

# Packet theory of conditioning and timing

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## Abstract

Packet theory is based on the assumption that the momentary probability of producing a bout or packet of responding is controlled by the conditional expected time function. Bouts of head entry responses of rats into a food cup appear to have the same characteristics across a range of conditions. The conditional expected time function is the mean expected time remaining until the next food delivery as a function of time since an event such as food or stimulus onset. The conditional expected time function encodes mean interval duration as well as the distribution form so that both the mean response rate and form of responding in time can be predicted. Simulations of Packet theory produced accurate quantitative predictions of: (1) the effect of reinforcement density (mean food–food interval) and distribution form on responding; (2) scalar variance in fixed interval responding; (3) CS–US and intertrial interval effects on the strength of conditioning; and (4) the effect of the ratio of cycle:trial time on the strength of conditioning. © 2002 Elsevier Science B.V. All rights reserved.

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## 1. Introduction

The past two decades have seen a growing interest in understanding the relationship between classical conditioning and timing. There is good reason for pursuing a more integrated approach because it is well-known that conditioning preparations result both in a changing magnitude of responding as a function of training and in an changing magnitude of responding as a function of time in an interval. Recent research has suggested that timing and conditioning may emerge simultaneously during the acquisition process (Bevins and Ayres, 1995; Holland, 2000; Maes

and Vossen, 1992; Kirkpatrick and Church, 2000b), providing further support for integrative approaches.

The attempts at integration have included real-time models (e.g. Blazis et al., 1986; Sutton and Barto, 1981, 1990), the temporal encoding hypothesis (Savastano and Miller, 1998), and rate expectancy theory (Gallistel and Gibbon, 2000; Gibbon and Balsam, 1981).

The real-time models incorporate a representation of time into associative learning models. These models posit that there is a pattern of strengths stored at the time of reinforcement (unconditioned stimulus delivery), with strength increasing as a function of conditioning trials and as a function of time since stimulus onset. Thus, timing and conditioning are fully integrated and

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are represented by the same pattern of strengths in memory.

The temporal encoding hypothesis purports that conditioning involves temporal learning as well as the formation of associations. Temporal learning occurs through the establishment of a temporal map that specifies the duration and order of stimulus events. Temporal and associative learning are presumed to occur in parallel, but temporal learning can mediate the expression of associative learning.

Rate expectancy theory is a time-based account of the conditioning process that includes a conditioning module and a timing module that operate in a serial fashion with conditioning occurring first. Conditioning occurs through a rate comparison process. The rate of reinforcement in the presence of the stimulus (number of reinforcements in the stimulus/time in the stimulus) is compared to the rate of reinforcement in the background throughout training (number of reinforcements in the background/time in the background). Once the rate of reinforcement in the presence of the stimulus is detected as larger than the rate in the background, responding during the stimulus occurs. Timed responses are produced once conditioning is established through Scalar expectancy theory (Gibbon and Church, 1984; Gibbon et al., 1984). A pacemaker emits pulses that are sent to an accumulator. At the time of reinforcement, the number of pulses in the accumulator are stored as a separate item in reference memory. The decision of when to respond in an interval is determined by a ratio comparison between the number of pulses in the accumulator at the current time and the number of pulses in an item that is randomly selected from reference memory. When the ratio exceeds a threshold, then responding begins.

These three approaches are each unique, and each has its own strengths and weaknesses (see Kirkpatrick and Church, 2000b; Church and Kirkpatrick, 2001 for reviews of timing and conditioning models). The purpose of the present paper is to present a fourth unique approach, Packet theory. In the interest of integration, Packet theory was developed with the intention of bringing together a set of phenomena in the area

of conditioning and timing that have traditionally required separate explanations. For the purposes of the present paper, the set of phenomena include: (1) the observation that strength of conditioning is similar regardless of whether a fixed or variable duration CS is used (Kamin, 1960; Kirkpatrick and Church, 1998; Libby and Church, 1975); (2) the strength of conditioning appears instead to depend on the duration of the intervals that comprise the conditioning procedure such as the CS–US interval, the intertrial interval, and the trace interval; and (3) the observation that the temporal gradients of responding during fixed and random intervals are different in shape despite similar rates of responding (Kirkpatrick and Church, 1998; Libby and Church, 1975).

The default assumption is that conditioning with a random duration CS results in the acquisition of conditioned responding in the absence of any timing, whereas conditioning with a fixed duration CS results in the acquisition of both conditioning and timing. For example, Gallistel and Gibbon (2000) have proposed a separate module that ‘decides whether there is one or more (relatively) fixed latencies of reinforcement, as opposed to a random distribution of reinforcement latencies. This fourth process mediates the acquisition of a timed response’ (p. 307). However, this assumption becomes problematic when considering interval distributions that are intermediate between fixed and random. For example, would timing occur with a fixed interval with some small, added variance? How about with moderate amounts of added variance? At what point does one draw the line? Lund (1976) argued that the degree of temporal control over behavior decreases as the degree of variability increases, so that fixed intervals exhibit strong temporal control but (exponential) random intervals exhibit no temporal control over behavior. But, again one needs to postulate a special variability detector that can determine the degree of temporal predictability. A much simpler alternative would be to assume that the form of responding reflects the temporal properties of an interval distribution, even random interval distributions.

Packet theory was developed to explain both the timing and conditioning of responding in ba-

sic conditioning procedures using the same mechanism to predict responding under different interval distributions. This paper will present evidence that responding under fixed and random distributions can be modeled with a single process, as well as other distributions. In addition, packet theory naturally predicts the effects of interval durations in classical conditioning paradigms, and (surprisingly) predicts the effect of the cycle:trial ratio on conditioning. Because the model is early in development, the domain is still somewhat restricted. A set of proposals for expansion will be developed in the discussion.

## 2. Packet theory

Packet theory derives its name from the observation that many operant and respondent behaviors such as lever presses, keypecks, orienting responses, magazine behavior, and drinking occur in bouts (e.g. Blough, 1963; Corbit and Luschei, 1969; Fagen and Young, 1978; Gilbert, 1958; Mellgren and Elmsore, 1991; Nevin and Baum, 1980; Pear and Rector, 1979; Robinson et al., 2000; Schneider, 1969; Shull et al., 2001; Skinner, 1938; Slater and Lester, 1982). Because of their multi-response nature, bouts of behavior have a temporal structure—the responses that make up a bout occur in a time series. Kirkpatrick and Church (2002a) reported that four different measures of temporal structure of bouts were unaffected by procedural variations of interval duration and distribution form across 12 groups of rats receiving fixed time (FT), random time (RT), or tandem FT RT schedules between successive food deliveries. Two of the measures are shown in Fig. 1: the number of responses in a bout and the time between successive responses in a bout (the interresponse times). Bouts of magazine behavior contained a geometrically distributed random number of responses and there was an exponentially-distributed random time between successive responses. The bouts of magazine behavior were invariant across different groups, indicating that the bout may be treated as a basic unit of behavior. The invariance of bouts is consistent with prior findings that short IRTs

are relatively insensitive to experimental manipulations compared to longer IRTs (Blough, 1963; Schaub, 1967; Shull and Brownstein, 1970) in that bouts of behavior are typically composed of short IRTs.

