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Importance Sampling for Reinforcement Learning with Multiple Objectives

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Abstract

This thesis considers three complications that arise from applying reinforcement learning to a real-world application. In the process of using reinforcement learning to build an adaptive electronic market-maker, we find the sparsity of data, the partial observability of the domain, and the multiple objectives of the agent to cause serious problems for existing reinforcement learning algorithms.

We employ importance sampling (likelihood ratios) to achieve good performance in partially observable Markov decision processes with few data. Our importance sampling estimator requires no knowledge about the environment and places few restrictions on the method of collecting data. It can be used efficiently with reactive controllers, finite-state controllers, or policies with function approximation. We present theoretical analyses of the estimator and incorporate it into a reinforcement learning algorithm.

Additionally, this method provides a complete return surface which can be used to balance multiple objectives dynamically. We demonstrate the need for multiple goals in a variety of applications and natural solutions based on our sampling method. The thesis concludes with example results from employing our algorithm to the domain of automated electronic market-making.

Thesis Supervisor: Tomaso Poggio
Title: Professor of Brain and Cognitive Science

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I know this thesis would have been more difficult and of lesser quality were it not for

the patience and trust of my advisor,
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and the faith and love of my parents.

Thank you.

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Chapter 1

Introduction

"A little learning is a dangerous thing."
Essay on Criticism. part ii. line 15.
Alexander Pope

Designing the control algorithm for the robot can be difficult for many robotic tasks. The physical world is highly variable: the same exact situation seldom arises twice, measurements of the world are noisy, much of the important information for a decision is hidden, and the exact dynamics of the environment are usually unknown. When the robot is created, we may not be able to anticipate all possible situations and tasks. In many applications, writing software to explicitly control the robot correctly is difficult if not impossible.

Similar situations arise in other areas of control. Virtual robots, or software agents, have similar difficulties navigating and solving problems in electronic domains. Agents that search the world wide web for prices or news stories, programs that trade securities electronically, and software for planning travel itineraries are all becoming more popular. They don't operate in the physical world, but their virtual environments have many of the same characteristics. The agents have actions they can take, such as requesting information from online services or presenting data to the user. They have observations they make, such as the web page provided by a server or the user's current choice. And they have goals, such as finding the best price for a book or finding the quickest way to travel from New York to Los Angeles.

This thesis considers learning as a tool to aid in the design of robust

algorithms for environments which may not be completely known ahead of time. We begin in this chapter by describing reinforcement learning, some of its background, and the relationship of this work to other algorithms and methods. Chapter 2 develops the main algorithm and theoretical contributions of the thesis. Chapters 3 and 4 extend this algorithm to deal with more complex controllers, noisy domains, and multiple simultaneous goals. Chapter 5 uses these techniques to design an adaptive electronic market-maker. We conclude in chapter 6 by discussing the contribution of this work and possible future directions.

1.1 Task Description

A learning algorithm has the potential to be more robust than an explicit control algorithm. Most programmed control policies are designed by beginning with assumptions about the environment's dynamics and the goal behavior. If the assumptions are incorrect, this can lead to critically suboptimal behavior. Learning algorithms begin with few assumptions about the environment dynamics and therefore less often fail due to incorrect assumptions. However, as with all adaptive methods, the trade-off is that the algorithm may perform poorly initially while learning. The relaxed assumptions come at the cost of a more general model of the environment. In order to be effective, the algorithm must use experience to fill in the details of the environment that the designer left unspecified.

In practice, it is not unsurprising that hybrid systems that have adaptation for some parts and engineered preset knowledge for other parts are the most successful. Yet, for this work, we will try to make only the most necessary assumptions so as to push the learning aspects of agent control as far as possible.

There are a number of separate fields of learning within artificial intelligence. Supervised learning is the most common. In a supervised learning scenario, the agent is presented with a number of example situations and the corresponding correct responses. Its task is to generalize from the examples to a rule or algorithm that will produce the correct response for all situations. Bishop (1995) has a good introductory description of supervised learning and the related field of unsupervised learning. Schölkopf, Burges, and Smola (1999) and Jordan (1999) show some examples of more current research in this area.

Supervised learning requires a teacher who can give enlightening examples of what to do in which situation. This is often difficult. While we might know that it is useful for the robot to move forward in

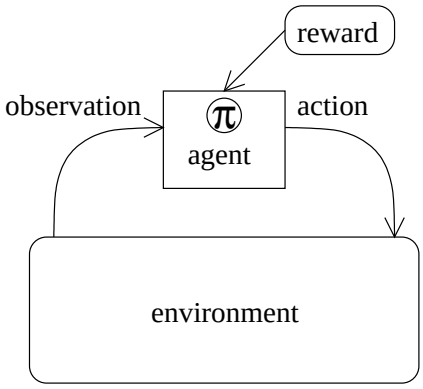


Figure 1.1: Block diagram of the reinforcement learning setting

order to progress down the hallway, the exact ideal velocity to get to the destination without colliding into obstacles is probably unknown. Supervised learning usually requires a human trainer; if an algorithm already exists to produce the correct response to all situations, the task has been already solved and no learning is required. Human training can be expensive and requires that someone already understands a significant portion of the desired solution. Instead, it is often easier to specify how well the agent is doing rather than what the agent should be doing. While "how well" is less informative than "what," an indication of the quality of the current situation can often be supplied continuously for all situations, usually without human intervention.

Reinforcement learning (RL) takes this approach. The quality of situation is embodied by rewards (and their sum, the return). Figure 1.1 shows a block diagram of the interaction cycle. The agent is the part of the world that learning algorithm controls. In our examples above, the agent would be the robot or the internet application. The environment encompasses all of the rest of the world. In general, we limit this to be only the parts of the world that have a measurable effect on the agent. The symbol π is used to stand for the controlling policy of the agent. The reinforcement learning algorithm's job is to find a policy that maximizes the return.

The reward is not part of either the agent or the environment but is a function of one or both of them. The task of the agent is to maximize the return, the total reward over all time. It might be in the agent's best interest to act such as to decrease the immediate reward if that

leads to greater future rewards. The agent needs to consider the long-term consequences of its actions in order to achieve its objective. The reward defines the agent's objective and is a fixed part of the problem's definition. Whether it is defined by the system's designers or is a signal from the environment is left unspecified. For the purposes of this thesis, it is assumed to be fixed prior to invoking learning.

All parts of this model are unknown to the learning algorithm. The learning algorithm knows the interface to the world (the set of possible actions and observations), but no more. The dynamics of the environment, the meaning of the observations, the effects of actions, and the reward function are all unknown to the agent. As the agent interacts with the environment, it experiences observations and rewards as it tries actions. From this experience, the algorithm's job is to select a control policy for the agent that will, in expectation, maximize the total reward.

Narrowing the definition can be difficult without omitting some type of reinforcement learning. Kaelbling, Littman, and Moore (1996) do a good job of describing the many aspects to reinforcement learning and the range of the different approaches. The definition of return, the type of controller, and the knowledge about the task domain can vary. Yet, two properties are universal to almost all reinforcement learning research: time passes in discrete increments and the return is the sum of rewards, one per time step.

1.1.1 Agent-Environment Cycle

The discrete nature implies that the environment and the agent take turns (or are at least modeled that way). The system is a closed loop and thus the output generated by the agent affects the output generated by the environment and, symmetrically, the environment affects the agent. These changes are sequential and occur in time steps. Usually the environment is considered to be fixed to begin the cycle and the description takes an agent-centric point-of-view. The environment's output is called an observation (because it is what the agent senses about the environment) and the agent's output is called an action (because it is what the agent uses to affect the environment). The agent senses the current observation from the environment; the agent executes its controller policy to select an action; and the environment changes in response to the action (thus affecting the next observation). This completes one time step after which the cycle repeats.

After each time step, the agent receives a real scalar value called a reward. The return is the sum of all of the rewards across all time

steps. This sum can be undiscounted, discounted, or averaged. The latter two are popular for tasks with no stopping time because they prevent infinite sums. If we let r_t be the reward at time step t and T be the number of time steps, these definitions of return can be written as

$$\text{undiscounted: } R = \sum_{t=0}^{T} r_t$$

$$\text{discounted: } R = \sum_{t=0}^{T} \gamma^t r_t, \text{ for } 0 \leq \gamma < 1$$

$$\text{average: } R = \lim_{\tau \to T} \left[\frac{1}{\tau + 1} \sum_{t=0}^{\tau} r_t \right] .$$

For the discounted case, the parameter γ controls time horizon considered by the agent. For larger values of γ, the distant future is more relevant to the agent's goal. Smaller values of γ encourage the agent to optimize the more immediate rewards and not to worry as much about the far future. Both discounted and average reward are valid measures of return even if $T = \infty$.

1.1.2 Example Domains

We can now instantiate our robot and internet search scenarios from before, as reinforcement learning problems. In the case of electronic trading, the agent would be the trading program and the environment would consist of the other traders and the trading system. Actions might include placing bids on the market and querying news agencies for financial stories. Observations would include the current value of the traded securities, headlines from news sources, the current status of placed bids, and text from requested articles. The most obvious reward would be the current estimated value of the portfolio. The agent's task would be to request information and trade securities to maximize the value of its portfolio.

For robot navigation, the set of observations might be the current values of the sensors on the robot (*e.g.*, sonars, laser range finder, bump sensors). The actions allowed might be settings of the motor voltages for the robot. At each time step, the robot would receive a positive reward if it successfully navigated to the mail room and a negative reward if it collided with a wall. The learning task would be to find a control policy that drives the robot to the mail room as quickly as possible without colliding with walls. We could also take a higher level

view and provide the RL algorithm with more broad statistics of the sensor readings and change the set of actions to be target velocities or positions for fixed control subroutines (like PID controllers). With this more abstract view of the problem, the provided fixed procedures for sensor fusion and motor control become part of the environment from the RL problem formulation standpoint. This is a common method to provide domain knowledge to reinforcement learning algorithms in the form of known useful subroutines.

1.1.3 Environment Knowledge

Generally, it is assumed that the RL algorithm has no *a priori* knowledge about the environment except to know the valid choice of actions and the set of possible observations. This is what defines RL as a learning task. By trying actions or policies, the algorithm gains information about the environment which it can use to improve its policy. A fundamental struggle in reinforcement learning is achieving a balance between the knowledge gained by trying new things and the benefit of using the knowledge already gained to select a good policy. This is known as the exploration-exploitation trade-off and it pits immediate knowledge benefits against immediate return benefits. Although maximizing the return is the overall goal of the algorithm, gaining knowledge now might lead to greater returns in the future.

1.2 Environment Models

To aid in addressing RL in a mathematically principled fashion, the environment is usually assumed to be describable by a particular mathematical model. We first outline two of the basic models and then describe the types of RL algorithms that have been studied in conjunction with these models.

1.2.1 POMDP Model

The most general commonly-used model is the partially observable Markov decision process (POMDP). A POMDP consists of seven elements: $\mathcal{S}, \mathcal{A}, \mathcal{X}, p_s, p_x, p_0, r$. They are:

- $\mathcal{S}$ is the set of all possible environment states. It is often called the state space.
- $\mathcal{A}$ is the set of all agent actions. It is often called the action space.

- $\mathcal{X}$ is the set of all observations. It is often called the observation space.
- p_s is a probability distribution over $\mathcal{S}$ conditioned on a value from $\mathcal{S} \times \mathcal{A}$. It the probability of the world being in a particular state conditioned on the previous world state and the action the agent took and is often written as $p_s(s_t|a_{t-1}, s_{t-1})$.
- p_x is a probability distribution over $\mathcal{X}$ conditioned on a value from $\mathcal{S}$. It is the probability of an observation conditioned on the state of the world and is often written as $p_x(x_t|s_t)$.
- p_0 is a probability distribution over $\mathcal{S}$. It is the probability that the world begins in a particular state and is often written $p_0(s_0)$.
- r is a function from $\mathcal{S}$ to the real numbers. It is the reward the agent receives after the world transitions to a state and is often written as $r(s)$.

The generative POMDP model is run as follows. To begin, s_0 (the state at time step 0) is picked at random from the distribution p_0. From that point on, for each time step t (beginning with $t = 0$), the following four steps occur:

1. The agent receives reward $r(s_t)$.
2. Observation x_t is drawn from the distribution $p_x(x_t|s_t)$.
3. The agent observes x_t and makes calculations according to its policy. This results in it producing a_t, the action for this time step.
4. The new world state s_{t+1} is drawn from $p_s(s_{t+1}|a_t, s_t)$.

After these four steps, the time index increase (*i.e.*, $t \leftarrow t + 1$) and the process repeats.

There are variations on this basic POMDP definition. The reward can depend not only on the current state, but also on the last action taken. This new model can be reduced to a POMDP of the form above with an increase in the size of $\mathcal{S}$. The POMDP definition above can also be simplified either by making the start state deterministic, by making the observation a deterministic function of the state, or by making the transition function deterministic. Any of these three (although not more than one) simplifications can be placed on the POMDP model above without changing the class of environments modeled. Again, however, any of these changes might affect the size of $\mathcal{S}$. Finally, the

action space can be modified to depend on the observation space. This can have an effect on the problem difficulty but complicates the mathematical description unnecessarily for our purposes.

The POMDP model is Markovian in the state sequence. In particular, if one knows the current state of the system and all of the internals of the agent, no additional information about past states, observations, or actions will change one's ability to predict the future of the system. Unfortunately, this information is not available to the agent. The agent, while knowing its own internal system, does not observe the state of the environment. Furthermore, in the general case, it does not know any of the probability distributions associated with the environment (p_s, p_x, p_0), the state space of the environment $(\mathcal{S})$, or the reward function (r). It is generally assumed, however, that the agent knows the space of possible observations and actions ($\mathcal{X}$ and $\mathcal{A}$ respectively). The observations may contain anywhere from complete information about the state of the system to no information about the state of the system. It depends on the nature of the unknown observation probability distribution, p_x.

1.2.2 MDP Model

The POMDP model is difficult to work with because of the potential lack of information available to the agent. The MDP, Markov decision process, model can be thought of as a specific form of the POMDP model for which the observation space is the same as the state space (*i.e.*, $\mathcal{X} = \mathcal{S}$) and the observation is always exactly equal to the state (*i.e.* $p_x(x|s)$ is 1 if $x = s$ and 0 otherwise). Thus the model is fully observable: the agent observes the true state of the environment. The only other difference from the POMDP model is that the reward function is now stochastic to make the learning problem slightly more difficult. Formally, it is best to remove the observation from consideration entirely. The MDP consists then of five elements: $\mathcal{S}, \mathcal{A}, \mathcal{R}, p_s, p_0, p_r$. They are:

- $\mathcal{S}$ is the set of all possible environment states (state space).
- $\mathcal{A}$ is the set of all agent actions (action space).
- $\mathcal{R}$ is the set of possible rewards. $\mathcal{R} \subset \Re$.
- p_s is a probability distribution over $\mathcal{S}$ conditioned on a value from $\mathcal{S} \times \mathcal{A}$. It the probability of the world being in a particular state conditioned on the previous world state and the action the agent took and is often written as $p_s(s_t|a_{t-1}, s_{t-1})$.

- p_0 is a probability distribution over $\mathcal{S}$. It is the probability that the world begins in a particular state and is often written $p_0(s_0)$.
- p_r is a probability distribution over $\mathcal{R}$ conditioned on a value from $\mathcal{S}$. It is the probability of a reward conditioned on the current world state and is often written as $p_r(r_t|s_t)$.

The generative MDP model is run very similarly to the POMDP model. The beginning state s_0 is picked at random from p_0 as before. Three steps occur for each time step:

1. The reward r_t is drawn from the distribution $p_r(r_t|s_t)$.
2. The agent observes s_t and makes calculations according to its policy. This results in it producing a_t, the action for this time step.
3. The new world state s_{t+1} is drawn from $p_s(s_{t+1}|a_t, s_t)$.

After these three steps, the time index increases (*i.e.*, $t \leftarrow t + 1$) and the process repeats.

MDP models are often augmented by allowing the reward probability distribution to depend also on the action taken by the agent. This does change the model slightly, but not significantly for our considerations. Just as in the POMDP case, the MDP definition is sometimes augmented to allow the action set to depend on the state of the environment. This also slightly, but not significantly, changes the model. Although the agent observes the true state value at each time step, p_s, p_o, and p_r are still unknown. However, estimating them or functions of them is much easier than it would be for POMDPs because samples from the distributions are directly observed.

1.2.3 Previous Work

Value functions are the single most prevalent reinforcement learning concept. They do not play a role in this thesis, but are useful in understanding other algorithms. It is beyond the scope of this thesis to fully describe value functions, but we will outline their definition and use briefly.

Two types of value functions exist. V-values are associated with states and Q-values are associated with state-action pairs. Informally, $V^\pi(s)$ is the return expected if the environment is in state s and the agent is executing policy π. $Q^\pi(s, a)$ is the expected return if the environment is in state s, the agent executes action a and then on subsequent time steps the agent executes policy π.

Because in an MDP the agent can observe the true state of the system, it can estimate the quality (or value) of its current situation as represented by the value functions. The current state, as mentioned before, provides as much information as possible to predict the future and thereby the rewards that the agent is likely to experience later.

The most popular value function methods are temporal difference (TD) algorithms, the best known variants of which are Q-learning and SARSA. Sutton and Barto (1998) provide a nice unified description of these algorithms. In temporal difference algorithms, the value functions are updated by considering temporally adjacent state values and adjusting the corresponding value function estimates to be consistent. As an example, if the problem definition uses undiscounted reward, then consistent value functions will have the property that

$$V^{\pi}(s_t) = E[r_t + V^{\pi}(s_{t+1})]$$

for any state s_t. This expresses that the value of being in a state at time t should be equal to the expected reward plus the expected value of the next state. $V^{\pi}(s_t)$ should represent all future rewards. They can be broken down into the immediate next reward and all rewards that will occur after the environment reaches its next state ($V^{\pi}(s_{t+1})$). By keeping track of all value function values and modifying them carefully, a consistent value function can be estimated from experience the agent gathers by interacting with the environment. One possible method is for the agent to adjust the value of $V^{\pi}(s_t)$ towards the sum of the next reward and the value function at the next state. This uses the interactions with the environment to sample the expectation in the above equation.

Such methods have been very well studied and for environments which adhere to the MDP model, they work consistently and well. In particular for MDPs, we do not need to keep a separate value function for each policy. A number of methods exist for estimating the value function for the optimal policy (even if the policy is unknown) while learning. Once the value function has converged, it is simple to extract the optimal policy from it. Bertsekas and Tsitsiklis (1996) give a nice mathematical treatment of the convergence conditions for temporal difference methods in MDPs.

Yet, TD algorithms do not solve all problems. In many situations, the space of states and actions is large. If value function estimates must be maintained for every state-action pair, the number of estimated quantities is too big for efficient calculation. The amount of experience needed grows with the number of quantities to estimate. Furthermore, we might expect that many such estimates would have

similar values which might be able to be grouped together or otherwise approximated to speed up learning. In general, we would hope be to be able to represent the value function with a parameterized estimator instead of a large table of values, one for each state-action pair. Unfortunately, while some approximators forms do yield convergence guarantees (Boyan and Moore 1995), the class of allowable approximators is restricted.

For environments that are not fully observable, the situation is worse. The general POMDP problem is quite difficult. Even if the model is known (and therefore no learning needs to take place, the model must only be evaluated), finding the best policy is PSPACE-hard (Littman 1996) for the finite time episodic tasks of this thesis. Therefore, it is more reasonable to search for the optimal policy within a fixed class of policies or to settle for a locally optimal policy of some form. Unfortunately, temporal difference methods cannot yet do either. TD, SARSA, and Q-learning can all be shown to fail to converge to the correct best policy for some simple POMDP environments. While Q-learning can be shown to diverge in such situations, TD and SARSA have been shown to converge to a region. Unfortunately, the region of convergence is so large as to be useless (Gordon 2001). Thus, no performance guarantees can be made for any of these algorithms if run on POMDP problems.

However, value functions can be otherwise extended to POMDPs. Actor-critic methods have been used to extend value function methods to partially observable domains. Jaakkola, Singh, and Jordan (1995) and Williams and Singh (1999) present one such method and Konda and Tsitsiklis (2000) and Sutton, McAllester, Singh, and Mansour (2000) describe another. They use value function estimation on a fixed policy (this type of estimation is stable) to estimate the value for that policy and then improve their policy according to the gradient of the expected return of the policy as estimated by the value function. After each policy change, the old value function estimates must be thrown away and the new ones recomputed from scratch in order to maintain convergence guarantees.

Other more direct methods for POMDPs also exist. REINFORCE (Williams 1992) is the most classic and enduring RL algorithm for POMDPs. In this method, each policy trial is used to adjust the policy slightly and is then discarded. No value functions are required. It is similar to an actor-critic algorithm where the value function estimation is performed using only a single trial of the policy. In fact the hope of actor-critic methods such as that of Sutton, McAllester, Singh, and Mansour (2000) is that the use of a value function would

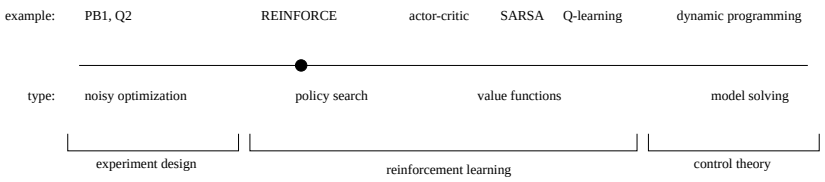


Figure 1.2: An abstract positioning of algorithms from reinforcement learning and associated areas. From left to right the line moves from fewer to more assumptions. We view the main contribution of this thesis as fitting in roughly at the position of the dot.

reduce the variance of the gradient estimate and lead to faster convergence in comparison to REINFORCE. However, initial theoretical results (McAllester 2000) seem to indicate that there is no extra gain with such a variance reduction. In fact, the update rule may be the same in formula and differ only in method of calculation.

VAPS (Baird and Moore 1999) is a different method for using value methods with POMDP environments. It combines the criteria from REINFORCE and SARSA to create a single algorithm. It is relatively new and its success is as of yet unevaluated.

