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## An empirical evaluation of a serious simulation game architecture for automatic adaptation

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**Abstract:** This paper presents an architecture designed for serious simulation games to automatically generate game scenarios adapted to player's level and knowledge. We detail two central modules of the architecture: (1) the player model and (2) the adaptation module. The player model estimates the current knowledge of the player using a Bayesian Network (BN). The evidence variables in the BN are assigned through the observation of player's actions and the current state of the simulation. Considering the estimated player's knowledge and skills, the adaptation module uses automated planning algorithms to dynamically adjust the parameters of the simulation, in order to generate scenarios that will be well suited to improve player's knowledge and skills. We implemented our proposed game architecture in a simulation serious game named Game of Homes. The purpose of this game is to teach the basis of real estate. The player is a virtual real estate broker in a city who has to seek for brokerage contracts, estimate the value of houses, fix asked prices, perform visits, and close the deals. The player competes with other brokers driven by artificial intelligence (AI). We conducted a pilot experiment with human participants (N=10) to validate our architecture in Game of Homes. On day 1, participants were asked to take a pre-test about real estate skills taught in our game. On day 2, participants played Game of Homes for approximately 90 minutes and then filled up a motivation questionnaire. On day 3, participants took a post-test. Preliminary results show that in addition to induce strong motivation among the players, Game of Homes significantly improved real estate skills between pre-tests and post-tests. Results suggest that our serious game architecture allows (a) to induce learning process by providing content adapted to the player progression and (b) to keep the player motivated and interested during the game by adapting the challenge and providing new content.

**Keywords:** player model, game adaptation, game scenarios, serious simulation game, assessment in games-based learning.

### 1. Introduction

Serious games can be defined as computer-based learning environments, which are built on the model of video games. There are numerous kinds of serious games, as there are for video games. This paper focuses on serious *simulation* games. Simulations allow the creation of real-world scenarios in which the player can experience a variety of situations, apply acquired knowledge to many new contexts, and use different strategies to achieve goals (Gredler, 2004). Furthermore, in game simulations, "consequences for one's actions occur in the form of other participant's actions or changes in (or effects on) the complex problem or task the student is managing", and this happens in real time (Gredler, 2004, p. 574). We believe that simulation games are appropriate to develop expertise in a domain by generating realistic real-world scenario in which gamers are cognitively as well as motivationally engaged at a deep level.

Maintaining motivation is essential in both gaming and learning (Mayer, 2011). A bored player can easily keep doing irrelevant actions or even worse, he may give up the game (Baker et al, 2010). Moreover, in many video games and serious games, the player evolves through scenarios including the same elements with the same features, which become rapidly understandable for him. He is then more likely to "game the game" (Baker et al, 2006). A simulation should provide unique scenarios including elements with particular features. Furthermore, behaviors of Non-Playable Characters (NPC) in the simulation could always not only be new to the player, but also challenge him (Beaudry et al, 2010). Simulations allow novelty of scenarios in serious games that should arouse curiosity, motivation and a feeling of control.

Many video games and serious games are based on scripted scenarios, in which the progression of the story and levels are predefined (Schell, 2008). This approach is certainly easier to code and provides control of the learning process in the game by designers, as the game progression is made to fit the majority of learners. However, it can also be a limitation, because it does not take into account the variety of learners, who have different prior knowledge in the domain of expertise, and different learning styles, in both quality and speed (Lopes and Bidarra, 2011). Serious games aim to teach specific content to each player as well as to entertain him, in order to improve his learning by keeping him interested in the game. To do so, they need to fit each player characteristics, by providing more difficult learning contexts to expert players to keep them interested, or by providing easier learning contexts to beginner players to prevent them to give up the game. Moreover, in case of complex domains of expertise, it is often impossible or too long to predict all events that could occur. Game scenario adaptation is an important feature to improve the gaming experience as well as the learning process. Adaptation in serious games should provide a better and a faster way to learn among each player.

Adaptation in video games and serious games was proposed by some authors who mainly focused on challenged adaptation in games (Lopes and Bidarra, 2011; Beaudry et al, 2010). Others focused on adaptation of narrative scenarios in serious games (Li and Riedl, 2010), and adaptation of pedagogical scenario in serious games (Niehaus and Riedl, 2009). Very few of these study proposed, in addition to a model or an architecture of adaptation in games, an empirical evaluation of generated scenarios. This evaluation is essential to confirm the benefits of adapted pedagogical scenarios over scripted scenarios.

In this paper, we propose an architecture for serious simulation games which allows real-time generation of learning scenarios adapted to the player. We then present implementation of our architecture in a serious simulation game we designed, called Game of Homes. Finally, we present an empirical evaluation of our architecture in Game of Homes.