The structure of bouts is one type of temporal structure incorporated into packet theory. The other type of structure is the organization of bouts in time. This second type of temporal structure will be the primary focus of the present paper. The differentiation between the internal

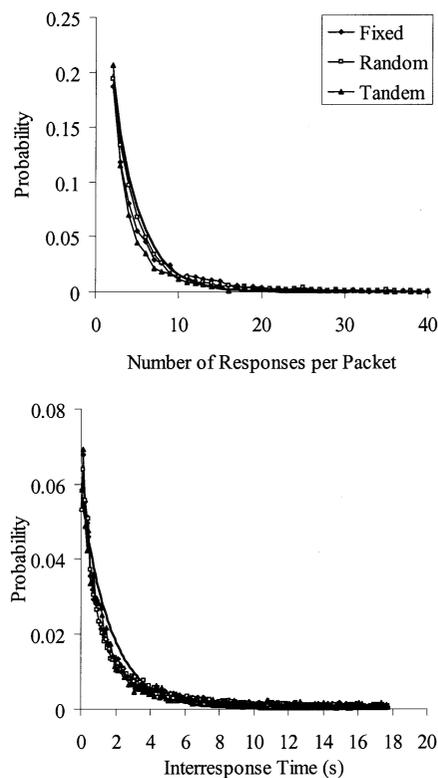


Fig. 1. The temporal structure of bouts of behavior. Top panel: the probability of observing bouts containing a particular number of responses for groups of rats that received fixed, random, or tandem fixed random intervals between successive food deliveries. There had to be a minimum of two responses in a bout (single responses were viewed as isolated cases and not bouts). Bottom panel: the distribution of interresponse times in a bout for groups of rats that received fixed, random, or tandem intervals between successive food deliveries. The solid line through the data is the fitted geometric (top panel) or exponential (bottom panel) function used to estimate the parameters for generating bouts in the model. Adapted from Kirkpatrick and Church (2002a).

and external structure of bouts is related to the analysis of behavior on operant schedules of reinforcement as consisting of periods of engagement in reinforced behavior alternating with periods of disengagement (Blough, 1963; Gilbert, 1958; Mellgren and Elmsore, 1991; Nevin and Baum, 1980; Pear and Rector, 1979; Shull et al., 2001). However, the current analysis goes beyond this tradition by specifying the temporal structure of both the bouts and the bout-generating function. The bouts are generated by the conditional expected time function (Kirkpatrick and Church, 2000b, 2002a), which is the mean time remaining until food as a function of time in an interval. The equation for the conditional expected time function for a distribution with a known density function is given in Eq. (1).

$$E_t = \int_{x=t}^{\infty} \left( \frac{1}{S_t} x f(x) \right) dx - t \quad (1)$$

$S_t$  is the survival function at time  $t$ ; the survival function is the probability that food hasn't yet been delivered as a function of time in an interval:

$S_t = 1 - \left( \int_{x=0}^t f(x) dx \right)$ . The term  $dx$  is the size of the time step between successive calculations, and is typically set to 1 s. The density function,  $f(x)$ , is determined by the type of interval distribution that is used and can be found in most standard statistical texts (e.g. Evans et al., 1993). For example, the density function for an exponential random interval is  $f(x) = (1/b) e^{-x/b}$ , where  $b$  is the mean of the random interval. The conditional expected time function is determined for any distribution of intervals. The importance of this function is that rats appear to be sensitive to the conditional expected time remaining in an interval. That is, rats may in some fashion detect the mean time until food in an interval. This will be demonstrated more fully in Section 4.

Packet theory proposes a simple mechanism by which the conditional expected time function controls behavior. Fig. 2 demonstrates the emergence of the conditional expected time function for an exponentially-distributed random interval. There are three modules in the theory: perception, memory and decision. The equations and details of implementation are given in the following section.

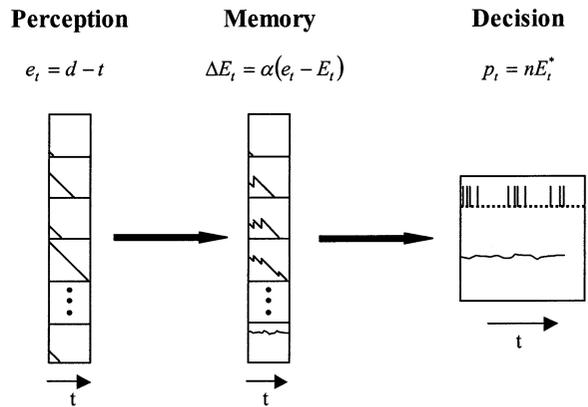


Fig. 2. A diagram of packet theory for a random time schedule of reinforcement. Perception: the current interval determination ( $e_t$ ) for a series of intervals, with different trials shown in different boxes in the column. Memory: the conditional expected time function as a function of time in the interval ( $E_t$ ) as a function of trials of training. The conditional expected time function was calculated by a linear weighting of perceptual functions. Decision: the probability of producing a packet ( $p_t$ ) as a function of time in the interval. The top portion above the dashed line demonstrates hypothetical times when packets might be fired.

The diagram of the perceptual module contains a representation of a set of intervals received in training, with each interval in a separate box. The perceptual process generates an expectation for each interval received during training,  $e_t$ . The individual expectations are not generated in real time, but rather are constructed once food is delivered. There is a record of the duration between the previous predictor event(s) and the time of food delivery ( $d$ ). Once the trial is finished, the new expectation is represented by a linear decreasing function, which starts at  $d$  and decreases to 0. In a fixed interval, the perceptual functions will always be the same, but in a random interval, the functions will differ across trials (leftmost portion of Fig. 2).

Each individual expectation is added to memory, which contains the weighted sum of all of the input intervals received thus far. The function in memory is the conditional expected time function,  $E_t$ , for the set of intervals received up to the most recent interval. The amount of weight given to a new expectation,  $\alpha$ , can be manipulated. When  $\alpha$  is small, new intervals receive little weight. This

creates a memory structure that is more stable, but takes longer to adjust to changes in interval duration or distribution form. The form of the conditional expected time function will be different for different types of interval distributions. For example, the conditional expected time function for a fixed interval decreases linearly from the value of the fixed interval, reaching 0 at the time of reinforcement, whereas the conditional expected time function for a random interval is constant at the mean of the random interval. The emergence of the conditional expected time function for a random interval is demonstrated in the middle portion of Fig. 2. As progressively more intervals are added to memory, the conditional expected time function flattens and stabilizes, with some fluctuation around the mean interval duration.

Responses that occur during an interval in anticipation of food delivery are controlled by the decision module, which contains two parts: (1) the determinant of the probability of producing a packet; and (2) the temporal structure of packets.

The probability of packet occurrence,  $p_t$ , is determined by a transform of the conditional expected time function multiplied with a responsiveness parameter  $n$ . The conditional expected time function is transformed by reversing its direction and converting times into probabilities (see Section 3). The end product is a probability function that is inversely related to the conditional expected time function. The sum of the probabilities in this function is equal to  $n$ , which is the expected number of packets per interval.

There are two ways of changing responsiveness in the model. One is the conditional expected time to food. Shorter intervals produce shorter expectations, which in turn produce higher probabilities of responding. The other source is the parameter  $n$ , which is an event salience parameter. Different events that trigger anticipatory responding (e.g. food delivery, the onset of a light) will support different rates of response. The parameter  $n$  can be used to adjust response rates for different events of different salience.

