Development of a Novel Intelligent Social Game Design Learning Platform-'Gamewiz'

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Abstract—**This project involves the research, design, development and evaluation of a novel intelligent social game design learning platform that has been named 'Gamewiz'. This platform enables users to create, share and play games created with an Nanyang Technological University(NTU) developed Game Editor on the web. 'Gamewiz' leverages game design to teach computational thinking via social game design learning.**

The novel intelligent 'Gamewiz' platform was designed with a 3-tier architecture and developed utilising HTML, Less, CSS, JavaScript, jQuery, PHP, MySQL, AJAX and Apache. 'Gamewiz' was further enhanced with the incorporation of Sentiment Analysis to provide effective visual feedback to children. Rules derived from Association Rule Mining were implemented on the site for recommendation. 'Gamewiz' places an emphasis on the core principles of human computer interaction and has been developed with extensive user research.

'Gamewiz' is a pioneer in this nascent field with immense interest indicated for its commercial deployment by education service providers.

Keywords-Computational Thinking; Game Design; Social Learning; Design Thinking

I. INTRODUCTION

Computational thinking is a vital skill for the 21st century. In today's increasingly digital and data intensive world, it is necessary to supplement a child's analytical development with computational thinking in addition to reading, writing and arithmetic[1]. Computation thinking is a way of solving problems, designing systems and understanding human behavior by drawing on concepts fundamental to computer science [2].

In order to make computational thinking accessible and approachable for children, a context that is familiar to them is required. This context is most readily provided by games, which due to their motivational nature and ease of engagement, have been long prevalent in education[3]. Computer games are now becoming more widely used to teach core subject knowledge due to its higher capacity to attract and retain students via Game Based Learning. Game Design combines the worlds of Game Based Learning and Computational Thinking. Game Design spurs computational thinking and creativity as students have to create worlds with defined rules and clear objectives and there often are multiple solutions to a problem. For Game Design, social learning is an essential process that promotes peer learning and provides a support network for learning.

This project will encompass the following key areas:

- Preliminary research is done to identify how to improve the Game Editor to increase student's receptiveness to learning computational thinking via game design.
- Development of the platform is done to provide users the ability to learn game design with social learning.
- Sentiment Analysis (SA) and rules generated via Association Rule Mining (ARM) are incorporated to the platform.
- Evaluation of the platform is done with users (children and educators). The value and effectiveness of incorporating SA and rules implemented via ARM is evaluated.

II. LITERATURE REVIEW

A. Computational Thinking and Game Design

Central to the notion of Computational Thinking is the ability to translate or encode ideas into representations that leverage computational power[4]. This ability can be enhanced with the notion of computational literacy in which people are both consumers and producers of computational artifacts, creating a two way literacy[5].

Game Design, in particular, is a creative process that encourages a growth mind-set, in which open goals can be set and support can be provided to enable learners to realize their own visions of their games, encouraging students to learn from mistakes and grow[6]. Design environments such as Alice, Toontalk, AgentSheets and Scratch have shown that providing an growing reference collection of designs, enabling peers to support one another to develop skills through feedback and creating safe spaces to learn to program without fear are powerful supports in learning how to think computationally[7].

Social learning also fosters a sense of community and provides the ability to learn and mirror the best practices of successful game designers, enhancing computational thinking. These practices further promote agency in design work as designers learn to express their perspectives via feedback[8].

B. Feedback via Sentiment Analysis

Feedback is a crucial element in learning contexts[9]. The process of feedback from peers is a scalable way to help the users of the platform improve through knowledge of strengths and weaknesses of the game.

Sentiment Analysis (SA) is the computational study of people's opinions, appraisals and emotions toward entities, events and their attributes[10]. The application of SA to social learning for children is a novel concept. SA provides an effective feedback mechanism, by summarizing the general sentiment in the comment. This can be very effective for children as they have short attention spans[11] and is encouraging compared to a rating system. The visualization of SA, with results being expressed in the form of an image, is especially effective for children, as they tend to be visual and lose interest with large amounts of text.

