Design and Implementation of Intelligent Tutoring System using Enhanced Personalization in e-Learning

Smruti Nanavaty

Abstract: A review of different E-learning Experience considers the need for personalization of learning contents to enhance the experience of learners. The current scenario of education shows that more and more learners are using e-learning to earn their degrees, build upon their knowledge base and acquire new skills. E-Learning is a $56.2 billion industry today and will double by 2017. Statistics show that by 2019, roughly half of all educational institutions will offer e-Learning based training. This initiates the study of various methodologies which analyze the profiles, learning styles, behavior, and capabilities for mapping the appropriate learning content to appropriate user. A review of approaches and methods was conducted by studying articles of past 9 years (2006-2015) by extracting information for techniques used for improving e-learning experience. A five stage literature review of personalization of learning contents using various approaches was conducted. The strengths and weaknesses followed by gaps in the related work are discussed. Further an intelligent tutoring model is proposed as the solution to enhance personalisation in e-learning.

Keywords: e-Learning, personalization, data mining, learning styles, contents and behaviour, e-learning platforms, intelligent tutoring systems, recommender system, blended approach

1. Introduction

The present research is presented with a view to study personalization and adaptation of learning contents to the e-learners based on their requirements. With the advance in IT, human knowledge and learning content have an incredible increase in the quantity and variety of digital content. The trends have implications on the quality and relevance of knowledge and learning content delivered to organization workers and e-learners. The benefits of using e-learning are obvious but the process is effective only if the learner is provided with appropriate learning objects, aligned with his learning style, capabilities and requirements. As a result of this growing online knowledge and learning content there is an urgent need of designing learner centric e-learning systems.

There are many factors that influence the extent of learning. These would include factors such as learner’s learning style and motivation for learning. An important role of e-learning content providers is to recognize that their pedagogy and educational material must cater for the individual learner’s requirements. There is an immediate need to move away from “one size that fits all” paradigm and offer personalized learning experience. Based on reviews undertaken for improving the e-learning experience, a comprehensive approach for enhancing the e-learning experience is proposed.

2. Literature Review

Instructors use various tools to deliver the online contents to e-learners. The challenge for content developers is to provide appropriate content to the users to satisfy their individual needs.

Improving e-Learning experience through Personalization of e-learning contents

This method deals with providing appropriate contents to the learners after analyzing the learner’s needs and capabilities. Static Personalization deals with collecting the necessary data from the user and then analyzing the data using techniques of Data Mining to find individual needs and providing learning contents useful to them. Dynamic Personalization involves studying and analyzing the behavior and capabilities of the users and then dynamically mapping the contents to the user. Intelligent Tutoring Systems and Recommender System consider developing a middleware or an agent based model to use the data from the learning systems to provide a recommendation for the requirements of the learners. Major challenge for e-content designers is that the content should be user specific and should satisfy the needs of various different learners. Moreover it is difficult to dynamically map the contents to the user’s specific needs and the users may not be able to specify the needs correctly.