1.3 Contribution

Figure 1.2 shows one possible ranking of algorithms from fewest to most assumptions about the world. On the far left is the problem of function maximization from limited stochastic samples. In this problem, the goal of the algorithm is to find the parameters that maximize a particular unknown function. The algorithm can propose parameter settings (called experiments) and in response receive the value of the true function at that point, possibly corrupted by noise. Examples of algorithms in this domain include the Q2 algorithm (Moore, Schneider, Boyan, and Lee 1998), pairwise bisection (Anderson, Moore, and Cohn 2000), and response surface methods (Box and Draper 1987). Reinforcement learning can be viewed as a subset of this problem. If we can describe the class of policies we are willing to consider by a set of parameters, experiment design can solve the problem by proposing parameter settings (policies) and observing the return experienced by executing the proposed policy. The goal of the experiment design algorithm is the same as the reinforcement learning goal: to maximize the

value of an unknown function.

In the middle of the figure is a sampling of RL algorithms organized by their world assumptions. On the left are algorithms which assume POMDP environments and on the right are algorithms which assume MDP environments.

On the far right is the problem of control given a known world model. The world model is described completely and the goal of the algorithm is to find a policy that maximizes the expected return. No experience needs to be gathered from the world. Instead, the algorithm can compute based on the given model without interacting with the world. When finished, it should have found an optimal policy for acting in the described environment.

We classify only the algorithms in the middle as reinforcement learning. The class of problems labeled "experiment design" does qualify as learning because with each new sample from the world, the algorithm can do better on the next trial. However, it does not adapt the view of a dynamical system that is essential to reinforcement learning. Each trial is considered a black box out of which only the return is used. When applied to reinforcement learning, the observation, action, and reward sequences contain potentially useful information that is ignored. Conversely, the problems labeled "control theory" do qualify as reinforcement problems because they seek to maximize the series of rewards from a dynamical system. However, there is no learning involved. The algorithm has no need to gather experience in the world in order to arrive at a better policy; it has already been presented with the complete world model.

Yet, the positioning of the algorithms along the line is as much about influences as it is about assumptions. REINFORCE shares a lot in common with general function maximization algorithms. In fact, it employs the popular and generic gradient ascent maximization algorithm modified only slightly because of the domain constraints of reinforcement learning. Similarly on the opposite end, temporal difference methods draw their roots from the dynamic programming methods based on Bellman equations used to solve known MDPs.

Although actor-critic methods explicitly acknowledge partial observability, they are placed near temporal difference learning because they are an attempt to solve the problem by importing the value function ideas from MDP solution methods. We place this thesis near the other end of the RL spectrum. The most fundamental new contribution of this thesis is the importance sampling algorithm presented in the next chapter. Its motivation is from the left side of the figure. Instead of extending methods from MDP algorithms to work on

POMDP problems, this thesis extends methods from stochastic optimization and estimation which are more general than reinforcement learning. However, we do so without ignoring the information inherent in the sequential control problem.

Problems such as the electronic market-marking agent in chapter 5 have forced us to search for new solution methods. The hidden state inherent to this and other problems makes temporal difference techniques untenable. Unfortunately methods aimed at POMDPs such as REINFORCE and actor-critic architectures forget all previous data each time the policy is modified. For RL to be a viable solution method, it must learn quickly and efficiently. We, therefore, need a method that makes use of all of the data to make maximally informed decisions. Finally, we found that most problems from real applications do not have a single obvious reward function. Designing multiple reward functions separately, each to describe a different objective of the agent, is simpler and leads to more natural designs. The techniques of this thesis are designed to address these three considerations: partial observability, scarce data, and multiple objectives.

We make what we feel are a minimal number of assumptions about reinforcement learning and develop an algorithm to solve this general problem. Such an approach is not without flaws. Most problems are not as difficult as the most general reinforcement learning problem can be. By making few assumptions, the algorithm is inclined to treat all problems as equally and maximally difficult. Because this thesis presents a novel solution method, we have concentrated on theoretical and experimental results for the algorithm's most basic forms. However, we feel confident that, despite its current generality, useful biases and heuristics can be added to allow better performance on practical applications. We are not convinced that all of the useful biases are towards full observability and value function approaches. By starting from the other end of the spectrum we hope to develop a framework that more easily allows for the incorporation of other types of heuristics and information. We do not dismiss the usefulness of values functions and temporal difference algorithms; we present this work as an alternative approach. Hopefully the connection between the two approaches will become clearer in the future.

Chapter 2

Importance Sampling for Reinforcement Learning

"Solon gave the following advice: 'Consider your honour, as a gentleman, of more weight than an oath. Never tell a lie. Pay attention to matters of importance.' "
Solon. xii.
Diogenes Laërtius

In this chapter, we jump right in and develop an algorithm for reinforcement learning based on importance sampling and greedy search.

There are a number of different ways to organize the experience of the agent. For this thesis, we use the episodic formulation. The agent's experience is grouped into episodes or trials. At the beginning of each trial, the environment is reset (the state is drawn from p_0). The agent interacts with the environment until the end of the trial when the environment is reset again and the cycle continues. The agent is aware of the trial resets. We are using fixed-length episodes: a trial lasts for a set number of time steps. The current time step index may or may not be available as part of the observations (it is not available for any the problems in this thesis). We use the undiscounted return definition. Because the number of time steps is fixed, there are no real differences among the various return definitions.

2.1 Notation

Throughout the thesis, we will use the following consistent notation to refer to the experience data gathered by the agent. s represents the hidden state of the environment, x the observation, a the action, and r the reward. Subscripts denote the time step within a trial and superscripts denote the trial number.

Let $\pi(x, a)$ be a policy (the probability of picking action a upon observing x). For this chapter, we will consider only reactive policies (policies that depend only on the current observation and have no memory). Memory is added in the next chapter.

h represents a trial history[1] (of T time steps). h is a tuple of four sequences: states (s_1 through s_T), observations (x_1 through x_T), actions (a_1 through a_T), and rewards (r_1 through r_T). The state sequence is not available to the algorithm and is for theoretical consideration only. Any calculations performed by the algorithm must depend only on the observation, action, and reward sequences. Lastly, we let R be the return (the sum of r_1 through r_T).

We assume the agent employs only one policy during each trial. Between trials, the agent may change policies. π^1 through π^n are the n policies tried (n increases as the agent experiences more trials). h^1 through h^n are the associated n histories with R^1 through R^n being the returns of those histories. Thus during trial i, the agent executed policy π^i resulting in the history h^i. R^i is used as a shorthand notation for $R(h^i)$, the return of trial i.

2.2 Overview of Importance Sampling

Importance sampling is typically presented as a method for reducing the variance of the estimate of an expectation by carefully choosing a sampling distribution (Rubinstein 1981). For example, the most direct method for evaluating $\int f(x)p(x)\,dx$ is to sample i.i.d. $x_i \sim p(x)$ and use $\frac{1}{n}\sum_i f(x_i)$ as the estimate. However, by choosing a different distribution $q(x)$ which has higher density in the places where $|f(x)|$ is larger, we can get a new estimate which is still unbiased and has lower variance. In particular, we can draw $x_i \sim q(x)$ and use $\frac{1}{n}\sum_i f(x_i)\frac{p(x_i)}{q(x_i)}$ as the new estimate. This can be viewed as estimating the expectation of $f(x)\frac{p(x)}{q(x)}$

[1] It might be better to refer to this as a trajectory. We will not limit h to represent only sequences that have been observed; it can also stand for sequences that might be observed. However, the symbol t is over-used already. Therefore, we have chosen to use h to represent state-observation-action-reward sequences.

with respect to $q(x)$ which is like approximating $\int f(x)\frac{p(x)}{q(x)}q(x)\,dx$ with samples drawn from $q(x)$. If $q(x)$ is chosen properly, our new estimate has lower variance. It is always unbiased provided that the support of $p(x)$ and $q(x)$ are the same. Because in this thesis we only consider stochastic policies that have a non-zero probability of taking any action at any time, our sampling and target distributions will always have the same support.

Instead of choosing $q(x)$ to reduce variance, we will be forced to use $q(x)$ because of how our data was collected. Unlike the traditional setting where an estimator is chosen and then a distribution is derived which will achieve minimal variance, we have a distribution chosen and we are trying to find an estimator with low variance.

2.3 Previous Work

Kearns, Mansour, and Ng (2000) present a method for estimating the return for every policy simultaneously using data gathered while executing a fixed policy. By contrast, we consider the case where the policies used for gathering data are unrestricted. Either we did not have control over the method for data collection, or we would like to allow the learning algorithm the freedom to pick any policy for any trial and still be able to use the data. Ng and Jordan (2000) give a method for estimating returns from samples gathered under a variety of policies. However, their algorithm assumes the environment is a simulation over which the learning algorithm has some control, such as the ability to fix the random number sequence used to generate trials. Such an assumption is impractical for non-simulated environments.

Importance sampling has been studied before in conjunction with reinforcement learning. In particular, Precup, Sutton, and Singh (2000) and Precup, Sutton, and Dasgupta (2001) use importance sampling to estimate Q-values for MDPs with function approximation for the case where all data have been collected using a single policy. Meuleau, Peshkin, and Kim (2001) use importance sampling for POMDPs, but to modify the REINFORCE algorithm (Williams 1992) and thereby discard trials older than the most recent one. Peshkin and Mukherjee (2001) consider estimators very similar to the ones developed here and prove theoretical PAC bounds for them. This chapter differs from previous work in that it allows multiple sampling policies, uses normalized estimators for POMDP problems, derives exact bias and variance formulas for normalized and unnormalized estimators, and extends importance sampling from reactive policies to finite-state controllers.

In this chapter we develop two estimators (unnormalized and normalized). Section 2.5 shows that while the normalized estimator is biased, its variance is much lower than the unnormalized (unbiased) estimator resulting in a better estimator for comparisons. Section 2.7 demonstrates some results on a simulated environment.

2.4 Importance Sampling Estimator

Policy evaluation is the task of estimating the expected return of a fixed policy. Many reinforcement learning algorithms use such an evaluation method as a key part to maximizing the expected return, although there are algorithms which do not explicitly compute expected returns.

Usually an RL algorithm will fix a policy to be evaluated (a target policy). It will then perform either on-policy or off-policy evaluation. In the former, the algorithm executes the target policy (possibly repeatedly) and uses the experience to evaluate the expected return. In the latter, the algorithm executes a different policy and uses the experience to evaluate the expected return of the target policy.

We will extend the generality slightly further. Instead of picking the target policy ahead of time, we will allow the agent to collect experience with any desired series of execution policies. We develop an estimator that can take this data and estimate the expected return for any target policy. This will prove useful for efficient use of data.

2.4.1 Sampling Ratios

Every policy induces a probability distribution over histories. The probabilities associated with the policy combined with the probabilities of the environment produce a complete distribution over histories. The returns are a deterministic function of the history. Therefore, we desire to calculate $E[R(h)|\pi]$ where the expectation is taken with respect to the history probability induced by the policy π.

A key observation is that we can calculate one factor in the probability of a history given a policy. In particular, that probability has

the form

$$\begin{aligned} p(h|\pi) &= p(s_0) \prod_{t=0}^{T} p(x_t|s_t)\pi(x_t, a_t)p(s_{t+1}|s_t, a_t) \\ &= \left[p(s_0) \prod_{t=0}^{T} p(x_t|s_t)p(s_{t+1}|s_t, a_t) \right] \left[\prod_{t=0}^{T} \pi(x_t, a_t) \right] \\ &\stackrel{\triangle}{=} W(h)A(h, \pi) \ . \end{aligned}$$

$A(h, \pi)$, the effect of the agent, is computable whereas $W(h)$, the effect of the world, is not because it depends on knowledge of the hidden state sequence. However, $W(h)$ does not depend on π. This implies that the ratios necessary for importance sampling are exactly the ratios that are computable without knowing the state sequence. In particular, if a history h was drawn according to the distribution induced by π and we would like an unbiased estimate of the return of π', then we can use $R(h)\frac{p(h|\pi')}{p(h|\pi)}$ and although neither the numerator nor the denominator of the importance sampling ratio can be computed, the $W(h)$ terms from each cancel, leaving the ratio of $A(h, \pi')$ to $A(h, \pi)$ which can be calculated. A different statement of the same fact has been shown before by Meuleau, Peshkin, and Kim (2001). This fact will be exploited in each of the estimators of this thesis.

2.4.2 Importance Sampling as Function Approximation

Because each π^i is potentially different, each h^i is drawn according to a different distribution and so while the data are drawn independently, they are not identically distributed. This makes it difficult to apply importance sampling directly. The most obvious thing to do is to construct n estimators (one from each data point) and then average them. This estimator has the problem that its variance can be quite high. In particular, if only one of the sampled policies is close to the target policy, then only one of the elements in the sum will have a low variance. The other variances will be very high and overwhelm the total estimate. We might then use only the estimate from the policy that is most similar to the target policy. Yet, we would hope to do better by using all of the data. To motivate the estimator of the next section (which allows for multiple sampling distributions), we first demonstrate how importance sampling can be viewed in terms of function approximation.

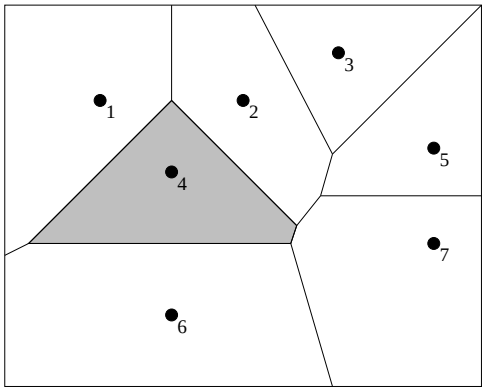


Figure 2.1: An example nearest-neighbor partitioning for seven sampled points in a two-dimensional policy space. The shaded region is the basin for sample 4 and the area of this region we denote α^4.

Importance sampling in general seeks to estimate $\int f(x)p(x)\,dx$. Consider estimating this integral by evaluating $\int \hat{f}(x)\hat{p}(x)\,dx$ where $\hat{f}$ and $\hat{p}$ are approximations based on data of f and p. In particular, with a bit of foresight we will choose $\hat{f}$ and $\hat{p}$ to be nearest-neighbor estimates. Let $i(x)$ be the index of the data point nearest to x. Then the nearest-neighbor approximations can be written as,

$$\hat{f}(x) = f(x^{i(x)})$$
$$\hat{p}(x) = p(x^{i(x)}) \ .$$

We now must define the size of the "basin" near sample x^i. In particular we let α^i be the size of the region of the sampling space closest to x^i. In the case where the sampling space is discrete, this is the number of points which are closer to sampled point x^i than any other sampled point. For continuous sampling spaces, α^i is the volume of space which is closest to x^i (see figure 2.1 for a geometric diagram). With this definition,

$$\int \hat{f}(x)\hat{p}(x)\,dx = \sum_i \alpha^i f(x^i)p(x^i) \ .$$

Both $\hat{f}$ and $\hat{p}$ are constant within a basin. We calculate the integral by summing over each basin and multiplying by its volume.

α^i cannot be computed and thus we need to approximate it as well. Let $q(x)$ be the distribution from which the data were sampled (we are

still considering case of a single sampling distribution). On average, we expect the density of points to be inversely proportional to the volume nearest each point. For instance, if we have sampled uniformly from a unit volume and the average density of points is d, then the average volume nearest any given point is $\frac{1}{d}$. Extending this principle, we take the estimate of α^i to be inversely proportional to the sampling density at x^i. That is, $\alpha^i = k\frac{1}{q(x^i)}$. This yields the standard importance sampling estimator

$$\int f(x)p(x)\,dx \approx \frac{1}{n}\sum_i f(x^i)\frac{p(x^i)}{q(x^i)} \ .$$

More importantly, this derivation gives insight into how to merge samples from different distributions, $q^1(x)$ through $q^n(x)$. Not until the estimation of α^i did we require knowledge about the sampling density. We can use the same approximations for $\hat{f}$ and $\hat{p}$. When estimating α^i we need only an estimate of the density of points at α^i to estimate the volume near x^i. The temporal ordering of the samples or which distributions they come from is not important. Our only goal is to estimate how much volume is in each basin. We therefore take the mixture density, $\frac{1}{n}\sum_i q^i(x)$ (the average of all of the sampling densities) as the density of points in sample space. Applying this change results in the estimator

$$\sum_i f(x^i)\frac{p(x^i)}{\sum_j q^j(x^i)} \ .$$

which, when translated to the POMDP estimation problem, becomes

$$\sum_{i=1}^{n} R^i \frac{p(h^i|\pi)}{\sum_{j=1}^{n} p(h^i|\pi^j)} \ . \tag{2.1}$$

This estimator is unbiased (the full derivation is shown in the appendix) and has a lower variance than the sum of n single sample estimators. The variance of an estimator depends on how much the sampling distribution and the target distribution differ. The variance of the estimator is worse for smaller sample weights (in general). The estimator of equation 2.1 uses a mixture sampling distribution for the weights. Therefore, if one sampling distribution is close to the target distribution, it helps increase all of the weights. However, if instead we were to take the sum of n single sample estimators, the same single useful sampling distribution would cause only one element in the sum to have low variance; the other elements would have very small weights and their high variance would swamp the benefit provided by that single term.

2.4.3 Normalized Estimates

We can normalize the importance sampling estimate to obtain a lower variance estimate at the cost of adding bias. Previous work has used a variety of names for this including weighted uniform sampling (Rubinstein 1981), weighted importance sampling (Precup, Sutton, and Singh 2000), and ratio estimation (Hesterberg 1995). All importance sampling estimators have weights applied to the samples. We therefore prefer the term normalized importance sampling to indicate that the weights sum to one. Such an estimator has the form

$$\frac{\sum_i f(x^i)\frac{p(x^i)}{q(x^i)}}{\sum_i \frac{p(x^i)}{q(x^i)}} .$$

This normalized form can be viewed in three different ways. First, it can be seen just as a trick to reduce variance. Second, it has been viewed as a Bayesian estimate of the expectation (Geweke 1989; Kloek and van Dijk 1978). Unfortunately, the Bayesian view does not work for our application because we do not know the true probabilities densities. Hesterberg (1995) connects the ratio and Bayesian views, but neither can be applied here.

Finally we can view the normalization as an adjustment to the function approximator $\hat{p}$. The problem with the previous estimator can be seen by noting that the function approximator $\hat{p}(h)$ does not integrate (or sum) to 1. Instead of using $\hat{p} = p(x^{i(x)})$, we make sure $\hat{p}$ integrates (or sums) to 1: $\hat{p} = p(x^{i(x)})/Z$ where $Z = \sum_i \alpha^i p(x^i)$. When recast in terms of our POMDP problem the normalized estimator is

$$\frac{\sum_{i=1}^n R^i \frac{p(h^i|\pi)}{\sum_{j=1}^n p(h^i|\pi^j)}}{\sum_{i=1}^n \frac{p(h^i|\pi)}{\sum_{j=1}^n p(h^i|\pi^j)}} . \tag{2.2}$$

2.5 Estimator Properties

It is well known that importance sampling estimates (both normalized and unnormalized) are consistent (Hesterberg 1995; Geweke 1989; Kloek and van Dijk 1978). This means that as the number of sample grows without bound, the estimator converges in the mean-squares sense to the true estimate. Additionally, normalized estimators have smaller asymptotic variance if the sampling distribution does not exactly match the distribution to estimate (Hesterberg 1995). However, our purpose behind using importance sampling was to cope with few

data. Therefore, we are more interested in the case of finite sample sizes.

The estimator of equation 2.1 is unbiased. That is, for a set of chosen policies, $\pi^1, \pi^2, \ldots, \pi^n$, the expectation of the estimate evaluated at π is the true expected return for executing policy π. The expectation is over the probability of the histories given the chosen policies. Similarly, the estimator of section 2.4.3 (equation 2.2) is biased. In specific, it is biased towards the expected returns of $\pi^1, \pi^2, \ldots, \pi^n$.

The goal of constructing these estimators is to use them to choose a good policy. This involves comparing the estimates for different values of π. Therefore instead of considering a single point we will consider the difference of the estimator evaluated at two different points, π_A and π_B. In other words, we will use the estimator to calculate an estimate of the difference in expected returns between two policies. The difference estimate uses the same data for both estimates at π_A and π_B.

We denote the difference in returns for the unnormalized estimator as D_U and the difference for the normalized estimator as D_N. First, a few useful definitions (allowing the shorthand $R_X = E[R|\pi_X]$ where X can stand for A or B):

$$
\begin{aligned}
\overline{p}(h) &= \frac{1}{n}\sum_i p(h|\pi^i) \\
\tilde{p}(h,g) &= \frac{1}{n}\sum_i p(h|\pi^i)p(g|\pi^i) \\
b_{A,B} &= \iint [R(h) - R(g)]\frac{p(h|\pi_A)p(g|\pi_B)}{\overline{p}(h)\overline{p}(g)}\tilde{p}(h,g)\,dh\,dg \\
s^2_{X,Y} &= \int R^2(h)\frac{p(h|\pi_X)p(h|\pi_Y)}{\overline{p}(h)}\,dh \\
\overline{s^2_{X,Y}} &= \int (R(h) - R_X)(R(h) - R_Y)\frac{p(h|\pi_X)p(h|\pi_Y)}{\overline{p}(h)}\,dh \\
\eta^2_{X,Y} &= \iint R(h)R(g)\frac{p(h|\pi_X)p(g|\pi_Y)}{\overline{p}(h)\overline{p}(g)}\tilde{p}(h,g)\,dh\,dg \\
\overline{\eta^2_{X,Y}} &= \iint (R(h) - R_X)(R(g) - R_Y) \\
&\qquad \frac{p(h|\pi_X)p(g|\pi_Y)}{\overline{p}(h)\overline{p}(g)}\tilde{p}(h,g)\,dh\,dg
\end{aligned}
\tag{2.3}
$$

Note that all of these quantities are invariant to the number of samples provided that the relative frequencies of the sampling policies remains fixed. $\overline{p}$ and $\tilde{p}$ are measures of the average sampling distribution. The

other quantities are difficult to describe intuitively. However, each of them has a form similar to an expectation integral. $s^2_{X,Y}$ and $\eta^2_{X,Y}$ are measures of second moments and $\overline{s^2_{X,Y}}$ and $\overline{\eta^2_{X,Y}}$ are measures of (approximately) centralized second moments. $\frac{b_{A,B}}{n}$ is the bias of the normalized estimate of the return difference.

