It’s About Time: Temporal Representations in Synthetic Characters

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Abstract
Early work in autonomous agents (by researchers such as Brooks) minimized the importance of representation. Similarly, early models of behavioral conditioning in animals (such as the Rescorla-Wagner model) minimized the use of representation, using only simple associative connections. However, recent work by Gallistel is able to explain the results of a wider variety of conditioning experiments by using a conditioning model that requires animals to represent time and rate information. By incorporating time and rate into the representations used by autonomous agents, we may similarly be able to produce a wider variety of learning phenomena in those agents. I propose to augment the behavioral architecture of the Synthetic Characters group with the representations of time and rate proposed by Gallistel to perform classical conditioning. Success will be measured by our ability to demonstrate new forms of adaptation in the autonomous creature that result from our ability to perform conditioning.

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Introduction

In order to survive in a dynamic environment, many self-regulating systems make use of representations that effectively model important aspects of the world. Two representations fundamental for living systems are the passage of time, and the rate at which they experience relevant stimuli.

Early models of behavioral conditioning, such as the Rescorla-Wager model, minimized the use of representation and speak simply of animals forming and strengthening associations between stimuli. While the model is successful at explaining certain phenomena, there is a wide range of phenomena that it is unable to model without substantial trouble, such as the ability to learn an expected latency of reinforcement. Recent studies by Gallistel and others have considered the possibility that models of time and rate are fundamental to conditioning phenomena. Gallistel proposes two new models, Scalar Expectancy Theory and Rate Estimation theory, that require that an animal be able to represent the length of the interval between stimuli, and the rate of reinforcement associated with various stimuli. Using these models, Gallistel is able to account for a number of conditioning phenomena that can not be explained using the Rescorla-Wagner model (Gallistel 1990), and does so in a clear and elegant way.

Similarly, much of the early work in behavior-based artificial intelligence minimized the importance of representation (Brooks 1991). Recent work in the Synthetic Characters group has involved incorporating time into the representations of a behavior-based system. This use of temporal representations is a bit ad-hoc, in that we use multiple representations spread throughout the system in a way that works, but is perhaps not as elegant as one would wish. However, the use of time in the representation has allowed us to model the kind of applied operant conditioning that underlies dog training. The sorts of learning that can occur within the current framework include Thorndike’s Law of Effect, wherein the relative frequency of behaviors reflects the relative value of their apparent consequences; cue learning, in which the system identifies contexts in which particular actions are most reliable; behavioral shaping, in which the system learns the best way in which to perform a given action so as to improve its chances of desirable consequences; the length of time to persist in a given action; and the relative reliability of actions.

We are interested in re-implementing much of the learning mechanism using a more principled model of time that pays attention to the sort of details Gallistel attends to in the SET and RET models. For example, Rate Estimation Theory involves a temporal contingency matrix that will require us to maintain and analyze rate-of-reinforcement information. Such a mechanism will need to operate in real-time with dozens of potential stimuli. Further, the dog training paradigm requires that we consider trace conditioning, in which the unconditioned stimulus (the reward) comes after the conditioned stimulus has been removed. There is no explicit model for trace conditioning in the published literature (Gallistel, pers. comm.), and we will need to incorporate some such model into the system.

By incorporating representations that allow us to implement Scalar Expectancy Theory and Rate Estimation Theory, I propose to develop a model that allows agents built within the Synthetic Characters framework to reproduce the conditioning phenomena that SET and RET are able to explain. Should time permit, I will explore extending these models to allow us to reproduce trace conditioning phenomena.
Background
This study will combine the research of the Synthetic Characters group with work from the field of behavioral neuroscience.

The Synthetic Characters Group
The Synthetic Characters group designs autonomous and semi-autonomous creatures that inhabit graphical worlds. We seek to extend the work and philosophy of ethologically-inspired creature design formulated in (Blumberg 1996). Previous extensions of the work have considered observation-based expectation generation (Kline 1999), the use of a character-based architecture for camera control (Tomlinson 1999), the use of classification techniques within the framework (Ivanov, Blumberg et al. 2000), extensions to characters’ motor systems with applications to music (Downie 2001), and the use of quaternion-based animation blending techniques (Johnson 2001).

