Predicting the result of a Managerial Game using a Multi-Label Prediction Models

Sandro Radovanović, Nikola Zornić, Boris Delibašić, Aleksandar Marković, Milija Suknović
University of Belgrade – Faculty of Organizational Sciences
Jove Ilića 154, 11000 Belgrade, Serbia
{sandro.radovanovic, nikola.zornic, boris.delibasic, aleksandar.markovic, milija.suknovic}@fon.bg.ac.rs

Abstract*. The allocation of human resources in the managerial environment is a hard task to perform and to learn. The cost of a real-life experience is very precious. Therefore, companies develop managerial games to provide near real-life experience for decision-makers. The teaching process could benefit if the outcomes of the managerial game could be predicted. Namely, the teacher could adjust teaching materials according to the expected result. Besides predicting an outcome, one would like to predict the emotions of the decision-maker. Having this in mind, we employed multi-label prediction models for prediction an outcome of the game and emotions of the decision-maker. The AUC ranges 0.62-0.66 for the classification of emotions, and ~0.76 for the outcome of the managerial game.*

Keywords. Managerial games, Multi-agent games, Predictive Modelling, Multi-label Classification.

1 Introduction

A complex business environment requires managers to constantly learn, experiment, and gain new insight into how the team would work under some assumptions and how effective a goal can be achieved with the resources at hand. Effectiveness of the team and efficiency of the manager depends on the complex relationships between the skills of team members, characteristics, time and productivity. Real-life expertise and experience can have a high cost of experimenting, and potential cost in time, financial, and human resources. Therefore, one can employ managerial games where managers can employ different strategies, different compositions of teams and other decision-making strategies that can result in better or worse results. This is seen as a winning strategy for bridging a gap between science and decision-making research (von Winterfeldt, 2013).

Having this in mind, one would like to create a teaching strategy to learn the decision-making frameworks as real as they can be. Another benefit of managerial games is for candidate selection. Namely, as a part of the candidate selection process employer can require candidates to play a managerial game. However, one might want to go one-step further. Instead of evaluating teaching strategies and process selection one can predict whether a person will perform the team composition task and solve the problem at hand (Tavcar et al, 2017). In this paper, we learn the predictive model that can predict whether a person will optimally solve the team composition task knowing decision-making strategies, personal characteristics, and experience. Being able to predict the efficiency of the manager and effectiveness of the team one can optimize business performance. Instead of predicting the performance, we will also predict the response of the manager in terms of results. More specifically, after each game manager responds in terms of happiness, anger, surprise, etc. Since the team effectiveness depends on the manager response (Treffers et al., 2019) one would be motivated to predict this as well.

In this paper, we will utilize multi-label predictive models that predict team efficiency in solving a given set of tasks. The reasoning why multi-label predictive models are selected is the fact that it is expected that emotions after the managerial game are associated with the efficiency of the team. More specifically, we expect that predictive performance will be better if the predictive model utilizes information about the relation between efficiency and emotions.

The contributions of the paper are twofold. We propose a multi-label prediction model, which predicts the effectiveness of the team compared to the satisfactory result. Additionally, we predict the emotions of the decision-maker that are as important as the managerial game itself. The second contribution is the inspection of the effects if there are statistical differences between gender and education in winning the managerial game.

The remainder of the paper is structured as follows. In Section 2, significant background research is presented. A literature review consists of two subsections. The first part will explain common decision-making learning approaches in managerial games. The second part will explain what has already been done in the field of data analysis in managerial games and motivate the paper. In Section 3, we will propose the methodology. We will explain the data, multi-label classification, and experimental setup. In Section 4, we will present the results and provide a discussion of the results. Finally, in Section 5 we will conclude the paper and provide a plan for future work.

2 Literature Review

Decisions made by a manager are a result of experience, knowledge, intuition, heuristics, etc. In a gaming scenario, one would like a manager to explain the decision-making process and provide reasoning for a decision. From a decision theory perspective, several approaches can be employed (Wang & Ruhe, 2007). The most prominent ones are going to be briefly explained.

One can find frameworks for explaining decisions based on risk, uncertainty, inter-temporal decision-making or complex decisions. Risk is a condition in which the expected values of a decision-maker for one or more criteria are bound to a finite number of states that occur according to some probability distribution (Hollard et al., 2016). Knowing the framework decision-maker can take into account states and recalculate expected utility and, thus, make a better decision.

