Extending the Learning by Teaching Canvas System: Maximising Academic Learning Time

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Abstract

Time plays an integral role in the realm of e-learning modules. plaimi previously described a canvas for composing e-learning modules. By transitivity, time needs to play an integral role in this canvas. This paper investigates some of the ways it can play said role. Four angles are considered: insights offered by viewing a module composition as a chronicle of modules, the importance of length estimation in time allocation, heightening retention via spaced repetition, and synchronisation attempts at facilitating collaborative learning. The features discovered by this investigation are discussed in a principled learning context, which particularly emphasises academic learning time. Some concrete suggestions are made; to implement: order-awareness, user estimation of module length, spaced-repetition-awareness, and post-module self-assessment. Suggestions for further research are also given.

Contents

1 Introduction 2
2 Motivation 2
3 Ideas 3
  3.1 Chronicling .......................................................... 3
  3.2 Estimation ............................................................ 4
  3.3 Repetition ............................................................. 6
  3.4 Synchronisation ......................................................... 6
4 Further research 9
5 Conclusion 9

List of Figures

1 An imagined popular canvas ........................................... 3
2 A canvas optimised for collaboration ................................. 9
1. Introduction

In an effort to foster learning by teaching, plaimi have previously described a canvas for intuitively composing e-learning modules\([1]\). This system indirectly emphasises chronology, which plaimi previously explored in the tempuhs system\([2]\).

The canvas system lets users drag and drop e-learning modules onto it, and then arrange the data flow of the system, thereby effectively arranging the modules into a chronology of modules (a composition of modules). By looking at the modules as a chronology, and considering the role time plays in principled learning, there are several insights available to us.

This paper describes some such insights. It motivates the insights, and explore them in some detail. This includes elaborating and elucidating the concepts, as well as giving some notes on their potential implementation. There are numerous challenges that the papers elects to not ignore, and seeks to mitigate.

Since we are designing a system for learning, it is important that any features we consider for inclusion have a sound scientific foundation. The insights offered and features discussed are thus considered in a scientific context.

There are four angles explored by the paper. Insights afforded by chronicling and ordering are presented in Section 3.1. Estimation, both by way of users estimating their modules’ time frame, and by the system automatically estimating it, is discussed in Section 3.2. Spaced repetition as a way of improving retention is explored in Section 3.3. Finally, features related to synchronous collaboration and timeslot synchronisation are described in Section 3.4. We also take the time to make a few remarks regarding future research in Section 4.

2. Motivation

When designing a learning experience, it is essential to consider time. This includes an awareness of allocated, engaged, and academic learning time (ALT), lest dead time incurs for want of understanding. Allocated time is the amount of time allocated for learning. Engaged time is time spent actively attempting to learn. ALT is time spent engaged in appropriate learning that leads to high levels of success\([3]\); i.e. time spent in the flow. Flow is the state of being fully immersed and focused on an activity\([4]\).

There is a very slight but persistent correlation between allocated time and achievement\([5, 6, 3]\). Engaged time is modestly correlated with achievement\([5, 7, 3]\). ALT leads to more learning\([6]\, and the rate of ALT is highly correlated with achievement\([5, 7, 6, 3]\). Related to our canvas system we also take note that interactive engaged time lead to higher achievement than non-interactive engaged time\([7, 3]\).

Pre-laptop era research demonstrates unequivocally that school pupils only spend roughly half of their in-class time engaged in learning\([3]\). Laptop era research shows that students with laptops, compared to those without, spend more time engaged in learning, develop better critical thinking skills, and are more self-reliant. Additionally, laptop users are significantly higher-achieving than their non-laptop-using counterparts\([8]\). There is no indication that this research should not extend to today’s era of laptops coexisting with tablets and sophisticated mobile phones in the classroom.

When considering the canvas system, we need to seek not only to maximise engaged time, but also to allow e-learning modules authors to think about how their module will fit into allocated time. Furthermore, situated learning environment professionals, e.g. teachers at primary schools, necessarily need consider allocated classroom time when choosing which modules to use.