The most recent implementation, which has been under construction since January of 2000, features an agent-based brain architecture in which a form of learning occurs in multiple systems. The implementation is showcased in “sheep|dog: Trial by Eire,” an interactive installation in which a user controls, using a voice command interface, a semi-autonomous shepherd who herds sheep with Duncan, the autonomous sheepdog. In a separate installation, a form of reinforcement learning can be used to train Duncan to perform tricks on vocal command, an early version of which is described in (Yoon, Burke et al. 2000).

Brief System description

![Figure 1](image)

Figure 1: Current top-level system diagram, showing flow of information through the architecture.

Figure 1 provides a high-level view of the “brain architecture” of a single character in the current Synthetic Characters system. The Sensory System filters sensory data the creature obtains from the world. The Perception System classifies the sensory information and
organizes it into Working Memory. The Action System uses the information in Working Memory to perform action selection, and performs other tasks such as object-of-attention selection and gait selection. The Navigation System assists the Action System by allowing a creature to move into position. The Motor System uses animation-blending techniques to carry out the requests of the other systems.

Existing Perceptual representations
A number of perceptual representations already exist within the Synthetic Characters framework. When combined, these representations have allowed us to implement an Operant Conditioning paradigm. The components of the architecture most relevant to this work are the Perception System and Working Memory. We describe these systems here in more detail, and identify the learning mechanisms used to implement the dog-training paradigm.

“Percept Tree”
A Percept is described by Richards as being a maximal node in the preference ordering of a state space (Richards, Feldman et al. 1992). We use the term here similarly. Percepts act as detectors that indicate of how probable it is that a given sensory data record matches the Percept.

Percepts are organized in a Percept Tree. This is a hierarchical structure in which percepts are arranged from most general at the root (the “WhateverPercept,” which always returns 1.0), to most specific at the leaves (such as the “‘Sit’ Sound Percept” in Figure 2, which would only return values close to 1.0 when it detects an utterance that sounds like the word “Sit”). This has allowed contextual learning to take place, in which the virtual creature (such as the dog in the dog training paradigm) begins with a very general hypothesis about the appropriate context in which to perform an action, and moves down the tree towards more specific contexts in which an action is reliably followed by a reinforcer. When an Actiontuple (described below) identifies the need to learn about more specific perceptual context, it can add nodes to the percept tree.

![Percept Tree Diagram](image)

**Figure 2:** Sample section of a creature's percept tree.

Working Memory
After data records are processed by the Percept Tree, they are added into Working Memory as structures called Beliefs. Beliefs represent objects or other entities in the dog’s world. Each belief contains a history of how the various Percepts in the percept tree evaluated against this Belief. They are used to maintain percept histories, and provide the creature with a representation of object persistence.
Existing Action-selection representations

The atomic element of the action selection mechanism is referred to as an Actiontuple. In brief, an Actiontuple describes the creature’s assessment of the value of performing an action, for a specific amount of time, in a particular context. Each Actiontuple contains three sections: a trigger context, which describes the conditions under which the Actiontuple should be activated; the action itself, the “adverb” which describes how to perform the action, and the action context, which describes which Beliefs should be being acted upon; and the doUntil context, which describes the conditions under which the behavior should terminate. One of the timing mechanisms in the system is now contained in the doUntil contexts.

Figure 3: Anatomy of an Actiontuple. Each Actiontuple contains at least the trigger, action and doUntil contexts. Some also contain action contexts that parameterize the action, and describe which Beliefs should be acted upon.

Associated with the entire Actiontuple is a “goodness” value that describes how valuable the creature believes this Actiontuple to be – or, put another way, how accurate a hypothesis this trigger-action-doUntil combination is. The mechanism is outlined in Downie’s Master’s thesis (Downie 2001). Actiontuples are the structures used to implement the dog training learning paradigm described above.

Figure 4: Anatomy of an ActionGroup. Different tuple-selection mechanisms within the ActionGroups provide for persistence, “startle” and innovation mechanisms.

The trigger contexts of most Actiontuples are based on the activity of Percepts within Working Memory. For example, the presence of the “Food Shape Percept” in one of the Beliefs in Working Memory will serve as a trigger for an “eat food” Actiontuple which contains “eat” as its action, the food as its action context, and “until the food is gone” as the doUntil context.

