Sharing Behaviors in Games and Social Media

Harri Ketamo

***Abstract*—**User generated media highlights sharing: Sharing videos, images and texts in social media, as well as sharing character outfits and maps in games. However, behavior is one of the aspects that are not shared. The aim of this study is to show how user generated behaviors can be shared in different types of games and social media applications. The examples about sport games and educational games are based on MindFarm AI technology that enables end users to construct human-like behavior by only teaching. MindFarm emulates the human way to learn: According to cognitive psychology of learning, our thinking is based on conceptual representations of our experiences and complex relations between these concepts and experiences. Phenomena when the mental structure change is called learning. In the near future user-generated behaviors can be developed and shared, as all other user-generated content. According to examples on this study, game- and media developers can design extensions that enable users to easily construct behaviors. From a game consumer point of view, the most interesting part is in developing behaviors, sharing them and finally playing with them, or against them.

***Keywords*—**Artificial Intelligence, Games, Learning, Social Media, User Generated Content

I. Introduction

User-generated content, such as the choice of a game character's outfit, its textures and clothing, as well as editing game scenarios, has been an integral part of games for a long time. It seems that users require features and activities that can be personalized and shared. However, there is no such interest in sharing behavior, strategies or game character personalities.

On the other hand, users produce colossal sets of content in social media. In fact, there are that much content that user cannot avoid a feeling about information overload. Nevertheless, there are no possibilities to share a personal agent that can harvest the content and bring in front only the highly personalized interesting content. All in all, this is not completely because of a lack of technologies for modeling and sharing AI -related contents [1].

Unlike visual objects, sounds or texts, behavior is a complex phenomenon. This complexity has set limits for developing AI's that could enable behavior construction without programming or scripting. In fact, AI programming traditionally requires not only programming skills, but mathematical skills also. Another point of discussion is whether game AI is about intelligence or behavior. Baekkelund [2] argued that game AI is far more difficult to determine than academic AI. Furthermore, while academic AI research focuses on perfect or optimal behavior, game AI should be entertaining: Game AI is allowed to cheat or be 'stupid' in order to achieve the illusion of intelligent and entertaining behavior. In fact, it is easy to build the perfect opponent; the challenge is to build an entertaining opponent [3].

Sports behavior modeling is challenging. Several games have received negative feed-back related to unrealistic non-player character behavior. Furthermore, in some multi- player games it is relatively easy to guess when one is playing against AI and when one is playing against another human player. On the other hand, the construction of human-like behavior in, e.g. football and hockey is very challenging. Even steering behaviors are surprisingly complex [4]. One other interesting approach can be found in Forza Motorsport, a game in which AI can learn to play like the player does in terms of driving patterns.

However, when discussing learning and behavior, we have to make a distinction between behavior as cognitive behavior and behavior as scripted behavior.

Behavior modeling has a long research background: Neural and semantic networks, as well as genetic algorithms, are utilized to model a user's characteristics, profiles and patterns of behavior in order to support or challenge the performance of individuals. Behavior recording have been studied and used in the game industry for a good time. In all recent studies the level of behavior is limited, more or less, to observed patterns. [5][6][7]. Furthermore, agent negotiation and it's scripted behavior [8] as well as agent based information retrieval [9] in web-based information systems has been studied for a long time.

In economical game theory [10] an agent behavior is widely studied in terms of Nash equilibrium. In this the agents are assumed to know the strategies of the other agents, and no agent has anything to gain by changing only its own strategy. A theory about existence of finite number of agents and their arbitrary relations based on other agent [11] describes a set of attributes or properties that are useful when evaluating the agent behavior: 1) every agent is an entity (Unity), 2) every agent exists even it does not have a physical characteristics (Existence), 3) every agent chose to be in a

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state of direct knowledge with other agent according to its free will (Acts) and 4) every agent is different from others in what it is (Whoness).

In this study, user behavior, competence and learning were seen as Semantic (neural) network that produces self-organizing and adaptive behavior/interaction. The behavior is evaluated in terms of the theory about existence of finite number of agents. The AI technology developed, emulates the human way to learn: According to cognitive psychology of learning, our thinking is based on conceptual representations of our experiences and relations between these concepts. Phenomena when the mental structure change is called learning.

