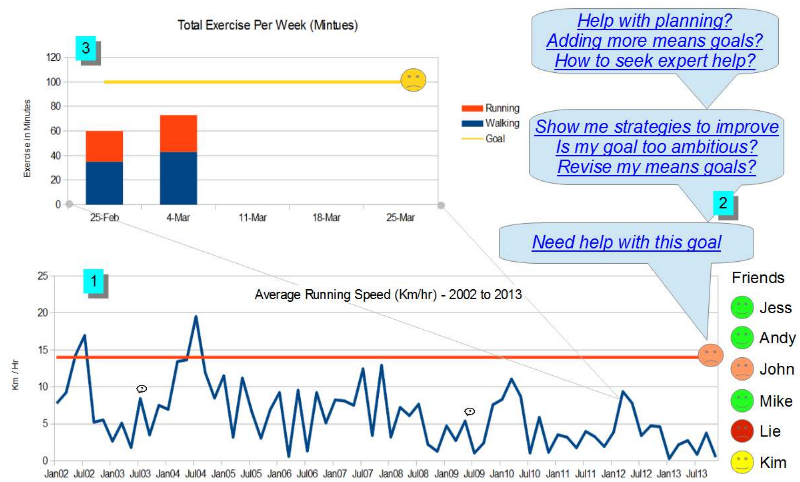

Fig. 2. Graph showing average running speed over 10 years period from 2002 to 2013.

be complete e.g., not all devices are waterproof so person needs to take them off while swimming. A benefit of combining data is that multiple sensors data may be complementary. For example, a desktop PC application detects computer use and seat sensor records sitting on a chair and both detects user may be sitting. However, a person may be sitting and not use computer or use computer and not sitting on a smart chair. When combined, these sensors can provide a better longitudinal view of user's sitting behaviour. Lifelong user modeling can facilitate consolidation of data from different sensors and provides foundation to improve accuracy of inferences. In addition, users may want to analyse the data over the long term to see patterns of behaviour. Figure 3 shows how inactivity data can be presented to show breakdown such as driving, computer use and watching TV. Combined with interface elements introduced in Use Case 1 Figure 1 and figure 2, there is potential to further personalise interfaces to make sense of data.

Use Case 3 : Learn at least 2000 common usage words and passing language proficiency test.
In this scenario Alice is not a native English speaker and sets the long term goal of learning at least 2000 words in common usage. Lifelong learner model [15] can allow applications to capture data and scaffold for Alice to reflect on her progress and learning strategies. Figure 4 plots the number of words she learnt over time versus the mean lower and upper bound of other learner's progress. It shows her progress is only slightly better than lower bound indicating she should review her learning strategy for improvement. Combined with potential scaffolding elements illustrated in use case 1 figure 1 and figure 2, we can scaffold reflection and improve long term learning.

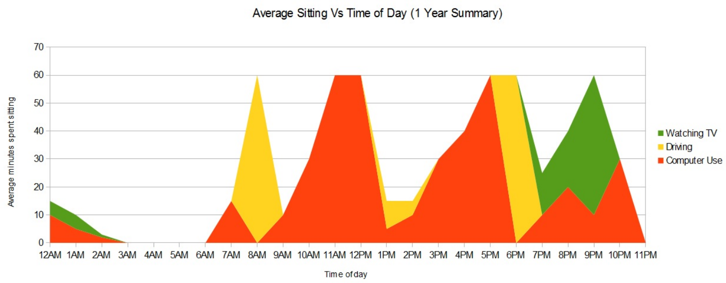

Fig. 3. Chart showing average sitting time over time of day (1 Year).

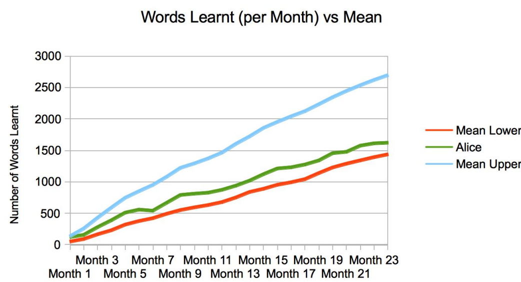

Fig. 4. chart showing average sitting time over time of day in minutes.

