

# 1 Agradecimientos

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## 2 Resumen

Decisions are part of our daily lives, and it appears as if some kind of process is evaluating second to second all of our options. In all of such situations a big question arises, should I go for the well-known option or should I take my chances a look for a new one?. This **exploration-exploitation dilemma** is also present in both, foraging for resources and **semantic search**. As such, both problems can be seen as decision-making processes where resources and semantic contents locations are unknown, and somehow one must establish an efficient criterion for searching in an efficient way. Certain search patterns, which are ubiquitous across many taxa, seems to provide an optimal way for foraging through a previously unknown environment. Given that both semantic search and foraging share similarities, an evolutionary co-option of the mechanisms controlling foraging for semantic search is discussed. Underlying strategies for searching through patchy environments, neural implementations of exploration-exploitation control and internal aspects of foraging are discussed in hopes of providing an evolutionary framework for semantic search research.

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## 4 Índices de ilustraciones

## 5 Introduction

### 5.1 Semantic search

Semantic memories are memories about the meaning of things, this conceptual knowledge allows us to interact and recognize objects, plan the future and remember the past (Binder and Desai, 2011). Given such pivotal role, the way that we 'navigate' through such memories will determine how we interact with the world. The space in which the 'navigation' occurs has been called semantic space, this corresponds to an abstraction where semantic memories are placed in a multi-dimensional space, and the connection between them are defined by some vector assigning the relationship between each one in every dimension (Lund and Burgess, 1996). In humans, however, that way that semantic memories organize into such space is not clear (Benedek et al., 2017).

Free recall tasks, which prompt the participant to recall as many objects pertaining to a certain category in a limited amount of time, have observed a 'patchy' distribution of such memories (Hills et al., 2009), this patchy distribution refers to a significantly faster retrieval time when the participant is within a certain category (which is determined beforehand), more than when they're not. The idea of a semantic space, with distances between semantic contents, was first developed by supervised semantic network modeling based on lexical co-occurrence (Lund and Burgess, 1996), which found correlations between the distances calculated by the model and human retrieval times, giving the possibility to model human memory in such a way.

The specific way this 'distance' exists in the brain is not known, however, earlier lesion studies showed that specific neurological damage affect specific semantic categories (Hillis and Caramazza, 1991), pointing that this categories have some physical distance between them. Functional neuroimaging data points in a similar direction, but is not clear whether the structure represents actual semantic categories or some modality-specific sub-divisions (Caramazza and Mahon, 2003; Binder et al., 2009). Network science studies have indicated that, within category elements, present lower average shortest path length, higher clustering coefficient and lower network modularity, implying that semantic contents are distributed in dense clusters pertaining to each category, and that access to items within a category have efficient access between them compared to another category (Benedek et al., 2017).

Given a semantic space with a clustered-patchy distribution, the question of how to efficiently retrieve such contents arises. Free recall tasks points that ,inter-retrieval intervals (IRI), when participants are producing items within a given category are significantly shorter than when they are not (Abbott et al., 2015). IRI on this type of task have shown to be following a Lévy probability density distribution with an exponent near 2 when the retrievals are more efficient (Rhodes and Turvey, 2007).

Patterns describing such inter-retrieval intervals have been compared to that of food-

foraging (Rhodes and Turvey, 2007), this suggest a notion of distance between memory contents that has been observed when participants are asked to represent in a 2D space such memories (Montez et al., 2015).

## 5.2 The exploration-exploitation dilemma in foraging and semantic search

Human semantic memory have been represented by relatively simple networks, where semantic contents are de 'nodes' and the proximity metric (categorical or associative similarity) is represented in the edges of this network. Such models and empirical evidence in human recall tasks (Hills et al., 2012), show that search within closely related contents (or withing a category) are retrieved faster that when such items are outside such category. However, the number of contents for each category are finite, so certain strategy must be employed in order to guide the exploration of this contents. Given this finite condition, a sequential decision making problem is at face, at every step the decision to stay within a category or to change to another (possibly more profitable category) must be made, and such decision will impact further decisions. This could be stated as a non-stationary environment, where the expected reward for each category is being constantly updated to an unknown value, and in order to determine such value the agent must explore it's options. However, in order to profit, at some point in time, it also must exploit a category in order to maximize it's reward. This is known as the exploration-exploitation dillema.

This dilemma observes the question of wether the agent should extract resources (retrieve a semantic content) from the current patch in which the value is known (i.e. exploitation) or wether it should explore other patches to gain information about their value. One can assume that the organism should pick the patch/category with the highest recent value, but this could lead to selecting a sub-optimal patch or category if better options exists, or if its calculated value is simply subject to many high degrees of noise (Hernandez-Leal et al., 2016).

To solve the exploration/exploitation dilemma several algorithms and notions, such as expected and unexpected uncertainty have been proposed (Mehlhorn et al., 2015), where a sensible threshold is given to the agent to control expectations of rewards, such that exploitation of a given patch is not stopped by a single low reward in face of multiple high rewards. These algorithms try to solve the many problems that arise when trying to act within this dilemma. Deciding is not easy because, while in a non-depleting patch, the patch exploitation would always be the optimal decision, the problem turns more complicated when exploitation depresses current resources, and the value of all patches is not known. Which in turn, adds that the organism must somehow determine an optimal policy for exploring and exploiting. Early experiments on birds showed a 50:50 sample algorithm, where the bird sampled equally two patches and for the rest of the time stayed in the better one (Krebs et al., 1978). More recent work has established the notion of simple heuristic-like rules such as energy reserves to decide how intensively forage for food (Higginson et al., 2018). Furthermore

it has been pointed that humans use different algorithms depending on the situation, this has been shown using stationary sequential tasks (Gershman, 2018). These findings suggest that the exploration-exploitation dilemma is likely to be solved by using the properties of the environment the organism is in (Fawcett et al., 2014; Hernandez-Leal et al., 2016).

