PASTIS: A PROGRAM FOR CURVE AND DISTRIBUTION ANALYSES

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Running head: Curve and Distribution Analyses

Abstract

Reaction time data afford different types of analyses. One type of analysis, called curve analysis, can be used to characterize the evolution of performance at different moments over the course of learning. By contrast, distribution analysis aims at characterizing the spread of reaction times at a specific moment. Techniques to deduce free parameters are described for both types of analyses, given an a priori choice of the curve or distribution one wants to fit, along with statistical tests of significance for distribution analysis. These techniques are the log likelihood technique, if the probability density function is given; otherwise, a root-mean-square-deviation minimization technique is used. A program called PASTIS is presented which searches for the optimal parameters of the following curves: power-law, exponential and e-based exponential, and the following distributions: the Weibull and the Ex-Gaussian. Some tests of the software are presented.

PASTIS: A PROGRAM FOR CURVE AND DISTRIBUTION ANALYSES

Curve analysis can be used to characterize reaction times (RT) collected over different sessions. The chief concern of this type of analysis is the improvement of RT, more specifically the rate of the improvement, and the performance that would be expected after an infinite amount of practice (Newell and Rosenbloom, 1981). By contrast, distribution analysis is usually concerned with RTs obtained during one session. Distribution analysis can be used to locate outlier RTs and to test models of RT data (Ratcliff, 1978).

These two types of analyses are not mutually exclusive, but rather complementary. Curve analyses can describe mean RTs at different moments in time, while distribution analyses give a closer look at a specific moment. In fact, the results of curve and distribution analyses performed on a given set of data should converge in order to provide a coherent interpretation.

In order to perform curve and distribution analyses, one must first select likely functions to fit the data. Some candidate distributions for RTs are the Log-Normal and the Gamma, also known as the Erlagian (Ulrich and Miller, 1994). Other distributions have also been considered (see Luce, 1986). In this paper, we focus on the Ex-Gaussian and the Weibull distributions. With respect to curve analysis, we will be concerned mostly with the famous power-law and a possible alternative, the exponential curve.

Techniques used to compute the values of the free parameters of these various functions will be discussed first. Then, a program called PASTIS is presented that can perform the analyses discussed. Finally, the results of tests made to evaluate the capabilities of the program will be presented.

Curve Analysis

Curve analysis of RT data is often done in studies concerned with automatization of performance (Logan, 1988, Lasaline and Logan, 1992, Kramer, Strayer, and Buckley, 1990). Figure 1 illustrates the evolution of performance that typically occurs over practice, by showing the results of a fictional nine-session experiment. Mean RTs per session are presented along with a curve that fits them.

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insert Figure 1 about here

This plot has three parameters of interest: the value of performance prior to any learning (parameter b), the value of performance after infinite learning (parameter a), and the rate c at which performance drops toward the asymptote, usually called the learning rate.

Current theories of automatization try to account for changes in mean RTs with practice. However, this is not the sole measure of performance that could be used; one could be interested in the behavior of median RT, for example. Instead of summary measures, one could also attempt to fit raw data. It is important to note that these fits may yield very different results, since the functions considered are non linear. It is therefore important that researchers choose the right measure of performance in view of the theory tested. In this section, we will talk about mean RTs. However, PASTIS can handle raw data as well as summary measures.

<u>The Power-Curve</u>

In a very influential paper, Newell and Rosenbloom (1981) argued that the equation which best characterizes the relation between mean RT (M) and sessions of practice N is:

$$M = a + b\,(N + e)^{-c}$$

where a, b, and c represent the theoretical asymptote, the starting value, and the learning rate, and where e quantifies the amount of pre-experimental practice. Since most researchers assume that subjects are totally naive toward the task, they set e to zero (see however Heathcote and Mewhort, 1995). The most common form of the power-law is thus stated as:

$$M = a + b\,N^{-c} \qquad (1)$$

The free parameters are constrained to be greater or equal to zero, and, in the Exponential curve presented later (equation 5), the c parameter must be smaller or equal to 1 since it is a rate of learning, expressed in percentage.

The search for the best possible values of the free parameters is done using a minimization algorithm. The algorithm used in PASTIS is STEPIT (Chandler, 1965).[1] Another search algorithm called PRAXIS was developed by Brent in 1973, and implemented in C by Gegenfurtner (1992). Although we did not proceed to a systematic exploration of the capacities of both algorithms, our experience with curve analysis showed that PRAXIS converged faster on a set of estimates than STEPIT. However, parameters obtained using STEPIT often provided a better fit of the data. For distribution analysis, the two algorithms performed equally well. We therefore decided to incorporate STEPIT into PASTIS.