In terms of constructive psychology of learning, people actively construct their own knowledge through interaction with the environment and through reorganization of their mental structures. The key elements in learning are accommodation and assimilation. 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 [12].

The novelty value of this study is in approach: to build technologies that enable easy construction of intelligent and human like behaviors.

II. Research objectives and method

The aim of this study is to show how user generated behaviors can be shared in different types of games. The game genres for this study are educational games and fighting (sports) games.

The challenge/novelty of the study is in the game settings: In order to share user generated behaviors, we should have a computational model that can be

1) easy to construct (user experience point of view)

2) extensible and scalable (useful for game and media developers)

3) transferrable and reusable

In educational game the behavior model is about mental conceptual structures. In sports games - fighting games in this case - character behavior is not about knowledge; it is about strategy and decision-making.

In social media, the common method to increase information accessibility is tagging. However, when tags are used only as single words, we easily end up to information overload. Furthermore, in social media, we do not have standardized way to tag content. In fact, tagging the content in an optimal way is a difficult task for several reasons: Cultural background, educational background, community and its social behavior, as well as context1 where tagging is constructed affects enormously to the selection of tags. Unclear, or in worst case misleading, tagging leads to information loss in social media. Furthermore, tagging can be seen as a one key element when building platforms for personalized and adaptive media services.

As we know, behavior is a consequence of learning, to some extent. The general assumption is that AI that can learn conceptual structures can learn strategies. The study can be seen as being a traditional design study with iterative cycles. The procedure of development was limited to the following:

1) Define what kind of activities are observed and taught in these cases.

2) Construct interface for teaching behavior (according to definitions).

3) Evaluate behavior and decisions in terms of the theory about existence of finite number of agents.

Evaluation is not meant to be done in terms of cognitive sciences: it is only done in order to evaluate the usefulness of the method.

The examples are based on MindFarm AI technology that enables end users to construct human-like behavior by only teaching. MindFarm emulates the human way to learn: According to cognitive psychology of learning, our thinking is based on conceptual representations of our experiences and complex relations between these concepts and experiences. Phenomena when the mental structure change is called learning.

The MindFarm AI technology is based on the author's previous work: research articles have been published from the point of view of cognitive science [13][14] and from a technological point of view [15][16].

III. Sharing behaviors in educational games

In AnimalClass a learner can teach conceptual structures in mathematics, the sciences, languages and arts to virtual pets (teachable agents). After teaching, players can send (share) their AI's to different competitions. AnimalClass is based on the theories of the cognitive psychology of learning: conceptual learning, inductive learning and conceptual change.

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.

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, (fig 1) 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.

In fig. 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.

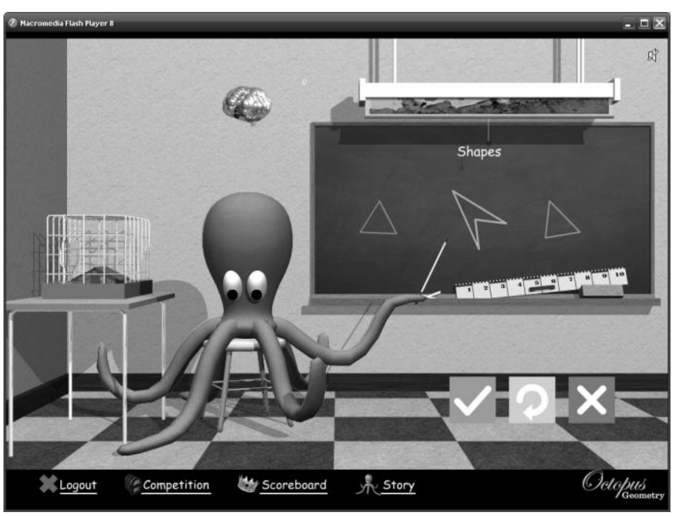

Fig. 1. Question construction and judging in Animal Class, the Pre-School Geometry Game.

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 (fig. 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.

