Learning Artificial Intelligence in Large-Scale Video Games

— A First Case Study with Hearthstone: Heroes of WarCraft —

Master Thesis Submitted for the Degree of
MSc in Computer Science & Engineering

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Video Games, Then and Now

- Then, the problems to solve were representable easily

  → Example: *Pac-Man*

  - Fully observable maze
  - Limited number of agents
  - Small, well-defined action space

- Now, the problems feature numerous variables

  → Example: *StarCraft*

  - Vast, partially observable map
  - Complex state representation
  - Prohibitively large action space, difficult to represent

Video Games, Then and Now

Games continue to feature richer environments...

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... but designing robust AIs becomes increasingly difficult!

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$\Downarrow$

Making AI learn instead of being taught: a better solution?

Objectives of this Thesis

1. Design & study of a theory for creating autonomous agents in the case of large-scale video games

   → Study applied to the game *Hearthstone: Heroes of Warcraft*

2. Develop a modular and extensible clone of the game *Hearthstone: HoW*

   → Makes us able to test the theory practically

Problem Statement

1. State Vectors

- World vector $w \in \mathcal{W}$ contains all information available in a given state

  $\rightarrow$ Everything is not relevant

- If $\sigma(\cdot)$ is the projection operator such that

$$\forall w \in \mathcal{W}, s = \sigma(w)$$

is the relevant part of w for the targeted application, we define

$$\mathcal{S} := \{\sigma(w) \,|\, w \in \mathcal{W}\}$$

the set of all state vectors.

Problem Statement

2. Action Vectors

- Available actions have unknown consequences
- Let $\mathcal{A}$ be the set of available actions in the game
- Let $\mathcal{A}_s$ be the set of actions that can be taken in state $s \in \mathcal{S}$

Problem Statement

3. State Scoring Function

- There should exist a bounded function

$$\rho : \mathcal{S} \to \mathbb{R}$$

having the following properties:

$$\begin{cases} \rho(s) < 0 & \text{if, from } s \text{ info, the player is considered as likely to lose,} \\ \rho(s) > 0 & \text{if, from } s \text{ info, the player is considered as likely to win,} \\ \rho(s) = 0 & \text{otherwise.} \end{cases}$$

- Based on expert knowledge

Problem Statement

4. Problem Formalization

- Games follow discrete-time dynamics:

$$\tau : \mathcal{S} \times \mathcal{A} \to \mathcal{S} \mid (s_t, a) \mapsto s_{t+1} \text{ for } a \in \mathcal{A}_{s_t}, \quad t = 0, 1, \ldots$$

- Let R_ρ be an objective function whose analytical expression depends on ρ:

$$R_\rho : S \times \mathcal{A} \to \mathbb{R} \mid (s, a) \mapsto R_\rho(s, a) \text{ for } a \in \mathcal{A}_s.$$

Problem Statement

4. Problem Formalization

- $R_\rho(s, a)$ is considered uncomputable from state s

  $\rightarrow$ Difficulty to simulate side-trajectories in large-scale games

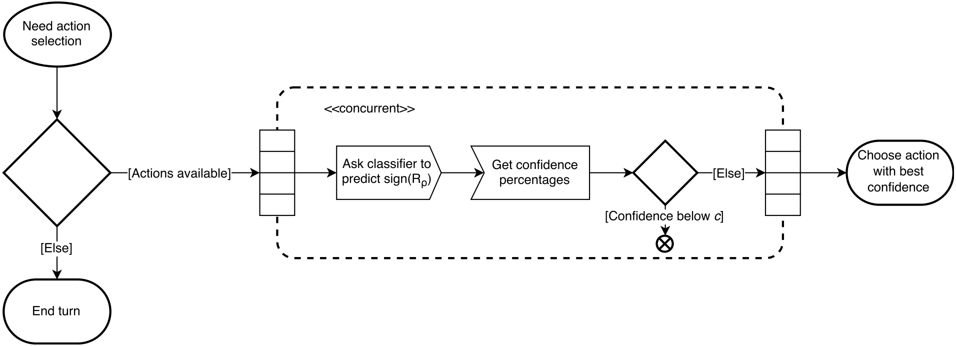
- Find an action selection policy h such that

$$h : S \rightarrow \mathcal{A} \mid s \mapsto \underset{a \in \mathcal{A}_s}{\operatorname{argmax}} \; R_\rho(s, a).$$

Getting Intuition on Actions from State Scoring Differences

- Our analytical expression for R_ρ:

