Semantic networks -based teachable agents in an educational game

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Abstract: The aim of the study was to apply teachable agents into educational game meant for children less than 12 years of age and evaluate the outcome in context of cognitive psychology of learning. The study was done in two phases: design phase and evaluation phase (N=300). The design of the game was done in order to support relatively free use of teachable agents in an easy-to-use environment. The main findings of the study were a clear causality between quality of the taught semantic networks in game world and players' knowledge in real life and an evidence that learning away is an important feature when trying to enable conceptual change in educational games.

Key-Words: Game AI, Reinforcement learning, Conceptual learning, Semantic networks, Serious games

1 Introduction

According to cognitive psychology of learning, people actively construct their own knowledge through interaction with the environment and through reorganization of their mental structures [1][2][3]. The key elements in learning are accommodation and assimilation. In terms of Conceptual Change [4], accommodation describes an event when a learner figures out something radically new, which leads to a change in his/her mental conceptual structure. Assimilation describes events when a learner strengthens his/her mental conceptual structure by means of new relations.

Semantic networks, also known as conceptual graphs, are knowledge representations constructed with directed or undirected graphs [5][6]. Semantic neural networks (SNN) are generally used for processing natural languages [7]. However, Semantic neural networks as knowledge representations are relatively extensible and they have been used, for example, to model mental disturbances [8]. On the other hand SNN can be utilized to model the characteristics of users, profiles, patterns of behavior, and skill levels in order to support or challenge the performance of individuals. Furthermore, semantic networks can be used in order to uncover patterns behind conceptual change.

The virtual pets in Animal Class [9][10] learns by adding new concepts to their conceptual structures and strengthening the structure by means of adding new relationships between concepts. This assumed similarity between human learner and machine as learner has been a key element during the design and evaluation of the Animal Class. The traditional goal of AI is to make machines perform cognitive tasks that humans can do, or try to do. In the game industry, the definition of AI is extended so that the most important task of a game's AI is to entertain. It is allowable for game AI to cheat or be 'stupid' in order to achieve the illusion of intelligent behavior [11]. The balancing issue is also challenging within the domains of game development and AI research: It is easy to create a poor or perfect opponent; the challenge is building a reliable and entertaining opponent [11][12].

In Animal Class the intelligence of opponents and game balancing is constructed by game players themselves: the virtual pets are teachable intelligent agents and game mechanics are based upon their behavior. Technically, the game AI in Animal Class is based on a dynamically extensible Semantic (neural) network [13][14]. Related learnable methods for behavior recording [15][16] and behavior mining [17][18], have been studied and used in the game industry for some time. The biggest difference between methods developed in this study and reviewed methods are in aim: When most of the learnable methods in game AI's are focusing on recording and repeating human behavior in game world, methods in this study aims to model and uncover the causes and consequences behind the behavior.

From educational point of view, there have been several good solutions that apply the idea of learning-by-teaching. For example, Hietala & Niemenrepo [19] studied teachable agents as peer learners and Vogt [20] introduces methods for applying teaching and guessing in language education. Maybe one of the best-known learning-by-teaching approaches in education is Betty's Brain [21]. In recent literature, software agents has been studied widely as part of educational technology from systems point of view [22] to detailed applications, such as carrier selection [23]. Also effectiveness of the intelligent systems has been on focus [24].

The difference between these educational games and Animal Class is in the type of learning and the age of learners: While most solutions are based on deductive (top-down) types of learning, meant for students older than 16 years, Animal Class is based on inductive learning, or in other words reinforcement learning. In some sense, the game AI in Animal Class learns to learn: the algorithm learns its own inductive bias based on previous experience. Furthermore, the game AI also deals with inductive transfer, or transfer learning: knowledge gained while learning one set of concepts can be applied into new, but related enough, conceptual domain.

2 Structure of the study

The aim of the study is to apply teachable agents into educational game and evaluate the outcome in context of cognitive psychology of learning. The study is divided into two main phases: the design phase and the evaluation phase. The study is a design study with empirical evaluation (N=300).

