I do not know what I may appear to the world; but to myself I seem to have been only like a boy playing on the seashore, and diverting myself in now and then finding of a smoother pebble or a prettier shell than ordinary, whilst the great ocean of truth lay all undiscovered before me.

- Sir Isaac Newton

University of Alberta

Game-Independent AI Agents for Playing Atari 2600 Console Games

by

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Abstract

This research focuses on developing AI agents that play arbitrary Atari 2600 console games without having any game-specific assumptions or prior knowledge. Two main approaches are considered: reinforcement learning based methods and search based methods. The RL-based methods use feature vectors generated from the game screen as well as the console RAM to learn to play a given game. The search-based methods use the emulator to simulate the consequence of actions into the future, aiming to play as well as possible by only exploring a very small fraction of the state-space.

To insure the generic nature of our methods, all agents are designed and tuned using four specific games. Once the development and parameter selection is complete, the performance of the agents is evaluated on a set of 50 randomly selected games. Significant learning is reported for the RL-based methods on most games. Additionally, some instances of human-level performance is achieved by the search-based methods.

Acknowledgements

I have been very fortunate to have an enjoyable and fruitful learning experience here in University of Alberta, and for this I am most grateful to my supervisor, Michael Bowling. He has provided me with the opportunity to work on a research topic that I am truly passionate about, given me enough academic freedom to experiment and learn on my own, and yet he has always been there to guide me when I was lost and confused.

I am very thankful to my fellow graduate students who have generously and patiently shared their knowledge and expertise and have been instrumental for the completion of this thesis. In particular, I would like to thank Marc Lanctot and Chris Rayner for sharing their knowledge and getting me started with the Atari 2600 hardware and the emulation tools, Mohammad Shafiei for sharing his insights on the concepts behind the UCT algorithm, and Michael Johanson for offering his expertise on running batch simulations on computer clusters. Our late night discussions with Amir-Massoud Farahmand have been some of the best learning experiences I have had through the last two years. I am very grateful to him, who has been both an inspiring colleague and a good friend.

I am indebted to the team behind Stella, the Atari 2600 emulator, for releasing their work as open-source and allowing me to build my toolset on top of their code. I would also like to thank Richard Sutton and the RLAI group for releasing the source code of their Tile-Coding and Sarsa(λ) implementations. I hope that releasing my own code base as open-source will be similarly beneficial to other researchers and hobbyists.

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Chapter 1

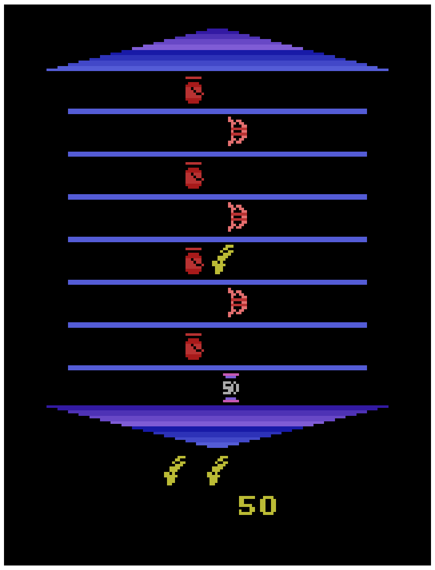
Introduction

Atari 2600 was a popular second generation game console, released in 1977. With a 1.19 MHz CPU, 128 bytes of RAM , and no frame buffer, it offers minimal hardware capabilities compared to a modern game console. Nonetheless, Atari 2600 programmers learned to push the capabilities of this limited hardware and there were numerous shooter, action-adventure, and puzzle games developed for the platform. Many popular arcade games, including Space Invaders, Pac-Man, and Donkey Kong were also ported to the Atari 2600. Atari shipped over 25 million units of the console, which became the dominant console of the second generation of game consoles. A rich library of over 900 game titles, simple 2D graphics, and availability of open-source emulation software make the Atari 2600 an attractive platform for developing and testing AI algorithms. Figure 1.1 contains screenshots of four Atari 2600 games.

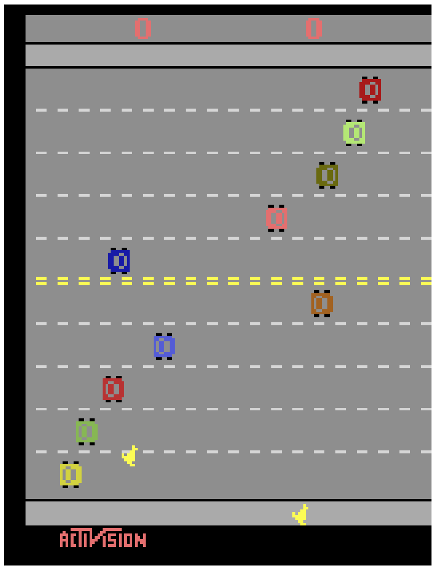
1.1 Problem Statement

The aim of this thesis is to develop AI agents that play Atari 2600 console games. We are particularly interested in game-independent agents, i.e., agents that are able to play in at least a large set of Atari 2600 games. As such, no game-specific assumption or prior knowledge is used in their design or fine-tuning beyond that which is expected to be common across a diverse set of games. For instance, knowledge that the PC is yellow in a given game will not generalize to other games and so is not used. However, assumptions that hold true in a large set of games are permitted. For example, while designing an agent we may assume that the important game entities have distinct colors.

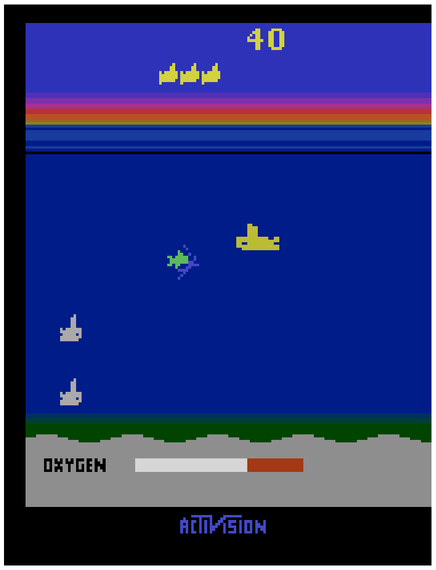
We consider two types of AI agents: learning based and search based. The learning based agents use the Sarsa(λ) algorithm and features generated from the game screens and the console RAM to learn to play an arbitrary game. The search based agents use the Atari 2600 emulator as a generative model to generate a state-action for any given game. Full-tree search as well as UCT is applied to this tree with the goal to play as well as



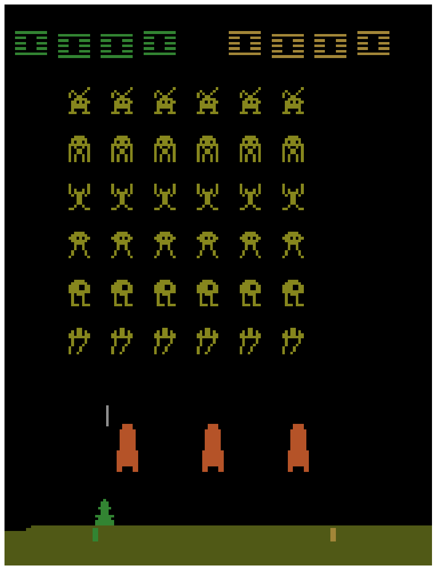
(a) Asterix



(b) Freeway



(c) Seaquest



(d) Space Invaders

Figure 1.1: Screenshots of four Atari 2600 games

possible by only exploring a small subset of the large state-space. We acknowledge that our current experiments are limited to one or two specific methods from a large body of possible approaches, and as such the observations will be limited to these specific methods.

1.2 Motivation

1.2.1 Artificial Intelligence in Games

Artificial Intelligence algorithms that can play classic or video games have been studied extensively. Research in classic games has resulted in Deep Thought for chess [Campbell et al., 2002], Chinook for checkers [Schaeffer et al., 2005], TD-Gammon for backgammon [Tesauro, 1994], and Polaris for poker [Bowling et al., 2009]. For AI researchers who work on solving various games, there is a recurring question that needs to be addressed: why dedicate limited resources to solving games instead of tackling the real-world problems in which the field of Artificial Intelligence can contribute to the daily quality of human lives? In other words, why spend resources on solving chess, if what we need is self-driving cars with near zero collision rates? Why play checkers, if what we want is an intelligent maid robot that can cook, vacuum, and wash the dishes?

The motivation for developing AI agents that can play games is threefold. First, games offer controlled, well-understood, and easily abstracted environments, with well-defined measures of success and failure. These properties make games suitable platforms for developing and testing AI algorithms. The methods developed and the knowledge gained from working in these controlled environments can later be applied to the real-world problems which are generally messier and harder to measure performances, but still require the same AI sophistication.

Additionally, games are excellent platforms for showcasing the capabilities of the latest AI techniques to the public. In 1997, when Deep Blue defeated Garry Kasparov, a great wave of excitement was generated among regular, non-academic people about Artificial Intelligence. This is because people understand chess, and respect the complexity involved in playing it well. Back in 1997, the AI community was not able to develop collision-free autonomous cars or achieve many other longer-term goals of the field. Showcasing an agent that mastered chess helped the public understand what the AI community was capable of at the time.

Finally, with the recent growth of commercial video games into a multibillion-dollar industry, there is now even more motivation for studying agents that can learn to act intelligently in games [Lucas, 2009, Laird and Lent, 2000]. Non-repetitive, adaptive, interesting, and in summary *intelligent* behavior offers a competitive edge for commercial games. As the game graphics peak at image-like quality, and as the game consoles offer more and more computational power that can be spent on complex learning algorithms, the importance of better game AI will only increase.

1.2.2 Atari 2600: an Attractive Platform for AI Research

The Atari 2600 game console is an excellent platform for developing and demonstrating AI algorithms. Bellow, we list a number of the properties that make the Atari 2600 an attractive medium for AI research:

- **Large and diverse game library**: There are over 900 game titles developed for the Atari 2600 console. These game vary from arcade-style shooter games (e.g., *Space Invaders*) to complex action-adventure games (e.g., *Adventure*) and even board-games (e.g., *Video Chess*). This enables a researcher to implement an AI method once and then evaluate it on a large and diverse sets of games.

- **Multiple sources of relatively simple features**: Game consoles offer many sources of features for learning tasks, including graphics, sounds, and even the console memory. An advantage of the Atari 2600 over the more modern game consoles is that it offers relatively simple features. Modern consoles generate sophisticated 3D graphics and multi-channel surround sound. On the other hand, most Atari 2600 games have simple 2D graphics, elementary sound effects, and utilize only 128 bytes of memory. This simplicity makes Atari 2600 games a more practical starting point for developing general AI techniques for video games.

- **Discrete and small action-space**: Unlike modern consoles with multiple analogue inputs, an Atari 2600 joystick can only capture 8 discrete directions and one action button. Combined together, Atari 2600 games use a maximum of 18 discrete actions[1].

- **Free and open-source emulator**: There are number of free and open-source emulators for the Atari 2600, including: Stella[2], z26, and PC Atari Emulator. Having access to open-source emulation software allows researchers to develop AI agents with minimal exposure to the low level details of how Atari 2600 games and hardware function. ALE, our learning environment discussed in section 4.2, is built on top of Stella.

- **High emulation speed**: Since the Atari 2600 CPU runs at only 1.19 megahertz, it can be emulated at a very high speed on a modern computer running at two to three gigahertz. Our learning environment, ALE, can emulate games as fast as 2000 frames per second.

[1]The action are: *Up, Down, Left, Right, Up-Left, Up-Right, Down-Left, Down-Right, Up-Fire, Down-Fire, Left-Fire, Right-Fire, Up-Left-Fire, Up-Right-Fire, Down-Left-Fire, Down-Right-Fire, Fire, NoAction.*

[2]http://stella.sourceforge.net

- **Generative model**: As we will discuss in section 3.1, an Atari 2600 emulator can be used as a generative model, which given a state and an action, can generate the following state. The generative model can be used in both search-based and learning-based methods.
- **Single-player and multi-player games**: In addition to single-player games, many Atari 2600 games offer two-player modes, supported by attaching a second joystick to the console. This makes the Atari 2600 an attractive platform for multi-agent learning. In this thesis, however, we only focuses on single-agent learning and search.

1.2.3 More Generic Evaluation of AI Methods

Most empirical evaluation of AI algorithms is performed on a small set of problems. Each field has a few problems that most new approaches are demonstrated on[3]. To evaluate a new method, researchers often implement it on these common problems and compare the results with the results from previous algorithms. However, evaluating a new method on one or two problems provides little evidence of how the new method would fare in a broader and more generic sets of experiments. In other words, showing that method A slightly improves the results of method B on the Mountain-Car problem, does not necessarily imply that it will also do a better job in playing Robocup-Soccer or flying a helicopter. Furthermore, to achieve the best possible performance, an individual parameter search is often performed for each problem. It is not always clear how much work is involved in the parameter search, and how easily a new set of parameters can be found for a different problem.

The diverse game library available for the Atari 2600 enables us to evaluate a new method on a large set of games, each with its own unique state dynamics and reward signals. Furthermore, we can divide the games into a training and a test set. An AI method is developed and tuned on the training games, and is later evaluated on the test games. Compared to performing the parameter search and the evaluation on the same problem, this generic evaluation method provides a better insight into how well an AI algorithm would perform on a new and untested problem. As it will be shown in section 2.8.5, developing an agent that can play a single Atari 2600 game can be fairly easy. What is much more challenging is generating agents that can play a large set of different games.

1.3 Related Work

Through the last decade, there has been a growing interest in developing AI agents that can play some aspects of video games [Lucas, 2009, Buro, 2004]. In Real-Time Strategy (RTS) games, a few examples include: Chung et al.'s abstract strategic planning in a game

[3]For instance, there is Mountain-Car in the field of reinforcement learning, Blocksworld in planning, and 15-puzzle in heuristic search.

of capture-the-flag using Monte Carlo simulations [Michael Chung, 2005], Ponsen et al.'s unit movement control in a simplified version of Battle of Survival using Hierarchical RL [Ponsen et al., 2006], and Ponsen's generation of dynamic scripts for playing Wargus using Evolutionary Algorithms [Ponsen, 2004]. Examples in First-Person Shooter (FPS) games include Smith et al.'s RL-based approach for coordinating bots in Unreal Tournament [Smith et al., 2007] and McPartland and Gallagher's method for learning the navigation task in a maze environment using Sarsa(λ) [McPartland and Gallagher, 2008]. In Computer Role-Playing Games (CRPGs), Spronck et al. use dynamic scripting to learn combat behavior in the popular Neverwinter Nights game [Spronck et al., 2006], and Cutumisu et al. approach the same problem using a variation of Sarsa(λ) with action dependent learning rates [Cutumisu et al., 2008].

There is also a recent interest in developing agents that can play a complete side-scrolling arcade-style game. In 2009, two AI competitions were organized on agents that can play entire levels of Infinite Mario, a clone of Nintendo's popular Super Mario Bros game. The RL 2009 Competition [Mohan and Laird, 2009] requires the agents to use reinforcement learning to learn to play the game. The learning agents are given a state representation containing the location of the player character (PC) and other monsters, as well as the types of the individual tiles on the screen. The agents receive a positive reward once the level is complete, and a small negative reward on all other states. The Mario AI Competition[4], on the other hand, does not limit the agents to a specific approach. Indeed, the participants are encouraged to use "evolutionary neural networks, genetic programming, fuzzy logic, temporal difference learning, human ingenuity, [and] hybrids of the above"[5]. Playing an Atari 2600 game was previously attempted by Diuk et. al., who illustrated the performance of their Object-Oriented Rmax algorithm by teaching the Player Character to pass the first screen of the game *Pitfall* [Diuk et al., 2008].

A shared characteristic between all the above examples, and (to our knowledge) all previous attempts of learning to play video games, is that each agent is designed and tuned to play a single game. Therefore, all the essential game properties (e.g., the location of the PC and important NPC's, health levels, and timers) are either explicitly included in the state representation, or can be easily extracted form it. Also, game-specific abstractions are often performed to deal with the large state-space. Furthermore, the reward signal may be shaped in a way to accelerate the learning.

One of the key distinctions of the methods described in this thesis is their generic nature. The agents are expected to be able to play in at least a large set of Atari 2600 games. As such, no game-specific assumption or prior knowledge is used in their design or fine-tuning

[4]In association with the IEEE Consumer Electronics Society Games Innovation Conference 2009 and with the IEEE Symposium on Computational Intelligence and Games

[5]http://julian.togelius.com/mariocompetition2009/

beyond that which is expected to be common across this diverse set of games. In this regard, this research is more closely related to the field of *Domain-Independent Planning*, and more particularly *General Game Playing (GGP)*. The aim of planning is to generate a sequence of actions that transitions the environment from the initial state to a goal state. Planning is *domain-indipendent* if there is no reliance on specific structures of a single domain [Wilkins, 1984]. In General Game Playing, the goal is to develop agents that can play generic, finite and discrete games [Genesereth and Love, 2005]. Both domain-independent planning and GGP share the *generic* characteristic of our methods. That is, the agents are expected to solve different problems, and use no task-specific assumptions or prior knowledge. Also, similar to our search-based methods, they have generative models that allow the agents to simulate the consequence of their actions.

The key difference between these domains and the problems explored in this thesis is that both domain-independent planning and General Game Playing require an explicit declaration of the state representation and transition in a logic-based formal language. Our methods on the other hand only use the content of the game screen and console RAM (in the case of learning agents) or the emulator as a *black box* generative model (in the case of search-based agents). Requiring a formal definition of problems differentiates domain-independent planning and General Game Playing from this research in two important ways. First, the formal definition of a problem can be used as a source for generic heuristics [Haslum et al., 2005, Clune, 2007]. Also, since the formal language is generated by human agents, defining more complex games can become impractical. In theory, it is possible to define and play popular arcade games like Space Invaders or River Raid in both domain-independent planning and General Game Playing. However, in practice defining the complex dynamics of these games in a formal language is prohibitively expensive.

1.4 Contributions

The key contributions of this thesis are as follows:

- Introducing the Atari 2600, with its diverse set of games, as an attractive platform for developing and demonstrating game AI algorithms.