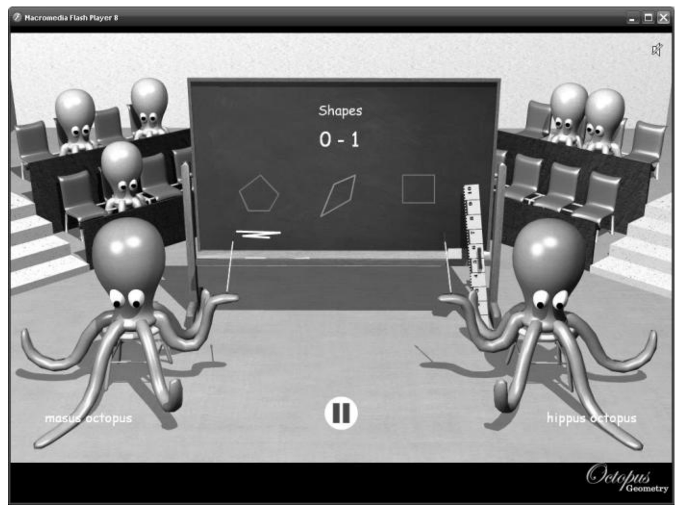

Fig. 2. Competition in Animal Class, the Pre-School Geometry Game.

From behavior sharing point of view, the children feels easy to teach their game characters. Even 6 years old preschoolers could easily taught their virtual pets. Competing against friends' pets were the most fun in the gameplay.

In some cases the children were confused when their virtual pet could be inside several friend’s gameplay at the same time. Furthermore, some children couldn’t understand, how the gameplay could continue in their friend’s computers, though they shut down their computers. However, all of the players did understand the idea of sharing game character’s behavior. Furthermore, they were very interested in seeing their character in another game. This supports the assumptions that sharing behaviors can be successful in games.

IV. Sharing behaviors in sports games

Traditionally, pattern –based methods are used in fighting game AI’s. This means that the focus is on a character’s movement patterns, such as: “action A → action B → action C”. In other words, the next action is calculated as a probabilistic model. In this model, we do not take the opponent’s actions into account. Another approach is

Stimulus-Response –pairs, familiar from behaviorism: “stimulus=attack, response=blocking”. Contrary to the pattern -model, the stimulus-response model does not have a history. A third possible approach is statistical: in accordance to the history, “what is a probable action against a certain opponent”. This can be referred to as spots betting: “in accordance with its history, this team will win”.

In all cases, the most important feature is feedback: what is the success of such activity? Without the feedback function, the AI would definitely not produce entertaining behavior.

When starting points were summarized, the AI’s observation needs were defined as follows: AI should learn patterns of activities, stimulus-response pairs and opponent statistics. All this should be supported by feedback data. The teaching/observation environment was designed as a web-form in order to support easy usability. The teaching tool can be used without any background material, but in this paper, the teaching is based on real video material. The idea is that a user can have two open windows (Figure 3): a window for video material that he/she wants to use in the background, and another window for the teaching tool.

Figure 3. Teaching an AI in accordance with real world material.

A user makes observations in terms of patterns, stimulus-responses, opponents and success from video footage. Each activity is recorded one by one (Figure 3). In this sense, the recording is relatively time-consuming and requires patience. When comparing this teaching tool to the teaching in AnimalClass, it should be noted that teaching this AI is too difficult for small children. In any event, most fighting games are forbidden for users who are under the age of 15 years.

In this study, we decided to focus on Taekwon-Do, because of the relatively small number of activities during a fight. Furthermore, in Taekwon-Do, the rules define successful actions in a way that can be clearly seen. The person behind the virtual character’s behavior is four times World Champion, Ismo Mäkinen. Ismo’s behavior was taught in accordance with three one round fights. In reality, teaching should be based on more observations. In this case, it was desirable for the mental conceptual model (AI) to remain as small as possible in order to produce readable visualizations of semantic networks behind decision-making. Teaching takes approximately 40 minutes.

