Maximising Gain for Minimal Pain: Utilising Natural Game Mechanics

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Abstract

This paper considers the application of natural games mechanics within higher education as a vehicle to encourage student engagement and achievement of desired learning outcomes. It concludes with desiderata of features for a learning environment when used for assessment and a reflection on the gap between current and aspired learning provision. The context considered is higher (tertiary) education, where the aims are both to improve students' engagement with course content and also to bring about potential changes in the students' learning behaviour.

Whilst traditional approaches to teaching and learning may focus on dealing with large classes, where the onus is frequently on efficiency and on the effectiveness of feedback in improving understanding and future performance, intelligent systems can provide technology to enable alternative methods that can cope with large classes that preserve the cost-benefits. However, such intelligent systems may also offer improved learning outcomes via a personalised learning experience.

This paper looks to exploit particular properties which emerge from the game playing process and seek to engage them in a wider educational context. In particular we aim to use game engagement and *Flow* as natural dynamics that can be exploited in the learning experience.

Keywords

Game mechanics; intelligent learning systems; technology enhanced learning.

Introduction

The aim of this paper is to consider the application and effectiveness of game mechanics in learning activities. This approach of gamification is gaining in interest and popularity (Renaud and Wagoner, 2010), but often focusses on educational games for teaching, rather than applying game mechanics to a traditional content. The point is subtle: gamification is different from learning games; gamification involves using game mechanics in non-game contexts as opposed to learning games where learning is achieved through the process of playing (Deterding et al, 2011). The claim is that the emergent properties of game playing are valuable pedagogical techniques that can be applied to other learning experiences. Whilst games are often used in teaching of young children, as the level of education increases the focus often moves to more traditional models of tell, do and assess. The traditional teaching style (e.g. chalk and talk), whilst effective for many students, does not engage all and has been linked to significant failure rates and corresponding drop-out rates faced within many educational systems across the world (Felder et al, 1998).

Characteristics of the problems produced by the traditional approach are the high risk, high stake nature of assessment – in particular the typical scenario where students can have little feedback on their relative performance prior to actually submitting and receiving marks on their end of course examinations (Knight 2002). Natural game dynamics, where the ethos is have a go, and if you fail, have another go, are the antithesis of this allowing multiple attempts and instant feedback.

As a background to this it has been proposed that everyday life embraces the character of play (Huizinga 1938). In *Homo Ludens* (Playing Man) Huizinga introduced the idea of the play element of culture and the scoping of this concept. To act in society is to play. Another type of play can be role playing and the deliberate choice to present yourself in a certain way, e.g. for personal satisfaction, fantasy fulfilment, eliciting the desired responses from others, or just out of curiosity. Goffman (1959) used a theatrical metaphor to describe how we are all actors in a performance that is culture and society. This is even more the case when we think about the presentation of Self in Virtual Life. In a game like World of Warcraft, males may have female characters and vice-versa (e.g. see Grace, 2012).

As Blow (2008) noted “All games inherently teach” and what they teach is often related to the goal of that game. Spencer (1968) notes the links and transferable skills between computer game playing and other programming activities. However, computer games are not just some magic chocolate coated broccoli or Trojan horse by which we can sneak through awkward bits of syllabi. We need to be aware of other dynamics that are important here. Csíkszentmihályi (1990) introduces the notion of *Flow* in which he proposes that people are happiest when totally engrossed and engaged in their current activity, cutting out all other things going on around. The idea fits nicely into our of notion employing gamification in order to (inherently) teach. In designing activities, the aim would be to utilise game type mechanics to encourage the state of flow – perhaps through suitable challenges and feedback. However we also need to consider what dynamics might lead to loss of Flow. Dynamic game mechanics for risk, reward, or failure need to preserve this Flow, so, for example when you return after being zapped you need to wind time back a bit to give another go, dropping the character back at the point of being zapped last time only for this to be immediately repeated is only going to lead to frustration and potential loss of Flow. In order to preserve this Flow then, users need appropriate and reachable challenges and continual feedback, which if done right, is inherently what a game gives you. Thus attainment of goals and receipt of appropriate feedback and rewards is important. Continuous Flow would also imply the need for consistent reward.