- Achieving significant learning in *arbitrary* Atari 2600 games using Reinforcement Learning.

- Generating a state-action tree for any Atari 2600 game using the save-state/restore-state features of the emulator, and achieving human-level performance in a number of games using full-tree search and UCT.

- Employing a novel method for evaluating and comparing the player agents. The development and parameter search for all agents is performed on four predetermined games (*training games*). Once the agents are implemented and the required parameter are selected, their performance is evaluated on a set of 50 randomly chosen games (*test games*). To our knowledge, this is the first time that a number of game AI methods are evaluated on such a large set of problems. Similarly, this is the first time when the parameter search and the evaluation of AI methods are performed on two separate sets of problems.

1.5 Thesis Outline

Two distinct approaches are taken to generate agents that can play Atari 2600 games: RL-based (chapter 2) and Search-based (chapter 3). Each chapter includes the background material for the algorithms applied in it, as well as the results of the introduced agents on the training games. Chapter 4 presents the evaluation method, the experimental results on the test games, and an analysis of how certain game properties affect the learning performance of various methods. The thesis conclusion and a number of future directions for this research is presented in chapter 5. Appendix A defines the video game related terminology used through the thesis. A short description for each of the training games is provided in Appendix B. Finally, the Atari 2600 hardware specification is presented in Appendix C.

Chapter 2

Reinforcement Learning Agents using Gradient Descent Sarsa(λ)

This chapter demonstrates how the gradient descent Sarsa(λ) algorithm with linear function approximation can be used along with feature vectors generated from the game screen or the console RAM to learn to play Atari 2600 games. Section 2.1 presents a brief introduction to reinforcement learning and a number of fundamental concepts that are used within the rest of the chapter. Section 2.2 introduces a generic, model-free, RL-based framework for playing Atari 2600 games. Our three feature vector generation methods are explained in sections 2.3 to 2.5, followed by a description of the parameter search and experimental results of the RL-agents on the training games in sections 2.6 and 2.7. Finally, Section 2.8 explores a number of challenges in learning game-independent Atari 2600 games and possible future directions for this research.

Among a large body of possible reinforcement learning methods, Sarsa(λ) is selected for two primary reasons. First, Sarsa(λ) is a widely used algorithm that has been successfully applied on a large range of problems. Examples of the applications of Sarsa(λ) include RoboCup soccer keepaway [Stone et al., 2005], control of an all-terrain robot [Luders, 2007], and learning in 3D shooter games [McPartland and Gallagher, 2008]. Also, good performance in linear gradient descent Sarsa(λ) has a strong dependence on features that can estimate the value function linearly. This makes Sarsa(λ) a fitting algorithm as we explore various game-independent feature generation methods.

2.1 Preliminaries

This section provides a brief overview of reinforcement learning and a number of fundamental concepts that are required for the rest of this thesis. For a through introduction to reinforcement learning please refer to Sutton and Barto's book on the subject [Sutton and Barto, 1998].

2.1.1 Reinforcement Learning

Reinforcement learning (*RL*) is concerned with the problem of learning via interacting with an environment. The entity that performs the interactions and does the learning is referred to as the *agent*. The entire surrounding world that the agent interacts with is called the *environment*. We will be assuming that the agent interacts with the environment via a discrete and finite set of *actions*.

The representation of the environment that is available to the agent is referred to as the *state*, denoted by s. The states are usually assumed to have the *Markov property*, that is, each state should summarize all relevant information from past interactions. The *transition function* P determines how the state of the environment changes with regard to the agent actions:

$$P(s, a, s') = Pr(s_{t+1} = s' | s_t = s, a_t = a)$$

A *policy* π is a mapping from states to actions, and determines how the agent acts in different situations in the environment. A policy could be either deterministic, i.e., each state s is mapped to exactly one action a, or stochastic, in which case a state s is mapped to a vector containing the probability of taking each action in that state. The learning is guided by a *reward* signal, where the agent receives the reward r_t at each time step t. The reward signal can also be either deterministic or stochastic. The aim of the learning is to find a policy π^* which maximizes the expected sum of discounted future rewards.

A *finite Markov Decision Process* (*MDP*) is a tuple (S, A, P, R), where S is the set of states, A is the set of actions, P is the transition function and R is the reward function, mapping the state at the time t (s_t) to a reward of r_t. The *value* of state s under policy π, denoted by $V^\pi(s)$ is the sum of the discounted rewards we expect to receive if we start in state s and follow policy π:

$$V^\pi(s) = E_\pi \sum_{k=0}^{\infty} (\gamma^k r_{t+k+1} | s_t = s)$$

This is a case of an *infinite-horizon* task, since the time steps go to infinity. If the learning task naturally breaks into smaller sequences, the task is called *episodic*, and the value of a state is the expected sum of rewards until the end of the episode:

$$V^\pi(s) = E_\pi \sum_{k=0}^{T} (\gamma^k r_{t+k+1} | s_t = s)$$

where T is the length of an episode. V^π is often referred to as the *state-value function*, since it maps a state s to its value. Alternatively, we can define an *action-value function*, $Q^\pi(s, a)$, which is the discounted rewards we expect to receive if we start at state s, take action a, and then follow the policy π onward.

The aim of reinforcement learning is to find an *optimal policy*, that is, a policy that performs better than or as good as any other policy starting from any state-action:

$$\pi^* = \arg\max_{\pi} Q^{\pi}(s, a) \quad \text{for all } s \in S, a \in A$$

While the optimal policy may not be unique, there is a unique value function corresponding to all optimal policies. This is called the *optimal value function*, and is denoted by V^* or Q^*. Note that if the optimal value function is known, simply acting greedily with regard to it will give us an optimal policy :

$$\pi^*(s) = \arg\max_{a} Q^*(s, a)$$

When the dynamics of the environment (P and R) are known, the optimal value function can be calculated exactly by solving the linear system of the *Bellman optimality equations*. When the complete dynamics of the environment is not known, or when solving the full linear system is impractical due to the large state-space, there are methods that estimate the optimal value function by interacting with the environment and looking at samples of the state transitions and the received rewards. Section 2.1.3 presents an overview of Sarsa(λ), the algorithm we use in our RL-based agents to estimate Q^* based on sample interactions with the environment.

2.1.2 Function Approximation

Many interesting reinforcement learning problems have very large state-spaces, ranging from millions states to even much more. There are two problems associated with learning and updating the value of each state separately in a large state-space. First, storing an individual value $V(s)$ for every state becomes impractical. More importantly, very little *generalization* will be done. That is, if we learn that a value of a state is very high or very low, we do not generalize this to the neighboring states. This forces us to visit each of the billions of individual states multiple times in order to get a good estimate of its value. Function approximation allows us to overcome both problems.

When doing function approximation, each state s is represented by a vector of values $\Phi(s)$, known as the *feature vector*. The length of this vector, denoted by n, is usually much smaller than the number of states: $n \ll |S|$. The value of state s at time step t is estimated as a parametric function over the features of s and the current parameter vector θ_t:

$$V_t(s) = f(\Phi(s), \theta_t)$$

The aim of the learning now becomes finding the parameter vector θ^*, which corresponds to an approximation of the optimal value function V^*.

Linear functions are one of the most important and most widely used parametric functions for function approximation. With a linear function, the value of a state s at time t

becomes:

$$V_t(s) = \sum_{i=1}^{n} \theta_t(i)\Phi(s)(i)$$

This can also be extended to action value functions:

$$Q_t(s, a) = \sum_{i=1}^{n} \theta_t(i)\Phi_a(s)(i)$$

Here, $\Phi_a(s)$ is the feature vector corresponding to the (s, a) state-action pair.

We are particularly interested in the case of linear functions on *binary* feature vectors, i.e., when the values of the feature vector are either 0 or 1. One advantage of a binary feature vector is that instead of storing the complete feature vector, which may be very large and very sparse, we only need to keep track of the indices that are 1:

$$Q_t(s, a) = \sum_{i \in I(\Phi_a(s))} \theta_t(i) \tag{2.1}$$

where $I(\Phi_a(s))$ is the set of *one*-indices in the current feature vector $\Phi_a(s)$.

2.1.3 Gradient-Descent Sarsa(λ) with Linear Function Approximation

Sarsa(λ) is a widely used temporal difference method that stochastically approximates the optimal value function based on the state transition and the reward samples received from online interaction with the environment. The original Sarsa algorithm works as follows: At time step t, the agent is in state s_t. It then chooses an action a_t from an ϵ-greedy policy [1] based on its current estimate of the optimal value function Q_t. Consequently, the agent receives a reward of r_t and the environment transitions to state s_{t+1}. The agent then chooses action a_{t+1} based on the ϵ-greedy policy. The following temporal difference update is used to update the estimate of the action-value function based on the given $(s_t, a_t, r_t, s_{t+1}, a_{t+1})$ sample:

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha\delta$$

where

$$\delta = r_t + \gamma Q_t(s_{t+1}, a_{t+1}) - Q_t(s_t, a_t) \tag{2.2}$$

and α is the learning rate.

Sarsa(λ) extends the original Sarsa algorithm by introducing the idea of *eligibility traces.* Eligibility traces allow us to update the action-value function not only for the latest (s_t, a_t) state-action pair, but also for all the recently visited state-actions. To do this, an additional eligibility value is stored for every state-action pair, denoted by $e(s, a)$. At each step, the

[1] ϵ-greedy policies choose the action that maximizes the current value function with probability $(1 - \epsilon)$ and a random action with the probability ϵ. This is one solution to the well-known *exploration/exploitation* problem. That is, we need to insure that while the agent exploits the current estimation of the value function, it also visits other states enough to generate an accurate estimate for their values.

eligibility traces of all the state-action pairs are reduced by a factor of $\gamma\lambda$. The eligibility trace of the latest state-action $e(s_t, a_t)$ is then set to one [2]:

$$e_t(s,a) = \begin{cases} 1 & \text{if } s = s_t \text{ and } a = a_t \\ \gamma\lambda e_{t-1}(s,a) & \text{for all other state-action pairs} \end{cases}$$

After each $(s_t, a_t, r_t, s_{t+1}, a_{t+1})$ sample, δ is calculated the same as in equation 2.2. However, instead of only updating $Q(s_t, a_t)$, *all* state-action pairs are updated based on their eligibility:

$$Q_{t+1}(s,a) = Q_t(s,a) + \alpha\delta e_t(s,a) \quad \text{for all s,a} \tag{2.3}$$

When doing linear function approximation, instead of keeping an eligibility value for each state, the eligibility trace vector e_t keeps an eligibility trace for each item in the feature vector. On each time step, after reducing the eligibility vector by a factor of $\gamma\lambda$, the items corresponding to *one*-indices in the current feature vector are set to one. Additionally, we may wish to clear all the traces corresponding to all actions other than the current action a_t in state s_t:

$$e_t = \gamma\lambda e_{t-1} \tag{2.4}$$

$$e_t(i) = \begin{cases} 1 & \text{for all } i \in I(\Phi_{a_t}(s_t)) \\ 0 & \text{for all } i \in I(\Phi_{a'}(s_t)) \text{ and } a' \neq a_t \end{cases} \tag{2.5}$$

On each step, the following gradient-descent step is used to update the parameter vector:

$$\theta_{t+1} = \theta_t + \alpha\delta e_t \tag{2.6}$$

where δ is the same as in equation 2.2 and α is the learning rate. Figure 2.1 contains the pseudocode for gradient-descent Sarsa(λ) algorithm for an episodic task.

2.1.4 Optimistic Initialization

Optimistic initialization encourages the learning agent to explore unvisited states or unseen features. When doing function approximation, optimistic initialization is achieved by initializing the values of the weights vector Θ to a non-zero value. If the maximum state-action value in an MDP is known, the Θ values should be initialized such that for any state-action pair (s, a), $Q(s, a) = \sum_{i=1}^{n} \theta(i)\Phi_a(s)(i)$ is the maximum value possible.

2.1.5 Tile-Coding

Tile-coding is a method to generate binary feature vectors from multi-dimensional continuous values. In its most basic form, tile-coding is simply grid partitioning of scalar values. Each element in the partition is called a *tile* and it corresponds to a bit in the feature vector. The partition itself is called a *tiling*. With one tiling, exactly one bit will be 1 in

[2]The method we present here is called *replacing traces*. In the alternative approach, called *accumulating traces*, instead of setting the trace of the latest state-action pair to 1, its value is increased by 1: $e_t(s_t, a_t) = \gamma\lambda e_{t-1}(s_t, a_t) + 1$

```
Assume $\gamma$ (discount factor), $\alpha$ (learning rate), $A$ (set of available actions), $\epsilon$ (exploration/exploitattion constant), $\lambda$ are defined.
Let $n$ be the length of the feature vector
For $i \in \{1, ..., n\}$, $\theta(i) = \begin{cases} \frac{1}{n} & \text{Optimistic Initialization} \\ 0 & \text{Otherwise} \end{cases}$

$RL\_Start\_Episode(\Phi_0)$:
  1. $e = \vec{0}$
  2. $Q_0(a) = \sum_{i \in I(\Phi_{0,a})} \theta(i) \qquad \forall a \in A$
  3. $a_0 = Get\_\epsilon\text{-}greedy\_Action(Q_0)$
  4. return $a_0$

$RL\_Step(\Phi_t, r_t)$:
  1. $\delta = r_t - Q_{t-1}(a_{t-1})$
  2. $Q_t(a) = \sum_{i \in I(\Phi_{t,a})} \theta(i) \qquad \forall a \in A$
  3. $a_t = Get\_\epsilon\text{-}greedy\_Action(Q_t)$
  4. $\delta = \delta + \gamma Q_t(a_t)$
  5. $\theta = \theta + \alpha \delta e$
  6. $e = \gamma \lambda e$
  7. $e(i) = \begin{cases} 1 & \forall i \in I(\Phi_{t,a_t}) \\ 0 & \forall i \in I(\Phi_{t,a'}) \text{ and } a' \neq a_t \end{cases}$
  8. return $a_t$

$RL\_End\_Episode(\Phi_T, r_T)$:
  1. $\delta = r_T - Q_{T-1}(a_{T-1})$
  2. $\theta = \theta + \alpha \delta e$
```

Figure 2.1: Pseudocode for linear gradient-descent Sarsa(λ) with binary feature vectors

```
On start of the game:
  1. From the emulator, receive the screen matrix $X_0$, the RAM vector $M_0$, and the score
     received in the first frame $r_0$
  2. Generate a feature vector $\Phi_0$ from either $X_0$ or $M_0$
  3. $a_0 = RL\_Start\_Episode(\Phi_0)$
  4. Apply the action $a_0$ via the emulator

On each time step $t$ during the game:
  1. From the emulator, receive the screen matrix $X_t$, the RAM vector $M_t$, and the score
     received in this frame $r_t$
  2. Generate a feature vector $\Phi_t$ from either $X_t$ or $M_t$
  3. $a_t = RL\_Step(\Phi_t, r_t)$
  4. Apply the action $a_t$ via the emulator

On end of the game:
  1. From the emulator, receive the screen matrix $X_T$, the RAM vector $M_T$, and the score
     received in this frame $r_T$
  2. Generate a feature vector $\Phi_T$ from either $X_T$ or $M_T$
  3. $RL\_End\_Episode(\Phi_T, r_T)$
  4. Restart the game through the emulator
```

Figure 2.2: A generic RL-based agent

the resulting feature vector, and the remaining bits will be 0. However, we can have additional tilings, placed on top of each other with some offset. With n tilings, each point in the multi-dimensional space will be inside n tiles, and thus there will always be n non-zero values in the resulting feature vector. Larger sized tiles allow more generalization, while more number of tilings allow a higher resolution. The binary feature vector generated by tile-coding the continues variables $x_1, x_2, ..., x_n$ is denoted as: $TC(x_1, x_2, ..., x_n)^T$

2.2 A Generic RL-based Agent for Atari 2600 Games

We are interested in developing agents that learn to play generic games by interacting with them. At each time step t, the agent has access to the screenshots of the game as a matrix of color indices X_t, the score it received during the frame r_t, and whether the game has ended. In a special case, we allow the RAM-agent to have access to the console memory in a binary vector M_t. Aside from these, the agent is not given any additional information or prior knowledge about a game. Once the action a_t is chosen by the agent, it will be carried by the emulator and the game environment moves to the next state s_{t+1}. The learning task is episodic. Each episode starts at the point in the game when the player is able to start acting and ends when the game ends (e.g., the player character dies) or if we reach a predefined maximum number of frames per episode. At the end of each episode, the game is restarted through the emulator, and a new episode begins.

Figure 2.2 contains the pseudocode for a generic RL-based agent. While the agents presented in this chapter exclusively use Sarsa(λ), the methods *RL_Start_Episode*, *RL_Step*, and *RL_End_Episode* can be implemented using any episodic, online, reinforcement learning algorithm.

Feature representation is a very important task in most reinforcement learning problems. With linear function approximation, we are assuming that a meaningful value function can be represented as a linear combination of the generated features. If this assumption does not hold, even if the learning converges, the agent will not perform very well in the environment. Sections 2.3 to 2.5 will present three different feature generation methods for generic Atari 2600 games. The parameter search and experimental results on the training games for each method is discussed in Sections 2.6 and 2.7.

2.3 Feature Vector Generation based on Basic Abstraction of the ScreenShots (BASS)

The first feature generation method is based on looking directly at the colored pixels on the screen. This method is motivated by three observations of the Atari 2600 hardware and games:

1. While the Atari 2600 hardware supports a screen resolution of 160×210, game objects are often much larger than a few pixels. Overall, the important game events happen in a much lower resolution[3].
2. Many Atari 2600 games have a static background, with a few important objects moving on the screen. That is, while the screen matrix is densely populated, the actual interesting features on the screen are often sparse.
3. While the hardware can show up to 128 colors in the NTSC mode, it is limited to only 8 colors in the SECAM mode. Consequently, most games use a few number of distinct colors to distinguish important objects on the screen.

Based on these observations, a binary feature vector is generated by looking at the existence of each of the eight SECAM palette colors in a lower resolution version of the screens.