Sentiment classified as being positive, negative or neutral as viewed by a linear scale[10]. Sentiment classification is based on either supervised learning or unsupervised learning. Supervised learning is done via training on a data sample from a data source with correctly assigned classification. Unsupervised learning is done when hidden patterns in unlabelled input data are identified such that learning and organization of information takes place without an error signal to evaluate the potential solution.

While various techniques can be used for SA, the Naïve Bayes Model of SA is a simple but effective[12]. This is a supervised learning method, which learns and applies the classifier model from a probabilistic perspective. It estimates the posterior probability of a test example being in class. The class that has the largest posterior probability will be assigned to the test example. Incorporating the conditional independence assumption for Naïve Bayes classification, that each feature is conditionally independent to other features given the class, makes the equation as below:

$$P(A_1 = a_1, \dots, A_{|A|} = a_{|A|} | C = c_j) = P(A_1 = a_1 | C = c_j) * \dots * P(A_{|A|} = a_{|A|} | C = c_j) \quad (1)$$

C. Recommendation via Association Rule Mining

Recommendation is a key component in many web applications, to generate interest in the platform with suggestions that align with the user's tastes. This is especially key for a children's site as children have short attention spans and tend to lose interest easily and so the games they see first on the site should be aligned to their individual interest.

ARM aims to discover interesting relationships between variables in data[13]. An association rule is an implication in the form of X⇒Y, where X and Y are disjoint itemsets. Support(s) and confidence(c) are the important measures for association rules. Minimal support and minimal confidence levels are pre-defined to eliminate rules that are not very interesting or useful. Support of a rule is the fraction of records that contain X ∪ Y to the total number of records [13] Confidence of a rule is the proportion of the transactions containing X, which also contain Y[13].

Following that, one must first determine frequent itemsets, itemsets whose occurrences exceed a predefined support threshold. Second, one must generate association rules from those items constrained by minimal confidence. There are several algorithms for this, including the Apriori algorithm below, which is one of the most widely used algorithms:

Apriori (T, minSupport)
{ //T is the database and minSupport is the minimum support
L1= {frequent items};
for (k= 2; L_{k-1} !=∅; k++) {
C_k= candidates generated from L_{k-1}
//that is cartesian product L_{k-1} x L_{k-1} and eliminating any k-1 size itemset that is not
//frequent for each transaction t in database do{
#increment the count of all candidates in C_k that are contained in t
L_k = candidates in C_k with minSupport
}//end for each
}//end for
return $\cup_k L_k$;

Figure 1 : Apriori Algorithm [13]

III. Preliminary Research

A. Unity Developed Game Editor Enhancement

The NTU Unity Game Engine developed Game Editor, which allows users to design games, was leveraged to develop a game inspired by Flappy Bird to test it's usability. Monodevelop, the Integrated Development Environment that accompanies Unity was used for C# scripting and the Game Editor was integrated to a web platform via the Unity Web Player. Data logging code was also added to the Game Editor to analyze game data. The game developed is designed to be basic for ease in learnability during user research, with the players' sole input being pressing the space bar.

B. User Research and Finding

Based on the game developed, user testing is conducted with 73 students of ages 8-22 in which students designed and played games on the Game Editor. Based on the results of the survey, game data analysis and interviews with facilitators, it was determined that the Game Editor Application was most suitable for primary school children. Also, social learning and feedback from peers was deemed to be key element to enhance the Game Editor.

C. Market Research and Finding

Competitive analysis was completed to gain insight on the strengths, weaknesses, opportunitites and threats of the existing platforms. A field study was also conducted at an existing player's code camp. Based on the market research, user friendliness for children was deemed to be a core feature in terms of both form and design and the best practices of competitors were analysed. The key findings included the use of vibrant colours, attractive characters, simplicty of functionality and language as well as informative feedback and robust error handling. Several consulting sessions were held with representatives from an educational service provider for insights from an educational and business perspective for children. The key finding was that there was a need to make the platform aligned to the child's preference to increase his or her receptiveness.