## 2. A Serious Game Architecture for Automatic Adaptation

We designed an architecture, which apply to serious simulation games and allows the generation of adapted scenarios. Similarly to simulation games, the system implemented regarding our architecture generates one unique level composing the entire game session. Therefore, the system does not have to recreate a complete new world each time a new concept has to be taught. Our architecture allows the game system to modify the evolution of the simulation and thus creates new situations that will change the way of playing. This dynamic evolution of the simulation world represents the automatic generation of game scenarios to teach and train the player. Figure 1 shows the overall architecture for automatic adaptation, which is mainly composed by the player model and the adaptation module.

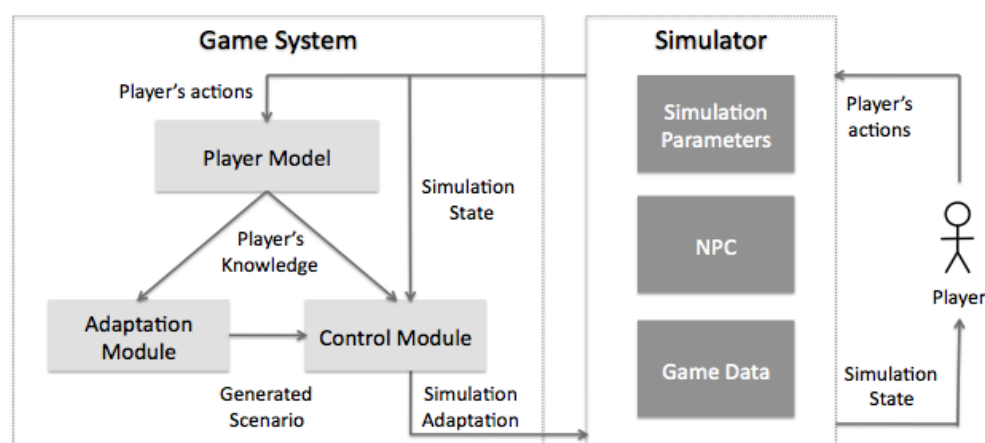


Fig. 1 Our serious simulation game architecture.

### 2.1 The Player Model

The player model represents the player's knowledge about the game and the domain of expertise to be learned. Its role is to estimate in real time the current knowledge of the player. When playing a serious game, there are two kinds of knowledge: the knowledge about gameplay mechanisms and the knowledge about the

domain of expertise. In order to assess the knowledge about gameplay, which is easily assessable by the game, the game system observes player's actions in the game. If he performs well, we can easily deduce that the player understands how the game works.

Estimating the knowledge about the domain of expertise is more complex, because we cannot directly observe the knowledge state of the player. So it is not possible to directly deduce if the player has learned the content to be learned only by checking game actions. To estimate this kind of knowledge, the player model is using a Bayesian Network (BN). With the BN, the game system is able to infer a belief about the player's knowledge, estimates players' level in the game, and deduces possible mistakes made by the players, by combining player's actions with other game elements like player's statistics or prior encountered game situations. It provides the probability that the player has acquired a specific knowledge by inferring an update level and state of knowledge among players. Figure 2 shows a generic model of the BN in our architecture.

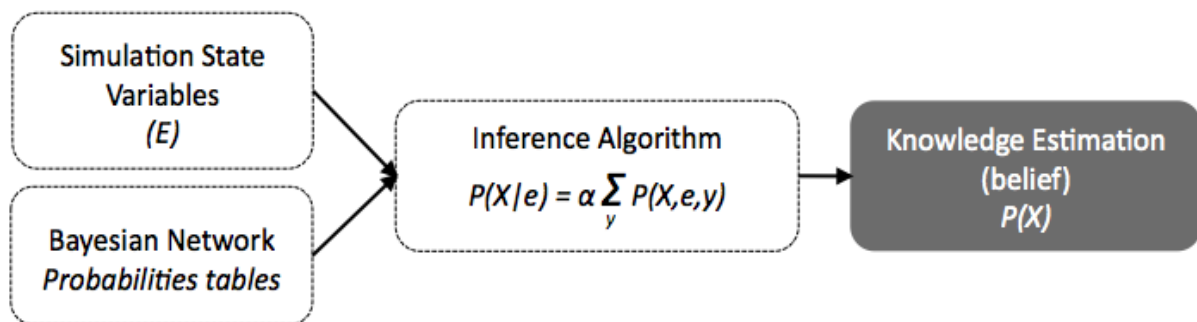


Fig. 2 Role of the Bayesian Network (BN) in our architecture.

The design of the BN needs a previous work of modelisation of the domain of expertise, in order to extract relevant knowledge to acquire from the domain of expertise. As every domain of expertise contains many complex skills, it is important to sparingly choose the skills to implement in the game. The more skills are chosen, the more complex the BN will be. Once the skills are chosen, we suggest to intuitively assign probabilities for each skill according to specific actions in the game (Probabilities tables). These probabilities can then be adjusted while testing the game.

