1 2 9 0

UNIVERSIDADE Ð
COIMBRA

Francisco Figueiredo Forte

THE EFFECTS OF SEMANTIC DISTANCE IN OBJECT RECOGNITION

A FEATURE-BASED AND BEHAVIORAL APPROACH

Dissertação no âmbito do Mestrado Interuniversitário em Neuropsicologia Clínica e Experimental, orientada pelo Professor Doutor Jorge Manuel Castelo Branco de Albuquerque Almeida e apresentada à Faculdade de Psicologia e Ciências da Educação da Universidade de Coimbra

Setembro de 2022

Faculty of Psychology and Educational Sciences of University of Coimbra

THE EFFECTS OF SEMANTIC DISTANCE IN OBJECT RECOGNITION

A FEATURE-BASED AND BEHAVIORAL APPROACH

Francisco Figueiredo Forte

Thesis submitted for the Interuniversity Master in Clinical and Experimental Neuropsychology, supervised by Professor Jorge Almeida and presented to the Faculty of Psychology and Educational Sciences of University of Coimbra

September 2022

1 2 9 0

UNIVERSIDADE Ð COIMBRA

Resumo

Título: Os efeitos da Distância Semântica no Reconhecimento de Objetos: Uma abordagem comportamental baseada em características

Palavras-chave: Conhecimento Conceptual; Ferramentas; Distância Semântica; Priming Semântico; Reconhecimento de Objetos

Um tema proeminente de investigação em neurociência cognitiva tem sido a organização do conhecimento conceptual no cérebro humano. Este conhecimento agrega vários tipos de informação, afetando diretamente o processo de reconhecimento de objetos. Este processo é também influenciado pelo grau de semelhança semântica entre dois objetos, que é definido pela quantidade de características que estes possuem em comum. Contudo, pouco se sabe sobre como cada tipo de informação influencia a quantidade de tempo necessária para distinguir entre dois objetos diferentes, a nível comportamental.

O atual estudo foi uma tentativa de responder a esta questão, no qual foi utilizada uma abordagem comportamental, baseada nas características dos objetos. Com esse fim, foram utilizadas duas bases de dados das quais foi extraído um grupo de 250 valores de semelhança semântica para "Geral"; "Função"; "Manipulação" e "Visão". Os valores foram calculados a partir das características partilhadas entre 80 objetos. Neste estudo, onze adultos saudáveis participaram numa experiência comportamental onde tiveram de premir uma tecla sempre que vissem uma imagem de um objeto que era diferente da que tinham observado anteriormente. Foi realizada uma análise de regressão linear múltipla para explorar as correlações entre as dimensões e os tempos de reação obtidos. Os resultados revelaram que o efeito da "Visão" foi positivamente significativo, mostrando que quanto mais características visuais são partilhadas entre dois objetos, mais devagar os distinguimos, obtendo assim tempos de reação mais longos. Curiosamente, mesmo não sendo estatisticamente significativo, a "Manipulação" mostrou uma tendência positiva na correlação entre a semelhança semântica e os tempos de reação, e a "Função" constitui-se como um elemento pouco informativo devido à impossibilidade de uma dispersão representativa de valores. Estes resultados demonstram ser promissores para a discussão sobre o papel da diversidade do conhecimento conceptual no reconhecimento de objetos.

Summary

Title: The effects of Semantic Distance in Object Recognition: A feature-based and behavioral approach

Keywords: Conceptual Knowledge; Tools; Semantic Distance; Semantic Priming; Object Recognition

A prominent subject of research in cognitive neuroscience has been the organization of conceptual knowledge in the human brain. This knowledge combines many types of information, directly affecting the process of object recognition. This process is also influenced by the degree of semantic similarity between two objects, which is defined by the number of features they have in common. However, little is known about how each type of information influences the amount of time required to distinguish between two different objects at the behavioural level.

The current study was an attempt to answer this question, which was addressed by a feature-based and behavioral approach. To do this, two databases were used from which a group of 250 semantic similarity values were extracted for “All Features”; “Function”; “Manipulation” and “Vision”. These values were calculated from the features shared between 80 objects. In this study, eleven healthy adults participated in a behavioral experiment where they had to press a key whenever they saw an image of an object that was different from the one they had just seen. A multiple linear regression analysis was performed to explore the correlations between the dimensions and the reaction times obtained. Results revealed that the effect of “Vision” was positively significant, showing that the more visual features are shared between two objects, the slower we are to distinguish them, thus obtaining longer reaction times. Interestingly, although not being statistically significant, “Manipulation” showed a positive trend in the correlation between semantic similarity and reaction times, and “Function” seems to be an uninformative element due to the inability of a representative dispersion of values. These results shed a light on the role of the diversity of conceptual knowledge in object recognition.

Acknowledgements

To Professor Jorge Almeida, who guided me and contributed to my development at academic level. For the integration in his research group, which provided me with enriching experiences. For the demand, for making me think critically about what we are doing and helping to determine strategies that clarify the path to follow.

To the doctorate researcher Daniela Valério, for the closeness in all the work developed along this path and for being an example in terms of scientific precision, competence and professionalism. For the trust and autonomy that was given to me and for the demand in the accomplishment of each stage, which allowed me to improve my role as a researcher. For the patience, support, commitment, and valuable advice.

To the whole Proaction Lab team, for the help and companionship. To Lénia for the good mood, knowledge sharing and inspiration. To Patrícia Fernandes for her complicity, friendship and for making the difficult days lighter and cheerful. To Patrícia Frazão for her help and excellent work in data collection and to the participants who agreed to participate in this study, only with the desire to contribute to the knowledge in the area of neurosciences.

To my mother, for the love, humour, truth, confidence and strength. For always being here. For being my greatest admirer.

To my sister, for being my best friend and for always believing in me. To CBO.