4 Requirements for a lifelong user model with scaffolding for self monitoring and reflection

Lifelong user model provides us the foundation to support meta-cognitive scaffolding for self monitoring, reflection and goal setting. We have identified a number of use cases and illustrated how some of these tools can be utilised to achieve this. In this section we describe requirements for future systems to effectively utilise lifelong data and to support long term goals. We present these requirements under three perspectives.

4.1 Capture and present data in a way users can use effectively.

From the user's perspective, to utilise vast amounts of personalised data over long term and how they relate and contribute towards one's long term goals is a daunting proposition.

☐ **Capture data over the long term.**
It is important that data is captured and kept over long term as it would allow us to monitor progress, reflect on user behaviour and provide better personalisation.

- [ ] **Capture data from different devices.**
Data can come from an ecosystem of devices (e.g., fitbit, desktop, mobile phone, fixed cameras) and a system should support capture and combining of this data.

- [ ] **Address key personalisation problems.**
Future systems needs to address problems of *privacy, invisibility of personalisation, errors in user model, wasted user model* and *control* as described in [16]. Key concepts being users need to be aware and take control of what system knows about them and how it uses this information (*invisibility, control*), avoid silos of data (*wasted use model*) and control privacy.

- [ ] **Help people interpret data.**
It is not sufficient to simply capture data but also turn it into useful information. Visualisations and interfaces should allow users to answers questions such as have they met their goals, reasons for failure and how to improve. Interfaces should be easy to interpret yet provide enough capability to perform analysis. An approach might be to provide meta-cognitive scaffolding based on lifelong user model data (e.g., level of computer literacy, academic ability etc.) to improve meta-cognition. An example of a framework that can support this is the Personis platform described in [15]. The concept of separating the lifelong user model with applications and views allow us to better personalise interface.

4.2 Personalisation and control of data.

It is important for system to capture user preferences and how they want to interact with their own data and user models. A system should also follow certain guidelines to support user interaction and visualisations.

- [ ] **Personalisation of data and user interfaces**
Different people have preferences for how they want to interact with their data [5] so it is important to allow for a certain level of control.

- [ ] **Aggregated and abstracted views.**
When dealing with lifelong user data that represents a large dataset it becomes necessary to provide an aggregated views [7] or abstracted views [17]. They can also be unobtrusive and potentially motivational [14]. A system can also provide interactive capabilities to allow users to drill down for more detailed or localised view of the data

- [ ] **Controlling how you view your data.**
A system should provide capabilities to control the level of abstraction and aggregation, where and how to display data, how information can be shared. 'Alice' may choose to show daily walking and jogging data with her personal trainer but only an abstracted *"smilie"* face of goal achievement with friends. System should enable users to scrutinise [15] their user model. E.g., system

decide not to show weight data over time as she never looked at this information in the past. However, upon reflection of her jogging performance, Alice decides that she does want to know about her weight.

- ☐ **Trust, confidence and coherence of data.**
  It is important to foster trust and confidence in a system [10] to support and motivate users. Interface should not mislead or be misinterpreted otherwise it may result in loss of confidence. For example, Alice only wears her fitbit sensor during exercise and also sometimes forgets to wear it. System should indicate not all data is available and prompt for input or correction.

4.3 Support long term goals.

Our key objective is to support users in meeting their long term goals. The list of questions below identifies the key challenges a system should aim to support.