Moreover, and more importantly, the system must strive for the maximisation of ALT by eliminating material that is either too easy or too difficult, or otherwise unsuitable to the learner. The system admits the possibility of non-linear adaptive compositions of e-learning modules — and it would not be unfaithful to the original concept to attach the utmost importance to this goal — leading to a great opportunity to further elevate the present ALT ratio both in and out of classrooms.
In addition to maximising learning, we also seek to maximise motivation (willingness to engage) and minimise procrastination (unwillingness to engage; the absence of (self-regulated) performance[9]). First, we suppose that our canvas system is a gamified system, and thus it is inherently comparable to a game in several ways[10]. This is intended design[1]. Furthermore, designing e-learning modules is a subset of instructional design, which is fundamentally similar to game design[4]. Then we accept that ALT in our system is a form of flow. This is a reasonable conjecture, because flow state works by precisely the same mechanics as ALT: performing at the edge of one’s competency, guided by feedback[11]. This is altogether the point of ALT, as designed and desired to manifest in our gamified system. From this follows several insights.

Flow has a number of different desirable properties. It is intrinsically linked to motivation and widely accepted as one of the fundamental reasons people play games[4], and thus an emphasis on flow might cause people to use our canvas system. It follows immediately from the law of readiness (and indirectly from the law of effect) that learners learn best when motivated[4], and the whole point of our system is for our users to learn. Additionally, presence of flow is significantly negatively correlated with procrastination, and absence of flow is significantly positively correlated with procrastination[9].

Consequently, we must conclude that ALT — and by extension time — as a concept is intrinsic to our system.

3. Ideas

3.1. Chronicling

The canvas system may be aware of the chronology in a composition. After all, it is already there indirectly. As a motivation, let’s consider an imagined popular canvas. Let \( m, n, o, p, \) and \( q \) be modules. Let \( m \rightarrow n, n \rightarrow o, n \rightarrow p, o \rightarrow p, \) and \( p \rightarrow q \) be possible flows, where \( \rightarrow \) is a binary operator signifying that the user is sent from the module given as its left-hand side argument (lhs) to the module given as its right-hand side argument (rhs). This canvas is shown in Figure 1.

![Figure 1: An imagined popular canvas](image)

Some self-evident properties here include that the successor of \( m = n \), and the successor of \( n = o/p \). Module relations are transitive with respect to order, so the successor of \( n = q \) via the successor of \( o = q \), and the successor of \( p = q \) — all the way down to the successor of \( m = q \). Alternatively, by symmetry, we can say that the predecessor of \( q = m \).

Ordering is trivial to store in module metadata, and via very simple mathematical operations we are afforded a lot of useful insights. Just from the above, several concrete features are easily imagined.

- We can suggest that authors of compositions that contain e.g. module \( m \) might be interested in modules \( n, o, p, \) and \( q \).
- Authors with modules \( m \) and \( q \) on the canvas could be recommended to insert modules \( n \) and \( o \) in-between them. This is particularly interesting if the system has other useful metadata. E.g. if \( q \) is generally considered to be very difficult, and \( n \) and \( o \) is considered to augment \( m \) significantly in preparing for \( q \), \( n \) and \( o \) should be strongly recommended to the author of a canvas with \( m \) and \( q \) in them.
- Authors with modules \( m, n, o, \) and \( p \), on their canvas could have \( p \) recommended as a supplement for \( o \) — or as an alternative
to \( o \). The latter would be extra useful if we have useful time estimates, forthy it may e.g. be that \( p \) fits the desired composition estimate better than \( o \).

- Authors that have module \( o \) may be recommended \( p \) irrespective of the other modules in their composition, e.g. in the aforementioned time constraint scenario.

As touched on above, combining chronology insights with other metadata, we may make several observations.

As an example, let \( n : T, q : U, \) and \( o, p : V \), where \( : \) can be read “has-type”, i.e. \( \text{lhs is a module, and rhs is the type of module (e.g. news article, scientific paper, video, game, or quiz). Then let } t \) be a function that takes a module as its input, and returns the module's type metadata as its output. If a user has \( n \) and \( q \), we can recommend \( o \) and \( p \) as above. But \( to = tp \) means that \( V \) is potentially interesting. Thus we can safely recommend the set of other modules with the same type as \( o \) and \( p \), i.e. \( \{ tm = V | m \in M \} \), where \( M \) is the set of all modules.