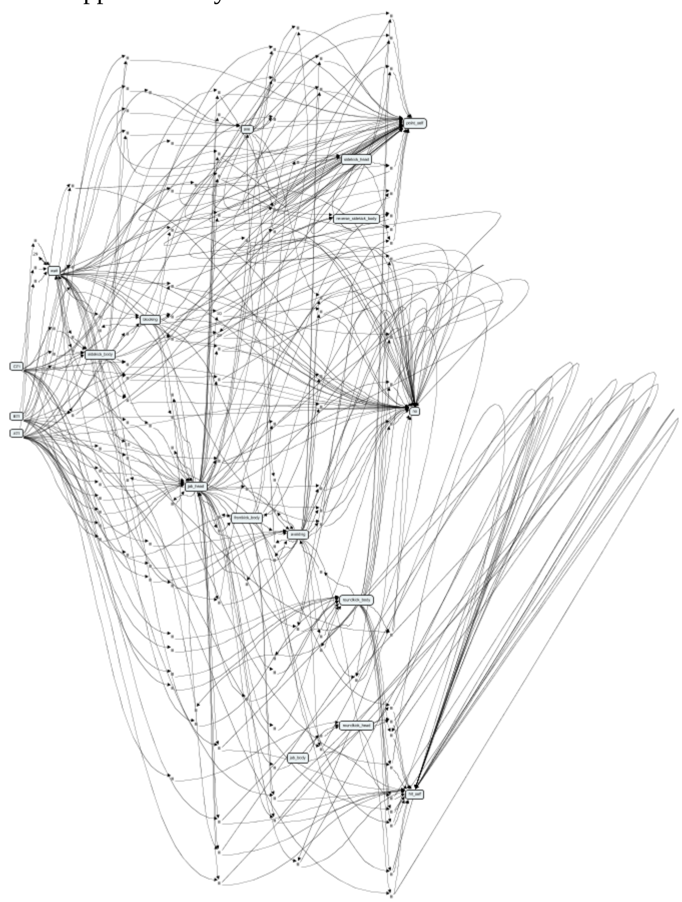

Figure 4. The semantic network in a user-generated character’s AI.

In Figure 4, the semantic network, with opponent-, pattern- and stimulus-response relations, is visualized. Each node represents an action (a kick, a punch, blocking, moving) and vertices represent the dependencies between the actions. Each vertex does have a weight that is used when computing the probabilities between transitions. What is remarkable is, that the number of nodes is relatively small compared to number of vertices (relations). This is because in modelling, all of the concepts are unique and they can have numerous relations under opponent-, pattern- and stimulus-response labels. This complexity makes, not only visualizations difficult to read, but the decision-making algorithm is also dependent on estimation functions. In this study, we are focusing only on a general framework.

The semantic network can also be visualized according to stimulus-response pairs, patterns of actions and opponent statistics. When focusing on patterns (Figure 5), we can estimate the behavior as a continuous process. Figure 5 can be read like Figure 4: nodes represent actions and weighted vertices represent the possible next actions. In brief, Ismo's fighting behavior, in terms of patterns and according to our teaching, is relatively straightforward: jabs and round kicks.

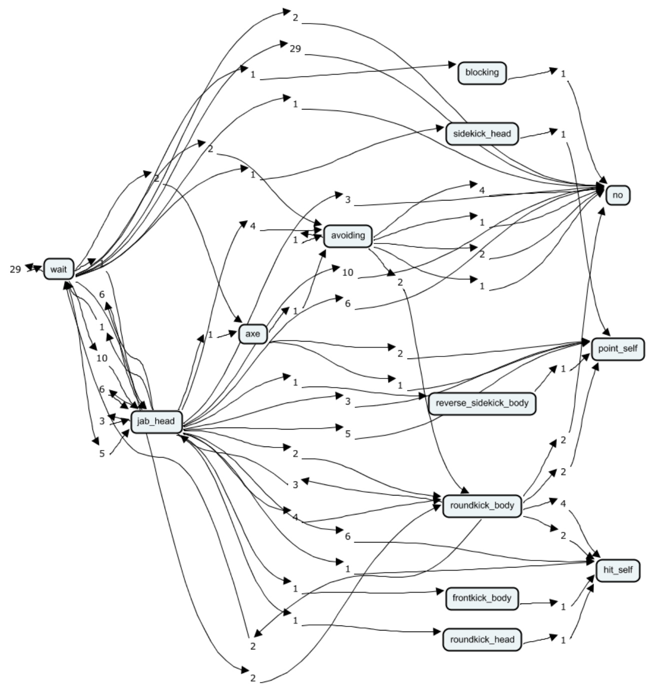

Figure 5. A pattern -related semantic network for a user-generated character's AI.

