



Normative decision rules in changing environments

Nicholas W Barendregt^{1*}, Joshua I Gold², Krešimir Josi³, Zachary P Kilpatrick¹

¹Department of Applied Mathematics, University of Colorado Boulder, Boulder, United States; ²Department of Neuroscience, University of Pennsylvania, Philadelphia, United States; ³Department of Mathematics, University of Houston, Houston, United States

Abstract We study the normative decision rules that govern behavior in changing environments. In these environments, the set of available options changes over time, and the value of each option changes as well. We consider a simple version of this problem, where the environment changes in a way that is analogous to the *Wald* decision problem (Wald, 1945). We show that the normative decision rule in this environment is a simple extension of the *Wald* decision rule. We also show that the normative decision rule in this environment is a simple extension of the *Wald* decision rule. We also show that the normative decision rule in this environment is a simple extension of the *Wald* decision rule.

*For correspondence: nicholas.barendregt@colorado.edu

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Editor's evaluation

The manuscript is an excellent contribution to the field of decision-making in changing environments. The authors provide a clear and concise analysis of the problem, and their results are both novel and important. The manuscript is well-written and easy to read, and it is a pleasure to recommend it for publication.

Introduction

Normative decision rules in changing environments are a central topic in decision theory. In these environments, the set of available options changes over time, and the value of each option changes as well. This is a challenging problem, and it is not clear what the normative decision rule should be. In this paper, we study this problem and show that the normative decision rule is a simple extension of the *Wald* decision rule.

mal function, ... non-malignant ... cancer ...

ξ (the final) is a random variable with a Gaussian distribution, $\xi \sim \mathcal{N}(0, \sigma^2)$. The initial condition is $y_0 = 0$. The transition probabilities are given by $P_{\pm}(y_n, \xi_n) = \frac{1}{\sigma} \exp\left(-\frac{(y_n - \mu_{\pm})^2}{2\sigma^2}\right)$, where $\mu_{\pm} = \mu \pm \rho y_{n-1}$. The forward and backward transition probabilities are $f_{\pm}(y_n) = \int P_{\pm}(y_n, \xi_n) \delta(y_n - \mu_{\pm}) dy_n$. The forward and backward transition probabilities are $f_{\pm}(y_n) = \int P_{\pm}(y_n, \xi_n) \delta(y_n - \mu_{\pm}) dy_n$. The forward and backward transition probabilities are $f_{\pm}(y_n) = \int P_{\pm}(y_n, \xi_n) \delta(y_n - \mu_{\pm}) dy_n$.

$$y_n = \ln \frac{\Pr(s_+ | \xi_{1:n})}{\Pr(s_- | \xi_{1:n})} = \ln \frac{f_+(y_n)}{f_-(y_n)} + y_{n-1}. \tag{2}$$

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$$V(p_n; \rho) = \max\{V_+(p_n; \rho), V_-(p_n; \rho), V_w(p_n; \rho)\}$$

$$= \max$$

m l l a c a g t t a g l c t o n l a c o m l t o l n a m t a t m m a -
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 o m g o m t m l m o n o c a g t t o n a a m t ().
 o n t a n a g o t t l t o l m o t t t o n t o n m t t t g l
 c a g t n a t a a m t t a e a g t t t t m t $R_i = 0$ a n t t m
 a R_c a g t a t t o a t n a m t a t t a a t t o n

$$R_c(t) = (R_2 - R_1)H_{\theta}(t - 0.5) + R_1. \tag{5}$$

t t a t c t o m e a g a R_1 o t e a g a R_2 a $t = 0.5$.
 o t t g l e a g t t o m a t t o l n a m t t t a l m o t a n t o m
 c a t t t m l o c o l l a t g t o l c a a t c o t t c t o n m o t t o
 c a t t t o l n a m t t c c a l l c a a t t o n t n a m t o t t t o n t
 o t g l t c c a g t n a c o n g t t o n c o m n a o t o - a n t -
 c a g t a a l t (