To my father, for the values instilled and the hug that heals everything. This wouldn't be fun without you.

To my dear aunt Cristina Galhano, for the care, trust and sharing. For having allowed all this. To my aunts João, Ana and Mané, for always being my home and real meaning of unconditional love and support. To my grandfather João, for his omnipresence and eternal inspiration.

To the real companions of my life, Francisca, Mariana and Joana, who were indispensable every day. For the love, authenticity, active listening, strength. For showing me how important it is to support and be supported.

To Claudia and Diego, for being my special mentors during this master, for helping me to see the world in a different way, for the intensity of the moments, for the growth, and for all the care and affection. To Bárbara and Nadja, for the friendly word, for the hug at the right moment and for, together, having managed to build a place that we call Home.

To Professor Margarida Lima, for making me understand that I am always on the way. No words can explain the privilege that this meeting has been. To Group 4.

To theatre, for being my source of energy, and for the opportunity of personal development and rediscovery. To Interdito, for the family. To Pepa and Gil, for allowing me to do things I would never do in my life. To Fatias de Cá, for the experiences in other worlds and for having given me the gift of the friend of all hours, Inês.

To Francisco, for the good things.

To Aveiro, Madrid and Coimbra, for the adventures and misadventures that were part of my academic journey.

Finally, to me, for one more achievement. For all that is to come

This thesis was supported by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme, "ContentMAP", with the grant number 802553. I was funded by FCT, through the base funding of the CINEICC Strategic Project, with the reference UIDB/PSI/00730/2020.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

CSA	Conceptual Structure Account
DSH	Domain-Specific Hypothesis
EBA	Extrastriate Body Area
FC	Feature Correlation
FD	Feature Distinctiveness
FBA	Fusiform Body Area
FFA	Face Fusiform Area
HSE	Herpes Simplex Encephalitis
OUCH	Organised Unitary Content Hypothesis
PPA	Parahippocampal Place Area
RT	Reaction Time
SD	Semantic Distance
SP	Semantic Priming
SFT	Sensory/Functional theory
tDCS	Transcranial Direct Current Stimulation

1. Introduction

Do you think we are quicker to distinguish between a knife and a fork or between a knife and a glass? If the answer was the knife and the glass, then you are in agreement with what has been discovered in the literature (Valério & Almeida, in prep). Most likely, you would justify your answer by saying that the glass is much more distinct from the knife than the fork, i.e., the glass is more distinct from the knife, it shares less features (semantic information). Importantly, these features may relate to distinct kinds of information, for example: information about an object's function (what is it used for?), manner of manipulation (how is it used?), and visual properties (what does it look like?). Given the variety of information types that could be employed in our capacity to distinguish between objects, in this case tools, I wanted to develop a method to operationalize the weight of each in this process and be able to answer questions like the following: Is visual information as important as information from the function of objects? Is manipulation information more crucial in in distinguishing between two objects?

A better understanding of this topic and the possible differences between these types of information leads to deeper knowledge about an essential component of human cognition that is the capacity to recognize objects and the way object knowledge is organized in the brain. This is fundamental for understanding object recognition since it limits the type of theories and possibilities to comprehend this phenomenon. Moreover, accessing the information we store about an object is essential for interacting with the world around us, playing a key role in our survival and evolution, and is therefore a vitally important cognitive function.

For the field of cognitive neuroscience and neuropsychology, the existence of a specific brain network devoted to object recognition has been a pertinent subject of great interest (Almeida et *al.*, 2010; Devereux et *al.*, 2018; Mahon & Caramazza, 2011; Valério et *al.*, in prep, Victoria et *al.*, 2019). It is yet unknown, though, how the degree of similarity between two target objects determines how accurately and fast we are able to distinguish them.

In this thesis, I use behavioral data to define a model that integrates and clarifies the quantitative influence of distinct types of information that define an object (independent variables) on the time it takes to distinguish between two different objects (dependent variable).

In the first section of this thesis - “Background” - I will review current approaches to object recognition, focusing on semantic distance. In the second section, following a summary of the study's objectives, I will present the "Methods" section, which includes a thorough explanation of the sample used, the experimental procedure, and results. The third section - "Discussion and conclusion" - will look at the findings and relate them to recent research evidence. Additionally, I will draw a conclusion, outline the study's major contributions to the scientific community, and talk about some potential future research and perspectives.

1.1. Background

In the field of cognitive neuroscience, inherent to the process of understanding how the human brain organizes conceptual knowledge about the world, object recognition emerges as one of the most remarkable abilities, acting as a bridge between vision and cognitive processes such as categorization, reasoning, and language (Hummel, 2013).

Over time we create visual representations that allow us to recognize objects in our daily lives, however, the importance of these representations goes beyond just telling us what we are looking at. They also provide support for visual reasoning, that is, we are able to recognize a spoon not only as the object called spoon and that is characterized by being elongated and having a metal shell that serves for eating, but we are also able to produce other types of inferences, such as, for example, the spoon being the object that measures the quantity of ingredients for a recipe (Hummel, 2013).

Human beings are especially good at visually recognizing objects, and when they do, they can portion the object into its parts, perceiving not only the value of each component, on each own and the interconnections between them. Moreover, they are also able to recognize familiar objects and distinguish between numerous classes of known objects (Hummel, 2013).

Numerous authors have devoted years analysing the organization of information by evaluating brain-damaged patients with category-specific semantic impairments (e.g., Hillis & Caramazza, 1991; Humphreys & Riddoch, 1987; Tyler et *al.*, 2011; Warrington & McCarthy, 1983; Warrington & Shallice, 1984). In their research, a selective impairment was observed for the ability to classify a specific object category throughout the applied tasks (e.g., picture matching, stimuli identification, object recognition), although other semantic categories were relatively preserved (e.g., Capitani et *al.*, 2003; Caramazza & Mahon, 2003).