We assume that a matrix of background color indices[4] S, and a mapping $\sigma_{[0,127]\Rightarrow[0,7]}$ from the NTSC color indices to the SECAM palette indices are defined. On each time step, the feature vector generation method is given a matrix of color indices X. A new screen matrix $\hat{X}$ is generated by removing the static background and mapping the indices to the SECAM palette:

$$\hat{X}(y,x) = \begin{cases} \sigma(X(y,x)) & \text{If } X(y,x) \neq S(y,x) \\ -1 & \text{Otherwise} \end{cases} \tag{2.7}$$

[3]This is partially due to the limited hardware capabilities of the Atari 2600 which prohibits moving thousands of small objects on the screen. Another possible reason for having relatively large objects on the screen is to allow the players to enjoy the game with some distance from their small TV screens.

[4]See section 2.4.1 for the method used to detect the static background

The new screen matrix $\hat{X}$ is then divided into a grid of m by n blocks. For each block $B_{i,j}, i \in \{1, ..., m\}, j \in \{1, ..., n\}$ an 8-bit vector $v_{B_{i,j}}$ is generated, such that:

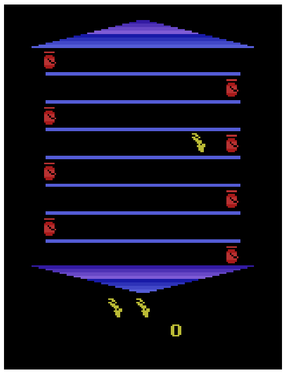
$$v_{B_{i,j}}(c) = \begin{cases} 1 & \text{If color } c \text{ exists in the block } B_{i,j} \\ 0 & \text{Otherwise} \end{cases} \tag{2.8}$$

The resulting 8-bit vectors are concatenated to generate an $m \times n \times 8$ bit vector v_l. Informally, what this vector captures is whether there is an object of a certain color in each part of the screen. For instance, $v_l(1) = 1$ indicates that there is an object with color index 1 in the upper left corner of the screen. For example, in the case of the game Asterix, the vector v_l captures if there is a green object (which is the color of the player character), a red object (collectable objects), or a pink object (enemy units) in each sub block of the screen. Figure 2.3 presents a visualization of how the screenshots from three of the training games compare with their corresponding abstracted version. Each cell in the grid represents the SECAM colors present in that sub block. A black cell indicates that all the pixels in this block are identical to the background. Note that the resulting abstraction is often much more sparse than the original screenshot.

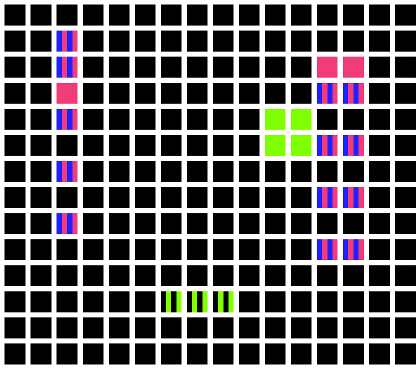
Aside from the existence of objects in different locations, we are also interested in the relation between them. For instance, in the case of the game Asterix, it is important to know if there is a green object (player character) in the centre of the screen *and* a red object (collectable object) to the right of it. Linear function approximation is unable to capture these pair relations on its own, so the relation between objects needs to be represented in the feature vector. To capture the two-object relations, a new vector v_q is generated which contains all the pairwise AND's of the items in V_l. The vector v_q represents the existence of pairs of objects of different colors in various parts of the screen. For instance, $v_q(1) = 1$ signifies that $v_l(1) = 1$ *and* $v_l(2) = 1$, which in turn means that there is an object with color index 1 *and* an object with color index 2 in the upper left corner of the screen.

For each action $a \in A$, the corresponding feature vector Φ_a is a $(|v_l| + |v_q|) \times |A|$ bit binary vector, which contains the concatenated vectors v_l and v_q in the location corresponding to action a, and 0's everywhere else.

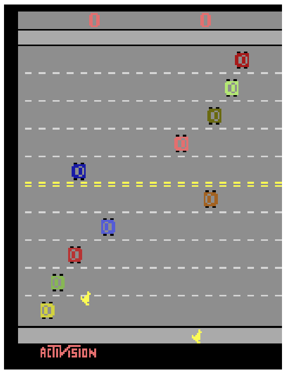
Figure 2.4 shows the pseudocode for the BASS feature vector generation method. Note that this pseudocode generates the full feature vector Φ. In practice, this vector will be very sparse, and we will only store the *one*-indices $I(\Phi)$. The *BASS-Agent* is based on combining the linear gradient-descent Sarsa(λ) algorithm (Figure 2.1) with the BASS feature vector generation method.



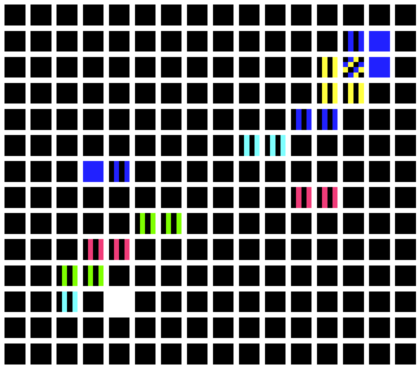
(a) Asterix (screenshot)



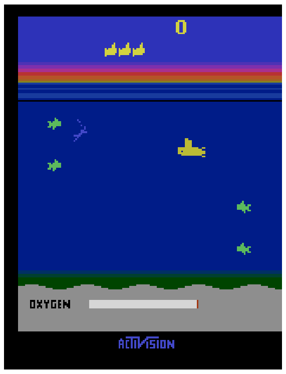
(b) Asterix (abstract)



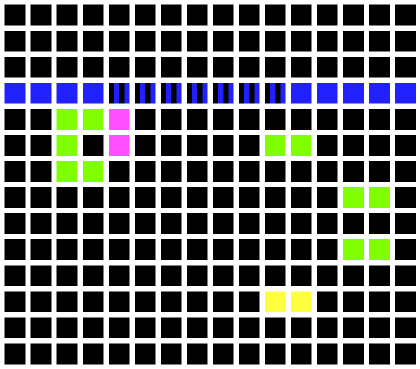
(c) Freeway (screenshot)



(d) Freeway (abstract)



(e) Seaquest (screenshot)



(f) Seaquest (abstract)

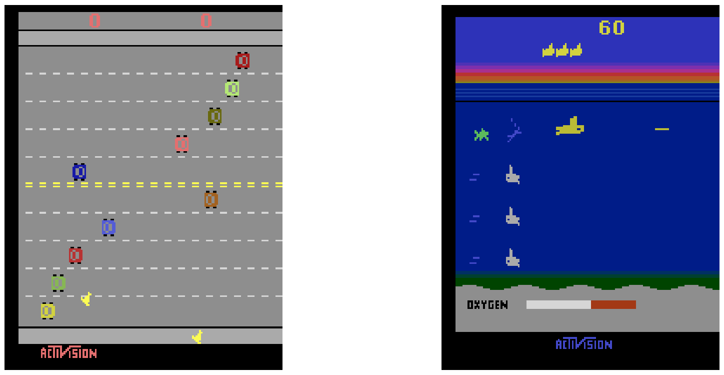
Figure 2.3: A visualization of screenshot abstraction in BASS, with a 14×16 abstraction grid.

Assume h, w (height and width of the screen), S (background matrix), σ (mapping from NTSC to SECAM palette), and m, n (height and width of the grid for screen abstraction) are defined.

```
generate_feature_vector(screen_matrix $X$):
  1. Generate a mapped matrix $\hat{X}$ with background removed:
        for $y = 1$ to $h$:
            for $x = 1$ to $w$:
                $\hat{X}(y,x) = \begin{cases} \sigma(X(y,x)) & \text{If } X(y,x) \neq S(y,x) \\ -1 & \text{Otherwise} \end{cases}$

  2. Divide $\hat{X}$ into a grid of $m \times n$ blocks $B_{i\in\{1,...,m\},j\in\{1,...,n\}}$
  3. For each sub block $B_{i,j}$ generate an 8-bit vector $v_{B_{i,j}}$. Concatenate these vectors to
     produce $v_l$:
        $v_l = []$
        For $i = 1$ to $m$, $j = 1$ to $n$:
            For $c = 1$ to 8:
                $v_{B_{i,j}}(c) = \begin{cases} 1 & \text{If color } c \text{ exists in the block } B_{i,j} \\ 0 & \text{Otherwise} \end{cases}$
            $v_l = concatenate(v_l, v_{B_{i,j}})$

  4. Generate $v_q$ by pairwise $AND$'ing the items of $v_l$:

        $v_q((i-1)|v_l| + j) = AND(v_l(i), v_l(j)) \quad \forall i \in \{1, ..., |v_l|\}, j \in \{i, ..., |v_l|\}$

  5. Generate the final feature vector $\Phi$ from $v_l$ and $v_q$:
        $v = concatenate(v_l, v_q)$
        $k = |v|$
        for $a \in A$ [a], $\Phi_a(i) = \begin{cases} v(i + ak) & ak \leq i \leq (a+1)k \\ 0 & \text{Otherwise} \end{cases}$

  6. Return $\Phi$
```

[a]Here we assume that each discrete action $a \in A$ is assigned an integer value between 0 and $|A| - 1$.

Figure 2.4: Feature Vector Generation based on Basic Abstraction of the ScreenShots (BASS)



(a) (b)

Figure 2.5: Sample screenshots from the training games Freeway (a) and Seaquest (b). Note that while there are many objects on each screen, they are all instances of a few number of classes (*Chicken* and *Car* in the case of the game Freeway, and *Fish, Swimmer, PlayerSubmarine, EnemySubmarine, PlayerBullet* and *EnemyBullet* in Seaquest).

2.4 Feature Vector Generation based on Detecting Instances of Classes of Objects (DISCO)

This feature generation method is based on detecting a set of classes of game entities and locating instances of these classes on each screen. The method is motivated by the following observations on Atari 2600 games:

1. Similar to the BASS method, we note that many Atari 2600 games have a static background, with a number of game entities moving on the screen.
2. These entities are often instances of a few *classes* of objects. For instance, as Figure 2.5 demonstrates, while there are many objects on a sample screenshot of the game Freeway, all of these objects are instances of only two classes: *Chicken* and *Car*. Similarly, all the objects on a sample screen of the game Seaquest are instance of one of these six classes: *Fish, Swimmer, PlayerSubmarine, EnemySubmarine, PlayerBullet, EnemyBullet*.
3. The interaction between two objects can often be generalized to all instances of the classes that the objects belong to. For instance, in the game Freeway, the knowledge that a particular instance of the *Chicken* class hitting a particular class of the *Car* class in the middle of screen is bad can be generalized to all instances of *Chicken* and all instances of *Car*, anywhere on the screen[5].

Based on these observations, the DISCO feature vector generation works by detecting classes of game objects, and looking at the relation between instances of these classes on each screen. Detecting interesting moving objects and following them from frame to frame is part

[5]Describing the environment in terms of classes, objects, and the relations between them and attempting to generalize the learning across objects is common in the field of relational reinforcement learning[Tadepalli et al., 2004].

of an important field in computer vision, called *tracking*. There are numerous deterministic and probabilistic approaches proposed to solve this problem in the tracking literature[6]. For the purpose of this research, we are using very simple methods to deal with the tracking problem[7]. This is done in the following steps:

- Before the RL-agent starts acting in the game (pre-computation):
  - **Background detection:** The static background matrix S is detected from a set of game screens. In our experiments, the sample game screens are generated by acting randomly in each game[8].
  - **Blob extraction:** the static background is subtracted and a list of moving blob objects is detected from each game screen.
  - **Class discovery:** a set of classes of objects C is detected from the extracted blob objects.
- While the RL-agent is acting in the game:
  - **Class instance detection:** Once the RL-agent starts acting, on each time step, instances of classes $c \in C$ are detected from the current screen matrix.
  - **Feature vector generation:** A feature vector is then generated from these detected instances.

The following sections explain each of the five steps in details.

2.4.1 Background Detection

A histogram-based method is used to detect the static game background. Given a set of sample screenshots, a histogram is generated for every pixel on the screen, counting the colors that appear in that pixel. The background color for a pixel is then set to the most frequent color in that pixel. Figure 2.6 contains the pseudocode for this method.

Although simple, this method often works well in games with a static background. This is because it does not need to deal with noise or a moving camera, two of the main challenges in background detection tasks[9].

2.4.2 Blob Extraction

The goal of blob extraction is to find connected regions from the screen matrix, after the static background is removed. This is done in two steps. First, a sequential labeling algo-

[6]See [Yilmaz et al., 2006] and [Forsyth and Ponce, 2002] for overviews on the current tracking methods employed in the computer vision community

[7]We note that employing more advanced computer vision techniques can potentially improve the current results.

[8]They could also be generated by having one of the search-based or RAM-based agents play the game.

[9]This is only true when the assumption of a static background holds. For games with a moving background, this method will not perform very well and a more advanced background detection method is required.

```
Assume $h, w$ (height and width of the screen) is defined.

detect_background(screen_matrix $[X_1, X_2, ..., X_n]$)
  1. Initialize a histogram for each pixel on the screen:
        for $i = 1$ to $h$:
            for $j = 1$ to $w$:
                $h_{ij} = \vec{0}$

  2. Go through the screenshots and fill in the histograms:
        for $f = 1$ to $n$:
            for $i = 1$ to $h$, $j = 1$ to $w$:
                $h_{ij}(X_f(i,j)) = h_{ij}(X_f(i,j)) + 1$

  3. For each pixel, pick the most frequent color as the background color:
        for $i = 1$ to $h$:
            for $j = 1$ to $w$:
                $S(i,j) = \arg\max_c(h_{ij}(c))$

  4. Return $S$
```

Figure 2.6: Pseudocode for histogram-based background detection

rithm [Horn, 1986] marks 8-connected regions which share the same color. These regions are then compared with the regions labeled on the previous frame, and the neighboring blobs that are moving with the same velocity are merged together. The merging step allows us to detect blob objects of different colors, or objects with small gaps between their subparts. Figure 2.7 contains the pseudocode for our blob extraction method. Figure 2.8 shows the original game screen, the static background detected, the initial labeled regions, and the final merged blobs for the games Freeway and Seaquest.

2.4.3 Class Discovery

A class of objects is a collection of all shapes that represent an entity in a game. Often, these shapes represent different animation frames of an entity. They can also represent obscured or clipped versions of other shapes in this class.

Our general approach to discovering classes of objects is to look at a sequence of game screens $[X_1, X_2, ..., X_n]$, and for each object o_t on screen X_t, try to find the object o'_{t-1} that represents the same entity in the previous frame X_{t-1}. If o'_{t-1} is found and it is different from o_t, we can conclude that the two shapes belong to the same class.

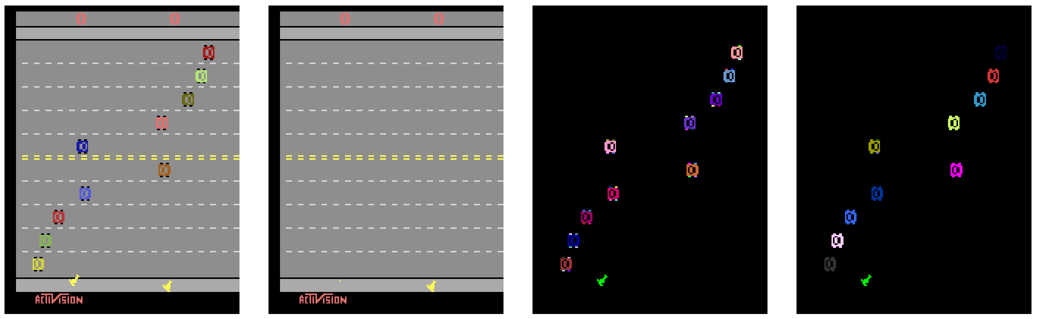
To find the object that represents the same entity in the previous frame, we assume that any two sequential animation shapes o'_{t-1} and o_t have the following properties:

1. $distance(o'_{t-1}, o_t) < d$. That is, the two objects are relatively close to each other. This is because objects cannot move arbitrary fast on the screen or the player would not

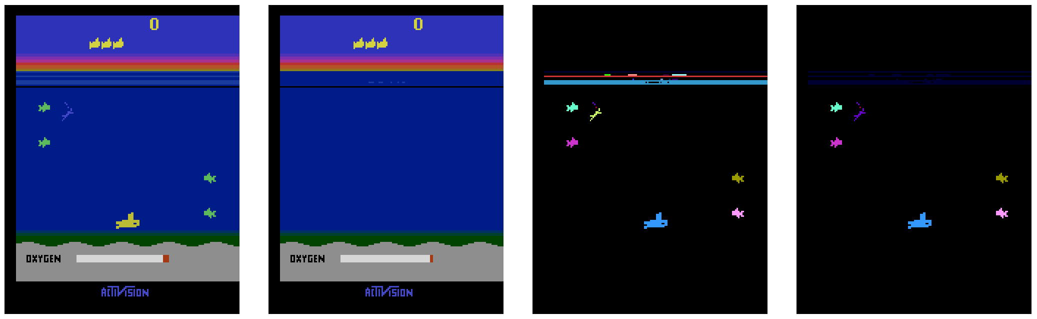
```
Assume $h, w$ (height and width of the screen), and $S$ (background matrix) are defined.
blob_extraction($X_t$):
    $R_t = sequential\_labeling(X_t)$
    $R_t = merge\_equivalent\_regions(R_t, R_{t-1})$
    Each labeled region in $R_t$ is now an extracted blob object
    Return a list of the extracted objects in $R_t$

sequential_labeling($X$):
    let $R$ be the $h \times w$ region labels matrix
    $region\_counter = 1$
    For $i = 1$ to $h$, $j = 1$ to $w$:
        If $X(i,j) = S(i,j)$
            $R(i,j) = 0$    (background pixel)
        For $(\Delta_y, \Delta_x) \in \{(-1,-1), (-1,0), (-1,1), (0,-1)\}$:
            If $X(i,j) = X(i + \Delta_y, j + \Delta_x)$
                $R(i,j) = R(i + \Delta_y, j + \Delta_x)$
        If $R(i,j)$ is still unassigned
            $R(i,j) = region\_counter$
            $region\_counter = region\_counter + 1$

    (second pass: merging connected regions)
    For $i = 1$ to $h$, $j = 1$ to $w$:
        For every immediate neighbor of $X(i,j)$:
            If the two pixels have the same color but are assigned to different regions,
            merge the two regions

    Return $R$

merge_equivalent_regions($R_t, R_{t-1}$):
    For each region $r$ in $R_t$:
        Find a nearby and similar [a] region $r'$ in $R_{t-1}$
        Calculate $velocity(r)$ based on the distance between $r$ and $r'$

    For each region $r$ in $R_t$:
        For each neighboring region $r'$:
            if $velocity(r) = velocity(r')$, merge $r$ and $r'$

    Return the merged regions
```

[a]See section 2.4.3 for details on how similarity and closeness are defined.