- ☐ **Set new and better long term goals.**
  Elements of the system can provide meta-cognitive scaffolding to support goal setting. For example, system can tell Alice that she is usually too overconfident and she may be too ambitious with 14km in 1 hour and teach her to improve her ability in setting goals for the future.
- ☐ **How to achieve long term goals.**
  System can provide scaffolding to help set means goals to achieve their long term end goals. For example, Alice sets her long term goal of running City2Surf 14 Km in 1 hour within 1 year. System can draw on her current routines to suggest a program of means goals to incrementally increase the speed and distance of her regular jogging over the period of 1 year.
- ☐ **Monitoring of long term goals.**
  Scaffolding should support monitoring of progress and reflect on whether users have achieved their long term goals. Users should be allowed to scrutinise goals, inferences and seek help if required.
- ☐ **Maintaining motivation over long term.**
  Systems that targets to help users achieve long term goals should aim to provide some kind of motivation and support mechanism over long term. For example, this may be achieved through providing accurate information, timely reminders [8] and social encouragement [24] and can be based on the user lifelong user model.

5 Discussion and conclusions

Growing and widely available pervasive devices, storage and communication allow us to collect and store very granular and personal data over the long term. In this paper, we discussed this through 'Alice' a hypothetical person who has different types of long term goals and how she can combine different data and example interface elements to achieve this. We discussed lifelong user modeling [15], meta-cognitive scaffolding techniques [4] and interface designs that can be applied to this domain of long term goals. Finally, it presented the requirements for systems as guidelines for how future systems and studies can utilise these techniques. Suggested future work include performing evaluation on these techniques and their strength and weaknesses. We can also assess suitability for different use cases, scenarios and types of long term goals.

References

1. fitbit. http://www.fitbit.com/. Accessed: 2013-04-01.
2. Roger Azevedo, Jennifer G Cromley, Daniel C Moos, Jeffrey A Greene, and Fielding I Winters. Adaptive content and process scaffolding: A key to facilitating students self-regulated learning with hypermedia. *Psychological Testing and Assessment Modeling*, 53:106–140, 2011.
3. Roger Azevedo, Jennifer G Cromley, and Diane Seibert. Does adaptive scaffolding facilitate students ability to regulate their learning with hypermedia? *Contemporary Educational Psychology*, 29(3):344–370, 2004.
4. Roger Azevedo, Amy Witherspoon, Amber Chauncey, Candice Burkett, and Ashley Fike. MetaTutor: A MetaCognitive tool for enhancing self-regulated learning. In *Proceedings of the AAAI Fall Symposium on Cognitive and Metacognitive Educational Systems*, pages 14–19, 2009.
5. Debjanee Barua, Judy Kay, and Cécile Paris. Viewing and Controlling Personal Sensor Data: What Do Users Want? In Shlomo Berkovsky and Jill Freyne, editors, *Persuasive Technology*, volume 7822 of *Lecture Notes in Computer Science*, pages 15–26. Springer Berlin Heidelberg, 2013.
6. Susan Bull and Judy Kay. Open Learner Models. In Roger Nkambou, Jacqueline Bourdeau, and Riichiro Mizoguchi, editors, *Advances in Intelligent Tutoring Systems*, volume 308 of *Studies in Computational Intelligence*, pages 301–322. Springer Berlin Heidelberg, 2010.
7. Stuart K Card, Jock D Mackinlay, and Ben Shneiderman. *Readings in information visualization: using vision to think*. Morgan Kaufmann, 1999.
8. Sunny Consolvo, Predrag Klasnja, David W. McDonald, and James A. Landay. Goal-setting considerations for persuasive technologies that encourage physical activity. In *Proceedings of the 4th International Conference on Persuasive Technology - Persuasive '09*, page 1, New York, New York, USA, April 2009. ACM Press.
9. Sunny Consolvo, Peter Roessler, and BrettE. Shelton. The CareNet Display: Lessons Learned from an In Home Evaluation of an Ambient Display. In Nigel Davies, ElizabethD. Mynatt, and Itiro Siio, editors, *UbiComp 2004: Ubiquitous Computing*, volume 3205 of *Lecture Notes in Computer Science*, pages 1–17. Springer Berlin Heidelberg, 2004.
10. B J Fogg. *Persuasive Technology: Using Computers to Change What We Think and Do*, volume 5 of *The Morgan Kaufmann series in interactive technologies*. Morgan Kaufmann, 2003.
11. Claudia Gama. Metacognition in interactive learning environments: the reflection assistant model. In *Intelligent Tutoring Systems*, pages 668–677. Springer, 2004.
12. Sten Govaerts, Katrien Verbert, Erik Duval, and Abelardo Pardo. The student activity meter for awareness and self-reflection. In *Proceedings of the 2012 ACM*