Up to this point semantic search has been introduced as a type of search through a cognitive space, which is ruled by the exploration-exploitation dilemma. Furthermore, the type of space in which this occurs was compared to that of physical foraging (Hills et al., 2009) because of the patchy distribution of 'resources' found in both cases.

## 6 Models for a semantic search heuristic

The problem stated, asks for a way that is cognitively plausible, for conducting semantic searches. Such a way could be provided by the use of certain primitive heuristics. A heuristic is a way to handle information, that ignores part of it, is relatively fast in getting to a decision, and gets a 'good-enough solution' that is often the best in many scenarios where the optimal one is intractable (Gigerenzer, 2008). To provide a candidate heuristic is necessary to submit computational models that allows to finely define such heuristic and make testable predictions (Gigerenzer, 2008). To define the underlying heuristics of semantic search two main models will be presented one 'rule based' and other of stochastic nature. Secondly, an heuristic must be supported by some specific structure capable of producing the behavior predicted by the heuristic, for that neural implementations of such strategies will be discussed.

### 6.1 Rule-based behavior: optimal foraging

A prime exponent of rule-based strategies is the optimal foraging theory (OFT). The OFT is one of the most well-known theories in the area of foraging behavior since it provides a model that assumes both an optimal forager and a patchy environment (Bartumeus and Catalan, 2009). Within OFT, the forager is constantly updating the value (resource acquisition rate) of staying in a patch versus leaving it for another one, since it is naturally assumed that as permanence time increases, the resources of the current patch depresses. Given that a forager uses energy to get to another patch, and also wants to optimize the ratio between energy expenditure and caloric gain, it must establish a rule for doing so in an efficient way. This rule is given by the marginal value theorem (MVT). MVT dictates that an optimal forager should leave its current patch when the acquisition rate drops below that of the habitat average (Charnov, 1976).

OFT provides a policy for decision making during food foraging. The first part of such policy deals with the problem of how much time should the forager stay in a given patch, so as not to miss the opportunity of potentially better patches and, at the same time, effectively attain the resources of the current one. The second part is to determine the optimal movement pattern or path the forager should take when traveling from patch to patch. OFT largely avoided this issue (i.e. how to travel from patch to patch) assuming previous knowledge of habitat resource distribution. However, this probably is not the case for most organisms.

Cognitive, perceptive or habitat dependent limitations make such previous knowledge difficult (Bartumeus and Catalan, 2009). Thus, the way that an organism adjusts its search behavior is of utmost importance. Random walks have been extensively used to evolutionary describe such patterns (Bartumeus and Catalan, 2009; Fioriti et al., 2015; Humphries et al., 2012; de Jager et al., 2013). Evolutionary arguments for certain types of random walks such as the Levy walk (Wosniack et al., 2017) assume that evolution optimizes the most efficient



search strategies. However, this view has been criticized (Pierce and Ollason, 1987), mainly because it is impossible to prove that a given behavior was selected for a specific function, and as such test for optimality proves to be extremely difficult. Furthermore, it has been noted that theoretical driven predictions do not necessarily match the data (Pierce and Ollason, 1987). However, in contrast to these criticisms the point of optimal models for its heuristic value is proposed (Parker and Smith, 1990).

## 6.2 Random walks

A random walk movement model is, basically, a stochastic process that defines two elements: (1) the step length, which is drawn from a certain probability distribution and, (2) a turning angle or direction change which is also drawn from a particular distribution. In the Levy-walks, turning angles are drawn from a uniform distribution and the step lengths from a Levy-stable distribution (Bartumeus, 2007). Modeling search patterns using this kind of random walk can be viewed as neglecting the fact of memory, especially in organisms with higher cognitive abilities, mainly because there is no parameter that captures the fact that, through memory, an organism can recall previously visited places or patches with high amount resources and so on. However, the scale of the search deserves special attention. As an organism might gain significant knowledge from a restricted area but not from all his habitat, and even in the case of substantial habitat knowledge, the interaction of other organisms with the environment may spoil prediction from that previous knowledge, forcing the need to constantly gather information (Patrick et al., 2017). Hence, having an efficient random process for the search pattern might be useful even when higher cognitive capabilities are provided (Bartumeus, 2007). Aside from considering cognitive capabilities, an important point is to determine whether such modeled patterns do have an internal process that generates them, otherwise, such pattern would not provide much information of the organism's behavior, and would appear more as a coincidence. For instance, it has been discussed whether Levy-walks can appear as a result of resources properties, that is, when the organism previously knows a resource location, but the value of this resource obeys a power-law distribution, rather than from an underlying Levy-process within the organism (Benhamou, 2007).

## 7 A case of co-option

7.0.1 Introduce the concept of co-option, emphasis on behavioral or search traits

7.0.2 From where semantic search is co-opted from ? introduce foraging

7.0.3 How this came to be

## 8 Neural implementations

8.0.1 Once a strategy/heuristic is identified, it is necessary to identify the structure underlying it

8.0.2 Base on exploration exploitation dilemma

## 9 State dependent foraging

## 10 Conclusions

## 11 References

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