





Metagame analysis for team-based competitive games D. Maurel, S. Lefebvre ISEP - 9/5/2017

Context – Objectives - Contributions

CONTEXT:

The metagame of a given game is the set of the common methods applied by the players in order to maximize their in-game efficiency in a competitive context. Its analysis may be conducted through the analysis of players' in-game behaviour also known as Player Modelling (PM). [Dereszinski2011] presents a method to analyze solo-game metagame.

OBJECTIVES :

- Be able to extract metagame components with as little expert knowledge as possible.
- · Use players' behaviours to infer team behaviour
- Create a game independent approach to favor reusability

CONTRIBUTION:

An extension to the work of [Dereszinski2011] also based on Hidden Markov Models (HMM) to analyze team-based games metagame.

Case-study

CASE-STUDY:

League of Legends (LoL):

- Competitive multiplayer game
- 2 teams of 5 players
- Fight each other to destroy enemy base





Metagame:

- Well known with distinct roles per player
- Allow to discuss results from expert point of view.

Focus on positions:

- Player positioning on the map crucial to maintain team efficiency.



• Analyze evolution of team in-game formation

Challenges – Previous Method

CHALLENGES:

In general : Heterogeneous data, unsupervised learning, validation of the resulting model, behaviour of the sum instead of the sum of the behaviours

State of the art : No other method found which allows to describe team behaviour.

PREVIOUS METHOD:

[Dereszinski2011] :

- HMM based system : fitted to analyze temporal sequences of actions, in this case, game unit build order
- Focused on a specific period of time (0-7 min) of the video game Starcraft

Results :

- Successfully learn predominant build orders
- Resulting model can be used to predict player actions
- Graphical representation of the available strategies



Taken from [Dereszinski2011]





Experimental Results

DATABASE: 1000 matches of high level players with one snapshot of the game state every minute. Levels are here important because it ensures that the players will base their behaviours on the current metagame of LoL.

RESULTS:







Real positions

Blurred positions

Learnt positions

Different learnt position

Metagame elements: A No error at t=0 : Initial positions of the players identified

Images:

- Use of blurred images to improve the resistance of the error to small position variations
- Several known points of interest (\bigcirc) found by the system and the positionung of the players around them
- Several strategic points where the players have to be (\diamondsuit)

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Extension

EXTENSION:

A Each low state represents a game state for a player.

- B The model learned, called low HMM, is used as an action sequence encoder.
- C Each learning sequence is encoded to get the probabilities for a sequence to be in a given state at a given moment (also known as forward probabilities).
- D Those probabilities are gathered to get teams behaviours sequences
- **E** A HMM learns a model of team behaviour using previous sequences



- B First phase of the game ("laning" for t<10~15 min) identified: phase known to have precise positions for each player
- C Loss of precision when switching from the first to the second phase which is less static than the first one.
- D Oscillations of the error because of the lack of games longer than ~45 min.

Limitation:



t (min)

- Granularity of the samples is to low for the game: map crossable in 20 seconds
- Need more refined data to determine the system efficiency

References - Contact

[Dereszinski2011] Dereszynski, E. W., Hostetler, J., Fern, A., Dietterich, T. G., Hoang, T. T., & Udarbe, M. (2011, October). Learning Probabilistic Behavior Models in Real-Time Strategy Games. In AIIDE.

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