Theoretical packets were modeled after the bout characteristics shown in Fig. 1, with a random number of responses and a random interre-

sponse interval between successive responses in a packet. The term ‘packet’ will be used to refer to the bursts of behavior that are actually produced by the model, whereas the term ‘bout’ will be used to refer to bursts in behavior observed in data from the rats or from the model output. The model responded with packets of behavior as a function of the mean time remaining in the interval, which is the conditional expected time function. Packets were produced probabilistically, so the number of packets per interval and the time of packet occurrence varied from interval to interval. The structure of the packets also varied from packet to packet because the theoretical packets (like the rat’s packets) contain random numbers of responses emitted with random interresponse times between successive responses in a packet. The next section contains the model equations and description of model implementation for simulation.

### 3. Packet theory implementation

The individual expectation functions in the perceptual component of the model were implemented using Eq. (2). The determination of the interval between the most recent food delivery and the previous predictor event(s) at time  $t$  ( $e_t$ ) is the difference between the total interval duration,  $d$ , and a series of time steps between the predictor event and food delivery  $t$ . Thus, at the time of the predictor event ( $t = 0$ ), the current expectation ( $e$ ) for a 90-s interval would be  $90 - 0 = 90$ , 1 s later the expectation would be  $90 - 1 = 89$ , and at the time of food delivery ( $t = 90$ ) would be  $90 - 90 = 0$ . The current expectation is calculated for time steps 0 to  $d$  in an interval.

$$e_t = d - t \quad \text{for } 0 \leq t \leq d \quad (2)$$

The conditional expected time function in memory was updated with a linear weighting rule. In the simulations, after the first interval was completed the current expectation from the first interval was transferred directly into memory. On successive intervals, the expectation in memory was updated using Eq. (3). The change in the conditional expected time function is the differ-

ence between the most recent expectation,  $e$ , at time  $t$  and the conditional expected time function in memory,  $E$ , at time  $t$  multiplied with the weighting constant  $\alpha$ . Individual expectations are combined into memory only over the time steps occupied by that interval. For example, a 90-s interval would be added to memory only over time steps 0–90. The expectation in memory after 90 s would be unchanged.

$$\Delta E_t = \alpha(e_t - E_t) \quad 0 \leq t \leq d \quad (3)$$

The probability function,  $p_t$ , is a transform of the conditional expected time function, multiplied with a constant  $n$ , given in Eq. (4a). The parameter  $n$  is a responsiveness parameter that is the expected number of packets in an interval. The probability function and transformed expectation (Eq. (5b)) were calculated for time steps 0 to  $D$ , where  $D$  is the mean interval duration. For time steps greater than  $D$ ,  $p_t$  was set to the value reached at time step  $D$ . This was necessary for implementation of the model on exponential random intervals, where the majority of intervals fall below the mean. Very long intervals can be observed but only infrequently, which creates instabilities in the expectation function at times longer than the mean interval duration. Also, on fixed intervals, there is no information for calculation of  $p_t$  beyond time step  $D$  because the conditional expected time function is only defined over the fixed interval duration.

$$p_t = nE_t^* \quad 0 \leq t \leq D \quad (4a)$$

$$p_t = p_{t=D} \quad t > D \quad (4b)$$

The transformed expectation,  $E_t^*$ , was calculated by first transposing the conditional expected time function to get  $E'_t$  (see Eq. (5a)). The transposed conditional expected time function increased linearly for fixed, remained relatively constant for random, and increased and then remained relatively constant for tandem fixed random durations.

$$E'_t = \max(E_t) - E_t \quad (5a)$$

The second step in calculating the probability function was to normalize the transposed function to get the transformed expectation  $E_t^*$  (see Eq.

(5b)). The transformed expectation is equal to the transposed expectation at time  $t$  divided by the sum of the values of the transposed expectation over times 0 to  $D$ . Dividing by the sum of the transposed expectation creates a transformed expectation that can range from 0 to 1, with the sum of the values of the transformed expectation equal to 1.0. The effect of dividing by the sum will be more apparent in the following section, where the model predictions of the effect of interval duration on response rate are demonstrated. If the mean expected time to food is long (i.e. the sum of the transposed expectation is large), then the probability of responding will be lower at any given point in an interval. The model therefore predicts that response rates will be lower overall if the interval duration is longer.

$$E_t^* = \frac{E'_t}{\sum_{t=0}^D E'_t} \quad (5b)$$

The model produced packets that contained the same temporal structure as the bouts of head entry behavior produced by rats. The functions for generating the model packets were determined by fitting an exponential function to the interresponse time distributions and a geometric function to the distribution of the number of responses in a packet. These fits are shown in Fig. 1 as a solid line through the data. Both the exponential and geometric functions have only a single parameter, which is the mean of the distribution. The means derived from the fits were used to produce the model packets. The model determined the number of responses in a packet,  $\eta$ , by sampling randomly from a geometric distribution:  $\eta = (\ln(X)/\ln(1 - (1/3.7))) + 1$ , where  $X$  was a uniformly-distributed random number between 0 and 1. This produced packets with a minimum of 2 and a mean of 4.7 responses. Each pair of responses in a packet was separated by a random interresponse time ( $\delta$ ), with a mean of 1.7 s:  $\delta = -1.7 \ln(X)$ , where  $X$  was a uniformly-distributed random number between 0 and 1. If the model was in the middle of one packet and a new packet was called for, the model continued to deliver the old packet and added on the new packet. Thus, there was both temporal and re-

sponse summation of packets when two packets overlapped. In the data generated by the model, two packets that ran together would appear as one longer bout.

Simulations of packet theory were conducted in MatLab. In all cases, the model received a training program identical to the rats. The model produced anticipatory packets if the probability of a packet,  $p_t$ , exceeded a uniformly distributed random number between 0 and 1. For some of the data sets, the model also produced reactive packets (of magazine behavior) following food reinforcement. Reactive packets were generated with the same rules as anticipatory packets, except that reactive packets occurred with probability  $\rho$ . Rats do not always produce magazine behavior following food delivery. The model also sometimes failed to 'eat' the food immediately after delivery.

All responses and all reinforcements were written into a data file with a time stamp. The format of the output from the model was the same as the data from the rats so that the same data analysis routines could be used for both.

There was no formal fitting routine used by the model so that the model simulations may not represent the very best fit that could be obtained by the model. Simulations were conducted by manually changing parameter values until a reasonably good fit was obtained. For the most part, reasonable fits were obtained within two or three attempts at simulation. In all cases, the value of  $n$  and  $\alpha$  were not allowed to vary between conditions in the same experiment, but were allowed to vary between experiments. There can be different values of  $n$  for different types of events that may initiate timing. This allows for differences in the salience of events that initiate timing on the rate of responding in the interval. In the present paper, simulations were conducted on procedures that involved up to three different events that signaled food delivery: the prior food delivery, stimulus onset, and stimulus termination.