If we let \( p : W, \) and arrive at the conclusion that \( p \) should be suggested from another metric — we have that the successor of \( n = o|p \) in the imagined popular canvas, so \( o \) and \( p \) are similar in other ways than \( to \) and \( tp \) — we could recommend \( \{ tm = to, \) or \( tm = tp | m \in M \} \), i.e. the set of all modules with either \( V \) or \( W \) as their type.

These insights hold for other things than types. As an example take : to be “has-topic”, and \( t \) to be a function from a module to its topic. The system could also look at a combination of different metadata to work out heuristics for how to suggest modules.

Satisfied with a sufficient motivation for chronology-awareness, we now turn to the implementation of it. The core idea of plaimi’s tempuhs system seems to be tailored to our use case. The cons are that it needs extended expressiveness for the relationships of chronology elements (called timespans in tempuhs), and that it has not been put to the test for production use when several users are considered. The pros are that it is known to deal with a lot of data, and that it offers good guarantees of representing our data logically, and preserving said logic. Using tempuhs would allow us to distil canvases into timespans, which lets us consider the time aspect carefully. It is reasonable to think that several new insights are attainable if we go this route.

3.2. Estimation

In Section 3.1, modules are considered in relation to each other. Thus everything is happy days. However, in this section we consider estimating the time a module takes, which proves to be a quite complicated endeavour.

Being able to estimate the time a module takes to complete is useful for the author of the module and the module users both. This would be a conservative augmentation both in terms of technical and philosophical impact, making it perhaps less interesting than other prospects explored in this paper, but at the same time perhaps all the more immediately useful.

It is easy to conceive of the practical aspects of this idea. There are two levels to it. First, let authors of modules estimate the amount of time a module will take, and store it as module metadata. The design changes involved are quite small, the programming required is minuscule.

There is some benefit to this, but the obvious issue is that the estimator might be wrong. It may be wrong in several ways for several reasons. Conceivably the estimation reflects what the author is aiming for rather than what the author has actually achieved. To put it simply: they might be wrong.

The next logical step then becomes to accumulate how much time users actually spend. This is more complicated to implement, but not too complicated. We will require client-side executable code to achieve this, which means that any prevention of such code will prevent us from gathering useful data. This is not too worrying as there will be little reason for users to prevent this code from running, meaning that few users will do so. When viewed in isolation, the performance penalties of this code will be neg-
ligible.

But there are several weaknesses to the metric itself. Naïvely accumulating how long a user spends on a particular website results in a plethora of useless data. Two easily imagined extrema are users leaving a website up for a very long time, and users immediately leaving the website. It is similarly easy to imagine why this would happen. As one example of each:

1. Consider a primary school pupil visiting a website during the very end of instruction time, and leaving it up until the next instruction time (e.g. visiting it at the end of Friday, and leaving it up through the weekend).
2. Consider a user visiting the wrong website and immediately leaving it.

Accounting for those specific problems is non-trivial. Normally, a standard deviation cutoff would suffice adequately, but in our case we are faced with something like a tri-modal distribution. Maybe it’s a leptokurtic distribution. That would be nice. But unfortunately, it might be, or it might not be. That’s a lot worse. And it’s about to get worse. Because it might be leptokurtic, and then it might change into a fat-headed distribution. And then it might reverse back again. And then it might become heavy-tailed. Etc. The modules might even have different distributions (that change as more people visit them.) If you have a leptokurtic distribution in two modules, a heavy-tailed distributed module, and two fat-headed and fat-tailed distributions, what then of the composition of these five modules? What then when the third becomes leptokurtic and the fourth becomes heavy-tailed? Doing this properly is not going to be trivial.

Are we having fun yet? Because it’s about to get even more fun. Consider having a quiz about monoids in semigroup theory. The author estimates it to take $n$ minutes. A primary school student and a maths postgraduate go through the quiz. The estimation can in this situation be wrong in two ways — too short and too long. This raises the question — is the estimation in general useful at all?

