Predicting Leadership during Crisis Management

Abstract — Recording, modelling, analyzing human behavior is an important first step in predicting it. Here we report on a study that utilizes data mining techniques to predict leadership based on game play data. We analyzed 2700 gameplays to examine if we could find a prediction algorithm for leadership that is significant and meaningful. Our results showed an algorithm that leads to an 81% correct prediction of leadership competency, which increased the baseline by 15%. Insights derived from this study could be utilized in designing, for example, personalized learning environments.

1 Introduction and background

Recording, modelling, analyzing human behavior is an important first step in predicting it. This paper reports on a study utilizing data mining techniques to predict a leadership construct based on game play data. The learning objective of the game is to become aware (1) of devilish dilemmas during crisis situations, and (2) of the adopted leadership style in dealing with these dilemmas.

The game (Figure 1) is a Dilemma game [1] that is offered as a training solution for judgment and decision-making in crisis management theatres. In the game the players need to make choices regarding dilemmas during a crisis management scenario and the crisis team is providing information to the dilemma at hand. In fact, all Dutch mayors are trained with this 2D interactive turn-taking narrative game for the last 5 years.

Figure 1: Crisis management Dilemma game

We operationalized three leadership dimensions. Note that these leadership dimensions make sense to the Dutch context but in general indicate (a) an external orientation towards the community / municipality (People person), (b) the organizer of formal decision making processes (Figurehead), and (c) an internal orientation in making sure that internal organization procedures are followed (Administrator). After game play individual feedback (Figure 2) is shared and discussed among peers creating a social dynamic context in which intrapersonal learning takes plays. The debriefing is facilitated and moderated by a trainer.

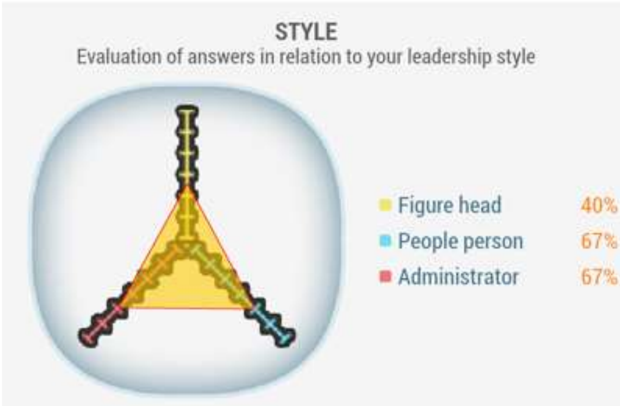

Figure 2: Individual feedback discussed among peers

2 Technical Approach and methods

The Conceptual Assessment Framework CAF-Model [2] was used to map the operationalization of latent traits (student model / leadership model) to the operationalization of assessment tasks (task model) (see Figure 3).

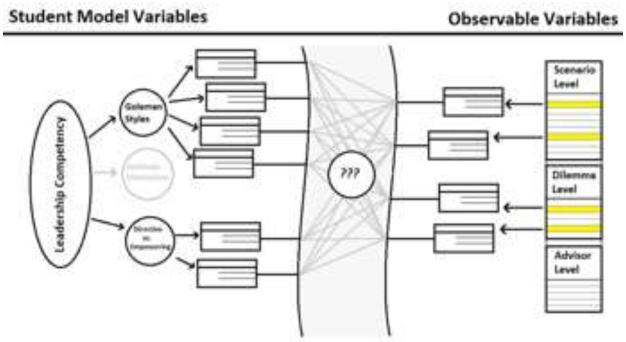

Figure 3: Conceptual Assessment Framework CAF-Model Linking student model variables to observable variables

We used the Waikato Environment for Knowledge Analysis (WEKA) toolbox [3] and several embedded machine learning techniques to predict the leadership classes. Cross validation was performed to define the training and test data set. Basically, the total data set is divided in 10 parts, and every part is the test set in a 10 times run. Our gameplay dataset consists of 2700 played games and each game has 8 dilemmas. Thus, our total dilemma set is 8 x 2700 = 21600 in-stances. Our data log file contains 80 observable attributes per instance from which we extracted 27 meaningful instances that we used for this analysis. This data was captured over the last 5 years over the course of numerous training sessions for professionals in crisis management organizations in the Netherlands.