The means and variances are[2]

$$\begin{aligned}
E[D_U] &= R_A - R_B \\
E[D_N] &= R_A - R_B - \frac{1}{n} b_{A,B} \\
\mathrm{var}[D_U] &= \frac{1}{n}(s^2_{A,A} - 2s^2_{A,B} + s^2_{B,B}) \\
&\quad - \frac{1}{n}(\eta^2_{A,A} - 2\eta^2_{A,B} + \eta^2_{B,B}) \\
\mathrm{var}[D_N] &= \frac{1}{n}(\overline{s^2_{A,A}} - 2\overline{s^2_{A,B}} + \overline{s^2_{B,B}}) \\
&\quad - \frac{1}{n}(\overline{\eta^2_{A,A}} - 2\overline{\eta^2_{A,B}} + \overline{\eta^2_{B,B}}) \\
&\quad - 3\frac{1}{n}(R_A - R_B) b_{A,B} + O(\frac{1}{n^2}) \ .
\end{aligned} \tag{2.4}$$

The bias of the normalized return difference estimator and the variances of both return difference estimators decrease as $\frac{1}{n}$. It is useful to note that if all of the π^i's are the same, then $\tilde{p}(h,g) = \overline{p}(h)\overline{p}(g)$ and thus $b_{A,B} = R_A - R_B$. In this case $E[D_N] = \frac{n-1}{n}(R_A - R_B)$. If the estimator is only used for comparisons, this value is just as good as the true return difference (of course, for small n, the same variance would cause greater relative fluctuations).

In general we expect $b_{A,B}$ to be of the same sign as $R_A - R_B$. We would also expect $\overline{s^2_{X,Y}}$ to be less than $s^2_{X,Y}$ and similarly $\overline{\eta^2_{X,Y}}$ to be less than $\eta^2_{X,Y}$. $\overline{s^2_{X,Y}}$ and $\overline{\eta^2_{X,Y}}$ depend on the difference of the returns from the expected return under π_X and π_Y. $s^2_{X,Y}$ and $\eta^2_{X,Y}$ depend on the difference of the returns from zero. Without any other knowledge of the underlying POMDP, we expect that the return from an arbitrary history be closer to R_A or R_B than to the arbitrarily chosen value 0. If $b_{A,B}$ is the same sign as the true difference in returns and the overlined values are less than their counterparts, then the variance of

[2]For the normalized difference estimator, the expectations shown are for the numerator of the difference written as a single fraction. The denominator is a positive quantity and can be scaled to be approximately 1. Because the difference is only used for comparisons, this scaling makes no difference in its performance. See the appendix for more details.

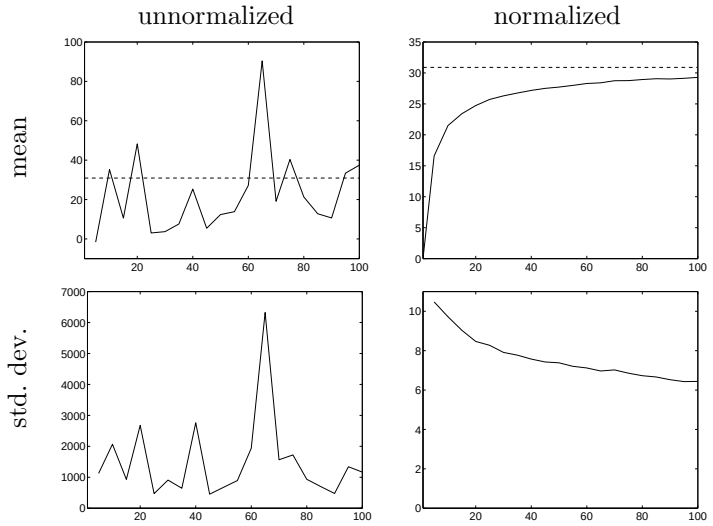


Figure 2.2: Empirical estimates of the means and standard deviations as a function of the number of trials points for the unnormalized and normalized estimates of the return differences. The data were collected by executing the policy corresponding to the point $(0.4, 0.6)$ in figure 2.3. The estimators were evaluated at the policies $(0.3, 0.9)$ and $(0.4, 0.5)$. Plotted above are the means and standard deviations of these estimates averaged over 10000 experiments. The horizontal dashed line on the plots of the mean represent the true difference in returns.

the normalized estimator is less than the variance of the unnormalized estimator.

These results are demonstrated empirically in figure 2.2 where we compare the estimates for the problem described in section 2.7. We took samples from a single policy and then used the data to estimate the difference in returns between two other policies. We ran this experiment 10000 times for each sample size from 5 to 100 at increments of 5. The empirical means and standard deviations are plotted. The standard deviation of the unnormalized estimator is hundreds of times greater than the normalized estimator's standard deviation even for this small, unnoisy problem.

The normalized plots fit the theoretical values well: the bias decreases as $\frac{1}{n}$ and the standard deviation as $\frac{1}{\sqrt{n}}$. The unnormalized plots demonstrate that even 10000 trials are not enough to get a good

estimate of the bias or variance. The unnormalized mean should be constant at the true return difference (no bias) and the standard deviation should decay as $\frac{1}{\sqrt{n}}$. However, because the unnormalized estimator is much more asymmetric (it relies on a few very heavily weighted unlikely events to offset the more common events), the graph does not correspond well to the theoretical values. This is indicative of the general problem with the high variance unnormalized estimates.

2.6 Policy Improvement Algorithm

We can turn either of these estimators into a greedy learning algorithm. To find a policy by which to act, the agent maximizes the value of the estimator by hill-climbing in the space of policies until it reaches a maximum. The agent uses this new policy for the next trial. After the trial, it adds the new policy-history-return triple to its data and repeats with the new estimator.

We use a table of conditional probabilities to represent the policy. The hill-climbing algorithm must be carefully chosen. For many estimates, the derivative of the estimate varies greatly in magnitude (as shown in figure 2.4). Therefore, we have found it best to use the direction of the gradient, but not its magnitude to determine the direction in which to climb. In particular, we employ a conjugate gradient ascent algorithm using a golden-ratio line search (Press, Teukolsky, Vetterling, and Flannery 1992).

As with most numerical optimization methods, care also must be taken in coding the algorithm. Although standard problems with numerical accuracy exist, the primary difficulty is with boundary conditions. The optimal policy often lies on multiple boundary conditions. Boundary conditions require that all policy probabilities be bounded away from zero by a positive constant[3] and that the proper sets of policy parameters sum to one. It is important to allow the optimization procedure to easily move along a boundary when the gradient points into the boundary (although not exactly perpendicular to it).

In our implementation, for each probability distribution we keep track of the set of constraints currently active. The constraint that all values sum to 1 is always active. If the line search extends past one of the other boundary constraints (namely that each value must be greater than some small positive constant), we active that constraint. If the gradient points away from a constraint into the valid search region, we clear that constraint. Each gradient calculated is projected

[3]This is to insure that all histories have a positive probability under all policies.

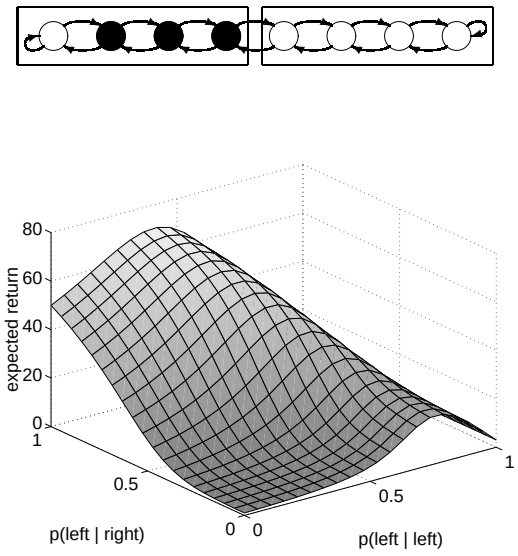


Figure 2.3: Top: Diagram of the left-right world. This world has eight states. The agent receives no reward in the outlined states and one unit of reward each time it enters one of the solid states. The agent only observes whether it is in the left or right set of boxed states (a single bit of information). Each trial begins in the fourth state from the left and lasts 100 time steps. Bottom: The true expected return as a function of policy for this world. The optimal policy is at the point $(0.4, 1)$ which is the maximum of the plotted function.

onto the subspace defined by the current active constraints. Any policy constructed during the line search is checked against all constraints and projected into the valid region if it violates any constraints.

As a final performance improvement, we reduce the chance of being stuck in a local minimum by starting the search at the previously sampled policy that has the best estimated value. The estimated values of previously sampled policies can be updated incrementally as each new trial ends.

2.7 Results

Figure 2.3 shows a simple world for which policies can be described by two numbers (the probability of going left when in the left half and the probability of going left when in the right half) and the true expected return as a function of the policy. Figure 2.4 compares the normalized

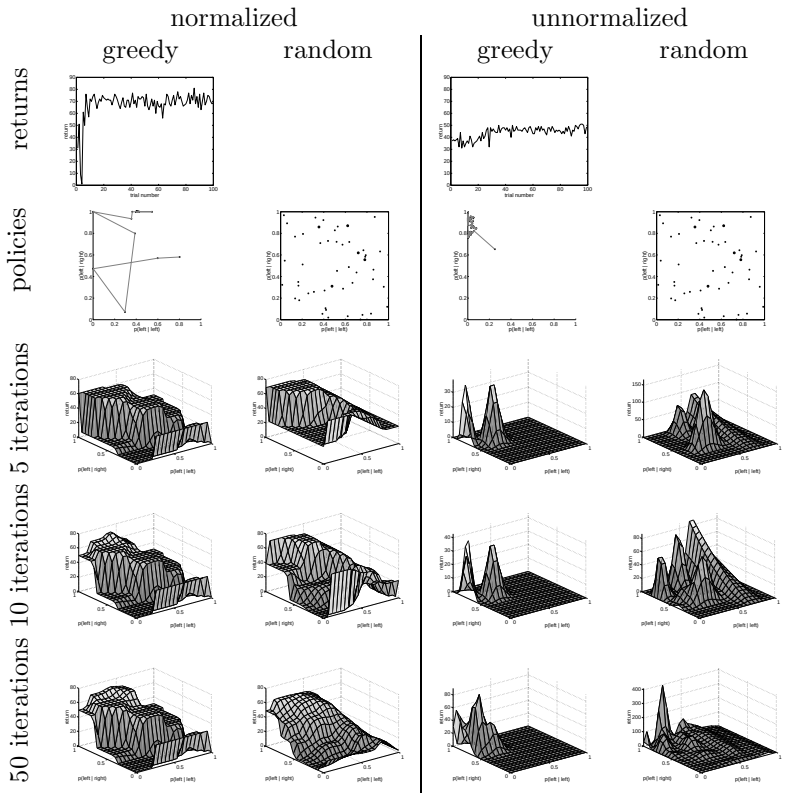


Figure 2.4: Comparison of the normalized and unnormalized estimators for single set of observations. For each estimator, the return estimates are shown plotted after 5, 10, and 50 iterations (samples). The left columns are for the greedy policy selection algorithm and the right columns are for uniformly sampled policies. The first row shows the returns as a function of trial number. The second shows the path taken in policy space (or, for right columns, the random samples taken). Both estimators were given the same sequence of data for the random case. The last three rows show the plots of the estimated returns as a function of the policy for increasing numbers of trials (compare to the right half of figure 2.3). For the normalized estimator, the random sampling of policies produces a better return surface in general, whereas the greedy algorithm quickly maximizes the return (within 10 trials) and provides a better estimate of the surface near the maximum. The unnormalized estimator is plagued by large variance and produces poor results.

(equation 2.1) and unnormalized (equation 2.2) estimators with both the greedy policy selection algorithm and random policy selection. We feel this example is illustrative of the reasons that the normalized estimate works much better on the problems we have tried. Its bias to observed returns works well to smooth out the space. The estimator is willing to extrapolate to unseen regions where the unnormalized estimator is not. This causes the greedy algorithm to explore new areas of the policy space whereas the unnormalized estimator gets trapped in the visited area under greedy exploration and does not successfully maximize the return function.

Chapter 3

Extensions of Importance Sampling

"A liar should have a good memory."
Institutiones Oratoriæ. iv. 2, 91.
Quintilian

We now move beyond reactive policies with action distributions specified as tables. Although they are a good starting place, they are not always practical. Many domains have too many observations (possibly a continuous space of observations) to make a table possible. Additionally, a single instantaneous observation seldom captures all of the necessary information. In this chapter we examine two extensions to the previous algorithm: we allow for policies with memory and with function approximators. We conclude the chapter with a pragmatic extension to the greedy search algorithm that will prove useful for more noisy environments such as the one in chapter 5.

3.1 Memory

Memory is an important aspect to successful manipulation of the world. Many memory models have been tried in the past. In this thesis, we explore adding a fixed memory space that can be read and modified as desired by the agent. In particular, we use a finite-state controller model. In this model, the agent has an internal state which, in addition

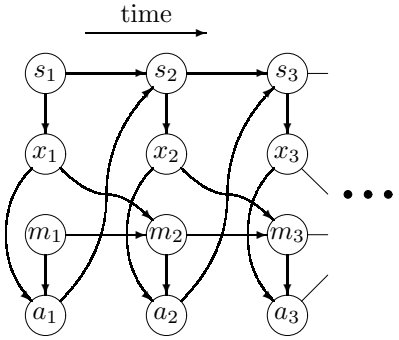


Figure 3.1: Dependency graph for agent-world interaction with memory model. This is the same as the standard POMDP model except that the current action depends on previous observation through the current memory state.

to the observation, affects the action probabilities. This model has been studied before in conjunction with POMDP learning (Meuleau, Peshkin, Kim, and Kaelbling 1999) but not with importance sampling which allows a greater information gain.

3.1.1 Finite State Machine Model

At each time step, the agent reads the value of the memory along with the observation and makes a choice about which action to take and the new value for the memory. The policy now expands to the form $\pi(x, m, a, m') = p(a, m'|x, m)$, the probability of picking action a and new memory state m' given observation x and old memory state m. The space of allowable memory states is fixed to a finite set, $\mathcal{M}$. If $|\mathcal{M}| = 1$, there is only one memory state and the model reduces to the reactive policy class of the previous chapter. The meanings of the memory states are not defined. It is up to the RL algorithm to construct a policy which makes use of the memory in an intelligent manner.

3.1.2 Memory Ratios

Let us factor the policy distribution, thereby limiting the class of policies realizable by a fixed memory size slightly but making the model simpler. In particular we consider an agent model where the agent's policy has two parts: $\pi_a(x, m, a)$ and $\pi_m(x, m, m')$. The former is the

probability of choosing action a given that the observation is x and the internal memory is m. The latter is the probability of changing the internal memory to m' given the observation is x and the internal memory is m. Thus $p(a, m'|x, m) = \pi_a(x, m, a)\pi_m(x, m, m')$. By this factoring of the probability distribution of action-memory choices, we induce the dependency graph shown in figure 3.1.

If we let M be an arbitrary memory sequence $m_1, m_2, \ldots, m_T$, $p(h|\pi)$ can be written as

$$\begin{aligned}
&\sum_M p(h, M|\pi) \\
&\quad = \sum_M p(s_0)p(m_0) \prod_{t=0}^{T} (p(x_t|s_t)\pi_a(x_t, m_t, a_t) \\
&\qquad\qquad \pi_m(x_t, m_t, m_{t+1})p(s_{t+1}|s_t, a_t)) \\
&\quad = \left[p(s_0) \prod_{t=0}^{T} p(x_t|s_t)p(s_{t+1}|s_t, a_t)\right] \\
&\qquad \left[\sum_M p(m_0) \prod_{t=0}^{T} \pi_a(x_t, m_t, a_t)\pi_m(x_t, m_t, m_{t+1})\right] \\
&\quad \stackrel{\triangle}{=} W(h)A(h, \pi) \ ,
\end{aligned}$$

once again splitting the probability into two parts: one for the world dynamics and one for the agent dynamics. The $A(h, \pi)$ term now involves a sum over all possible memory sequences.

The beauty of this formulation is that it makes it explicit that the memory sequence does not affect the return except through the action sequence. In particular, notice that the formula directly expresses that the probability of a history involves marginalizing out the memory sequence. A memory sequence only indirectly affects the return through its effect on the action sequence. This explicit modeling of the memory dynamics allows a single trial's experience to affect every policy that could have produced the action sequence without considering the memory sequence that occurred. Note that the history does not include the memory sequence and the memory is not part of the data remembered from a trial. It is not needed to estimate $A(h, \pi)$.

3.1.3 Hidden Markov Models

Computing the sum in $A(h, \pi)$ directly would take too long. However, $A(h, \pi)$ is exactly the probability of an input-output hidden Markov model (IOHMM), a slight variation of the general HMM[1]. In particular, this new problem has the same structure as figure 3.1 except that the state sequence and all connected edges are removed. $A(h, \pi)$ is the probability of an action sequence in this new problem where the observation sequence is fixed. Linear time algorithms are well known for computing the probability of an action sequence and its derivative for IOHMMs using dynamic programming. A good discussion of such algorithms for the HMM case can be found in Rabiner (1989). Bengio (1999) discusses extensions of HMMs including IOHMMs. For completeness, we will give a quick overview of the results needed for the importance sampling.

For a general sequence $z_1, z_2, \ldots, z_n$, let $z_{i,j}$ represent the subsequence from i to j (*i.e.*, $z_i, z_{i+1}, \ldots, z_j$) for simplicity of notation. We will define recurrence relations on two quantities. The first is $\alpha_i(m) = p(a_{1,i}, m_i = m | x_{1,T}, \pi_m, \pi_a)$. Its recurrence is

$$\alpha_{i+1}(m) = \pi_a(x_{i+1}, m, a_{i+1}) \sum_{m'} \pi_m(x_i, m', m) \alpha_i(m')$$

which expresses that the probability of having memory m after $i+1$ time steps is equal to probability of producing the generated action with that memory bit multiplied by the sum the probability of all the different ways the agent could have transitioned from the previous memory state m' to the current memory state multiplied by the probability the agent was previous in memory state m'. We are counting up the number of ways of getting to memory m at time $i + 1$ while still producing the observed action sequence. To do this we rely on the same set of probabilities for the previous time i.

The second recurrence relation covers the tail of the sequence. It is $\beta_i(m) = p(a_{i+1,T}, m_i = m | x_{1,T}, \pi_m, \pi_a)$:

$$\beta_i(m) = \sum_{m'} \pi_m(x_i, m, m') \pi_a(x_{i+1}, m', a_{i+1}) \beta_{i+1}(m') \ .$$

This has a similar interpretation, but working backwards through the data. The recurrence base cases are $\alpha_1(m) = p(m)\pi_a(x_1, m, a_1)$ and

[1] Note that the observations in RL become the states in the HMM model and the actions in RL become the observations in the HMM model. We will continue to use the same terminology and will not switch to the HMM naming convention.

$\beta_T(m) = 1$. Because of the Markov property,

$$p(a_{1,T}, m_i = m | x_{1,T}, \pi_a, \pi_m) = \alpha_i(m)\beta_i(m) \ .$$

The probability of the entire sequence can be found by computing $\sum_m \alpha_i(m)\beta_i(m)$ for any value i ($i = T$ is nice because then we don't have to compute the β sequence).

To maximize the estimator for the greedy search, we require the derivative of the probability with respect to the parameters as well. Without repeating the derivation, the necessary equations are

$$\frac{\partial A(h,\pi)}{\partial \pi_a(x,m,a)} = \sum_{i|a_i=a, x_i=x} \frac{\alpha_i(m)\beta_i(m)}{\pi_a(x,m,a)}$$

$$\frac{\partial A(h,\pi)}{\partial \pi_m(x,m,m')} = \sum_{i|x_i=x} \alpha_i(m)\beta_{i+1}(m')\pi_a(x_{i+1}, m', a_{i+1}) \ .$$

3.1.4 Results

We can now use the same normalized importance sampling estimator with finite-state controllers instead of reactive policies. The calculation of the importance sample ratios has become more complex, but the rest of the estimator remains the same. The estimator has explicit knowledge of the working of the memory. For algorithms that can only work with reactive policies, the memory cannot be explicitly modeled. In such cases the memory is added as part of the environment. The action space is augmented to include memory changing actions and the observation space is enlarged to include the current status of the memory (see Peshkin, Meuleau, and Kaelbling (1999) as an example of this approach). The memory appears to the agent just like any other portion of the environment. This means that the agent must needlessly learn the dynamics of its own memory. With our explicit memory model, the learning algorithm understands that the goal is to produce the correct action sequence and uses the memory state to do so by coordinating the actions in different time steps.

The load-unload problem of figure 3.2 is a traditional POMDP problem. A cart sits on a line with five discrete positions. When the cart makes it to the left-most state, the cart is filled. When the cart arrives in the right-most state with a full cart, the cart is emptied and the agent receives one unit of reward. The agent can observe the position of the cart, but not the contents (*i.e.* it does not know whether the cart is full or empty). To achieve reasonable performance, the actions must depend on the history. We give the agent two memory states

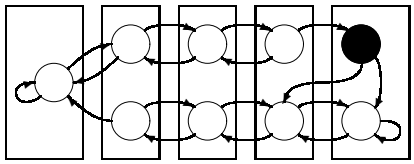


Figure 3.2: Diagram of the load-unload world. This world has nine states. The horizontal axis corresponds to the positioning of a cart. The vertical axis indicates whether the cart is loaded. The agent only observes the position of the cart (five observations denoted by boxes). The cart is loaded when it reaches the left-most state and if it reaches the right-most position while loaded, it is unloaded and the agent receives a single unit of reward. The agent has two actions at each point: move left or move right. Attempting to move off the end leaves the cart unmoved. Each trial begins in the left-most state and lasts 100 time steps. Optimal performance is 13 deliveries.