Ismo's stimulus-response –map (Figure 6) is far more interesting from a game behavior point of view. In short, we can see that jabs are thrust under almost all conditions (stimulus), while round kicks are done under limited conditions. Furthermore, the probability of getting points is high with a round kick, but is this due to the round kick or because of starting conditions? We could produce interesting, versatile behavior for game characters in keeping with this model.

When all three layers of different behavioral information are summarized, we have a relatively detailed probabilistic model of behavior. In this case the teaching is done in detail and the model could be interesting in terms of sports science. However, in this study, we are not determining how well the model fits reality. We are focusing on intelligent, believable and entertaining behavior.

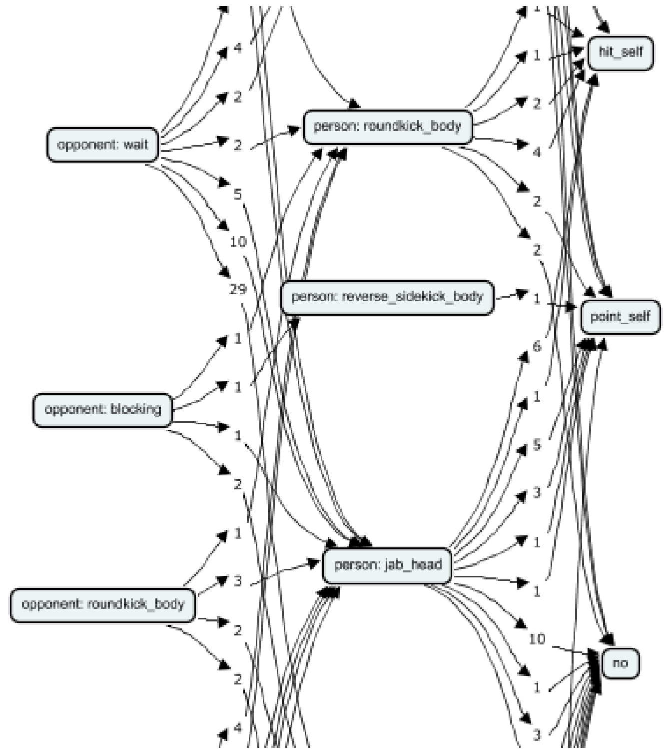

Figure 6. A partial stimulus-response -related semantic network for a user-generated character's AI.

In order to evaluate believable behavior, a character's decision-making (Figure 7) needs to be simulated. Simulation requires information about previous actions and the opponent's current action (stimulus) in order to compute probable responses. The simulation tool orders the most probable responses. In testing, the wait –action got too controlling a role, which means that a new estimation function to control wait's and pauses should be designed in future studies. This was partially due to the teaching. Wait cases were labelled as 'wait' whether they were strategic wait's or pauses in activity.

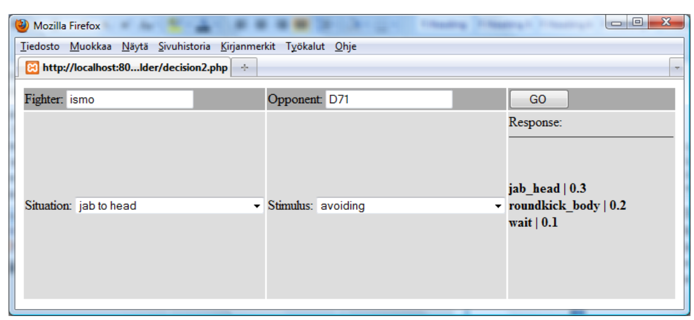

Figure 7. A simulation tool for evaluating decision-making with a user-generated AI.

Comparisons of similarities between user-generated AI and real behavior (absolutely believable) were made by comparing the responses given by AI to responses observed from another of Ismo's fights. This fight was not one of those that had been used as teaching material for the AI. In Figures 8 and 9 the use of simulation is explained in more detail.

In Figure 8 an action starts with a wait-action. According to the AI, the most probable non-wait action by Ismo is 'a jab to the head', which actually was the next action. After this, the most probable action by Ismo according to the AI is 'a jab to the head' again. In this section the AI manages to produce believable behavior.