So then the next step is to tie estimation to knowledge. I.e. we need to know how much the user knows about something, and derive estimations based on how much similarly knowledgeable users know about the same thing. This is non-trivial enough to not warrant any more examples. The observant reader “gets the picture”, as it were.

Let’s take a step back before we end up with a horror story instead of a paper. Let’s look at the benefits and opportunities afforded to us by implementing this.

Authors may receive useful analytics regarding their modules. Some banal analytics are “users are spending longer on this module than you thought they would”, and “these modules in your composition are approximately of the same length, but this fourth one takes a lot longer”. The former suffers from the context problem, but the latter is actually rather pleasant. Indeed most things we can say about one module in relation to some other modules in the same composition is usually immediately useful without a Ph.D in statistics.

While module authors are rewarded with feedback, module users are provided with useful information on how they want to spend their time, which makes our system interrupt flow more seldom. Users may search for modules and compositions based on time estimates. The same benefit applies to indirect users. E.g. classroom teachers might search for the compositions that yields the highest ALT to allocated time ratio.

Module authors can be said to be module users as well, in that they will often remix modules, and they benefit in a similar manner to module users. They can e.g. search for modules that fit their estimated composition length.

To make estimates useful for users (including indirect users and remixers) the programmer needs a statistics Ph.D or so to deal with transforming the data, and then contextualising it. To make estimates useful for authors, they will likely need a Ph.D themselves. We should however try our best to help them make sense of it. Perhaps authors should have to complete an introduction to statistics composition before being able to access their analytics.
3.3. Repetition

The law of recency states that learning degrades over time, and the law of exercise says that learning is increased through repetition\[4\]. A common solution to this problem is discussed in the paper that initially proposed the canvas\[1\], namely spaced repetition (combined with testing); i.e. studying across several separated sessions in time rather than spending the same amount of time in a single session.

This often leads to higher retention, and is one of the most reliable findings in human learning research (echoed in hundreds of studies, the first of which dating to the 1800s). It has been predictably demonstrated in both children and adults, and for both trivial knowledge (simple facts) as well as advanced concepts\[12\]. It has also been shown to be beneficial in realistic (applied) contexts\[13, 12\].

As we’ve already discussed\[1\], spaced repetition with testing is a credible learning method, and thus appealing feature to include in our canvas. The initial canvas system was nevertheless designed without an emphasis on spaced repetition, in order to provide a more general framework. Spaced repetition is usually provided for rather specific and well-defined knowledge (translate this word to German, solve this equation for x, etc.), and arguably makes less sense for a news article leading up to a discussion. The canvas is merely a way to glue things together, where “things” is an ever so broad term. Another issues is that finding the optimal spacing gap is notoriously difficult, and inherently contextual (there is no “one-size-fits-all” solution)\[12\].

As it stands, centering the entirety of the canvas’s design on spaced repetition is unlikely. But it is altogether conceivable to augment it with a separate system specialising in spaced repetition. As an example, there is nothing that precludes the canvas from facilitating a system which focusses on spaced repetition.

The modules and compositions thereof would need metadata tailored to the spaced repetition model of learning, but this is not in itself a difficult task. The amount of work to at the very least be natively spaced-repetition-aware is very low, and the benefits may be disproportionately high for systems that may want to use the canvas system. Consequently, it is likely a good idea to make at least that much effort.

The next level of effort would be to include a way for learners to self-assess retention, in a manner similar to what Anki\[1\] and similar programs do. There must be a way to mark a module as spaced-repetition-aware, which will then let the user self-assess its learning effect at the end of it. This is a feature which is useful regardless of spaced repetition, as we are now able to say something about our users’ retention level based on self-assessment. By extension we can say something about the retention success of modules. It trivially also follows that we may say something about assessment, both from the perspective of a user, and of a module. Assessment can be made into an interactive and engaging affair through our system’s avatar feature\[1\].

The final step is to actually encourage repeating somehow. This is likely out of scope for our system for now. There is however, as mentioned, nothing precluding an external system from augmenting our system with this.