#### 4. Form and rate of responding

Packet theory was developed primarily to explain the form of the response rate gradient and

overall rate of responding during interval-based procedures. It is fairly well-established in the timing literature that interval distribution form has a profound impact on the form of responding, with fixed intervals resulting in increasing response rates and exponentially-distributed random intervals resulting in relatively constant response rates (Catania and Reynolds, 1968; Kirkpatrick and Church, 2000a,b; LaBarbera and Church, 1974; Libby and Church, 1975; Lund, 1976). Moreover, a couple of studies have examined the effect of tandem intervals made up of a fixed duration plus an exponentially distributed random duration with a determined mean. Thus, food cannot occur for some minimum fixed duration after which food occurs at a random time with a defined mean waiting period. There are no external cues associated with the fixed and random components. Here, the form of responding is a combination of fixed and random response rate functions, with increasing response rates during the fixed portion and relatively constant response rates during the random portion of the interval (Kirkpatrick and Church, 2000b).

The effect of interval distribution form on the timing of responding is demonstrated in the left column of Fig. 3, which contains response rate functions obtained from groups of rats that received food reinforcements on FT45, FT90, FT180, and FT360 s; RT45, RT90, RT180, and RT360 s; and tandem FT45 RT45, FT45 RT90, FT90 RT45, and FT90 RT90 s schedules between successive food deliveries. The form of the conditional expected time function for a fixed interval is linearly decreasing, for a random interval is constant, and for a tandem interval is linearly decreasing over the fixed portion and constant over the random portion.

The rate of head entry responses into the food cup is displayed as a function of time since the previous food delivery. There was an initial high rate of food cup behavior during the first 5 s of the food–food interval in all groups, presumably due to consumption of the previously delivered food pellet. Thereafter, the functions reflected the effect of distribution form on the form of the anticipatory response gradient. The response rate functions are inversely related to the conditional

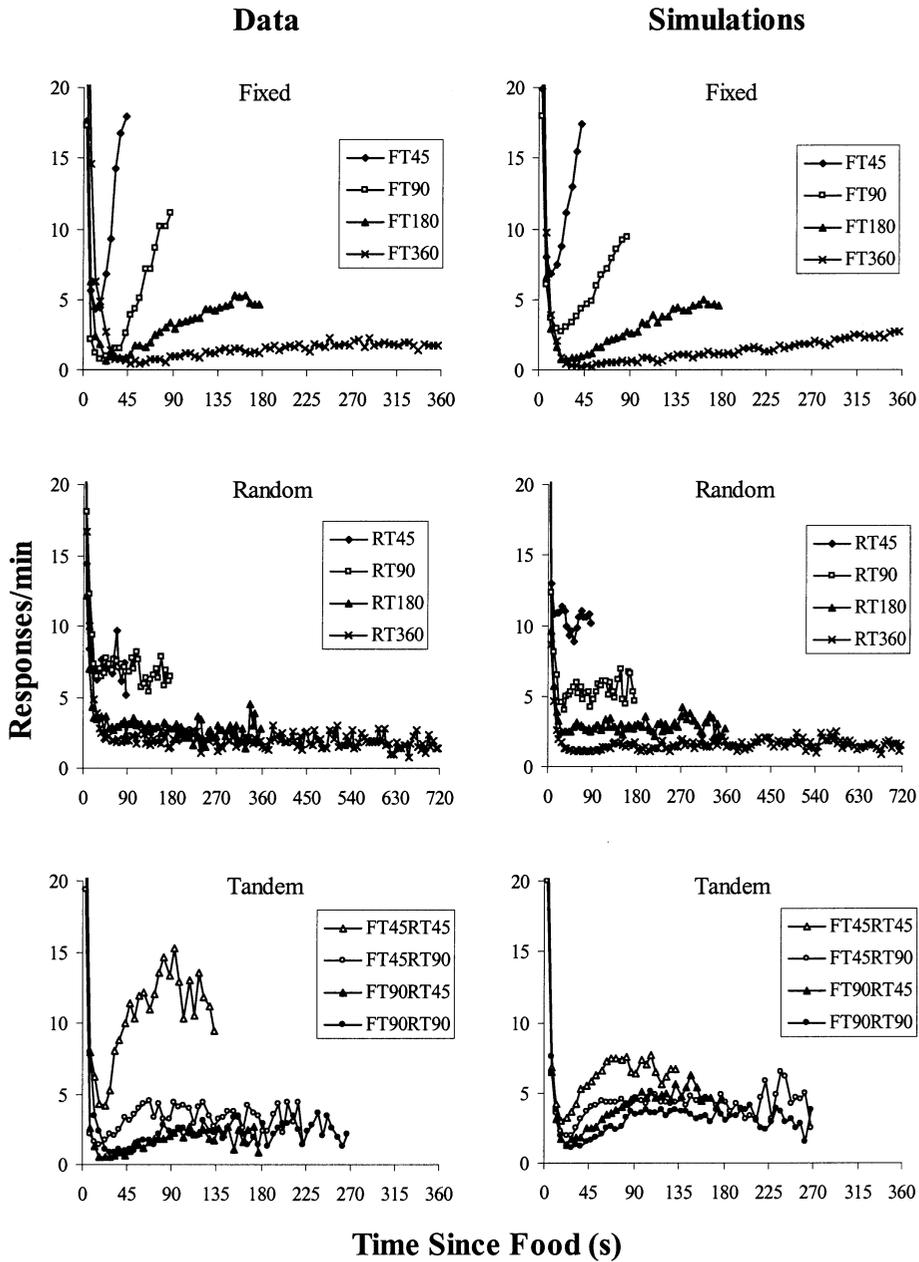


Fig. 3. Left column: data from rats that received fixed (top), random (middle) or tandem (bottom) intervals. Each panel contains the response rate (in responses/min) as a function of time since food for different groups of rats that received different mean durations between successive food deliveries. Right column: simulation results from packet theory conducted on the same procedures as the rats. The model received fixed (top), random (middle) or tandem (bottom) intervals. Each panel contains the response rate produced by the model as a function of time since food. Adapted from Kirkpatrick and Church (2002a).

expected time function. This relationship suggests that the rats were sensitive to the mean time remaining in an interval. The functions for the tandem fixed random groups are perhaps the most interesting because there were no external cues to signal the fixed and random components. The rats appeared to detect that there was a minimum delay between successive food deliveries (the fixed portion) after which food was delivered at a random time with some mean (the random portion).

Simulations of Packet theory were conducted using the same procedures as the rats received. The simulation was conducted for a total of 1920 reinforcements (the same number as the groups of rats received). The parameter settings and goodness-of-fit measures can be found in Table 1. The right column of Fig. 3 contains the output of the simulations. Each panel of the figure contains the response rates produced by the model as a function of time since food.

Packet theory produced response rate functions that were highly similar to the data from the rats. The overall fit of the model to the data was reasonably good (see Table 1), with  $\omega^2$  values exceeding 0.8 for all but one group. The poor fit

of the model was to the FT45 RT45 s group, where the model under-predicted the mean response rate. Another failure of the model was that it predicted the RT 45-s condition should have a higher response rate than the RT 90-s condition, whereas these two conditions yielded quite similar response rates in the rats. It is not clear why the two RT conditions failed to produce different response rates given that the rate of reinforcement was doubled in the RT 45-s condition. Doubling of the reinforcement rate would normally produce a noticeable increase in response rate (e.g. De Villiers and Herrnstein, 1976).

The inadequacies in prediction of response rates by the model occurred because the responsiveness parameter,  $n$ , was fixed for all groups. If  $n$  had been allowed to vary across conditions, then response rates could have been predicted accurately. However, allowing  $n$  to vary across conditions of the same experiment greatly increases the flexibility of the model. It was decided that some trade-off in accuracy was worth restricting model flexibility because flexible models achieve highly accurate fits by absorbing random variance in the data (Cutting, 2000).