3. Key Findings with Solution Approaches

This section discusses solution approaches which have been used by the researchers to validate or simulate their results and findings, the type of methodologies adopted, technology platform and details of hardware/ software used to obtain or validate their results.
<table>
<thead>
<tr>
<th>Ref. No.</th>
<th>Study type</th>
<th>Purpose</th>
<th>Data Input</th>
<th>Data source</th>
<th>Data size</th>
<th>Parameters studied</th>
<th>Methodology</th>
<th>Software / Tools</th>
<th>Performance Parameters</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>[15]</td>
<td>Prototype Design and evaluation</td>
<td>Multi-agent system for Web Intelligent Tutoring</td>
<td>Student Profile database, Student feedback</td>
<td>User Profile database Questionnaire from students of Southwest University of China</td>
<td>320</td>
<td>Frequency of use</td>
<td>Mathematical Model for recommendation</td>
<td>Mathematical equation</td>
<td>Strongly disagree to strongly agree: 5 point scale</td>
<td>Average for Personalization: 4.43</td>
</tr>
<tr>
<td>[14]</td>
<td>Experiment al study</td>
<td>Ontology Extraction Method for Adaptive Learning</td>
<td>Short messages on online discussion forum for 10 minutes Questionnaire for assessment</td>
<td>Postgraduate students of management course</td>
<td>Topics 1 to 10 and topics 41 to 50 First 1000 web pages retrieved via Google Search API</td>
<td>Accuracy Cohesiveness Isolation Hierarchy Readability</td>
<td>Context sensitive text mining Fuzzy domain ontology extraction algorithm Concept extraction : BMI method Relation extraction : SSIM method</td>
<td>Java Server Pages 2.1 Servlet 2.5 TouchGraph Apache Tomcat 6.0 web server</td>
<td>Mean score For concept map Assessment: Very Good Good Average Bad Very poor</td>
<td>Mean scores: Accuracy: 4.23 Cohesiveness: 4.22 Isolation: 4.15 Hierarchy: 4.31 Readability: 3.95</td>
</tr>
<tr>
<td>[17]</td>
<td>Experiment al</td>
<td>Motivation Prediction</td>
<td>Intrinsic - extrinsic motivation</td>
<td>Questionnaire data of students for behavior pattern</td>
<td>180</td>
<td>Motivation Indexes: - Autonomous - Controlled - e-learning motivation, - no. of hits</td>
<td>Likert type scale - P-value - statistical procedures - Correlation for motivation Index</td>
<td>SPSS</td>
<td>- Fairly constant - Slightly irregular - Quite irregular</td>
<td>Positive correlation of extrinsic factor for controlled Motivation</td>
</tr>
<tr>
<td>[24]</td>
<td>Experiment al study</td>
<td>Mining educational data to improve adaptation in e-learning</td>
<td>Normalised Learners log, resources info., activities log</td>
<td>LMS MOODLE</td>
<td>66 students</td>
<td>Effect of Algorithmic Induction of Decision trees, pruning tactics on classification accuracy</td>
<td>Data Clustering : KSimpleMeans Clustering Data Classification : ID3-Decision Tree</td>
<td>J48 Algorithm Learning style wise clustering Ranked attributes</td>
<td>Clustered Instances Concrete LS: 38% Concept LS: 35% Observe LS: 21% Experiment: 6% Highest Rank 0.72531</td>
<td></td>
</tr>
<tr>
<td>[5]</td>
<td>Experiment al study</td>
<td>Personalised learning LearNFit using dynamic learner’s personality</td>
<td>Students learning style and preference using a set of 60 questions</td>
<td>Students of Computer Information Systems at FSSM, UCAM, Morocco</td>
<td>Control Group : 24 Experime ntal Group : 24</td>
<td>Post test : Mean Score Standard deviation T value P value</td>
<td>Student t-test, Kolmogrov-Smirnov-test for checking distributions</td>
<td>Mathematical model</td>
<td>Post test score T value = 4.53 P value = 0.02</td>
<td></td>
</tr>
<tr>
<td>Reference</td>
<td>Study Type</td>
<td>Dataset</td>
<td>Content Type</td>
<td>Data Set</td>
<td>Social Data</td>
<td>Topics</td>
<td>Predictive Utility</td>
<td>Latent Dirichlet Allocation for Document-Topic Coefficient Matrix Integrated Recommendation Algorithm built</td>
<td>WEKA Chi-Square Evaluator</td>
<td>Mean Significant Difference</td>
</tr>
<tr>
<td>-----------</td>
<td>------------</td>
<td>---------</td>
<td>--------------</td>
<td>----------</td>
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<td>--------</td>
<td>-------------------</td>
<td>---------------------------------------------------------------------------------</td>
<td>---------------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>[27]</td>
<td>Case study</td>
<td></td>
<td>Problem solving and activity data, test and quiz data</td>
<td>Study 1: Log file from HTML-Tutor Study 2: iHelp data university of Saskatchewan</td>
<td></td>
<td></td>
<td>Accuracy, True positive rates</td>