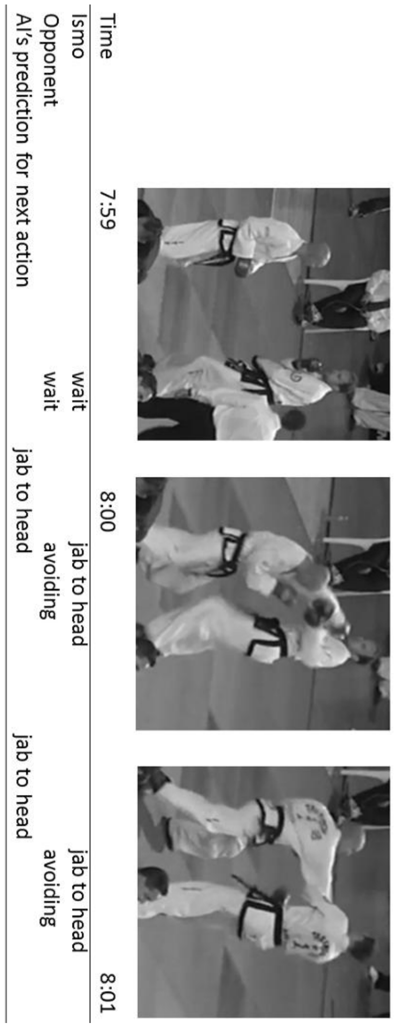

Figure 8. Example: Photos of actions and a timeline with Ismo's actions, the opponent's actions and the AI's prediction of the next action.

In Figure 9 the following actions are presented. In this case, the AI made a completely wrong prediction. It keeps predicting that the most probable action is 'a jab to the head', the second suggestion was 'a round kick to the body' and the third action, 'a front kick to the body'. In reality, Ismo made a reverse side kick to the head. Also the last prediction went wrong completely.

The pattern described in Figure 9 was due to too small a sample or limited teaching data or it was due to Ismo's creativity. Creativity is something that we cannot model. However, in terms of entertaining and believable behavior, this is not a problem and the AI did not fail. In terms of sport sciences, the AI failed.

After the whole fight was simulated, an interesting outcome was discovered. More than 85% of the real world responses are mentioned in the simulation tool list. Furthermore, nearly 70% of the most probable responses (according to AI) were really Ismo's responses in the real fight. This result is promising in terms of entertaining and believable behavior.

Figure 9. Example: Photos of moves and a timeline with Ismo's actions, the opponent's actions and the AI's prediction of the next action.

In terms of behavior sharing, this kind of modeling enables completely new way of playing games: Use is no longer seen as end-user, but more like co-producer. When AI's can be easily taught and shared like video clips today, the expectations of human-like AI behavior can be partially fulfilled. The possibilities of behavior modeling do not limit on sports games. In fact, in certain level all games, even games like Pac-man can apply shared behaviors.

V. Sharing behaviors in social media

Social media services, such as YouTube and Flickr, contain enormous number of content valuable for professional purposes. If the requested theme can be effectively searched or recognized, teacher can easily construct the course material from social media sources. However, the search engines are not optimal for professional purposes: Search engines can list numerous pieces of content that matches more or less perfectly to keywords. After search there are thousands of pieces of content to check manually if they really fit to the requested subject.

A common method to increase information accessibility in social media applications is tagging. However, when tags are used only as single words, we easily end up to information overload. Furthermore, we do not have standardized way to tag content. In fact, tagging is very subjective and more research is needed in order to improve user experiences and information retrieval in social media.

In this study the user generated AI methods were extended to learn individual information retrieval processes. The main difference between Teachable Media Agents and game AI's in previous sections is in philosophy of learning. When AnimalClass AI and sports game AI were taught in terms of inductive learning, the Teachable Media Agents are taught in both deductive and inductive means. Technologically and computationally the agents are based on similar Semantic Neural Networks.