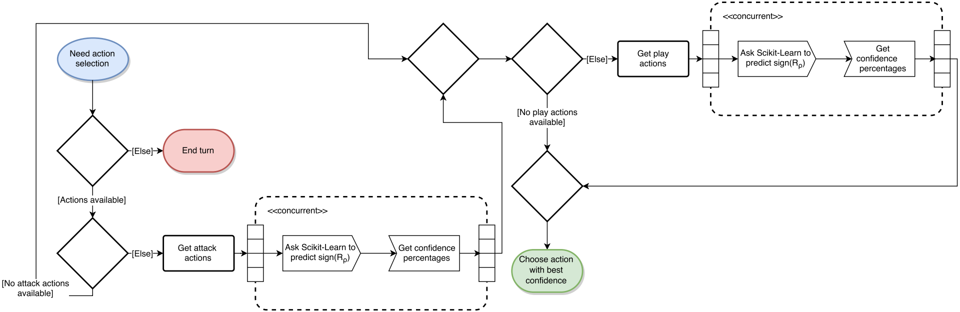
$$R_\rho(s, a) := \rho(\tau(s, a)) - \rho(s).$$



Report erratum – In Figure 3.2, the classifier is asked to predict the sign of R_ρ, and not ρ.

Nora: Design & Results

Action Selection Process



Report erratum – In Figure 4.5, the classifiers are asked to predict the sign of R_ρ, and not ρ.

Caveats

- Memory usage

  → Approx. 14GB is needed to keep the models in RAM

  → Fix: tree pruning and parameters tuning

- Play actions classifier underestimates the value of some actions

  → Random target selection is assumed after playing an action that needs a target

  → Fix: Two-step training

Results

Matchup	**Win rate**
Nora vs. Random	93%
Nora vs. Scripted	10%...

But compared to the random player performance...

Results

Matchup	Win rate
Nora vs. Random	93%
Nora vs. Scripted	10%
Random vs. Scripted	$<$ 1% !

- Nora applies some strategy the random player does not
- Qualitatively, this translates into a board control behavior

  $\rightarrow$ Never target her allies with harmful actions, even though it is allowed

  $\rightarrow$ Accurate understanding of the Fireblast special power

Conclusion

Any questions?

Thank you for your attention.

Appendix – Why Extremely Randomized Trees?

- Ensemble methods can often surpass single classifiers

  $\rightarrow$ From a statistical, computational and representational point of view

- Decision trees are particularly suited for ensemble methods

  $\rightarrow$ Low computational cost of the standard tree growing algorithm

  $\rightarrow$ But careful about memory...

- Random trees suited for problems with many features

  $\rightarrow$ Each node can be built with a random subset of features

- Feature importances

  $\rightarrow$ Useful for designing the projection operator $\sigma : \mathcal{W} \rightarrow \mathcal{S}$

Appendix – Computation of the ExtraTrees Classifier Confidence

- It is the predicted positive class probability of the classifier
- Computed as the mean predicted positive class probability of the trees in the forest
- Predicted positive class probability of a sample s in a tree:

$$\frac{\#\{s' \in \text{leaf in which } s \text{ falls} \mid s' \text{ labelled positive}\}}{\#\{s' \in \text{leaf in which s falls}\}}$$

Appendix – Basics of Hearthstone: Heroes of WarCraft

- Stylized combat game
- Cards are obtained by drawing from your deck
  → Your hand is hidden to your opponent

Goal: Make the enemy player's hero health go to zero.

Appendix – Basics of Hearthstone: Heroes of WarCraft

- Cards are played using a resource: the Mana

  → Minions that join the battle

  → Spells

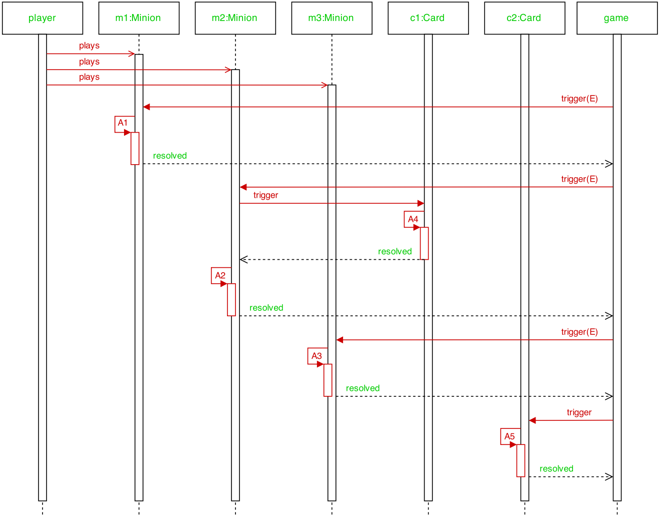
- Rules are objects in the game

  → Game based on creating new and breaking/modifying rules

Appendix – Basics of Hearthstone: Heroes of WarCraft

Appendix – Basics of Hearthstone: Heroes of WarCraft

Things Might Get Tricky...!



Appendix – The simulator

- *Hearthstone: HoW* simulator created with C++/Qt 5
  - → Modular, extensible
  - → Cards are loaded from an external file
  - → Quite a challenge!
- Definition of JARS for describing cards in a user-friendly way
  - → Just Another Representation Syntax
  - → Context-aware, JSON-based language
  - → Makes it easy to create and edit cards without coding