Sometimes, the decision-maker does not have all the information needed to calculate the expected utility of the decision. In an example, the decision-maker lacks the information about the possible states and, thus, cannot calculate the likelihood of each state and its value. In that case, one needs to invest more resources to obtain enough knowledge and make a better decision. This framework is called decision making under uncertainty (Sproten et al., 2018).

Although these two frameworks are the most important ones in the business teaching and economic theory one can find newer frameworks that take into account the sequence of the decisions as a base for better decision making. This is called inter-temporal decision processes (Namboodiri et al., 2014). The idea is that the reward of action is having a delayed effect. Therefore, one must add time perception to achieve a larger expected reward in a limited period. (Li et al., 2018; Rambaud & Takahashi, 2019)

In a complex decision-making situation (De Bruijn & Ten Heuvelhof, 2010) there is no correct choice. Instead, multiple alternatives warrant further experimentation before committing to a single approach. Decision-makers must use a systematic approach to frame the problem and divide it into simpler ones.

The second part of the literature review presents papers regarding data analysis for managerial games. With the emergence of the big data paradigm, the shift from the behavioural analysis of a decision process to analytical analysis gained strength. Several research areas emerged such as computational social choice (Chang et al., 2014). Computational social choice has many tasks, one of them being understanding the decisions of a person or a group that affect the behaviour of the whole group (i.e. team, organization, or even a country). One of the first efforts to understand the decision-making process is presented in (Yu et al., 2014). Multi-agent game platform *AgileManager* was used to help understand how people delegate tasks to their employees. The platform gave the context of each task and set of resources, i.e. employees with characteristics, such as competence, capacity, skills, and working days and the task was to finish the project with satisfactory results. However, to have a teaching moment every resource has associated uncertainty. This means that the results of the same setup of a team will yield different results that correspond to some known distribution with expected reward (mean reward) and expected deviation. It is stated that this type of experience helps decision-makers make better decisions in real-life settings.

However, having multi-agent managerial games as a learning method for gaining experience of a decision-maker can yield a non-satisfactory result due to the human perception of a game. As a solution, one must set up agents in such a manner that they accurately infer human emotions. Such agents are called affective agents. In paper (Yu et al., 2015; Gebhard et al., 2018) emotions that are identified are happiness, sadness, excitement, bored, surprised, and angry. These are core emotions that can be aroused in decision-makers as a result of a game.

Affective agents do affect the process of managerial game effectiveness. It is shown in the paper (Lin et al., 2015; Jerčić et al., 2018) that can predict a user's emotions are as important as the managerial game itself. The reasoning is that believable interactions in human-agent setup make the teaching method more real-life and trusted. Having the above mentioned in mind for multi-agent managerial games is important to create the game as realistic as it can be, as well as being able to identify emotions from the decision-maker. For the problem, authors are trying to handle this can be mapped as a multi-label prediction problem. Namely, one would like to predict the result of the game based on the characteristics of a decision-maker, and also to predict the emotions from the decision-maker at the same time.

A typical approach to solving managerial games is in the field of reinforcement learning. Namely, it is learned to solve the managerial game though an additional agent that acts as a decision-maker (virtual decision-maker). Virtual decision-maker plays the managerial game and optimizes the decision process instead of real-life decision-maker. To the best of our knowledge, the first effort in learning the resource allocation in managerial games is learning multi-armed bandits. In a paper (Stone & Kraus, 2010) the goal was to create the best possible two-person team which will optimize reward. This is done in such a manner that one agent observes the other agent and recommends which action the second one should perform. One can find the usage of multi-armed bandits for the problem at hand. In a paper (Zhou et al., 2018) one can find a model for optimal team composition that is based on structural contingency theory. Namely, the team organization is divided into multiple multi-arms bandits problem which learn with some constraints the structure of the team that will solve the problem at hand. An extension of the multi-armed bandits includes the adaptation of the synergy graph team formation algorithm using multi-armed bandits as shown in paper (Liemhetcharat & Veloso, 2017).