Figure 2.7: Blob Extraction Pseudocode



(a) Original Screenshot (b) Detected Background (c) Extracted Blobs (Pre-Merge) (d) Extracted Blobs (Post-Merge)



(e) Original Screenshot (f) Detected Background (g) Extracted Blobs (Pre-Merge) (h) Extracted Blobs (Post-Merge)

Figure 2.8: Background Detection and Blob Extraction for the games Freeway (a-d) and Seaquest (e-h). In the Extracted blob panels, each color indicates a distinctly labeled region.

be able to see them.

2. $shape\_similarity(o'_{t-1}, o_t) > s$. That is, the two objects are relatively similar to each other. Generally, if the animation shapes change drastically from frame to frame, the game will look jumpy and hard to follow[10].

To find o'_{t-1} corresponding to o_t, we look at all the objects in X_{t-1} which are within d-pixel neighborhood of o_t. Among these objects, if the object that is the most similar to o_t passes the $shape\_similarity(o'_{t-1}, o_t) > s$ test, it will be assigned as o'_{t-1}. Figure 2.9 contains the pseudocode for our class-dicovery approach. Figure 2.10 shows the discovered classes and the shapes associated to each class for the game Freeway. Note that the second and the third classes both represent the *Car* game entity. Also, the last class, with only one shape, does not represent any meaningful entity in the game.

There are two main problems with the current method of class discovery. The first problem is that in addition to the real game entities, the method discovers many *junk classes*. These classes often correspond to frequently changing areas in the game background. The waterline in the game Seaquest (Figure 2.3e) is an example of a local area with frequently

[10]It is common for Atari 2600 games to have shapes that change considerably in color from frame to frame. Therefore, when looking at objects similarity, we only consider the shapes of the objects and not their coloring.

```
Assume $d, s$ (distance and similarity thresholds) are defined.
discover_classes($[X_1, X_2, ..., X_n]$):
    C = []
    for $t = 2$ to $n$:
        $O_t = blob\_extraction(X_t)$
        for $o_t \in O_t$:
            if $o_t$ is already in any class $c \in C$
                $o_t.class = c$
                continue
            $o'_{t-1} = find\_prev\_obj(o_t)$
            if $o'_{t-1}$ exists:
                $c = o'_{t-1}.class$
                $o_t.class = c$
                $c.add\_shape(o_t)$
            else:
                Let $c_{new}$ be a new class
                $c_{new}.add\_shape(o_t)$
                $C.insert(c_{new})$
                $o_t.class = c_{new}$
    Return C
```

Figure 2.9: Class Discovery Pseudocode

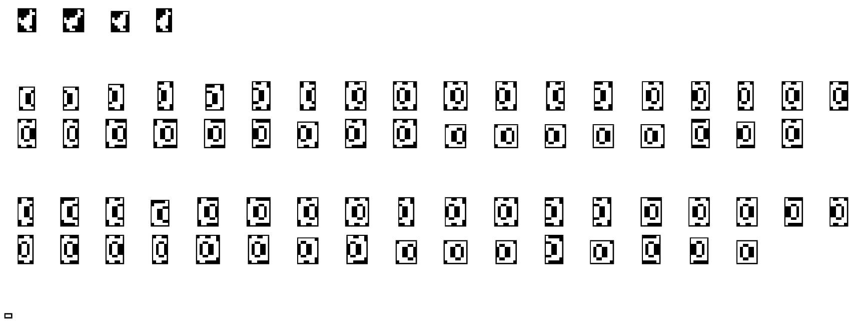


Figure 2.10: Discovered classes in the game Freeway. Each horizontal section contains the shapes belonging to a class.

changing background. We attempt to address this issue by filtering out classes that do not appear on the screen frequently enough or are limited to a very small area on the screen.

A second problem with the current approach is that shapes of a single game entity can be assigned to multiple classes. For example, if there are two different shapes of a single class on the very first frame, two separate classes will be created for them. This is particularly problematic because, as we will discuss in section 2.4.5, the length of the feature vector grows quadratically with the number of classes. To address this, if the number of discovered classes is too large for feature vector generation, classes that contain similar objects are automatically merged together. The merging process is continued until we are left with an acceptable number of classes.

```
*Assume $C$ (discovered classes) and $L$ (list of all shape objects for all classes, sorted by size
from larger to smaller) are defined*
*For each $c \in C$, $\Psi_t(c)$ will hold the instances of the class $c$ detected on the screen $X_t$*
detect_class_instances($X_t$):
    For $o \in L$:
        Scan the foreground pixels of $X_t$ for a match to $o$
        If there is a match:
          1. Mark the matching pixels of $X_t$, to prevent a rematch to a smaller shape
          2. $c = o.class$
          3. Let $\psi_{new}$ be a new instance, containing the coordinate of the match
          4. $\Psi_t(c).add(\psi_{new})$
    Return $\Psi_t$

calculate_instance_velocities($\Psi_t$, $\Psi_{t-1}$):
    For $c \in C$:
        For $\psi_t \in \Psi_t(c)$:
            $\psi'_{t-1}$ = nearest instance to $\psi_t$ in $\Psi_{t-1}(c)$
            $\psi_t.velocity = distance(\psi_t, \psi'_{t-1})$
```

Figure 2.11: Pseudocode code for class instance detection and calculating instance velocities

2.4.4 Class Instance Detection

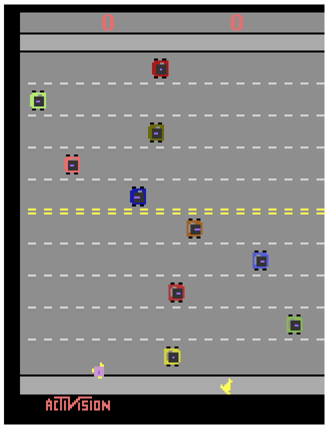
Class instance detection is the process of finding instances of the previously discovered classes on a given screen. More precisely, for every class $c \in C$, we want $\Psi_t(c)$ to contain the list of the coordinates and velocities of all instances of class c on the screen X_t. To achieve this, a list of all shape objects of all classes is generated. This list is then sorted by size, from larger to smaller. For each shape object o in this list, the game screen is scanned to see if there is a match between the shape object and a set of non-background pixels on the screen. Once a match is found, the matching pixels on the screen are marked to prevent a second match to a smaller object. The centroid of the matching pixels is then added to $\Psi_t(o.class)$.

To calculate the velocity of each instance $\psi_t \in \Psi_t(c)$, we find its corresponding instance ψ'_{t-1} in the list of instances of class c during the previous frame ($\Psi_{t-1}(c)$). The velocity is determined based on the distance between ψ_t and ψ'_{t-1}.

Figure 2.11 contains the pseudocode for class instance detection and calculation of the instance velocities. Figure 2.12 presents the class instances detected in the games Freeway and Seaquest.

2.4.5 Feature Vector Generation

Once we are able to detect instances of the discovered classes on the current screen, the next step is to generate a feature vector based on these instances. We would like the feature vector to capture the following concepts:


(a)

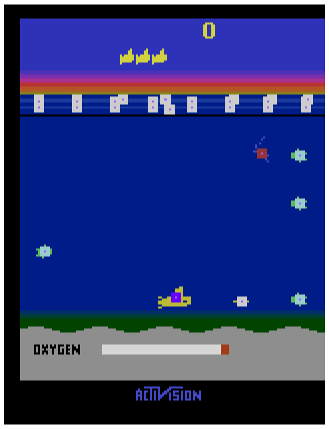

(b)

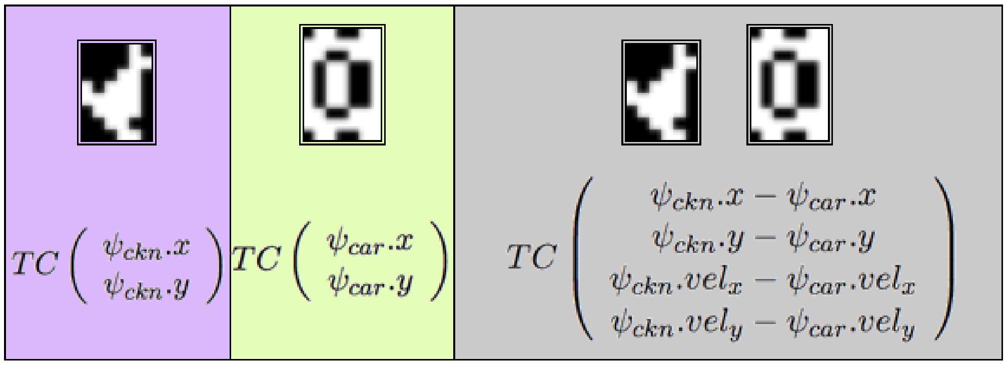
Figure 2.12: Class instances detected in sample screens of Freeway and Seaquest. Each colored square represents an instance of a discovered class. The small white lines indicate the calculated object velocities.

- *Presence* of at least one instance of each class. In many games the knowledge that a particular entity is on the screen or not is a big indication of how the agent should act.
- The *absolute position* of each instance. For example, in the game Freeway, the y-value of the PC character is highly predictive of the expected future reward.
- The *relative position and velocity* of every pair of instances. This will allow the agent to learn and generalize over the interaction of game entities.

A discovered class can have from zero to hundreds of instances on a given screen. This results in a problem of how to generate a fixed-length feature vector from a varying number of instances. We will first discuss the feature vector generation method in a toy example where each class has exactly one instance on the screen. Once the simple case is clear, we will introduce our method for handling multiple instances of each class.

Imagine a fictional version of the game Freeway, in which at any time step t, we have exactly one instance of the *Chicken* class ψ_{ckn} and exactly one instance of the *Car* class ψ_{car}. Figure 2.13 demonstrates how a feature vector can be generated from these two instances. The first part of the feature vector contains the tile-coding of the absolute position of ψ_{ckn}. Similarly, the second part contains the tile-coding of the absolute position of ψ_{car}. The final part contains the tile-coding of the relative position and relative velocity of the two instances:

$$\Phi = concat\left(TC\begin{pmatrix}\psi_{ckn}.x\\ \psi_{ckn}.y\end{pmatrix}, TC\begin{pmatrix}\psi_{car}.x\\ \psi_{car}.y\end{pmatrix}, TC\begin{pmatrix}\psi_{ckn}.x-\psi_{car}.x\\ \psi_{ckn}.y-\psi_{car}.y\\ \psi_{ckn}.vel_x-\psi_{car}.vel_x\\ \psi_{ckn}.vel_y-\psi_{car}.vel_y\end{pmatrix}\right)$$



$TC\begin{pmatrix}\psi_{ckn}.x\\ \psi_{ckn}.y\end{pmatrix}$
$TC\begin{pmatrix}\psi_{car}.x\\ \psi_{car}.y\end{pmatrix}$
$TC\begin{pmatrix}\psi_{ckn}.x-\psi_{car}.x\\ \psi_{ckn}.y-\psi_{car}.y\\ \psi_{ckn}.vel_x-\psi_{car}.vel_x\\ \psi_{ckn}.vel_y-\psi_{car}.vel_y\end{pmatrix}$

Figure 2.13: An illustration of the feature vector generated for the game Freeway, in the simple case where there exists exactly one instance of each class. The feature vector consists of three sections. Each section contains a binary sub-vector generated by tile-coding the displayed variables.

The next step is to expand this method to the more realistic case, in which multiple instances of a class can exist on the screen. To generate a fixed-length feature vector, we note that while the number of instances of each class is variable, the overall number of discovered classes is constant. Consequently, a sub-section of the feature vector is reserved for each discovered class, as well as each pair of classes. When we have multiple instances of a class c_1, a sub-vector is generated for each instance. The sub-vectors are then added together and placed in the section of the feature vector reserved for class c_1:

$$\Phi[c_1] = \sum_{\psi_i \in \Psi(c_1)} TC\begin{pmatrix}\psi_i.x\\ \psi_i.y\end{pmatrix}$$

where $\Phi[c_1]$ is the section of the feature vector reserved for the class c_1. Similarly, all possible pairings of the instances of two class c_1 and c_2 are added together, and populate the section reserved for the pairing of the two classes:

$$\Phi[c_1, c_2] = \sum_{\psi_i \in \Psi(c_1), \psi_j \in \Psi(c_2)} TC\begin{pmatrix}\psi_i.x-\psi_j.x\\ \psi_i.y-\psi_j.y\\ \psi_i.vel_x-\psi_j.vel_x\\ \psi_i.vel_y-\psi_j.vel_y\end{pmatrix}$$

Figure 2.14 illustrates this approach for an imaginary screen of the game Freeway, with one instance of the class *Chicken* and two instances of the class *Car*. With two discovered classes, the final feature vector will have three sections: one reserved for the absolute position of the *Chicken* class, one reserved for the absolute position of the *Car* class, and one reserved for the relative position and velocity of (*Chicken*, *Car*) pair. Since we only have one instance of the class *Chicken*, the position of this one instance is tile-coded and placed in the first section of the feature vector. With two instances of class *Car*, each instance is tile-coded individually and the resulting vectors are added together and placed in the second section of the feature vector. Similarly, the pairs of the one instance of *Chicken* and each instance of

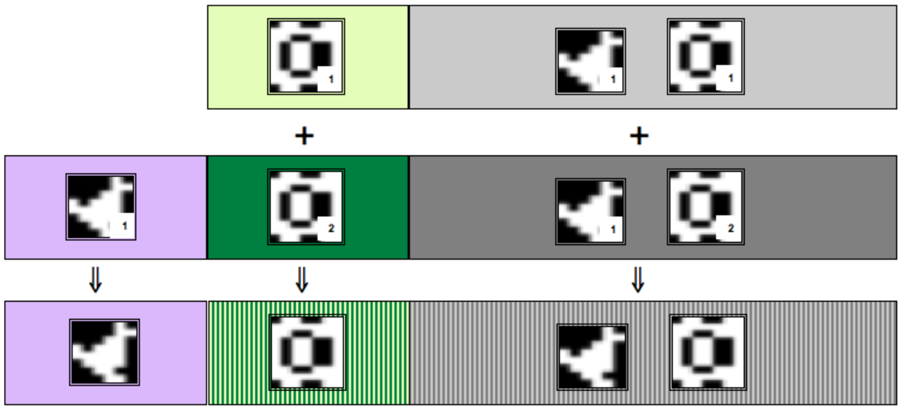


Figure 2.14: Conceptual figure of feature vector generation for the game Freeway, where we have one instance of class *Chicken* and two instances of the class *Car*.

Car are tile-coded individually, added together, and placed in the final part of the feature vector.

Finally, for each class $c \in C$ a single bit is reserved on the feature vector to indicate the case when no instance of the class c is present on the current screen. This will allow the function approximation method to assign non-zero values to the case when no instance of a class is present.

Figure 2.15 presents the pseudocode for feature vector generation based on *Detecting Instances of Classes of Objects (DISCO)*. Note that the presented pseudocode generates a full feature vector. Similar to the *BASS* method, in practice we like to store the non-zero indices only. However, the feature vector generated by *DISCO* is not a binary vector. To store values that are larger than one, the indices for these values are represented multiple times. For instance, a full vector $v = [1, 0, 0, 0, 0, 0, 3, 0, 2]$ can be represented as $I(v) = [0, 6, 6, 6, 8, 8]$. This will allow us to use the same gradient-descent Sarsa(λ) algorithm (figure 2.1) on a non-binary feature vector.

2.5 Feature Vector Generation based on Console Memory (RAM)

Unlike the previous two methods, which generate feature vectors based on the game screen, this method generates a feature vector based on the content of the console memory. The Atari 2600 has only $128 \times 8 = 1024$ bits of random access memory[11]. The complete internal state of a game (including the location and velocity of game entities, timers, and health indicators) must be stored in these 1024 bits. For a human player, it is close to impossible

[11]Some games include additional RAM on the game cartridge. For instance the *Atari Super Chip* included an additional 128 bytes of memory [Montfort and Bogost, 2009]. However, the current approach only considers the main memory included in the Atari 2600 console.

```
Assume C (list of discovered classes) is defined.

generate_feature_vector(screen_matrix $X_t$)
  1. $\Psi_t = \mathit{detect\_class\_instances}(X_t)$
  2. $\mathit{calculate\_instance\_velocities}(\Psi_t, \Psi_{t-1})$

  3. Generate the absolute position sections of the feature vector
        for $c \in C$:
            $\Phi[c] = \sum_{\psi_i \in \Psi_t(c)} TC \begin{pmatrix} \psi_i.x \\ \psi_i.y \end{pmatrix}$

  4. Generate the relative position/velocity sections of the feature vector
        for $c_1 \in C$:
            for $c_2 \in C$:
                $\Phi[c_1, c_2] = \sum_{\psi_i \in \Psi_t(c_1), \psi_j \in \Psi_t(c_2)} TC \begin{pmatrix} \psi_i.x - \psi_j.x \\ \psi_i.y - \psi_j.y \\ \psi_i.vel_x - \psi_j.vel_x \\ \psi_i.vel_y - \psi_j.vel_y \end{pmatrix}$

  5. For each class c, reserve one bit at $\Phi[\emptyset_c]$ that is one when there is no instance of c on
     screen:
        for $c \in C$:
            $\Phi[\emptyset_c] = \begin{cases} 1 & \text{if } |\Psi_t(c)| = 0 \\ 0 & \text{Otherwise} \end{cases}$

  6. Return $\Phi$
```

Figure 2.15: Feature Vector Generation based on Detecting Instances of Classes of Objects (DISCO)

to figure out how to play a given game by only looking at these seemingly random bits. The purpose of our RAM-based agent is to investigate if an RL-based agent can learn how to play a given game using feature vectors generated only from the content of the memory.