Actiontuples are arranged in arbitration mechanisms called ActionGroups. The ActionGroups arbitrate which Actiontuple will be selected on every tick, using a mechanism that takes the trigger contexts of non-active Actiontuples and the doUntil context of the action Actiontuple as inputs. Actiontuples are able to innovate new Actiontuple children with new trigger contexts that are added to their parent tuple’s ActionGroup.

To summarize, we have identified a number of locations within the representations of the current system where learning occurs. The addition of percepts to the percept tree allows the
creature to be increasingly specific when classifying perceptual input. New Actiontuple children can be created with trigger contexts that are associated with new percepts. The action context of an Actiontuple provides the “adverb” used to shape an action. The doUntil context provides the behavior with a learnable timing mechanism. ActionGroups provide potentially dynamic arbitration mechanisms for selecting the active Actiontuple on every tick.

**Time, Rate and Conditioning Representations**

In Time, Rate and Conditioning, Gallistel and Gibbon provide details of two theories that account for a broad range of conditioning phenomena. These theories depend on an animal’s ability to learn temporal intervals between events, as well as rates of reinforcement. In Scalar Expectancy Theory, animals store in memory the reinforcement latency (the time between the onset of a stimulus and a subsequent reward signal). In Rate Estimation Theory, they store the rates of reinforcement for stimuli. The authors contrast their paradigms with the existing paradigms, and present a veritable library of experimental data to support their claims (Gallistel and Gibbon 2000). What is exciting about the model is that by assuming the existence of representations of time and rate, Gallistel et. al. are able to explain a wide range of disparate conditioning phenomena in a simple and elegant way.

**Scalar Expectancy Theory: the “When” decision**

Scalar Expectancy Theory, or SET, pertains to the onset of the conditioned reflex (CR), revealing both “when” and “for how long” the CR should occur.

In terms of the framework described above, the “when” decision provides the time window during which an Actiontuple’s trigger context should be high. Scalar Expectancy Theory explains how the uncertainty about the true value of a remembered magnitude is proportional to the magnitude. Two assumptions – that the decision variable used to determine a response is a ratio, the denominator of which is the learned reinforcement latency, and the numerator of which is the elapsed time since the conditioned stimulus; and that estimates of duration read from memory have scalar variability – are necessary to explain scale invariance in the distribution of conditioned responses.

**Rate Estimation Theory: the “Whether” decision**

Scalar Estimation Theory assumes that the animal has already determined whether or not a stimulus merits a response. In the Rate Estimation Theory model, this decision is based on an animal’s growing certainty that that stimulus has a substantial effect on the rate of reinforcement. In simple conditioning, as Gallistel puts it, this appears to be determined “by the subject’s estimate of the maximum possible value of the rate of background reinforcement given its experience of the background up to a given point in conditioning.” Gallistel provides a model (which we do not reproduce here) for how animals determine the true rates of reinforcement for each stimulus and uses this to determine whether or stimulus merits response. He demonstrates how this model accounts for experiments that employ fixed and variable rates of reinforcement.

**Related Work**

Using a simple perception-output mapping, Braitenberg ascribed to his vehicles affective qualities ranging from love to fear, representing one of the original forays into the realm he called synthetic psychology (Braitenberg 1986). Reynold’s boids algorithm represented the
first behavior-controlled animation (Reynolds 1987). Tu and Terzopolous’s physically-based artificial fish model incorporates a perceptual model and a behavior system (Tu and Terzopolous 1994). Perlin’s Improv system is designed to create interactive actors. As opposed to beginning with intelligence, Perlin is interested fundamentally in creating “actors” with powerfully scripted behaviors. His World whiteboard mechanism is similar to ours, although he makes no mention of honesty mechanisms (Perlin and Goldberg 1996). A number of recent commercial software products have focused on interactive characters, including PF-Magic’s Dogz series (PF.Magic 1996), and Cyberlife’s Creatures series (Cyberlife 1998). This work will be integrated with the existing work of the Synthetic Characters group, described and referenced in detail above.

In many ways, Gallistel’s timing model contrasts sharply with the standard model of conditioning, mathematically formalized by Rescorla and Wagner in (Rescorla and Wagner 1972) and (Wagner and Rescorla 1972), and described by Domjan in (Domjan 1998). Gallistel outlines the differences between the two models in (Gallistel and Gibbon 2000) using a “questions with different answers” format.