## 2.2 The Adaptation Module

The adaptation module adapts game contents in order to improve the player's learning and to keep him motivated. Game contents are represented by the simulation as such, more specifically by simulation parameters, NPCs and game data.

The adaptation module decides what is the best long-term strategy to choose to both speed up and enhance the learning process. AI planning enables the selection of a sequence of actions or situations – also called plan – to achieve a goal. Every action has preconditions (needed to execute an action) and effects (produced by the action). In our architecture, planning consists on discovering the best sequence of in-game situations knowing the current player's knowledge state, in order to achieve better and faster learning of the domain of expertise. This sequence of in-game situations represents the game scenario, which represents the pedagogical scenario as well. The adaptation module decides which skills the player first needs to learn, and how to optimize the learning progression in the game. The planning process is represented as such in the adaptation module:

- states: player's knowledge estimation;
- actions: in-game situations which include a pedagogical goal to achieve (previously designed);
- actions preconditions: prior knowledge needed to achieve the situation;
- actions effects: supposed impacts on the player's learning.

Each planned scenario generated by the adaptation module is composed by these elements. It is important to note that in-game situations or actions are not predetermined as this point; their values will be fixed by the control module. This feature in the adaptation module allows more flexibility in scenario generation and guarantees generation of a unique scenario every time. We suggest to present a default scenario to the player in order to initialize the estimation of the player's knowledge. At a certain point in the game, the adaptation module generates a pedagogical plan according to this preliminary evaluation.

### 2.3 The Control Module

The role of the control module is to execute the plan generated by the adaptation module. When preconditions of the next plan action are satisfied, the adaptation module changes game contents according to the player's knowledge level. The control module then modifies in real time the simulation parameters in order to present new situations to the player, to guarantee the stability of these situations, to change NPCs' behaviors, and to provide help to players in need. If the preconditions are not validated, the control module asks the adaptation module to generate a new plan more adapted to the player's current knowledge state.

Our architecture includes in the simulation the presence of NPCs, which play the same role as the player and therefore act as direct opponents. We argue that the presence of opponents in serious simulation games guarantees challenge for players and is important to keep their motivation high. The control module can modify NPCs' behaviors according to the player's current level of expertise, which can be for example aggressive for expert players, assuring a fair challenge for them.

At last, the control module consults the adaptation module in order to identify the player's mistakes in the game. According to these mistakes, the control module commands the display of help messages to the player. Our architecture includes two kinds of help messages:

- help about gameplay, or how to play the game;
- help about knowledge, or what knowledge to have to succeed in the game.

This adaptation allows the game system to efficiently adapt the game on the entertainment part or the learning part. The game environment renews itself and therefore engages the player and keeps him motivated. Moreover, we are also able to create very specific educational situations to evaluate players' knowledge.

### 3. Game of Homes

To validate our architecture, we developed the serious simulation game named Game of Homes. This game aims to teach the basics of real estate transactions. These basics include, among other skills, how to choose a brokerage contract, how to evaluate the price of a property, and the different steps of a sale process. The game takes the form of a virtual world simulation; it is not divided into different game levels as it consists of a single level. Figure 3 shows the graphical interface of Game of Homes.