The first part of the generated feature vector, denoted by v_l, simply includes the 1024 bits of RAM. We note that Atari 2600 game programmers often use these bits not as individual values, but as part of 4-bit or 8-bit words. Fortunately, doing linear function approximation on the individual bits can capture the value of the multi-bit words. For instance, assume that the programmers of the game Freeway store the y-value of the *Chicken* location in a 4-bit word stored in address 16 to 20. Furthermore, let us assume that the optimal value of a state is linearly proportional with the y-value of the *Chicken* in that state, with a constant of 0.2. Linear function approximation can capture this relation as:

$$V^* = 0.2 \times 1 \times v_l[19] + 0.2 \times 2 \times v_l[18] + 0.2 \times 4 \times v_l[17] + 0.2 \times 8 \times v_l[16]$$

We are also interested in the relation between pairs of values in memory. To capture these relations, a new vector v_q is generated which contains all the pairwise AND's of the bits in V_l. Note that a linear function on bits of v_q can capture multiplication products of both 4-bit and 8-bit words. This is because the multiplication of two n-bit words a and b can be expressed as a weighted sum of the pairwise products of their bits:

$$\begin{aligned}[a_{n-1}a_1a_0] \times [b_{n-1}b_1b_0] = \quad & 2^0b_0a_0 + 2^1b_0a_1 + ... + 2^{n-1}b_0a_{n-1} + \\ & 2^1b_1a_0 + 2^2b_1a_1 + ... + 2^nb_1a_{n-1} + \\ & ... \\ & 2^{n-1}b_{n-1}a_0 + 2^nb_{n-1}a_1 + ... + 2^{2n-2}b_{n-1}a_{n-1}\end{aligned}$$

Figure 2.16 shows the pseudocode for the memory based feature vector generation method. Note that this pseudocode generates the full feature vector Φ. In practice, we will only store the *one*-indices $I(\Phi)$. The *RAM-Agent* is based on combining the linear gradient-descent Sarsa(λ) algorithm (figure 2.1) with the feature vector generated by this method.

2.6 Parameter Search

There are two sets of parameters that need to be set for the reinforcement learning based agents. The first set of parameters are related to the feature vector generation methods. For instance, in the class discovery step of the DISCO-Agent (section 2.4.3), two thresholds d and s determine the closeness and similarity of objects. Similarly, two parameters m, n are required in the BASS-Agent to define the height and width of the abstraction grid. Feature generation parameters are set to values that generally seem to work well in the training games.

The second set of parameters belong to the Sarsa(λ) algorithm. These parameters are: α (learning rate), ϵ (exploration/exploitation rate), γ (discount factor), and λ. Additionally, as

```
generate_feature_vector(ram_vector $M$)
    1. $v_l = M$
    2. Generate $v_q$ by pairwise $AND$'ing the items of $v_l$:
           $v_q(1024(i-1)+j) = AND(v_l(i), v_l(j)) \quad \forall i \in \{1, ..., 1024\}, j \in \{i, ..., 1024\}$
    3. Generate the final feature vector $\Phi$ from $v_l$ and $v_q$:
           $v = concatenate(v_l, v_q)$
           $k = |v|$
           for $a \in A$, $\Phi_a(i) = \begin{cases} v(i+ak) & ak \leq i \leq (a+1)k \\ 0 & \text{Otherwise} \end{cases}$
    4. Return $\Phi$
```

Figure 2.16: Feature Vector Generation based on Console Memory (RAM)

Parameter	**BASS**	**DISCO**	**RAM**
α (Learning Rate)	0.1	0.01	0.3
λ	0.5	0.5	0.3
Optimistic Initialization	Yes	Yes	Yes
ϵ (Exploration / Exploitattion Rate)	0.1	0.1	0.1
γ (Discount Factor)	0.999	0.999	0.999
m (Screen Abstraction Grid Height)	14		
n (Screen Abstraction Grid Width)	16		
d (Distance Thresholds for Class Discovery)		0.1	
Maximum Number of Classes		10	

Table 2.1: Sarsa(λ) parameter values used in our experiments. The first three values are set by doing a parameter search on the training games. The other parameters are set to values that seem to generally work well in the same set of games.

discussed in section 2.1.4, with Sarsa(λ) there is an option of doing Optimistic Initialization. For each RL-agent, the values for α, λ, and wether to do Optimistic Initialization are chosen by doing a parameter search on the training games[12]. Table 2.1 contains the final parameter values for the RL-agents.

2.7 Experimental Results on the Training Games

The performance of each agent is compared against two hand-coded agents. The *Random Agent* chooses a random action on every frame. The *Best-Action Agent* first finds the single action that results in the highest rewards, and returns that same action on every frame. A t-test is performed to insure that the comparisons with the Random and Best-Action agents are statistically significant ($p = 0.05$). In certain cases, we are interested in comparing the

[12]The range of parameters searched for α is between 0.00001 and 0.3, and the range for λ is between 0.3 and 0.8.

Game	**Average Reward per Episode**					
	BASS	DISCO	RAM	Best-Action	Random	Author
Asterix	$402^{\dagger}$	$301^{\dagger}$	$545^{\dagger}$	250	156	1380
Freeway	0	0	0	5	0	12.4
Seaquest	$129^{\dagger}$	$61^{\dagger}$	$119^{\dagger}$	41	27	1286
SpaceInvaders	$105^{\dagger}$	53	$105^{\dagger}$	92	59	458

Table 2.2: Results of the three reinforcement learning based agents on the training games. The results specified by † are significantly higher than both the Best-Action and Random agents results ($p = 0.05$).

performance of an agent with the performance of a typical human player. In these cases, we report the score received by the author playing the game for the same amount of time, averaged over five trials. We note that the numbers reported here are by no means close to the best performance of an expert player, but rather the performance of a typical human player with little practice on a given game. The results are averaged over the last 1000 episodes, after 18×10^6 steps of training. Please see sections 4.1 to 4.3 for an overview of the evaluation method and the details of the experimental setup.

Table 2.2 summarizes the results of the three RL-based agents on the training games. Figure 2.17 shows the learning progress of the RL-agents on the training games. Except for the game Freeway, all three agents perform significantly better than both the Random Agent and the Best-Action agent. However, we note that none of the results are close to the performance of a typical human player.

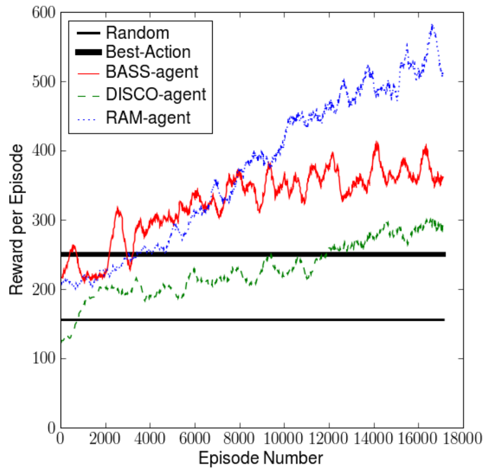
2.8 Discussion

This section explores a number of challenges for our Sarsa(λ) agents to match the performance of humans, and possible steps that can be taken to overcome them.

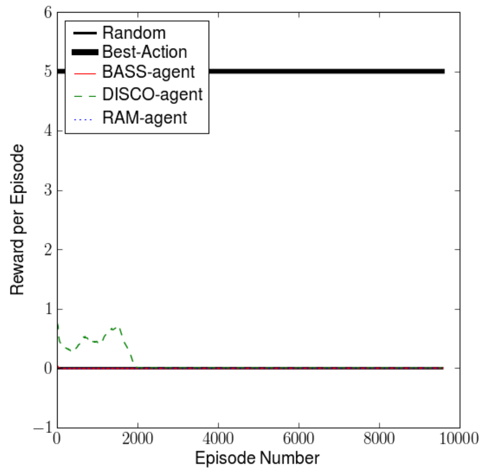
2.8.1 Sensitivity to the Learning Rate (α)

While performing parameter search for the RL-agents, we noted that all three agents are very sensitive to the learning rate parameter α. For each agent/game pairing, there is a small range of α values in which the agent performs reasonably well, while for other values it does performs poorly[13]. Table 2.3 presents the α and λ values for the top five performances of the RAM-Agent on three of the training games. Note that the RAM-agent performs best on the game Asterix when $\alpha = 0.3$ while its best performance on the game Freeway is with $\alpha = 10^{-5}$. Furthermore, the rest of the parameter search results show that the RAM-Agent does not perform very well on Asterix with $\alpha = 10^{-5}$(average reward = 117) and it performs very poorly on Freeway with $\alpha = 0.3$ (average reward = 0).

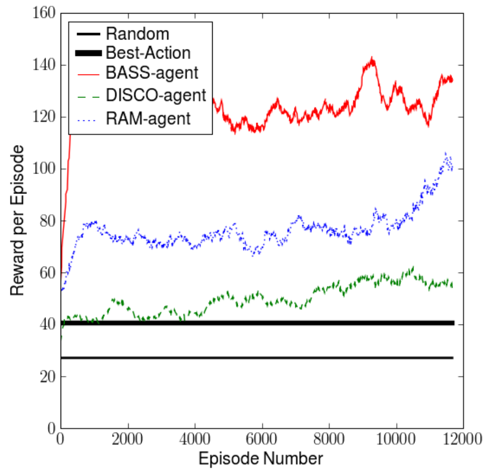
[13]The gradient-descent function approximation can even diverge for some larger values of α.



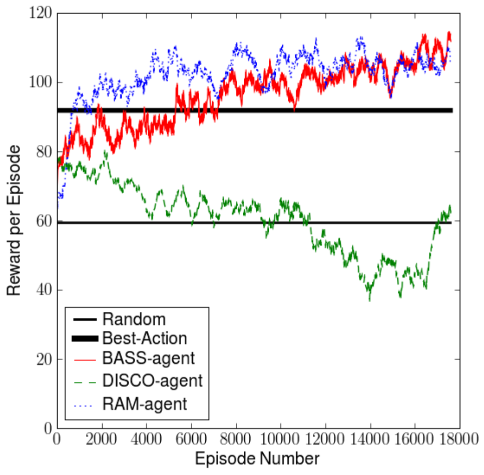
(a) Asterix



(b) Freeway



(c) Seaquest



(d) SpaceInvaders

Figure 2.17: Learning progress for the RL-agents on the training games. Each point on the graphs is a moving average over 200 episodes. The two horizontal lines indicate the average performance level for the Random and BestAction agents.

Asterix			**Freeway**			**Seaquest**		
reward	α	λ	reward	α	λ	reward	α	λ
545	3×10^{-1}	0.3	2.3	1×10^{-5}	0.5	135	1×10^{-1}	0.3
478	3×10^{-1}	0.5	2.3	1×10^{-5}	0.8	127	1×10^{-2}	0.3
452	3×10^{-1}	0.8	2.2	1×10^{-5}	0.3	121	1×10^{-2}	0.5
398	1×10^{-1}	0.3	2.1	1×10^{-4}	0.8	119	3×10^{-1}	0.3
377	1×10^{-1}	0.5	2.0	1×10^{-4}	0.5	115	1×10^{-1}	0.5

Table 2.3: Sarsa(λ) (with optimistic initialization) parameter values for the top five performances of the RAM-Agent on three of the training games. Rewards are averaged over 1000 episodes.

Asterix			**Freeway**			**Seaquest**		
reward	θ	λ	reward	θ	λ	reward	θ	λ
575.63	1×10^{-6}	0.5	0.02	5×10^{-5}	0.8	123.88	1×10^{-5}	0.5
532.33	1×10^{-6}	0.8	0.02	1×10^{-4}	0.3	108.51	1×10^{-5}	0.8
531.33	1×10^{-6}	0.3	0.02	1×10^{-5}	0.8	104.54	1×10^{-5}	0.3

Table 2.4: The meta-learning rate (θ) and λ for the top three performances of the RAM-agent with iDBD on three of the training games. Rewards are averaged over 1000 episodes.

The state dynamics, reward signal, and shape of the optimal value function can be completely different for two distinct games. In a way, playing two different games is comparable to solving two entirely unrelated problems. Therefore, it is not unexpected that each game has its own optimal learning rate, and it is difficult to find a common learning rate that performs well across all games.

The alternative to using a static learning rate is to use a *meta-learning* method that can learn α from previous experience. We implemented two meta-learning methods: Delta-bar-Delta [Jacobs, 1987] and iDBD [Sutton, 1992]. Both methods keep a separate learning rate for each item in the weights vector Θ. The intuition behind both methods is to look at the historic changes in the learning rate of each item, and increase it if the previous updates have similar signs and decrease it if the updates have opposite signs. In other words, when the updates are in the same direction, we probably are not making large enough changes. On the other hand, if the updates are in opposite directions, then we are probably making too big of steps and should decrease the learning rate. Both methods have a number of *meta parameters* determining the initial values and the step size for updating the learning rates.

In our experiments, neither of the meta-learning methods performs noticeably better than the static α approach. Similar to the static learning rate approach, both Delta-bar-Delta and iDBD are sensitive to the meta parameters, and each agent/game pair performs best with a different set of meta parameters. For instance, Table 2.4 presents the meta-learning rate (θ) and λ for the top five performances of the RAM-agent with iDBD on three of the training games. Once again, there is a different range of θ values in which the agent performs well. Atari 2600, with a substantial number of games each having a unique reward structure and value function, is an excellent platform for developing and testing meta-learning methods for reinforcement learning.

2.8.2 Delayed Rewards and Delayed Consequences

In an MDP with *delayed rewards* the agent receives rewards of zero in most of the states, and only receives a non-zero reward after it has executed a complex sequence of actions [Conn and Peters, 2007]. Decision problems with delayed rewards are well known to be complicated and hard to solve [Laud and DeJong, 2003]. It is important to note that one of the main reasons for learning a value function is to address this issue. However, problems with very sparse rewards are inherently hard problems, which are even challenging for the human mind. As an example, consider a two-handed bandit with two possible actions: *Left* and *Right*. The bandit always returns a reward of zero, except if the sequence of $\{25 \times Left, 25 \times Right, 50 \times Left\}$ is exactly followed, in which case it returns a very large reward. Without any prior knowledge on the bandit, finding an optimal policy (or even a policy the performs relatively well) is an extremely difficult problem, even for a human agent.

Since the game score is the only reward signal used, many Atari 2600 games end up with very delayed rewards. This is because games often do not give intermediate scores. That is, the player only receives a score once she has finished accomplishing the required task. For instance, in the game Freeway the agent will receive rewards of zero in every state until the *Chicken* finishes crossing the street. At this point, the agent will receive a non-zero reward in one state and then will continue receiving zero rewards again.

In addition to delayed rewards, some Atari 2600 games involve other delayed consequences that further complicate the learning task. For instance, there is a relatively long delay (over 100 frames) in both games Seaquest and Space-Invaders between the time that the player character dies and the time when the player-agent is informed of this death. Furthermore, as in the case of the game Asterix, a *death animation* may be shown to the player which changes the game screen considerably during this delay. The death delay and animation can lead the learning algorithm to blame the wrong features for the death of the PC, which further complicates the learning task.

A parallel to the delayed rewards, and another challenging situation, is when a game provides only a narrow path to survival and most action sequences lead to a game-over. For instance, in the game Seaquest, when the player character is at the bottom of the screen and the oxygen tank is near empty, the player needs to immediately come to the surface (that is, perform an action sequence similar to $[up, up, ..., up]$) or the game will be over. This is challenging to learn, since the ϵ-greedy exploration is unlikely to produce the correct action sequence.

2.8.3 Complex Value Function

Many Atari 2600 games have optimal value functions that are far more complex than what the linear combination of the current generated features can estimate. The assumption behind using linear function approximation is that the presence or absence of each feature only has an additive effect on the value function. This assumption does not always hold in Atari 2600 games. Consider the following two stages in the game Seaquest:

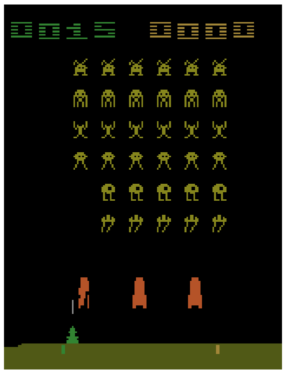


Figure 2.18: Screenshot from the game SpaceInvaders demonstrating the Non-Markovian property of an Atari 2600 game screen. Note that from this screenshot alone one cannot tell if the bullet (the vertical white line) is moving upward or downward.

1. Before rescuing five swimmers, the player needs to rescue swimmers while shooting at fishes and other submarines. At this point, going to the surface should be avoided, since the player will lose a swimmer.
2. After rescuing five swimmers, the player needs to immediately go to the surface and receive a large score. Rescuing more swimmers has no effect at this point.

The optimal policy for the game dramatically changes with a small variation on the screen (appearance of the fifth rescued swimmer at the bottom of the page). States that were previously estimated to have a high value (states associated with rescuing a swimmer) suddenly have a low value. On the other hand, some low value states (states with the player character on the surface) suddenly have a high value. Linear function approximation on any of our current feature generation methods is unable to capture this complexity in the value function. To address this, one can either use a non-linear function approximation method (e.g., neural networks) or generate more complex feature vectors.

2.8.4 Non-Markovian States

As discussed in section 2.1.1, the states of an MDP are assumed to have the Markov property. That is, each state should summarize all relevant information from the past interactions. However, the Markov assumption often breaks when generating a feature vector from the current game screen. Figure C.1 illustrates how the Markov assumption breaks in a screenshot of the game SpaceInvaders. Note that this screenshot does not summarize all relevant information from the past history. Particularly, from this screenshot alone one cannot tell if the bullet (the vertical white line) is moving upward or downward. This is important information, since not knowing the direction of the bullet prevents us from determining if we are in a good state, i.e., the PC has just shot a bullet at the *Aliens*, or in a bad state, i.e., the PC is about to be hit by a bullet from the *Aliens*.

A possible way to address this problem is to include the screenshot or the content of memory from the previous time step. For instance, in the BASS method, we can generate an abstract version of both the current scree and the previous screen, and then look at pairs of items in both screens. Finally, note that the DISCO-agent already addresses this problem to some extent, since it looks at the previous screen to determine the velocity of each game entity. Also, the content of RAM must be Markovian, since it contains the full state of the game.