The value that PASTIS attempts to minimize is the root-mean-square-deviation (RMSD) statistic given in equation (2), which reduces discrepancies between expected and observed means. Note however that there is no guarantee that the minimization algorithm will yield the smallest RMSD value. Indeed, the multidimensional space defined by the possible parameter values along with the corresponding RMSD may contain numerous local minima in which the algorithm can get trapped.

$$RMSD = \sqrt{\tfrac{1}{n}\sum_{i}^{n}(E_i - O_i)^2} \qquad (2)$$

In equation 2, i indexes the n sessions, O_i is the observed mean RT at session i, and E_i is the expected mean RT at session i, given a set of parameters a, b, c.

One approah for testing the significiance of the fit would be to linearize the relation between RTs and time of evaluation N, and use tests based on least-square methods. Subtracting a from both sides of equation 1 yields $M - a = b\,N^{-c}$. Computing logarithm gives $\log(M - a) = \log(b) - c \log(N)$, a linear function with a slope of -c, and an intercept of log(b). However, least-squares methods usually require that experimental error be independent, additive, and normally distributed. But, as Sternberg (1969) pointed out, these assumptions, if valid before the transformation, are certainly destroyed after the logarithmic transformation. The Kolmogorov-Smirnov test (also called the Kolmogorov one-sample test; see Conover, 1980) could be used to test the normality of the residuals. However, Heathcote, Popiel and Mewhort (1991) preferred to use the non-parametric Wilcoxon sign test (see Bates and Watts, 1988 for further reading in this issue).

A Special Case Of The Power-Law Curve Analysis: Logan's Theory

Logan's exemplar theory of automatization predicts that both the mean and the standard deviation (SD) of RTs should decrease with practice following a power-law function, and that the learning rate should be the same for both measures (Logan 1988). Equations relating mean RT (M) and standard deviation (SD) are thus:

$$M = a' + b'\,N^{-c}$$

$$SD = a'' + b''\,N^{-c} \qquad (3)$$

PASTIS can be used to simultaneously fit M and SD with a common c parameter.

The Exponential Curve

Heathcote and Mewhort (1995) recently contested the power-law of practice suggesting that the exponential curve could provide a better characterization of the evolution of RTs. One reason for rejecting the power-law is that the parameters obtained often have implausible values. Heathcote and Mewhort's survey of the literature on power-law shows that the asymptote a, for instance, is often evaluated to be equal to zero. Exponential fits do not show the same pathology.

The exponential function relating mean RT (M) to practice session N is:

$$M = a + b(1-c)^N \qquad (5)$$

where a, b, c have the same interpretations as in the power function. However, learning rates c are on a different scale.[2]

Equation 5 can be linearized using a log transformation of the M - a value. However, this function will be linear with respect to N, instead of log (N) for the power curve.

The exponential equation 5 has been used by Rescorla and Wagner (1973) as a model for associative strength in Pavlovian conditioning.

Distribution Analysis

Distribution analyses have been done in tasks such as visual search (Ratcliff, 1978, Hockley, 1984), recognition (Ratcliff and Murdock, 1976), letter arithmetic (Logan, 1992), and signal detection (Hohle, 1963). It has also been used to generate simulated data and to test assumptions about truncation or use of medians (Ulrich and Miller, 1994, Ratcliff, 1995).

RT distributions can be represented in a variety of ways (Luce, 1986). The two best known are the probability density function (PDF), which gives the probability to observe a certain RT, and the cumulative function (see Figure 2).

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insert figure 2 about here

Information about the central tendency and the standard deviation, as well as the skewness (seen as an asymmetry in the distribution) are best visualized using the PDF.

The Ex-Gaussian Distribution

Originally used by McGill in 1963, the Ex-Gaussian distribution is a combination (convolution) of a Gaussian (normal) distribution and of an exponential distribution. This distribution is known to provide a good fit for RT data in different tasks. The PDF is formulated as: (Heathcote, in press, Dawson, 1988)

$$f(RT) = \frac{1}{\tau} e^{\frac{\mu}{\tau} + \frac{\sigma^2}{2\tau^2} - \frac{RT}{\tau}} \Phi\left(\frac{RT - \mu - \sigma^2/\tau}{\sigma}\right) \qquad (6)$$

where τ stands for the average of the exponential component, μ and σ are the mean and the standard deviation of the normal component, and Φ expresses the standard Gaussian integral (see Kennedy and Gentle, 1980, for a numerical approximation). The mean of such a distribution is $\mu+\tau$, while the standard deviation is $(\sigma^2+\tau^2)^{½}$.