<td>Simple Logistic Classification 2 validation studies Statistical methods Pair t-test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[23]</td>
<td>Experiment</td>
<td>User centric</td>
<td>retrieval of Learning objects</td>
<td>Topic - Sub-topic Author Age Educational level Time Space – Geo Learning space</td>
<td>LMS logs</td>
<td>400</td>
<td>Topical, Personal and Situational Relevance</td>
<td>Min-Max Normalization Technique Z-score Normalization K-mean &amp; SOM for clustering and scatter plot</td>
<td>TANAGRA tool kit</td>
<td></td>
</tr>
<tr>
<td>[11]</td>
<td>Experiment</td>
<td>Attribute –</td>
<td>based recommender system for Learning Resource by Learner Preference tree</td>
<td>Historical accessed resources</td>
<td>Metadata for Architectural Contents in Europe</td>
<td>1148 Learners 12000 resources</td>
<td>Number of neighbours (5-40)</td>
<td>MAE, MACE, Normalized mean absolute error, Rank accuracy metrics, Bayesian Network, Correlation Learner Preference Tree</td>
<td>Statistical techniques</td>
<td>Precision, Recall for recommender system MAE for prediction quality metric</td>
</tr>
<tr>
<td>[21]</td>
<td>Suggestive</td>
<td>Track learning pattern and personalising using adaptive recommender agent (IPBARA)</td>
<td>Log of navigation sequence of learner</td>
<td>LCMS application server</td>
<td>-</td>
<td>Signature pattern of learners</td>
<td>Concept manager, pattern recogniser, User behaviour analysis, generate user navigational patterns in application env. Algorithm : gen_signature pattern, Gen_Repetitive_S eq</td>
<td>Mathematical model used</td>
<td>Generation of concept map tree by concept map manager Generation of signature pattern by Recommender</td>
<td>Successful</td>
</tr>
<tr>
<td>--------------------------</td>
<td>-------------------------------------------------</td>
<td>-----------------------------------------------</td>
<td>-------------------------------------------------</td>
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<td>-----------------------------------------------</td>
<td>-----------------------------------------------</td>
<td>-----------------------------------------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[26] Comparitative Study</td>
<td>Predicting Academic performance using learning analytics in VLE</td>
<td>Student-system Interaction Logs, report logs for each classification</td>
<td>MOODLE logs interactions, Data from informal learning processes outside VLE</td>
<td>Number of interactions for each course Moderating factors like Agent Frequency Mode</td>
<td>Multiple linear regression between student interactions Variance of dependent variable as linear combination of independent variables Data analysis of backward multiple regression</td>
<td>SPSS 18 (PASW)</td>
<td>Average interaction per course for each classification</td>
<td>No relation between creating class interaction and final academic performance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[1] Case Study</td>
<td>User Behaviour Mining for personalisation in e-Learning system</td>
<td>Learner behaviour, learning progress, learning resources used, test taken, homework library content</td>
<td>History of learner behaviour Client side Web logs Server logs</td>
<td>Not mentioned</td>
<td>Personalised recommendatios</td>
<td>Web- Browser Plugin technology</td>
<td>XML file for learner history</td>
<td>Behaviour mining in personalised recommendation engine</td>
<td>Support for individual learning</td>
<td></td>
</tr>
<tr>
<td>[3] Prototype Design and Evaluation with experimentation</td>
<td>Interoperable Intelligent Tutoring System</td>
<td>Student Maths Activity Data</td>
<td>Student Interaction with the course and tutor interfaced with MOODLE, Odjioo, SRTE &amp; SCORM Cloud</td>
<td>Not mentioned</td>
<td>Grading Skills Students : Skilometer (0% -100%)</td>
<td>Comparison of functionality and features of LMS and GRAPPLE Approach, T-Maestro Approach and Prototype</td>
<td>PROLOG or LISP for inner and outer Loop Dreamweaver IDE for web development RELOAD IDE for SCORM-PIF</td>
<td>Functionalitie s : – Inner Loops – Outer Loops Features : - Supports - Provides</td>
<td>Prototype satisfied all functionalit ies and features</td>
<td></td>
</tr>
<tr>
<td>[22] Experiment al study</td>
<td>Student Classification for academic performance using Neuro Fuzzy Logic</td>
<td>Four categories of data good, satisfacto ry, good, very good</td>
<td>Questionnaire, Quizzes on Entrepreneurs hip class in JTETI UGM</td>
<td>71 respondents 13 questions</td>
<td>Percentage value for Categories</td>
<td>Student Classification Model evaluated using RMSE Training data processed by ANFIS Editor generating Sugeno fuzzy type and split the membership function</td>