In a seminal paper, Warrington and Shallice (1984) described the discrepancies related to visual identification and auditory comprehension in four patients who made a partial recovery from herpes simplex encephalitis (HSE) and provided with substantial evidence for category-specific deficits. In particular, the study's main finding was the evidence for category specificity because there was a significant overall discrepancy between the ability to recognize non-living things (i.e., inanimate objects), and the inability to recognize living things (i.e., animals and plants) and food. Complementary to the aforementioned, Warrington and McCarthy (1983) presented patient V.E.R., a global dysphasic who had suffered a major left hemisphere infarction. This patient presented preserved ability to recognize living things and an impairment in recognizing non-living things.

The work made by Warrington and her team have shown that different types of information (or categories) can be dissociated, as they have been described as independently impaired, increasing the need for a theoretical framework to adequately explain category-specific deficits (Warrington, 1981; Warrington & McCarthy, 1983; Warrington & Shallice, 1984). With the intention of deepening knowledge and explaining the dissociations observed between the retention and loss of knowledge of living or non-living things, some theories have emerged.

It is currently possible to distinguish between two types of theoretical approaches that attempt to explain the organisation of conceptual knowledge according to different underlying basic principles: theories based on the correlated structure principle, which claims that the organization of conceptual knowledge reflects the way objects properties are statistically related in the world; and theories based on the neural structure principle, stating that knowledge is organized according to representational restraints imposed by the brain (Capitani et *al.*, 2003).

One of the theoretical hypotheses under the correlated structure approach is the Organised Unitary Content Hypothesis (OUCH) emerges (Caramazza et *al.*, 1990). According to OUCH, members of the same superordinate category typically have a lot in common and the characteristics that define an item (such as a dog, chair, etc.) are strongly intercorrelated and are frequently represented together (Caramazza et *al.*, 1990). This theory predicts that categories can be selectively spared if they are limited in their semantic conceptual space, and this selective damage will affect all forms of knowledge in that category but presents the critical issue of not grounding the nature and organization of semantic information (Capitani et *al.*, 2003; Caramazza & Shelton, 1998). Thus, OUCH is characterized by being a vague model, since it is able to explain any category-specific deficit through the damage of the region of the semantic space that corresponds to the type of information impaired (Caramazza & Shelton, 1998). The model's major primary flaw is that OUCH does not provide an explanation for patterns of category-specific deficits that have been verified, since they seemed to respect the tripartite distinction animal/plant/artifact, and not some other category (Caramazza & Shelton, 1998).

Another important model proposed under the correlated structure approach was proposed by Tyler and Moss (1997; 2001) and focused on a feature-based approach (Moss et *al.*, 2002) for understanding conceptual representations. According to the Conceptual Structure Account (CSA), category-specific effects are mostly the result of systematic variations in the underlying structure of concepts in distinct categories and domains.

This new model of conceptual representation tried to account for category-specific without the premise that there are distinct subsystems for the storage of living and nonliving things. CSA was very similar to the model proposed by Devlin et *al.* (1998), which first represented concepts as vectors distributed over two types of semantic information, perceptual and function*al.* Devlin et *al.* (1998) were specifically concerned to incorporate additional characteristics for the vector representations, which allowed the model to account for category-specific deficits caused by non-selective damage to a given percentage of all properties as well as selective damage to one of the aforementioned types of semantic information.

As a result of this reasoning, Feature Distinctiveness (FD) and Feature Correlation (FC) were the additional characteristics that helped to explain these variations that contributed to the structuring of concepts, both between and within categories and domains (Devlin et *al.*, 1998; Tyler et *al.*, 2000). On Feature Distinctiveness, on one hand, we find features shared by all or most category members (such as "has legs" for animals), while on the other, we find more distinctive features that are present in the semantic representation of only or a few members of a semantic category (e.g., "has a long neck", which is true only for giraffe). Regarding Feature Correlation, two features are said to be correlated if one pair member is present in the semantic representation of a particular concept and there is a markedly increased likelihood that the other pair member will also be present in the same representation (for instance, if the concept includes the property "can fly", it is likely to also include the property "has wings") (Tyler et *al.*, 2000). To illustrate the aforementioned, when finding a picture of an elephant among other pictures of animals, it will be more valuable to know that an elephant has a trunk then to know that it has legs (see Zannino et *al.*, 2006). Furthermore, since several studies show that correlated features are more resistant to neurological damage than less correlated ones, the role of feature correlation is not one of utility but rather of resistance against neurological damage (Devlin et *al.*, 1998).

According to CSA, a severe deficit for living things will be noticed when damage is relatively mild, but a disproportionate deficit for non-living things will only occur when damage is so severe that all that is left in the system are the highly correlated shared perceptual and function features of living things (Moss et *al.*, 1998; Moss & Tyler, 2000; Tyler et *al.*, 2000). However, patient JJ presented a pattern that showed a disproportionate deficit for non-living things and a relatively preserved performance for living things. Consequently, the CSA is unable to account for this patient's performance (Hillis & Caramazza, 1991).

Another set of theories is based on the neural structure principle, which states that the organization of conceptual knowledge is determined by representational limits (modalities or domain specificity) internal to the brain – specifically, the brain holds numerous subsystems which are dedicated to the processing of different types of information (such as visual, auditory, motor, etc.), and the ability to identify different categories of objects is dependent on the specific internal mechanisms of each subsystem (Capitani et *al.*, 2003).