Other approaches utilize common reinforcement learning techniques such as the Q learning algorithm (Zhang et al., 2019). This algorithm tries to estimate the set of actions that will lead to the maximization of the reward. Compared to multi-armed bandits, this adds one level of complexity due to estimating the set of actions. Namely, Q learning algorithms must explore a sequence of actions that lead to optimal reward while multi-armed bandits find the best action according to state. The sequence of actions that lead to an optimal managerial game can be solved using metaheuristics as well. Therefore, one can find the application of genetic programming (Li et al., 2015) and particle swarm optimization (Fang et al., 2012). Also, state of the art techniques such as deep reinforcement learning and actor-critic method is used (Barriga et al., 2019).

Our research aims to fill the gap in the area. Namely, we would like to create a prediction model that will allow a decision-maker to compose a team for the problem at hand during a managerial game. The model will report either to a decision-maker or to a teacher what the probability of efficiently solving the task is and at the same time provide to the teacher what the expected emotions of the decision-maker are. This way, the teacher and/or decision-maker can guide the learning process toward solving the problem, for example, some of the decision-making frameworks. Another research question that is lacking in managerial games is the effect of gender and education. To the best of our knowledge, research of that kind from a data analysis point of view is missing in the literature. By answering this question, perhaps a more detailed data-based discussion about the effects of gender and education in team composition could be achieved.

3 Methodology

The Methodology section will consist of two parts. First, we will explain the data at hand. Then we will provide a hypothesis and brief explanation of algorithms used, as well as experimental setup.

3.1 Data

The data used in this research originates from research conducted in the paper (Yu et al., 2017). The data is obtained from the managerial game called Agile Manager, where the task was to coordinate a team of ten workers for a given task. The data was collected from December 2013 to October 2016. Due to clarity, each table will be labelled with italic letter.

There are six tables, which explain the process of the managerial game. First, table *User* explains the demographics of the user of the managerial game, i.e. decision-maker. Besides having demographics attributes, one can find personality survey questions obtained from the Ten-Item Personality Inventory survey and affective-oriented features of the user obtained from the Positive and Negative Affect Schedule survey. There are in total 1,144 users in the database.

Each user has to solve *Game Level* in one instance of the game. There are in total six game levels according to the difficulty of the game. Each game level besides having the difficulty assigned had the focus on either speed or quality of the game. Therefore, the user was given before solving a level a clear sign whether it is more important to perform quickly or with higher quality. Each level contains from 20 to 30 tasks.

Every *Task* has its difficulty, deadline and estimated effort required for solving that task. During a *Game Session*, the user plays a level by assigning *Worker Agents* to a task. Every worker agent has a level that is translated to the probability of solving the given task given the timeframe, the maximum number of units that can be given to that worker agent and speed vs. quality indicator, which is a signal that worker agent can perform quickly or with high quality. There are in total 20 worker agents, from which the user selects 10 for the game session. During the game session, each worker gets a reputation, which helps the decision-maker in the assignment process. Namely, if a worker solves the problem within a given period and with satisfactory speed and quality, reputation improves, otherwise reduces. Assignments of worker agents to tasks are saved in *Decisions*. For each game session, the managerial game saves a result. Namely, one can obtain a user score and compare that score with the score obtained from the adversarial player that was played by the artificial user. If the user score is higher than the artificial user score, one can say that the task was solved satisfactorily. Additionally, the emotion caption system records the emotions of the player during the game. Emotions that are reported are happiness, sadness, excitement, boredom, anger, and surprise.

There are in total 9,854 game sessions and 495,533 decisions in the dataset.

3.2 Experimental Setup

After an examination of the literature review, we derived two hypotheses.

- Are there differences in performance based on gender and based on education?
- Can we predict whether a user will compose a team that will satisfactorily solve the problem at hand while predicting the emotions of the decision-maker?

To answer the first research question we will use traditional statistical analysis. Namely, we will use the Chi-Square test of independence (Sharpe, 2015). More specifically, we will utilize the information available in the table *User* where one can find gender and education of the decision-maker and information in the table *Game Session* where the signal whether a user solved the level with satisfactory results. If needed Benjamini-Hochberg post hoc tests will be performed (Benjamini, 2010).

For the second research question, we will utilize a multi-label classification. The idea of multi-label classification is to predict more than one label in the data using adapted data mining and machine learning algorithms. More specifically, one would like to utilize the potential dependencies between labels to obtain better predictive performance. We will use a binary relevance (BR) approach that does not model label dependency. Modelling label dependency allows predictive models to "see" values of other labels during the learning process and, after, during the prediction process (Montañes et al., 2014). The approach that will be used is called Classifier Chain (CC). This approach introduces partial conditioning in labels. Namely, a list of labels is provided where the next label on the list uses information about the labels that are previous in the list. For base learners of the BR and CC approach, we used the Gradient Boosted Trees classifier (GBT).

