The Potential for Using Artificial Intelligence Techniques to Improve e-Learning Systems

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Abstract: There has been significant progress in the development of techniques to deliver more effective e-Learning systems in both education and commerce but our research has identified very few examples of comprehensive learning systems that exploit contemporary artificial intelligence (AI) techniques. We have surveyed existing intelligent learning/training systems and explored the contemporary AI techniques which appear to offer the most promising contributions to e-Learning. We have considered the non-technological challenges to be addressed and considered those factors which will allow step change progress. With the convergence of several of the required components for success increasingly in place we believe that the opportunity to make this progress is now much stronger.

We present a description of the fundamental components of an adaptive learning system designed to fulfil the objectives of the teacher and to develop a close relationship with the learner, monitoring and adjusting the teaching based upon a wide variety of analyses of their knowledge and performance. This is an important area for future research with the opportunity to deliver significant value to both education and commerce. The development of improved learning systems in conjunction with trainers, teachers and subject matter experts will provide benefits to educational institutions and help commercial organisations to face critical challenges in the training, development and retention of the key skills required to address new, emerging technologies and business models.

Keywords: Adaptive learning systems, evaluation of intelligent tools, adoption of e-Learning by teachers and learners, education and career training, artificial intelligence

1. Introduction

There appears to be considerable potential to make significant steps forward in the application of Artificial Intelligence (AI) to learning systems. A variety of AI techniques (Russell & Norvig 2002) can be applied in real-time to analyse learner behaviour, tailor learning components to learner abilities and knowledge, and to exploit the very large quantities of subject and student data available in both the education and commercial sectors. The development of learning systems in conjunction with trainers, teachers and subject matter experts will provide benefits to institutions across the board, from career/vocational development, re-validation and re-training through to higher education and school. This potential has existed for some time, and while research to date has found a variety of work discussing and modelling how individual AI techniques can be applied to different aspects of learning systems and student achievement (for example Gligora Marković, et al., 2014) very few examples of comprehensive learning systems that exploit AI techniques have been identified to date.

Bridging the gap between emerging techniques in AI and Machine Learning (ML) described in section 2 and the essential pedagogy (the theory and practice of education) has proven to be a significant challenge (Jenkins, et al., 2014). However, we believe that the opportunity to make step change progress is now much stronger with the convergence of several of the required components for success increasingly in place. These are:

- The availability of appropriate learning platforms, with almost all learners owning computing devices both inside and outside of the learning setting.
- The increasing quantity and quality of the data (subject and analytics) available to the analytical learning systems using AI.
- The technology (hardware and supporting software) is now powerful enough to handle and exploit the quantity and complexity of data and algorithms necessary for success.
- Institutions are putting more emphasis into this area – exploiting e-learning opportunities and looking for efficiency gains (Johnson 2014).
- Learners are increasingly interested in learning and developing their knowledge on-line at least in parallel with the traditional classroom/campus model.

As a result, the deployment of AI and ML techniques in Technology Enhanced Learning (TEL) has the potential for accelerated growth and adoption. In particular, exploring how AI and ML techniques can be applied to the development of adaptive learning systems, this includes the classification and representation of subject matter knowledge. The latter refers to the organisation of the subject knowledge and the rules and the processes which connect them into a logical structure that:

- Is comprehensive and efficient for the learning system, as well as for the creation, validation and future manipulation by the subject matter expert (SME).
- Is capable of incorporating all the relevant interconnections between the information in a similar way to the way our own brains do.
- Allows the learning system itself to automatically self-organise and search for further connections and rules (Mo et al. 2012).

The aim of this paper is to identify ways in which current research is addressing how contemporary artificial intelligence techniques can be used to improve technology enhanced learning.

2. An Overview of the Literature

In this section the current status and best practice in the four foundational areas of this research: Pedagogy; Technology Enhanced learning; Relevant Artificial Intelligence and Machine Learning Techniques; Survey of Intelligent Learning/Training Systems**;** are discussed:

Pedagogy

Pedagogy continues to be a major area of research with significant on-going work into the field of Technology Enhanced Learning, alongside increased understanding of the behaviours and needs of both learner and tutor (Jenkins, et al., 2014). The latest in the Open University series of Innovating Pedagogy reports (Sharples, et al., 2014) identifies ten innovations that are expected to transform education, from threshold concepts and bricolage to learning to learn and learning design informed by analytics. This body of work, including a very wide variety of field trials and extensive data provides a firm foundation upon which to analyse existing TEL techniques, approaches and learning systems, and to identify the critical factors necessary for the successful definition, design and development of step-forward adaptive learning systems including subject matter knowledge classification. For example, modelling student performance and applying learning analytics is critical to the review of any application of pedagogical concepts (Tempelaar, et al., 2015).