Technology enhanced learning incorporates a wide variety of uses of technology, and in this paper we will consider the personalisation functions that can be provided through this media. In focussing on the individual learner, we will use an approach that, through the use of intelligent learning systems, adapts the questions to the apparent knowledge base of the student. Randomisation of elements of the assessment can then allow for an individual test for the student, enabling greater confidence in the outcome of the assessment; see Gordon (2009) for an example of this type of approach.

Background: Traditional Learning Games

In this section we will review some traditional approaches to using games in a learning context and illustrate the differences of these approaches to utilising games as opposed to gamification.

WEST (Brown and Burton, 1978) is based on the game *How the West Was Won*. The game involves traversing a series of towns which the player seeks to land on (or can skip onto the next town in certain circumstances). There are also special squares that if landed on advance the position of the player (shortcuts). If the player lands on a square currently occupied by their opponent then the opponent is knocked back two towns. It is a turn taking place board game using three dice (spinners). In order to determine the user move they take the rolled numbers and construct an arithmetic expression employing the mathematical operations of addition, multiplication, subtraction, and division. In addition to this the system attempted to employ a coach in the manner of a Guided Discovery System, to prompt, on occasion, opportunities for strategic improvements to play to be learnt. So the basic act of playing, plus additional prompting from the coach aims to promote the use of basic numerical skills. Thus from our perspective here WEST has very traditional recognisable didactic components albeit with the twist of discovery learning. It clearly attempts to be an intelligent tutoring system.

Wumpus (Yob, 1999) was a game that required the user to display aptitude in logic, probability, decision theory, and geometry. Challenges included the Wumpus itself - a vicious monster that will try to end your life – and the outcome that, if you get things wrong, you can also end up dead by falling to the centre of the earth. WUSOR-II (Carr and Goldstein, 1977; Goldstein, 1977, 1979; Stansfield et al, 1976) was a coach designed to improve play in Wumpus by improving knowledge of the above skills. The system employed what we would now describe as four Agents, namely: an Expert, a Psychologist, a Student Model and a Tutor. Each of these agents contributes to a combined WUSOR-II dialog with the player explaining the game logic in terms of the principles outlined above and suggesting what they should do and why. The interaction is one of an explicit didactic coach with computer expertise informing a naïve and willing learner.

Shopping on Mars (Hennessy et al, 1989) used shopping as the cohesive story to support informal calculations for 8-12 year old school pupils. Essentially the task of the game was to go shopping. Pupils would receive a shopping list before they entered the game that listed a number of items that could be purchased from a shop. However, the shops that they had to encounter were located on different planets where these planets used the metaphorical scaffolding of our own Solar System. The twist was that each Planet used a monitory system that was based on different number systems (e.g. binary, ternary, quaternary, octal, and decimal). The task/game of purchasing the items on the list from the Planet’s shop thus became one of mental arithmetic using different bases. The play element was shopping and the desired outcome was mathematical understanding of and proficiency in using alternative bases.

These three examples illustrate a traditional model of user and computer tutor/coach. What we wish to do here is to consider an alternative set of dynamics to learning interaction. One that exploits the natural emergent dynamics of game play as a vehicle to learning.

Theory

Assessment can be an effective driver of student behaviour – providing clear guidance to learners of what areas are perceived by the teacher to be of importance and should be focussed upon (Gordon, 2009). Given a significant variety of students with a broad range of individual motivations for learning, having some framework to assist in directing their study and activity can be helpful and this can be achieved through a combination of formative and summative assessment (e.g. Garrison et al, 2011; Gordon, 2009; Looney, 2011). Of particular note is the importance of student engagement in this activity; something which our approach aims to exploit.

Technology enhanced learning offers a number of benefits to the instructor, especially in the context of higher education where large class sizes and an increasingly varied cohort means that individual attention for students can be constrained, and the opportunity to identify and assist those students that would most benefit is limited (Alexander et al, 2002).