The importance of considering perception and learning together was emphasized by Barlow in (Barlow 1990), in which he concludes that perception must play an important role in providing a representation that promotes the efficient learning of predictive associations.

Motivation
In the context of behavioral neuroscience, this work will provide a basis for examining and testing Gallistel’s timerate model. We will gain insight into the strengths and weaknesses of SET and RET, and assess how these theories might be extended to account for trace conditioning phenomena. Conant and Ashby, among others, have noted that every good regulator of a system must be a model of that system (Conant and Ashby 1970). While an animal does not regulate time, the internal temporal representations necessary to reproduce conditioning phenomena might inform us as to which aspects of the temporal axis are important to a living system.

In terms of behavior-based systems design, this work will provide insight into how to implement a conditioning model into an adaptive virtual creature. It will require us to design new representations for time and rate information, and integrate them into the existing behavior-based system. The algorithms and components designed using this principled, details-oriented approach should hopefully supersede the ad-hoc temporal representations in the current system. An ethologically-inspired conditioning model may find application outside of synthetic character design in the more general field of autonomous agents.

Plan
I propose to implement the representations that will allow us to reproduce SET and RET within the existing framework. I will begin by considering representations for inter-percept timing information, including the temporal contiguity matrix necessary for RET and described by Gallistel in (Gallistel and Gibbon 2000).

When SET and RET can be reproduced within the Synthetic Characters framework, I will work on modeling trace conditioning paradigms. In trace conditioning, the unconditioned stimulus (US) does not occur during the conditioned stimulus (CS), but rather some time after it terminates.
Endgoal
I will develop the representations necessary to reproduce the results of SET and RET, implement them into the Synthetic Characters framework, and provide semi-autonomous visualization tools that allow an observer to study their development and the effects they have on the learning mechanism.

Success will be measured by our ability to successfully integrate the Gallistel model into our behavior architecture, and to replicate the kind of learning ability one sees in dogs, both in training paradigms and less supervised settings. We will be particularly interested in evaluating the kinds of phenomena that Gallistel’s model allows us to model that our current approach does not.

Addendum
After reviewing the first draft of this thesis proposal, DCGS requested the following additional information: a timeline of milestones and goals, and a more thorough explanation of the “deliverables” that will mark the project’s completion.

Timeline

Present – Mid-February
- Continue survey of ethological literature and related work, seeking direction from readers
- Continue exploring applications of time/rate learning to the work of the Synthetic Characters & Pet Projects groups at the Media Lab
- Experiment with partial implementations within the Synthetic Characters framework

Late February
- 23 Feb: Complete first implementation of the conditioning model into Synthetic Characters framework
- 28 Feb: Provide progress report, discussing state of implementation, to thesis readers

Early March
- Continue research on the basis of feedback from thesis readers
- Begin implementation of final representation into Synthetic Characters framework
- 9 March: Finalize experiments that will be used to demonstrate the system

Late March
- Complete implementation of representation and experiments
- 31 March: Provide copy of implementation to readers

April
- Write first draft of thesis
- 21 April: Provide draft of thesis to readers

Late April – Early May
- Complete writing of thesis
- 4 May: Provide draft of thesis to readers
- 11 May: Submit thesis
Deliverables
In addition to a thesis document that details this study, I will implement the representations necessary to reproduce the results of SET and RET as a module within the Synthetic Characters framework. An implementation that works within the framework will allow us to address the following:

- Do autonomous creatures that employ this time/rate representation behave as Gallistel’s model predicts?
- Can we replicate the kind of time/rate learning that one sees in dogs, both in training paradigms and less supervised settings?
- Which learning phenomena can be modeled using Gallistel’s model that cannot be replicated using existing representations within the framework?

I will address the above questions regarding the representation’s efficacy. In doing so, I will provide and document a visualization module that demonstrates time/rate learning occurring within an autonomous creature.

As indicated on the above timeline, all of this will take place in consultation with the thesis readers, and a preliminary implementation of the system will be completed by mid-March. The implementation, its visualization tool and the test projects will also be made available when the thesis document is submitted in May.

References