Whereas distribution form primarily affects the form of the response rate gradient, mean interval duration (e.g. reinforcement density) primarily affects the overall rate of responding in an interval. Longer intervals generally result in lower response rates than shorter intervals (e.g. De Villiers and Herrnstein, 1976; Herrnstein, 1970). The negative relationship between mean interval duration and mean response rate is non-linear and can be fit by exponential, power, or hyperbolic functions (e.g. De Villiers and Herrnstein, 1976).

The effect of interval duration on response rate is shown in Fig. 4, which contains the mean response rates as a function of mean interval duration, plotted on double-log coordinates (Kirkpatrick and Church, 2002a). The filled symbols in the figure are the mean rates across the rats in each group and the open symbols are results of the Packet theory simulations. These are the mean response rates taken from the groups of rats that received temporal conditioning procedures with FT, RT, and tandem FT RT schedules (see Fig. 3). There was a negative relationship

Table 1  
Parameter values for simulation data in Fig. 3

Group	$\alpha$	$N$	$\rho$	$\omega^2$
FT45	0.05	1.7	0.55	0.911
FT90	0.05	1.7	0.50	0.887
FT180	0.05	1.7	0.60	0.991
FT360	0.05	1.7	0.85	0.955
RT45	0.05	1.7	0.65	0.893
RT90	0.05	1.7	0.80	0.908
RT180	0.05	1.7	0.70	0.932
RT360	0.05	1.7	0.70	0.828
FT45RT45	0.05	1.7	0.60	0.657
FT45RT90	0.05	1.7	0.55	0.846
FT90RT45	0.05	1.7	0.60	0.910
FT90RT90	0.05	1.7	0.70	0.954

Simulations were ran for 1920 reinforcements on fixed time, random time or tandem fixed time random time schedules of food delivery, with different mean interval durations ranging from 45 to 360 s. The model received the same number of reinforcements as the rats.  $\alpha$ , weight given to new durations entering into memory;  $n$ , expected number of packets per interval;  $\rho$ , probability of firing a reactive packet.

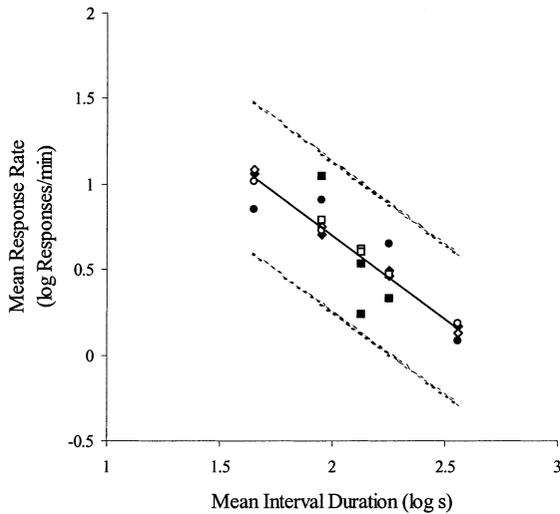


Fig. 4. The effect of mean interval duration on mean response rate for fixed, random, and tandem fixed random intervals of different durations in a temporal conditioning procedure. Mean response rate and mean interval duration are expressed as base 10 logarithms. There was a negative relationship between interval duration and response rate for both the model (open symbols) and the rat (closed symbols) data. The solid line through the points is the best-fitting linear regression conducted on the data from the rats. This function had a slope of  $-0.98$ . The dashed lines on either side of the regression are the upper and lower boundaries of a 95% confidence interval. All of the data from the rats and the model fell within the confidence interval band. The different shaped symbols code the different types of distributions received by the rats and model: diamond = fixed interval, circle = random interval, square = tandem interval. Adapted from Kirkpatrick and Church (2002a).

between interval duration and response rate that was characterized by a power function. A regression analysis revealed that log interval duration was a predictor of log response rate, but distribution form was not. The slope of the regression line was  $-0.98$ . All of the data fell within the 95% confidence interval boundaries of the regression fit (dashed lines). The model simulations of mean response rates accounted for 74.5% of the variance in the data.

The prediction of mean response rate as a function of interval duration emerges from packet theory because the sum of the probability function ( $p_i$ ) over the range of time steps 0 to  $D$  is equal to  $n$  (the expected number of packets per

interval). Longer interval durations will have a lower probability of packet generation per second compared to shorter intervals. If the expected number of packets ( $n$ ) is 2.0, then the mean probability of a packet per second in a 10-s fixed interval will be 0.2, in a 20-s fixed interval will be 0.1, etc. There will be the same number of packets in the 10-s interval as in the 20-s interval but the packets will occur in half the span of time. This relationship was supported by the linear regression fits to the rat data in Fig. 4 that had a slope very near  $-1$  on a log-log scale (i.e. a power function with a slope of  $-1$ ).

In addition to predicting the form and rate of responding, packet theory also produces the scalar property of timing when fixed intervals are delivered. The scalar property (Gibbon, 1977) is demonstrated in the top panel of Fig. 5, which contains data from fixed interval schedules with reinforcements occurring every 30, 300 or 3000-s (Dews, 1970). The data from Dews (1970) are a classic example of the scalar property on fixed interval schedules of reinforcement. This data set was used instead of the data in Fig. 3 because the FT45 s function did not superpose with the other groups; this may have been due the initial reaction response to food delivery which was still ongoing when this group began their anticipatory responding. The data in Fig. 5 are plotted on relative time (proportion of total interval duration) and relative rate (proportion of terminal rate) scales, demonstrating that the functions superpose. The scalar property of timing is an example of Weber's law. The 'error' in timing grows in proportion to the total duration.

Packet theory predicts scalar timing because the spread of the conditional expected time function, and hence the spread of the probability function ( $p_i$ ), grows in proportion to the interval duration. For example, the spread of a 90-s fixed interval will be twice that of a 45-s interval. The scalar property is the observation that response rate depends on relative time in the interval; Packet theory predicts that the relative probability of a response depends on the relative time in

the interval,<sup>1</sup> which translates directly into relative response rate because of the invariance in the packet characteristics.

The bottom panel of Fig. 5 contains the simulations of Packet theory on 30, 300 and 3000 s fixed intervals between successive food deliveries. The simulations were conducted for 1000 reinforcements each. The parameter settings for all three groups were:  $\alpha = 0.05$  and  $n = 1.2$ . There were no packets elicited by food delivery ( $\rho = 0$ ). When the functions from the theory are plotted on relative time and rate scales, they superpose. The solid line through the data points in the top panel is the average of the three functions generated by Packet theory (bottom panel). The fits of the data yielded  $\omega^2$  values of 0.990, 0.994, 0.996 for the 30, 300 and 3000 s intervals, respectively.

In sum, Packet theory can account for several features of timed responses through a relatively simple mechanism. The conditional expected time function encodes the mean time remaining in an interval, which affects both the form of the response rate gradient and the overall rate of responding. The theory will now be applied to simple classical conditioning procedures to demonstrate the predictions of interval duration effects on the strength of conditioning.