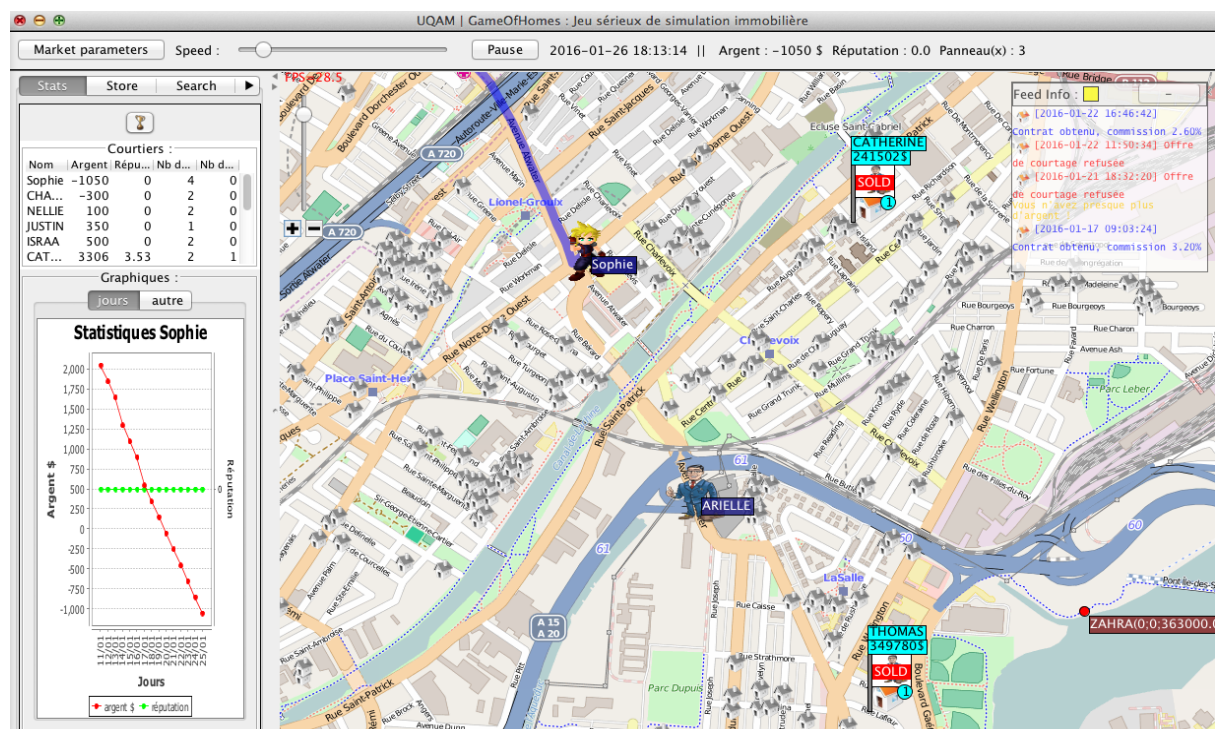


Fig. 3 Screenshot of Game of Homes.

In the game, the player plays the role of a real estate broker whose goal is to become the best broker in a given city, represented in a city map format. To accomplish this goal, he needs to earn as much money as possible and keep a good reputation. He can move his avatar on the map by double-clicking on the desired location. The game focuses on the selling part of real estate transactions. In the game, the player offers his services to support homeowners in selling their property. He negotiates with homeowners to get a brokerage contract, assesses the property value, and manages the sale by carrying out advertising, giving house tours to potential buyers, adjusting the selling price, and finally negotiating with buyers and recommending offers to the seller. When the house is finally sold, the broker earns an amount of money equals to the sale price multiplied by the commission rate. His reputation level is also adjusted depending on how he performed. During each activity, the gameplay allows the player some flexibility: for example, he can choose to fix the selling price higher if he believes he can sell to a higher price. Hence, the player can execute various strategies all along the game, and appreciate the outcomes of his actions.

To make the game more realistic and improve learning, the simulated environment is based on real data. The game takes place in real cities represented by maps that are imported from the OpenStreetMap project. The houses characteristics appearing in the game are derived from real public houses listings. We try to provide an environment close to reality as much as possible to allow the player to learn more about the selected city and its market reality (for example, which sectors cost more and which ones are cheaper). However, the virtual environment is not just a copy of a real city market. The environment evolves and each game is unique: for example, the features of properties are never the same, neither are the owner's requirements or the buyers' needs. This allows us to provide a large variety of scenarios, which correspond to in-game dynamic changing situations of this virtual environment.

To make the game even more challenging, the player is not the only real estate broker in the game. There are NPCs, which represent other brokers sharing the same goal as the player, and therefore act as direct competitors. In addition to competing against other brokers controlled by the game, the player needs to interact with other artificial agents. There are therefore three types of artificial agents in the game: sellers, buyers and brokers. The rules of each type of agent are inspired from observable behaviors from real-world expert brokers. To make their decisions realistic and unpredictable for the human player, a few rules integrate random decisions.

### **3.1 The Player Model in Game of Homes**

Before conceiving the player model, we collected relevant documents about real estate transactions, which include professional websites, real estate websites, regulation texts, government websites, etc. The resulting model focuses on procedures which determine skills to be developed in the game, concepts and their definition needed to apply skills, principles which determine strategies to be acquired, and facts which determine examples presented in the serious simulation game.

Figure 4 presents the Bayesian Network (BN) implemented in Game of Homes. We choose to focus on two main skills: (1) Obtaining relevant brokerage contracts, and (2) Estimate the selling price. The BN estimates the probabilities that the player acquires them. Because of the non-observable characteristics of these skills, the BN needs to use evidence variables, which can be either players' actions or simulation states (or both), to estimate these skills. We build probabilities tables for each skill.