An exploration of the latest pedagogical research confirms the breadth and depth of formal understanding of the art and science of education available to the designers of learning systems, albeit with continuing adjustments being made to educational best practice. It would be impractical to incorporate every component of available research conclusions and recommended approaches and it is therefore important to focus upon those which are fundamental, and wherever possible allow real time decision making based upon incisive learner interaction and individual based learning history and data to determine the system approach.

An aspect of the development of any learning system is an understanding of the variety of individual learning styles (Graf 2007). Graf's paper illustrates the considerable variety of research and opinion on an individual's learning criteria. Basing an approach on all of these would be very challenging, while any non-formal method of deciding which ones to select could result in a flawed approach. Therefore, in designing an effective adaptive learning system we can choose one of two distinct approaches:

- Incorporating a formal method of automatically detecting the learner's learning style (Feldman, et al., 2014).
- Allowing the system to explore and exploit the actual learning style being displayed by the learner by capturing and analysing all and any parametric data (e.g. even including the colours of the content) available to the system, i.e. collecting as much data as possible to allow the algorithms to decide what's best for the specific learner. This is the approach taken by Realizeit (Realizeit 2015) which has proven successful in their adaptive learning product.

A learner's cognitive style (the way an individual thinks, perceives and remembers information) is another key pedagogical concept where there is some evidence that exploiting an understanding of these concepts has improved student learning achievement (Chipman 2010). This is an area for research and potential exploitation, although it is important to note that there has been conflicting evidence on whether cognitive style makes any difference when designing Adaptive Learning Systems (Mampadi et al. 2011).

Technology Enhanced Learning

The field of TEL has been the subject of much research and practice, in a very wide range of techniques and approaches ranging from classroom management and collaborative learning to MOOCs and gamification (Glover 2013). An analysis of TEL research published between 2009 and 2014 (Schweighofer & Ebner 2015) recorded 4567 papers, dealing with aspects from demographical differences to learner/teacher issues and technical infrastructure. The majority of these papers focus upon Higher Education with only 38 papers addressing business.

However, the commercial world is facing critical challenges in the training, development and retention of key skills, exacerbated by new, emerging technologies and business models, giving organisations business critical dependencies on the relevant subject matter experts (SMEs) and on leadership/talent development (Bhatia & Kaur 2014). These challenges are presenting a major threat in many organisations, limiting business opportunities and weakening their ability to compete (Schuler et al. 2011). Developments in TEL and in particular in the progress of adaptive learning systems already explored in HE (Lilley & Piper, 2009) have the potential to make a dramatic difference in addressing these challenges.

Commercial organisations are increasingly automating their training programmes to allow them to be delivered globally, asynchronously and electronically. These training modules can be stand-alone or part of a classroom based blended learning package and are ideal for situations where a large number of geographically separated learners are targeted. Typically, these modules are delivered as on-line question and answer based dialogues, presenting the learner with explanatory information, occasionally including video material, followed by marked exercises. The learner repeats the course until the pass level is reached and at each subsequent re-take the questions are varied from a set database.

In the UK Higher Education (HE) sector, progress in the numbers of on-line courses available to students has been modest in recent years (see Table 1), giving rise to concerns that the investments in TEL are not addressing pedagogical needs (Jenkins, et al., 2014). As identified by Jenkins "supplementary use of the web to support module delivery remains the most common use of TEL" and as can be seen from the table, fully online modules are a very small proportion.

Table 1: Proportion of all modules or units of study in the TEL environment in use across the UK HE sector (Walker et al., 2014)

Sector mean	2014	2012	2010	2008	2005	2003
Category A – web supplemented	39%	39%	46%	48%	54%	57%
Category Bi – web dependent, content	27%	29%	26%	24%	16%	13%
Category Bii – web dependent, communication	9%	10%	17%	13%	10%	10%
Category Biii – web dependent, content and communication	21%	18%	18%	13%	13%	13%
Category E – fully online	3%	3%	3%	4%	6%	5%

The 2014 summative HE Academy report on flexible technologies (Barnett 2014) observed that the drive towards greater flexibility is now being influenced by a combination of the marketisation of HE, the demands of students as consumers, the potential of new technologies and the apparent potential for making HE available to a wider audience at lower unit costs.