The Weibull Distribution

The Weibull is known to describe the distribution of minima from independent samples of identically distributed random variables. It has been used by Logan (1992) to further support his exemplarist theory of automaticity.

The cumulative function of a Weibull is given by the formula:

$$F(RT) = 1 - e^{-\left(\frac{RT-a}{b}\right)^c}$$

where a and b are additive and multiplicative scaling factors, and c is an exponential factor, sometimes called the shape factor. The mean and the standard deviation of a Weibull are expressed by:

$$M(RT) = b\,\Gamma(1 + 1/c) + a$$

$$SD(RT) = b\,[\Gamma(1+2/c) - \Gamma(1+1/c)]$$

where Γ is the gamma function (if x is integer, $\Gamma(x + 1)$ return x!).

The PDF of a Weibull is given by:

$$f(RT) = \frac{c}{b^c}(RT - a)^{c-1} e^{-(\frac{RT-a}{b})^c} \quad (7)$$

Techniques Used To Search Parameter Space

The search for the best possible values of the free parameters of the distribution is done using the same minimization algorithm as in curve analysis. In all the cases, the space is three-dimensional and all parameters are constrained to be positive or null. In the case of the Weibull, the additive parameter cannot be greater than the minimum RT.

The value that is minimized depends on the nature of the equation that needs to be fitted. For the vast majority of PDF, the best technique to use is the maximum likelihood function. This function is known to find the best estimators when they exists and are unique. Thus, an algorithm minimizing -L should tend toward a correct estimate of the free parameters, if a sufficiently high number of observation is made. The likelihood function is given by:

$$L(\theta) = \Pi\, f(RT_i)$$

where θ represents a given set of parameters (for example: $\{\mu, \sigma, \tau\}$), and Π is the product for all the observed RTs. To avoid overflow, we chose to compute a related value that has the same properties:

$$\ln L(\theta) = \Sigma \ln (f (RT_i)) \qquad (8)$$

This statistic will be minimum for the set θ that best fits the empirical data.

If the number of observations per subject is small, it is possible to pool individual RT distributions to obtain a group distribution that preserves the shape of the component distributions. Ratcliff (1979) has shown that stable estimates of the distribution's parameters can be obtained using Vincent averaging. See also Dawson (1988), and Heathcote, Popiel and Mewhort (1991).

To discover which distribution gives the best fit, a goodness-of-fit statistic called Akaike's information criterion (AIC) can be computed for each fit (reported in Maddox and Ashby, 1993). The AIC is defined as:

$$AIC(D_i) = -2 \ln L_i + 2 N_i$$

where N_i is the number of free parameters in a specific distribution analysis (indexed by i), and $\ln L_i$ is the log likelihood of the fitted data. By including a term that penalizes a model for extra free parameters, it is possible to compare across models having a different number of parameters. The model that provides the most accurate account of the data is the one with the smallest AIC.

Description of PASTIS

PASTIS (from French: Programme d'Analyse Statistique de Tendance et de dIStribution) is a UNIX-based program written in C. It can read any text file, as long as data are separated by at least one space, or by tab characters. Columns can be in arbitrary order, and there may be extra columns containing information not used for the analysis. Two operating modes are available: i) In interactive mode, PASTIS displays a prompt and waits for the user to enter options, one at a time. Errors in specifying the options are more easily detected in this mode. ii) In command mode, the options are specified on the same line as the call to PASTIS, and separated by at least one space. This method is faster, and allows the use of pastis in shell files. All the following examples are issued as a command line.

Table 1 gives an overview of the type of analysis that can be performed using PASTIS. It also mentions the type of data that should be provided to it.

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insert Table 1 about here

A summary of the necessary options to make the program run are listed below:

-r *file* : indicates which input *file* contains the data;

-c *x* : *x* indicates the total number of columns in the input file;

-d *x* : *x* indicates which column contains the dependent variable;

-a *name-of-analysis* : *name-of-analysis* indicates the type of curve or distribution analysis (see Table 1 for the possible names; upper case is mandatory)

Many analyses need other options. For example, **pastis -r data.dat -c 10 -d 3 -a PLAWCURVE c2** will analyze the power-law curve exhibited by the data contained in the file data.dat. This file has a total of 10 columns, and mean RTs are in column 3 (start counting at 1). **c2** indicates that the session of evaluation is specified in column 2.