Traditional and electronic games utilise a number of mechanisms to encourage people to engage with and play them, often for no greater reward than to participate and potentially to win. Computer games are recognised as particularly effective at engrossing players – with some players spending hundreds of hours interacting with the computer environment. Some studies focus on the use of interactivity (graphics and action) to develop the engagement (Prensky, 2000). The key feature of interest in games for this paper are the game mechanics they utilise to enthral the players, and whether such mechanics can be utilised in other contexts to provide equal levels of engagement. This falls into the area of gamification, the approach of utilising game mechanics and game design in other contexts (Deterding at al, 2011 and Kapp, 2012). For this paper the concern is how to give improved approaches to learning processes and assessment by exploiting techniques of interaction and reinforcement, thereby encouraging desired learner behaviours and thus the intended learning outcomes.

The key characteristics identified from the game arena that are relevant to this approach are:

- *Multiple attempts*: both within an individual game and over a game lifetime e.g. classic arcade games or longer skill acquisition like Guitar Hero;
- *Low risk from submission*: having a go is what is important and there are no repercussions if you mess up;
- *A personalised/unique experience*: a game can remember who you are and can adapt accordingly and thus individualises the learning experience (e.g. Self, 1974; Wen et al, 2012);
- *Adaptive difficulty:* as you get more experience a game can change to suit you or to counter you – maybe involving different levels e.g. after Super Mario or the use of machine learning (Laird, 2001);
- *Immediate feedback:* in terms of how they are doing and what they need to progress further. This is an inherent property of typical game based interaction;
- *High scores and league tables*: utilising competition and challenge to encourage attempts.

These characteristics map onto a range of desirable features for a teaching application. The multiple attempts of the activity can make it low risk to the students – they can use it to explore what is expected and promote mastery. This is quite different to typical summative assessments that are based on a single final submission, or worse a catch all final exam that seems designed to find what they do not know. The low risk submission clearly links to allowing multiple submissions, where they receive the highest mark from all of their attempts (their "High Score"), not on any specific one. This can reduce the stress and focus on a particular attempt – in further contrast to traditional summative assessments. Personalisation here can take a variety of formats – providing unique values/data sets of questions (from a bank or via personalised selection) are all ways in which an assessment can be made unique to the student. This allows them to be able to discuss approaches and issues with fellow students, but reduces the likelihood of collusion in the actual submissions. Further to this, establishing a unique experience for the user may involve customisation (from the game perspective) where the user makes choices about their assessment experience.

Adaptive difficulty is a specific area of personalisation – where the activity (in this case knowledge or skills that are assessed) varies depending on the success/current measured skill level of the learner. The key thing is to keep the user engaged in the activity by consistently presenting a rolling challenge. Key rewards or incentives can paradoxically be derived both from winning and losing a game (Jool, 2013). There are various ways in which such adaptive approaches can be done – and utilising intelligent learning systems can provide this. Computer based assessment also offers the opportunity for that individualised feedback (whether a mark, a profile, or some other formative information). When considering testing of knowledge and skills, one approach is the flexi-level style (Lord, 1980). Here, questions are ordered in terms of their perceived difficulty and/or complexity, and a tree like structure can be used to determine pathways through the assessment material. In practice, such flexible learning can be best managed by technology, rather than by the learner themselves (Lilley and Pyper, 2009). It is notable that this set of features is only achievable for a large cohort with the use of technology. Scalability of the solution depends on being able to provide this to hundreds (or more), rather than just for small classes.   Engagement in this activity can be linked back to Csíkszentmihályi's optimal experience through Flow, using an appropriate level of challenge with timely feedback.

Methods

This paper summarises results from utilising this game mechanics approach in a long study for over a decade, with around 2000 students taking part on a first year module within their degree course. The approach has been to analyse the performance of the students at entry to the course, and to compare that with their final mark in the assessment within that module. The course content is mathematical topics at the interface from further (secondary) education to that expected for higher (tertiary) education, as expected for our Computer Science family of degree programmes. Student behaviour has been monitored through the system, along with some informal feedback from students and a number of support staff who assist students requiring help with material covered in the assessment. Whilst the case considered in this paper is one based on applying game mechanics in the context of teaching and learning of mathematics for computer scientists, the technique has more widespread applicability; as we will see, the key points are about allowing flexibility to the students rather than the specific nature of the material.