IV. Development Of Platform

A. System Implementation

The platform development followed the Software Development Life Cycle (SDLC) Waterfall Model. The Waterfall Model was selected as the requirements of the project were clear based on the rigorous user and market research conducted. The product definition was also stable and there were no ambiguous requirements. The 'Gamewiz' platform is divided into three key modules, Create games, Share Games and Play Games and other modules.

- Create Games: This module enables users to create games using the Game Editor. Upon building a game, they can name it and save it online. Users also get feedback from other players on the game they have created via a comment and like system. SA is used to analyse the comments and provide immediate visual feedback to users on the overall sentiment of the comments.
- Share Games: This module enables users to share games they have created using the Game Editor on a desktop version for instance, on the web platform. Moreover, users also have the ability to share on Social Media platforms such as Facebook, Twitter, Pinterest, Google+ or email it to their friends.
- Play Games: This module enables users to play games created by other users. The games displayed to the user are prioritised based on rules determined from ARM. Users also have the opportunity to comment on the games created and offer their feedback.
- Registration: Users can register on the system and create accounts. CAPTCHA is implemented for security purposes. It also requests for information on their age, gender and knowledge of programming, which is used to display games that tends to be more preferred by users of that profile.
- Login/Logout: Users can login to the system, which would enable them to comment and save games created on the platform as well as logout.
- User Profile: The user profile enables users to manage their account by changing their password or email.

B. Sentiment Analysis Implementation

SA was incorporated via the phpInsight tool, which performs SA by using a dictionary of words that are categorized as positive, negative or neutral and a Naïve Bayes algorithm to calculate sentiment. To improve accuracy, noise words are removed. Each comment is taken as an input and there is an output as to whether the review is positive, neutral or negative. Supervised learning is conducted by estimating the probability of a word occurring given a sentiment based on examples of positive, neutral and negative sentiment and counting rate of occurrence in each class. The conditional probability for the Naïve Bayes classification is modified as below:

$$P(sentiment \mid sentence) = P(sentiment)P(sentence \mid sentiment) \,/\, P(sentence) \quad (2)$$

The independence assumption can be leveraged such that P(sentence|sentiment) is the product of P(token|sentiment) across all the tokens in the sentence. By doing so, any sentence with an unseen token is prevented from having a score of zero. Laplace smoothing is done via the extra 1 and the count of all tokens. The P(token|sentiment) can be estimated as below:

$$P(token|sentiment) = count(this\ token\ in\ class) + 1/count(all\ tokens\ in\ class) + count(all\ tokens) \quad (3)$$

The tool is extended to allow for immediate feedback on 'Gamewiz'. Comments provided for each game are analyzed and its sentiment is determined dynamically and immediate visual feedback is provided to the user. The visualizations are happy face for positive class, neutral face for neutral class and sad face for negative class respectively to effectively summarize the sentiment for children. The visualizations have encouraging messages for children to motivate them in their learning process.

C. Association Rule Mining Implementation

Data collected from user research is used to conduct ARM to elucidate the interesting correlations that exist. This is used to identify a preliminiary version of rules. These rules are implemented on the 'Gamewiz' web application to prioritize showing games aligned to the user's preferences. When a user logs in, based on the profile of the user, taking into account his age, gender and knowledge of programming, the order in which the games created by his friends' changes with most preferred games first. This makes the platform more attractive as children have short attention spans that need to be captured immediately with games of their interest.

ARM was performed using Weka 3.6.11, a Data Mining Software developed at The University of Waikato[14]. Preprocessing of data involved the conversion of the user data collected to a Attribute-Relation File Format (.arff) in order to allow compatibility with Weka. This is done to maintain format independence of the data. The results from data mining using Weka are implemented on 'Gamewiz'.

V. Results and Discussion

A. Platform

The platform was tested for its functionality, usability, interface and compatibility to ensure a consistent and effective performance before undergoing a usability evaluation to determine the effectiveness of the platform.