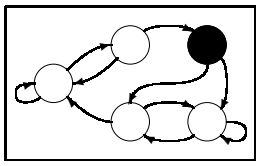


Figure 3.3: Diagram of the blind load-unload world. This world has five states. The horizontal axis corresponds to the positioning of the cart. The vertical axis indicates whether the cart is loaded. The agent is completely blind: no matter what the state of the world, it observes the same thing. The world is also only three lengths long, making for the potential for shorter deliveries. Other than these differences, the problem is the same as the one in figure 3.2. Each trial begins in the left-most state and lasts 100 time steps. Optimal performance is 25 deliveries.

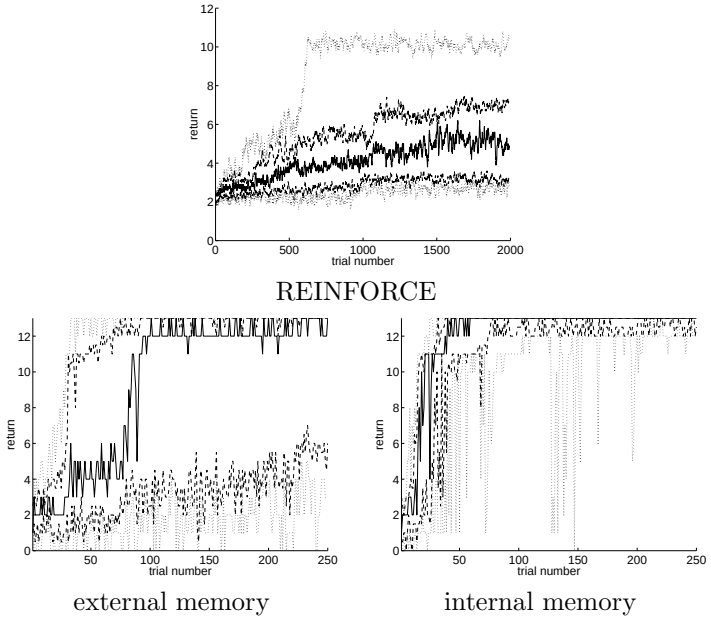
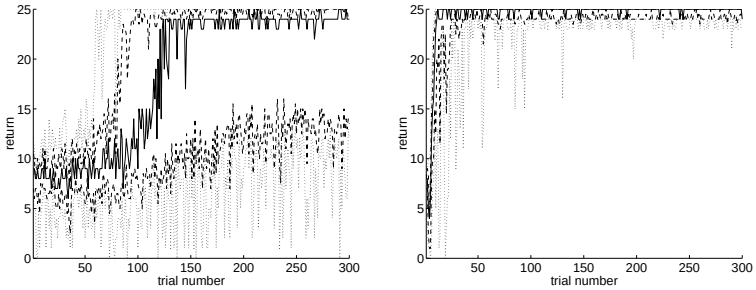


Figure 3.4: Comparison of REINFORCE to normalized importance sampling on the problem in figure 3.2. All graphs were generated from 10 runs of the algorithm. The plotted lines are the (from top to bottom), maximum, third quartile, median, first quartile, and minimum returns for each time step across the 10 runs. At the top are the results from REINFORCE with external memory. On the left are the results from normalized importance sampling with external memory. On the right are the results for normalized importance sampling with internal memory.



external memory internal memory

Figure 3.5: Comparison of placing the memory bits externally as part of the environment to modeling them explicitly as an internal part of the agent for the problem in figure 3.3. Both graphs were generated from 10 runs of the normalized importance sampling algorithm. The plotted lines are the (from top to bottom), maximum, third quartile, median, first quartile, and minimum returns for each time step across the 10 runs.

(one memory bit); this results in twenty independent policy parameters. Figure 3.4 compares using the importance sampling estimate in two different ways to the REINFORCE algorithm (Williams 1992). We consider both "external" memory where the memory is made to be part of the environment (*i.e.* the action space is now all possible combinations of moving and setting the memory bit and the observation space is all possible combinations of position and memory state) and "internal" memory where the memory model is explicit as described in this chapter. REINFORCE can only use external memory. On the left is the result of running the REINFORCE algorithm with an external memory representation. In the middle is the result of using external memory with the normalized importance sampling estimator. And, on the right is the result of using internal memory with normalize importance sampling. The REINFORCE results are for the best settings for the step size schedule and the bias term. Yet, it still frequently gets stuck in local minima and only 2 out of the 10 experiments manage to converge to a near-optimal solution (in roughly 500 trials). By comparison, the importance sampling algorithm usually converges in approximately 100 trials with external memory and almost always converges within 50 trials with internal memory.

To consider a more drastic example, we constructed a blind load-

unload problem, as shown in figure 3.3. In this case, we give the agent four memory states (two memory bits). Figure 3.5 compares the result of internal and external memory for the normalized importance sampling estimate. Again, we see a clear gain by explicitly modeling the memory dynamics. With an increase in the importance of memory, we see an increase in the difference between external and internal memory representations. Whereas figure 3.4 demonstrates a 2-fold speed-up, figure 3.5 demonstrates a 10-fold speed-up due to internal memory.

3.2 Function Approximation

In all of the examples up to this point, the policies have been represented by a table of conditional probabilities. Each value in the table is a separate parameter of the policy, modulo the condition that certain sets sum to 1. Yet, for large observation-action spaces, this often proves to be an untenable method. It results in too many parameters for the quantity of training data available. Usually, the full space of policies is not necessary anyway. By considering only a small parameterized set of policies, we can limit the search space and, in turn, the data required.

Consider the left-right problem of the previous chapter. If the problem were completely observable (*i.e.* the agent knew its exact position and not just whether it was in the left or right half) there would be 8 independent parameters for just this simple example. Yet, as with most problems with a spatial layout, we can expect adjacent observations to have similar policy parameters. Therefore, instead of using a table of probabilities, we will make the probabilities parameterized functions of the observation and action. Our algorithm will now search for the parameters which maximize the return. Note that this means that we will not be searching for the function approximator that best approximates the ideal policy, but rather that we will be searching for the best policy within the space of policies allowed by the function approximator. This is just as in the previous sections. We were not searching for the reactive (or finite-state controller) policy that is most similar to the ideal policy but rather the one that performs best within the specified set of policies. Its relationship in policy space to the ideal policy is unknown.

3.2.1 Policy Weights

These policy parameters are often called weights. For most policy parameterizations the agent's factor of the probability of a history,

$A(h, \pi)$, and its derivative with respect to the weights can be calculated in closed form. This is all that is necessary to extend the importance sampling estimator and the greedy search algorithm to the function approximation case. Instead of maximizing by calculating the derivative with respect to the probabilities in the table, we calculate the derivative with respect to the weights and update the weights. The probability tables of the previous sections can be viewed as one type of function approximator with each entry in the table as a separate weight.

To make this more concrete, we will instantiate this idea in terms of a linear Boltzmann distribution approximator (returning to reactive policies). We will assume that all observation-action pairs (x, a) have an associated feature vector $\phi_{x,a}$. We will discuss the construction of these features later. The weight vector w is of the same dimensionality as the feature vectors. The Boltzmann distribution takes the form

$$\pi(x, a) = p(a|x) = \frac{e^{w^T \phi_{x,a}}}{\sum_{a'} e^{w^T \phi_{x,a'}}} \ .$$

The agent's factor of the probability of a history is simply the product of the above formula over each of the observation-action pairs in the history: $A(h, w) = \prod_t \pi(x_t, a_t)$. The derivative of a single observation-action pair is

$$\frac{\partial \pi(x, a)}{\partial w} = \pi(x, a) \left(\phi_{x,a} - \sum_{a'} \phi_{x,a'} \pi(x, a') \right) \ .$$

This makes the derivative of an entire history

$$\frac{\partial A(h, w)}{\partial w} = A(h, w) \sum_t \left[\phi_{x_t,a_t} - \sum_{a'} \phi_{x_t,a'} \pi(x_t, a') \right] \ .$$

For distributions like the Boltzmann that are normalized across actions, certain care must be taken in designing the features. In particular, for the Boltzmann distribution, any feature which is constant across actions (even if it varies across observations) will make no difference in the final policy. It will result in a constant being added to the exponents in both the numerator and the denominator of $\pi(x, a)$, thus resulting in multiplying both numerator and denominator by the same amount. The net result is no change. There is no point in including features which do not depend on the action.

Often the observation and action spaces each have their own obvious set of features. However, simply concatenating those features together will not produce a good feature space for Boltzmann distributions. The

observation features will provide no descriptive power as noted above. The action features will allow differentiation among the actions, yet such differences in probabilities will be constant across all observations. The end results is a policy class that ignores the observations entirely. Instead, we propose using the product space. If the observation feature space has d_o dimensions and the action feature space has d_a dimensions, the product space has $d_o d_a$ features: one for each pair of observation and action features. The value of a feature can be constructed in many ways. We have found the product to be the most effective. Thus, if the current observation has the features $(1, 3, 0)$ and the current action has the features $(2, 5)$, $\phi_{x,a} = (2, 6, 0, 5, 15, 0)$.

3.2.2 Results

To illustrate this technique, we return to the left-right example of the previous chapter, but with full observability. Thus the observation at each time step is the true position of the agent along the line. We do not wish to estimate 8 separate parameters, so we will restrict the class of policies allowed. In particular, we will only allow reactive Boltzmann distributions as described in the previous section. The observation features will be the position and the constant 1. The action feature will be a single value: 0 if the action is to the left and 1 if the action is to the right. Using the product space feature construction, this results in two features. The first is 0 if the action is to the left and is the position of the agent if the action is to the right. The second feature is 0 is the action is to the left and 1 if the action is to the right. In order to insure that the weights stay bounded and that there is always a non-zero probability of taking any action at any time, we will constrain the weights to lie within an axis-aligned box with sides from -2 to $+2$.

Figure 3.6 shows the true expected return as a function of the two policy parameters. Figure 3.7 details the results of the estimator when run with random policies and when used for greedy optimization. Because of the complete observability of the problem (and the fact that our policy class is not too restricted), the agent can do better on this problem than on the left-right problem of the previous chapter where the agent had a reactive policy with partial observability.

3.3 Controlled Search

Especially in highly stochastic environments, the greedy search algorithm employed so far to direct new policy choices can cause problems.

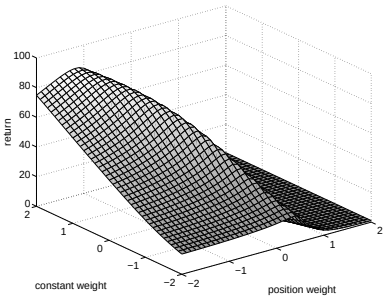


Figure 3.6: The true return as a function of the parameters of the policy for the fully-observable left-right. The optimal policy in this space is at the point $(-1.2, 2)$.

The normalized importance sampling estimator extrapolates to unseen points and thereby can overestimate the advantages of particular policies. To be specific, let us assume that the policy space exists on a single line. If the policies corresponding to the points 0.3 and 0.4 have been tried and the first produced a return of 0 and the second produced a return of 1, the estimator might produce an estimate as shown in figure 3.8. In this case, greedy maximization would select the next policy as far to the right as possible.

If the algorithm is correct in this extrapolation, everything is fine. If the algorithm is incorrect, the new sample will help to fix the estimate as shown by the dashed line in figure 3.8. Provided the samples are indicative of the true underlying expected return, this will produce acceptable behavior as the algorithm performs a rough approximation of a binary search. In fact, this bias towards the extremes of a policy space can use useful. Such extremes usually correspond to more deterministic policies which often are the optimal policies in practice.

Yet, this bias can also be a source of problems. If the samples are highly stochastic, the algorithm may be searching in the wrong half of the space. Given only two samples, there is a high probability (almost 0.5 for very random environments) that the true expected return function is greater on the opposite side than the samples indicate. To solve this, the algorithm will need to take enough samples close to the two points already sampled to determine the true expected returns (or values near enough to the true values to be able to make an informed decision). Notice that in figure 3.8, the sample on the right side did little to affect the estimate in the middle. Were the samples in the middle

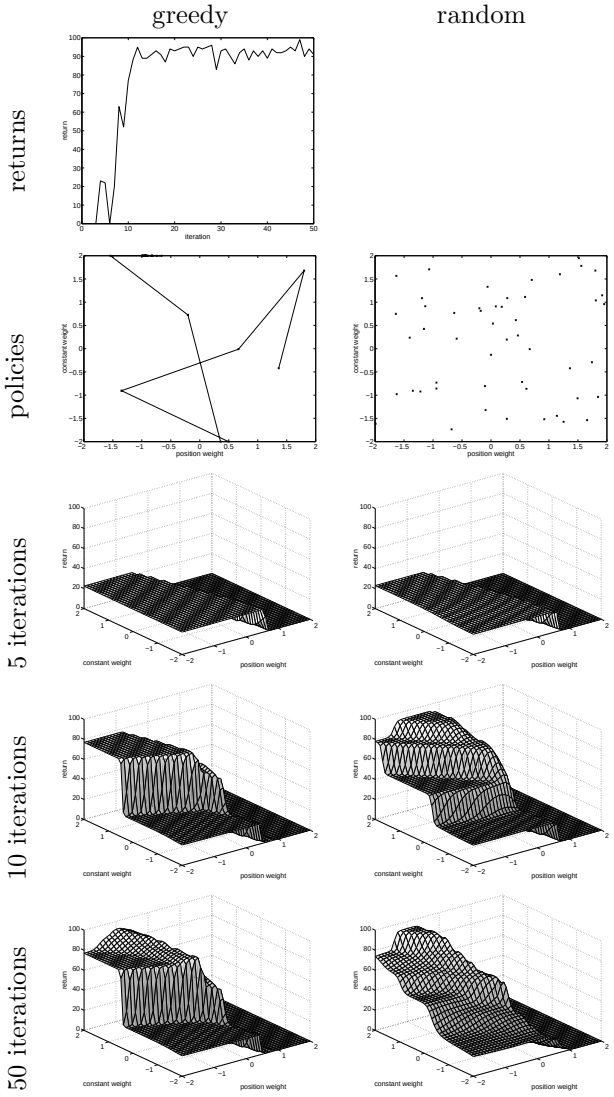


Figure 3.7: Returns, policies, and implicit return surface for the normalized importance sampling algorithm with parameterized policies for the fully-observable left-right world. Top plot is the return as a function of the trial number. The next plot shows the policies chosen (greedily on the left and randomly on the right). The final three plots are of the estimated return surface after 5, 10, and 50 trials.

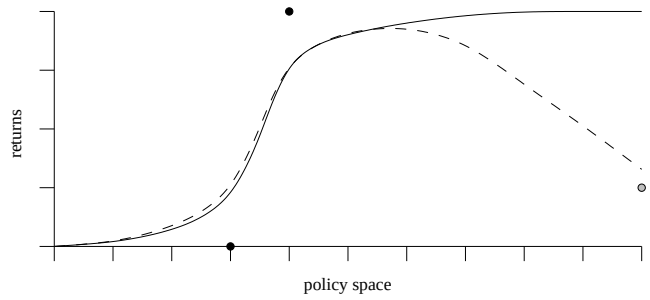


Figure 3.8: Hypothetical one-dimensional example. The solid curve might have been produced by the two solid sampled points. Upon sampling the lightly shaded point on the left, the curve might change to the dashed one. See text for details.

far from the true expected value, it would take many new samples from the far right side before the estimate in the middle became correct.

Therefore it might be wise to reduce the variance of the estimator at sampled points before extrapolating to new regions of the policy space. The new samples, selected to decrease the variance, should be policies similar enough to the old policies so that the new histories have reasonably high likelihood under the old policies. Otherwise, they will have low importance sampling ratios and not affect the return much at the old points.

This creates a dilemma. On the one hand, we would like to exploit the information gained from the original two samples and jump to the current maximum of the estimated return function. Yet, we might also like to verify the information gained before taking such a large jump. This is an example of the exploration-exploitation dilemma mentioned in chapter 1. In higher-dimensional policy spaces the problem becomes more pronounced. Search in the "wrong" half of the space is a bigger penalty because of the greater size of that half.

The most obvious solution is to take multiple samples from each policy chosen: instead of changing the policy by maximizing every trial, we could modify the algorithm to only change the policy every k trials. However this can be wasteful. If a new chosen policy is near other samples, its variance may already be small. Forcing multiple samples from this new point would be needless. In general, it would seem better to simply limit the maximization routine to stay within the part of policy space in which we are confident of our estimated return. This

insures that any new chosen policy will already have low variance due to its proximity to previous samples.

We have not yet developed an entirely principled way of achieving this. Techniques in experiment design like response surfaces (Box and Draper 1987) have found ways to deal with the variance in the environment. However, such methods, as mentioned in the introduction, are more general than reinforcement learning. We would like to exploit our knowledge about the environment dynamics inherent to reinforcement learning problems. While we have a variance formula for the estimator (shown in the previous chapter and detailed in the appendix), this formula requires specific knowledge of the environment which the algorithm does not have. We have not found a good method for estimating the needed probability distributions. Instead, we take a more pragmatic view.

The source of variance in the estimate comes from misestimating the probabilities of histories and a sparse sampling of the history space. Thus, in the estimator

$$\frac{\sum_i R^i \frac{p(h^i|\pi)}{\sum_j p(h^i|\pi^j)}}{\sum_i \frac{p(h^i|\pi)}{\sum_j p(h^i|\pi^j)}},$$

the returns, R^i, are deterministic whereas the weights associated with them are the source of the error. In fact, there is an implied 0 weight to all histories we have not yet sampled. As mentioned above, this error is difficult to compute, so instead, we will assume the reverse: the weights are correct and fixed, and the returns are random variables. Thus, our estimator is the linear combination of random variables. If we furthermore assume that all of the returns have the same variance σ^2 and let $w_n^i(\pi)$ be the normalized weight for return R^i, then the variance of our estimator is $\sigma^2 \sum_i (w_n^i(\pi))^2$. So, while the absolute magnitude of the variance cannot be determined (σ is unknown), we can determine the relative variances among the estimates for difference policies.

To use this knowledge, we limit the range of the policy search to areas where $\sum_i (w_n^i(\pi)^2)$ is less than a threshold θ. If no such regions exist, we reuse the sampled policy with the best estimated value instead thereby decreasing the variance near that sample. θ is application dependent and must be set on a case-by-case basis. Although it is unfortunate to add a tuning parameter to the algorithm, we have found it to be invaluable (despite the lack of theoretical justification) for achieving convergence in reasonable time. All of the results in chapter 5 use this method.

Chapter 4

Balancing Multiple Goals

"I do perceive here a divided duty."
Othello. act i. sc 3.
William Shakespeare

The importance sampling methods of the previous chapters estimate the entire return surface. Therefore, they can be used not only to find the policy with the maximum return, but they can also be used to find other important or interesting policies. In this chapter, we develop two methods for balancing multiple objectives simultaneously that utilize the complete return surface characterization.

Others have previously considered the case of multiple objectives. In particular, Gábor, Kalmár, and Szepesvári (1998) describe the notion of partial orderings over solutions and develop a framework based on MDPs. Geibel (2001) applies this idea to balancing expected return and risk. In section 4.2, we use these ideas but work with POMDP models and extend the estimators of the previous chapters.

For section 4.3 we take a different approach. Instead of attempting to optimize all objectives simultaneously, we fix a minimum necessary performance with regard to one or more of the objectives and then optimize the rest of the objectives as before. This makes different guarantees on the performance of the resulting policy. Each technique is applicable to a different type of objective.

This chapter differs from our previous work (Shelton 2001) in that it does not take a game theoretic approach to balancing. We achieve the same results but can guarantee qualities of performance that were not possible with the our prior method.

4.1 Rewards as Goals

Many agents have multiple objectives. The pedagogical example from robotics is an office service robot. The robot needs to deliver mail to employees' offices, stock the printer with paper, and keep its battery charged. Designing a return function for each of these tasks independently is simple. However, designing a return function that balances each of these tasks can be more difficult.

Consider the case of mail delivery and paper restocking. We might give the agent one unit of reward each time mail is delivered or paper is restocked. If we only consider the mail delivery, the agent does the right thing: it delivers mail as often as possible. The same is true of the paper restocking. However, put together, the agent will only fulfill one of its duties: whichever is easier or quicker. There is no sense in restocking the paper at all if mail delivery is faster and results in the same reward.

We can try to solve this by reweighting or discounting the rewards. Yet, this does not solve the real problem. These rewards are difficult to combine because they were not designed to be combined. Each specifies the successfulness of completing a particular goal. However, their sum (or any other fixed combination) has no guarantee to represent a desirable objective on its own.

Note that in some cases separate goals can be combined. For instance, a store may wish to both sell as many products as possible and charge the highest price. However, there is a clear way of combining the two objectives. The overall goal is to maximize profits for which the proper objective is the multiplication of the price and the number sold (ignoring fixed costs). In this chapter, we are interested in situations for which such a combination is unknown or impossible.

Such an example naturally arises when there are multiple users of a system. Each user might express his or her content with the system through rewards. Optimizing the total content of the users is not as simple as optimizing the sum of their rewards. One user might decide to reward twice as often or with twice the force as another. That should not necessarily result in this user gaining twice the control over the behavior of the agent. Limiting the amount of reward possible from

a given user does not solve the problem; it merely deafens the agent's ability to correctly distinguish the preferences of its users.

Whether each reward represents an objective or a user's desire, we will call each separate reward signal a source. We are considering problem for which rewards are comparable within the same source, but are not comparable across sources.

4.1.1 Related Work

The same problem also arises in the context of social choice theory. We recommend Resnik (1987) as a good introduction to the subject. In a social choice problem, each objective corresponds to a citizen and the goal is to pick a single global policy based on all of the citizens' individual preferences. Most of the work does not promote direct calculation or single unique solutions. The necessary computations to achieve the answer are, for our domain, intractable and for most situations do not yield a single solution, but a set of possible solutions with no principled way of selecting among them.

The most promising areas of social choice theory deal with utility functions. Utility functions directly correspond to the expected returns in our application. However, these methods assume utilities can be compared across individuals (or reward sources). We are unwilling to make this assumption. For our problem, we would like to be able to design each reward function for each objective independently without consideration as to how it will dovetail with the other reward functions. Furthermore, each reward source might be associated with an individual user in which case it certainly undesirable to assume that the rewards provided by one user can be directly compared against those of another user. Personal style may cause two people with the same preferences to manifest them in different reward techniques.