As noted above, the traditional teaching model utilises high risk, high stake assessments, typically with only one opportunity to take it, with reassessment for those who fail. Further, reassessment success is typically capped in terms of the mark that can be achieved. This contrasts with computer games, where players have minimal risks (they may lose lives - which they may actually enjoy doing so (Joul, ibid)) but can retake, and learn through failure and reattempt.

The assessment in this case was based on a mix of multiple choice and symbolic answers to mathematical questions, covering topics considered highly relevant to computer science applications. The assessment was based on the Diagnosys tool (Appleby, 1997), and included randomisation of some variables in the questions, so that each student took a unique test. Diagnosys itself includes a number of gamification features – with the concepts of lives, time limits and adaptive difficulty. The teaching framework itself introduced other gamification based approaches.

The approach considered is one that meets our stated criteria, adopting the specific game mechanic principles alongside more general characteristics of games, in a number of ways as follows:

- Utilise a *turn based* question game style: for a test/quiz on topics;
- *Multiple lives*: to encourage preparation and work within a test, a 5-*lives* mechanic is used so that students can try re-answering specific questions – but only have 5 chances to use this in a particular session (game);
- *Multiple attempts*: players (students) may attempt the activity (replay the game) as many times as they wished, with advice that they should achieve at least a threshold (pass) mark of 40%;
- L*ow risk from submission*: the assessment description is explicit that the students will achieve the highest mark from their set of submissions, and the overall assessment was only weighted as 10% of that module's mark. Thus the incentive is always to have another go, your personal High Score will always still stand and be your returned mark;
- *A personalised/unique experience*: the system utilises a number of randomisation features so that students get questions that are specific to them, and whilst of a similar nature to that done by other students, the specific questions are different;
- *Catch-up (Adaptive difficulty):* the system adopts a knowledge tree/network to identify and order different skills. Depending on the students' early answers, different selections are made for later skills and questions;
- *Interaction - Immediate feedback*: with computer based marking of the questions, students can receive an immediate mark, along with a profile of the skills that the system believes the specific student knows, along with those that the student should review. This is akin to scoring in gaming though potentially with extra detail;
- *Publication of lists of high scores*: identified by student ID to provide some level of anonymity. Encourages students as they see what performance is possible, and can keep trying to improve their position in the league.

A further characteristic with this approach was to move the onus of the activity to the students – they were able to use the software and engage with it for an entire semester (12 weeks), and there was no pressure or chasing up on them to use it beyond the standard setting of an assessment activity.

Whilst these characteristics reflect a number of features in standard computer based assessment tools, they also identify a number of deficiencies in such tools, especially when it comes to implementing flexi-level and personalised features.

Results and discussion

This approach of utilising game mechanics within a testing framework on mathematical concepts has been used and iteratively refined for over a decade. Results have been collated and compared within that period, giving an extensive dataset on which to base the later discussion and conclusions. Results from a recent cohort (2011-2012) of that data are presented here to illustrate the key outcomes from this activity. Table 1 shows the total number of attempts for students for the 2011-12 cohort, which consisted of 80 students (completing the module and excluding withdrawals).

Table 1: record of number of attempts (2011-2012 cohort)

Number of attempts	Count
1	24
2	16
3	13
4	8
5	2
6	5
7	4
8	3
9	3
10	1
11	0
12	0
13	0
14	1

As can be seen from this data, the mean number of attempts was 3.3, with the majority of students (just under 70%) attempting the activity more than once. Student behaviour here can be encouraged in a number of directions – firstly there is doing the test, secondly is in terms of achieving a pass mark (passing a game level), and finally in terms of improving their knowledge and skills beyond the threshold level to a point where they are getting true value added from their learning (achieving a High Score). Figure 1 illustrates the tail off in the number of attempts. Whilst this is for the 2011-12 cohort only, similar patterns emerged for prior cohorts, where students took the opportunity to retake the activity a number of times. There was no significant change in the entry profile (subjects or grades). It is notable that a number quickly – after up to 3 attempts - had achieved a mark they were content with. Given the threshold nature of the assessment, and the varied character of the cohort, this is not considered a cause for concern.