Specification of the session number is mandatory for curve analysis. This specification allows the data lines in the input file to be in any order. Missing data is also allowed. If the data gathered during one session were lost due to computer failure, for instance, then PASTIS would compute estimates for the remaining sessions. Finally, the specification of the session number allows input of more than one measure per session. As mentioned earlier, PASTIS can operate on raw data.

Further commands are also available (the [ ] denotes an optional part):

-b c*x* [c*x*' ...]	: break the input file according to values in column x. Many columns may be used, repeating cx', cx"...).
-f c*x*=y [c*x*'=*y'* ...]	: filter file for lines where column x have the value y. There may be more than one filtering criterion.

Suppose column 1 contains subject number, then **pastis -r data.dat -c 10 -d 3 -b c1 -a PLAWCURVE c2** will make a separate analysis for each subject, while **pastis -r data.dat -c 10 -d 3 -f c1=1 -a PLAWCURVE c2** will only examine data for subject one.

-s p*x*=*y* [p*x*'=*y*' ...]	: give starting value of y to parameter x at the beginning of the search.
-h p*x*=*y* [p*x*'=*y*' ...] or p*x*<*y* or p*x*>*y*	: hold the value of parameter number x to be equal to, greater than, or lesser than value y. The parameters' number are given at the beginning of an analysis.

The p*x*<*y* and p*x*>*y* of the -h option can be combined to produce an interval in which parameter *x* is free to vary. In this case, the user must insure that the lower bound is smaller than the upper bound.

Parameters that are not set by the -s or -h options receive default values based on heuristic choices. For the Ex-Gaussian distribution, the default values are those suggested by Heathcote (in press), namely: τ = 0.8 sample standard deviation, μ = sample mean - τ, and σ = 0.6 τ. For the Weibull distribution, a = sample minimum - 3%, b = sample mean - a, and c = 1.4. Considering that the sample minimum may be due to an anticipatory response, the starting value for a will often be smaller than the estimated value. This is why the sample minimum is reduced only by a small amount. The starting value for b is related to the sample mean, following the equation defining the mean of a Weibull distribution. Finally, choice of the starting value for c was simply based on our experience.

For curve analysis, the asymptote a = sample minimum - 3%, the amplitude b = 2 (sample mean - sample minimum), and c = 0.8, except for the curve of equation 5, in which case c takes the value 0.2. Note that when the data consist of means, the sample minimum will not reflect only anticipatory responses. The starting value chosen for a assumes that the last mean RT is close to asymptote. The starting value for b could have been related to the sample maximum. However, with raw data, the sample maximum may be due to a deadline imposed by the experiment. So we decided to use the sample mean in setting the starting value of b. Finally, the starting values of c are based on our experience, and they are within the range usually found in the litterature.

For example, pastis -r data.dat -c 10 -d 3 -h p3=0.9 -a PLAWCURVE c2
will analyze the curve with the learning rate kept constant at value 0.9.

Finally, some other commands are:

-o	: help page;
-v	: verbose output (recommended);
-g	: display data information (used for debugging);

A Test of PASTIS

We tested the abilities of PASTIS to produce the correct value of free parameters in various sets of simulations. The first set was concerned with curve analysis. Data were generated using a power equation in the first two cases presented in Table 2, and an exponential equation in the last two cases. In half of the simulations, 10% of uniformly distributed random noise was added to the simulated data to see if PASTIS would converge toward the correct solution. In the other simulations, no noise was added, so the fit should be near perfect with the correct analysis.