Even in social choice theory, the notion of comparable utilities is questionable. It is uncertain how to elicit true comparable utilities from people. The area of mechanism design or implementation theory (Mas-Collel, Whinston, and Green 1995; Green and Laffont 1979) deals directly with this problem, but in the context of an extensible universally desired good, money. Without the ability to pay or charge the citizens (or objectives), we cannot employ the algorithms and methods from that area of research.

4.1.2 Notation

We modify the standard POMDP framework slightly to include multiple sources. We keep the state space, action space, and observation spaces as well as the starting state, state transition, and observation probabilities the same as in the regular definition. However, we modify the reward function. Although still a deterministic function of the state, the reward function is now a vector quantity with each dimension representing the reward from a different source.

The goal of the agent is no longer to optimize a scalar quantity but rather to simultaneously optimize all of the expected returns (each return is the sum of one dimension of the reward vector). In some special cases it may be possible to maximize all of the returns simultaneously. However, in general, a trade-off must be made among the sources. For this problem, there is no single correct or optimal solution. We propose two solution methods that each have different solution guarantees.

For notation, we will let $R(\pi)$ be the estimate expected return for following policy π. $R(\pi)$ is therefore a vector of length m, the number of reward sources. $R_i(\pi)$ will denote the ith element of that vector. Each element is estimated individually with its own importance sampling estimator.

4.2 Policy Equilibria

A reward function implies an ordering over policies. In particular, we can infer that π_A is preferred to π_B if and only if $R(\pi_A) > R(\pi_B)$. Many reward functions are consistent with a single policy preference ordering. We define reward restructuring as any change to the reward function that does not change the policy preference ordering. We would like to develop an algorithm that is insensitive to reward restructuring for all reward sources. This rules out direct maximization of a fixed function of the sources' rewards or returns. For example, if a source multiplies all of its rewards by 3, it has not changed its preferences. However, it has changed the preferences implied by the fixed combination. Unless there are no other sources, those sources have no preference, or the fixed combination ignores the other sources, the change in the rewards of one source will change the fixed combination of the sources differentially depending on the rewards from the other sources. This results in different fixed combination rewards and therefore a different optimal policy.

Combining policies seems like a more promising route. Whereas we are unable to compare the returns, policies for the same agent in the

same environment are necessarily comparable. It is in the policy space that the algorithm must make the trade-off among reward sources; it must produce a single policy. The most obvious method is to find the optimal policy for each return source and then take their average. This can have disastrous results. Imagine a robot moving down a corridor faced with an obstacle. If one source prefers navigating to the left of the obstacle and the other prefers navigating to the right of the obstacle, the average policy might keep the robot moving straight, thus plowing directly into the obstacle. Mostly likely, both sources would have preferred anything over moving into the obstacle.

4.2.1 Policy Climbing

Certainly any policy π for which there exists a policy π' such that $R_i(\pi) < R_i(\pi')$ for all sources i is not a good policy. We know that all sources would be better off if the agent executed policy π' instead of π. At a global scale, it may be difficult to insure that solutions satisfy this notion of a good policy. However, at a local scale, it is simple. We want to find a policy for which no source's return gradients have a positive dot product with all of the other sources' return gradients. More specifically, we are at a local optimum π if

$$\forall v,\ \exists i \mid \langle v, \frac{\partial R_i(\pi)}{\partial \pi} \rangle \leq 0 \ .$$

This implies that at such an optimum no instantaneous change, v, in the policy will produce a new policy that is not worse for at least one of the return sources.

The obvious search algorithm is therefore to begin with a policy and continue to climb all return surfaces at the same time by picking changes to the policy that have a positive dot product with all return derivatives. There are two main specifications left in such an algorithm. First, which direction, of the many with non-negative dot product with all gradients, should be selected for each step. And second, how should the initial policy should be selected.

To pick a step direction, let Δ_i be the gradient of the return of source i with respect to the policy parameters evaluated at the current policy. We can then calculate $\overline{\Delta}_i$, the normalized direction with a non-negative dot product with all of the gradients which has the highest dot product with Δ_i. $\overline{\Delta}_i$ is the vector on the unit sphere which has the largest dot product with Δ_i while still satisfying the constraint of non-negative gain for all of the returns. Any vector Δ that is a convex combination of $\overline{\Delta}_1, \overline{\Delta}_2, \ldots, \overline{\Delta}_m$ satisfies all of the non-negative

dot product constraints. We fix a set of convex combination coefficients based on the relative importance of the various return sources. Note that because $\overline{\Delta}_i$ is normalized, the magnitude of change in the returns does not matter; only the local relative preferences matter.

Picking the initial policy at which to begin the climb is important. In particular, this choice specifies the performance guarantee of the final policy: the final policy will have returns no worse than the initial policy. For this reason, we pick the initial policy to be a mixture of the best policies for each of the return sources individually. A mixture policy is a policy that, at $t = 0$, randomly picks one of its component subpolicies and then executes that single subpolicy for the entire trial. Thus, the expected return of a mixture policy is a weighted average of the expected returns of its components where the weights are the same as the weights on the mixture's subpolicy. The weights of the mixture can be selected to be the same as the weights of the direction combination or different depending on the type of solution desired.

The joint maximization algorithm is shown in figure 4.1. Step 1 is accomplished by the maximization detailed in the previous chapters. The gradient in step 3 is with respect to all parameters (all subpolicy parameters and the mixture parameters). The constraint satisfaction program of step 4 in general can be difficult. However, with a small number of constraints, it can be solved quickly by searching all possible combinations of active constraints. The α-values are the starting policy combination coefficients. They specify the relative importance of the sources in selecting the starting policy; the starting policy dictates the performance guarantees for the algorithm. The β-values are the gradient combination coefficients. While hill-climbing, they specify the relative importance of increasing each source's return. η is the maximum step size.

A number of interesting parameter combinations are possible. If $\alpha_i = \beta_i$ for all sources i, then these values represent the global relative importance of maximizing each source. If $\beta_i = 0$ for some i, then the algorithm does not maximize R_i but rather just enforces the constraint $R_i(\pi) \geq \sum_j \alpha_j \max_{\pi'} R_j(\pi')$, that the return from this source be no worse than the return from the mixture of individually optimal policies.

4.2.2 Algorithm

Just as we previously took a maximization procedure and turned it into a greedy RL algorithm, we can do the same with the procedure of figure 4.1. Before each trial, the agent runs the joint maximization algorithm to find a new policy. The joint maximization procedure is

Input: $R_1(\pi), R_2(\pi), \ldots, R_m(\pi)$
Output: π
Parameters: $(\alpha_1, \alpha_2, \ldots, \alpha_m)$, $(\beta_1, \beta_2, \ldots, \beta_m)$, η
Constraints: $\sum_i \alpha_i = 1$, $\sum_i \beta_i = 1$

1. Using the single source maximization procedure, for all sources i, let θ_i be the parameters of the maximization of R_i over all policies in the input policy class.

2. Let Φ be the parameters of a mixture policy with mixture weights $\alpha_1, \alpha_2, \ldots, \alpha_m$ and subpolicies with parameters $\theta_1, \theta_2, \ldots, \theta_m$.

3. For all sources i, let Δ_i be the gradient of R_i evaluated at the mixture policy with parameters Φ.

4. For all sources i, let $\overline{\Delta}_i$ be the vector in gradient space with the largest dot product with Δ_i subject to the constraints that the magnitude of $\overline{\Delta}_i$ be 1 and $\overline{\Delta}_i \cdot \Delta_j \geq 0$ for all sources j.

5. If $\overline{\Delta}_i$ does not exist for any source i, quit and return the mixture policy Φ. Otherwise, let $\Delta = \sum_i \alpha_i \overline{\Delta}_i$

6. If $|\Delta| = 0$ quit and return the mixture policy Φ.

7. Normalize Δ to be unit length.

8. Let $\Phi' = \Phi + \eta\Delta$.

9. If $R_i(\Phi') \geq R_i(\Phi)$ for all sources i, let $\Phi = \Phi'$ and jump back to step 3.

10. Let $\eta = \eta/2$.
    If η is too small, return the mixture policy Φ
    Otherwise, jump back to step 8.

Figure 4.1: Joint maximization search algorithm

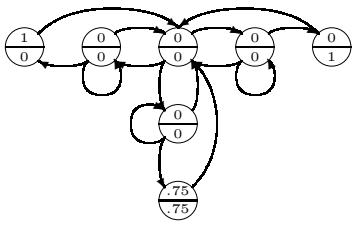


Figure 4.2: Diagram of the cooperate world. The world state is fully observable. The center state has three choices (each a different "arm"). Each middle state of an arm has three choices: go back, stay in the center, move to the end. From the end states the agent has no choice but to return to the center. The top number in a state is the reward from source 1 upon entering the state. The bottom number is the reward from source 2. Trials last for 20 time steps.

given the current estimated return functions based on the data collected so far. These functions may incorporate the controlled search method from the previous chapter and limit the valid area of search to those policies with small estimated variance. The agent executes the policy returned by the joint maximization procedure and then adds it and the observed history to its data. Using the new data set, it reiterates for the next trial.

4.2.3 Results

Figure 4.2 shows a test world for comparing the joint maximization method of the previous section to other techniques. Note that while source 1 would prefer the left arm of the POMDP and source 2 would prefer the right arm, the lower arm is an acceptable compromise which is better than randomly picking between the left and right.

Figure 4.3 shows the results of running the joint maximization procedure of this chapter against two other possible methods. The "mixture" procedure is to find the optimal policies for each source independently (using the importance sampling from the previous chapters) and then compose a final policy that is a weighted mixture policy of the found optimal policies. The "sum maximization" procedure is to maximize the weighted sum of returns using the importance sampling from the previous chapters. For the joint maximization, we let $\alpha_i = \beta_i$.

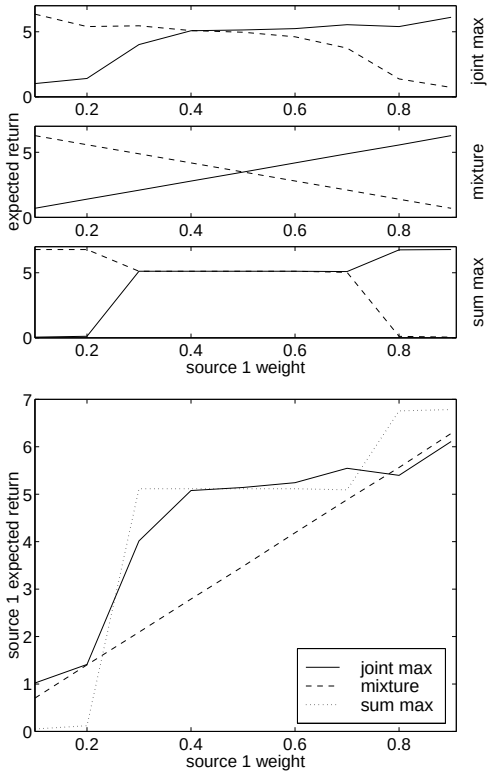


Figure 4.3: Comparison of three methods of weighted cooperation: joint maximization, mixture (picking a policy as a weighted mixture of the individually optimal policies for each source), and sum maximization (maximizing the weighted sum of rewards). Each method was run on the world of figure 4.2 for a range of source weights. Plotted are the expected returns for the resulting policies as a function of the weight for source 1 (the weights for both sources sum to 1). At the top are the plots for both sources (the solid line is source 1 and the dashed line is source 2) for each of the methods. At the bottom, the plots for source 1 are combined in a single plot for comparison.

The first important thing to notice is that the sum maximization method has a very strange plot. In fact, the two transitions are much steeper than shown. Because the graph was created by sampling the weights at 0.1 intervals, the steps appear to be gradual. In fact, they are vertical rises owing to qualitatively different solutions. The transition points are at 0.25 and 0.75 because of the nature of the environment. Furthermore, the sum maximization method is highly sensitive to reward restructuring. Changing one of the source's rewards while still keeping its objectives the same (for instance, multiplying all of the rewards by a positive constant) results in a drastically different solution.

The second observation is that the mixture method does not exploit the cooperation possible between the two sources. Both sources would be better off if they each traded a trip down their respective arms of the POMDP for two trips down the lower arm. However, the mixture method does not exploit this. Although the mixture method is invariant to reward restructuring, it fails to find any method to satisfy both objectives simultaneously.

Finally, the joint maximization method seems to perform fairly well. Due to randomness of the environment and the maximization method, this curve from a single run is a little noisy. However, it is invariant to reward restructuring, it finds cooperative solutions, and it provides for weights that allow a large range of balances between the two sources.

4.3 Bounded Maximization

The previous section allowed for joint maximization of all objectives. We could guarantee that the found policy was better than a mixture of individually optimal policies. However, sometimes we would like a different guarantee. Instead of insuring that the policy surpasses the unknown mixture policy, we might instead wish to insure that for some objectives, the resulting policy is better than an absolute set constant. This is a slight relaxation of the condition that that algorithm be insensitive to reward restructuring: the minimum return specified by the algorithm designer must be changed with any reward restructuring. However, in many circumstances (like the market-marking application of the next chapter), absolute performance measures can be set without complete knowledge of the solution. Especially in situations where the return function is known to the designer, or where it has a well-understood interpretation, this is a viable approach.

For the case of robot navigation towards a goal, we may wish to insure that the robot hits obstacles with probability less than some

constant. However, within the space of policies that achieve this first objective, we want to minimize the time-to-goal. Thus, we have two reward functions. The first penalizes for collisions and the second rewards the robot for making it to the goal (reduced by some function of the time the robot took). We want to find an algorithm for maximizing the second subject to a constraint on the first.

4.3.1 Algorithm

We will designate some of the reward sources as constraint sources. For these sources, we will associate a fixed minimum return. The optimization algorithms from previous chapters can be modified to search only within areas of the policy space for which the estimators' values for the constraint sources is greater than the minimum returns.

Once again we can use a greedy search algorithm. If there is only one unconstrained reward source, we maximize the single source using the conjugate gradient ascent algorithm from chapter 2. If there are multiple unconstrained reward sources, we maximize them using the joint maximization algorithm in figure 4.1. To insure that the constraints are satisfied, a few changes to the algorithms must be made.

Both algorithms use the maximization algorithm from chapter 2. This algorithm requires a valid starting point selected from among the sampled policies. If no sampled policy exists whose estimated returns satisfy the constraints, we discard the goal of maximization with respect to the constraints and instead try to maximize the constrained sources. In particular, we order the constrained sources and select the first constrained source i for which no sampled policy conforms to all of the constraints on sources $j \leq i$. We then maximize the source i subject to the constraints on the sources $j < i$. Thus, if we are concentrating on maximizing constrained source i, we know that one of the sampled policies obeys all source constraints from 1 to $i-1$. Continuing in this manner will insure we eventually find a policy that satisfies all of the constraints if such a policy exists. At that point we can return to optimizing the unconstrained sources.

Additionally both algorithms search the policy space by evaluating the returns and gradients of each source's estimators. To insure that the algorithms stay within the space of valid policies, we augment the return evaluation routine to return a very small value (*i.e.*, $-\infty$) if any constrained source's estimator has a value less than the source's constraint at the evaluation policy.

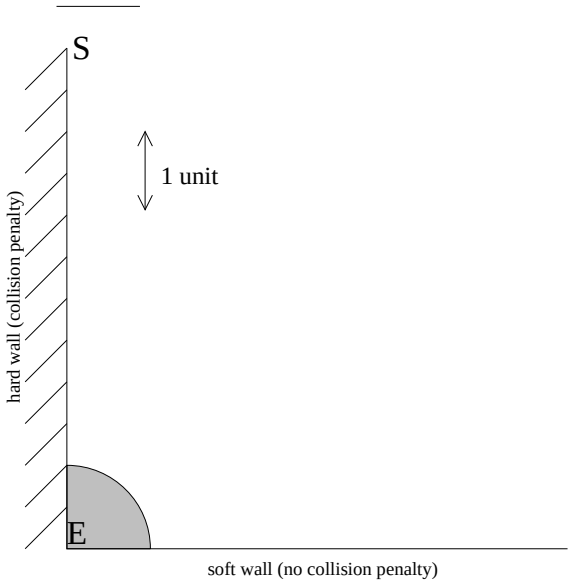


Figure 4.4: Diagram of the simulated robot collision world. The goal is for the robot to move from the start position (S) to the end position (E) without hitting the left-hand wall. At each time step, the robot has the option of moving left, right, or down. There is a 25% chance that the robot will move in a direction 45^o to the left from the desired direction and a 25% chance it will move 45^o to the right from the desired direction on any given time step. Each time step moves the robot 1 unit of length. The robot automatically stops when it is within 1 unit of the end position. For every time step it spends within 1 unit of the end position, it is rewarded one unit of reward. Additionally, a separate reward source rewards -1 unit of reward each time the robot hits the left-hand wall. Each trial lasts for 20 time steps.

4.3.2 Results

Figure 4.4 shows a very simple abstracted robot control problem. The mobile robot begins at point S. Its goal is to arrive in the shaded region as quickly as possible avoiding the left wall. At each time step, it moves 1 unit of distance. It can choose to move left, right, or down. There is a 50% chance the robot will actually move 45^o either to the left or right of the intended direction. The robot has two sources of reward. The first rewards it for every time step during which it is in the shaded

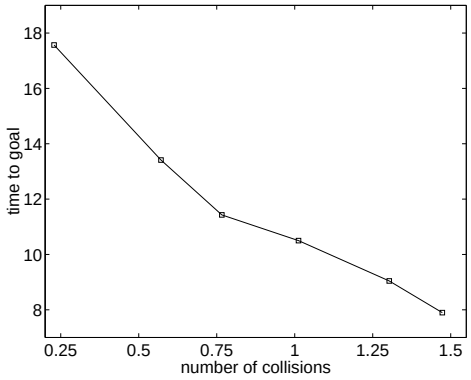


Figure 4.5: Plot of expected time to reach the end position against the expected number of collisions for the environment of figure 4.4. The maximization algorithm was designed to achieve the minimal time for a given expected collision constraint as described in the text.

area. The second penalizes it for every time step it runs into the left wall.

It is impossible to achieve perfect performance in this domain. No matter how careful the robot is, if it wants to arrive at the goal position, there is some chance it will collide with the wall. We ran the minimum reward constraint algorithm with this world for a range of maximum allowable collisions (a maximum number of collisions translates to a minimum reward for the collision reward source). In particular we required the expected number of collisions to be less than values from 0.25 to 1.5 at increments of 0.25. After each run of the algorithm had converged, we measured the true expected number of collisions and the true expected time-to-goal by running 10000 separate trails with the resulting policy. The results are shown in figure 4.5 for a Boltzmann distribution policy class with six observation features: the cross product of the state features (the constant 1, the x-position, and the y-position) and two binary action features (the first is 1 only if the action is to the left and the second is 1 only if the action is to the right).

While the data points do not quite line up with the required minima, they are very close. Although the resulting graph is close to a line, it is slightly concave demonstrating that there is some gain to being careful. Furthermore, nothing about the structure of the trade-off between collisions and time-to-goal was assumed. We could go back and find

a formula relating the number of collisions to the time-to-goal. Using this formula, we could make the desired trade-off between the two objectives with standard reinforcement learning. However, this presumes we already know the graph of figure 4.5. The technique of this section does not assume any prior knowledge about the relationships between the reward sources.

Chapter 5

Electronic Market-Making

"Grace is given of God but knowledge is bought in the market."
Bothie of Tober-na-Vuolich
Arthur Hugh Clough

In this chapter, we apply the algorithms developed to the problem of running a market-making system automatically. We begin with an overview of market-making and some of the literature to motivate the problem and our approach. We then apply importance sampling to solve the reinforcement learning problem for two market models. The first has theoretical bounds to which to compare our results. The second is more complex and allows us to balance competing objectives of the market-maker.

5.1 Market-Making

Many economic markets, including most major stock exchanges, employ market-makers to aid in the transactions and provide a better quality market. Each commodity has one or more market-makers assigned to it. All transactions in the market go through a market-maker. The market-maker is responsible for setting prices and volumes for buying and selling. If a market-maker quotes a buy price and volume (an ask quote), this requires the market-maker to honor that price for all buy

orders up to the quantity indicated by the volume. The symmetric obligation holds for sell orders (bid quotes).

Market-makers supply an advantage to the market. By consolidating the trading in a few agents, the market becomes more efficient. Traders wishing to buy and sell do not need to find each other or wait for each other's arrival. Additionally, by quoting a single price which is guaranteed for all traders, market-makers remove the price fluctuations that occur in markets where buyers and sellers must come to their own agreement for a price individually for each transaction. Markets with market-makers have greater volumes and better price stability.

Market-makers themselves benefit from their position as well. They have an informational advantage over regular traders because they get to see all (or many in some cases) of the orders. The average trader does not have such information and can only see transactions which actually take place and not all of the bids and asks that led to the final selling price. This advantage allows market-makers to make better predictions about the true value of a good and thereby better profits. This is regulated by rules applied to market-makers and by competition in the case of multiple market-makers. However, such an advantage is not without some risk. The market-maker trades using his or her own personal inventory. Negative inventory puts the market-maker at risk should the value rise and positive inventory has a similar risk should the value drop.

5.1.1 Automating Market-Making

Many major markets are now electronic. The NASDAQ is a distributed trading system completely run through networked computers. It uses competing market-makers (usually one per major trading company) to maintain a high quality market. However, the demands on human market-makers are high. A typical market-maker will be responsible for 10 to 20 securities. At any given moment, it is only feasible for the market-maker to be actively attentive to 2 to 3 of them. The market-maker is generally losing potential profit or volume on the other securities.

The last few years have also seen the growth of on-line trading systems. These systems are also entirely electronic and usually employ no market making. Orders are crossed against the other orders that happen to be present at that time of the trade and otherwise are dropped.

