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...
Video Games, Then and Now

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... but designing robust AIs becomes increasingly difficult!
Video Games, Then and Now

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... but designing robust AIs becomes increasingly difficult!

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
  $$\mathcal{S} := \{\sigma(w) \mid w \in \mathcal{W}\}$$
  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 $s \in S$
Problem Statement

3. State Scoring Function

- There should exist a bounded function

\[ \rho : S \rightarrow \mathbb{R} \]

having the following properties:

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

- Based on expert knowledge
Problem Statement

4. Problem Formalization

- Games follow discrete-time dynamics:
  \[
  \tau : S \times A \to S \mid (s_t, a) \mapsto s_{t+1} \text{ for } a \in A_{s_t}, \quad t = 0, 1, \ldots
  \]

- Let \( R_\rho \) be an objective function whose analytical expression depends on \( \rho \):
  \[
  R_\rho : S \times A \to \mathbb{R} \mid (s, a) \mapsto R_\rho(s, a) \text{ for } a \in A_s.
  \]
Problem Statement

4. Problem Formalization

- $R_\rho(s, a)$ is considered **uncomputable** from state $s$
  - Difficulty to simulate side-trajectories in large-scale games

- Find an action selection policy $h$ such that

$$h : S \rightarrow A \mid s \mapsto \arg\max_{a \in \mathcal{A}_s} R_\rho(s, a).$$
Our analytical expression for $R_\rho$:

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

Report erratum – In Figure 3.2, the classifier is asked to predict the sign of $R_\rho$, and not $\rho$. 

Need action selection

[Actions available]

<<concurrent>>

Ask classifier to predict sign($R_\rho$)

Get confidence percentages

[Confidence below c]

[Else]

Choose action with best confidence

[End turn]
Nora: Design & Results
Report erratum – In Figure 4.5, the classifiers are asked to predict the sign of $R_\rho$, and not $\rho$. 
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

<table>
<thead>
<tr>
<th>Matchup</th>
<th>Win rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nora vs. Random</td>
<td>93%</td>
</tr>
<tr>
<td>Nora vs. Scripted</td>
<td>10%…</td>
</tr>
</tbody>
</table>

But compared to the random player performance…
Results

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<tr>
<td>Random vs. Scripted</td>
<td>&lt; 1% !</td>
</tr>
</tbody>
</table>

- **Nora applies some strategy the random player does not**
- **Qualitatively, this translates into a board control behavior**
  - Never target her allies with harmful actions, even though it is allowed
  - 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
  → From a statistical, computational and representational point of view

- Decision trees are particularly suited for ensemble methods
  → Low computational cost of the standard tree growing algorithm
  → But careful about memory...

- Random trees suited for problems with many features
  → Each node can be built with a random subset of features

- Feature importances
  → 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:

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