Recent analysis of 4567 TEL publications between 2009 and 2013 (Schweighofer & Ebner 2015) recognises the breadth and depth of on-going research into TEL approaches, summarising key aspects to be taken into account in TEL implementation. These analyses show learners' aspects, including learning behaviour, strategy and style, as well as interaction and participation, as the largest focus of research in the more technologically focused publications.

In the future it is likely that it will be the demands and imperatives of the students and/or the commercial learners that prove to be a major driver in TEL adoption, not only for its educational merit, but in order to enable them to support the stresses of combining work, study and personal life (Jefferies & Hyde 2010, Fabris 2015). Intensified by trends in social media, the integration of on-line, hybrid and collaborative learning alongside the rise of data driven learning and assessment are all strong pressures for increasing the adoption of TEL in HE (Johnson 2014).

Relevant Artificial Intelligence and Machine Learning Techniques

In parallel, there has been considerable progress in the field of Artificial Intelligence (AI) and its related subjects with substantial on-going research in both the academic and commercial worlds. Since early 2014 the level of media interest in the field has noticeably increased with articles in the news such as: 2029, the year when robots will have the power to outsmart their makers (Kurzweil 2014) and Driverless cars trialled on UK roads for first time in four towns and cities (Dearden 2015). This steady increase in public awareness (albeit in more populist topics) will facilitate a more open approach to considering AI as a practical tool in real life activities, and in respect of this research in its application to learning systems in both educational and commercial areas.

Of particular relevance to learning systems are continued developments in Machine Learning (ML), which aims to determine how to perform important tasks by generalizing from examples (Hastie et al, 2005). This includes data mining which is a technique for analysing and extracting data, correlations and patterns from large data sets and turning it into useful information. Other commonly used techniques are:

- Neural networks, which are composed of a large number of highly connected processing nodes working in unison to solve specific problems.
- Support Vector Machine (SVM) which allows us to classify data in a way in which we can then analyse new data points to confidently identify which solution space they fit within.
- Decision trees which allow us to create a tree-like picture of decisions and alternative next steps and to determine a strategy to reach a defined goal.

Other AI techniques to be considered are:

- Knowledge Based Systems (sometimes referred to as Expert Systems), which use a set of rules to solve problems based upon stored expert knowledge (Höver & Steiner 2009).
- Fuzzy logic which allows us to use degrees of truth/accuracy in data analysis rather than the black or white ones and zeroes or yes and no's traditionally used in systems (Benabdellah 2015).
- Roulette wheel algorithms which select the best fitting solutions to problems combined with fuzzy logic have been deployed to maximise learning path choice (Benabdellah 2015) and to predict student motivation (Sivakumar & Praveena 2015).
- Ant Colony optimisation is an algorithm for establishing the optimal paths in data and processes in a similar way to how ants behave (Sivakumar & Praveena 2015).

These techniques are critical for exploiting the very large subject matter and student/learner data sets now available in order to develop powerful new learning systems. These data sets are no longer capable of real-time analysis by using manual or orthodox IT techniques due to:

- The very large quantity of data that is available to be captured and exploited.
- The level of complexity of the interdependencies of large numbers of data classes/attributes, requiring multi-dimensional analysis (Tempelaar, et al., 2015).

Suitable techniques for continued research and development are grouped under Adaptive Learning Systems (ALS), Intelligent Tutor Systems (ITS), Cognitive Systems and Predictor/Recommender Systems. The line between Intelligent Tutoring Systems and Adaptive Learning Systems has become increasingly blurred. In the past ITSs tended to be subject matter specific, developing from what can be described as "flowcharted learning" into increasingly sophisticated systems deploying AI techniques. The field of adaptive learning has allowed these systems to develop a close relationship with the learner, monitoring and adjusting the teaching and creating idealised learning paths based upon a wide variety of analyses of their knowledge and performance (Marengo, et al., 2015). This level of automated judgement is made by understanding the learner profile, their learning style and their base knowledge of the subject area (Marengo, et al., 2015).