Usability testing of the platform developed was conducted with 6 primary school children aged between 8-12. All of the children gave an above 4 out of 5 rating to the 'Gamewiz' platform. Student comments include, "Very fun and exciting making and playing the games" and "I like 'Gamewiz' because I can share my created games with my friends". In order to compare the effectiveness of the 'Gamewiz' platform, the children were surveyed on their keenness to design games on the 'Gamewiz' platform versus just the Game Editor. The following graph shows a marked improvement in the children's desire to use 'Gamewiz'.

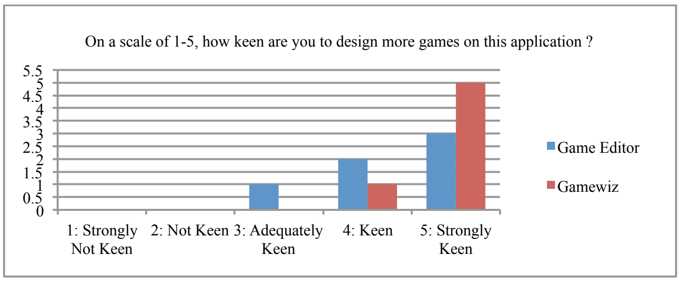

Figure 2 : Result of users' receptiveness to Gamewiz

The 'Gamewiz' platform was demonstrated to educational and business experts from educational service providers who strongly endorsed the platform as an effective way to teach computational thinking and creativity to children and was further keen to utilize the platform for commercial activities, demonstrating the business viability of the platform. The usability evaluation was a preliminary one and hence the data obtained is limited due to the small sample size. Further fine grain evaluation can be done with a larger sample size and the platform can be refined further.

B. Sentiment Analysis

User evaluation indicates positive response to comment feedback with SA visualization.

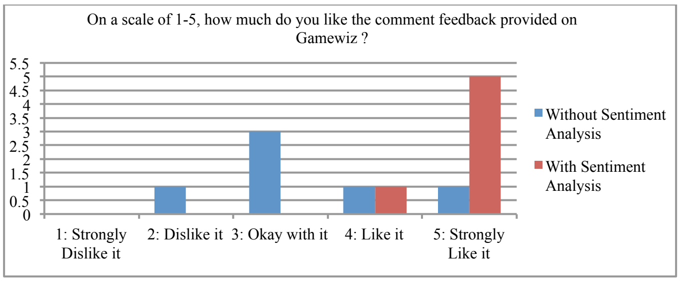

Figure 3 : Result of users' receptiveness to Sentiment Analysis

Performance evaluation of the SA tool on 'Gamewiz' was conducted. 105 data sets of comments for the game, out of which 35 were positive, 35 were negative and 35 were neutral, were tested and have been summarized via a Confusion Matrix as below:

TABLE I. Confusion Matrix for SA Tool

	Predicted Sentiment Class			
Actual Sentiment Class		Positive	Neutral	Negative
	Positive	28	5	2
	Neutral	4	27	4
	Negative	4	5	26

The following table indicates the key performance measures of the SA tool.

TABLE II. Performance Measures for SA Tool

	Positive	**Neutral**	**Negative**
Precision	0.7778	0.7297	0.8125
Recall	0.6512	0.7714	0.7429
F-measure	0.7089	0.7499	0.7761
Overall Accuracy		0.7714	

Analyzing the Confusion Matrix, it can be seen that the tool produces a balanced matrix with roughly consistent percentage correctness numbers of accuracy, recall, precision and F measures. This indicates that the tool is performing well overall in terms of its ability to classify comments into positive, negative or neutral classes.

The SA tool has an accuracy of around 77.14%, which is slightly below the top performing tools when benchmarked to other commercial tools in the market. Analysis of commerical tools indicates that the accuracy of commerical products is around 80% for the best performing ones [15] and around 50-60% for the lower performing ones[16]. Thus, it can be inferred that the tool is quite effective in analysing the text though it has potential to be developed further.