The goal of this chapter is to demonstrate the ability of reinforcement learning to fill the need for automated market-making. For the case of the NASDAQ, a learning system could fill the role of an "au-

topilot" by taking care of stocks in a more intelligent manner while being supervised by a human market-maker. This would allow a human market-maker to more successfully manage a large set of securities. In the case of small on-line trading systems, the system could replace the existing naive order crossing mechanism to provide a better market to its traders.

5.1.2 Previous Work

The understanding of the price formation process in security markets has been one of the focal points of the market microstructure literature. There are two main approaches to the market-making problem. One focuses on the uncertainties of an order flow (the time series of orders placed) and the inventory holding risk of a market-maker. In a typical inventory-based model, the market-maker sets the price to balance demand and supply in the market while actively controlling its inventory holdings. The second approach attempts to explain the price setting dynamics employing the role of information. In information-based models, the market-maker faces traders with superior information. The market-maker makes inferences from the orders and sets the quotes. This informational disadvantage is reflected in the bid-ask spread (the difference between the buy and sell prices quoted by the market-maker).

Garman (1976) describes a model in which there is a single, monopolistic, and risk neutral market-maker who sets prices, receives all orders, and clears trades. The dealer's objective is to maximize expected profit per unit time. Failure of the market-maker arises when it runs out of either inventory or cash. Arrivals of buy and sell orders are characterized by two independent Poisson processes whose arrival rates depend on the market-maker's quotes. Essentially the collective activity of the traders is modeled as a stochastic flow of orders. The solution to the problem resembles that of the Gambler's ruin problem. Garman studied several inventory-independent strategies that lead to either a sure failure or a possible failure. The conditions to avoid a sure failure imply a positive bid-ask spread. Garman concluded that a market-maker must relate its inventory to the price-setting strategy in order to avoid failure. Amihud and Mendelson (1980) extend Garman's model by studying the role of inventory. The problem is solved in a dynamic programming framework with inventory as the state variable. The optimal policy is a pair of bid and ask prices, both decreasing functions of the inventory position. The model also implies that the spread is positive, and the market-maker has a preferred level of inventory. Ho

and Stoll (1981) study the optimal behavior of a single dealer who is faced with a stochastic demand and return risk of his own portfolio. As in Garman (1976), orders are represented by price-dependent stochastic processes. However, instead of maximizing expected profit, the dealer maximizes the expected utility of terminal wealth which depends on trading profit and returns to other components in its portfolio. Consequently the dealer's risks play a significant role in its price-setting strategy. One important implication of this model is that the spread can be decomposed into two components: a risk neutral spread that maximizes the expected profits for a set of given demand functions and a risk premium that depends on the transaction size and return variance of the stock. Ho and Stoll (1983) extend this to a multiple-dealer scenario. The price-dependent stochastic order flow mechanism is common in the above studies. All preceding studies only allow market orders traded in the market. O'Hara and Oldfield (1986) attempt to incorporate more realistic features of real markets into their analysis. Their paper studies a dynamic pricing policy of a risk-averse market-maker who receives both limit and market orders and faces uncertainty in the inventory valuation. The optimal pricing strategy takes into account the nature of the limit and market orders as well as inventory risk.

Inventory-based models focus on the role of order flow uncertainty and inventory risk in the determination of the bid-ask spread. The information-based approach suggests that the bid-ask spread could be a purely informational phenomenon irrespective of inventory risk. Glosten and Milgrom (1985) study the market-making problem in a market with asymmetric information. In the Glosten-Milgrom model some traders have superior (insider) information and others do not. Traders consider their information and submit orders to the market sequentially. The market-maker, which does not have any information advantage, sets its prices, conditioning on all the available information such that the expected profit on any trade is zero. Specifically, the specialist sets its prices equaled the conditional expectation of the stock value given past transactions. Its main finding is that in the presence of insiders, a positive bid-ask spread would exist even when the market-maker is risk-neutral and make zero expected profit.

Most of these studies have developed conditions for optimality but provided no explicit price adjustment policies. For example, in Amihud and Mendelson (1980), bid and ask prices are shown to relate to inventory but the exact dependence is unavailable. Some analyses do provide functional forms of the bid/ask prices (such as O'Hara and Oldfield (1986)) but the practical applications of the results are limited due

to stringent assumptions made in the models.

The reinforcement learning models developed in this chapter make few assumptions about the market environment and yield explicit price setting strategies. We will start with a simple model where theoretical analysis is possible and then move to a more complex model with multiple objectives.

5.2 Simple Model

Our goal for this section is to develop a simple model that adequately simulates the strategy of a trading crowd given the quotes of a market-maker. Information-based models focusing on information asymmetry provide the basis for our basic model. In a typical information-based model, there is a group of informed traders or insiders who have superior information about the true value of the stock and a group of uninformed traders who possess only public information. The insiders buy whenever the market-maker's prices are too low and sell whenever they are too high based on their private information; the uninformed simply trade randomly for liquidity needs. A single market-maker is at the center of trading in the market. It posts the bid and ask prices at which all trades transact. Due to the informational disadvantage, the market-maker always loses to the insiders while breaking even with the uninformed.

5.2.1 Model Description

To further illustrate this idea of asymmetric information among different traders, consider the following case. A single security is traded in the market. There are three types of participants: a monopolistic market-maker, insiders, and uninformed traders. The market-maker sets one price at which the next arriving trader has the option to either buy or sell one share. In other words, it is assumed that the bid price equals the ask price. Traders trade only with market orders. All orders are executed by the market-maker and there are no crossings of orders among traders. After the execution of an order, the market-maker can adjust its quotes given its knowledge of past transactions.

To further simplify the problem, we allow the market-maker to have negative inventory and cash. We assume the resources of the company running the market-making are vast enough to allow this. Furthermore, the position is liquidated at the end of the day, limiting the risk of such a method. For real markets, the details of the market's closing are

complex and individual to the particular market. However, because the securities can shift and change overnight, it is common practice for market-makers to return their inventory to zero at the close of the market. The closing mechanism for many markets also serves to converge on a single price for each security. This means that calculating the profit at the end of the day is reasonable and in many cases part of the normal closing function of the market. For simplicity, events in the market occur at discrete time steps. In particular, events are modeled as independent Poisson processes. These events include the change of the security's true price and the arrival of informed and uninformed orders.

There exists a true price p^* for the security. The idea is that there is an exogenous process that completely determines the value of the stock. The true price is to be distinguished from the market price which is determined by the interaction between the market-maker and the traders. The price p^* follows a Poisson jump process. In particular, it makes discrete jumps, upward or downward with a probability λ_p at each time step. The size of the discrete jump is a constant 1. The true price, p^*, is given to the insiders but not known to the uninformed traders or the market-maker.

The insider and uninformed traders arrive at the market with a probability of λ_i and $2\lambda_u$ respectively.[1] Insiders are the only ones who observe the true price of the security. They can be considered as investors who acquire superior information through research and analysis. They compare the true price with market-maker's price and will buy (sell) one share if the true price is lower (higher) than the market-maker's price, and will submit no orders otherwise. Uninformed traders will place orders to buy and sell a security randomly. The uninformed merely re-adjust their portfolios to meet liquidity needs, which is not modeled in the market. Hence they simply submit buy or sell orders of one share randomly with equal probabilities λ_u.

All independent Poisson processes are combined together to form a new Poisson process. Furthermore, it is assumed that there is one arrival of an event at each time step. Hence, at any particular time step, the probability of a change in the true price is $2\lambda_p$, that of an arrival of an insider is λ_i, and that of an arrival of an uninformed trader is $2\lambda_u$. Since there is a guaranteed arrival of an event, all probabilities sum up to one: $2\lambda_p + 2\lambda_u + \lambda_i = 1$.

Each trial of the market represents one trading day. The market begins with the true price and the market-maker's price both set to the

[1] Buy and sell orders from the uninformed traders each arrive at a probability of λ_u.

arbitrary value of 100. At every time step the market-maker observes whether a buy, a sell, or neither took place and has the chance to increase or decrease its price by 1 unit. At the end of the trading day (100 time steps), the inventory is liquidated at the current true price resulting in the profit (or loss) of the market-maker.

The uninformed traders represent noise in the market. By randomly trading, they obscure the information available from the informed traders' trades. The market-maker cannot differentiate between orders placed by informed traders and those placed by uninformed traders. For the results in this chapter, we use the term noise to represent the level of uninformed traders in the market. We set $\lambda_i = 5\lambda_p$ and $\lambda_u = \text{noise} \times \lambda_i$.

This market model resembles the information-based model, such as Glosten and Milgrom (1985), in which information asymmetry plays a major role in the interaction between the market-maker and the traders. The Glosten and Milgrom model studies a market-maker that sets bid and ask prices to earn zero expected profit given available information, while this model examines the quote-adjusting strategies of a market-maker that maximize sample average profit over multiple episodes, given order imbalance information. This model also shares similarities with the work of Garman (1976) and Amihud and Mendelson (1980) where traders submit price-dependent orders and the market-making problem is modeled as discrete Markov processes. But instead of inventory, here the order imbalance is used to characterize the state.

5.2.2 Theoretical Analysis

The observation provided to the market-maker for a given time step in this model is one of "buy," "no order," or "sell." For algorithms without memory, this often is not enough to produce a good policy. Many values can be calculated from the sequence of observations including cash and inventory. For our reactive policies we have chosen to use a measure of imbalance on which to base the agent's actions. We define the imbalance to be the number of sell orders received subtracted from the number of buy orders received since the last change in the market-maker's price. Therefore if the market-maker changes price, the imbalance is set to zero. Otherwise the imbalance is increased for each buy order and decreased for each sell order.

We previously studied this model in Chan and Shelton (2001). Of the set of policies based on imbalance, the symmetry of the problem clearly indicates that the optimal policy will also be symmetric. In particular, if a certain imbalance causes the market-maker to lower

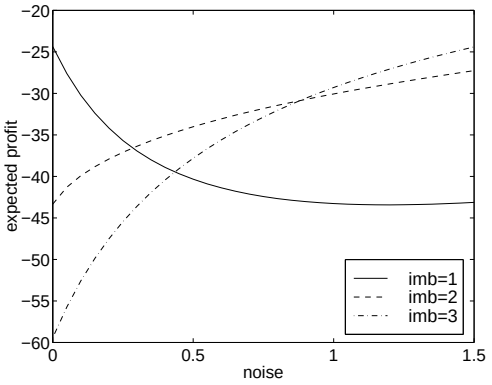


Figure 5.1: Plot of theoretically derived expected profits as a function of the noise in basic model for three deterministic policies. $imb = 1$ is the policy of changing the price as soon as the imbalance gets to ± 1. $imb = 2$ is the policy of changing the price as soon as the imbalance gets to ± 2. $imb = 3$ is the same for ± 3.

its price, the negative of the same imbalance should cause the market-maker to raise its price. For deterministic policies, this leaves only a few sensible options. In particular, the agent should select an imbalance threshold. If the imbalance is greater than this threshold, it should lower its price because there are too many buys indicating its current price is too high. Similarly, if the imbalance is less than the negative threshold, it should raise its price. Figure 5.1 shows the true expected return as a function of the noise in the environment for executing one of three basic policies. Each policy corresponds to deterministically changing the price when the imbalance reaches a different level. The figure is exact and calculated by converting the environment-agent pair into a Markov chain and then finding the exact expectation of the chain. This calculation is not available to the agent because it depends on knowledge of the environment; we present it here to illustrate features of the domain.

Figure 5.2 compares the expected return from the best of this policy class to the expected return from executing a hold policy of never adjusting the price. We chose to compare to the hold policy for two reasons. The first is that there is no randomness in the hold policy, so all of the variability is inherent in the environment model. The second is that the hold policy is not an unreasonable policy. It is the best

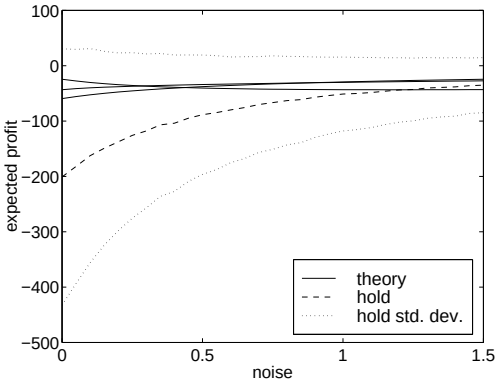


Figure 5.2: Plot of the expected profit of the hold policy against the optimal policies (see figure 5.1). The solid lines are the best reactive policies based on the imbalance. The dashed line is the performance of a policy that never changes prices. The dotted lines are one standard deviation above and below the performance of the hold policy. Note that the variance in the market is much larger than the differences among the optimal imbalance policies.

the agent can do without taking the observations into consideration. Certainly there are many worse algorithms in the policy space to be explored by the agent. Not only are all of these imbalance thresholding policies performing much better than the hold policy, but it is easy to see the tremendous randomness in the data. The dotted line shows the standard deviation of returns from the hold policy. This large variance plays a major role in the difficulty of the problem. Single samples have little information alone. Compared to the noise, all of these deterministic imbalance-threshold policies appear approximately the same. To discern among them is difficult because of the noise. The variance of the samples swamps the differences in returns. Although reinforcement learning algorithms will have many more policies to consider than just these three, figure 5.1 can be used to gauge the success of a particular learning method by placing a reasonable target performance.

5.2.3 Results

We previously used temporal difference methods to approach exactly the same environment (Chan and Shelton 2001). We got good results

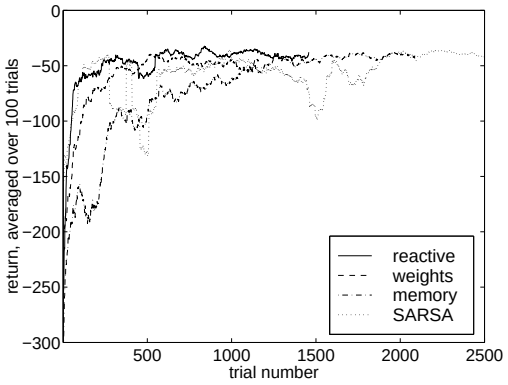


Figure 5.3: Examples of typical runs for the importance sampling estimator with different policy classes as compared to SARSA.

using SARSA although not with Q-learning which agrees with others' experiences comparing SARSA and Q-learning on POMDP problems (Lock and Singh 1998). However, our results with SARSA were not satisfactory. In order to produce consistent convergence, we had to provide a reward at each time step. For profit, this meant setting the reward at a particular time to be the change in the true net worth of the market-maker (cash plus the inventory liquidated at the current true price). Such a reward requires knowledge of the true price of the stock. As noted in the market description, such knowledge should only be available at the closing of the market. Although it was not supplied in the observations, it still entered into the algorithm's calculations. In this thesis, we tackle the more difficult and realistic problem where no reward is given until the final time step.

As noted in the previous section, the market-market observes at each time step whether a buy, sell, or no order took place. This is insufficient information to perform well in noisy markets. We therefore tied four different policy classes:

1. Reactive table policy based on imbalance: For this policy, we used the standard original estimator from chapter 2. The observation was the current imbalance (calculated as in the previous section). The observation was bounded at 3 and -3. If the true imbalance was greater than 3, the observation was set to be 3 (similarly with imbalances less than -3). Otherwise, the integer observation value was directly used as the observation.

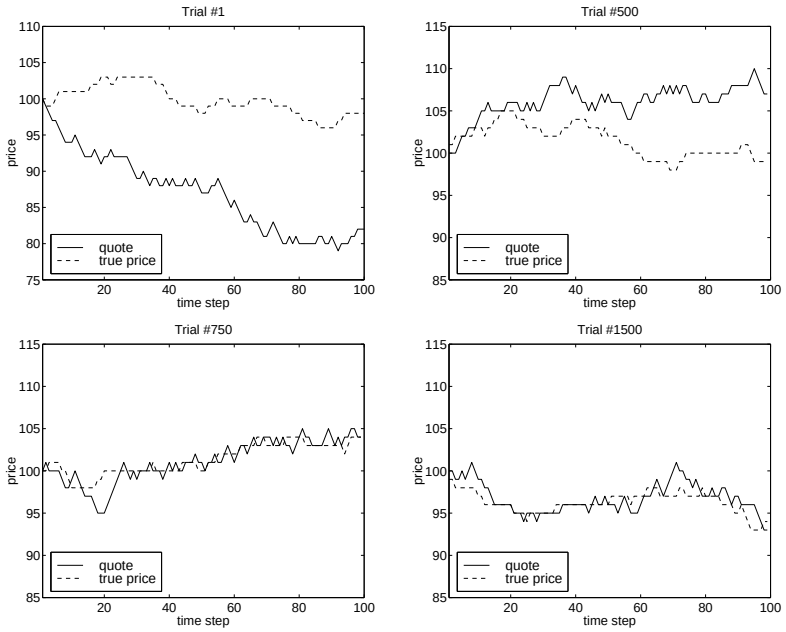


Figure 5.4: Sample episodes from running the importance sampling estimator with the reactive policy in the market with noise 0.2. Shown are the true and market-maker's prices during an episode for trail numbers 1, 500, 750, 1500. The run was stopped after trial 1500 when the algorithm converged. It had actually settled to the correct solution by trial 1000. However, small fluctuations in the policy caused the automated stopping criteria to wait for another 500 trials before declaring convergence.

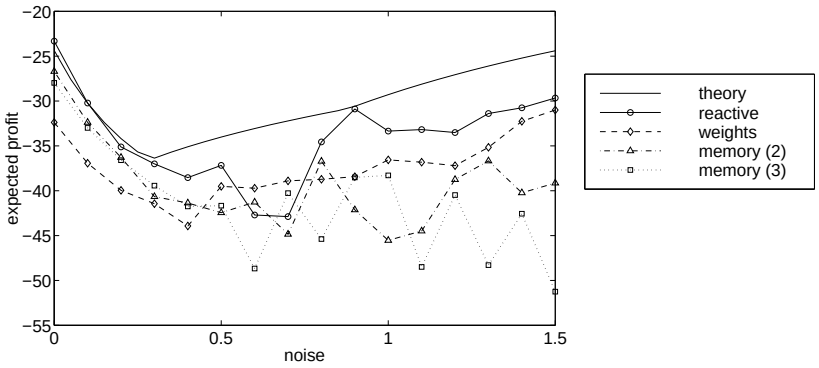


Figure 5.5: The expected return of the found policy as a function of the noise in the model. Three different policy classes were tried. They are detailed in the text. Compare to the theoretical results shown in figure 5.1.

2. Policy weights based on Boltzmann distribution using imbalance: For this policy, we used the Boltzmann distribution for a policy class with weights as in section 3.2. The observation feature vector had four features. The first two were 1 and the imbalance if the action was to lower the price. Otherwise, they were both 0. The second two were 1 and the imbalance if the action was to raise the price (and otherwise 0).

3. Memory policy with 2 memory states based on the raw observations: For this policy, the imbalance was not computed automatically for the agent. Instead, it was given two memory states (as in section 3.1) and the raw observations of buy, sell, or no action.

4. Memory policy with 3 memory states based on the raw observations: as above, but with three memory states.

We let θ (from section 3.3) be 0.03 for all experiments in this chapter to combat the noise inherent in the problem. The experiments were run until on twenty consecutive trials, no policy parameter changed by more than 0.01 and the estimated return for the policy changed by no more than 0.1. We ran each of these four policy classes on the market model, varying the noise from 0.0 to 1.5 at increments of 0.1.

Figure 5.3 compares a sample run of each algorithm and SARSA (using the reactive table policy class based on imbalance) for a market

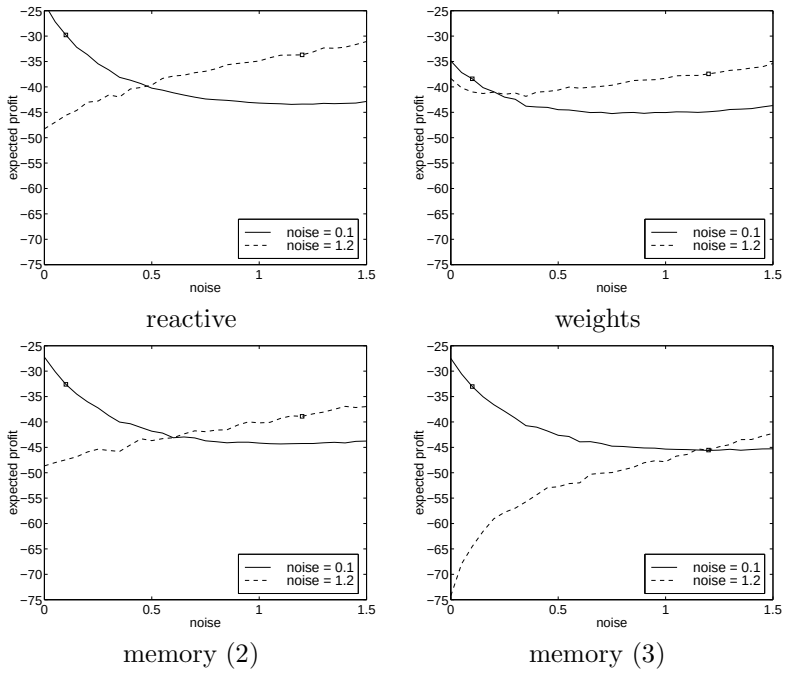


Figure 5.6: Plots of the expected profit as a function of the noise for the solutions found at market noise of 0.1 and 1.2. The top row is for the reactive table policy class and for the Boltzmann distribution reactive policy class (from left to right). The bottom row is for memory policies observing the raw buy-sell order flow with either 2 or 3 memory states. The boxed points are the points the graphs were optimized for. The differentiation in the plots demonstrates that the solutions found are sensitive to the market dynamics and change with the noise in the market.

with noise of 0.2. We can see that the SARSA method takes longer to converge and can become unstable later. It often will jump to strange policies after seeming convergence. Faster annealing of the SARSA learning rate causes the algorithm to fail to converge. Although not as apparent due to the smoothing, the SARSA algorithm produced some very negative returns for a couple of trials in a row and then returned to its previous performance (this can be seen by the dips in the graph at about 500 and 1500 trials). By comparison, the importance sampling estimators behave more nicely in this partially observable environment.

To show the adaptation of the learning algorithm, figure 5.4 shows the price dynamics for three episodes during one run of the algorithm. We can see that as the agent gathers more experience, it is better able to track the true price of the stock.