2.1. Research tasks

The research tasks for implementation and evaluation are following:

1) How to apply semantic network based machine learning in educational games for children less than 12 years of age?

2) How to enable learning away, unlearn and forget in game AI without decreasing the usability from human-computer interaction point of view?

3) What is the relation between semantic network taught during the game play and player's personal skills in subject?

4) How do the AI's capability to learn away, be evaluated in terms of cognitive psychology of learning?

2.2 Experimental group and procedure

Experimental group 1 (n=59) was formed for laboratory testing in co-operation with elementary school teachers who like to use educational games as part of their teaching. Members in experimental group played either Animal Class, The Pre-School Geometry Game or Animal Class, A 6th Grade Mathematics Game. Experimental group was tested empirically before and after playing the game with paper based test. Test instrument was based on Finnish curriculum about elementary school mathematics, and basically the test instrument was designed to measure similar skills that the learning material was dealing with. In this study, pre-test score, post-test score, improvement and quality of conceptual structure was used as explanative factors - they were not considered as results of study.

The procedure for the experimental group 1 was following: Before the playing session, all pupils took a pre-test. The pre-test was administered very formally. It took approximately 10 minutes to complete the pre-test. Playing session was started immediately after the pre-test. The experimental group 1 played the game in subgroups. In every game session there were two researchers and two teachers present who helped the pupils with computers etc. Teachers and researchers did not help pupils with mathematics, geometry or game strategy related themes, but they were allowed to discuss about playing the game in general with the pupils. The playing session lasted approximately two hours. All other needs were minor compared to playing. The post-test was taken a day after the playing session. The post-test was similar to the pre-test as the test as well as a procedure.

Experimental group 2 (n=231) was formed in order to study the AI's capability to learn away in real life situations with high ecological validity. The concept of ecological validity is used to describe how natural the test situations in experimental behavioral studies are. According to Loomis and Blascovich [25], the traditional relationship between experimental control and ecological validity of research is negative: when experimental control of research is high, the ecological validity is low, and in contrast, when the ecological validity of research is high, the experimental control is low.

The procedure of the experimental group 2 was following: The teacher started the game play at most suitable time during the field test month. The instructions for teachers were related to how the game is played. Pedagogical instructions were as minimal as possible: only examples about good practices were provided. Because the aim of the experimental group was to receive as ecologically valid data as possible, there was no mandatory procedure for playing the game. The experimental group 2 was observed only virtually, thus there were no pre- and post-tests in this group.

2.3 Measures and variables

The main measured variables of the study are related to nature of the formation of the conceptual structure. Focus is on following actions: is the player strengthening the network or is he/she changing the structure of the network? The data collected in experimental group consist of quantitative values like pre-test score, post-test score and improvement between tests and quality of conceptual structure. The quality of the conceptual structure is calculated as a binary correlation between matrix transformations of the observed conceptual structure taught by players and true/formal structure, constructed by authors. This data was used as explanative factors - not as results of study.

3 Results

The results of the study are discussed in two chapters: Results received during design phase and results received during evaluation phase.

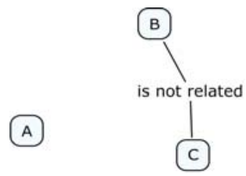
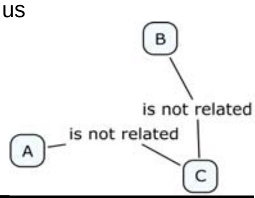
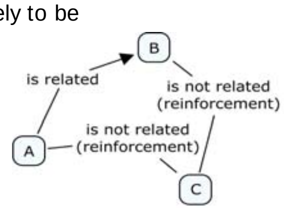
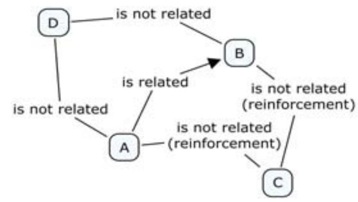
3.1 Applying semantic networks in educational games

The pedagogical idea of Animal Class is to put a learner (player) into the role of a teacher. The background of the game is in Learning by Doing, Learning by Teaching and Learning by Programming. In Animal Class the player has complete freedom to teach the virtual pet however s/he wants, even wrongly. This possibility of teaching wrongly is a crucial feature in order to enable learning away.