The SA tool is based on Naïve Bayes Algorithm which has an independence assumption among attributes that the real world data does not always satisfy(ie: corelation between two words). This is a limitation that needs to be addressed to improve the performance of the tool. The tool can potentially be enhanced by combining it with methods such as Neural Networks which can handle correlation and dependence between input variables.

C. Association Rule Mining

1) Rules Generated :

Using a dataset of 139 transactions from user research studies, the Weka Data Mining software was used to mine for rules that were subsequently implemented on the 'Gamewiz' platform. The following figure shows the results from performing ARM. The minimum support for all rules is 0.1, while confidence level is 0.9. Rules, which have a game type on the right hand side of the rule, are selected for implementation. When the games on the Play section of Gamewiz are displayed, the users of the profile, given by the left hand side, will have the game type on the right hand side prioritized.

1. gender=female knowledge=low 19 ==> game=flappyb 19 conf:(1)
2. gender=male age=8 knowledge=high 16 ==> game=flappyb 16 conf:(1)
3. gender=male age=11 knowledge=high 17 ==> game=shooting 16 conf:(0.94)
4. gender=female knowledge=low 28 ==> game=angryb 26 conf:(0.93)

Figure 4: Rules Implemented on Gamewiz

1) Performance Evaluation:

From the graph below, it can be seen that the students on average prefer the Play section with the rules implemented than without the rules implemented.

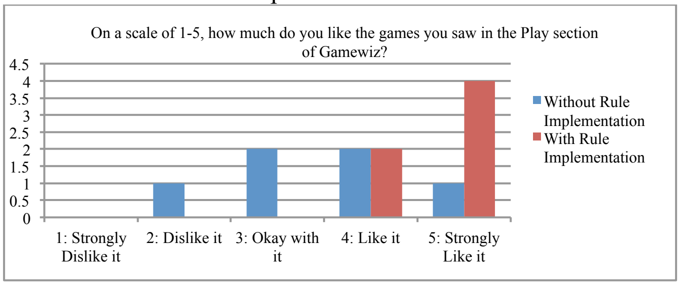

Figure 5: Result of users' receptiveness to Rule Implementation

Given the nascent nature of the 'Gamewiz' platform, the current implementation of ARM is a demonstration based on a small sample of real world data collected. With a larger dataset via more users and more data attributes collected, the rules that can be mined would be more accurate to the user's preference.

Moreover, the rules that are currently implemented on the 'Gamewiz' platform are static based on ARM of the data collected external to the platform. Moving forward, a way to programmatically perform ARM based on data collected via the 'Gamewiz' platform can be devised to generate rules and implement the rules dynamically on the site. This would enable the site's recommendation to be more sophisticated without the need for manual periodical change in rule implementation as per the current system.

VI. Conclusion and Recommendation

This project involved the research, design, development and evaluation of a novel intelligent social game design learning platform, named 'Gamewiz'. This was developed with the aim of increasing students' receptiveness to learning computational thinking via game design, specifically by enhancing the NTU developed Game Editor. Analysis of results obtained from survey of children and interview with educators indicated that the platform makes learning of computational thinking via game design not only more attractive but also more beneficial for children due to peer learning. Analysis of results from performance of the Sentiment Analyzer indicated that its performance is among the top performers in commercial tools.

The following are some recommendations for future work for the platform. Remixing of games, enhancing existing games created by other users, is currently a feature on the platform. This feature can be developed further as a core feature of the platform as it can help students who feel intimidated to design from scratch. A 'Game Data Analytics' feature can be implemented. Game creators can get feedback on the number of times their game was played, how long users played the game, what the score on the game was etc. This detailed data can be analyzed and visualized in a simple manner for children. With immediate real world feedback on the games, children can enhance their games via iterative development.

With a more sophisticated SA tool that has techniques that can handle correlations between words, more accurate feedback can be provided. Moreover, the dataset used for ARM is small as it is merely test the value of its inclusion on the platform. Given the successful evaluation, a technique to automate the collection of user profile and behavior data on the 'Gamewiz' platform and perform ARM dynamically can be developed for a more sophisticated recommendation.

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