At the beginning of the use, the end user gets his/her own agent, with which the user interacts. This personal media agent utilizes some pre taught agents (AI's) available on the system. Pre-taught agents reads social media services and organizes the information into databases and they cannot learn more. Therefore end user interacts only with personal agent, that builds all personalized semantic networks. These personalized semantic networks consist of relations between concepts found from tags, titles and comments. The pieces of contents are connected into one or more concepts in this high level semantic network. These agents can learn by the feedback of evaluations made by the end user. In other words, personal agents tries to match the high level conceptual structure and user taught conceptual structure. The idea behind the search is relatively close to image recognition with neural networks where images are replaced by concept maps.

The use case, in brief, is following: At first user describes the subject in focus by typing several key concepts (tags maybe) into UI's definition field, for example 'eyetracking and heatmaps'. Secondly, the first types of agents start to search all possible content related to keywords. Currently search is limited to YouTube, Flickr and Slideshare but new media services will be added on the list. The data received from these media services will be indexed and prepared for later use.

According to this raw data, the personal agent forms a high level semantics related to this task. In figure 5, the most relevant tags and their relations are visualized as tag cloud. Additionally to traditional tag cloud, this one is computed by applying cluster analysis in determining the places of the tags. This ensures, that neighbor tags are strongly related to each other. In traditional tag clouds, the tags are in random order. Furthermore, the tags that have strong explanative power are placed into red background.

Figure 5. Visualization about context formed by eyetracking and heatmaps -tags.

The agent constructs a rank ordered list about content according to semantic relations (figure 6). The user can evaluate the search results by clicking + or – symbols. After evaluations, the semantics will be re-computed. In general, the computing related to semantics are relatively heavy processes. Therefore the semantics are not necessarily computed after every evaluation: the semantics are re-computed in every 3-5 minutes. Evaluations are used in order to determine irrelevant tags and decrease their importance in semantic and in content rank.

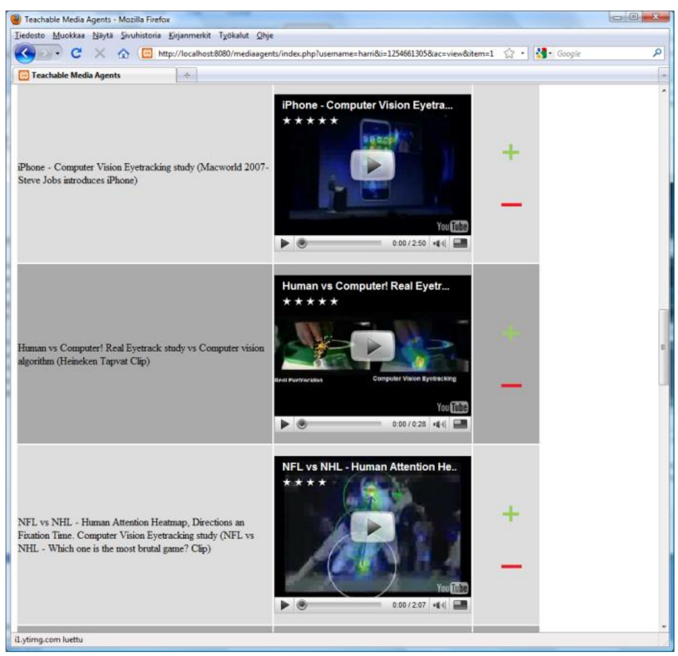

Figure 6. Screenshot from Teachable Media Agents UI: Semantically ranked clips from YouTube.

The semantics learned by personal media agent evolves through all assigned tasks: The learned semantic context is always a background for new tasks. This feature can be used to make effective agents for a certain limited search domain. On the other hand, when we switch to completely different search domain, we can receive interesting results.

In figure 7 the previous tasks were taken further by assigning a new task related to ‘contemporary arts and Picasso’. From the visualization we can see that word contemporary is related to words entertainment and modern while arts -tag is related to context of martial arts. Picasso is related to tags like artist and painter. In the visualization, the causes of the previous tasks can be seen, but the red-background area remains the same in most cases.