At the beginning of the game the player got his/her own virtual pet that does not know anything. Its mind is an empty set of concepts and relations. The pet learns inductively: Each teaching phase increases and strengthens the network of concepts. When the pet achieves a semantic network of a certain structure, it can start to conclude. In Animal Class teaching is always based on statements constructed by the player. The virtual pet answers according to its previous knowledge. If there is no previous knowledge, it will guess. The player then tells the pet if the answer is correct or not, and based on this, the pet forms relations between concepts.

Each teaching phase is recorded in a semantic (conceptual) network within the game AI with one or more 'is (not/option) related to', 'is (not) bigger', 'is (not) equal', etc. relations. In game play these relations are used logically: In a correctly-answered-question situation, the virtual pet accommodates or assimilates concepts and relations into its semantic network in accordance to the types of questions. During gameplay the conceptual structure in the virtual pet's AI develops. The following example (Table 1) describes the teaching and development of a sematic network in AI with a question of 'which one does not belong to the group'. In the following, 'Q' represents a question posed by the learner, 'R' represents answers made by the virtual pet and 'E' represents the evaluation done by the learner.

Table 1. Teaching a semantic network in Animal Class.

Phase	Action	Network
1	Q: which one does not belong to the group; A, B or C R: "A" (The pet guesses, because it does not have previous knowledge) E: false	empty 
2	Q: which one does not belong to the group; A, B or C (repeated question) R: "B" (Pet guesses from set [B,C] because of previous teaching) E: false	
3	Q: which one does not belong to the group; A, B or C (repeated question) R: "C" (The pet determines: A is not related to C and B is not related to C, which means that A and B are most likely to be related) E: true	
4	Q: which one does not belong to the group; A, B or D R: D (The pet deterimines that it had to be D because A is related to B E: true	

In the example, the learning was accompanied by 'is not related to' relations in the beginning. With 'is not related to' relations, the learning takes more time than with 'is related to' relations, that would have taken place if the pet had guessed correctly at learning phase 1. Another note to Table 1 is that, determining the probabilities and answers are based on the state of the network, not on single relations alone. If the overall state of the network is strongly opposite to the shortest relation between concepts, the overall state will override the shortest relation. In terms of contextual learning, we can say that the context affects causes and consequences on the machine learning side of Animal Class.

During gameplay, the semantic network will grow up to thousands of relations and a single teaching phase has only a limited effect on areas of the conceptual structure already taught. Understanding this phenomenon is valuable when trying to correct a wrongly taught part of the concept structure. Naturally, the wrong teaching could be corrected by teaching the correct structure enough times. The game AI uses all the taught information to back its decisions, and therefore it takes time to override wrong learning.

An interesting part of teaching is the possibility of teaching wrongly. Sometimes the wrong teaching was not due to low skills: for example at the beginning of geometry game, some pupils tried to teach colors instead of the expected shapes. In order to support reflective thinking, there was a brain icon, (Figures 1 and 2) that describes the quality of learning. If the quality increased, the brains got bigger, and if quality of learning decreased, the size of the brains got smaller. If the overall teaching was wrong, the brains were replaced by a cactus to show the player that he was doing something completely wrong. This kind of wrong teaching could be corrected by teaching correctly long enough to override the wrong learning.

The user interface was designed to be easy to use, but it should give enough freedom to make and evaluate complex expressions. In Figure 1 the player has constructed a question which consists of two triangles and one rectangle. When the question is ready, the player asks the octopus by clicking the 'ask' -button (balloon with three question marks). The octopus answers according to its previous knowledge.

After the octopus has given its answer by pointing out the shape it thinks does not belong in the group, the player should judge the answer: if the answer is correct, the player should click the green 'correct' -button. If the answer is false, the player should click the red 'wrong' -button. If the player notices that he has posed an impossible question or is uncertain, the question can be cancelled by clicking the yellow 'cancel' -button.