<sup>1</sup> The prediction of the scalar property emerges from Eqs. (5a) and (5b). For a fixed interval of 90 s, the conditional expected time  $E_t$  is equal to  $D-t$  where  $D$  is the fixed interval duration and  $t$  is the time in the interval (see Eq. (2)); at time 0 the conditional expected time is equal to the duration of the fixed interval,  $D$ . The transposed expectation  $E'$  (Eq. (5a)) therefore becomes  $D-(D-t)$  or  $t$ . In other words, the transposed expectation will increase linearly from 0 to 90 as time in the interval increases from 0 to 90. The transformed expectation,  $E^*$  (Eq. (5b)) now becomes  $E^* = t/\sum_{t=0}^D t$ . The sum of all  $t$  values between 0 and  $D$  is  $D(D+1)/2$  so that the transformed expectation is  $E^* = 2t/D(D+1)$ . Thus, the transformed expectation function and resulting probability function ( $p_t$ ) are proportional to  $t/D^2$ . The scalar property is observed when the response rate functions are normalized by dividing the response rate at each time by the maximum response rate. In other words, the probability of response ( $p_t$ ) is divided by the maximum probability of response. The maximum probability of response occurs at time  $t=D$  so that the relative probability of response as a function of time in an interval is determined by  $p_t/\max(p_t)$  which is proportional to  $(t/D^2)/D$  or  $t/D$ . Thus, the relative probability of responding is proportional to the relative time in an interval ( $t/D$ ), which is the scalar property.

#### 4.1. Interval effects in classical conditioning

There are three well-established effects of interval durations on the magnitude or probability of conditioned responding. The first is the interval between conditioned stimulus (CS) onset and unconditioned stimulus (US) delivery. This interval is often referred to as the CS–US interval, or the trial duration. In delay conditioning, where US delivery coincides with CS termination, the CS–US interval is the same as the stimulus duration. The magnitude of responding is often a direct

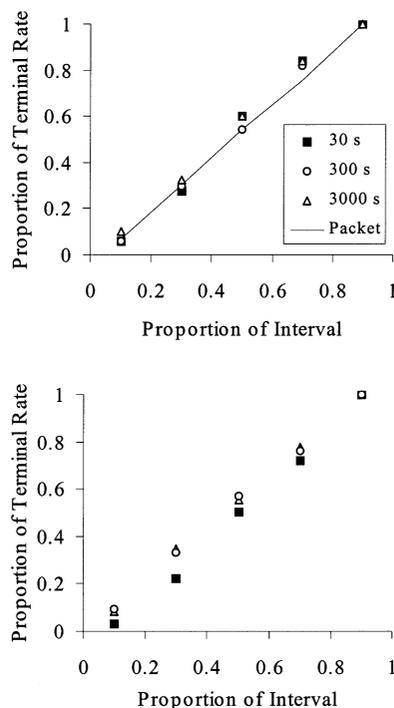


Fig. 5. Packet theory predictions of the scalar property of time perception. Each panel of the figure contains the response rate as a function of time in a fixed interval procedure. Response rates were transformed into relative rate by dividing response rates at each time by the terminal response rate. Time in the interval was transformed into relative time by dividing each time by the interval duration. Top panel: the three functions from 30- 300- and 3000-s fixed interval procedures superpose when plotted on relative time and rate scales. The solid line through the data is the mean fit of packet theory. Bottom panel: the three functions produced by the packet model simulations also superpose when plotted on relative time and rate scales, demonstrating the scalar property. Adapted from Dews (1970).

function of stimulus duration, with shorter stimuli resulting in stronger magnitudes of responding (e.g. Bitterman, 1964; Black, 1963; Gibbon et al., 1977; Salafia et al., 1975; Schneiderman and Gormezano, 1964). A second important interval is the interval between CS termination and US delivery in trace conditioning procedures. This interval is often referred to as the trace interval. Recent evidence has indicated that shorter trace intervals result in stronger magnitudes of trace interval responding (Kirkpatrick and Church, 2002b). The third important interval is the time between successive US deliveries. This interval is often referred to as the inter-trial interval or the cycle duration. Cycle duration is often negatively related to the magnitude of CS responding, with shorter cycles resulting in weaker responding (e.g. Domjan, 1980; Gibbon, et al., 1977; Salafia et al., 1975; Terrace et al., 1975). Recent evidence has suggested that cycle duration effects on the relative magnitude of stimulus responding are due to elevated responding during the intertrial interval, with shorter food–food cycles resulting in higher rates of responding in the intertrial interval (Holland, 2000; Kirkpatrick and Church, 2000b).

The effect of stimulus, trace, and cycle duration on the rate of responding is shown in Fig. 6. The figure contains the mean rates of head entry responding (in responses/min) produced by rats (filled symbols) and by Packet theory simulations (open symbols) as a function of interval duration for stimulus, trace, and cycle durations, plotted on double-log coordinates. The rates during the stimulus were taken from a delay conditioning procedure with stimulus durations of 15, 30, 60 or 120 s; all four groups of rats received fixed 180 s cycle durations between successive food deliveries (Kirkpatrick and Church, 2000b). The rates during the stimulus are plotted against stimulus duration. The rates during the cycle were taken from the intertrial interval period of a delay conditioning procedure with food–food cycle durations of 90, 180 or 360 s; all three groups of rats received a fixed 60-s stimulus duration (Kirkpatrick and Church, 2000b). The rates during the intertrial interval are plotted against cycle duration. The rates during the trace interval were taken from a trace conditioning procedure with a 60-s fixed

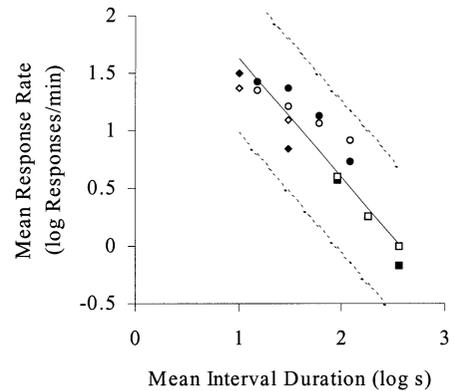


Fig. 6. The effect on mean interval duration on mean response rate for stimulus (time between stimulus onset and food delivery), cycle (time between successive food deliveries), and trace interval (time between stimulus termination and food delivery) durations, plotted on double log(base 10) coordinates. The mean response rates from both the rats (closed symbols) and the model (open symbols) were negatively related to mean interval duration, regardless of interval type. The solid line through the points is the best-fitting linear regression conducted on the data from the rats. This function had a slope of  $-1.04$ . The dashed lines on either side of the regression are the upper and lower boundaries of a 95% confidence interval. All of the data from the rats and the model fell within the confidence interval band. The different shaped symbols code the different types of intervals during which response rates were observed: diamond = trace interval, circle = stimulus, square = cycle.

duration between stimulus onset and food delivery, but with either 10- or 30-s trace intervals (Kirkpatrick and Church, 2002b). The rates during the trace interval are plotted against trace interval duration.

As seen in the figure, there is a negative relationship between interval duration and response rate, regardless of interval type. A linear regression analysis was conducted on log response rates from the rats (closed symbols) with variables of log interval duration and interval type (stimulus, cycle, or trace). The overall regression was significant ( $F(2,6) = 20.0$ ,  $P < 0.01$ ). Log interval duration predicted log response rate ( $t(7) = -4.1$ ,  $P < 0.01$ ), but interval type did not ( $t(2) = 0.3$ ). The solid line through the data is the best fitting regression function. This function had a slope of  $-1.04$ . The dashed lines on either side of the regression fit are the upper and lower boundaries

of a 95% confidence interval. All of the data from the rats fell within in the confidence interval.