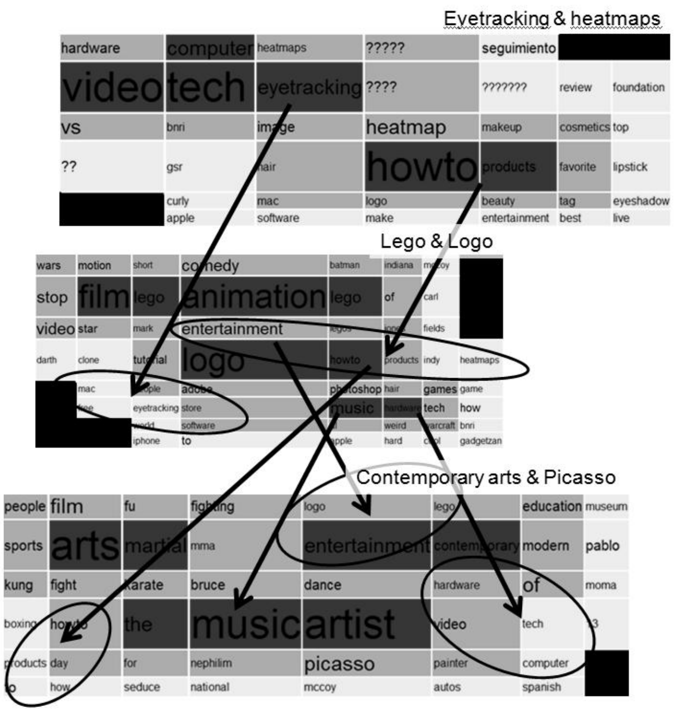

Figure 5. Visualization about context formed by previous tasks and ‘contemporary arts and Picasso’ -task. The semantics will evolve during the use. Each task and evaluation refines the semantics that effects to rank orders of the content. If new tasks are form completely different contexts, like in example, the causes can be seen in semantics.

VI. Conclusion

In the near future user generated behaviors can be developed and shared as all other user-generated content. Furthermore, game developers can design interfaces that enable users to teach versatile behaviors. User-generated behaviors can, e.g. replace AI controlled opponents or extend player's own team. Taught behavior model could be shared on the web. Games and/or developers can upload user-generated behaviors either as AI updates and extensions, or in a development phase. From a game consumer point of view, the most interesting part is in developing behaviors, sharing them and finally playing with them, or against them. Of course, simulated battles could be easily constructed within such a framework.

According to studies, users can relatively quickly and easily teach behavior to a game character. Furthermore, it has been determined that the character's behavior or competence is relatively similar to behavior in the real world, which means that character behavior is believable. In terms of theory about existence of finite number of agents, we can say that our modeling meets the criteria of unity as every agent is an entity itself. Also, the criteria about existence is answered, when every agent exists even it does not have a physical characteristics. Furthermore, every agent is different from others in what it is (whoness) and different especially in a way a user has taught the agent. However the criteria about acts depend on user: Nevertheless, every agent communicates in a state of direct knowledge with other agent, it cannot happen without user’s will: User decides about sharing the behaviors.

In terms of conceptual learning, the AI in AnimalClass emulates the way people learn: learning is about concepts and their relations. The behavior modeling makes it possible to model conceptual learning and thus uncover the frequencies, dependencies and patterns behind conceptual change and learning transfer. These results show the strengths of sharing behaviors: without capabilities of sharing the behavior, the kids wouldn’t spend that much time on school disciplines. On the other hand, if kids like the idea of sharing behaviors in an educational game, they would definitely love it in an entertaining game.

As mentioned earlier, the sports games comparisons are made only in terms of being believable behavior. One future branch of research could be in the field of applied sports science. It would be interesting to study how useful this kind of behavior modeling is for athletes and their coaches. What if sports media consumers and fans could be used as observers? By committing and rewarding the audience in this way, a specific sport business would most likely increase its entertainment value.

Problems related to information retrieval or semantics are widely studied, but not from learning point of view. By combining theories about cognitive psychology of learning and machine learning, we could make a completely new approach to decrease information overload. Teachable Media Agents are currently prototypes and according to preliminary studies, we can say that simulating human way to learn fits for this purpose.

This study was done in order to study the possibilities of conceptual learning in educational games, sports games and social media applications. The observed similarity between an artificial behavioral model and real world behavior shows the strength of the framework in producing believable behavior. One recognized challenge in applying complex computing to game AI's is time: game AI's are expected to be fast;

confusing pauses are not allowed. This means that the speed of AI must be increased. After this, the user generated AIs are ready to be embedded into a "real time" game application.

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