... e ag d'v, mal' a g t' n nm n' m l' c ag t' n' u
 al' a c a a' t' ol' nanc' a a a' t' c ag t' n a a' mla' m'
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 t' ol' m' t', g' anc, n' n nm n' t' g' l' c ag t' n' u' al' u'
 $m = \frac{2^2}{2}$ a' g' a' a' t' n' n'

$$\mu(t) = (\mu_2 - \mu_1)H_{\theta}(t - 0.5) + \mu_1. \quad ()$$

... t' t' g' l' e ag d'v, g' a n' n' t' mla' t' ol' m' t' m' t' n' a e ag
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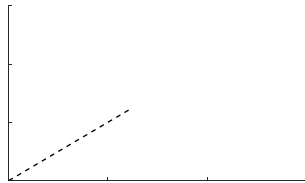
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The first step in the analysis was to determine the number of neurons that were recorded in each mouse. The number of neurons recorded in each mouse was determined by counting the number of neurons that were recorded in each mouse. The number of neurons recorded in each mouse was determined by counting the number of neurons that were recorded in each mouse. The number of neurons recorded in each mouse was determined by counting the number of neurons that were recorded in each mouse.



model, we first model a simple, and then a more complex, network structure. We then compare the results of the two models. We find that the simple model is able to capture the essential features of the network, while the more complex model is able to capture the details. This suggests that the simple model is a good approximation of the network, and that the more complex model is a more detailed representation. We then discuss the implications of these results for understanding the network structure and function.

Discussion

Our goal is to understand the network structure and function. We first model a simple, and then a more complex, network structure. We then compare the results of the two models. We find that the simple model is able to capture the essential features of the network, while the more complex model is able to capture the details. This suggests that the simple model is a good approximation of the network, and that the more complex model is a more detailed representation. We then discuss the implications of these results for understanding the network structure and function.

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modeling the non-monotonic relationship between the number of neurons and the number of connections in the brain. We show that the number of connections is not simply proportional to the number of neurons, but rather follows a power-law relationship.

The relationship between the number of neurons and the number of connections in the brain is a complex one. It is not simply a linear relationship, as one might expect. Instead, it follows a power-law relationship, where the number of connections increases much more rapidly than the number of neurons. This is a characteristic feature of many complex systems, and it suggests that the brain is a highly interconnected network.

The power-law relationship between the number of neurons and the number of connections in the brain is a key finding of this study. It suggests that the brain is a highly interconnected network, where a small number of neurons are connected to a large number of other neurons. This is a characteristic feature of many complex systems, and it suggests that the brain is a highly interconnected network.

Our results show that the number of connections in the brain is proportional to the number of neurons raised to a power of approximately 1.5. This is a significant finding, as it shows that the number of connections increases much more rapidly than the number of neurons. This is a characteristic feature of many complex systems, and it suggests that the brain is a highly interconnected network.

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$$\begin{aligned} V(p_n; \rho) &= \max\{V_+(p_n; \rho), V_-(p_n; \rho), V_w(p_n; \rho)\} \\ &= \max \left\{ \begin{array}{l} R_c p_n + R_i(1 - p_n) - t_i \rho, \\ R \end{array} \right. \quad \text{choose } s_+ \end{aligned}$$

SNR-change task thresholds

For a given SNR, the probability of a correct decision is given by the following equation:

$$\mu(t) = (\mu_2 - \mu_1)H_\theta(t - 0.5) + \mu_1.$$

where μ_1 and μ_2 are the mean values of the two classes, H_θ is the Heaviside step function, and t is the time. The probability of a correct decision is 0.5 at $t = 0.5$. The probability of a correct decision is 1.0 at $t = 1.0$ and 0.0 at $t = 0.0$. The probability of a correct decision is 0.5 at $t = 0.5$. The probability of a correct decision is 1.0 at $t = 1.0$ and 0.0 at $t = 0.0$. The probability of a correct decision is 0.5 at $t = 0.5$. The probability of a correct decision is 1.0 at $t = 1.0$ and 0.0 at $t = 0.0$.





Figure 1. Relationship between SNR and CDF. The CDF of the SNR changes as the SNR changes.

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Author contributions

Concepción V. Wang, Computational analysis, Mathematical analysis, Visualization, Writing - original draft, Writing - review and editing, Zaira Klacv, Computational analysis, Visualization, Writing - original draft, Writing - review and editing

Author ORCIDs

Concepción V. Wang  <https://orcid.org/0000-0002-3292-9428>
Zaira Klacv  <https://orcid.org/0000-0002-0192-0493>
Klára Klacv  <https://orcid.org/0000-0002-1933-3913>
Zaira Klacv  <https://orcid.org/0000-0002-2933-9418>

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Additional files

Supplementary files

 [c.c.txt](#)

Data availability

 [code and data available at figshare](#) <https://www.figshare.com/n/wang/c/12929a3999a004a934194a2>.

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