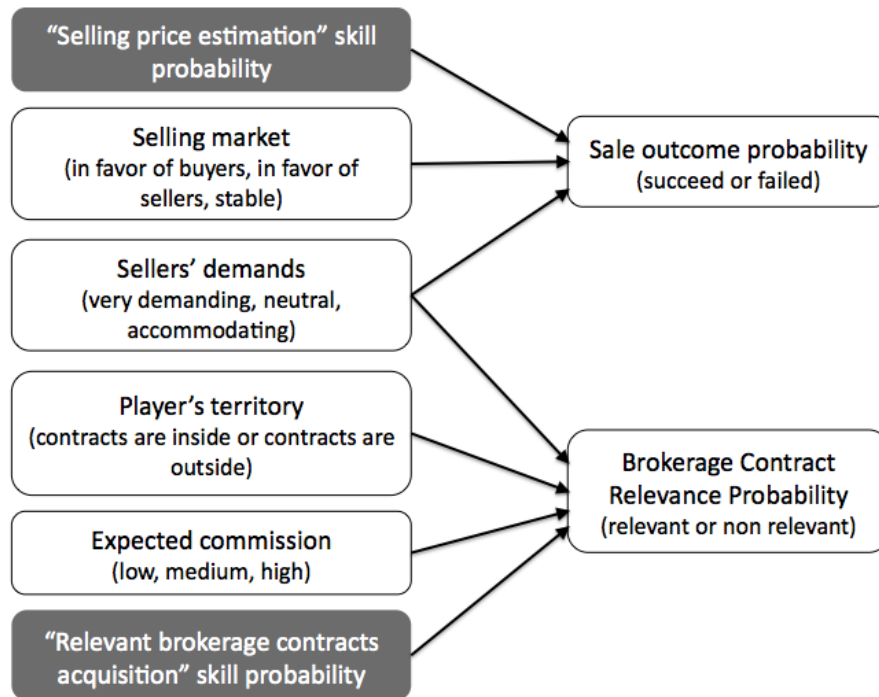


Fig. 4 The Bayesian Network in Game of Homes with estimated skills (grey rectangles) and evidence variables (white rectangles).

The BN compares each player's outcome action to the probability of action in the game to success (outcome of the sale property or relevance of the brokerage contract). This probability depends on the simulation parameters (selling market, sellers' demands, player's territory, expected commission) and the player's knowledge related to this action. By using the inference principle, the BN is able to determine the current player's knowledge. For example, if a player concludes successfully two sales properties (Sale1, Sale2) and failed one other (Sale3), the BN calculates the probability that the player knows how to estimate a selling price (called Skill1 here) ( $P(\text{Skill1})$ ) following this formula:

$$P(\text{Skill1} | \text{Sale1}, \text{Sale2}, \neg \text{Sale3}) = \alpha P(\text{Sale1} | \text{Skill1}) P(\text{Sale2} | \text{Skill1}) P(\neg \text{Sale3} | \text{Skill1})$$

where  $\alpha$  is a normalized factor.

The set of probabilities calculated by the BN are used by the adaptation module to decide the sequence of scenario best fitted the player's current knowledge.

### 3.2 The Adaptation Module in Game of Homes

We implemented the decision module with generic game high-level actions or scenarios that the control module has to specify. Eight different game scenarios can be planned by the decision module: two scenarios which aim to teach the basics of the two skills "Obtaining relevant brokerage contracts", and "Estimate the selling price", two scenarios which aim to develop these skills at the advanced level, two scenarios which aim to develop these skills at the expert level, and two scenarios including these two skills, one validating the understanding of the selling process and the management of several contracts, the other one testing if the player manages the two skills in crisis situations. This structure allows the adaptation module to target skills that need to be learned or improved among the players. The decision module can then generate a personalized pedagogical plan adapted to his knowledge level and his motivation level.

As shown on Figure 1, the simulation content in our architecture is represented by the simulation parameters, the NPCs and game data. All these elements can be adapted by the adaptation module:

- *Simulation parameters:* Modifying simulation parameters consists in changing how the player acts in the game (forcing him to take risks, leaving him the opportunity to be greedy). As an example of adaptation, the market can be changed, which will change the strategy to adapt to progress in the game, or the global parameters can be modified (how many different contracts brokers can have simultaneously, if there are special extra charges on sales, etc.). Although the actions of the game remain the same, the way to do them will differ.

- *NPC*: Changing the behavior of NPC mainly varies the challenge. It allows the control module to adapt the global difficulty in the game to the player level. For example, it can make the brokers more competitive or conversely weaker to get new contracts. It can also make buyers more discerning, sellers greedier, etc. The entertaining goal for the player is to become the best broker of the city, and these changes help the game to make this goal neither too easy nor too difficult to achieve in order to maintain the challenge as the player progresses.
- *Game data*: Changing the game data renews in-game situations. It allows the control module to create unique situations each time the player plays. For example, the game can change which houses are on the map, houses characteristics (according to the reality), in which city or part of the city the player plays, etc. In addition to renewing the game and making each game different, it also allows evaluation of the player on specific cases, which is an advantage for the teaching part.

## 4. Empirical Evaluation

We conducted a pilot experiment to empirically evaluate our serious simulation game architecture. We mainly want to verify that (1) players learned about real estate after playing Game of Homes, and (2) players felt challenged and motivated while playing Game of Homes. We hypothesized that (1) global score and scores for specific skills will be higher for post-tests than pre-tests (quantitative analysis), and (2) each score composing our motivation questionnaire will be higher than 3.5 / 7.

