A Machine Learning Approach to Predict the Winner in StarCraft based on Influence Maps*

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***Abstract*—Real-Time Strategy games are very popular test beds for Artificial Intelligence (AI) researchers. In this work we try to predict the winner of StarCraft©[1] games based on *influence maps*. Influence maps are numerical matrices representing the influence of each player's army in the map, and they are useful for different types of spatial reasoning. Our system reaches a level of precision similar to the human judges, although human judges base their predictions on a much more complex and abstract set of game features.**

***Index Terms*—Real-Time Strategy Games, Influence Maps, Machine Learning, Prediction, StarCraft.**

I. Introduction

Real-Time Strategy (RTS) games are very popular test beds for Artificial Intelligence (AI) researchers because they provide complex and controlled environments on which to test different AI techniques [7]. In this work we try to predict the winner as soon as possible based on the events that occur in the game. This role of professional observer arises naturally in most traditional sports like football or even eSports where different experts analyze what is happening during the game and explain their opinions regarding the strategies selected by the players or teams.

We based our predictions on influence maps (IM), a spatial and tactical representation of the game state, and some standard machine learning classifiers. IM were initially used in the context of the game of Go [9] and have been more recently used in RTS games for pathfinding and reactive decision making [2], [4], [5], [8].

In order to test our approach, we use two different datasets of StarCraft games. The first one contains 4-player games in which all the players were controlled by the internal StarCraft AI. The second dataset contains real 2-player games from specialized websites. We have studied the precision of the predictions in different moments of the game, the number of games required to train the learning algorithms and the stability of their predictions over time. Finally, we performed a small experiment to compare our results with the predictions made by some expert players and conclude that our results are comparable, but human experts base their predictions on a much more complex and abstract set of game features.

This paper is a brief summary of our previous work [6]. We encourage the interested reader to consult the original published version to fully understand the problem we try to solve, our approach and the results and conclusions.

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[1] http://us.blizzard.com/en-us/games/sc/

II. Influence Maps

Influence maps (IM) represent the influence of the game units in the map as a numerical matrix or grid. IM are easy to compute and allow different types of spatial reasoning such as identifying boundaries and areas of control. IM can help to visualize and analyze the tactical deployment of troops in the map, a key factor in most strategy games.

The basic idea is that each unit exerts its influence in a nearby area and the numerical influence value in each tile depends on the distance to the unit and the strength (or value) of the unit. Map tiles under the influence of several units accumulate their influences, so that the more units a player concentrates in an area, the greater will be the values of influence in that part of the map.

Although in 2-player games it is possible to use only one IM to represent the strength of both players using positive numbers for one player and negative numbers for the other, in the general case we need a different IM for each player. StarCraft maps are already divided in logical tiles (96x96 is a medium map) but that level of detail would result in very big IM. Fortunately, IM are matrices that can be easily scaled to smaller sizes to represent the state of the game with the desired level of detail. In our experiments we scale each original influence map to a 4x4 matrix so we only need 16 variables to represent the state of each player in the game and we can use the same representation no mater the original size of the map.

Expert	Precision (%)	Stable from (%)	Confident from (%)	Prec. AI DS (%)	Prec. Human DS (%)
Expert's average	72.22 (22.15)	41.43 (07.98)	67.38 (07.95)	76.46 (07.63)	67.99 (16.15)
SVM	70.37 (39.54)	21.67 (18.35)	NA	74.07 (23.13)	66.67 (57.74)
LDA	72.22 (26.06)	36.67 (26.58)	NA	66.67 (11.11)	77.78 (38.49)

TABLE I

Results from the experiment with expert players. The table shows average values and standard deviations.

III. Game Datasets

We used two different datasets of games. The first one contains 100 4-player games in which all the players were controlled by the internal StarCraft AI. These games were quite long, with an average duration of 72.5 minutes. We extracted the state of the game once every 30 seconds obtaining an average of 145 snapshots per game. The second dataset contains 200 2-player human games downloaded from BWreplays[2], a website that collects games from several specialized websites. Humans play very differently from AIs and the average game duration was 12.5 minutes. In fact, in several games one player defeats the other one with basic combat units in a few minutes and there is not enough time to develop technologies or to expand to new locations.

In games with several players, the chances to win depend to a great extent on the interactions among the other players. For example, the first two players to engage in combat will probably lose several units while the other players keep their armies intact. Another example is that any player who suffers successive attacks from different opponents will not have many chances to survive. One peculiarity of the 2-Human player games was that 80% of the games ended early because one player left when he though he had no opportunity to win. In those cases, we assigned the victory to the remaining player.

We obtained the best results using Linear Discriminant Analysis (LDA) [3] and Support Vector Machines (SVM) [1] with a polynomial kernel. In the first dataset (4-AI player games) we obtain an average precision of 66.62% but we need to wait until the last quarter of the game to predict the winner with precision over 80%. In the second dataset (2-Human player games) we obtain an average precision of 62.04% but we need to wait until the last tenth of the game to make a prediction with a precision of 80%. Human games are more challenging to predict (although there are only two players in the game) because of how fast one bad decision can unbalance the game.

IV. Evaluation with Experts

How good is our system when we compare it with expert human judges? We organized a small experiment in which 14 experienced StarCraft players tried to guess who was going to win in 6 previously recorded games (3 from each dataset). The human judges were asked to decide the winner 9 times in each game (at 10%, 20%, ..., 90% of the game duration) and they could move the camera around the map while the game was paused for as long as they wanted (there was no *fog of war* so all the units were visible).

[2]http://bwreplays.com/

Table I summarizes the results of the experiment. We show the results for the average of the 14 human judges and the 2 best classifiers. The columns represent the average precision and standard deviation, the moments of the game in which the predictions became stable and the experts felt confident, and the precision in each dataset.

We observed big differences among the participants in terms of precision (from 57.41% to 87.04%), but in average human judges obtained a precision of 72%, their predictions became stable at 41% of the game, and they feel confident about their prediction at 67% of the game. Our two best classifiers, SVM and LDA, obtained very competitive results and became stable much sooner than human judges.

V. Conclusions

We conclude that it is possible to build machine learning classifiers based on influence maps that can compete with human experienced players in the task of predicting the outcome of StarCraft games.

During the debriefing at the end of the session, we learned that humans base their decisions on a much richer set of features that we are not able to capture with influence maps. In particular, human judges are able to anticipate and recognize high level strategies and they realize when one player makes a fatal decision. On the other hand, human judges found the minimap very useful and minimaps are similar to influence maps.

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