3.4. Synchronisation

The canvas system is part of a project dubbed “Learning by Teaching”, and was originally conceived as a stepping stone towards cultivating learning by teaching, which fosters advantages that do not manifest if the learner relies exclusively on an external teacher in a situated learning environment\[14\]. Additionally, the canvas was designed to offer an intuitive way of graphically composing e-learning modules\[1\].

The stepping stone satiated by the canvas is authoring. As such, the canvas can be said to achieve “learning by authoring”, a process that covers gathering of learning material, and organising. As a result, the canvas software focusses on authors.

\footnote{\url{https://ankiweb.net/about}}
However, the compositions that are made on the canvas are only interesting insofar as they are used. We must therefore not neglect the end-users of e-learning in favour of the authors. Although we wish to encourage a learning effect from authoring modules, there will be some pure end-users that do not author anything. When focussing our attention on these end-users, we must consider collaborative learning, as discussion is shown to foster the development of critical thinking[15].

In the interest of collaboration, mechanisms for synchronising users are desirable. Three suggestions are discussed here;

- realtime (synchronous) collaboration,
- wait-for-me collaboration,
- and timeslot collaboration.

Exploring realtime collaboration offers several specific features. The collaboration may take place on two levels — using the modules, discussing the modules, or both.

First, let’s talk about collaboratively using and discussing modules in realtime. The immediate idea here is akin to Twitch Plays Pokémon, where over a million users for over two weeks voted on what to do at every step of the game ポケットモンスター 赤 (Poketto Monsutā Aka, known as Pokémon Red outside of Japan), in a strictly egalitarian manner, whilst discussing the game in a live chat[16]. The experiment is a significant phenomenon that demonstrates that social groups are able to unite in social contexts where obstacles are presented[17]. The experiment is largely transferable to users of our canvas system, in that there are several modules for which it is possible to have a group of people using them at the same time with e.g. the majority vote deciding how they progress. More sophisticated voting mechanisms such as Condorcet may be desirable to provide better overruling heuristics. Discussion may be directly transferred; i.e. a regular realtime chat is provided.

There are several ways of making this idea more sophisticated. Users may need to discuss and argue their views as to why e.g. one answer in a quiz is correct and others are not, in order to achieve a satisfactory outcome (per some voting heuristic), lest they be prevented from progressing. Discussion may be augmented with features that make it easy to refer to information within a composition. As an example, in a composition where the users are on module three, a quiz, they may wish to refer to module two, an article, to strengthen their argument. In this example the user needs a simple way of accessing previous modules, and a way of easily using them in a discussion.

If the reader is concerned that the idea has become too sophisticated now, fear not; there are equally many ways of distilling it down into simpler components. E.g. A chat by itself. This modest feature would be a rather large extension of the canvas system. Especially as it was argued against in the original implementation to avoid abusive behaviour[1].

Instead of each participant actively influencing module outcomes, a seat mode may be used. There are several conceivable implementations of this. One is that there is one (somehow elected) person in control all the time, that needs to act on behalf of the group. Another is a hot seat solution in which the seat holder changes based on some heuristic.

Modules that are merely articles or videos or other non-interactive learning material arguably benefit the least from realtime collaboration — fast readers must wait for slow readers, and that’s about it. This is where wait-for-me collaboration becomes useful. The general idea is that there are several synchronisation points where users must become synchronised. In the example above, it would be natural that if module one and two were reading material, these may be pursued independently. There is nothing precluding the joint existence of wait-for-me and realtime mechanics, so that once the users are synchronised, they may use a module — such as the quiz in module three — in collaborative realtime. Another useful combination is wait-for-me synchronisation at certain intervals, after which realtime discussion takes place. But wait-for-me mechanics have useful properties when viewed independently as well. One concrete example that is easy to imagine use-
ful is in a largely situated learning environment where it is desirable that all learners possess roughly the same information.

Timeslot collaboration is another useful idea for situated learning environments. It is additionally also useful for learners that want to collaborate across timezones, or following some self-imposed schedule. A timeslot mechanism would entail completing modules in certain timeslots. Teachers often set learning material per class per week in school, and gives homework based on rather tight timeslots, so this is a familiar concept. Again, it may be combined freely with the other two synchronisation methods. It may also be nested. E.g. a timeslot to do a module composition wherein wait-for-me mechanics are used for non-interactive learning material, culminating in a real-time quiz and subsequent discussion.