<td>ANFIS editor on Matlab’s Fuzzy Logic Toolbox</td>
<td>RMSE value</td>
<td>Average RMSE after 3 iteration : 0.25611</td>
<td></td>
</tr>
<tr>
<td>[9] Descriptive Analysis</td>
<td>Prototype for personalised Recommendation based on Hashtags on e-Learning System</td>
<td>User behaviour, user profiles, Datasets in Floksinor y</td>
<td>Web logs, LMS logs</td>
<td>Not given</td>
<td>Hash tag definitions, semantic distance between definitions for each hashtag</td>
<td>Clustering groups of similar definition using Markov Clustering Algorithm</td>
<td>PDF to organise hashtags in alphabetic order</td>
<td>Definition sense clustering</td>
<td>Floksinory Approaching 89.21831 with ground truth</td>
<td></td>
</tr>
<tr>
<td>[8] Experimenta l Case study</td>
<td>Design of longest common subsequence based on genetic algorithm</td>
<td>Chapters 8 Groups of LO Results of questionnaire</td>
<td>7 courses 6 groups based on initial sequence Questionnaire: bio-computing students</td>
<td>Common sequences</td>
<td>Algorithm personalising LOS based on students suggestions</td>
<td>Sequences Proposed by students</td>
<td>Mathematical model used</td>
<td>High efficiency</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[16] Experimentation analysis</td>
<td>Dynamic delivery of learning contents using text mining and ontology approach</td>
<td>Learning contents, learning log activities, forum logs, quiz scores</td>
<td>Learning logs from LMS</td>
<td>Quiz scores Learning material preference for 4 groups of students</td>
<td>Text mining using deterministic filtering rule, clustering Ontology approach for mapping learning contents</td>
<td>SPARQL to match learning style Recommendation using charts</td>
<td>Score: fair, good, excellent Chart to compare learning preference</td>
<td>Higher activity participation: excellent scores</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[25] Framework design and experimental evaluation</td>
<td>Framework based on fuzzy learner model and optimised Fuzzy Item Response Theory</td>
<td>Learners style characteristics LMS data log, Learning style Questionnaire</td>
<td>40 valid learners</td>
<td>Learners satisfaction feedback Educational success</td>
<td>200 rules generated for courseware recommendation Learners ability estimation: Maximum likelihood and Bayesian estimation procedure used for generating item information function</td>
<td>Mathematical model developed</td>
<td>Questionnaire: five point Likert Learners ability: Medium, High</td>
<td>More than 83% learners satisfied and showed educational progress</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[18] Experimental</td>
<td>Learning Style prediction</td>
<td>Normalized Learning style data, learning information Log files of learners</td>
<td>50 Learning style dimensions: - Sequential/GLOBAL - Active/reflective - Sensing/Intuitive - Visual/Verbal</td>
<td>Classification Clustering learners 6 runs of Learning Pattern Recognition</td>
<td>Cluster core construction algorithm Simulated Annealing Algorithm</td>
<td>Prediction accuracy</td>
<td>90% accuracy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[12] Experimental study</td>
<td>Personalised Learning Recommender System using Augmented Reality (AR) browser for fieldwork</td>
<td>Preferenc e Thesaurus each consisting of 165 DCG browsing behaviour</td>
<td>Animals and Plants 3DCG database, textbook database, Geometry database for Banff National Park</td>
<td>Frequency of 3DCG manipulations: Transfer Rotation Scaling Screenshot Annotation touch</td>
<td>Mapping animal and plant data to geographical information Create term behaviour matrix Summing behaviour vectors normalised with 1-norm Personal ranking based on similarity score</td>
<td>Query in excel Charts in excel using all results of classification of personalised ranking</td>
<td>Observation points: start and end for four users</td>
<td>AR browser boost motivation in fieldwork</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[13] Model Proposal</td>
<td>Recommend System for assessing student’s activity for supporting e-Learning</td>
<td>Students activity data via API or RSS Students of University of Rijeka, Croatia Web 2.0 tools</td>
<td>Not mentioned</td>
<td>Impact of recommender on students’ performance during e-tivities.</td>
<td>Algorithms and Rules for generating recommendation on the basis of activity, student, group models Surveys, interviews (students satisfaction)</td>
<td>Web 2.0 tools, SPSS</td>
<td>Points per e-cities for control and experimental group</td>
<td>System not tested with experimental group</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3.1 Gaps in the Published Research