### 4.1 Method

#### 4.1.1 Participants and design

This study was conducted with 10 participants who were recruited by advertisements placed in a campus university. The participants were between 23 and 34 years old (Mean age 30; SD 3), 6 men and 4 women), and were rewarded with 20 dollars for participation. We made sure that participants were not or had not been owners, because our serious simulation game aims to teach the basics of real estate.

The study used a pre-test/treatment/post-test design. During the treatment phase, the participants were asked to play Game of Homes displayed on computers, during 90 minutes. The pre-test and post-test were designed to assess the two main skills taught in Game of Homes: (1) Obtaining relevant brokerage contracts, and (2) Estimate the selling price.

#### 4.1.2 Procedure

The study was conducted during three consecutive days. Each session took place in a regular classroom equipped with computers.

- On day 1, participants were asked to take a pre-test about the two real estate skills taught in our game. This test was administered in written form that the participant had to fill in. It took on average 64 minutes to complete the pre-test.
- On day 2, participants played Game of Homes for approximately 90 minutes and then filled up a motivation questionnaire. At the beginning of this session, instructions about how to play the game were presented by trained experimenters.
- On day 3, participants took a post-test, also about the two real estate skills taught in our game. Exercises in the post-test were in the same format that the ones in the pre-test. This test was administrated in written form that the participant had to fill in. It took on average 47 minutes to complete the post-test.

#### 4.1.3 Measurement instruments

We chose to build our own measurement instruments for this study. As we wanted to make sure that our participants (1) learned about real estate after playing Game of Homes, and (2) felt challenged and motivated while playing Game of Homes, we conceived learning tests about real estate, as well as a motivation questionnaire adapted to our game.

*Learning pre-test and post-test about real estate.* We designed a pre-test and a post-test which aim to evaluate real estate skills, and more specifically about the two skills targeted in our game: (1) Obtaining relevant brokerage contracts, and (2) Estimate the selling price. The tests consist therefore of two sets of exercises. The first set proposes a city map to the participant displaying properties and their characteristics (real price,

owner's estimate price, quantity of rooms, surface area, agreed commission rate). The participant is asked to choose a precise number of relevant contracts among all available contracts, while justifying their answers (open questions). The second set propose a city map to the participant displaying properties and their characteristics (price of last sale, year of last sale, quantity of rooms and surface area), and a single property with only its rooms quantity and its surface area. The participant has to estimate the selling price for this particular property, while justifying his answer (open questions). At last, additional open questions ask the participant about his strategies used to select relevant contracts and to estimate selling prices. Tests were rated as follow: a maximum of 120 points for the first set of exercises, a maximum of 45 points for the second set of exercises, and a maximum of 55 points for additional questions (total score per test: 220 points).

*Motivation questionnaire.* We designed a motivation questionnaire adapted to our game. Some elements of our questionnaire are based on Malone and Lepper's (1987) work on individual intrinsic motivation while playing a game. These authors described four individual motivating factors: challenge, curiosity, control and fantasy. We also chose to incorporate some relevant elements from motivational models described by Lafrenière et al (2012) and Sweetser et al (2005). At the end, our own questionnaire aims to estimate in our game the feeling of (a) *challenge*: if goals, game level, difficulty, sensation of game adaptability, sensation of pressure provide enough and fair challenge to players (28 items; e.g., "I rapidly understood what need to be done to increase the score", "I felt that the game adjusted the level difficulty to my performance", "I felt nervous while I was playing the game"); (b) *curiosity*: if the game proposes new contents arousing players' curiosity and leads players to explore the environment (10 items; e.g., "The game allowed me to explore different features"); (c) *control*: if the game allows players to make different choices, which lead to significant and meaningful outcomes (9 items; e.g., "I had the feeling that my actions had significant outcomes in the game"); (d) *feedback*: if the game provides relevant and various feedbacks, and if players take them into account (9 items; e.g., "I kept checking my score while playing the game"); (e) *focus*: if the game allows players to focus on relevant elements, and therefore avoid distraction (7 items; e.g., "The game always kept my attention high"); (f) *immersion*: if the game induces sensation of flow (feeling of losing track of time) (6 items; e.g., "I lost the track of time while playing the game"); (g) *skills and game relevance*: if players see the relevance of the game in terms of developed skills about real estate (14 items; e.g., "I had the feeling that I had developed real estate skills after playing the game"). Participants responded to the items on a 7-point rating scale (0 = "Not true at all for me"; 7 = "Completely true for me"). For some items, participants had to write down their answers in sentences.

## 4.2 Results

### 4.2.1 Quantitative analysis: skills improvement between learning pre-test and post-test about real estate

To investigate skills improvement from pre- to post-test, we ran a t-test paired analysis between pre-test and post-test for (a) global score on both tests, (b) score for the first skill "Obtaining relevant brokerage contracts", (c) score for the second skill "Estimate the selling price" and (d) score for strategies about these skills. This t-test paired analysis revealed that (a) participants performed globally better on post-test ( $t(9) = -3.75, p < .05$ ) than on pre-test; (b) participants performed better on post-test for the first skill "Obtaining relevant brokerage contracts" ( $t(9) = -2.6, p < .05$ ) than on pre-test; (c) there was no difference in performance between pre-tests and post-tests for the second skill "Estimate the selling price" ( $t(9) = -0.92, p < .38$ ); and (d) participants performed better on post-test than on pre-test in terms of strategies ( $t(9) = -5.58, p < .01$ ).