Where naïve wait-for-me moves in the pace of the slowest participant at the risk of alienating the quicker participants, naïve timeslot synchronisation moves at a set pace and risks leaving the slower participants behind. These problems mean that the features may have exactly the opposite of our intended effect, maximising ALT, for some subset of users. Wait-for-me synchronisation needs to consider a method of progressing if one (or more) participants are slowing the group down, whilst timeslots need to consider a way of ensuring that participants are actually learning. Realtime in turn risks virtually all known problems with online social interaction. . .

Collaborative learning is most effective with an instructor that facilitates learning[15]. It then follows that we should seek to foster learning by instruction in addition to learning by authoring. Marrying the two (i.e. users acting as instructors of material they have themselves authored) gets us much closer to learning by teaching proper.

Consequently synchronisation should be extended to encompass instructors as well. There are several ways of achieving this. Instructors may provide realtime feedback whilst a group is going through a module, or discussing it. They may also act as the seat holder, thereby offering a potential solution to any social problems.

This entire section has a certain latent conjecture hanging over it: Synchronous collaboration is mostly interesting in a (semi) situated learning environment. However, this environment needn’t be a classroom setting. It just needs to be facilitated in the system that surrounds the canvas. Study groups or a similar mechanism in which learners may organise may be added, including potentially a matchmaking system, and a forum for getting in touch with potential collaborators. All of which are major undertakings and nigh-complete transformations of the original concept — this isn’t to be taken lightly.

Another problem with uncoordinated collaborators is the possibility of upsetting the precarious ALT by effectively making each collaborator adapt to each other. This could potentially result in every single collaborator following a sub-optimal pace, thereby harming the chances of achieving ALT, making this a negative feature rather than positive. Well put-together study groups alleviate this slightly, but not completely.

We elect not to explore potential implementation problems in detail in this section. Just like the core repetition idea discussed in Section 3.3, the ideas presented here are of such a magnitude as to warrant completely new user experience research. However, it is noteworthy that nothing discussed in this section is fundamentally difficult from a technological perspective. The user-interface and -experience design challenges are far greater (though not insurmountable).

Like we concluded with spaced repetition, it is entirely plausible that synchronous collaboration is best left to another system which augments the canvas. It may also be suitable as a special part of some expanded system, wherein the learning material itself is optimised for a collaborative premise. Collaborative material which enables critical thinking and discussion are likely to be more successful than users attempting to collaborate on material not designed with collaboration in mind.

With learning material optimised for collab-
oration, it is possible to approximate real world tasks to a higher degree. As an example, consider the software engineering composition visualised in Figure 2. Let $A$ and $B$ be the participants of this canvas. Let $a, b, c,$ and $d,$ be modules. Let $a \rightarrow b$ and $b \rightarrow d$ be flows unique to $A,$ and $a \rightarrow c$ and $c \rightarrow d$ unique to $B.$ The topic might be compilers. $a$ might be an introduction to compilers, then $b$ can be an introduction to frontend (lexing, parsing, etc.), and $c$ an introduction to backend (assembling, code-generation, etc.), and finally $d$ can be a quiz about both front- and backend fundamentals. This models real world collaboration in a sense. It is not unusual to divide up tasks like this in software engineering. The quiz might now be a realtime collaborative task in which the $A$ and $B$ must rely on each others’ knowledge in order to pass it. Through this process, it is plausible that $A$ will learn about compiler backends, and that conversely $B$ will learn about compiler frontends.

![Figure 2: A canvas optimised for collaboration](image)

The interactive nature of our canvas makes collaborative learning a natural fit. But the original design did not consider collaborative learning, and as such the augmentation must be considered too great to be done recklessly. User experience research is thus thoroughly recommended, and indeed necessary.

4. Further research

There are ideas worth exploring related to ALT that emphasise interactivity and assessment.

The law of exercise emphasises that in order to achieve the best learning results, practice and feedback must coexist[4].