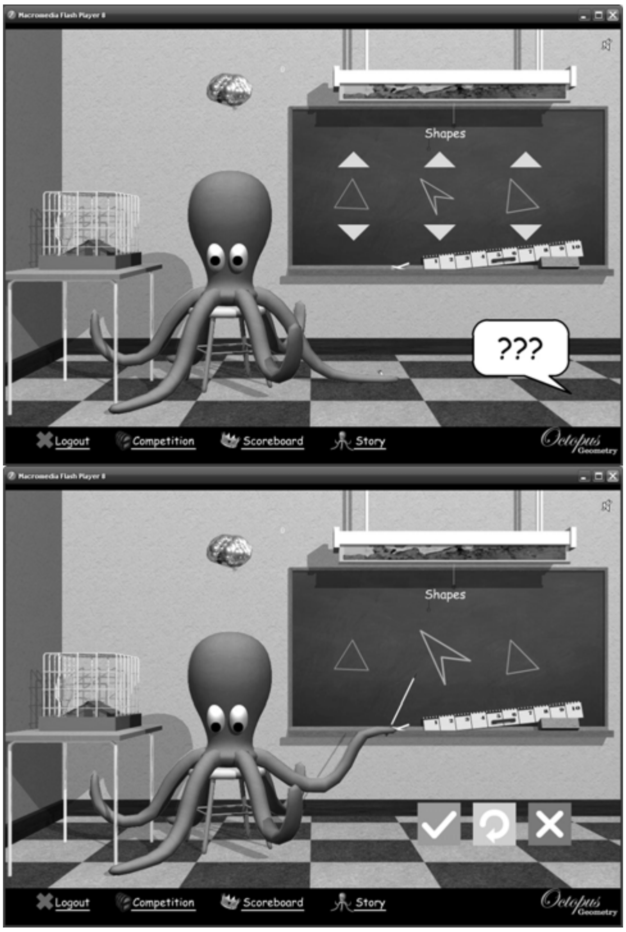


Figure 1. Question construction (upper screen) and judging (lower screen) in Animal Class, the Pre-School Geometry Game.

The teaching itself was found to be motivating. Even so, most pupils expected something more than just teaching. Therefore, a quiz challenge called the "Treasure of the Caribbean Pirate" was included into game as a competition between the pets. In the competition the game AI uses the same semantic networks that were taught in the classroom. In the competition a player can challenge his/her friend's octopus to play against him/her. Because all semantic networks are stored in a game server, a player can challenge opponents even if they are not online. The competition (Figure 2) is based on mechanics similar to teaching. The octopus needs to select which of the shapes does not belong in the group. Both octopuses' answer the same questions at the same time according to taught knowledge.