One such theory was originally proposed by Warrington and colleagues - the Sensory/Functional Theory (SFT). SFT starts from the premise that the semantic system is segmented into modality-specific semantic mechanisms: the sensory/visual subsystem, which processes the visual characteristics of objects, such as shape and texture, and the functional/associative subsystem that gathers information about non-sensory properties of the objects, such as their function, manner of manipulation, and the place where they can be found (Caramazza, 1998). Furthermore, they added that the ability to recognize and name living things depends on visual/perceptual information, whereas recognizing and naming non-living things depends on functional/associative information (Warrington & McCarthy, 1983, 1987; Warrington & Shallice, 1984). According to modality-specific theories, category-specific impairments are not actually categorical impairments but rather impairments to a type of information (e.g., visual, functional, etc.) that is necessary for the ability to distinguish between exemplars from distinct domains of objects (Capitani et *al.*, 2003).

Three predictions were then conceived based on the SFT: 1) since living things depend on the same type of knowledge (perceptual information), which has more correlated and less distinct properties than do artifacts, it is not possible to observe a dissociation within the domain of living things. (Capitani et *al.*, 2003). Importantly, this prediction does not hold patient EW, a 72-year-old woman who suffered a left cerebral vascular accident, presenting a disproportionately deficit in naming animals relative to other living things, such as fruits/vegetables (Caramazza & Shelton, 1998); 2) patients with specific-category deficits must necessarily have deficits in the modality or type of information that is associated within the impaired category, as shown by recognition/naming tasks (Capitani et *al.*, 2003). Later research has revealed patients who have impairments in both subsystems or in the subsystem that is opposite to what the theory has proposed (Basso et *al.*, 1988; Silveri & Gainotti, 1998); and 3) a deficit in one knowledge modality should be associated with a deficit for the item category that depends on that knowledge (Capitani et *al.*, 2003). Alternately from what the theory supports; patients were reported to have a deficit in visual/perceptual knowledge but no deficit for living things. Additionally, a deficit for non-living things was present (Miceli et *al.*, 2001). Putting all these facts together, this theory cannot explain category-specific semantic deficits.

Still based on the principle of neural structure, Caramazza and Shelton postulated the Domain-Specific Hypothesis (DSH, 1998). According to this hypothesis, conceptual knowledge is organized in domains such as “animals”, “conspecifics”, “fruits and vegetables” and “tools”, due to our evolutionary history (Mahon & Caramazza, 2003; Marques et *al.*, 2013; Santos & Caramazza, 2002; Shelton & Caramazza, 2001). In order to swiftly obtain food, avoid predators, or locate conspecifics for physical and social needs, evolutionary forces led to the creation of brain processes that are specialized in identifying specific sorts of categories. Evolutionarily motivated, there are neural circuits that are inherently designed to process a limited number of knowledge domains with efficiency (Shelton & Caramazza, 2001). This neural system is a network of brain areas, each of which processes information about the same domain or category of objects in a distinct way. Different components of a network may process sensory, motor, emotional, or conceptual information (Caramazza & Shelton, 1998, Santos & Caramazza, 2002).

The DSH postulated two predictions: (1) only categories that were fundamental throughout the evolutionary process may be selectively impaired after brain damage; (2) brain damage in a semantic category will disturb all types of information about the affected category in the same way that is both perceptual and functional information of an object (Caramazza & Mahon, 2003, 2006; Caramazza & Shelton, 1998).

Additionally, a brain region's domain-specificity develops as a result of its inherent connectivity with a network of other brain areas that similarly process information related to that domain, and depending on the category, the connectivity pattern that distinguishes each object category will change. This might provide a category-specific information flow that is important for creating object representations. (Almeida et al., 2013; Amaral et al., 2021; Garcea et al., 2019; Kristensen et al., 2016; Mahon & Caramazza, 2011; Mahon et al., 2013; Walbrin & Almeida, 2021). Moreover, evidence from studies that used transcranial direct current stimulation (tDCS), a neuromodulation technique, suggested that this network-specific connectivity can be modulated by disrupting processing in distal associative areas (Lee et al., 2019; Ruttorf et al., 2019).

1.2. Conceptual knowledge organization and semantic distance

Visual processing of objects involves several areas dedicated to distinct types of processing. A major division relates to the processing happening at two major streams: the dorsal stream, for object-directed action, and ventral stream, for the extraction of object identity (Goodale & Milner, 1992). Mahon and Caramazza have raised the proposal that it is the relationship between the ventral stream and the areas that are specialised in processing a particular type of object that allow domain-specific constraints to arise (2011). However, it has also been shown that structures within the dorsal visual processing stream also influence the identification of objects, namely manipulable objects (Almeida et *al.*, 2008, 2010; Mahon et *al.*, 2010). Furthermore, some category-specific brain regions are already well characterized (Mahon & Caramazza, 2011).

One of them is the face fusiform area (FFA) that showed to be significantly more active when subjects viewed stimuli of human faces (Kanwisher et *al.*, 1997). There is also the parahippocampal place area (PPA), which responds significantly to visual scenes, involving the ventral stream and spatial analysis brain regions (Epstein et *al.*, 1999) .

The extrastriate body area (EBA), which is dedicated in processing body parts, demonstrating the connections of the ventral stream and somatomotor areas (Downing et *al.*, 2001). Finally, the fusiform body area (FBA) demonstrated strong selectiveness to human bodies (Schwarzlose et *al.*, 2005).

Thus, while animals predominantly activate areas of the medial fusiform, which are implicated in processing attributes of visual form, and regions of the superior temporal sulcus associated with biological movement, tools preferentially activate the region of the left middle temporal gyrus that is anterior to the area that contains motion attributes as well as prefrontal regions associated with grasping (Devlin et *al.*, 2002; Mahon et *al.*, 2007; Tyler et *al.*, 2004).