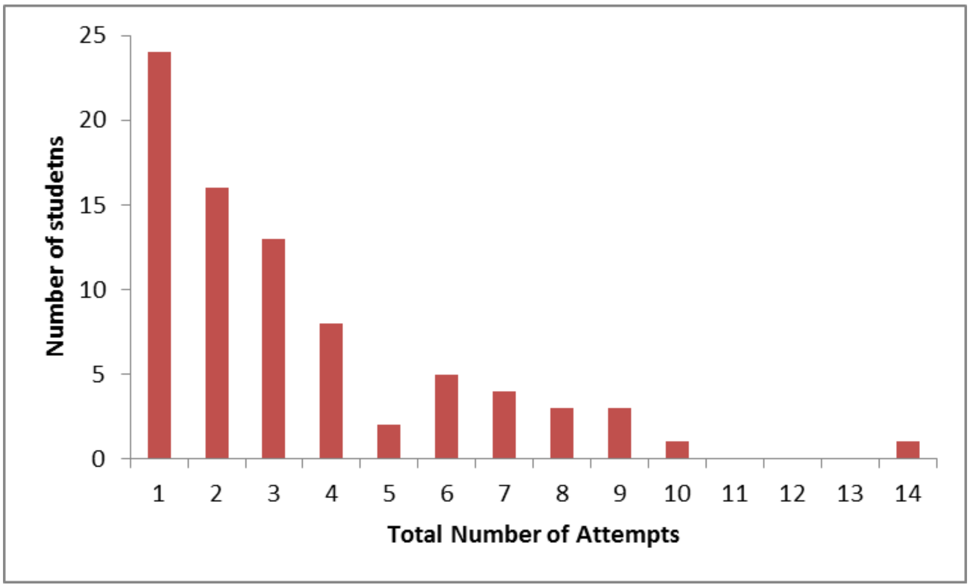

Figure 1: Number of students taking n-attempts

Figure 2 shows the behaviour of students from the 2011 cohort in attempts and marks. The diagram shows the marks achieved (y-axis) in a particular assessment, plotted against the actual assessment number. So for example, from Figure 1 we see that one student attempted the assessment 14 times, and this is illustrated in the longest trace in Figure 2, showing how this student improved their score through repeated attempts. Whilst a number were able to immediately get to a mark they were content with, most engaged a number of times, knowing that they had the potential to benefit from a higher mark (High Score) without risking their existing marks. The spread of single node paths for 1 attempt indicates that many students were content with their initial mark, and is clear from the first column in Figure 1 i.e. 30% were content to pass at their initial level. However, the range of starting points for paths of length 2 or more shows that initial marks were not an indicator of a willingness to have multiple attempts. The paths show improvements for students taking multiple attempts. For the 2011 cohort, the average improvement for those engaging with this activity was 27%, with one student increasing their performance by 88% (from an initial mark of 10%, up to a final mark of 98%). Note that the paths are displayed to show the mark per attempt, and does not directly indicate the time span – though in practice these were spread out across the 12 week period that this activity was live.