2.8.5 Challenge of Playing *Arbitrary* Games

We can summarize almost all of these challenges as the single challenge of trying to learn to play *arbitrary* games. When solving a specific problem, we are able to include our knowledge about the problem into the feature generation, reward signal, weights initialization, episode length, and other properties of the experiment. This is not the case when designing an algorithm to learn arbitrary problems.

The challenges listed in the previous sections can often be easily addressed when solving a single game. A suitable learning rate can be found using parameter search. Delayed rewards and consequences can be overcome using various *reward shaping* [Randløv and Alstrøm, 1998] techniques. Complex value functions can be simplified by customizing the feature vector and manually including important non-linear feature pairings. For instance, in the case of the complex value function for the game Seaquest (discussed in section 2.8.3), one can generate a customized feature vector by pairing the existence of the fifth rescued swimmer at the bottom of the screen with every other feature. The resulting vector is twice the size of the original vector, and is able to capture the dramatical changes of the value function with linear approximation.

To illustrate this point, a customized agent is implemented for Freeway, the game in which our current generic agents have the poorest performance. A game-specific feature vector is generated by tile-coding the y-coordinate of the *Chicken* with the x-position of each of the *Car*s. The agent receives a reward of -1 on each time step, except when it completely crosses the screen, in which it gets a reward of zero and the episode ends. We also experimented with a number of learning rates to find the most suitable α value for this game. After only 18000 time steps (0.1% of the usual training period) the Sarsa(λ) converged to a very good policy, generating an average of 13.5 scores per each minute of game play. This performance is even significantly better than the performance of the author playing this game.

Chapter 3

Search-based Methods

This chapter explains how a state-action tree can be generated for any Atari 2600 game by using the emulator to simulate the consequence of various actions in the future. General search methods can then be applied the generated tree to play a given game. Unlike the reinforcement learning methods discussed previously, there is no learning involved in the methods discussed here. Instead, the challenge is how to use a limited number of simulation steps in order to best play an Atari 2600 game.

Initially, it may appear that allowing the agent to peek into the future and see the consequence of its actions reduces playing Atari 2600 games to a trivial problem. However, the massive state-space of Atari games and the limited number of simulation steps that are allocated to the agent per each frame, make this problem far from trivial. As an example, consider a game with only 4 actions. At 60 frames per second, to look ahead only one minute into the game, the agent needs to simulate $4^{60*60} \approx 10^{2160}$ frames. This is clearly infeasible. Fortunately, the AI community has developed a rich arsenal of smarter strategies for exploring and pruning the state-action tree. These methods will allow us to act intelligently in the game, while only simulating a very small fraction of the full state-space.

3.1 Generating a State-Action Tree

The *save-state* and *restore-state* features of the emulator are used to generate a state-action tree. When issued a save-state command, the emulator saves all the relevant data about the current game, including the contents of the RAM, registers, and address counters, into a variable. Similarly, the restore-state command restores the state of the current game from a previously saved state.

Figure 3.1 demonstrates how the save-state/restore-state features can be used to generate a state-action tree. Originally, the agent is at some point in the middle of the game Seaquest (3.1a). Using save-state, the state of this node is stored into s_0, the root of the tree (3.1b). Next, we simulate taking the Left action for 15 frames (3.1c), and save the resulting state into state $s_{0,L}$(3.1d). We then restore the original state s_0 (3.1e), and simulate taking the Right action for 15 frames (3.1g). The resulting state is saved into state $s_{0,R}$ (3.1h). In this fashion, we can expand the full state-action tree.

Each node s in the tree contains:

- The state variable generated by the save-state command
- $r(s)$:the reward received during the simulation node s
- $V(s)$: cumulated discounted[1] reward of the sub-branch starting from s
- $C(s)$: set of child nodes of s

Note that since there is no natural ending for many Atari 2600 games, we need to impose an arbitrary limit on the expansion of the tree. In our approaches, we define a maximum number of simulation steps allowed per frame, denoted by M, and use it to limit the tree expansion.

3.2 A Generic Search-based Agent

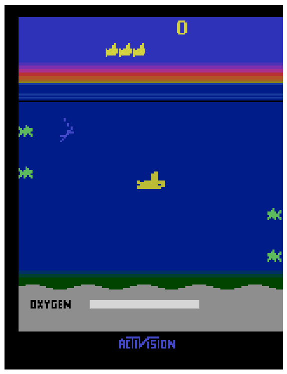
Figure 3.2 contains a simple overview of how a generic search-based agent can use the state-action tree to act in a game. When $k = 1$, the agent will choose a distinct action on every frame. However, since a human player cannot generate 60 distinct actions per second on a joystick, Atari 2600 games are often designed to require a much lower action frequency. In our experiments, we observe that the agent can act reasonably well in many games with k in the range of 10 to 20 (that is, 3 to 6 distinct actions per second). There is a tradeoff involved in setting the value of k: a smaller k value allows finer player action, since the agent can choose more distinct actions per second. On the other hand, a higher k value enables us to look further ahead into the game, and get a better estimate of the consequence of each action.

The function *generate_tree* expands the state-action tree starting from the state s_0 and limiting the tree expansion to kM simulation steps. It returns the action a at the root which corresponds to the sub-branch with the highest discounted sum of rewards. Any tree search algorithm can be used for the tree expansion. The following two sections demonstrate how *generate_tree* can be implemented using breadth-first search (Section 3.3) and UCT (Section 3.4).

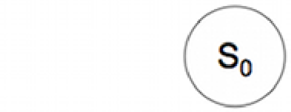
3.3 Full-Tree Search

A simple method to use for the search-based agent is to fully expand the tree breadth-first, until the maximum number of simulation steps is reached. Once the tree is fully expanded,

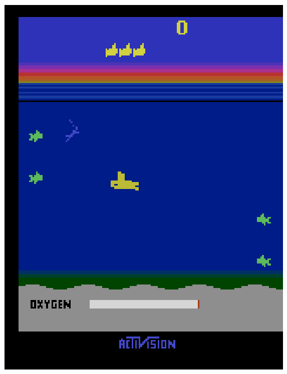
[1]Discounting the future values insures that the agent will go after rewards that are closer first.



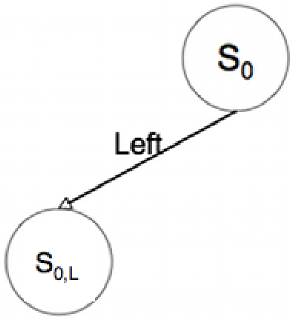
(a) Original state



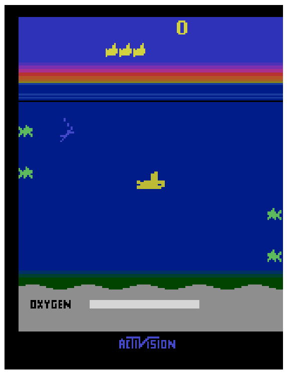
(b) S_0 set as root of the tree



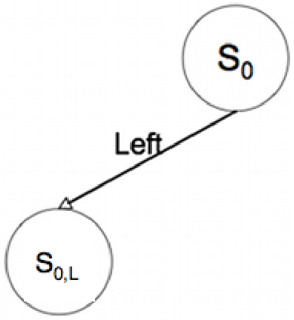
(c) Sim. Left for 15 frames



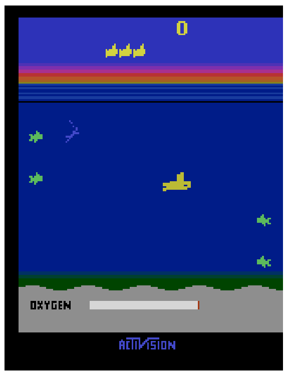
(d) Save-state the new state



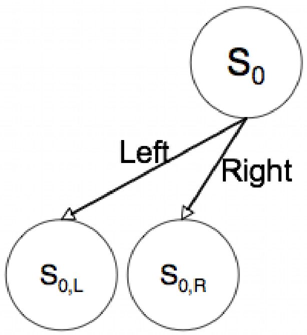
(e) Restore-stae S_0



(f)



(g) Sim. Right for 15 frames



(h) Save-state the new state

Figure 3.1: Illustration of how the state-action tree is built from some initial state S_0 for the game Seaquest, using the save-state/restore-state features of the emulator

```
Every $k$ frame:

 1. Save the current state of the game to $s_0$
 2. $a = generate\_tree(s_0)$
 3. Restore the state of the game back to $s_0$
 4. Repeat action $a$ for $k$ frames
```

Figure 3.2: A generic search-based agent

the node values are updated recursively from the bottom of the tree to the top:

$$V(s) = r(s) + \gamma \max_{c \in C(s)} V(c) \tag{3.1}$$

where γ is the discount factor.

3.3.1 Avoiding Death: A Simple Heuristic

"In any case avoid death, since our ancestors disapproved of it." -Obeyd Zakani, 14th century poet and satirist

In many arcade-style games, if a player can simply keep the Player Character (PC) alive, it always has the chance to collect more rewards later on in the game. This observation leads us to a simple heuristic which prunes the sub-branches of the tree that we know will end up with the death of the PC. More precisely, let $d(s)$ be 1 if we know that the branch starting from node s will certainly end up with the death of the PC. For a leaf node, $d(s)$ is 1 if the PC is dead in the state s. For a non-leaf node, we have:

$$d(s) = \prod_{c \in C(s)} d(c) \tag{3.2}$$

That is, a node is declared dead if all of its child nodes are also dead. When we update the value of a living node, we only consider the values of its children that are also not dead:

$$V(s) = r(s) + \gamma \max_{c \in C(s), d(c) = d(s)} V(c) \tag{3.3}$$

Once the tree expansion is complete, the search-based agent chooses a sub-branch of the root with the highest value, which is also not dead. If all sub-branches at the root level are dead, i.e., if the player will certainly die no matter what action it chooses, the agent will choose the sub-branch with the highest value.

Figure 3.3 shows the pseudo code for the full-tree search, doing a breadth-first search on the non-dead states.

3.3.2 Choosing Parameters

As discussed in 3.1, the maximum number of simulation steps allowed per frame (M), is an arbitrary limit imposed to bound the tree expansion. Ideally, a meaningful limit such as

```
(Assume $k, M, \gamma, available\_actions$ are defined)

function generate_tree (node $s_0$)

    $num\_simulations = 0$
    queue q
    q.push($s_0$)
    while ($num\_simulations < kM$ and not empty(queue))

        $s$ = q.pop()
        for each $a$ in $available\_actions$
            $s_a, r(s_a), d(s_a)$=simulate_game(start=$s$,steps=$k$,act=$a$)
            $C(s)$.insert($s_a$)
            $num\_simulations = num\_simulations + k$
            if $d(s_a) = 0$
                q.push($s_a$)
    update_values($s_0$)
    $a = \arg\max_{c \in C(s_0), d(c) = d(s_0)} V(c)$
    return $a$

function update_values(node $s$)

    for $c$ in $C(s)$:

        update_values($c$)
    $d(s) = \prod_{c \in C(s)} d(c)$
    $V(s) = r(s) + \gamma \max_{c \in C(s), d(c) = d(s)} V(c)$
```

Figure 3.3: Full-tree search with the avoiding death heuristic.

Game	Average Reward per Episode			
	Full-Tree Search	Best-Action	Random	Author
Asterix	1980†	250	156	1380
Freeway	2.7	5	0	12.4
Seaquest	161†	41	27	1286
SpaceInvaders	417†	92	59	458

Table 3.1: Results of the full-tree search-agent on training games, compared to the Best-Action and Random agents. Rewards are averaged over 100 episodes. Results specified by † are significantly higher than both Best-Action and Random agents results ($p = 0.05$).

"the highest M value that permits a real-time run" would be desirable. Unfortunately, none of the search-based agents are able to run in real-time under the current implementation. In choosing a value for M, we have attempted to find a value that results in a reasonably good performance and one that *could* (with some enhancements to the code) allow a real-time run. In our experiments, we are using a maximum of 4000 simulation steps per frame, which currently runs at a frame rate of about two frames per second. Improving the implementation of the save-state/restore-state features of emulator and simulating disjoint branches in parallel processes could allow the search-based agents to run in real-time with this limit.

The value of k is set to 20 frames (3 distinct actions per second) by running a parameter search on the training games. γ is set to 0.99.

3.3.3 Results for the Training Games

Table 3.1 summarizes the results of the Full-Tree Search Agent on the training games, with $M = 4000, k = 20$, and $\gamma = 0.99$. Please see sections 4.1 to 4.3 for an overview of the evaluation method and the details of the experimental setup.

In the case of the game Asterix, in which scores are abundant and easily reached, and both the scores and death are immediately revealed to the player, the full-tree search performs very well. However, the agent is not performing very well in any of the other three games. In the case of both Space-Invaders and Seaquest, the poor performance is due to a delay of over 100 frames between the moment that the PC is dead and the time when the player-agent is informed of this death. This delay makes the full-tree agent unable to predict and avoid death in either game. In the case of the game Freeway, while the PC never dies, the reward signal is very sparse. The player only receives a reward when the PC has completed passing the highway. At the beginning of the game, this reward signal is outside the reach of the full-tree search, and thus the agent acts randomly. The random move continues until the PC moves up enough in the highway so that the reward is reachable by the tree expansion, at which point the search-agent starts acting optimally, and immediately reaches the top of the highway.

Expanding the full state-action tree limits the agent to a very short window into the future. For instance, in a game with 10 actions, with $k = 20$ and $M = 4000$, the agent can look ahead for 80 to 100 frames, or less than two seconds. Therefore, when the consequences of the actions are immediate, in other words, when both the reward and death can be detected within a small window, the full-tree search agent performs well. This explains the good results obtained in the game Asterix. On the other hand, when the game has delayed consequences, i.e., when either the reward or detecting and avoiding death falls outside of this short window, full-tree search performs poorly.

3.4 UCT: Upper Confidence Bounds applied to Trees

As we discussed in the previous section, spending the simulation steps to fully expand the state-action tree results in a short look-ahead trajectory, which in turn results in poor performance in games with delayed consequences. A preferable alternative is to simulate deeper into the more promising sub-branches of the tree. To do this, we need to find a balance between expanding the higher valued branches and spending simulation steps on the lower valued branches to get a better estimate of their values. This is an instance of the well-known exploitation-exploration problem. Additionally, we can apply a t-step random simulation at the end of each leaf node to get an estimate of a longer future trajectory. These are the two key ideas in the UCT algorithm. The UCT algorithm, developed by Kocsis and Szepesvári [Kocsis and Szepesvári, 2006], can potentially allow the agent to simulate deeper into the more promising branches while addressing the exploration-exploitation problem and provide us with a method for a t-step random trajectory at the end of each leaf node.

3.4.1 Overview of the Algorithm

Instead of the breadth-first full expansion of the state-action tree, UCT iteratively adds single leaf nodes to the tree. During each iteration, the algorithm starts at the root of the tree and recursively chooses sub-branches until it reaches a leaf node. At a leaf node, the algorithm runs a t-step random simulation, and propagates the received rewards up the tree. Once all the siblings of a leaf node have received at least one visit, the search will expand the leaf node and add its child nodes to the tree.

Consider the problem of choosing a sub-branch $c \in C(s)$ to visit next during a UCT iteration. We may already have visited a number of child nodes of s before and have an estimate of their values. On one hand, it is desirable to visit the child with the highest value, since we are looking for a deeper expansion in the more promising sub-branches. On the other hand, we may have a poor estimate of the values of the other sub-branches. Therefore, we may want to choose a child node with a lower value, in order to improve our estimate of its value. UCT deals with this dilemma by treating it as a multi-armed bandit problem, and using a variation of UCB1, which is a “bandit algorithm”, to choose which child node to visit next. In particular, UCT chooses a child node $c \in C(s)$ that maximizes:

$$V(c) + C\sqrt{\frac{\ln n(s)}{n(c)}} \tag{3.4}$$

where $n(s)$ is the number of times node s has been visited, and C is a constant. The term C$\sqrt{\frac{\ln n(s)}{n(c)}}$ is called the UCT bias. It insures that with the appropriate value of C, the algorithm is consistent, i.e., "the probability of selecting the optimal action can be made to converge to 1 as the number of samples grows to infinity" [Kocsis and Szepesvári, 2006].

Figure 3.4 contains the pseudocode for UCT. Figure 3.5 presents a conceptual graph of how UCT expands the state-action tree. Note that the tree is explored much deeper in some branches compared to others.

3.4.2 Setting the UCT Bias Constant

According to Kocsis and Szepesvári, for the theoretical guarantees of UCT to hold, the following two inequalities need to be satisfied with an appropriate value of the bias constant C [Kocsis and Szepesvári, 2006]:

$$P\left(V(c) \geq V^*(c) + C\sqrt{\frac{\ln n(s)}{n(c)}}\right) \leq n(s)^{-4}$$
$$P\left(V(c) \leq V^*(c) - C\sqrt{\frac{\ln n(s)}{n(c)}}\right) \leq n(s)^{-4}$$

where s is any node in the tree, $V(c)$ is the estimated value of one of its child nodes c after $n(c)$ visits, and $V^*(c)$ is the true value of the child node.

In applications where the mean and variance of the reward is known, the constant C can be set beforehand. However, in the case of Atari 2600 games, the reward frequency and values change considerably both among different games and within various stages of the same game. Dealing with a similar issue in solving Real-time Strategy games with UCT, Balla and Fern suggests setting the bias constant to the same value as $V(c)$ [Balla and Fern, 2009]. This insures that the exploration bias and the action values are at least within the same order of magnitude[2]. Unfortunately, as Bella suggests, this choice has unknown theoretical implications.

Our approach to ensure that the action values and the exploration bias are within the same order of magnitude is to scale the action values down to $[-1, 1]$. This is done in two stages. First, all rewards are scaled down[3] to $[-1, 1]$. Furthermore, rewards are also divided

[2]In our discussions with Nathan Sturtevant, he reports that a number of teams in the General Game Playing competition [Genesereth and Love, 2005] are also employing a similar tactic. However, to the best of our knowledge, this has not been documented in any publications.