Evidence on category-specific deficits appear to favour the DSH over the competing hypotheses. First, damage to the living category may arise separately from damage to other categories. Second, it appears that this category is divided into the animate (including animals) and inanimate (including objects) domains (e.g., fruits and vegetables). Third, category-specific deficits are frequently linked to uniform conceptual knowledge loss, regardless of whether this conceptual information relates to an object's shape, function, or other conceptual features. These findings pose some challenges for OUCH-type theories and are clearly inconsistent with key assumptions obtained from SFT accounts, but they are entirely consistent with domain-specific evolutionary models (Capitani et *al.*, 2003). In light to this, I made the decision to use the DSH as the model for how conceptual knowledge is organized in the brain.

In addition to these two groups of theories, Zannino et *al.* (2006), based on the description of patient LI, discussed the role of Semantic Distance (SD), an indicator of the degree of semantic similarity between concepts that will be used to give a significant role in my explanation for the genesis of category-specific impairments (Zannino, Perri, Pasqualetti, Caltagirone, et *al.*, 2006a). The SD between two concepts will increase as a function of the number of distinctive features in its semantic representations, whereas the presence of several features shared by two concepts of the same semantic category will increase the semantic similarity, then decreasing SD (Zannino, Perri, Pasqualetti, Paola, et al., 2006).

LI was diagnosed with semantic dementia with a severe impairment to living things, and from the three major accounts to explain these deficits (SFT, CSA and DSH), an attempt was made to explain the case (Zannino, Perri, Pasqualetti, Paola, et *al.*, 2006).

While predictions from the previous theories focused on differences between categories, which ground category-deficits in disproportionate loss of semantic information in the affected category, SD did not follow that reasoning, then focusing on correlations and differences within the features of a category. In fact, Zannino et *al.* (2006) showed that a concept will be more difficult to distinguish from another when the semantic distance is nearly null, i.e., the concepts are semantically very close. On the other hand, when there is a greater semantic distance between the concepts, it is easier to distinguish them. Moreover, it was explained that living things were, on average, significantly closer to each other (less SD) because they share more common features, thus justifying the difficulty in LI when identifying them in a correct way (Zannino, Perri, Pasqualetti, Caltagirone, et *al.*, 2006b; Zannino, Perri, Pasqualetti, Paola, et *al.*, 2006).

One of the methods that has shown promise for providing relevant evidence to analyse the underlying factors in object recognition is feature norming. In those studies, it is asked to the participants to list the features they think are important for entities and objects (McRae & Cree, 2002). Furthermore, through the feature listing task, Zannino and his team discovered that the patient contained comparable knowledge between living and non-living things, thus highlighting SD as the only factor causally linked to worse LI performance on living things (Zannino, Perri, Pasqualetti, Paola, et *al.*, 2006).

Zannino and colleagues provided evidence that semantic distance may influence performances on semantic tasks (Cree & McRae, 2003; Montefinese et *al.*, 2015; Perri et *al.*, 2011; Zannino, Perri, Pasqualetti, Caltagirone, et *al.*, 2006; Zannino, Perri, Pasqualetti, Paola, et *al.*, 2006). This influence was also verified at the computational level by using a feature verification task. From attractor networks, a computational model used to map concepts to feature-based semantic representations, it was proved, as according to Zannino et *al.* (2006), that distinctive features activated a corresponding concept strongly than shared features (Cree et *al.*, 2006; McRae et *al.*, 1997). In the case described, semantic distance was crucial to determine the degree of knowledge about two extremely disparate domains (living and non-living things), but it was also essential to comprehend how information is gathered within the same domain, i.e., between concepts (such as knife and eraser) that share the same superordinate category (e.g., tools).

Behaviorally, this influence on tasks can be explained by semantic priming (SP), defined by the strong observation that people often answer faster to a target word, such as “knife”, when it is preceded by a semantically similar term, such as “fork”, as opposed to an unrelated word, such as "apple" (Neely, 1991). The time it takes to name or make a behavioral decision (i.e., click on a key) to the target is the most common way to assess response latency that it is thought to be directly tied to the amount of time needed for a word's node to activate (Neely, 1991).

1.3. Classification for the features of an object

The type of information that directly influences the intensity of semantic priming between two concepts is very diverse, as in several studies the strength of information types such as vision, function and manipulation has already been demonstrated. First, we have visual information, which comprises all the observed characteristics of an object. Almeida et *al.* (2014), showed that object elongation, a structural and also visual characteristic, can facilitate the visuomotor description of the objects that we use in our daily life. There is also functional semantic information as a crucial component of conceptual representations because it gives an object meaning in a cause-and-effect dynamic environment (Bright et *al.*, 2005). In this line, an artifact's purpose or function has a strong conceptual significance that is closely related to the physical shape of the object. For instance, the distinctive purposes of objects like a knife, a cup, and a spoon are determined by their various shapes (to cut, drink and scoop food respectively). We can identify extremely specific functional and perceptual characteristics that are genuinely distinctive even amongst things that have the same or very comparable functions (for example, a knife and scissors that are both used to cut). Thus, it is claimed that the functional properties of artefacts are relatively distinct and are fundamental in the recognition of an object (Bright et *al.*, 2005).

Additionally, in a study that assessed the contribution of the size of an object in the organisation of conceptual knowledge, Magri et *al.* (2021) revealed that the manipulation of an object (i.e., related to hand performance actions) constitutes an important descriptor that enables the characterisation of an object, particularly when it is small and has a high motor-relevance, namely tools. However, when employing an object, stored knowledge about its identity, function, and action knowledge regarding how to use must be integrated, as opposed to grasping an object, which depends on visuomotor changes over the object's intrinsic physical attributes (Almeida et al., 2010; Ni et al. 2019).