Figure 5.5 shows the expected returns (measured by 10000 separate trials taken after learning had converged) for each algorithm as a function of the noise. We notice that the two policies based on imbalance come close to meeting the theoretical bounds of the solid line. The two policies based on memory fair more poorly. However, it should be noted that, as shown in figure 5.2, all of these policies perform very well compared to holding even and the noise inherent in the model.

To demonstrate that the learned policies are sensitive to the particulars of the market environment (in this case, the noise), figure 5.6 compares the policies found at noise 0.1 to those found at 1.2. We took the policies found for both noise settings and plotted how those policies would perform across all noise levels. We can see that for each policy class, the algorithm finds a different type of solution and that the solutions found for noise 0.1 are different than those at 1.2.

5.3 Spread Model

The previous section demonstrates how reinforcement learning algorithms can be applied to market-making problems and successfully converge to competitive strategies under different circumstances. Although the basic model is useful because the experimental and theoretical results can be compared, one of its major limitations is the equality of the bid and ask prices. Without the bid-ask spread the market-maker suffers a loss from the market due to the information disadvantage. A natural extension of the basic model is to let the market-maker quote bid and ask prices. The rest of the market remains the same. Informed traders sell if the bid price is too high and buy if the ask is too low. Uninformed traders still trade randomly. Each transaction is for the

fixed volume of 1 share.

The market-maker now has two objectives. It wants to maximize profits to insure a stable business platform. It also wants to minimize the average spread. By minimizing spread, the market-maker insures better volume (more trades through the market-making system) because it provides more competitive prices. Because of the increased volume, the company running the market-maker can provide better deals to its private investors.

5.3.1 Model Description

To incorporate bid and ask prices to the model, the set of actions is augmented to include the change of the bid price and the change of the ask price. Thus the agent has 9 action choices corresponding to each possible pair of actions with respect to the bid and ask prices (each can be raised, kept the same, or lowered). The spread also enters the reward function to regulate the of market quality maintained by the agent. The profit and spread rewards are separate sources. The profit source is as in the previous model. The spread source's reward at a time step is the negative spread. Thus the return from this source is the negative sum of the spread over all time steps. In the basic model, the market-maker only aims at maximizing profit. By adding spread to the model, the market-maker also needs to consider the quality of market it provides. If it only seeks to maximize profits, it can create a huge spread and gain profit from the uninformed traders. Unfortunately, this results in low market quality and a loss in volume (as mentioned above). These objectives are not entirely competitive: some policies result in poor profits and large spreads. However, for the most part, increases in profit come at the expense of reduced spreads. The exact trade-off is a function of the market and unknown.

5.3.2 Results

The most natural method to balance the rewards is to fix a desired minimum expected profit find the minimal average spread policy subject to the profit constraint. Such a constraint may be set by the operators of the market-maker to insure reasonable profitability. For these experiments, we used the bounded maximization method from section 4.3 to achieve this goal. The average profit per day was fixed between -15 and 15 and the negative average spread (the second reward source) was maximized. The results from the previous section were assumed. The default policy therefore lowers the price if the imbalance is negative and

	imbalance -	imbalance 0	imbalance +
spread -	0/-	+/-	+/0
spread 0	-/-	0/0	+/+
spread +	-/0	-/+	0/+

Figure 5.7: How the imbalance-correcting reflex interacts with the agent's action to change the bid and ask prices. The table shows the resulting bid and ask changes for each combination of imbalance and action. Across the top are the imbalance values (negative, zero, or positive) which result in the midquote (the average of the bid and ask prices) decreasing, staying the same, or increasing respectively. This is a build-in reflex of the agent as found by the previous section's experiments. Down the side are the actions possible for the agent (decrease, maintain, or increase the spread). The combination of these two determine the changes to the bid and ask prices. The table lists the change as bid/ask. A "+" means that the corresponding value is increased by one unit. A "-" correspondingly means a decrease of one unit. A "0" implies the value is left unchanged.

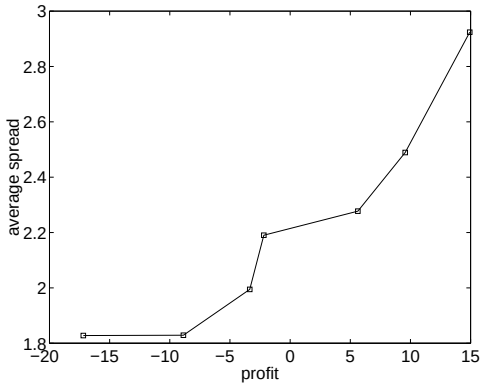


Figure 5.8: Plot of spread against profit with noise = 0.2. The algorithm was run with differing constraints on the maximum profit. Profit constraints ranged from −15 to 15 at intervals of 5. After the algorithm converged, the expected profit and spread were computed for the resulting policy by 10000 separate empirical trials. Plotted is the resulting empirical curve.

raises the price if the imbalance is positive. This is considered a reflex of the agent built in from the learned policy for the market environment without a bid-ask spread. The learning task then was to decide, based on the current spread, whether to increase, decrease, or maintain the current spread. Figure 5.7 details the resulting bid and ask changes as a function of the imbalance and the RL action. Note that an action to change the spread might result in the spread changing by 1 or 2 units depending on the imbalance. To keep the number of observation states reasonable, any spread greater than 4 is considered to be 4 for purposes of observations (the true spread is not bounded, only the observation of the spread).

Figure 5.8 shows the results for a reactive policy using probability tables. We notice that the profits do not line up exactly at even multiples of 5 as the constraints would require. At the point the algorithms were stopped, and the resulting policies evaluated (by 10000 separate empirical trials), the policies had not shifted and the return estimation had not changed for 20 consecutive learning trials. For every run, the algorithm's estimate of the expected profit was fixed exactly at the constraint value. The difference between the estimate and the true value is due to the noise in the environment. The 10000 separate evaluation trials were much better at determining the true estimated returns for the final policy than the learning trials which numbered only about 2000 and were spread over many different policies. However, considering the noise, the plot is good, with the possible exception of the "0 profit" point that seems to have found a local minimum a ways from the desired solution. The results here are an improvement on the corresponding results from our previous actor-critic algorithm (Chan and Shelton 2001). Figure 5.8 demonstrates better spreads for the same profits, although in our previous work the policy class was slightly different so a direct comparison may not be justified.

5.4 Discussion

We feel these results demonstrate the power of our importance sampling algorithm. The models of this chapter are highly stochastic and provide difficult challenges for RL algorithms. We were able to show that our algorithm is can find good solutions in the presence of noise while at the same time remaining sensitive to small differences in the market. Furthermore, we were able to successfully balance two major objectives of real market-makers in a simple framework that allows for a natural specification of the trade-off between the objectives.

Chapter 6

Conclusions

"Error has no end."
Paracelsus. Part iii.
Robert Browning

We feel this thesis represents the first major exploration of importance sampling for reinforcement learning. There have been only two previous uses of importance sample in RL. The first (Precup, Sutton, and Singh 2000; Precup, Sutton, and Dasgupta 2001) used importance sampling as a slight modification to temporal difference learning. The second (Peshkin and Mukherjee 2001) developed some theoretical bounds for importance sampling, but did not develop any algorithms or experimental results.

We have extended importance sampling to multiple sampling policies, demonstrated it can be calculated for not only reactive table-based policies, but also parameterized policies and finite-state controllers. We have given exact variance formulae for the estimates. Furthermore, we have demonstrated the power of the full return surface estimate provided by our importance sampling method in solving problems with multiple objectives. Finally, we have demonstrated its success on numerous small problems and ultimately on the practical and highly noisy domain of electronic market-making.

Electronic market-making is a real problem with few robust automatic techniques. Reinforcement learning shows promise of making useful progress on this practical and important domain. However, as this is the first serious use of importance sampling and only the second

attempt to apply reinforcement learning to market-making, there are a number of immediate and future problems to be tackled. We feel that all of them are possible given the foundations laid in this thesis.

6.1 Algorithm Components

The algorithm of this thesis is composed of a number of components. Each could individually benefit from some additional research.

6.1.1 Estimator Performance

We think the normalized estimator works very well given the minimal assumptions made. These assumptions allow the algorithm to work in almost any reinforcement learning scenario, yet we still take into consideration the temporal control problem inherent to reinforcement learning. The time series of observations, action, and rewards are explicit in calculating the importance sampling ratios. When combined with a greedy algorithm, the estimator produces quick learning.

Yet, we feel that two immediate extensions might help. The first is to provide error estimates or bounds on the return estimate. We have a formula for the variance of the estimator, but we still need a good estimate of this variance from the samples (direct application of the formula requires full knowledge of the POMDP). Although we provide a simple variance estimate of sorts in section 3.3, it is not theoretically rigorous.

Second, the estimate needs to be "sparsified." After n trials, computing the estimate (or its derivative) for a given policy takes $O(n)$ work. This makes the entire algorithm quadratic in the number of trials. However, a similar estimate could probably be achieved with fewer points. Remembering only the important trials would produce a simpler estimate.

More generally, improved insight and theory may come from more study of the basic research in importance sampling. Yet, it is difficult to bring the results from importance sampling to this problem. Importance sampling usually assumes that the designer has control over the sampling distribution. In our problem, we'd like to allow the agent to use experience that was sampled in any fashion. Whereas importance sampling often asks, "given an expectation to estimate, how should I sample to reduce the variance of the estimate?" we would like to ask "given a sampling method, how best should I estimate the expectation to reduce variance?" Hesterberg (1995) does list a number of

other importance sampling methods. Unfortunately none of them are computable in this case (recall that the full probability function is not available, only one factor of it).

Finally, it may seem disturbing that we must remember which policies were used on each trial. The return doesn't really depend on the policy that the agent wants to execute; it only depends on how the agent actually does act. In theory we should be able to forget which policies were tried; doing so would allow us to use data which was not gathered with a specified policy. The policies are necessary in this paper as proxies for the unobserved state sequences. We hope future work might be able to remove this dependence.

6.1.2 Greedy Search

The greedy search algorithms used are simple and can be effective for environments with little noise and where the optimal policies are near the boundaries of the policy space. However, not all problems exhibit these properties. Although the variance-controlled search algorithm of section 3.3 does help, it is not a complete solution. The greedy search is prone to getting stuck in local minimum and in general, the variance-control does not help in this respect. The most obvious example of local minima is in the simple problem of maximizing the estimated return function. This problem is unsurmountable in general and will only be improved with better general function maximization algorithms.

However, the more addressable and less fundamental difficulty is in picking exploration policies. Although, given enough samples, the estimate will eventually converge to the true return, if those samples are drawn from policies far from the optimal distribution, it may take a long time before convergence. In fact, it may take long enough that the algorithm appears to have converged to a suboptimal procedure even though the function maximization algorithm is not stuck in local minima. The problem is not that the maximization procedure could not find the global maximum of the return surface, but rather that the global maximum of the estimated return is actually only a local maximum of the true return.

The algorithm needs to select sampling policies for the potential information they will supply to the estimator in addition to the potential immediate return. Whether such a choice requires more assumptions about the environment is unclear. However, a more clever sampling procedure would certainly lead to faster convergence with fewer local minima problems.

6.1.3 Multiple Objectives

We do not feel that multiple objectives have been given enough attention in the RL literature. They are crucial to the application of RL to many real-world applications. It is often nearly impossible for a designer of a system to sit down and write out an exact expression for a single reward function that will lead to the desired behavior. More often it is only practical for the designer to create separate reward functions for each sub-behavior or sub-goal of the agent.

These sub-goals usually interact in one of a number of different ways first presented by Kaelbling (2001):

1. Conjunctive: The agent must achieve all goals.
2. Consecutive: The agent must perform each task in serial.
3. Simultaneous: The agent must maintain all goals at the same time.
4. Conditional: The agent must perform one goal while maintaining a minimum level of performance on another goal.

The first interaction form is difficult to define more carefully without specifying a single reward function that captures the way in which trade-offs among the goals should be balanced should they not all be maximally obtainable simultaneously. Without additional knowledge, it may not be practical to address this interaction style. The second form is well covered by standard reinforcement learning methods. Each policy is learned individually and executed in series. It makes the implicit assumption that achieving one goal does not undo the gains from achieving other goals.

The last two forms are addressed by this thesis. The simultaneous objectives are covered by the joint maximization algorithm of chapter 4 and the conditional objectives are covered by the conditional maximization algorithm of the same chapter. These two forms are particularly crucial for designing systems by multiple reward source specifications. The entire purpose for specifying multiple reward sources is that the exact method of combination is unknown. Both of the algorithms in this thesis have tunable parameters that have natural interpretations which regards to balancing the rewards, and yet do not require *a priori* knowledge about the optimal policy. In this way, the reward designer can create sub-goals and reason about the correct parameter settings to balance the objectives. Furthermore, the parameters can be adjusted easily if the resulting behavior does not match the designer's expectations.

We think that there is more to be done however. In particular, for the simultaneous objectives, a better overall objective needs to formulated so that different algorithms can be compared. Additionally, it would be nice if complex single reward sources could be automatically broken down into multiple sources. The additional complexity of the multiple sources may be overcome by the ease of learning with simpler reward function.

6.2 Market-Making

Not only are we excited about the possibilities of importance sampling for reinforcement learning, we are excited about the possibilities of reinforcement learning for market-marking. This domain is growing with the increasing number of markets moving to electronic domains. Not only is this a practical and useful problem to solve with many of the complications of real-world domains, it is an environment well-suited to electronic and algorithmic control. The market structure is mathematical, events occur at distinct points in time, and the entire environment is electronic making the interface simple. Market-making differs from general portfolio management in that market-makers have a legitimate information advantage allowing them to make a profit even in a rational market. The potential for useful algorithms is very high.

We also see great potential from the scalability of market-making. Additional information and model complexity can be added gradually much as we did in this thesis by first solving the basic market model and then using the results from that as reflexes for the policies of the spread model. We hope that this technique can continue, allowing the addition of more complex environment models involving additional information sources including financial news and related markets.

It would seem that any system employed in a real market will require adaptive features to allow it to adjust to market changes. Reinforcement learning and importance sampling in particular shows the promise of providing such adaptive systems.

Appendix A

Bias and Variance Derivations

We will assume that the policy we are evaluating is π_A and thus we are interested in estimating $E[R|\pi_A]$. Later, we will look at the difference between the estimate at point π_A and at point π_B. All sums are over the data points (1 through n) unless otherwise noted. Integrals will be over the space of histories. If the space of histories is discrete (as is the case for POMDPs), these should actually be sums. However, by using integrals for histories and sums for experience, the notation becomes clearer.

To aid in the derivation of the bias and variance of the estimators, we will define a few symbols to represent common quantities and simplify the notation.

$$\overline{p}(h) \stackrel{\triangle}{=} \frac{1}{n} \sum_i p(h|\pi^i)$$
$$\tilde{p}(h,g) \stackrel{\triangle}{=} \frac{1}{n} \sum_i p(h|\pi^i) p(g|\pi^i) \ .$$

These are mixture distributions that represent the average sampling distribution.

$$w_A^i \stackrel{\triangle}{=} \frac{p(h^i|\pi_A)}{\overline{p}(h^i)}$$
$$w_B^i \stackrel{\triangle}{=} \frac{p(h^i|\pi_B)}{\overline{p}(h^i)} \ .$$

These are the unnormalized sample weights for the estimates at π_A and π_B respectively.

$$\begin{aligned} R^i &\triangleq R(h^i) \\ r_A^i &\triangleq R^i w_A^i \\ r_B^i &\triangleq R^i w_B^i \\ R_A &\triangleq E[R|\pi_A] \\ R_B &\triangleq E[R|\pi_B] \ . \end{aligned}$$

Finally, these are the sampled returns, the weighted returns, and the true expectation values.

A.1 Unnormalized Estimator

First we consider the unnormalized estimator

$$U(\pi_A) = \frac{1}{n} \sum_i r_A^i \ .$$

Its mean can easily be derived as

$$\begin{aligned} E[U(\pi_A)] &= E[\frac{1}{n} \sum_i r_A^i] \\ &= \frac{1}{n} \sum_i E[r_A^i] \\ &= \frac{1}{n} \sum_i \int R(h^i) \frac{p(h^i|\pi_A)}{\overline{p}(h^i)} p(h^i|\pi^i) \, dh^i \\ &= \frac{1}{n} \sum_i \int R(h) \frac{p(h|\pi_A)}{\overline{p}(h)} p(h|\pi^i) \, dh \\ &= \int R(h) \frac{p(h|\pi_A)}{\overline{p}(h)} \frac{1}{n} \sum_i p(h|\pi^i) \, dh \\ &= \int R(h) \frac{p(h|\pi_A)}{\overline{p}(h)} \overline{p}(h) \, dh \\ &= \int R(h) p(h|\pi_A) \, dh \\ &= E[R|\pi_A] \\ &= R_A \end{aligned}$$

and thus $U(\pi_A)$ is an unbiased estimate of R_A. Similarly, we can derive that

$$\frac{1}{n}\sum_i E[r_B^i] = R_B$$
$$\frac{1}{n}\sum_i E[w_A^i] = 1$$
$$\frac{1}{n}\sum_i E[w_B^i] = 1$$

which will be useful later.

We can also find the variance of this estimator:

$$\begin{aligned}
&E\left[(U(\pi_A) \;-\; E[U(\pi_A)])^2\right] \\
&\qquad = E[(\frac{1}{n}\sum_i r_A^i)^2] - R_A^2 \\
&\qquad = \frac{1}{n^2}\sum_i E[(r_A^i)^2] + \frac{1}{n^2}(\sum_i E[r_A^i])^2 - \frac{1}{n^2}\sum_i E[r_A^i]^2 - R_A^2 \\
&\qquad = \frac{1}{n}\left(\frac{1}{n}\sum_i E[(r_A^i)^2] - \frac{1}{n}\sum_i E[r_A^i]^2\right) \\
&\qquad = \frac{1}{n}\left(\int R^2(h)\frac{p(h|\pi_A)}{\overline{p}(h)}p(h|\pi_A)\,dh - \right. \\
&\qquad\qquad \left. \iint R(h)R(g)\frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_A)p(g|\pi_A)\,dh\,dg\right) .
\end{aligned}$$

Although this might look a bit messy, there is sense in it. The quantity inside the parentheses is constant if, as n increases, the chosen policies (π^i) remain the same. This would happen if we kept the same set of trial policies and just kept cycling through them. In fact, if all of the π^i's are equal, then the second integral works out to just be R_A^2 as $\tilde{p}(h,g) = \overline{p}(h)\overline{p}(g)$ for this case. The first integral can be rewritten as $E[R^2\frac{p(h|\pi_A)}{\overline{p}(h)}|\pi_A]$ which looks more like a term normally associated with variances.

To make this (and future) derivations simpler, we add the following

definitions

$$
\begin{aligned}
s^2_{A,A} &\triangleq \frac{1}{n}\sum_i E[(r^i_A)^2] = \int R^2(h)\frac{p(h|\pi_A)}{\overline{p}(h)}p(h|\pi_A)\,dh \\
s^2_{A,B} = s^2_{B,A} &\triangleq \frac{1}{n}\sum_i E[r^i_A r^i_B] = \int R^2(h)\frac{p(h|\pi_A)}{\overline{p}(h)}p(h|\pi_B)\,dh \\
s^2_{B,B} &\triangleq \frac{1}{n}\sum_i E[(r^i_B)^2] = \int R^2(h)\frac{p(h|\pi_B)}{\overline{p}(h)}p(h|\pi_B)\,dh \\
\eta^2_{A,A} &\triangleq \frac{1}{n}\sum_i E[r^i_A]^2 \\
&= \iint R(h)R(g)\frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_A)p(g|\pi_A)\,dh\,dg \\
\eta^2_{A,B} = \eta^2_{B,A} &\triangleq \frac{1}{n}\sum_i E[r^i_A]E[r^i_B] \\
&= \iint R(h)R(g)\frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_A)p(g|\pi_B)\,dh\,dg \\
\eta^2_{B,B} &\triangleq \frac{1}{n}\sum_i E[r^i_B]^2 \\
&= \iint R(h)R(g)\frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_B)p(g|\pi_B)\,dh\,dg\ .
\end{aligned}
$$

Thus, $\mathrm{var}(U(\pi_A)) = \frac{1}{n}(s^2_{A,A} - \eta^2_{A,A})$.

A.2 Unnormalized Differences

Instead of computing the mean and variance of the normalized estimator (these quantities are too convoluted to be useful), we will now look at the difference of the estimator at two different policies, π_A and π_B. If we are using the estimator to guide a greedy search, then this is closer to a quantity we care about. In fact, we really care how the maximum of the estimator compares to the true maximum. That is too difficult to calculate. However, looking at the difference gives a better sense of how the estimator works when used for comparisons.

For the unnormalized estimator, $U(\pi_A) - U(\pi_B)$ is clearly an unbiased estimate of $R_A - R_B$. The variance of the difference can be

derived, similarly to the previous derivation, to be

$$E\left[\left(U(\pi_A) - E[U(\pi_A)] - U(\pi_B) + E[U(\pi_B)]\right)^2\right] = \frac{1}{n}\left(s^2_{A,A} - 2s^2_{A,B} + s^2_{B,B} - \eta^2_{A,A} + 2\eta^2_{A,B} - \eta^2_{B,B}\right) .$$

If we define q as

$$q_{A,B}(h) = p(h|\pi_A) - p(h|\pi_B)$$

then we can also write

$$\mathrm{var}(U(\pi_A) - U(\pi_B)) = \frac{1}{n}\left(\int R^2(h)\frac{q^2_{A,B}(h)}{\overline{p}^2(h)}\overline{p}(h)\,dh - \iint R(h)R(g)\frac{q_{A,B}(h)q_{A,B}(g)}{\overline{p}(h)\overline{p}(g)}\tilde{p}(h,g)\,dh\,dg\right) .$$

A.3 Normalized Differences

For the normalized estimator we are interested in

$$\frac{\sum_i r^i_A}{\sum_i w^i_A} - \frac{\sum_i r^i_B}{\sum_i w^i_B} = \frac{\sum_i r^i_A \sum_j w^j_B - \sum_i r^i_B \sum_j w^j_A}{\sum_i w^i_A \sum_j w^i_B} .$$

However, since the denominator is always positive and we only care about the sign of this quantity (because we are using the estimator to compare potential policies), we can concentrate on the numerator only. Furthermore, we can scale this quantity by any positive value. We will scale it by $\frac{1}{n^2}$ so that it is roughly the same as the unnormalized estimator and the variances can be compared.