In designing adaptive learning systems there are a significant number of potential techniques and models which can be deployed. Recent research into the prevalence of these show learner and domain knowledge modelling, adaptivity and content presentation as the most prevalent in learning systems, with cognitive style almost the least characterised (Gligora Marković, et al., 2014). In the US there is positive evidence of the increasing adoption of such systems. As discussed in section 3 below, the challenges are mainly organisational and not technological (Oxman & Wong 2014). The first commercial successes in learning systems in the US came from cognitive tutoring systems which delivered high school mathematics to over 475,000 students in 2007 (Raley 2012), showing that students performed 15-25% and 50-100% respectively better than the control group on skill knowledge and problem solving

Additionally, some progress has been made in the area of adaptive learning systems in the commercial area, with research into the benefits and risk areas from the learner's point of view. The results indicated a positive response to the alignment of adaptive learning to job roles and career paths, while removing the time wasted on non-relevant learning material. The research also reinforced the criticality of the input and capture of the expert knowledge (Höver & Steiner 2009).

Survey of Intelligent Learning/Training Systems

A number of successful, although mostly niche, systems have been developed and are in place in the field, alongside a variety of prototypes. As can be seen in Table 2, systems in the education sector dominate.

Table 2: Survey of "Intelligent" Learning/Training Systems Identified

Sector	Quantity	Percentage
Education sector	32	78%
Commercial/Public sector	3	7%
Both	6	15%
Total	41	100%

Of those surveyed, 17 (41%) have been developed by universities or as collaborative projects between university and industry. We estimate that approximately half (46%) are adaptive learning systems the details of which are shown in Tables 3, 4 and 5.

Adaptive learning systems adjust the learning experience based upon the student's progress, increasing the level of difficulty when they're progressing well, and slowing down if they need further instruction. The greatest progress appears to be where the knowledge base being addressed is embodied in comprehensively curated areas of knowledge, for example, STEMM subjects including mathematics and physics, and English education.

Table 3: Intelligent Learning/Training Systems in the Education sector

System	Developed by	Type	Key words
ActiveMath [P, J, S]	DFKI & Saarland University	Adaptive learning	Educational data mining. Natural Language Processing. Collaborative. STEMM.
ALEKS [P, J, S, U]	New York University and the University of California, Irvine	Adaptive learning	Web based. Knowledge space theory. STEMM, Accounting.
Algebra Tutor [S]	Carnegie Mellon	Intelligent tutoring	Artificial intelligence, cognitive, human computer interaction. Computer programming, STEMM.
Andes Physics Tutor [S, U]	Arizona State University	Intelligent tutoring	Highly interactive. STEMM.
Aplia [U, Po]	Stanford university	Adaptive learning	On-line homework system. Multiple subjects - STEMM, accounting, English, history, finance.
ASPIRE [J, U]	University of Canterbury (New Zealand)	Intelligent tutoring	Authoring. Develops web tutoring systems.
AutoTutor [U]	University of Memphis	Intelligent tutoring	Natural language. Speech engine. Newtonian physics, Introductory computer literacy.
Betty's Brain [P, S]	Vanderbilt & Stanford Universities	Cognitive	Metacognitive skills. STEMM.
Carnegie Learning [S]	Carnegie Mellon University	Adaptive learning Cognitive	Pedagogy. Cognitive science. Research led. STEMM.
CIRCSIM-Tutor [U]	Sponsored by US Naval Research Office	Intelligent tutoring	Dialogue based, natural language. Medicine.
DreamBox [P, J]	DreamBox	Adaptive learning	Game-like environment based. STEMM.
ESC101-ITS [U]	The Indian Institute of Technology, Kanpur, India	Intelligent tutoring	Programming.
eSpindle [P, J, S]	LearnThat	Personalised learning	US Spelling Bee system. Spelling.
eTeacher [S, U]	eTeacher	Adaptive learning	Intelligent agent. On-line assisted learning. System engineering course.
Grockit [S]	Kaplan	Adaptive learning	Collaborative. Game-like environment. STEMM.
Knewton [S, U]	Knewton	Adaptive learning	Content agnostic. Psychometrics and cognitive learning theory, Inference engine.