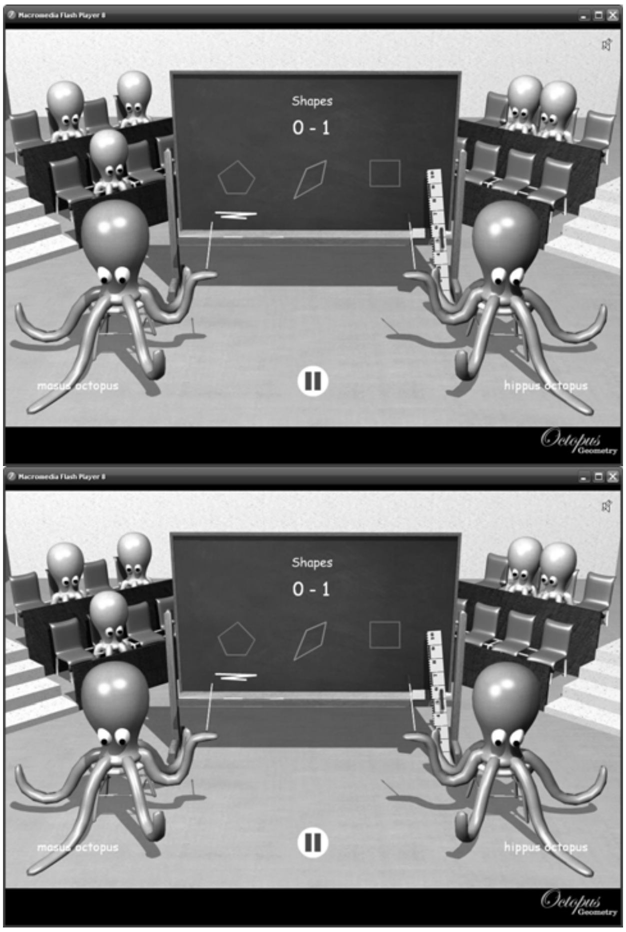


Figure 2. Competition in Animal Class, the Pre-School Geometry Game (upper screen) and Animal Class, A 6th Grade Mathematics Game (lower screen).

3.2 Enabling learning away and forget

Forget feature was implemented in an early release of the game. The idea of forgetting was to ensure that wrong kind of teaching will be wiped away in time. The implementation was based on randomly disappearing relations in semantic network. However, the players were confused when their teaching, even wrong kind of teaching, disappears suddenly. Furthermore, they claim that there are bugs in the game and they refused to believe that the disappearing of the relations was a feature. After this usability test, the feature was disabled.

Theoretically the feature of forgetting is interesting: it allows the conceptual structure to remain only strongest connections when weaker connections will disappear. However, this requires that there would be need for significant number of teaching phases.

Contrary to forgot, learning feature of away was understood clearly. Methodologically learning away was based on teaching a stronger opposite connection. For example, when the state of the semantic network is that A is related to B with two reinforcements, a player needs to teach at least three times that A is not related to B. Furthermore, is the state of the semantic network is strongly supporting that A is related to B from all possible routes from A to B, it requires significant number of teaching phases to override this kind of state of the network.

3.3 The relation between semantic networks and player's skills

When focusing on dependencies between the quality of conceptual structure and measured variables within experimental group 1, we can find out that the quality of the conceptual structure is strongly related to the post-test score ($r=0.457$, $p=0.009$). Because the pre-test and the post-test are dependent ($r=0.707$, $p=0.000$) the quality of the conceptual structure is also related to the pre-test score ($r=0.370$, $p=0.037$). However, the quality of the conceptual structure was not related to learning outcome ($r=0.0118$, $p=0.949$).

To fit the two age groups into the same scale for more detailed analysis, the players are divided into four groups according to their learning outcome (Table 2). We can observe that both groups achieved quite similar outcomes: More than half of the pupils in both groups scored good learning outcomes between the pre- and post tests.

Table 2. Learning outcomes in subgroups.

	Mathematics game	Geometry game
Winners: Those who achieved significant improvement during game play (50% higher score or more in the post test compared to the pre-test)	5 (~15%)	8 (~35%)
Gainers: Those who improved during game play (10 – 15% score improvement)	15 (~42%)	6 (~25%)
Neutrals: A group consisting of those who improved less than 10 % but more than -10%	10 (~28%)	5 (~20%)
Non-gainers: Those who scored 10% lower in the post test compared to the pre-test	5 (~15%)	5 (~20%)

chi-square=4,32, df=3, p=0.229

In this study the teaching phase and other human-computer interactions were recorded during game play. These recordings include the semantic network taught to the virtual pet during the game play. The semantic networks were qualitatively analyzed from within and between the four groups defined. The semantic networks provided an interesting point of view on game play, learning and gaming strategies in particular. The semantic networks also explained some success and loss factors that would not be found from statistical analyses.