[3]We are currently doing this in a naive way: all positive rewards are set to 1 and all negative rewards set to -1. It might be possible to keep track of the highest and lowest rewards received so far, and do this scaling in a more intelligent way.

```
 (Assume $k, M, t, \gamma, C, available\_actions$ are defined)

function generate_tree (node $s_0$)

    $num\_simulations = 0$
    while $num\_simulations < kM$
        $s = s_0$
        while $s$ is not leaf
            if $c \in C(s)$ exists with $n(c) = 0$
                $s = c$
            else
                $s = \arg\max_{c \in C(s)} \left( V(c) + C\sqrt{\frac{\ln n(s)}{n(c)}} \right)$

        If all siblings of $s$ have been visited at least once
            for each $a$ in $available\_actions$
                $s_a, r(s_a), d(s_a)$=simulate_game(start=$s$,steps=$k$,act=$a$)
                $n(s_a) = 0$
                $sum\_reward(s_a) = 0$
                $C(s)$.insert($s_a$)
                $num\_simulations = num\_simulations + k$
        $r_{mc}$ = do_random_simulation(start = $s$, steps = $t$)
        $num\_simulations = num\_simulations + t$
        updat_values(node = $s$, reward = $r_{mc}$)

    $a = \arg \max_{c \in C(s_0), d(c) = d(s_0)} V(c)$
    return $a$

 function update_values(node $s$, reward $r$)

    $n(s) = n(s) + 1$
    $sum\_reward(s) = sum\_reward(s) + r$
    $V(s) = r(s) + sum\_reward(s)/n(s)$
    if $s$ is not root
        $r = \gamma V(s)$
        update_values(node = $parent(s)$, reward = $r$)
```

Figure 3.4: UCT Pseudocode. Based on pseudocode presented by [Shafiei et al., 2009] and [Balla and Fern, 2009]

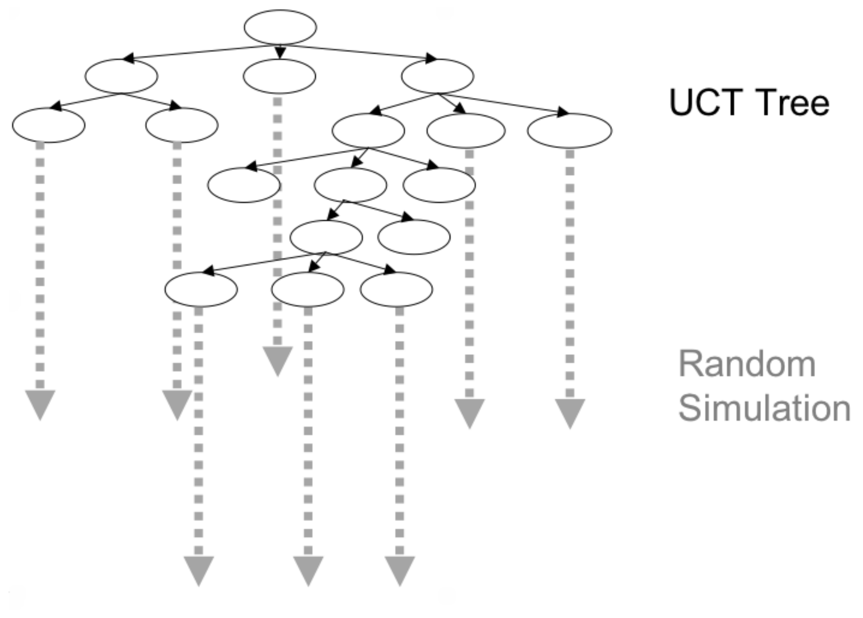


Figure 3.5: Conceptual graph of how UCT expands the state-action tree. Based on a graph by Wang and Gelly [Wang and Gelly, 2007].

by the depth of the tree that they were received on. That is, a reward received d nodes from the root of the tree will be rescaled as:

$$r = scale_{[-1,1]}(reward)d^{-1}$$

The latter also ensures that the tree expansion does not get biased toward the already deeper branches. Once the action values and the exploration bias are within the same order of magnitude, we try to find an exploration constant that generally works well in the training games, hoping that the trend will continue in the test games.

3.4.3 Avoiding Death in UCT

Since UCT only partially expands the state-action tree, detecting the dead nodes is not as straightforward as the full-tree search case, in which if all child nodes of a node s are dead, s is also labeled as dead. For instance, in the UCT case, consider a node s that has five child nodes, and we have only visited three of them. Even if all three child nodes are labeled as dead, we still cannot conclude that s is also dead, since a new unvisited child may find a way out of death.

Doing a random simulation at the leaf level also complicates the matter further. For instance, if the first n visits through the node s always end up in death of the PC, it is unclear whether all future runs through s will also end up fatally or if these were a number of unlucky runs and a future run will evade death.

Given the problematic nature of implementing the avoiding death heuristic in UCT, it may become appealing to discard it all together. However, from experiments on the training games, we observe that this heuristic makes a significant improvement to how the agent behaves in games. In particular, since the agent is generally looking at a very short trajectory into the future, maximizing the rewards alone can result in a very poor performance[4].

Bellow is our current approach to implement the avoiding death heuristic for UCT:

- For each node s, let $nd(s)$ be the number visits starting from node s that ended up in the death of the PC
- After each visit of node s, label it as dead if
    1. $nd(s) = n(s)$
    2. $n(s) > \delta$

where δ is the minimum death threshold. In other words, if every path through the node s has ended up in the death of the PC, and we have had at least a minimum number of visits through s, then it will be labeled as dead.

3.4.4 Results on the Training Games

Table 3.2 summarizes the results of the UCT Search Agent on the training games, with $M = 4000$, $k = 15$, $t = 100$, $C = 0.2$, and $\delta = 1$. The parameters were chosen by doing a parameter search on the same set of games.

We observe that the UCT algorithm performs better than the full-tree search in both Seaquest and Space-Invaders. This improvement is due to overcoming the delayed death problem by expanding deeper into the more valuable sub-branches of the tree and doing a random simulation at the leaf nodes. As an example, in the game Seaquest, the deepest node of UCT can be up to 600 frames ahead of the current frame, compared to 80 frames in the full-tree search. Nonetheless, we note that UCT is not always able to avoid death. For instance, in the game Seaquest, there are situations in which the player submarine is at the bottom of the screen and it needs to move to the top in a short period to refill its oxygen tank. In this case, a random trajectory is unlikely to move the PC all the way to the top, and as far as UCT can predict, all branches of the tree will be labeled as dead. A similar problem surfaces in the game Freeway, in which a random trajectory at the bottom of the highway is very unlikely to move the PC to the top. In this case, all sub-branches of the tree will have a value of zero, and similar to the full-tree search, UCT will end up acting randomly. The random movement continues until the PC is high enough in the screen that a

[4]The argument against only maximizing rewards in a short trajectory becomes stronger if we consider that many Atari 2600 games offer "suicidal scores", i.e., one final score that the agent receives as the PC is dying. For instance, in the game Seaquest, the player can crash her submarine into an enemy submarine and receive a score of 20 while watching the death animation.

Game	Average Reward per Episode				
	UCT	Full-Tree Search	Best-Action	Random	Author
Asterix	$1814^{\dagger}$	$1980^{\dagger}$	250	156	1380
Freeway	$5.2^{\dagger}$	2.7	5	0	12.4
Seaquest	$573^{\dagger}$	$161^{\dagger}$	41	27	1286
SpaceInvaders	$625^{\dagger}$	$417^{\dagger}$	92	59	458

Table 3.2: Results of the UCT search-agent on training games, compared to the Full-tree search, Best-Action and Random agents. Rewards are averaged over 100 episodes. Results specified by † are significantly higher than both Best-Action and Random agents results ($p = 0.05$).

random trajectory reaches the top of the highway and receives a positive reward. Finally, we note that UCT is performing slightly worst than the full-tree search in the game Asterix. In this game both the rewards and the PC death is within the reach of the full-tree expansion. The random simulations performed at the leaf nodes do not gain much for UCT, but limit it to expanding a smaller tree compared to the full-tree search.

In summary, when a random trajectory is able to receive rewards and both detect and avoid the death of the PC, a search-base agent using UCT performs well. On the other hand, when a random simulation does not receive any rewards (as in Freeway) or cannot avoid death (as in Seaquest), UCT will perform poorly.

3.5 Discussion

This section illustrated how we can generate a state-action tree for any Atari 2600 game, using save-state/restore-state features of the emulator, and how full-tree search and UCT perform on the training games. It is important to note that while only two search methods are presented here, the Atari 2600 console and its plentiful game library can now be used by the AI community as a platform for developing and testing various new search methods.

Combining the search techniques presented here with the learning techniques discussed in previous sections is an interesting future direction for this research. In particular, in many games, the search-based agent gives us a policy that if not the same as π^*, still out performs a typical human player. The question is how we can use this good policy to either learn faster or learn to perform better in the RL-based methods. A number of approaches for combining the learning and search methods will be discussed in Chapter 5.

Chapter 4

Evaluation Method and Experimental Results

This chapter contains an overview of our evaluation method, including the process of choosing the test games, a brief introduction to the emulation software, and the details of the experimental setup. The experimental results on the test games, as well as a number of observations on how certain game properties impact the performance of different agents is also presented.

4.1 Training and Test Games

To insure the generic nature of the methods developed in this thesis, the set of games that is used for designing and fine-tuning the agents is separated from the set of games that is used for their final evaluation. The first set, referred to as the *training games*, consists of four games: Asterix, Freeway, Seaquest, and Space Invaders[1]. The performance of the agents on these games is used for parameter search as well as overall design refinements.

The *test games* are a set of 50 games, used for the final evaluation of our agents. These games were randomly selected from a larger set of Atari 2600 games *after* the development process and parameter search for all agents was completed. To choose the test games, we started from the *List of Atari Games* in Wikipedia (August 18, 2009)[2]. Of the 595 games listed here, 123 games that have their own Wikipedia page, have a single player mode, are not adult themed or prototypes, and can be emulated in our learning environment were selected. From this list, 50 games were randomly picked and added to the test games.

4.2 Emulation Software

To simplify the implementation of the five AI agents and the task of evaluating them on 54 training and test games, we developed ALE (Atari 2600 Learning Environment). Built

[1]Appendix B provides a short description for each of the training games.
[2]http://en.wikipedia.org/w/index.php?title=List_of_Atari_2600_games&oldid=308675482

on top of Stella, a popular Atari 2600 emulator, ALE provides a simple object-oriented framework that separates the AI development from the low-level details of Atari 2600 games and the emulation process. ALE also uncouples the emulation core from the rendering and sound generation modules of Stella. This enables fast emulation on clusters with minimum library dependencies[3].

The game score is retrieved from the console RAM. To do this, the location of the game score needs to be manually extracted. In games like Boxing, in which the agent is playing against an AI opponent, the reward is calculated by subtracting the opponent score from the player score. The end of the game is usually detected by monitoring the number of lives the player has left. When this number decreases, the game is declared over and the current episode ends. Note that there may be a delay of up to 200 frames between the time that the player character dies and when the number of lives is actually decreased. As it will be discussed in section 4.4, this *death delay* has a significant impact on the performance of both of the RL-based and search-based agents.

4.3 Experimental Setup

The learning task is episodic. A new episode starts on the frame in which the player begins acting in the game. That is, the opening animation of the games are left out. Episodes end either when the game is over (e.g., when the PC dies) or after 1800 frames of game play. The RL-based agents interact with each game for 1.8×10^7 frames (i.e., a minimum of 10000 episodes). The average reward over the last 1000 episodes is reported as the final performance of an RL-based agent. Since there is no learning involved in the search-based agents and their performance generally has a smaller variance compared to the RL-based agents, the reported performance for the search-based agents is the average reward over 100 episodes[4].

4.4 Results on the Test Games

The performance results of all the agents on the test games is summarized in table 4.1. All five agents outperform the Random agent in over half of the games. For the RL-based agents, this result indicates that significant learning has in fact taken place. The percentage of the test games in which each agent performs significantly better than the Random and the Best-Action agents is presented in Table 4.2. The search-based agents achieve human-level performance in a number of games. Table 4.3 presents four games in which the search-based

[3]ALE is released as free and open source software under the terms of the GNU General Public License. For further information please visit: http://yavar.naddaf.name/ale

[4]The search-based agents are also much slower than the RL-based agents, running at about 2 frames per second. Running a search-based agent on a single game for 100 episodes already takes more than 24 hours of simulation time.

agents beat the performance of the author.

Table 4.1: Results of all agents on test games. The results specified by † are significantly higher than both the Best-Action and Random agents results ($p = 0.05$).

Game	**Average Reward per Episode**						
	BASS	DISCO	RAM	Full-Tree	UCT	Best-Act	Random
Alien	15.7†	14.2†	42.4†	75.6†	83.9†	3.0	6.4
Amidar	17.5†	3.0	33.3†	106†	217†	12.0	0.5
Assault	96.9	87.7	106	453†	629†	104	97.3
Asteroids	20.2	13.8	61.0†	137†	219†	2.0	21.7
Atlantis	53.9	56.0	60.5†	121†	127†	15.6	58.2
Bank Heist	10.8†	3.2†	309†	31.1†	59.1†	0.0	2.3
Battlezone	0.5	0.3	1.0†	2.8†	6.9†	0.6	0.3
Beamrider	133	120	151†	605†	605†	132	105
Berzerk	189	158	231†	101	152	200	118
Bowling	7.9†	7.6†	7.7†	3.5	3.4	0.0	6.9
Boxing	-1.0†	-7.4	-0.1†	192†	191†	-7.3	-5.0
Carnival	70.8	60.1	173†	332†	287†	0.0	85.7
Centipede	968	1147	1262	6530†	3215†	2011	991
Chopper Cmd	3.4†	2.4	3.8†	11.2†	18.4†	3.1	2.3
Crazy Climber	17.8†	5.8†	38.0†	12.0†	57.6†	0.0	2.5
Demon Attack	54.4	37.4	53.3	311†	315†	73.0	47.9
Double Dunk	-0.8	-1.3	-0.2	-2.1	0.5†	0.0	-0.6
Elevator Action	1.8†	0.1†	0.0	0.6†	0.2†	0.0	0.0
Enduro	4.6	3.4	6.5†	28.5†	46.9†	5.6	0.5
Fishing Derby	-19.8	-20.2	-20.8	-12.3†	-1.9†	-20.1	-20.4
Frostbite	47.2†	25.5	53.4†	126†	118†	40.0	18.1
Gopher	201†	78.7†	149†	367†	391†	0.0	31.0
Gravitar	30.6	34.7	54.4†	213†	496†	0.0	29.9
H.E.R.O.	68.2†	58.4†	70.7†	337†	6070†	0.0	13.1
Ice Hockey	-1.5	-1.8	-0.4†	-0.3†	2.1†	-0.6	-1.3
James Bond 007	1.3†	0.4	9.3†	14.1†	152†	0.0	0.0
Journey Escape	-11949.4	-13093.4	-7449.0	1841†	906†	-5391.7	-11664.4
Kangaroo	0.2†	0.1†	1.8†	3.6†	6.2†	0.0	0.0
Krull	576†	275†	817†	679†	1055†	0.0	241
Kung-Fu Master	7.1†	5.5†	15.4†	5.0†	10.2†	0.0	0.6
Montezumas Rev	0.0	0.0	0.0	0.0	0.0†	0.0	0.0
Ms. Pac-Man	328†	214†	544†	1924†	1777†	90.0	78.0
Name This Game	0.0	0.0	0.0	1227†	1253†	296	317
Phoenix	16.3†	16.7†	37.2†	216†	175†	2.0	11.4
Pitfall II	0.0	0.0	0.0	-0.2	0.0	0.0	-55.6
Pitfall!	0.0	0.0	0.0	-68.7	-40.0	3133	-76.7
Pooyan	302†	214†	579†	1311†	1283†	12.0	177
Private Eye	0.0	1.1	99.2†	47.1†	25.9†	0.0	-0.5
River Raid	1172†	789†	943†	1777†	110	758	564
Road Runner	0.9	0.1	9.6†	0.1	1.2	2.1	0.0
Robot Tank	1.8†	1.0	4.7†	0.5	0.4	1.1	0.3
Skiing	1.4†	0.2	2.4†	12.4†	15.8†	0.0	1.3
Solaris	0.1	0.2†	9.9†	13.5†	3.8†	0.0	0.0
Stargunner	1.3	0.8	1.7	3.3†	6.0†	2.0	1.2
Tennis	-0.9†	-0.9†	-1.0†	0.0†	0.0†	-1.0	-1.0

Table 4.1: Results of all agents on test games. The results specified by † are significantly higher than both the Best-Action and Random agents results ($p = 0.05$).

Game	**Average Reward per Episode**						
	BASS	DISCO	RAM	Full-Tree	UCT	Best-Act	Random
Time Pilot	2.1	2.0	3.0†	21.2†	25.6†	0.9	2.2
Tutankham	15.5†	17.3†	43.7†	53.7†	61.7†	0.0	4.2
Up'n Down	254	109	531†	2390†	5273†	254	43.6
Video Pinball	1853	1417	2051	2674†	3032†	1331	2105
Zaxxon	2.4†	0.0†	0.2†	1.2†	0.6†	0.0	0.0

Generally speaking, the performance of all agents compared to the Best-Action agent is slightly worst than their relative performance to the Random agent. In many games repeating the same action obtains considerable amounts of rewards (e.g., always going up in Freeway or always pressing Fire in River Raid). Outperforming this result can be a nontrivial and challenging task. As an informal observation, we note that in the game River Raid, human players often do not reach the second stage of the game on their first few trials. On the other hand, just pressing the Fire button always reaches the second stage. This results suggest that *policy search* reinforcement learning methods may be good candidates for learning in the Atari 2600 domain.

The search-based agents generally outperform the RL-based agents. This is expected, since the learning problem is generally more difficult than the search problem. The search-based agents have access to a fully generative model of each game, which allows them to simulate the consequences of their actions into the future. The RL-based agents do not have access to the full dynamics of the game, and can only see the consequences of the actions that were previously taken. The main challenge of the search problem is to address the exploration/exploitation problem in order to maximize the look-ahead horizon. The learning-based agents also need to deal with the exploration/exploitation problem. However, the learning problem also involves learning a mapping from each state to the expected future rewards in that state. This introduces a whole new set of challenges, including feature generation and function approximation.