An integral part to ALT is that the learner experiences high levels of success[3, 4]. Facilitating ALT is in principle straight forward, but for the balancing of difficulty of skill. Success requires a delicate balance in which tasks are challenging yet achievable. Feedback (the manner in which the learner perceives their progress) is intrinsically entangled with achieving this balance, and assessment is in turn intrinsically entangled with feedback[4].

It would be worthwhile further investigating augmenting non-linearity as a means to achieve the difficulty balance. There are numerous angles to investigate. For instance, modules may be interactively rearranged or hot-swapped based on difficulty.

In Section 3.3, naïve self-assessment is suggested. More sophisticated methods of assessment are worthy of investigation. One novel approach to interactively tutoring learners is Ask-Elle, a programming tutor for the Haskell programming language which provide students with feedback on incomplete programs, and give hints on how to proceed in order to solve a programming exercise[18]. The avatars of our extended system help the system to achieve a more human touch[1], and are practical candidates for such a tutoring system, which might double up as an assessment tool.

In Section 3.4, instructor-integration is briefly mentioned. Presently, module authors are primarily involved pre-learning. Attempts at involving them during learning in an instructor role would be worthwhile.

5. Conclusion

Time as a concept is intrinsic to the canvas system proposed by plaimi, as we want to maximise ALT. There are several promising insights available to us by viewing compositions as chronologies. This simple exercise in perspective offers insights that particularly manifest as suggestions we may offer the users based on chronology metadata. Knowing which modules tend
to follow others is simply extremely useful. It is also rather conceptually trivial. It does however not directly improve the ALT capabilities of our system per se.

Offering estimation mechanisms in module metadata may alleviate some time-management burdening for our users. It makes it easier for authors to find modules to fit their composition — particularly if they are making the composition for a situated learning environment in which allocated time must be carefully considered — and it makes it easier for module end-users to find suitable learning material. Allowing authors to embed man-made estimations as module metadata is a very modest but good extension, but the estimations are educated guesses at best. Furthermore, learning material time estimations depend heavily on the end-user. Therefore an even better extension would be to gather data and do contextual estimation for each user. This is however a very difficult problem.

Spaced repetition is accepted as often leading to higher retention and thus better learning. We could encode spaced repetition metadata in modules and compositions thereof, making our system spaced-repetition-aware, thereby further extending its usefulness and area of application. We could also implement an insight afforded from spaced repetition software — the notion of self-assessment immediately post-learning. This lets us say useful things related to retainment and assessment regardless of spaced repetition.

Collaborative learning can offer a positive learning effect, but if not done properly this might be antithetical to ALT. Synchronisation for collaboration may be done in realtime, in wait-for-me time, or by timeslots. Realtime collaboration in interactive learning material is an interesting prospect. So is synchronising users at given intervals, especially when combined with a realtime module, e.g. evaluation (a quiz or similar) after synchronising the users. Timeslots may be a useful way for especially teachers in classroom settings to ensure that learners have similar progress. These ideas all present difficult problems due to their invasive nature. Further investigation is encouraged to take place in a separate system with learning material optimised for collaboration, which might to some extent marry the advantages of ALT and collaborative learning.

To sum up, the following features should be implemented:

- order-awareness for chronology insights,
- author estimation of module length,
- a metadata framework for spaced repetition,
- and post-module self-assessment capabilities.

These are, not coincidentally, the most modest features proposed in the paper.

The following more invasive changes were discussed:

- system estimation of module length,
- contextualised (user-customised) estimation of module length,
- spaced-repetition encouraging,
- collaborative realtime module use,
- easy referring to modules and specific elements therein,
- wait-for-me collaboration in which users are periodically synchronised to the same module,
- timeslot collaboration to ensure that users are somewhat synchronised,
- various combinations and nesting of the proposed synchronisation methods,
- instructor-integration mechanics for collaborative learning,
- and a sub-system optimised for collaborative learning.

Further research is encouraged for all of these more invasive features. Collaborative learning is particularly interesting due to the weight of its potential augmentation. It is also particularly difficult due to its potential negative impact on ALT.
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