The content of the file PL1.dat was: 1 700.00; 2 572.30; 3 524.57; 4 498.96; 5 482.78; 6 471.55; 7 463.25; 8 456.84; 9 451.73; 10 447.55. The semi-colon denotes the new-line character. The first column is the session number, and the second is the mean RT obtained. The command line to perform the first analysis reported in Table 2 reads: **pastis -r PL1.dat -c 2 -d 2 -a PLAWC c1**

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insert Table 2 about here

Table 2 gives the RMSD and the parameters of the curves fitted. When the file contains no noise, the fit is close to perfect, with a slight advantage for the EXPO1.dat file. Free parameters obtained reflect original parameters with less than 0.1% deviation. Result are still good when noise is added to the data. Since an average of plus or minus 5% of noise was added to RTs varying from 400 to 700 msec (with a mean near 500 msec), we can expect an average deviation of 25 msec. The RMSD obtained with PASTIS are 14.22 ms and 20.32 ms for the two files with noise (PL2.dat and EXPO2.dat). Clearly, data generated using a specific equation were fitted very well when using the same type of equation in analysis. However, the EXPO2.dat simulation was also well fitted by a power-curve. This result calls for two important comments: First, the exponential and the power curves can be highly similar, given an appropriate set of parameters. Therefore, it is possible to obtain fits that are almost equally good for two different theoretical curves. Second, PASTIS does not provide a statistical test to discriminate among curves. This would require knowing the underlying nature of measurement noise, as discussed before.

Similar analysis were made concerning distributions. We used two files for the Weibull distribution. Both files had 34 data point, the second having 10% of uniformly distributed random noise added to the data. For the Ex-Gaussian, we used the same data set reported in Heathcote (in press), which contained only 10 data points. The parameters used for data generation and the results of analysis can be seen in Table 3.

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insert Table 3 about here

The Weibull data were better fitted when analyzed with the Weibull equation than with the Ex-Gaussian equation. The same was also true when noise was added to the simulation. Using the AIC statistic described previously, we find that there is a difference of 35.02 in favor of the Weibull interpretation in the simulation using W1.dat ($AIC_{weibull} = 466.96$ and $AIC_{ex\text{-}gaussian} = 502.00$).

Ex-Gaussian data reveal a surprise: they fit better using a Weibull equation than using the equation used to generate the data in the first place. This result may be due to the small number of observations in this file (n = 10). Since the likelihood statistic is asymptotic, it works better with a large number of observation. When analyzed using an Ex-Gaussian distribution, results are exactly the same as those reported by Heathcote (in press).

Availability

PASTIS works on any workstation equipped with the cc compiler. The FORTRAN extensions must be present since STEPIT exists only in FORTRAN language. PASTIS has no limitation on the length of the input file: if the file contains less than 500 numbers, the data are transferred to RAM, otherwise, numbers are read directly from disk, which slows down the speed of the program (a typical analysis takes less than a minute to complete) Input files are limited to 40 columns. The order of options does not matter, except that they must preceed the-a option which specifies and triggers the analysis.

The source files, along with a compiled version for Silicon Graphics computers, comes in a .tar.Z file (119K). Sample files are also available in another .tar.Z file (4K). These files can be obtained using a world-wide-web browser at **http:\\prelude.psy.umontreal.ca\~cousined\pastis**. Instructions to compile source code are also given.

References

Bates, D. M., & Watts, G. W. (1988). Nonlinear regression analysis and its applications. New York: Wiley.

Brent, R. D. (1973). Algorithms for function minimization without derivatives. Englewood Cliffs, New Jersey: Prentice-Hall.

Chandler, P. J. (1965). Subroutine STEPIT: An algorithm that finds the values of the parameters which minimize a given continuous function [computer program]. Bloomington: Indiana University, Quantum chemistry program exchange.

Cohen, D. J., Servan-Schreiber, & D., McClelland, J. L. (1992). A parallel distributed processing approach to automaticity. American Journal of Psychology, 105, 239-269.

Conover, W. J. (1980). ; Practical Nonparametric statistics. New York: Wiley.

Dawson, M. R. W. (1988). Fitting the ex-gaussian equation to reaction-time distributions. Behavior Research Methods, Instruments, & Computers, 20, 54-57.

Gegenfurtner, K. R. (1992). PRAXIS: Brent's algorithm for function minimization. Behavior Research Methods, Instruments, & Computers, 24, 560-564.

Gluck, M. A., & Bower, G. H. (1988). From conditioning to category learning: an adaptive network model. Journal of Experimental Psychology: General, 117, 227-2.

Heathcote, A. (In press). RTSYS: A computer program for the analysis of response time data. Behavior Research Methods, Instruments, & Computers.

Heathcote, A., & Mewhort, D. J. K. (1995). The law of practice. Paper presented at the 36th Annual Meeting of the Psychonomics Society.

Heathcote, A., Popiel, S. J., & Mewhort, D. J. K. (1991). Analysis of Response Time Distributions: An Example Using the Stroop Task. Psychological Bulletin, 109, 340-347.