Thus, we are interested in the bias and variance of the difference

$$D = \frac{1}{n^2}\sum_{i,j}(r^i_A w^j_B - r^i_B w^j_A) .$$

It is important to note that $r^i_A w^i_B = r^i_B w^i_A$ and thus when $i = j$ the two terms in the sum cancel. This leaves us with

$$D = \frac{1}{n^2}\sum_{i\neq j}(r^i_A w^j_B - r^i_B w^j_A) .$$

The bias derivation is similar to the variance derivations of the unnormalized estimator.

$$
\begin{aligned}
E[D] &= \frac{1}{n^2}\left(\sum_{i\neq j} E[r_A^i w_B^j] - \sum_{i\neq j} E[r_B^i w_A^j]\right) \\
&= \frac{1}{n^2}\left(\sum_{i,j} E[r_A^i]E[w_B^j] - \sum_i E[r_A^i]E[w_B^i]\right. \\
&\qquad \left. - \sum_{i,j} E[r_B^i]E[w_A^j] - \sum_i E[r_B^i]E[w_A^i]\right) \\
&= \frac{1}{n}\sum_i E[r_A^i]\frac{1}{n}\sum_j E[w_B^j] - \frac{1}{n}\sum_i E[r_B^i]\frac{1}{n}\sum_j E[w_A^j] \\
&\qquad - \frac{1}{n}\left(\frac{1}{n}\sum_i (E[r_A^i]E[w_B^i] - E[r_B^i]E[w_A^i])\right) \\
&= R_A - R_B - \frac{1}{n} b_{A,B}
\end{aligned}
$$

where we define $b_{A,B}$ as

$$
b_{A,B} = \iint [R(h) - R(g)] \frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)} p(h|\pi_A) p(g|\pi_B)\, dh\, dg \ .
$$

Again, if we fix the relative frequencies of the selected policies, $b_{A,B}$ is a constant as n increases. Thus, the bias of D decreases at a rate of $\frac{1}{n}$. In fact, if all of the π^i's are the same, $b_{A,B} = R_A - R_B$ and the expectation of the difference is

$$
\frac{n-1}{n}(R_A - R_B)
$$

which, except for $n = 1$, is just a scaled version of the true difference.

The derivation of the variance of D is slightly more involved but involves the same basic technique. First, however, we must make a brief detour. Consider, in general, calculating $E[\sum_{i\neq j, k\neq l} a_i b_j c_k d_l]$. We wish to break this sum up into independent components so that the expectations can be calculated. It involves a lot of algebra but the notion is fairly simple.

First we count up the different ways that the indices could coincide.

$$\begin{aligned}\sum_{i\neq j,k\neq l} a_i b_j c_k d_l = &\sum_{i\neq j\neq k\neq l} a_i b_j c_k d_l \\ &+ \sum_{i\neq j\neq k} (a_i c_i b_j d_k + a_i d_i b_j c_k + a_i b_j c_j d_k + a_i b_j d_j c_k) \\ &+ \sum_{i\neq j} (a_i c_i b_j d_k + a_i d_i b_j c_j)\end{aligned}$$

where the notation $i \neq j \neq k \neq l$ implies none of the indices equal each other. While the expectation can now be pushed through these three sums easily (because we know the indices to be different), we have the complication that the sums are difficult to compute. We therefore break each sum into a sum over all indices minus a set of sums accounting for when the indices are the same (and therefore should not have been included). As is usual with inclusion-exclusion calculations, we also have to add back in some sums which were subtracted out twice. The net result is

$$\begin{aligned}&E[\sum_{i\neq j,k\neq l} a_i b_j c_k d_l] \\ &\quad= \sum_{i\neq j\neq k\neq l} E[a_i]E[b_j]E[c_k]E[d_l] \\ &\quad\quad+ \sum_{i\neq j\neq k} (E[a_i c_i]E[b_j]E[d_k] + E[a_i d_i]E[b_j]E[c_k] + \\ &\quad\quad\quad E[a_i]E[b_j c_j]E[d_k] + E[a_i]E[b_j d_j]E[c_k]) \\ &\quad\quad+ \sum_{i\neq j} (E[a_i c_i]E[b_j d_j] + E[a_i d_i]E[b_j c_j])\end{aligned}$$

$$
\begin{aligned}
&= (\sum_{i,j,k,l} E[a_i]E[b_j]E[c_k]E[d_l] \\
&\quad - \sum_{i,j,k} E[a_i]E[b_i]E[c_j]E[d_k] + E[a_i]E[b_j]E[c_i]E[d_k] + E[a_i]E[b_j]E[c_k]E[d_i] \\
&\qquad + E[a_i]E[b_j]E[c_j]E[d_k] + E[a_i]E[b_j]E[c_k]E[d_j] + E[a_i]E[b_j]E[c_k]E[d_k] \\
&\quad + 2\sum_{i,j} E[a_i]E[b_i]E[c_i]E[d_j] + E[a_i]E[b_i]E[c_j]E[d_i] \\
&\qquad\qquad + E[a_i]E[b_j]E[c_i]E[d_i] + E[a_i]E[b_j]E[c_j]E[d_j] \\
&\quad + \sum_{i,j} E[a_i]E[b_i]E[c_j]E[d_j] + E[a_i]E[b_j]E[c_i]E[d_j] + E[a_i]E[b_j]E[c_j]E[d_i] \\
&\quad - 6\sum_{i} E[a_i]E[b_i]E[c_i]E[d_i]) \\
&+ (\sum_{i,j,k} E[a_ic_i]E[b_j]E[d_k] - \sum_{i,j} E[a_ic_i]E[b_i]E[d_j] \\
&\quad - \sum_{i,j} E[a_ic_i]E[b_j]E[d_i] - \sum_{i,j} E[a_ic_i]E[b_j]E[d_j] + 2\sum_{i} E[a_ic_i]E[b_i]E[d_i]) \\
&+ (\sum_{i,j,k} E[a_id_i]E[b_j]E[c_k] - \sum_{i,j} E[a_id_i]E[b_i]E[c_j] \\
&\quad - \sum_{i,j} E[a_id_i]E[b_j]E[c_i] - \sum_{i,j} E[a_id_i]E[b_j]E[c_j] + 2\sum_{i} E[a_id_i]E[b_i]E[c_i]) \\
&+ (\sum_{i,j,k} E[a_i]E[b_jc_j]E[d_k] - \sum_{i,j} E[a_i]E[b_ic_i]E[d_j] \\
&\quad - \sum_{i,j} E[a_i]E[b_jc_j]E[d_j] - \sum_{i,j} E[a_i]E[b_jc_j]E[d_i] + 2\sum_{i} E[a_i]E[b_ic_i]E[d_i]) \\
&+ (\sum_{i,j,k} E[a_i]E[b_jd_j]E[c_k] - \sum_{i,j} E[a_i]E[b_id_i]E[c_j] \\
&\quad - \sum_{i,j} E[a_i]E[b_jd_j]E[c_j] - \sum_{i,j} E[a_i]E[b_jd_j]E[c_i] + 2\sum_{i} E[a_i]E[b_id_i]E[c_i]) \\
&+ (\sum_{i,j} E[a_ic_i]E[b_jd_j] - \sum_{i} E[a_ic_i]E[b_id_i]) \\
&+ (\sum_{i,j} E[a_id_i]E[b_jc_j] - \sum_{i} E[a_id_i]E[b_ic_i])
\end{aligned}
\tag{A.1}
$$

and although this looks complex, most of the terms are irrelevant. For instance, consider the term $\sum_{i,j} E[a_id_i]E[b_jc_j]$ (the very last sum). In the derivation of variance, this sum would be instantiated with $a_i = r_A^i$,

$b_j = w_B^j$, $c_j = r_B^j$, and $d_i = w_A^i$. We can then rewrite it as

$$\begin{aligned}
\sum_{i,j} E[a_i d_i]E[b_j c_j] &= \sum_{i,j} E[r_A^i w_A^i]E[r_B^j w_B^j] \\
&= \sum_i \int R(h)\frac{p(h|\pi_A)p(h|\pi_A)}{\overline{p}(h)\overline{p}(h)}p(h|\pi^i)\,dh \\
&\quad \times \sum_j \int R(h)\frac{p(h|\pi_B)p(h|\pi_B)}{\overline{p}(h)\overline{p}(h)}p(h|\pi^j)\,dh \\
&= n^2 \int R(h)\frac{p(h|\pi_A)p(h|\pi_A)}{\overline{p}(h)\overline{p}(h)}\frac{1}{n}\sum_i p(h|\pi^i)\,dh \\
&\quad \times \int R(h)\frac{p(h|\pi_B)p(h|\pi_B)}{\overline{p}(h)\overline{p}(h)}\frac{1}{n}\sum_j p(h|\pi^j)\,dh \\
&= n^2 \int R(h)\frac{p^2(h|\pi_A)}{\overline{p}^2(h)}\overline{p}(h)\,dh \int R(h)\frac{p^2(h|\pi_B)}{\overline{p}^2(h)}\overline{p}(h)\,dh
\end{aligned}$$

where the two integrals are similar to those in equation A.1 in that they are constant quantities based on the difference between the sampling distribution and the target distributions. What is important is that converting $\sum_i p(h|\pi^i)$ into $\overline{p}(h)$ required pulling in a factor of $\frac{1}{n}$. Because there were two sums, this had to be done twice resulting in the n^2 term out in front. In general we need only to consider the highest order terms and so only the sums with three or four indices will need to be calculated. The rest will result in insignificant terms.

We can now approximate equation A.1 as

$$\begin{aligned}
\sum_{i\neq j,k\neq l} E[a_i b_j c_k d_l] \approx \\
&\sum_{i,j,k,l} E[a_i]E[b_j]E[c_k]E[d_l] \\
&- \sum_{i,j,k}\Big(E[a_i]E[b_i]E[c_j]E[d_k] + E[a_i]E[b_j]E[c_i]E[d_k] \\
&\quad + E[a_i]E[b_j]E[c_k]E[d_i] + E[a_i]E[b_j]E[c_j]E[d_k] \\
&\quad + E[a_i]E[b_j]E[c_k]E[d_j] + E[a_i]E[b_j]E[c_k]E[d_k]\Big) \\
&+ \sum_{i,j,k}\Big(E[a_i c_i]E[b_j]E[d_k] + E[a_i d_i]E[b_j]E[d_k] \\
&\quad + E[a_i]E[b_j c_j]E[d_k] + E[a_i]E[b_j d_j]E[c_k]\Big)
\end{aligned} \tag{A.2}$$

where the error in the approximation is $O(n^2)$.

In preparation for the variance of D, we add a few more definitions similar to those of equation A.1:

$$\begin{aligned}
u^2_{A,A} &\triangleq \frac{1}{n}\sum_i E[r^i_A w^i_A] = \int R(h)\frac{p(h|\pi_A)}{\overline{p}(h)}p(h|\pi_A)\,dh \\
u^2_{A,B} = u^2_{B,A} &\triangleq \frac{1}{n}\sum_i E[r^i_B w^i_A] = \int R(h)\frac{p(h|\pi_A)}{\overline{p}(h)}p(h|\pi_B)\,dh \\
u^2_{B,B} &\triangleq \frac{1}{n}\sum_i E[r^i_B w^i_B] \int R(h) = \frac{p(h|\pi_B)}{\overline{p}(h)}p(h|\pi_B)\,dh \\
\mu^2_{A,A} &\triangleq \frac{1}{n}\sum_i E[r^i_A]E[w^i_A] \\
&= \iint R(h)\frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_A)p(g|\pi_A)\,dh\,dg \\
\mu^2_{A,B} &\triangleq \frac{1}{n}\sum_i E[r^i_A]E[w^i_B] \\
&= \iint R(h)\frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_A)p(g|\pi_B)\,dh\,dg
\end{aligned}$$

$$
\begin{aligned}
\mu^2_{B,A} &\triangleq \frac{1}{n}\sum_i E[r^i_B]E[w^i_A] \\
&= \iint R(h)\frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_B)p(g|\pi_A)\,dh\,dg \\
\mu^2_{B,B} &\triangleq \frac{1}{n}\sum_i E[r^i_B]E[w^i_B] \\
&= \iint R(h)\frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_B)p(g|\pi_B)\,dh\,dg \\
v^2_{A,A} &\triangleq \frac{1}{n}\sum_i E[(w^i_A)^2] = \int \frac{p(h|\pi_A)}{\overline{p}(h)}p(h|\pi_A)\,dh \\
v^2_{A,B} = v^2_{B,A} &\triangleq \frac{1}{n}\sum_i E[w^i_A w^i_B] = \int \frac{p(h|\pi_A)}{\overline{p}(h)}p(h|\pi_B)\,dh \\
v^2_{B,B} &\triangleq \frac{1}{n}\sum_i E[(w^i_B)^2] = \int \frac{p(h|\pi_B)}{\overline{p}(h)}p(h|\pi_B)\,dh \\
\xi^2_{A,A} &\triangleq \frac{1}{n}\sum_i E[w^i_A]^2 = \iint \frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_A)p(g|\pi_A)\,dh\,dg \\
\xi^2_{A,B} = \xi^2_{B,A} &\triangleq \frac{1}{n}\sum_i E[w^i_A]E[w^i_B] \\
&= \iint \frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_A)p(g|\pi_B)\,dh\,dg \\
\xi^2_{B,B} &\triangleq \frac{1}{n}\sum_i E[w^i_B]^2 = \iint \frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)}p(h|\pi_B)p(g|\pi_B)\,dh\,dg\ .
\end{aligned}
\tag{A.3}
$$

We can now attack the variance of D.

$$
\begin{aligned}
&E[(D-E[D])^2] = E[D^2] - E[D]^2 \\
&= \frac{1}{n^4} E\left[\sum_{i\neq j, k\neq l} \left(r_A^i w_B^j r_A^k w_B^l - 2 r_A^i w_B^j r_B^k w_A^l + r_B^i w_A^j r_B^k w_A^l \right) \right] - E[D]^2 \\
&= \left[\frac{1}{n^4} \sum_{i\neq j, k\neq l} r_A^i w_B^j r_A^k w_B^l \right] - 2\left[\frac{1}{n^4} \sum_{i\neq j, k\neq l} r_A^i w_B^j r_B^k w_A^l \right] \\
&\quad + \left[\frac{1}{n^4} \sum_{i\neq j, k\neq l} r_B^i w_A^j r_B^k w_A^l \right] - E[D]^2 \\
&= \left[R_A^2 - \frac{4}{n} R_A \mu_{A,B}^2 - \frac{1}{n}\eta_{A,A}^2 - \frac{1}{n} R_A^2 \xi_{B,B}^2 + \frac{4}{n} R_A u_{A,B}^2 + \frac{1}{n} s_{A,A}^2 + \frac{1}{n} R_A^2 v_{B,B}^2 \right] \\
&\quad - 2\Big[R_A R_B \\
&\qquad - \frac{1}{n} R_A \mu_{B,A}^2 - \frac{1}{n} R_A \mu_{B,B}^2 - \frac{1}{n} R_B \mu_{A,B}^2 - \frac{1}{n} R_B \mu_{A,A}^2 - \frac{1}{n}\eta_{A,B}^2 - \frac{1}{n} R_A R_B \xi_{A,B}^2 \\
&\qquad + \frac{1}{n} R_A u_{A,B}^2 + \frac{1}{n} R_A u_{B,B}^2 + \frac{1}{n} R_B u_{A,B}^2 + \frac{1}{n} R_B u_{A,A}^2 + \frac{1}{n} s_{A,B}^2 + \frac{1}{n} R_A R_B v_{A,B}^2 \Big] \\
&\quad + \left[R_B^2 - \frac{4}{n} R_B \mu_{B,A}^2 - \frac{1}{n}\eta_{B,B}^2 - \frac{1}{n} R_B^2 \xi_{A,A}^2 + \frac{4}{n} R_B u_{A,B}^2 + \frac{1}{n} s_{B,B}^2 + \frac{1}{n} R_B^2 v_{A,A}^2 \right] \\
&\quad - R_A^2 - R_B^2 + 2R_A R_B + \frac{1}{n}(R_A - R_B) b_{A,B} + O(\frac{1}{n^2}) \\
&= \frac{1}{n}\Big[(R_A^2 v_{B,B}^2 - 2R_A u_{B,B}^2 + s_{B,B}^2) - (R_A^2 \xi_{B,B}^2 - 2R_A \mu_{B,B}^2 + \eta_{B,B}^2) \\
&\qquad (R_B^2 v_{A,A}^2 - 2R_B u_{A,A}^2 + s_{A,A}^2) - (R_B^2 \xi_{A,A}^2 - 2R_B \mu_{A,A}^2 + \eta_{A,A}^2) \\
&\qquad - 2(R_A R_B v_{A,B}^2 - R_A u_{A,B}^2 - R_B u_{A,B}^2 + s_{A,B}^2) \\
&\qquad + 2(R_A R_B \xi_{A,B}^2 - R_A \mu_{B,A}^2 - R_B \mu_{A,B}^2 + \eta_{A,B}^2) \\
&\qquad - 4(R_A - R_B)(\mu_{A,B}^2 - \mu_{B,A}^2) + (R_A - R_B) b_{A,B} \Big] + O(\frac{1}{n^2}) \ .
\end{aligned}
\tag{A.4}
$$

The fourth line came from applying the expansion of equation A.2 along with the definitions from equations A.1 and A.3.

At this point we need to introduce a few new definitions for the

final bit of algebra.

$$
\begin{aligned}
\overline{s^2_{A,A}} &\triangleq \frac{1}{n}\sum_i E[(r^i_A)^2] \\
&= \int (R(h)-R_A)^2 \frac{p(h|\pi_A)}{\overline{p}(h)} p(h|\pi_A)\, dh \\
\overline{s^2_{A,B}} = \overline{s^2_{B,A}} &\triangleq \frac{1}{n}\sum_i E[r^i_A r^i_B] \\
&= \int (R(h)-R_A)(R(h)-R_B) \frac{p(h|\pi_A)}{\overline{p}(h)} p(h|\pi_B)\, dh \\
\overline{s^2_{B,B}} &\triangleq \frac{1}{n}\sum_i E[(r^i_B)^2] \\
&= \int (R(h)-R_B)^2 \frac{p(h|\pi_B)}{\overline{p}(h)} p(h|\pi_B)\, dh \\
\overline{\eta^2_{A,A}} &\triangleq \frac{1}{n}\sum_i E[r^i_A]^2 \\
&= \iint (R(h)-R_A)(R(g)-R_A) \frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)} p(h|\pi_A) p(g|\pi_A)\, dh\, dg \\
\overline{\eta^2_{A,B}} = \overline{\eta^2_{B,A}} &\triangleq \frac{1}{n}\sum_i E[r^i_A] E[r^i_B] \\
&= \iint (R(h)-R_A)(R(g)-R_B) \frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)} p(h|\pi_A) p(g|\pi_B)\, dh\, dg \\
\overline{\eta^2_{B,B}} &\triangleq \frac{1}{n}\sum_i E[r^i_B]^2 \\
&= \iint (R(h)-R_B)(R(g)-R_B) \frac{\tilde{p}(h,g)}{\overline{p}(h)\overline{p}(g)} p(h|\pi_B) p(g|\pi_B)\, dh\, dg \ .
\end{aligned}
\tag{A.5}
$$

Most usefully, the following identities hold.

$$
\begin{aligned}
\overline{s^2_{A,A}} &= R_A^2 v^2_{A,A} - 2R_A u^2_{A,A} - s^2_{A,A} \\
\overline{s^2_{A,B}} &= R_A R_B v^2_{A,B} - R_A u^2_{A,B} - R_B u^2_{A,B} + s^2_{A,B} \\
\overline{s^2_{B,B}} &= R_B^2 v^2_{B,B} - 2R_B u^2_{B,B} + s^2_{B,B} \\
\overline{\eta^2_{A,A}} &= R_A^2 \xi^2_{A,A} - 2R_A \mu^2_{A,A} + \eta^2_{A,A} \\
\overline{\eta^2_{A,B}} &= R_A R_B \xi^2_{A,B} - R_A \mu^2_{B,A} - R_B \mu^2_{A,B} + \eta^2_{A,B} \\
\overline{\eta^2_{B,B}} &= R_B^2 \xi^2_{B,B} - 2R_B \mu^2_{B,B} + \eta^2_{B,B} \\
b_{A,B} &= \mu^2_{A,B} - \mu^2_{B,A} \ .
\end{aligned}
$$

The variance of D can now be expressed as (continuing from equation A.4)

$$
\begin{aligned}
E[(D-E[D])^2] = \frac{1}{n}\Big(&\overline{s^2_{A,A}} - 2\overline{s^2_{A,B}} + \overline{s^2_{B,B}} - \overline{\eta^2_{A,A}} + 2\overline{\eta^2_{A,B}} - \overline{\eta^2_{B,B}}\Big) \\
&- 3\frac{1}{n}(R_A - R_B) b_{A,B} + O(frac1n^2) \ .
\end{aligned}
$$

The first line is better than the variance of the unnormalized difference. The equation is the same except each quantity has been replaced by the "overlined" version. If we compare the two versions (equations A.1 and A.5) we can note that the non-overlined versions are all integrals averaging the $R(h)$ by some positive weights. However for the overlined versions, R_A or R_B are subtracted from the returns before the averaging. We expect that R_A and R_B to be closer to the mean of these quantities than 0 and thus the overlined quantities are smaller. In general, the variance of the normalized estimator is invariant to translation of the returns (which is not surprising given that the estimator is invariant in the same way). The unnormalized estimator is not invariant in this manner. If the sampled π^i's are all the same, $b_{A,B} = R_A - R_B$ and thus the second line is a quantity less than zero plus a term that is only order $\frac{1}{n^2}$.

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