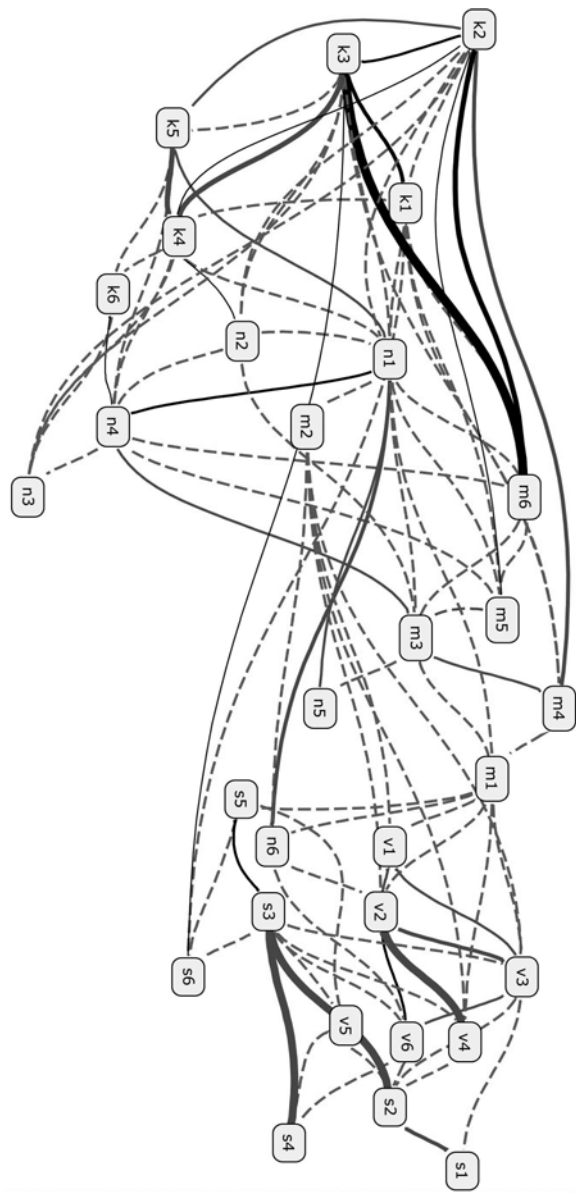


Figure 3. A typical winner's conceptual structure. 'K' represents a triangle on the map, 'N' represents a rectangle, 'V' represents a pentagon, 'S' represents a circle and 'M' represents other shapes. The number after the character is only an identifier.

In Figures 3 and 4 the semantic network of one typical successor and one typical non-gainer are presented. The structures consist of several nodes that are connected (assimilated) in a relatively complex way. In Figures 4 and 5 the connector line shows the nature of the relation: dotted lines represent not-same-kind -relations and continuous lines represent same-kind -relations. Completely black lines represent radical changes in artificial conceptual structures during game play (accommodation / conceptual change). These figures not only describe the semantic network in a virtual pet's mind, but also visualize the decision-making mechanism behind the game AI.

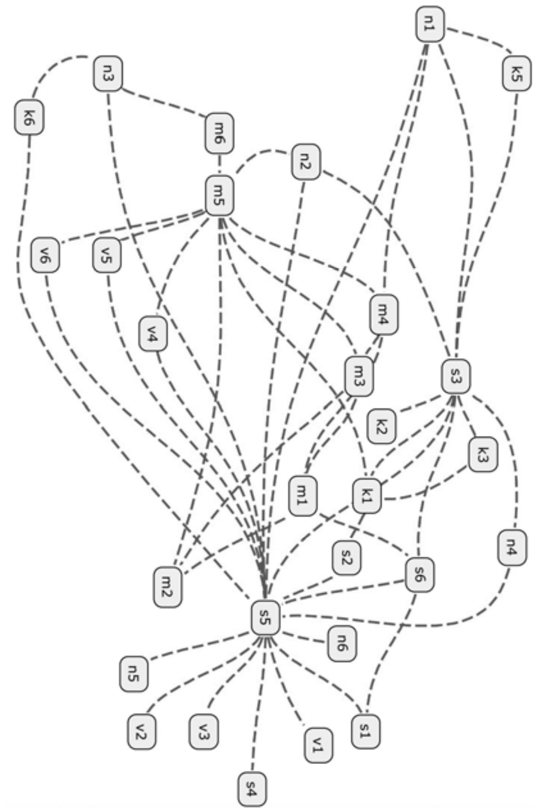


Figure 4. A typical non-gainer's conceptual structure.