Hockley, W. E. (1984). Analysis of response time distributions in the study of cognitive processes. Journal of Experimental Psychology: Learning, Memory and Cognition, 10, 598-615.

Hohle, R. (1965). Inferred components of reaction times as functions of foreperiod duration. journal of Experimental Psychology, 69, 382-386.

Kail, R. & Bisanz, J. (1992). The information-processing perspective on cognitive development in childhood and adolescence. Intellectual Development, New York: Cambridge University Press; Sternerg, R. J., Berg, C. A. (eds.), p. 229-277.

Kennedy, W. J., & Gentle, J. E. (1980). Statistical computing. New York: Marcel Dekker inc.

Kramer, A. F., Strayer, D. L. & Buckley, J. (1990). Development and transfer of automatic processing. Journal of Experimental Psychology: Human Perception and Performance, 16, 505-522.

Lassaline, M. E., & Logan, G. D. (1993). Memory-based automaticity in the discrimination of visual numerosity. Journal of Experimental Psychology: Learning, Memory and Cognition, 19, 561-581.

Logan, G. D. (1988). Toward an instance theory of automatization. Psychological Review, 95, 492-527.

Logan, G. D. (1992). Shapes of reaction-time distributions and shapes of learning curves: a test of the instance theory of automaticity. Journal of Experimental Psychology: Learning, Memory and Cognition, 18, 883-914.

Luce, R. D. (1986). Response times, their role in inferring elementary mental organization. New York: Oxford university press.

Maddox, W. T., & Ashby, G. F. (1993). Comparing decision bound and exemplar models of categorization. Perception and Psychophysics, 53, 49-70.

McGill, W. J. (1963). Stochastic latency mechanisms. Handbook of Mathematical Psychology, New York: Wiley.

Newell, A. & Rosenbloom, S. (1981). Chap. Mechanisms of skill acquisition and the law of practice. The Acquisition of Cognitive Skills..

Ratcliff, R. (1978). A theory of memory retrieval. Psychological Review, 85, 59-108.

Ratcliff, R. (1979). Group Reaction Time Distributions and an Analysis of Distribution Statistics. Psychological Bulletin, 86, 446-461.

Ratcliff, R. (1995). Methods for dealing with reaction time outliers. Paper presented at the 36th Annual Meeting, the psychonomics society, 1-11.

Ratcliff, R., & Murdock, B. B. (1976). Retrieval processes in recognition memory. Psychological Review, 86, 190-214.

Rescorla, R. A., & Wagner, A. R. (1973). A theory of pavlovian conditioning: variations in the effectiveness of reinforcement and nonreinforcement. Classical Conditioning II: Current Research and Theory; New-York: Appleton-Century-Crofts, p.64-99.

Sternberg, S. (1969). The Discovery of Processing Stages: Extensions of Donder's method. Attention and Performance II, Koster, W. G. (Ed.) Amsterdam: North-Holland, 267-315.

Ulrich, R., & Miller, J. (1994). Effects of truncation on reaction time analysis. Journal of Experimental Psychology: General, 123, 34-80.

Author's Note

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Request for reprint should be addressed to: Serge Larochelle, Département de Psychologie, Université de Montréal, C. P. 6128, Succ. Centre-ville. Montréal (Québec) Canada, H3C 3J7 or using e-mail at: cousined@PSY.Umontreal.CA. A postscript version is also available at **http://prelude.psy.umontreal.ca/~cousined/pastis.**

Footnotes

[1] We wish to thank Gordon Logan for sending us a copy of STEPIT.

[2] With a base change, equation (5) can be rewritten as:

$$M = a + b\, e^{-c'N} \qquad (5a)$$

a and b are the same in both equations. The c parameters are related by the formula: $c' = -\ln(1 - c)$. See Kail and Bisanz (1988) for an example of use of this formulation.

Table 1

Possible analyses in PASTIS, with the type of data needed, and their reserved name

analysis	type	type of data needed	reserved name	additional options
curve	exponential curve (eq. 5)	any	EXPONEN	cx*
	expo. (base e) (eq. 5a)	any	GEXPONEN	cx*
	power-law curve (eq. 1)	any	PLAWCURVE	cx*
	Logan's theory (eq. 3)	means and SD	GPLAWCURVE	cx cy**
distribution	Ex-Gaussian (eq. 6)	raw or vincentized data	EX-GAUSS	
	Weibull (eq. 7)	raw or vincentized data	WEIBULL	
summary data†		any	STATISTIC	

* x is the number of the column containing session of evaluation

** x is the number of the column containing session of evaluation and y is the number of the column containing standard deviation data

†: summary data computed are mean, standard deviation, skewness, kurtosis, and minimum.