1.4. Objectives

Here, I will focus on the visual recognition of one specific domain – tools. In our evolutionary history, the evolution of competent motor control and tool usage was crucial (Padberg et *al.*, 2007). Tools constitutes a type of item very specific since it differs from animate things in several aspects such as they can be moved, have a certain purpose, and are manipulable. Through the use of tools, people can change more aspects of their surroundings, from the simplest aspect to the most complex. We know that a knife cuts, has a blade and a handle, is elongated and can be found in the kitchen, whereas an eraser is for erasing, it is round, small and can be found in an office. Additionally, it was shown that non-living (such as tools) things typically had more distinguishing characteristics than live things (Cree & McRae, 2003). McRae et *al.* (1997) concluded that these features were shared if they tended to co-occur in the same fundamental level concepts, recovering what was established by semantic distance. In fact, Cree et *al.* (1999) conclude that featural overlap, a natural side-effect of distributed representations of word meaning, is the cause of semantic-similarity priming.

What remains to be explained in the phenomenon of object recognition, in the light of what is predicted by semantic distance, is the clarification of which features are more salient in determining the distinction between two objects.

In this thesis, my aim is to find out how different feature types will impact the time we take to distinguish between to manipulable objects. I particularly want to understand how these domains can impact semantic priming. Importantly, studying this phenomenon can provide invaluable information to the understanding of how conceptual knowledge is structured.

To test that, I took 250 pairs of objects, where I was capable to manipulate semantic distance, obtaining values that are relatively representative of the whole spectrum in all four dimensions (All Features, Function, Manipulation and Vision) and performed a behavioral experiment where I measured reaction times. According to the literature (Valério & Almeida, in prep), I predict that objects that share more characteristics (higher semantic similarity) will be more difficult to recognize from one another. Therefore, perceiving objects that are different from the adapted object will result in shorter reaction times. I expect to confirm this pattern by analyses in each of the four dimensions I used and emphasize this feature-based object similarity as an important variable in the understanding of conceptual knowledge.

2. Methods

This experiment aimed to understand the interference that each dimension of semantic information associated with objects has when we need to distinguish one object from a different one. During the task, participants viewed images of objects and were instructed to click on a keypad whenever the object changed. Reaction times (RT), in milliseconds, were analysed and used to define a model describing the relationship between the dimensions under study.

2.1. Participants

Eleven healthy right-handed adults (N = 11; mean age of 21.00 years, SD = 1.21, min = 19, max = 24; 10 females and 1 male) were recruited to take part in the experiment. Participants were part of the student population of the University of Coimbra. Written informed consent was obtained from all participants after a detailed description of the complete study in accordance with the declaration of Helsinki and the work was approved by the Ethics Committee of the Faculty of Psychology of the University of Coimbra, Portug*al*. Exclusion criteria for participation included left-handedness, caffeine intake two hours before sessions.

2.2. Stimuli

In this study, all stimuli were extracted from a database built in an unpublished study conducted as part of a PhD project in the lab (Valério & Almeida, in prep).

To create this database, based on previous research, 130 participants were asked to provide features from a list of 80 objects (Vigliocco et *al.*, 2002). No time or limits on the quantity of features to be generated were imposed. Some examples of attributes were: "it is heavy", "made of wood", "found in toolboxes", "used for cutting", among others. After collecting the data, based on the obtained descriptions, the characteristics of each object were grouped and, to confront the features shared among the objects, the cosine of similarity was calculated, for all combinations of pairs between the 80 objects (Bruffaerts et *al.*, 2013; McRae et *al.*, 2005).

Once the similarity values were acquired, a database was created with the different feature types, such as: All Features (which considers all type of features), Function and Vision. In addition to these, a database was also created for the Manipulation, which was independent of this database as it came from a parallel study.

From the combinations between the initial 80 objects on the list, 3160 pairs would emerge. As this would be an unworkable number to use in a behavioral task, for this study, 250 pairs of objects were selected.

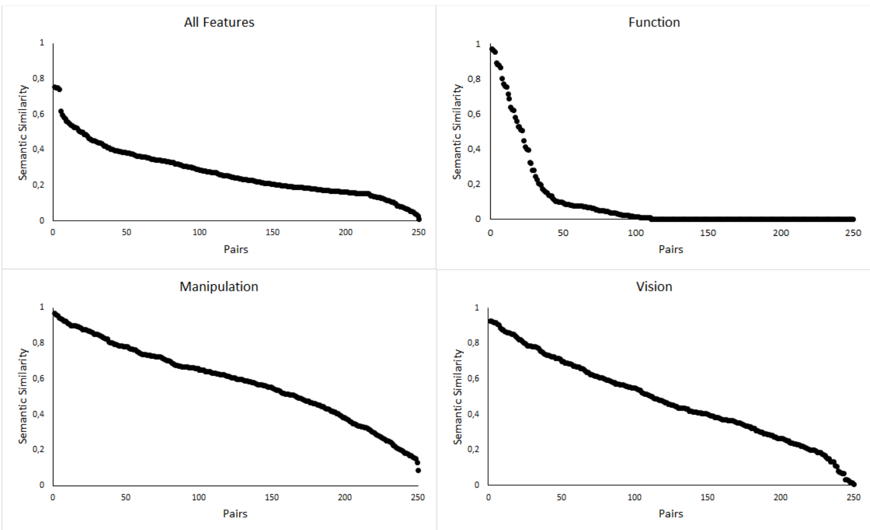
For the process of choosing pairs, the values between dimensions were subtracted, two by two, and the pairs outside the interval between -0.1 and 0.1 were excluded. This step resulted in a set of pairs that did not cover all the necessary dispersion of values, so pairs that resisted the filter with 0.2 and 0.3 were included. Finally, to reach 250 pairs, pairs were manually included to help complete the desired distribution of values (see Table A in Annexes).

The pairs were combined such that, for each of the four variables (All Features, Function, Manipulation, Vision), the similarity values of the defined pairs filled the widest range of values within the similarity interval, which ranged from 0 to 1 (Figure 1). The closer to zero, the less features two objects have in common and the closer to 1, the more features the objects have in common. The average similarity values between the five sessions did not show significant differences.