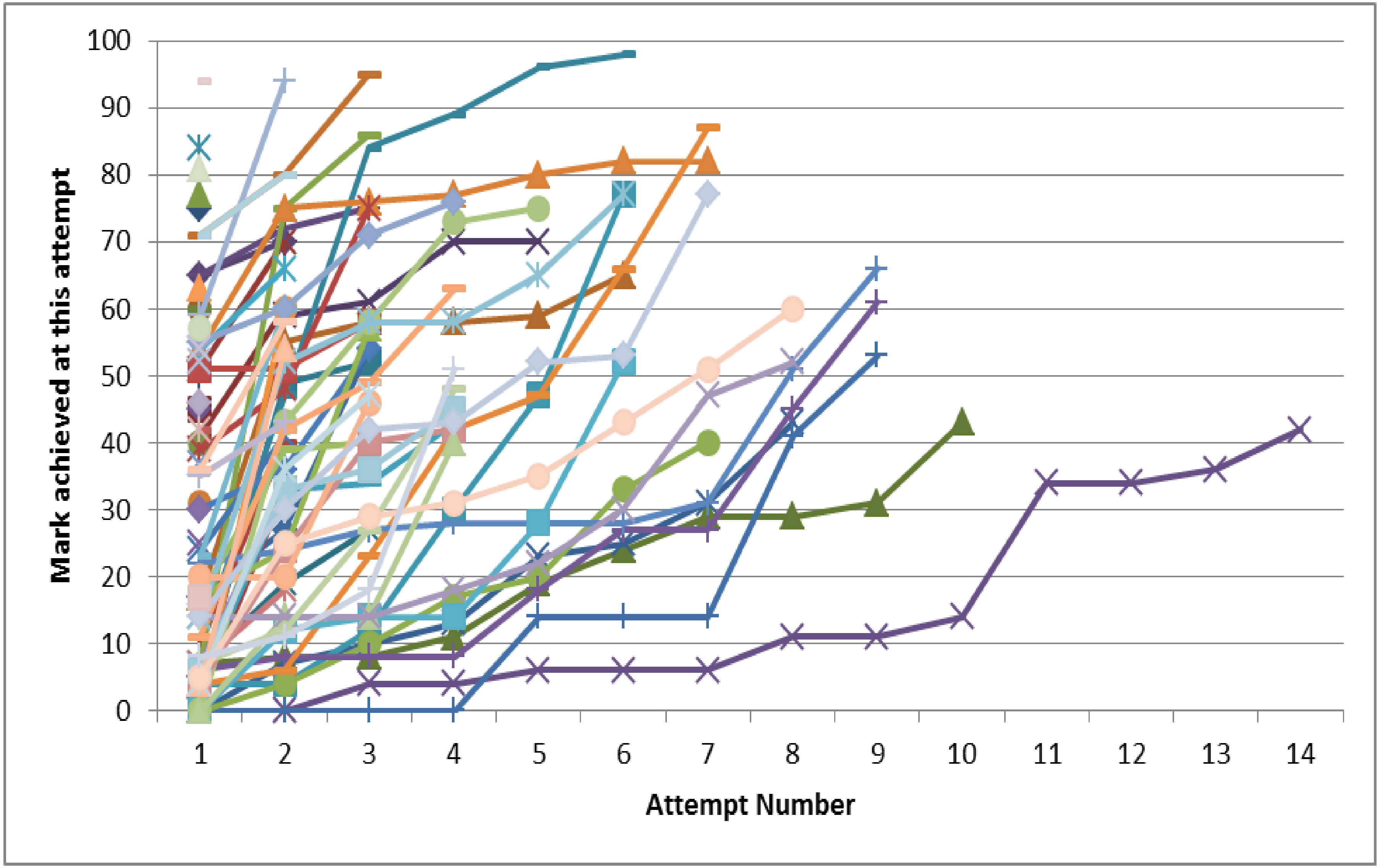

Figure 2: attempts versus marks over a semester

This approach has been used for over a decade. Concerning the last 5 years, table 2 shows the marks that students achieved on entry, compared to their final mark on this element of the module – this being assessed as questions in a traditional exam. The table also indicates some potential relative performance improvement. Whilst allowing more attempts may be assumed to improve the overall outcomes, the aim with this approach is to encourage students to engage with the work. Approximately 5% of the original students on the module withdrew or failed to complete the module. These have been removed from the data for **Figure 2**, but are included in the table 2 data. However, even with those figures included, allowing students to make use of the interactive and formative elements of the activity, with little support beyond some teaching resources and some optional extra tuition, the results show an improvement of 10% or more. The extra tuition is likely to have had an impact on the improvement in marks, but the intention was that engagement with this tuition would be encouraged by the gamification approach adopted for the module.