Beside classical modelling of labels, we will also use known adaptations of learning algorithms for multi-label. Those are going to be an adaptation of the kNN algorithm (Zhang & Zhou, 2007), a hierarchical ARAM Neural Network (HARAM) (Benites & Sapozhnikova, 2015) and adaptation of SVM algorithm for the multi-label setting called MLTSVM, but will be denoted as MLSVM (Chen et al., 2016).

Our experimental setup assumes that the predictive model is available before the decision-makers' game session. Therefore, our final dataset consists of 9,854 instances where each instance has the features in categories: 1) personal - gender, education, country, age, ten features explaining the personality of the user, twenty features explaining user affectivity, 2) design of the game level – speed or quality indicator, number of rounds, tasks per round, worker productivity rate, 3) user experience – total time spent playing a game, number of games played, and 4) decision-making strategy – task assignment using expected utility theory (decision making under uncertainty), task assignment using inter-temporal decision-making theory, task assignment using complex decision theory and other approaches to task assignment. The labels that are defined are the outcome of the game, i.e. solved the game with satisfactory results, and emotions of the user expressed in happiness, sadness, excitement, boredom, anger, and surprise.

To prevent overfitting, we performed a ten-fold cross-validation procedure. This means that the dataset is divided into ten subsets, called folds. Each fold is used exactly once as a test dataset, while the remaining ones are used for model training. For each fold, we measure the area under the ROC curve (AUC). Finally, performances are aggregated with average and standard deviation presented. It is worth to notice that performances are presented label-wise.

Since every learning algorithm has its parameters, we used inner ten-fold cross-validation for parameter optimization. A similar is done for a sequence of the classifier chain. The results that will be presented are shown for the best performing classifier chain.

4 Results and Discussion

The results and discussion section consists of two subsections, one for each research question.

4.1 Differences in gender and education

For the first research question, we will perform a Chi-Square test of solving the task successfully given the gender and education of the user.

For the gender of the user and solving the task successfully, we obtain the contingency table presented in Table 1.

Table 1. Contingency table for the gender of a decision-maker

Gender/Solve	False	True
Female	2,229	945
Male	4,442	2,222

Based on the presented contingency table value of the Chi-Square test statistic is 12.391 (p-value < 0.001). We can conclude that, based on the data at hand, male participants do have a higher percentage of solving the task by team composition.

For education, we obtain a contingency table presented in Table 2.

Table 2. Contingency table for the education of a decision-maker

Education/Solve	False	True
High School	847	395
Diploma	2,383	1,253
Bachelor	2,446	1,080
Master	175	77
Ph.D.	47	8
Other	773	354

It is obtained that the value of the Chi-Square statistic is 21.075 (p = 0.001). Since there are multiple groups and multiple testing, we utilized Benjamini-Hochberg post hoc tests which showed that there are statistical differences between Bachelor and Diploma group (p = 0.008), Bachelor and Ph.D. groups (p = 0.046), Diploma and Ph.D. groups (p = 0.024), and High School and Ph.D. groups (p = 0.046). We can conclude that decision-makers with a Diploma degree solved more problems compared to decision-makers with Bachelor's degrees and Ph.D. degrees and that decision-makers with High School and Bachelor's degrees are better than decision-makers with a Ph.D. degree. Although the results are counter-intuitive, the main reason for such performance is the correlation between education and the complexity of the game. More specifically, Ph.D. participants tend to play games that are more complex. Complexity is observed in multiple sources of uncertainty (team member performance and variability of output of the task). Thus, performances of Ph.D. participant is lower than expected. Also, high school and diploma participants played games that has the lowest complexity (player performance is a constant and output of the task can does not have a variability). Thus, they could easily calculate the expected value of the game. Participants with Bachelor and Master degree played games every type of games regarding complexity (easy, medium and hard). Therefore, their performance is very similar to the others.