As an example, the pair scissors/knife presents a cosine of similarity of .750 for All Features, 0.963 for Function, .492 for Manipulation, .692 for Vision. From these values I conclude that the two objects are quite close, since they share many features in all dimensions but the Manipulation, since they are used differently.

Figure 1

Semantic similarity values in each chosen dimension



Note. The Function graph's dispersion is limited and not particularly informative because only around 100 pairs had similarity values above zero. This happened in the pairs that did not share any features concerning the function (semantic similarity was zero). However, these same pairs were needed to complement the missing values in the dispersion of the remaining dimensions. The dispersion of values has been filled in the left variables.

The choice of pairs was made in order to maximise the distribution of values in the four dimensions, minimising the correlation of the data between the dimensions, so as to make them as independent as possible. The correlation coefficients between the dimensions are presented in Table 1, and as can be seen, there is some collinearity that could not be further minimised.

Table 1

Correlation coefficient between dimensions

Dimensions		Correlation coefficient
All Features	Function	.487
All Features	Manipulation	.070
All Features	Vision	.409
Function	Manipulation	.217
Function	Vision	-.230
Manipulation	Vision	-.107

Once the 250 pairs were chosen, I observed that some objects were present in numerous pairs (e.g., knife appeared in 13 pairs while bottle appeared in 2). Thus, the most repeated objects were paired in order to control for the number of times they appeared in each of the five sessions. In addition, in each session, the number of times these objects appeared as adaptor or deviant was also controlled for.

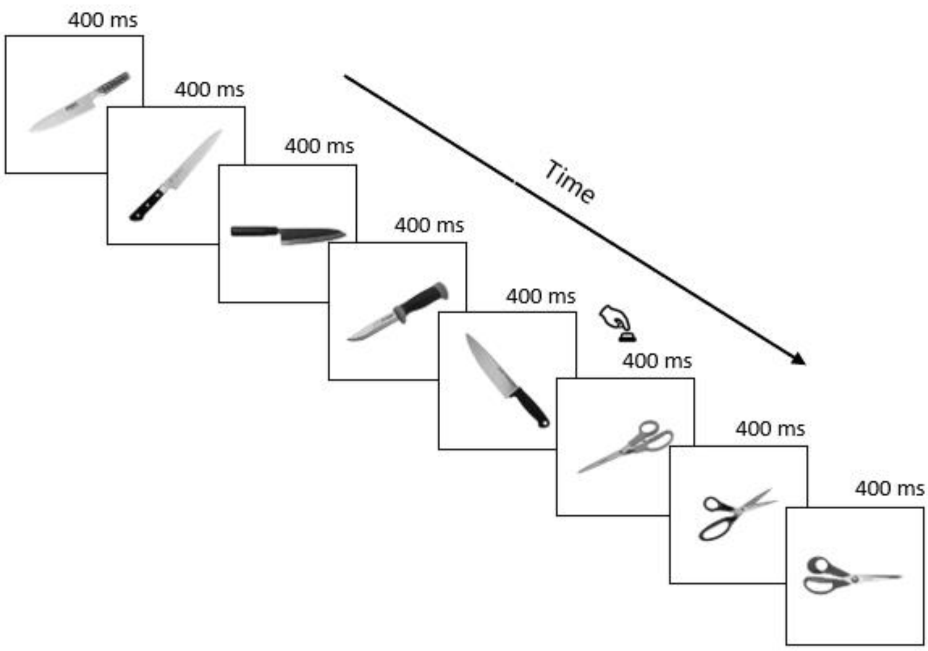
2.3. Procedure

Participants were instructed to press a key whenever the object they were looking at was different from the previous object (for example, when going from a knife to a hammer). They were also told that they did not need to press the key while different images of the same object appeared (e.g., different perspectives and types of knives). In order to make sure that they understood the purpose of the task, the participants were given a brief training session of 5 trials. These trials were not used in the analysis. Participants had a quick evaluation prior to commencing to make sure inclusion requirements were satisfied.

The experiment consisted in five sessions, each lasting approximately 35 minutes. Five distinct orders were created and passed to the participants in a random and counterbalanced order. In each session, 50 pairs out of 250 pre-defined pairs were used. The length of each trial was composed of a number of adaptation stimuli ranging from five to nine, plus three deviant stimuli. Participants viewed the same pair ten times, as each length was repeated twice, so every single session consisted of the presentation of 500 trials. Both the order in which the pairs appeared, and the length of the trial was randomised across sessions. Stimuli consisted of black and white images of objects under a white background and appeared on the screen for 400 ms with a refresh rate of 60 Hz (Figure 2). The object images that were used in this experiment were extracted from the image database of Valério and Almeida (in prep).

Figure 2

Experimental task



Note. We have the example of pair 188 (knife/scissors). In this case it is composed of five adaptors (various views of the knives) and three deviators (various views of the scissors). The aim is to click on the key when the image of the object changes, as quickly and accurately as possible.

The responses were collected with a button box (Cedrus Corp.), with the participant's dominant hand (right). I used MATLAB (version R2019.b) and a "A Simple Framework" (Schwarzbach, 2011) to present stimuli. Reaction times were measured and saved. Sessions were carried out without any interruption and followed the rule of always being scheduled with a minimum interval of one week. The participants, in all sessions, wore sound isolation headphones while performing the task to minimize outside noise.

2.4. Analysis

Outliers were identified as RTs that fell outside the range of 100 to 800 milliseconds, and in the initial data processing, they were subtracted from the averages. For each participant, and for all together, I calculated a mean, and a correspondent standard deviation (SD) for the RTs, one for each pair that was showed throughout the course of the five sessions (see Table A in Annexes).