The winners group differs from other groups: They tested different combinations (complexity of Figure 3), made mistakes and then corrected these mistakes (black lines in Figure 3). Those who benefited most from the game also had several more 'observed problem - reformulated strategy - corrected problem' -patterns than others. The non-gainers also have remarkably different semantic networks than the others (Figure 4). Their network consists of several weaknesses, for example, wrong connections or only 'not- same-kind' -relations.

3.4. Importance of learning away

Experimental group 2 (n=231) was formed in order to study AI's capability to learn away and forget. conceptual change. The data in experimental group 2 consisted of game related data and complete log data about behavior patterns during playing. Game related data include wins, losses and draws of competitions, quantities of different events and the quality of the conceptual structure, which is identical to quality of the conceptual structure measured with experimental group 1.

The variables related to patterns were 1) number of conceptual changes without explanative competition or break in playing, 2) number of conceptual changes observed directly after competition, 3) number of conceptual changes observed directly after a break in playing, 4) number of illusions of understanding strengthen without explanative competition or break in playing, 5) number of illusions of understanding strengthen directly after competition, 6) number of illusions of understanding strengthen directly after break in playing, 7) number of strengthening of the correct conceptual structure without explanative competition or break in playing, 8) number of strengthening of the correct conceptual structure directly after a competition and 9) number of strengthening of the correct conceptual structure directly after break in playing.

The experimental group 2 made more than 170000 observed events during playing (avg=543, std=980). The patterns and explanations of conceptual change are based on the analysis of this data. Players performed more than 21000 competitions (avg=91, std=312) and they logged in more than 4000 times (avg=18, std=36). The variance in playing behavior in general level was remarkably high. Therefore all variables related to behavior patterns were normalized in order to bring the nature of the behavior in front instead of the quantity of events.

The normalization was done in two phases: 1) case based normalization and 2) variable based normalization. Case based normalization was done by dividing each variable value by sum value formed by all nine observed values. The received value describes the (percent) distribution of events in variables. In variable based normalization, each case base normalized value was subtracted by variable's average and divided by variable's standard deviation. As a result of this normalization, each variable is in scale: avg=0, std=1.

The players were classified into similar clusters according to variables based on patterns of conceptual change. This grouping was done in order to find out if there are remarkable different player types in terms of conceptual change. The grouping was done by k-means cluster analysis. When the number of clusters was set to three (Figure 4), a relatively explanative view to conceptual change was received.

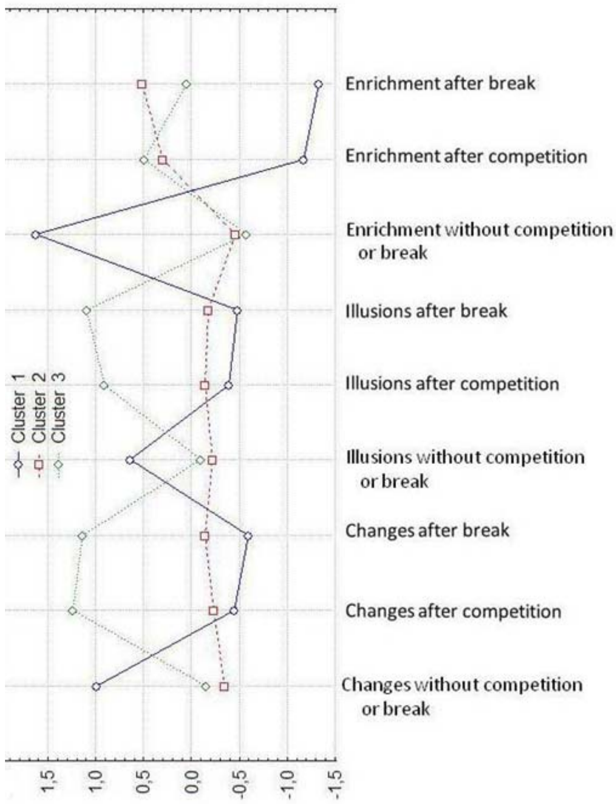


Figure 5. K-means clustering summary.

The means of general game statistics in each cluster are showed in table 3. On average, the members of the cluster 1 competed 18 competitions from which they on average won 8, lost 6 and 4 competitions were ended to draw. The quality of the conceptual structure was on average 11,7% of the maximum quality. Remarkable is that the indicator of the quality of the structure is very strict, and it is used only as a value for analysis, not as a result.