annual conference extended abstracts on Human Factors in Computing Systems Extended Abstracts - CHI EA '12, page 869, New York, New York, USA, May 2012. ACM Press.
13. William L Haskell, I Lee, Russell R Pate, Kenneth E Powell, Steven N Blair, Barry A Franklin, Caroline A Macera, Gregory W Heath, Paul D Thompson, Adrian Bauman, and Others. Physical activity and public health: updated recommendation for adults from the American College of Sports Medicine and the American Heart Association. *Medicine and science in sports and exercise*, 39(8):1423, 2007.
14. Nassim Jafarinaimi, Jodi Forlizzi, Amy Hurst, and John Zimmerman. Breakaway: an ambient display designed to change human behavior. In *CHI '05 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '05, pages 1945–1948, New York, NY, USA, 2005. ACM.
15. J Kay and B Kummerfeld. Lifelong learner modeling. *Adaptive Technologies for Training and Education. Cambridge University Press, New York*, pages 140–163, 2012.
16. Judy Kay and Bob Kummerfeld. Creating personalized systems that people can scrutinize and control: Drivers, principles and experience. *TiiS*, 2(4):24, 2012.
17. Tanyoung Kim, Hwajung Hong, and Brian Magerko. Design requirements for ambient display that supports sustainable lifestyle. In *Proceedings of the 8th ACM Conference on Designing Interactive Systems*, DIS '10, pages 103–112, New York, NY, USA, 2010. ACM.
18. Christopher Kay Knapper. *Lifelong learning in higher education.* Routledge, 2000.
19. J Maitland, S Sherwood, L Barkhuus, I Anderson, M Hall, B Brown, M Chalmers, and H Muller. Increasing the Awareness of Daily Activity Levels with Pervasive Computing. In *Pervasive Health Conference and Workshops, 2006*, pages 1–9, 2006.
20. D.B.a Portnoy, L.A.J.b Scott-Sheldon, B.T.a Johnson, and M.P.b Carey. Computer-delivered interventions for health promotion and behavioral risk reduction: A meta-analysis of 75 randomized controlled trials, 1988-2007. *Preventive Medicine*, 47(1):3–16, 2008.
21. Ido Roll, Vincent Aleven, Bruce M McLaren, and Kenneth R Koedinger. Improving students help-seeking skills using metacognitive feedback in an intelligent tutoring system. *Learning and Instruction*, 21(2):267–280, 2011.
22. H Lee Swanson. Influence of metacognitive knowledge and aptitude on problem solving. *Journal of educational psychology*, 82(2):306, 1990.
23. Sigmund. Tobias, Howard T Everson, and College Entrance Examination Board. *Knowing what you know and what you don't : further research on metacognitive knowledge monitoring.* College Entrance Examination Board, New York, 2002.
24. T Toscos, A Faber, K Connelly, and A M Upoma. Encouraging physical activity in teens Can technology help reduce barriers to physical activity in adolescent girls? In *Pervasive Computing Technologies for Healthcare, 2008. PervasiveHealth 2008. Second International Conference on*, pages 218–221, 2008.
25. J Uther and J Kay. VlUM, a web-based visualisation of large user models. *User Modeling 2003*, pages 145–146, 2003.
26. Hidde P van der Ploeg, Tien Chey, Rosemary J Korda, Emily Banks, and Adrian Bauman. Sitting time and all-cause mortality risk in 222 497 Australian adults. *Archives of internal medicine*, 172(6):494–500, March 2012.