Figure 5 illustrates that participants performed globally higher in the post-test comparing to the pre-test. Furthermore, it reveals that the average increase in performance from pre- to post-test is significant for the first skill "Obtaining relevant brokerage contracts" and strategies in the game, even though there were no significant differences for the second skill "Estimate the selling price".



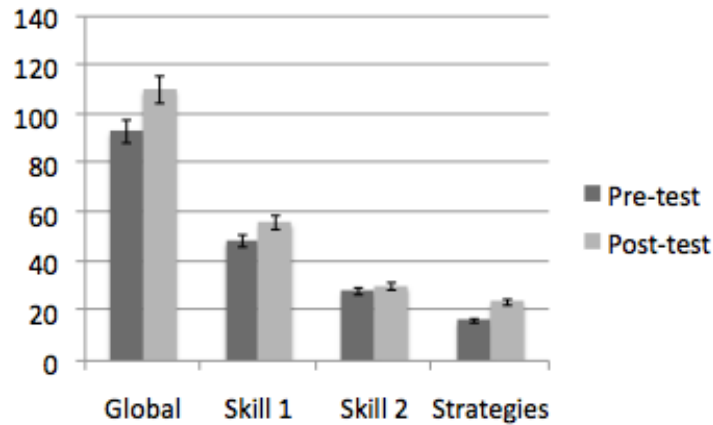


Fig. 5 Differences between pre-test and post-test scores.

#### 4.2.2 Qualitative analysis: motivation induced by Game of Homes among players

We compiled results from all motivation questionnaire and present here the main qualitative results. Participants mostly felt motivated while playing Game of Homes, and more specifically expressed that: (a) the game was challenging, because they clearly understood goals in the game (mean: 5.4/7), they felt that the game adjusted difficulty to their level (mean: 4.5/7); they sensed global adaptability of the game (mean: 4.7/7) and they felt pressure while playing the game (mean: 3.97/7); (b) the game induced feeling of curiosity among players (mean: 4.39/7); (c) they sensed that they had control while playing the game (mean: 5.13/7); (d) feedback in the game was perceived has meaningful et useful by players (mean: 4.63/7); (e) they were focused while playing the game (mean: 5.55/7); (f) they had the feeling they were involved in the game (mean: 4.98/7), and even though they all played approximately for 90 minutes, it seemed to them they had played 70 minutes on average; and (g) they had developed real estate skills after playing the game (mean: 5.12/7). Figure 6 illustrates that participants felt globally motivated and challenged while playing Game of Homes.

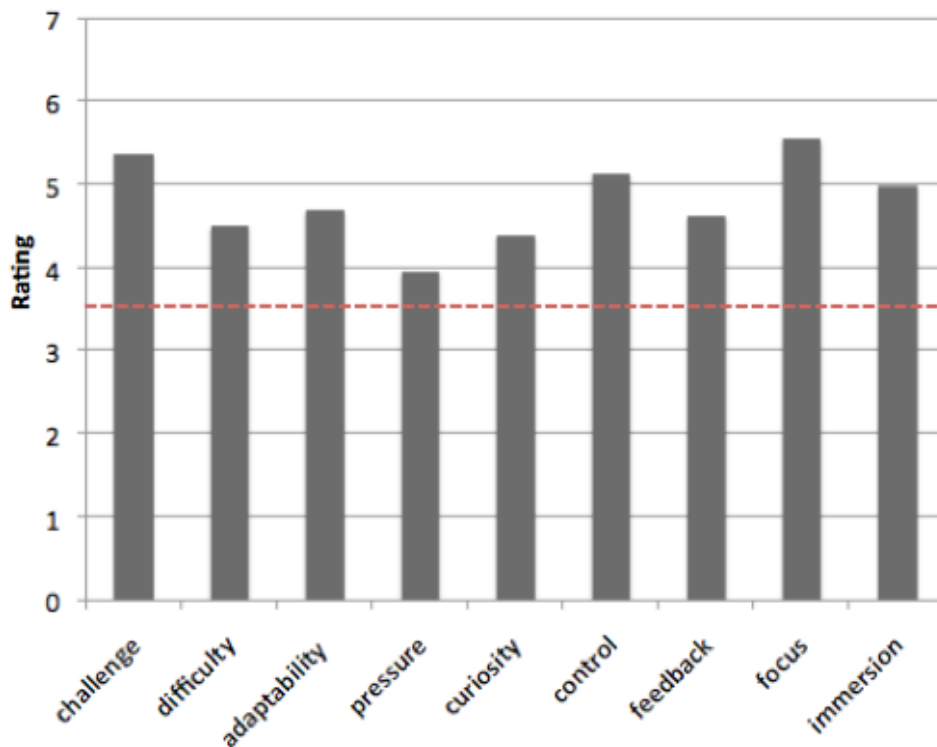


Fig. 6 Sensation of motivation among players (y axis represents rating scale scores).