After completing a review of more than hundred papers in the field of „Design of Intelligent tutoring systems using Enhanced Personalization in E-learning environment”, certain issues were found to be having a significant role in effective personalization for online learners. Some gaps found in the published research are:

- Learner’s information should be updated as the learner progresses through his e-learning course based on performances and behavior.
- Learner’s information could be collected and analyzed dynamically.
- Most of the researchers have proposed various recommender models but very few have provided experimental proof.
- It is necessary to keep track of learner’s performance and changes in the learning style and behavior and update his profile accordingly for effective personalization.
- It is desirable to build generic models that can be integrated to various Learning Management Systems for selecting and recommending appropriate learning objects to the learning.

3.2 Strengths in the Published Research

- Researchers worked in the area Personalization of e-learning contents by collection information about the users using various e-learning platforms and mediums and then statically analyzing them using various techniques like Data Mining, Link analysis, Network analysis and also Statistical analysis like ANOVA for aligning the appropriate contents to the e-learners to meet their specific needs.
- Most of the Researchers used Data Mining techniques like clustering, classification, associations, prediction, ontologies and artificial neural network as solution approach for mapping learning objects to learners.
- Most Researchers have implemented the model developed by them using MOODLE and fetched good results.
- Some Researchers have also tried to dynamically map the contents to matching the learner’s profile, needs and capabilities.

- Researchers proposed to build recommender and intelligent tutoring systems considering learning styles of the learners.

3.3 Limitations in the Published Research

- Very few Researchers collected learner’s information on e-learning platforms dynamically.
- Very few researchers provide dynamic mapping of learning contents to the user.
- Most of the Researchers have used static methods of collection and analysis of user information.
- Most of the researchers proposed various models for recommendation and personalization but very few researchers have considered its implementation or provide experimental proof for the same.

4. Discussion on Proposed Model

The main objective of the proposed model:

- To collect data related to Personalization parameters like user profile and Learning Styles and analyze them with reference to motivation and involvement for the learners from LMS.
- To create learning objects on the learning management system and group the learning objects into level.
- To select appropriate set of Personalization parameters and design a module to interface with LMS that includes feedback ensuing improved learning experience.
- To create ontology based mapping of learning objects based on students profile (static).
- To update the profile of the learner based on the behavior and performance of the learner.
- To implement and validate the model through some selected software and hardware setup.

4.1 Methodologies/Technologies to be used

The proposed model would be designed such that it can be integrated with any CMS or LMS, use the log files to classify the learners based on their capabilities using Felder-Silverman’s learning style theory, using data mining techniques. Based on the learning style and capabilities of learner, learning objects would be displayed. The learner can then choose to take an assessment for the learning objects.
and based on the GPA score the learner can then choose to progress to the next level and choose the learning objects from the next level. This design is close to traditional teaching learning model as after completion of learning the student is allowed to take assessment to capture learning outcomes. It is self-paced as the learner chooses learning objects and then chooses the assessment pattern (could be subjective or objective) as desired by the learner. The next level of learning objects are displayed once the learner completes the current level like in the gaming scenario where the user is always motivated and engaged to take up new challenges.

5. Conclusion

Review process was adopted in the area of e-Learning and different approaches of personalization using statically generated data collected on the e-Learning platforms and also dynamically generated data in the virtual environment of e-learning were reviewed with the aim of enhancing experience of e-learners. It was found that most of the researchers worked in the area personalization of e-learning contents by collection information about the users using various e-learning platforms and mediums and then statically analyzing them using various techniques like Data Mining, Link analysis, Network analysis and also Statistical analysis like ANOVA for aligning the appropriate contents to the e-learners to meet their specific needs. Some Researchers have used the above techniques for future prediction of the grades. Most Researchers have implemented the model developed by them using MOODLE and fetched good results. Some Researchers have also tried to dynamically map the contents to matching the learner’s profile, needs and capabilities. From the above discussion, it is found that very few Researchers collected the learner’s information on an e-learning platform dynamically. Very few researchers provide dynamic mapping of learning objects to users. Most of the Researchers used static methods of collection and analysis of information. Comprehending all the above points it is found that more work can be done for analyzing the e-learner’s information and allocating the learning content dynamically. More work can be done to analyze the cognitive style of the learners and align the learning contents to their needs and requirements. Capabilities of Learning Management systems can be enhanced using tutoring or recommender systems for improved personalization of learning contents.

References

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