System	Developed by	Type	Key words
Knowledge Sea II [U, Po]	University of Pittsburgh	Adaptive learning	Computer programming.
KnowRe [J, S]	KnowRe	Adaptive learning	Game-like environment based. STEMM.
Mathematics Tutor [J, S]	University of Massachusetts	Adaptive learning	STEMM.
Mathspring [P, J, S]	Univ of Massachusetts	Adaptive learning	Intelligent tutoring. Math.
Memorangapp [U, Po]	MIT	Memory reinforcement.	Spaced repetition. Medicine.
MyLab, Mastering [U, Po]	Pearson	Adaptive learning	On-line learning. Multiple subjects.
PlanetSherston [P]	Sherston	Personalised learning	Game play learning.
PrepMe [S]	Stanford, University of Chicago, CalTech	Adaptive learning	Virtual classroom. STEMM.
PrepU [U, Po]	PrepU, collaboration with UCLA	Adaptive learning	Quiz engine. STEMM.
REALP [J, S]	Worcester Polytechnic Institute, Carnegie Mellon	Personalised learning	Based upon a tool designed to investigate the development time for tutoring systems. Reading comprehension.
Scootpad [P, J, S]	Scootpad	Adaptive learning	Behaviour tracking. Prediction. STEMM.
SmartTutor [A]	University of Hong Kong	Adaptive learning	Personalised on-line distance learning. Generic.
Snapwiz [U, Po]	Wiley	Adaptive learning	Collaborative. STEMM, Languages, Business, Social Science.
SpellBEE [P, J, S]	Brandeis University	Artificial Intelligence Machine learning	Education research tool.
Why2-Atlas [U]	UCLA	Natural language	Textual analysis system. STEMM.
ZOSMAT [J,S]	Atatürk University	Intelligent tutoring	Classroom based. STEMM.

[Key: Primary, Junior, Secondary, University, Postgraduate, Adult]

Table 4: Intelligent Learning/Training Systems in the Commercial/Public sector

System	Developed by	Type	Key words
aNewSpring	aNewSpring	Adaptive learning	Corporate Learning Management System. Blended and hybrid learning
CODES	Universidade Federal do Rio Grande do Sul	Learning system	Web-based. Musical prototyping specific for non-musicians.
SHERLOCK	University of Pittburgh	Intelligent Tutoring System	Decision trees. Student competence and performance model. USAF technician specific.

Table 5: Intelligent Learning/Training Systems in the Education & Commercial sector

System	Developed by	Type	Key words
Alelo	University of Southern California	Virtual Role-Play simulations	Pedagogical agents as social actors. Multimedia. Cyberlearning.
Cardiac Tutor	University of Massachusetts Medical School	Adaptive learning/Intelligent tutoring	Real time simulation. Knowledge based. Medicine, cardiology specific.
Desire2Learn, LeaP	Brightspace	Adaptive learning	Predictive analytics.
ELM-ART	Freiburg University of Education	Adaptive learning	Web-based. LISP programming specific
Realizeit	CCKF/Realizeit	Adaptive learning	Content agnostic. Supervised & Unsupervised learning. Classification trees. Fuzzy Logic.
Smart Sparrow	University of New South Wales in Sydney	Adaptive learning Intelligent tutoring Data mining	Educational data mining. Content agnostic.

These systems are dominated by those focussed upon the education sector, but we should expect increasing interest from the commercial world, since individuals will be faced with a number of different careers during their working life as industries are created, evolve and disappear. The development of new and more intelligent methods of supporting these aspirations will become very important to both individuals and organisations, presenting the opportunity to deliver significant value, in terms of reducing training and re-validation costs, in accelerating training delivery and in considerable enhancement of people's personal experience in learning.

In terms of organizational & geographical traction, analysis of existing systems can be summarised as follows:

- The field of education is leading the way in both research and in the development of learning/training systems:
  - Primary, secondary, university education, with STEMM the most popular subject areas. (Table 3).
  - MOOCS have made rapid progress, however the completion rates are less than 7% (Jordan 2014).
- Business/vocational research and learning/training systems are currently running a poor second (Tables 4 and 5) with Medicine appearing more often than others in the area of applying intelligent techniques to areas including diagnosis and training.
- The requirement for distance learning appears to be an early TEL driver.
- Geographically, traction is the highest in the US, followed by the UK, followed by Europe, with Australia showing up intermittently in searches.

3. Challenges to be addressed and related discussion

While the adoption of TEL continues to gain traction, there are a number of organisational/non-technological challenges that must steadily be addressed and in particular kept in mind in the design, development and deployment of these systems:

Organisational

- Systems can be expensive both to develop and to implement.
- Organisational conservatism – the prevailing attitude of "what we have works fine..", and the need to evidence benefits.
- Requires the cooperation and support of individuals across both organisations and organisational levels (Barnett 2014).

Administrative/political:

- Integration of TEL into the existing curriculum (Oxman & Wong 2014).
- Overcoming resistance from competing methods and their champions.

The needs and concerns of the teacher/trainer:

- Teacher/trainer resistance – the need for persistence while under significant pressure to deliver improved student grade performance dealing with high workloads (Wang & Hannafin 2005).
- Requires the cooperation and input of domain subject matter experts.