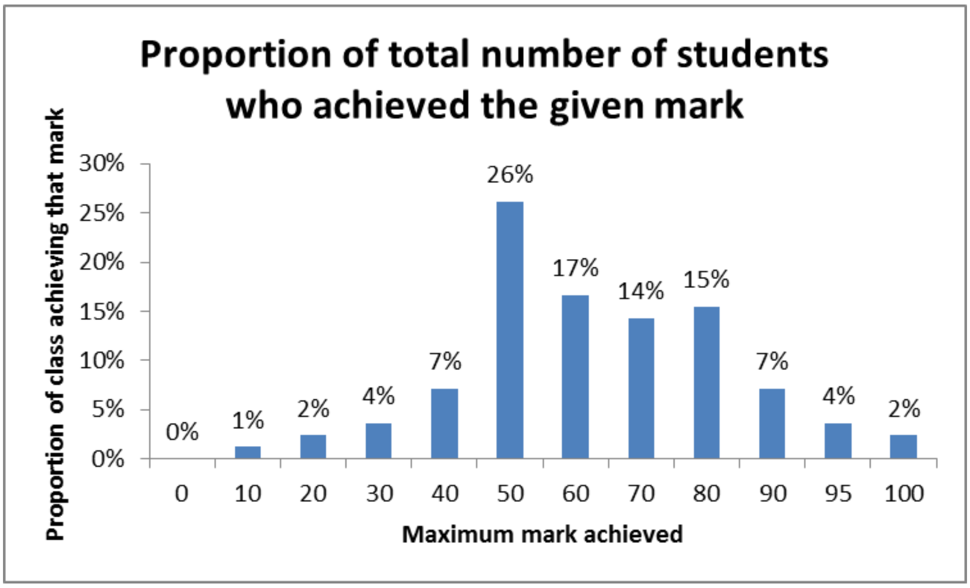

Figure 3: Proportion of students achieving the given maximum mark

This type of analysis can also be considered under the growing area of learning analytics. Gathering data on student behaviour is illuminating and may assist in planning teaching and learning strategies. Figure 3 shows that whilst 7% had a failing mark (<40) in the assignment, another 7% settled for a pass mark, whilst the largest majority (26%) settled for a mark in the 2:2 degree range; though noting this is only one part of a modules assessment, and in a certificate stage that does not formally affect the final degree classification.

Table 2: improvements in performance from repeated attempts (2007 to 2011 cohorts)

Year	Initial Mean Mark	Final Mean Mark	Improvement
2007	38%	48%	10%
2008	36%	49%	13%
2009	31%	47%	16%
2010	39%	49%	10%
2011	34%	56%	22%

Feedback from tutors supporting these students provides some empirical evidence that students followed up the personal profiles given by the software to get specific support on topics that they could use for later attempts with the system. This provides some evidence that students behaviour was modified and that they were indeed engaging with the material outside of the confines of the standard classes or when taking the assessment themselves. Reviewing the number of attempts and the profile of final marks shows that a number of students took the opportunity for multiple attempts, though there is little correlation between the number of attempts and final mark; some students took the opportunity to attempt to achieve a pass mark, others to get a high score. Interviews with students showed that some wanted to get a near perfect mark, and kept attempting this until they achieved a mark in the high 90's.

Conclusions

From the above it can be concluded that the use of game mechanics and more general game-like characteristics can encourage students to engage with learning materials. This is distinct from using games to deliver learning material.

A suitable computer assessment environment should mirror the characteristics and support the game mechanics already identified as follows:

- Allowing for multiple attempts / supporting the use of a (configurable) set of lives within an assessment;
- Allowing the representation of the knowledge network and dependencies, and react to these according to the student answer;
- Support randomisation of content – with a bank of equivalent questions/tasks (in terms of topics);
- Provide immediate formative feedback, as part of an overall summative process;
- Promote a "have a go ethos" and the attainment of "High Scores";
- Have fun and play.

Whilst some aspects of these characteristics are supported in some forms of computer based assessment environments, the entire range is not generally supported. The limited assessment approaches built into many current Virtual Learning Environments (VLEs) illustrate that many people are not utilising such approaches, nor even requesting support for these features. Support for these would allow gamification dynamics to be built on otherwise conventional Virtual Learning Environments: thus allowing for the benefits of this approach. A possible further extension of the work here would be to investigate how the notion of *Flow* and engagement might be better supported in the spirit of *ludentis* (play). To what extent could students/players be encouraged to buy into the task rather than see it as a set of academic goalposts that need to be aimed at? Perhaps a suitable way forward is to include a notion of game play alongside the game mechanics to shift the task away from a "maths ability test" to a fun Freshman Year Game Challenge, albeit with a bit of maths involved.

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