The members of the cluster 2 competed on average 89 competitions from which they on average won 33, lost 37 and 19 competitions were ended to draw. The quality of the conceptual structure was on average 17,2% of the maximum quality.

Members of the cluster 3 competed on average 185 competitions from which they on average won 80, lost 64 and 41 competitions were ended to draw. The quality of the conceptual structure was on average 38,7% of the maximum quality.

The clusters were formed according to normalized data, but the differences in behavior are still clearly seen in quantities. We assume that members of the cluster 3 gained most of the playing because the quality of the conceptual structure was strongly related to measured skills after gameplay. Members in cluster 3 played more than other groups, their pets' had significantly better conceptual structures than other groups' pets (t>4, p=0.000 in both cases) and they got significantly more wins in competitions than other groups (t>2, p>0.03 in both cases). Differences in draws and losses were not so significant. Clusters 1 and 2 did not differ significantly from each other.

Table 3. General game statistics in each cluster.

	Cluster 1 (n=53)	Cluster 2 (n=134)	Cluster 3 (n=44)
Quality of the conceptual structure	11,7%	17,2%	38,7%
Competitions won	8	33	80
Competitions ended to draw	4	19	41
Competitions lost	6	37	64

The means of the normalized behavior patterns in each cluster can be read from figure 5. The members of the cluster 3 were sensitive to perceive the cognitive conflicts that lead to conceptual changes after the competitions. They also processed the playing experiences between the playing sessions and therefore they had conceptual changes directly after the breaks. The members of the cluster 3 had also illusions of understanding during playing. However, there is a logical causality between changes and illusions: if the players wouldn't have illusions of understanding, they couldn't reach any conceptual changes. In other words, if you don't have anything to fix, you probably don't fix anything.

Members of the cluster 1 and 2 did not have conceptual changes either after competitions or after breaks. However, the qualities of the conceptual structure they have taught to their pets were significantly lower than qualities of the taught conceptual structures within members of cluster 3.

4 Conclusion

The aim of the study was to apply machine learning into educational game and evaluate the outcome in context of cognitive psychology of learning. The study was divided into two main phases: the design phase and the evaluation phase.

The design and implementation of the game was done in order to support relatively free teaching of a virtual pet in an easy-to-use environment. The game AI was based on a dynamically extensible semantic network that enables conceptual learning as well as learning away. The empirical evaluation was done under laboratory conditions and in the real world, which reflects the validity of the results in two ways: The laboratory setting enables measure behavior in controlled environment. The behavior that would be missed in controlled environment was collected in real world that increases the ecological validity of the research.

A strong relation between quality of taught semantic network and players' knowledge, measured in real life, is an important finding in order to develop new methods for studying conceptual learning in more details. In terms of behavior, the gameplay more resembles 'Learning by Doing' than professional teaching. In other words, players that managed well made more conceptual changes in their virtual pets' semantic networks. According to results of this study, the conceptual changes in game world also occurred in the players' mental conceptual structures in real world. This was observed as positive learning outcome.

When summarizing the results of this study, we can say that learning away is a crucial feature in order to enable good learning outcome. Those children who had used learning away features systematically during the game play had taught significantly better semantic networks to their virtual pets. On the other hand, freedom to teach any kind of conceptual structures as well as learning away are the features that would be difficult to implement without use of semantic networks.

Semantic networks seem to have potential as a method behind game AI in educational game development. On the other hand, educational researchers will benefit the data modeled in semantic networks, in order to analyze conceptual change in details. The strengths of the semantic network applications is in the complexity and extensibility of the models that could be constructed. Furthermore, there are numerous analysis methods, algorithms and visualization tools designed for graph –based data.

In future studies about semantic networks in educational games, the attention will be paid on combining constructive psychology of learning and reinforcement learning methods in order to build machines that can learn and behave like humans do. Such agents can be used in versatile software agent –based applications as well as knowledge representations for behavioral research.

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