The needs and concerns of the student/learner:

- Ensuring student/learner motivation and early identification of disenchantment (Oxman & Wong 2014).
- Continuous feedback to ensure the maintenance of a continuously accurate student model (progress measurement, learning rates, proven alternative learning paths).

Technical

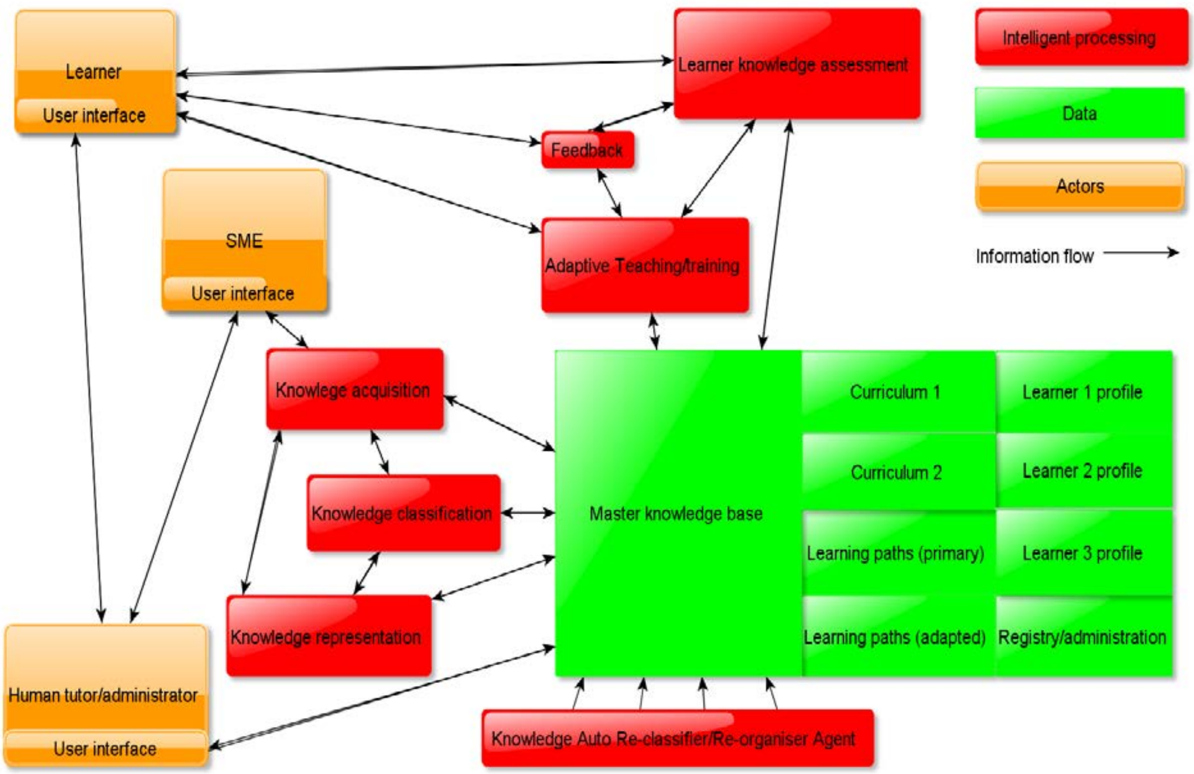
- The modelling of such a complex cognitive task.
- Incorporating the essential pedagogy. For example, effective feedback to the learner and very careful use of hints to ensure that deep learning is developed.
- Integration with all user platforms - mobile, fixed, on-line/off-line, social.
- Ability to exploit rapidly developing technologies/platforms.
- Necessity of systematic and regular update of domain subject matter.

4. Conclusion

We have identified the scope for contemporary AI techniques to be used in the development of adaptive learning systems and have undertaken a thorough review of existing intelligent learning/training systems in both education and commercial sectors. While some progress has been made there is scope for further work.

Accordingly, we have put together a conceptual framework for an Adaptive Learning System, including all major components as shown in Figure 1.

Figure 1: Adaptive Learning System Conceptual Framework showing human intervention (actors), intelligent processing, data structures and information flows



Future work comprises the establishment of the important features that determine the success of learning systems from the pedagogical perspective based upon research and recent practice. Initial work will be to pilot an analysis of student performance using existing data which we will then use to develop an adaptive learning system. We shall then refine the conceptual framework in line with the latest and emerging pedagogical and AI/ML research and design, implement, test and evaluate an adaptive learning system using contemporary AI techniques.

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