Table 2

Results of curve analyses performed on simulated data

	computed	parameter values			%	best fit obtained		parameters*		
file	with	1	2	3	noise	analysis	RMSD	1	2	3
PL1.dat	Power-law	400	300	0.8	0%	PLAWC	0.044	400.28	299.69	0.8015
						EXPOC	6.340	455.06	447.16	0.4624
PL2.dat	Power-law	400	300	0.8	10%	PLAWC	14.22	459.19	292.83	2.0653
						EXPOC	16.14	466.35	1202.4	0.7643
EXPO1.dat	Exponential	400	300	0.4	0%	PLAWC	4.64	328.33	254.52	0.5771
						EXPOC	0.0022	400.00	300.00	.0400
EXPO2.dat	Exponential	400	300	0.4	10%	PLAWC	19.81	396.35	171.56	0.9443
						EXPOC	20.32	418.91	274.67	0.4744

*: In curve analysis, parameters 1, 2 and 3 produced by PASTIS correspond to a, b and c respectively.

Table 3

Results of distribution analyses on simulated data

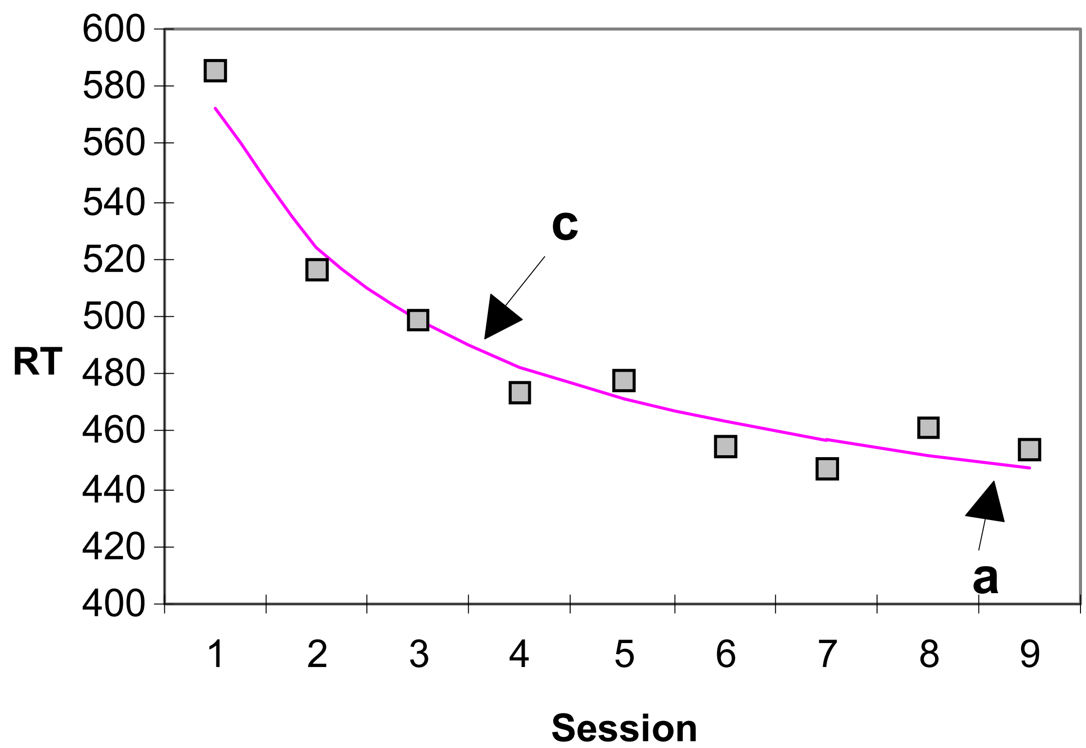
	generated	parameter values			%	best fit obtained		parameters*		
file	with	1	2	3	noise	analysis	-log likelihood	1	2	3
W1.dat	Weibull	300	400	1.3	0%	WEIBULL	230.48	350.4	236.6	1.36
						EX-GAUSS	248.00	518.5	59.9	154.3
W2.dat	Weibull	300	400	1.3	10%	WEIBULL	231.15	350.2	226.8	1.26
						EX-GAUSS	250.48	492.4	58.3	178.1
EX-GAU.dat	Ex-gaussian	500	50	100	0%	WEIBULL	55.57	474.2	96.4	1.0
						EX-GAUSS	64.93	495.8	24.0	73.7