4.2 Predicting the outcome of the game

As already explained in the experimental setup section, we utilized several strategies for multi-label predictions. Namely, we wanted to predict the outcome of the game (user solved the game on the satisfactory level) and emotions of the user after the game expressed in happiness, sadness, excitement, boredom, anger, and surprise. Learning algorithms were binary relevance (BR), classifier chain (CC), multi-label kNN algorithm (kNN), adaptation of neural network (HARAM), and adaptation of SVM algorithm (MLSVM). The results in terms of average and standard deviation of AUC over folds are presented in Tables 3, 4 and 5.

Table 3. Predictive performance for the outcome of the game

Label	Outcome
BR	**0.760±0.001**
CC	**0.760±0.001**
kNN	0.619±0.019
HARAM	0.754±0.027
MLSVM	0.697±0.021

As can be seen from the results, predicting the outcome of the managerial game is difficult. Namely, BR and CC that use GBT performed the best. Adaptation of existing algorithms for multi-label prediction, kNN, HARAM, and MLTSVM performed worse compared to GBT.

Table 4. Predictive performance for emotions happiness, sadness, and excitement

Label	Happiness	Sadness	Excitement
BR	0.589±0.018	0.607±0.016	0.616±0.023
CC	**0.624±0.025**	**0.623±0.021**	**0.659±0.015**
kNN	0.554±0.016	0.553±0.017	0.559±0.026
HARAM	0.614±0.021	0.604±0.016	0.657±0.019
MLSVM	0.604±0.019	0.602±0.012	0.644±0.023

We can observe that emotions are hard to predict. Namely, AUC is worse compared to the prediction of the outcome. The emotion of happiness and sadness have AUC ~0.62, which means that the predictive model barely recognizes differences between emotions. The situation with excitement is better in terms that AUC is ~0.66. Again, the best performing algorithm is the classifier chain with GBT.

Table 5. Predictive performance for emotions boredom, anger, and surprise

Label	Boredom	Anger	Surprise
BR	0.589±0.020	0.560±0.023	0.613±0.023
CC	0.624±0.025	0.626±0.021	**0.653±0.019**
kNN	0.548±0.024	0.551±0.030	0.558±0.021
HARAM	**0.627±0.031**	**0.631±0.035**	0.644±0.027
MLSVM	0.612±0.024	0.622±0.027	0.639±0.024

A similar conclusion can be drawn for the emotions boredom, anger, and surprise. It is very hard to predict emotions from the data at hand. However, emotions boredom and anger were best predicted by adaptation of neural network for multi-label called HARAM, while surprise was best predicted using classifier chain and GBT.

By observing the results, one might conclude that usability of the result is questionable. To the best of our knowledge, this is the first attempt in trying to predict both results and emotions in advance. Predictions of winning the game are at satisfactory level, while emotions are very hard to predict. This is due to complexity of recognizing the emotions.

5 Conclusion

In this paper, we tried to answer two research questions. The main goal was to try to predict the outcome of the managerial game, i.e. whether a decision-maker will manage to organize a team that will solve the problem at hand. Besides predicting the outcome, an additional level of complexity is the possibility to predict the emotions of the decision-maker. It has been shown that emotions influence employee happiness and proper emotions have to be shown. Our approach for the given task was using multi-label prediction models. This methodology is suitable for the problem at hand because we try to predict multiple labels that do have some dependency, i.e. emotions depend on the outcome of the game. The results suggest that the outcome of the game can be predicted at a satisfactory level. Namely, the best performing multi-label model had AUC ~0.76. This means that for a random satisfactory result and random non-satisfactory result our model can differentiate in 76% of the cases which one is a satisfactory result. On the other hand, emotions are hard to predict with AUC ranging from 0.62 to 0.66.

Another research question was to inspect gender and education on the outcome of the managerial game. For that purpose, we performed the statistical analysis. More specifically, we performed the Chi-square test of independence. We showed that male decision-makers tend to perform better compared to female decision-makers. Besides, we tested the effect of education on the outcome of the game. We can conclude that decision-makers with a Diploma degree solved more problems compared to decision-makers with Bachelor's degrees and Ph.D. degrees and those decision-makers with High School and Bachelor's degrees are better than decision-makers with a Ph.D. degree are.

As a plan for future work, we would like to gain more insight into what are the key points based on which prediction model made a decision, i.e. explain the predictions. This type of analytical insight could give better feedback to the teacher and decision-maker about why the effect is going to be achieved. Additionally, we would like to perform a more detailed prediction model with a model for each decision in the managerial game process, not only for the game itself.

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