Compared to the full-tree search, UCT gets significantly better results in over half of the games ($p = 0.05$). This is because the full expansion of the state-action tree limits the full-tree search agent to a very short look-ahead horizon. On the other hand, UCT simulates deeper into the more promising branches of the tree and therefore usually has a longer look-ahead trajectory.

Among the RL-based agents, the RAM-agent has the highest overall performance. A possible explanation for this is that the content of the console memory is inherently Markov, i.e., the content of the RAM is a state that contains all relevant game information from the past. As discussed in Section 2.8.4, this is not always the case in the other RL-based

Agent	**Outperforms**		
	Random	Best-Action	Both
BASS	72%	56%	56%
DISCO	56%	48%	42%
RAM	90%	74%	76%
Full-Tree	88%	86%	84%
UCT	94%	88%	86%

Table 4.2: The percentage of the test games in which each agent performs significantly better than the Random and Best-Action agents

Game	**Average Reward per Episode**		
	Full-Tree Search	UCT	Author
Beam Rider	604.9	605.3	457
Boxing	192	191	3
Centipede	6530	3215	1876
Up and Down	2390	5272	898

Table 4.3: Search-based agents with human-level performance

methods. Aside from the Markov property, it could also be the case that compared to the feature vectors generated from the game screens, the console RAM provides a better representation of the important features of the games.

4.5 Impact of Game Properties on Agents Performance

To understand the varying performance of the agents on different games, we look at a number of game properties and how they impact the performance of the learning and search based methods. Some of the properties considered are related to the specific assumptions made by the methods (e.g., important game entities having distinct colors in BASS), while others are well-established challenges in general learning and planning tasks (e.g., having delayed rewards). Table 4.4 contains the full list of extracted properties for the test games. We note that not all of the game properties have a well defined and concrete definition, and some can be rather subjective. Bellow is a short description for each column:

- **SB** (Static Background): True in games in which the majority of the game screen has a static and non-scrolling background.
- **FC**: True when the important game entities belong to a few classes of 2D objects
- **DC**: True when the important game entities have distinct colors in the SECAM palette.
- **PF**: True when all game entities are present on every frame. Some Atari-2600 games draw the game entities on alternating frames to save processing power. For these games, this property will be false.

- **DR** (Delayed Rewards): True in the games in which a random trajectory is very unlikely to receive a positive reward.
- **DD** (Death Delay): The number of frames between the moment that the game is over and the time when the player-agent is informed of it.
- **NPS** (Narrow Path to Survival): True in games in which only a certain sequence of actions can avoid the death of the PC. In other words, a game has the NPS property if random trajectories are unlikely to survive in it.

Table 4.4: Test Games Properties

Game	SB	FC	DC	PF	DR	DD	NPS
Alien	✓	✓	×	✓	×	70	×
Amidar	✓	✓	✓	×	×	1	×
Assault	✓	✓	✓	×	×	58	×
Asteroids	✓	✓	×	✓	×	11	✓
Atlantis	✓	✓	✓	✓	×	NA	✓
Bank Heist	×	✓	✓	✓	×	140	×
Battlezone	×	×	✓	✓	×	128	✓
Beamrider	×	✓	✓	✓	×	242	×
Berzerk	✓	✓	✓	✓	×	170	×
Bowling	✓	✓	×	✓	×	NA	×
Boxing	✓	✓	✓	✓	×	NA	×
Carnival	✓	✓	✓	✓	×	NA	×
Centipede	✓	✓	✓	×	×	175	✓
Chopper Cmd	×	✓	✓	✓	×	59	×
Crazy Climber	×	×	✓	✓	×	180	×
Demon Attack	✓	✓	×	✓	×	65	×
Double Dunk	✓	✓	×	×	✓	NA	×
Elevator Action	×	✓	✓	×	✓	50	✓
Enduro	×	×	✓	✓	×	NA	×
Fishing Derby	✓	✓	✓	✓	✓	NA	×
Frostbite	✓	✓	✓	✓	×	208	✓
Gopher	✓	✓	✓	✓	×	1	✓
Gravitar	✓	✓	✓	×	×	80	✓
H.E.R.O.	×	×	✓	✓	×	107	×
Ice Hockey	✓	✓	×	✓	×	NA	×
James Bond 007	×	✓	✓	✓	✓	44	✓
Journey Escape	×	×	×	✓	×	NA	×
Kangaroo	✓	✓	✓	×	×	86	×
Krull	×	×	✓	×	×	63	×
Kung-Fu Master	×	✓	✓	✓	×	38	×
Montezumas Rev	✓	✓	✓	✓	✓	54	✓
Ms. Pac-Man	✓	✓	✓	×	×	74	×
Name This Game	✓	×	×	✓	×	140	✓
Phoenix	✓	✓	✓	✓	×	166	×
Pitfall II	×	×	✓	✓	✓	189	✓
Pitfall!	×	×	✓	✓	✓	NA	×
Pooyan	✓	✓	✓	✓	×	101	✓
Private Eye	×	×	✓	✓	✓	NA	×
River Raid	×	×	✓	✓	×	176	✓

Table 4.4: Test Games Properties

Game	SB	FC	DC	PF	DR	DD	NPS
Road Runner	✓	✓	✓	✓	×	147	✓
Robot Tank	×	×	✓	✓	×	140	✓
Skiing	✓	✓	✓	✓	×	NA	×
Solaris	×	×	✓	✓	✓	40	×
Stargunner	✓	✓	×	✓	×	130	×
Tennis	✓	✓	✓	✓	✓	NA	✓
Time Pilot	✓	✓	×	×	×	201	×
Tutankham	×	×	✓	×	×	86	×
Up'n Down	×	×	✓	×	×	197	✓
Video Pinball	✓	✓	✓	✓	×	1	×
Zaxxon	×	×	✓	✓	✓	126	✓

While various patterns can be extracted from this data, most of the relations are not statistically significant with the current number of test games. For instance, having all game entities present on every frame does seem to have a positive impact on the performance of both the BASS and DISCO agents, i.e., agents with feature vectors generated from the game screens. However, since the difference is not statistically significant at an acceptable level, this could very well be a random pattern. Below, we list three properties that do have a statistically significant ($p = 0.07$) impact on the performance of one or more of the player agents:

1. As expected, the BASS agent performs better in games in which the important game entities have distinct colors under the SECAM palette. It performs better than both the Random agent and the Best-Action agent in 65% of games in which entities have distinct colors, as opposed to only 20% of games that do not have this property.

2. The *death delay*, i.e., the number of frames between the moment that the game is over and the time when the player-agent is informed of it, has a negative impact on the performance of the search-based agents. This is particularly true for the UCT agent, in which there is a significant correlation of -0.35 between the number of frames in the death delay and the probability of winning against both Random and Best-Action agents. A similar correlation (-0.25) holds for the Full-Tree search agent, however it is not statistically significant.

3. As discussed in sections 2.8.2 and 3.4.4, having *delayed rewards*[5] is a major challenge for both learning and search based methods. This is confirmed by the results from the test games. As Table 4.5 illustrates, all agents perform better in games that do not have delayed rewards.

[5]Games with delayed rewards are games in which the agent receives rewards of zero in most of the states, and only receives a non-zero reward after it has executed a complex sequence of actions. Here, to have a more concrete definition, we only consider a game to have delayed rewards if random trajectories are very unlikely to receive positive rewards in it.

	BASS	DISCO	RAM	Full-Tree	UCT
Games With Delayed Rewards	**30%**	30%	**50%**	**60%**	80%
Games Without Delayed Rewards	**62%**	53%	**80%**	**93%**	90%

Table 4.5: Comparison of the performance of the agents on games with and without delayed rewards. Each cell value presents the percentage of the games in which the given agent performs better than the Best-Action agent. Columns with a statistically significant difference between the two values are printed in **bold**.

The extracted game properties also allow us to make an observation on the type of games in which the RL-agents outperform the search-based agents. As mentioned in the previous section, the search-based agents generally outperform the RL-based agents. However, there are still a number of games in which the RL-based agents perform better than the search-based agents. Most of these games can be categorized into two groups:

1. Games in which a random trajectory is not likely to receive rewards, e.g., Elevator Action and Private Eye.
2. Games in which the *death delay* is large, e.g., Bank Heist, Berzerk, Road Runner, and Robotank.

Search-based agents perform well when the look-ahead trajectory is able to receive rewards and both detect and avoid the death of the PC. Since there is no learning involved, when either the reward or the end of the game is not detectable in the look-ahead horizon, the search-based agents perform poorly. Additional interactions with the game does not improve the performance of a search-based agent. The RL-based agents, on the other hand, are able to do value propagation which allows them to broadcast the value of delayed rewards and delayed consequences to previous states. Delayed rewards and delayed consequences are still challenging obstacles, but the RL-agents have a chance of overcoming them over time.

Chapter 5

Conclusion and Future Work

This thesis introduced the Atari 2600 as an attractive platform for developing and evaluating AI algorithms. Three reinforcement learning agents were developed that use features from the game screen as well as the console RAM to learn to play generic Atari 2600 games. Furthermore, it was demonstrated how by using the save-state/restore-state features of the emulator, a state-action tree can be generated for any Atari 2600 game. Full-tree search as well as UCT was applied on the generated trees, aiming to play as well as possible by only exploring a very small fraction of the large state-space. To insure the generic nature of our methods, four specific games were used to design and fine-tune the agents, and later fifty randomly chosen games were used for evaluating their performance. The experimental results show that significant learning has taken place in the RL-based agents, while the search-based agents achieve human-level performance in a number of games. Among the RL-based agents, the RAM agent has the best performance, possibly because it is the only RL-agent with truly Markov states. The results also show that UCT performs significantly better than the full-tree search in over half of the games. While the search-based agents generally outperform the RL-based agents, there are still a number of games (mainly those with either delayed rewards or large death delays) in which the RL-based agents perform better. Finally, the results show that the death delay and delayed rewards have a significant negative impact on the performance of the player agents, making these important challenges for ongoing research. Sensitivity to the learning rate (α) and having to deal with complex value functions and Non-Markovian states are other critical obstacles for the learning agents.

This work has only started to scratch the surface of the problem of playing generic Atari 2600 games. A number of possible future directions for this research are discussed bellow:

- The large and diverse set of test games, with wide range of reward functions and state transition dynamics, provide an excellent opportunity for a comprehensive comparison between various RL methods. All three RL-based agents in this thesis use Sarsa(λ) as their learning method. It will be interesting to investigate how other Reinforcement

Algorithms compare with Sarsa(λ), when applied on the same feature vectors and run on the same set of games.

- Sensitivity to the learning rate (α) is a major setback in our RL-based agents. Our experiments with meta-learning methods such as Delta-bar-Delta and iDBD does not seem to improve this problem. We note that the Atari 2600, with a substantial number of games each having a unique reward structure and value function, is an excellent platform for developing and testing new meta-learning methods for reinforcement learning.

- The RL-based agents need to deal with large and sparse feature vectors, with only a small fraction of the features being important for approximating the value function. These properties make the learning problem in Atari 2600 games an excellent candidate for applying *regularized* reinforcement learning methods [Farahmand et al., 2009, Loth and Davy, 2007].

- Combining the search-based and the RL-based methods is another exciting future direction for this research. In particular, in many games the search-based agents generate policies that if not optimal, still play on the level of a typical human player. The question is how these good policies can be used to help the RL-based methods either learn faster or learn to perform better.

  A simple approach for integrating the search and learning methods is to do a short look-ahead search before choosing an action in the reinforcement learning methods. When choosing a greedy action at time step t, instead of returning the action that maximizes $Q_t(s_t, a)$, we can generate a small state-action tree with its root at s_t and return the action associated to the branch with the highest value. This is similar to the method employed by Tesauro in TD-Gammon [Tesauro, 2002], in which a k-ply search is performed before returning an action. Tesauro also uses the value function learned by the TD method to *forward prune* the search tree.

  The Dyna-2 algorithm [Silver et al., 2008] presents another approach for combining the learning and search methods. In Dyna-2, the agent estimates two value functions: the first one, referred two as the *permanent learning memory*, is updated from real experience, and the second one, called the *transient planning memory*, is updated from simulated experience. The permanent memory is updated similar to the Sarsa algorithm. Additionally, at each state the agent performs a local sample-based search and updates its transient memory. A greedy action is then selected from a linear combination of both the permanent and transient memories.

  Learning Real Time A* (LRTA*) [Korf, 1990], a real time heuristic search which updates its heuristic estimates on every step, is another possible approach for combining the search and learning methods. In LRTA*, the agent starts with an initial heuristic function. On each step, the agent acts greedily based on the current heuristic function. LRTA* then updates the heuristic estimate for the previous state based on the heuristic value of the new state.

Offline batch supervised learning is yet another possible approach for integrating the search and learning methods. A set of samples can be collected from a search-agent playing a given game. A supervised method can then be applied to learn a mapping from the feature vectors to the actions taken. The resulting classification model can be used to generate an *imitation agent*.

Appendix A

Video Game Terminology

Bellow, we provide a short definition for some of the video game related terminology used through the thesis:

Video Game Console: Computer systems designed specifically for playing video games. Unlike the generic Personal Computers, game consoles often do not allow users to install arbitrary software. They also usually do not provide a keyboard and mouse interface, and interaction with the system is only through the provided game controllers. To this date, there has been seven generations of videogame consoles, starting from the Pong in the first generation to the Wii, Xbox 360 and PlayStation 3 in the seventh (current) generation.

Emulator: "A piece of hardware/software that allows a user to execute game software on a platform for which the software was not originally intended. For example, video game emulators allow a personal computer to function almost identically to a video game console or an arcade game system". [Conley et al., 2004]

Save-State: Saving the current state of a game by dumping the content of RAM. Console emulators often implement save-state (also known as *freeze-state*) to let players save their games even when the game or the system does not provide a save feature.

Restore-State: Loading the state of a game from a RAM dump previously saved through save-state.

Game Cartridge (a.k.a Game ROM): A removable cartridge with a Read-Only Memory device, containing the binary content of a console game. Some game cartridges may also include additional RAM or hardware expansions.

Player Character (PC): The character in a game that is controlled by the player.

Non-Player Character (NPC): A character in a game that is not controlled by the player. NPC's can be enemies or allies.

Appendix B

Description of the Training Games

This section provides a short description for each of the four training games. The descriptions are useful to better understand some of the examples provided through the thesis. Figure 1.1 contains a screenshot for each of the four games.

B.1 Asterix

Asterix is an Atari 2600 video game, developed by Steve Woita and published by Atari in 1982. Released for the European market, the game is essentially a slightly modified version of the Atari 2600 game Tad. The player controls the Asterix's character. The aim of the game is to collect the sprites resembling magic potions while avoiding the sprites resembling lyres. Each time Asterix collects a magic potion, the player receives a score of 50. The game is over when the player character is hit by a lyre. There are five possible actions in the game: *Up*, *Down*, *Left*, *Right*, and *No-Action*.

B.2 Freeway

Freeway is an Atari 2600 video game, developed by David Crane and published by Activision in 1981. The gameplay is very similar to the popular arcade game Frogger. The player controls the yellow chicken, and the goal of the game is to reach the top of the highway while avoiding the passing cars. Once the chicken reaches the top of the highway, the player receives a score of one, and the chicken moves back to the bottom of the screen. In the hard mode, in which we run our experiments, when the chicken is hit by a car, it moves all the way back to the bottom of the highway and needs to start again. The player character never dies, and the game only ends after two minutes of gameplay. There are three possible actions in the game: *Up*, *Down*, and *No-Action*.

B.3 Seaquest

Seaquest is an Atari 2600 video game, developed by Steve Cartwright and published by Activision in 1982. The player controls a yellow submarine, and the goal of the game is to destroy waves of coming sharks and enemy submarines, while rescuing the swimming divers who are being chased by the sharks. The submarine has a limited supply of oxygen, displayed as a shrinking white bar at the bottom of the screen. If the oxygen supply reaches zero, the player submarine explodes and the game ends. To resupply on oxygen, the player needs to bring up the submarine to the surface. The player receives a score of 20 for killing a shark or destroying an enemy submarine. The game does not award any immediate scores for rescuing divers. However, the rescued divers are important in two ways. First, they are essential for resupplying on oxygen at the surface. If the player has rescued at least one diver, bringing the submarine to the surface will consume one of the divers and the player receives a full tank of oxygen. If the player has not rescued any divers, once the submarine reaches the surface, it will explode and the game ends. Also, collecting six divers (without losing any of them for resupplying on oxygen) and coming up to the surface results in a large score of 1000. The game ends when the oxygen supply reaches zero or if the player submarine is hit by either a shark, an enemy submarine, or bullets from the enemy submarines. There are ten possible actions in the game: *Up*, *Down*, *Left*, *Right*, *Up-Fire*, *Down-Fire*, *Left-Fire*, *Right-Fire*, *Fire*, and *No-Action*.

B.4 Space Invaders

Space Invaders on the Atari 2600 is a port from the popular arcade video game designed by Tomohiro Nishikado, and released in 1978. The player controls a laser cannon at the bottom of the screen that can be moves to the left and right. The aim of the game is to destroy the 48 space aliens before they reach the bottom of the screen. The aliens move horizontally and randomly fire bullets toward the bottom. There is a different score associated for destroying aliens from different rows: 5 in the first row, 10 in the second row, until 30 scores for the sixth row. The game ends if an alien reaches the bottom of the screen or the or the player character is hit by an alien bullet. We note that there is a bug when emulating Space Invaders in Stella, and not all game entities are rendered on all frames. In particular, the alien bullets and the protective barriers are often missing from the screen for several seconds.

Appendix C

Atari 2600 Technical Specifications

Bellow is a brief description of the Atari 2600 hardware specification. For a more detailed description, please see [Montfort and Bogost, 2009].

- **Release Date**: October 1977
- **CPU**: 8bit, 6507 MOS Technology
- **CPU Clock**: 1.19 MHz
- **RAM**: 128 bytes
- **ROM**: External game cartridge. 4KB maximum capacity (more can be addressed via bank switching)
- **Resolution**: 160 $\times$ 192 pixels
- **Colors**: 128 colors (NTSC palette), 104 colors(PAL palette), 8 colors (SECAM palette)
- **Sound**: 2 channel mono sound (with frequency, volume, noise control)

Figure C.1: The Atari 2600 Video Computer System

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