3 Innovations, research findings, etc

We did some experimentations with the WEKA toolbox and found that several data mining techniques – based on various methods – resulted in different predictive performances. It was found that some models based on the available in-game observable variables resulted in significant better predictions as compared to the baseline (Zero R 65%). Our results showed an algorithm that leads to an 81% correct prediction of a leadership competency class (in this example we looked at the 'Figurehead' competency). In addition, since the data driven approach leads to a good prediction, one may becoming interested in understanding which model parameters (out of the 27) contributed most (Figure 4), and if we can find a reasonable explanation for these.

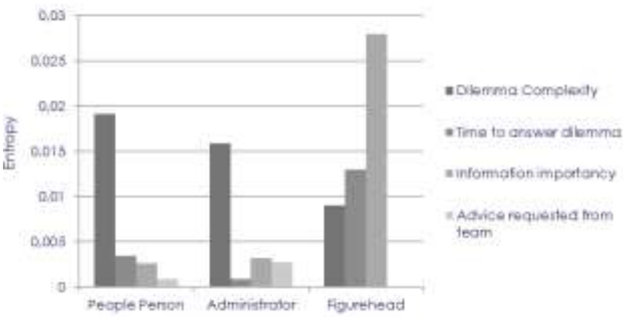

Figure 4. Model parameter contribution; 4 out of 27 available model parameters contributed most.

For example, the model parameter 'information importancy' pops-out indicating that the 'information' provided by the NPCs during game play is considered relevant by the players. Indeed, a Figurehead type of person is one that focuses heavily on the organization of formal decision making processes during crisis management situations. Therefore, it makes sense that all information provided by the crisis management team is considered to be potentially relevant in the decision-making process. Note, that this line of reasoning was provided by a trained game scenario writer who is also subject matter expert in this domain.

Our aim is to develop robust predictive models on the basis of which learning instructions could be given to the trainees during game play to increase their learning journey. For example, providing on-the-fly recommendations to the player depending on the learning goal in order to maximize his/her learning experience. This can be done by suggesting alternative course of actions (e.g. using scaffolds, instructions) to the player / trainee. We are currently working on this in more detail in a related study [4].

In addition, another possible application is the comparing analyses and prediction of leadership between geographical regions. For example, to examine how leadership differentiates across safety and security areas, provinces, states or even countries. An impression of such data visualization is depicted in Figure 5.

Figure 5. Leadership across geographical areas

Further, the model driven Dilemma game engine includes an authoring tool to adjust, refine or build new Dilemma scenarios. For example, the Fog of War game (Figure 6) [5] has the similar game flow, however, the background visualization, NPCs and scenario narrative, feedback model is applied to the military domain. In this case, leadership unfolds in terms of diplomacy, defense and development dimensions (3D comprehensive approach model). One may gather game play data for this game and utilizing our analyzing pipeline for leadership predictions in for example, the Naval domain.

Figure 6: Fog of War Dilemma game

4 Lessons learned

Since this was an exploratory study, utilizing machine learning techniques actually asks for a variety of experts. For example, the learning architect and trainer need to specify what they want to know in terms of competencies or skills. How to assess these in order to provide adequate feedback to the trainee. This requirement leads to the game developer who needs to design and implement the data models from the learning perspective to capture a set of meaningful predictors. The data analytics expert needs to understand the learning goal and game model to apply machine learning techniques (or deep learning frameworks). Thus, fit for purpose predictions based on machine-learning algorithms depend on domain knowledge in the specific field of application.

5 Conclusions

We showed a game based learning solution for training leadership skills during crisis management scenarios. Data logs of 2700 game plays were used exploring machine learning techniques for predicting leadership. We found an algorithm that outperformed the baseline. The potential that machine learning (and deep learning frameworks) may bring could be used to design, for example, personalized learning experiences.

References

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