Simulations of packet theory were conducted using the same procedures as were given to the rats. The simulations were conducted for 1000 reinforcements. Parameter settings for the different groups are given in Table 2. Different values of  $n$  were used for food expectations (i.e. responding in the intertrial interval), stimulus onset expectations (responding during the stimulus duration), and stimulus termination expectations (responding during the trace interval). The output from the theory was analyzed in the same manner as the data from the rats. All of the theory simulations (open symbols in Fig. 6) fell within the 95% confidence interval boundaries of the regression fit to the rat data. The packet theory simulations corresponded with the data reasonably well ( $\omega^2 = 0.837$ ) and there were no systematic deviations of the theory fits from the data.

The predictions of mean response rate as a function of interval duration in Fig. 6 are the same as the earlier predictions in Fig. 4: longer interval durations will have a lower probability of packet generation per second compared to shorter

intervals, thereby causing lower overall response rates. The fact that the relationship between log interval duration and log mean response rate has a slope of  $-1$  for temporal (Fig. 4), delay (Fig. 6), and trace (Fig. 6) conditioning procedures is quite remarkable. There appears to be a general effect of interval duration regardless of the type of time marker and type of procedure, at least with the limited range of types employed here.

In addition to effect of stimulus, cycle and trace interval duration on response rate, Gibbon and Balsam (1981) have demonstrated that the stimulus:cycle ratio is a strong predictor of the magnitude of responding during the stimulus in delay conditioning procedures. The stimulus:cycle ratio is often referred to as the duty cycle. The duty cycle is an index of the percentage of the cycle between successive reinforcements that is taken up by the stimulus. When the stimulus occupies a higher percentage of the cycle (large duty cycle), responding during the stimulus is weaker than when the stimulus occupies a lower percentage of the cycle (small duty cycle). The negative relationship between the magnitude of conditioned responding and duty cycle has been reported previously in both pigeon autoshaping (c.f. Gallistel and Gibbon, 2000; Gibbon and Balsam, 1981) and rat goal-tracking paradigms (Holland, 2000; Kirkpatrick and Church, 2000b; Lattal, 1999).

Fig. 7 displays the relationship between duty cycle and the strength of conditioning during the stimulus (closed symbols; Kirkpatrick and Church, 2000b). Stimulus conditioning was measured with a discrimination ratio, which was the stimulus response rate divided by the stimulus response rate plus the intertrial interval response rate.

The output from Packet theory in Fig. 7 (open symbols) was taken from the simulations conducted on the delay conditioning procedure with stimulus intervals of 15, 30, 60 or 120 s and cycle durations between successive food deliveries of 90, 180 or 360 s. Parameter settings are given in Table 2. The packet model predicted the duty cycle effect on conditioning, and corresponded closely with the data from the rats ( $\omega^2 = 0.956$ ). The duty cycle effect on conditioning emerges directly from the predictions of interval duration effects on

Table 2  
Parameter values for simulation data in Fig. 6

Interval	$\alpha$	$n_1$	$n_2$	$n_3$
S 15 s	0.05	1.7	2.2	0
S 30 s	0.05	1.7	2.2	0
S 60 s	0.05	1.7	2.2	0
S 120 s	0.05	1.7	2.2	0
C 90 s	0.05	1.7	2.2	0
C 180 s	0.05	1.7	2.2	0
C 360 s	0.05	1.7	2.2	0
T 10 s	0.05	0	2.2	1.8
T 30 s	0.05	0	2.2	1.8

Simulations were ran for 1000 reinforcements on delay or trace conditioning procedures. Delay conditioning procedures were used for stimulus durations (S) ranging from 15 to 120 s and for cycle durations (C) ranging from 90 to 360 s. Trace conditioning procedures were used for trace interval durations (T) of 10 or 30 s.  $\alpha$ , weight given to new durations entering into memory;  $n_1$ , expected number of packets per interval for food-initiated intervals;  $n_2$ , expected number of packets per interval for stimulus onset-initiated intervals;  $n_3$ , expected number of packets per interval for stimulus termination-initiated intervals.

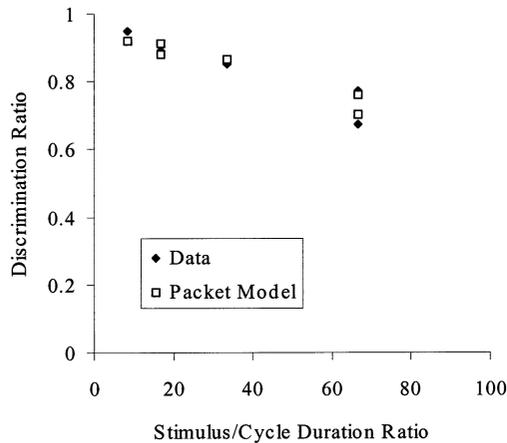


Fig. 7. Packet theory predictions of the effect of duty cycle (stimulus:cycle duration ratio) on the strength of conditioning during a stimulus in a delay conditioning paradigm. The duty cycle is the percentage of the food–food cycle that is occupied by the stimulus. The strength of conditioning was measured by a discrimination ratio. Adapted from Kirkpatrick and Church (2000a,b).

absolute response rate. The duty cycle is the ratio of stimulus:cycle duration. The discrimination ratio (measure of conditioning) is the ratio of stimulus:cycle responding. Take, for example, the effect of increasing stimulus duration while holding cycle duration constant. With a food–food cycle duration of 180 s and a stimulus duration of 30 s, the duty cycle will be 30/180 or 0.17. If stimulus duration is increased to 60 s, the duty cycle will increase to 60/180 or 0.33, the rate of responding during the stimulus will decrease, and the discrimination ratio will therefore decrease. In other words, increasing the duty cycle (by increasing stimulus duration) will decrease the discrimination ratio, as shown in Fig. 7. The effect of cycle duration occurs for the same reason, but in the reverse direction. With a stimulus duration of 60 s and a cycle duration of 180 s, the duty cycle is 60/180 or 0.33. Increasing cycle duration to 360 s results in a decrease in duty cycle to 60/360 or 0.17, a decrease in responding in the intertrial interval (see Fig. 6), and an consequently an increase the discrimination ratio. Thus, decreasing the duty cycle (by increasing cycle duration) will increase the discrimination ratio, as shown in Fig. 7.

By using a timing mechanism that encodes the mean timing remaining until food from different events, Packet theory can successfully predict the effect of interval duration on the magnitude of the conditioned response, as well as predicting the effect of duty cycle on the relative magnitude of responding. All of the predictions of the theory emerge directly from the conditional expected time function, with no added assumptions.