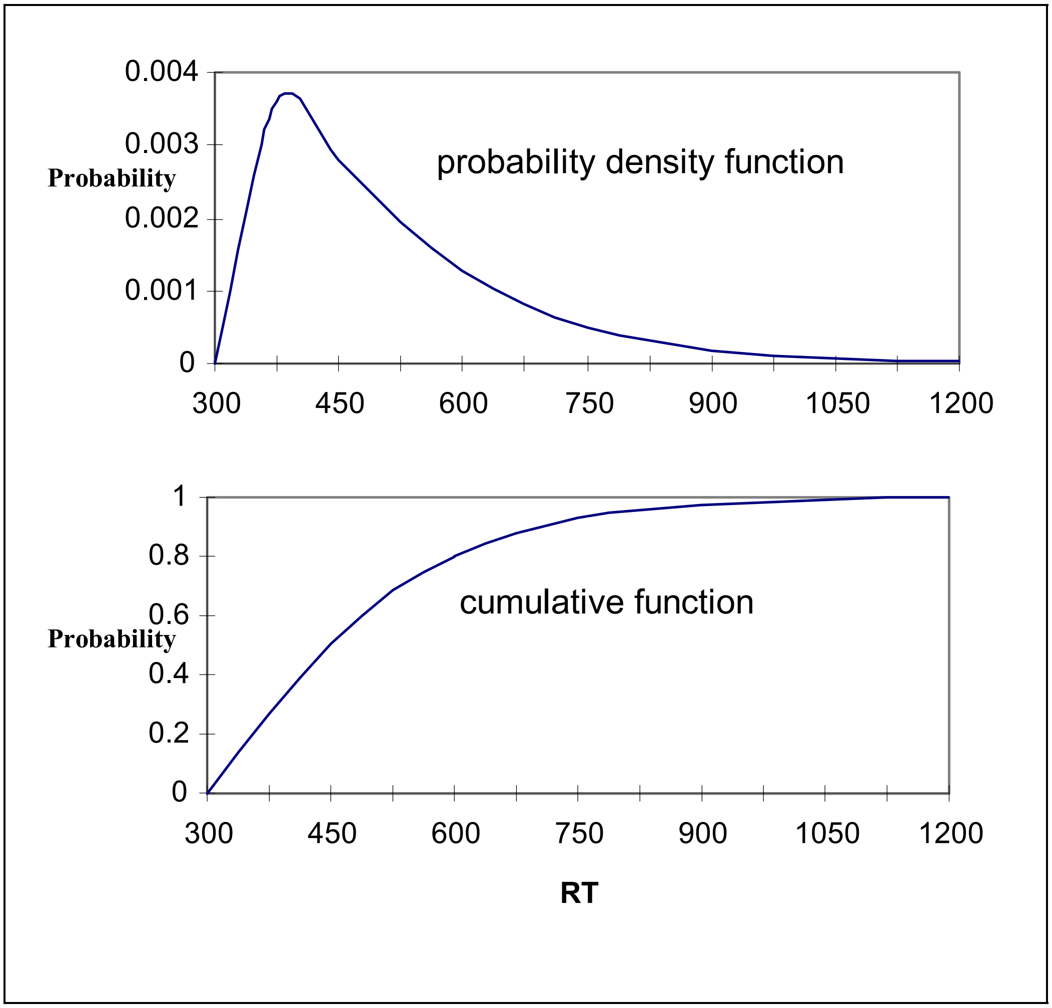
*: For the Ex-Gaussian distribution, parameters 1, 2 and 3 correspond to μ, σ and τ respectively, and for the Weibull distribution, they correspond to a, b and c.

Figure Caption

Figure 1. Simulated data and the curve that best describes the speed-up in RT

Figure 2. Two representations of a distribution


600
580
560
540
520
500
480
460
440
420
400
RT
c
a
1
2
3
4
5
6
7
8
9
Session


0.004
0.003
0.002
0.001
0
Probability
probability density function
300
450
600
750
900
1050
1200
1
0.8
0.6
0.4
0.2
0
Probability
cumulative function
300
450
600
750
900
1050
1200
RT