## 5. Conclusion

In this paper, we addressed the problem of adapting game content to a player in order to improving the learning process and keep the player motivated while playing a serious simulation game. Because trying to predict the majority of game situations and to propose a content adaptation in each case are time-consuming, laborious and complicated, we proposed an approach based on Bayesian network and planning algorithm. This architecture was conceived to be generalized to other serious games quite easily.

Using planning instead of scripted adaptation is both profitable for players and developers. It is easier for developers to maintain the game when it was modified and it is quicker to cover the majority of game's situations. The progression is more pleasant for the player because the content is closer to his expectations, and in the case where he replays the game, the game remains interesting and adapted to his new level and he will always meet new situations.

We conducted an experiment which 10 participants played the serious simulation game called Game of Homes implemented with our architecture. Results showed that participants globally improved their skills in real estate after playing Game of Homes. Furthermore, the serious simulation game kept players motivated and challenged. These results suggest that automatic generation of pedagogical scenarios in serious simulation game enhance learning. Indeed, players developed rapidly (during a 90 minutes game session) basics concepts of real estate domain, while enjoying it. We plan to conduct more experiments to analyze players' logs in details, in order to study different plans generated by the planning system in our architecture.

As it has been mentioned in the introduction of this paper, many games and serious games are designed with predefined scenarios, and we choose to highlight the benefits of automatically generated scenarios. As future work and in order to confirm that adapted scenarios in serious games lead to better and faster learning, we will compare players' learning in both conditions: scripted scenarios and automatically generated scenarios.

## References

- Baker, R. S., Corbett, A. T., Koedinger, K. R., Evenson, S., Roll, I., Wagner, A. Z., Naim, M., Raspat, J., Baker, D. J., and Beck, J. E. (2006). "Adapting to when students game an intelligent tutoring system". In *Proceedings of the Intelligent Tutoring Systems Conference* (pp. 392-401). Springer Berlin Heidelberg.
- Baker, R. S., D'Mello, S. K., Rodrigo, M. M. T., and Graesser, A. C. (2010). "Better to be frustrated than bored: The incidence, persistence, and impact of learners' cognitive-affective states during interactions with three different computer-based learning environments". *International Journal of Human-Computer Studies*, Vol 68, No. 4, pp 223-241.
- Beaudry, E., Bisson, F., Chamberland, S., and Kabanza, F. (2010). "Using Markov decision theory to provide a fair challenge in a roll-and-move board game". In *Computational Intelligence and Games, 2010 IEEE Symposium on* (pp. 1-8). IEEE.
- Gredler, M. E. (2004). "Games and simulations and their relationships to learning". *Handbook of research on educational communications and technology*, Vol 2, pp 571-581.
- Lafrenière, M. A. K., Verner-Filion, J., and Vallerand, R. J. (2012). "Development and validation of the Gaming Motivation Scale (GAMS)". *Personality and Individual Differences*, Vol 53, No. 7, pp 827-831.
- Li, B., and Riedl, M. O. (2010). "An Offline Planning Approach to Game Plotline Adaptation". In *Proceedings of the 6th Annual AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*.
- Lopes, R., and Bidarra, R. (2011). "Adaptivity challenges in games and simulations: a survey". *IEEE Transactions on Computational Intelligence and AI in Games*, Vol. 3, No. 2, pp 85-99.
- Malone, T. W., and Lepper, M. R. (1987). "Making learning fun: A taxonomy of intrinsic motivations for learning". In R. E. Snow & M. J. Farr (Eds.), *Aptitude, Learning and Instruction III: Conative and affective process analyses* (pp. 223-253). Hillsdale, NJ: Erlbaum.
- Mayer, R. E. (2011). "Towards a science of motivated learning in technology-supported environments". *Educational Technology Research and Development*, Vol 59, No. 2, pp 301-308.
- Niehaus, J. and Riedl, M. (2009). Toward scenario adaptation for learning. In *Proceedings of the Conference on Artificial Intelligence in Education : Building Learning Systems that Care : From Knowledge Representation to Affective Modelling*, No. 3, pp 686-688. IOS Press.
- Schell, J. (2008). *The Art of Game Design : A book of lenses* (1st éd.). Morgan Kaufmann Publishers Inc.
- Sweetser, P., and Wyeth, P. (2005). "GameFlow: a model for evaluating player enjoyment in games". *Computers in Entertainment*, Vol 3, No. 3, pp 3-3.