## 5. Packet theory evaluation

With regard to the current implementation, there are a number of unique predictions of packet theory: (1) the response rate as a function of time in an interval is inversely related to the conditional expected time to food for fixed, random, and tandem intervals. The theory predicts that timing will occur on any interval distribution and makes explicit predictions of the form of the response rate gradient. Further experimentation will be required to determine whether the theory accurately predicts the form of the response gradient on a wider range of interval distributions. (2) The mean response rate is inversely related to the mean expected time to food, regardless of interval distribution or type of time marker (e.g. food, CS onset, etc.). (3) The relationship between mean interval duration and mean response rate produces the effects of CS–US, intertrial, and trace intervals on the strength of conditioning. (4) The relationship between mean interval duration and mean response rate produces the effect of duty cycle on the strength of conditioning. Because the duty cycle predictions emerge from the effect of the individual stimulus and cycle durations on response rate, packet theory asserts that there should be deviations from stimulus:cycle ratio invariance when the stimulus and cycle durations are short. A recent experiment by Holland (2000) demonstrated distinct violations in ratio invariance with shorter pairs of intervals. This prediction of packet theory stands in contrast to rate expectancy theory (Gallistel and Gibbon, 2000), which purports that ratio invariance should hold regardless of the absolute durations of the pair of intervals that make up the ratio, and appears to

favor an absolute-interval approach to explaining the duty cycle effect.

There are a number of strengths of packet theory. One strength is simplicity. There are three parameters of the model that were manipulated in the present fits:  $\alpha$  the weighting parameter for updating memory,  $n$  the expected number of packets per interval, and  $\rho$  the probability of producing a reactive magazine entry packet following food. The parameter  $\rho$  was only used for the fits in Fig. 3, where the rats produced magazine entry responses following food delivery.

Another strength is inflexibility. An inflexible theory should have a limited number of possible outcomes for a particular procedure. Packet theory is highly inflexible because the conditional expected time function in memory is determined by the set of input intervals. The weighting parameter  $\alpha$  only affects the impact of recently presented intervals on the form of the function in memory. Overall responsiveness can be manipulated with the parameter  $n$ . This parameter does add flexibility to the model, but for the present implementations it was required that  $n$  be fixed at the same value for all conditions in a particular experiment. If  $n$  were allowed to vary between conditions, the goodness-of-fit of the model would increase, but with the trade-off of increased model flexibility.

The model also accurately fit most of the data. Across Figs. 3–7, there were more than 1000 data points, many of which were independent. The only poor fit of the model was to the tandem FT45 RT45 s group in Fig. 3, where the model under-predicted response rate but correctly predicted the form of the response rate gradient. The overall fit of the model across all of the various conditions and experiments was  $\omega^2 = 0.9$ .

A final strength of the model is parsimony. The predictions of the effect of intervals on the timing and conditioning of responding have traditionally required separate explanations. Moreover, the effects of interval duration on conditioning have been treated independently from the effects of interval duration on timing. The most important contribution is the prediction of rate and form of responding across a variety of procedures and interval types using a single mechanism and a

limited number of parameters. Packet theory predicts that ‘timing’ occurs under any interval distribution, even random exponential, and that the same mechanism is used for determining the form and rate of responding under different types of interval distributions.

Although there are a number of strengths of packet theory, there are also weaknesses. One is generality of the model. A general theory should fit many measures of responding obtained under many different procedures. For packet theory to be considered truly general, it will need to be applied to a wider range of measures of behavior and a much wider range of phenomena.

The current implementation of packet theory only examined theoretical fits to response rate functions averaged over many trials. The model makes clear predictions of responding on individual trials that need to be formally tested. One unique prediction of packet theory is that there should be clear deviations from the break-run pattern that is typically reported in fixed interval schedules (Schneider, 1969). The model predicts that on long intervals there will be clearly defined (and perhaps multiple) short bouts that will increase in probability as a function of time. However, on shorter intervals, the pattern of responding will more closely resemble a break-run because the high probability of a packet will cause multiple packets to run together near the end of the interval. In the current set of procedures, the schedules did not result in a high enough probability of packet production to observe a change from short bouts to break-run, so this prediction will need to be tested at some later point.

The model also should be extended to predict other behaviors. The extension to other discrete-response paradigms such as lever pressing and keypecking should be relatively simple. The temporal characteristics of the packets (number of responses and interresponse time) can be changed to accommodate different responses. The model may also be able to deal with single-response paradigms. For example, a packet of eyeblink responding would typically contain a single response that would change in magnitude over time. The temporal characteristics of the eyeblink could be encoded in the packet module. Continuous

responses such as conditioned freezing or maze running may be modeled as a bout of engagement that lasts for a typical duration, perhaps with some variance. Interestingly, overall running speed in an ally appears to be determined by the relative time spent engaged in running; there is little change in running speed during a period of engagement (Cotton, 1953; Drew, 1939).

There are a number of issues that need to be resolved in the next implementation of the model so that the model can fit data from a wider range of procedures. First, responding on fixed intervals is often an ogive. The current version of the model only is capable of predicting straight-line increases in response rate (Fig. 5). This could be addressed by adding a threshold to the decision component of the model. Currently, packets are produced whenever the probability of a packet exceeds a uniformly distributed random number between 0 and 1. A threshold with some mean and variance could be added to the model to produce ogival response rate functions, but further work will be needed to determine the appropriate type of threshold to add, without disrupting the model's capability to predict the data in the current article.

Another limitation is there is no means of ceasing responding after the expected time of reinforcement has passed, as in the peak procedure (Roberts, 1981). In the current implementation of the model, the probability of producing a packet remains at the value that was reached when  $t = D$ . On fixed intervals, the probability remains at the value that is reached when food is expected to occur. Thus, the model currently predicts that responding on the peak procedure will increase up until the normal time of food delivery and then remain high. One possible approach is to assume that packets continue to be initiated after the expected time of food, but only until the expected number of packets,  $n$ , is reached. Packets are produced probabilistically, so often the expected number would not be reached by the time that food is expected. These packets could then be delivered probabilistically until they are exhausted. This would produce a decrease in response rate after food is expected. However, further work needs to be conducted to determine

whether the form of the peak function would be correct under these circumstances.

Finally, there are a number of rules of implementation that need to be worked out. For example, the model currently assumes that only reinforcement produces an update. However, it may be desirable to have other events produce updates, such as stimulus onset and termination events. This may be necessary to expand the model's domain to predict phenomena such as sensory preconditioning, wherein the times between two consecutively presented non-reinforced stimuli appear to be learned and later transferred when one of the stimuli is reinforced (see Barnet et al., 1997). Also, there are resetting rules in the model. Currently, it is assumed that an expectation function resets to its initial value whenever food is delivered, or the event that is associated with the expectation recurs (e.g. if there are multiple stimulus onsets in a food–food interval, the stimulus-onset expectation will reset to its initial value each time). Finally, there are combination rules to work out when there are multiple expectations active at once. The model currently assumes that these expectations are independently active and packets that are fired by each expectation sum together. However, there are conditions under which expectations likely compete, such as in the blocking paradigm.

## 6. Summary and conclusions

Packet theory is a new account that integrates conditioning and timing phenomena using a simple singular mechanism. The theory is capable of explaining a number of basic conditioning and timing results including the form and rate of responding under different interval distributions, the scalar property, stimulus, cycle, and trace interval effects in conditioning, and duty cycle effects on conditioning. Although the theory needs further work to fit a wider range of response forms (e.g. peak procedure, ogives) under a wide range of procedures, the current implementation is a parsimonious account of responding on time-based procedures. The present report lends support to the notion that timing and condition-

ing may be integrated into the same theoretical framework and offers a unique time-based account of the conditioning process. It is hoped that the success of the model within this limited set of procedures will inspire further research into the role of timing mechanisms in the conditioning process.

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