To test for the hypothesis, two multiple linear regressions were conducted, and the selected explanatory variables were based on type of semantic information that each dimension integrated. The aim was to explore, through the definition of a model, the correlations between the semantic similarity values of each dimension in study and the RTs produced. Explained variance was evaluated through the coefficient of determination, R^2. Regression coefficients and p-values were presented to show the magnitude and significance of the relationship between RTs and predictor variables.

3. Results

In this analysis, I obtained one model by calculating a multiple linear regression to predict RTs on All Features, Function, Manipulation and Vision (Table 2). In Model 1, it was found a statistically significant regression equation ($F(4,249) = 8.738$, $p < .001$, $R^2 = .125$). The variables All Features, and Function were significant predictors in this model. All Features had a positive impact (β = 63.731, $p < .01$), and Function had a negative impact (β = -31.069, $p < .05$).

The results in Model 1 revealed the presence of multicollinearity between database variables, because All Features resulted from information extracted from Vision and Function variables. When two or more variables are collinear it is no longer possible to guarantee a linear association between two variables without this actually being explained by the correlation coefficient between them.

Consequently, since the high correlation between the independent variables (see Table 1) was what truly explained the explained variance ($R^2 = .125$), it was necessary to adapt the analysis so that it could more clearly observe the independent power of each variable during this task.

Thus, the prior analysis was repeated, but excluding the variable All Features (Model 2). A significant model resulted ($F(3,249) = 7.936$, $p < .001$, $R^2 = .088$). Vision was the only significant predictor of RT ($p < .001$).

Figures 3-5 confront the RTs produced by the participants with those that the Model 2 predicted. Regarding Function, there was a concentration of data on the Y-axis since there were numerous pairs that contained a similarity value equal to zero. Otherwise, the results did not reveal a significant trend, being dispersed along the semantic similarity spectrum. In the Manipulation variable, no significant response trend was found. With regard to Vision, a response pattern was visualized. The trend reveals that longer RTs are seen when semantic similarity values are closer to 1, which corresponds to objects that share more visual information.

Table 2

Summary of the results

Variable	Model 1		Model 2	
	β	**p-value**	**β**	**p-value**
All Features	63.731	$.002^{***}$	not included	not included
Function	-31.069	$.013^{**}$	-5.388	.576
Manipulation	16.569	$.077^{*}$	16.357	.087
Vision	18.010	$.099^{*}$	39.353	$1.1\text{E-}05^{***}$

p-value	1.3E-06***	4.5E-05***
Constant	423.589	428.506
R^2	.125	.088

Note. * p < .1 ** p < .05 *** p < .01.

Figure 3

Response trend and predicted response in Function

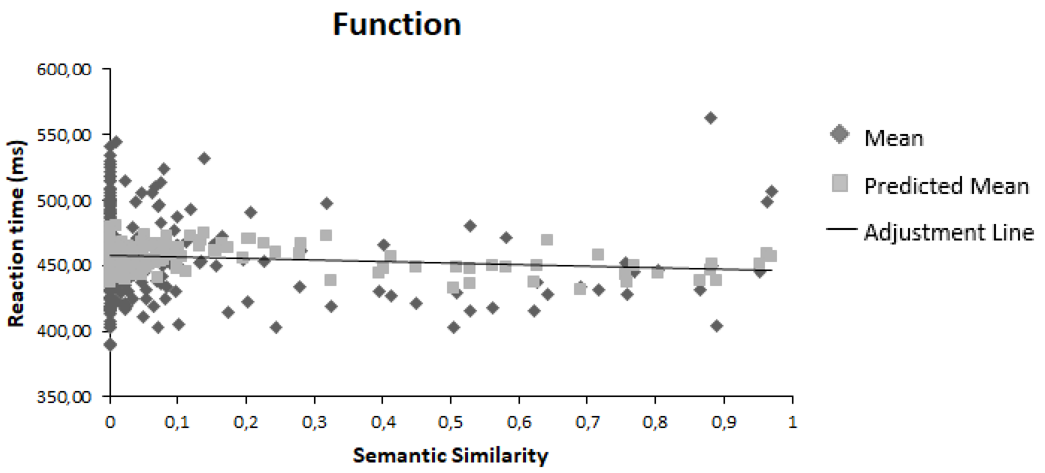


Figure 4

Response trend and predicted response in Manipulation

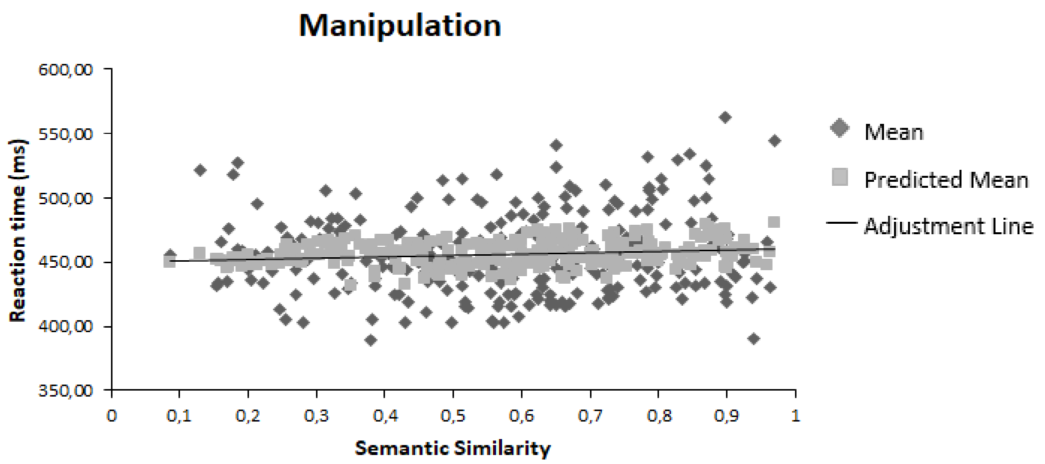
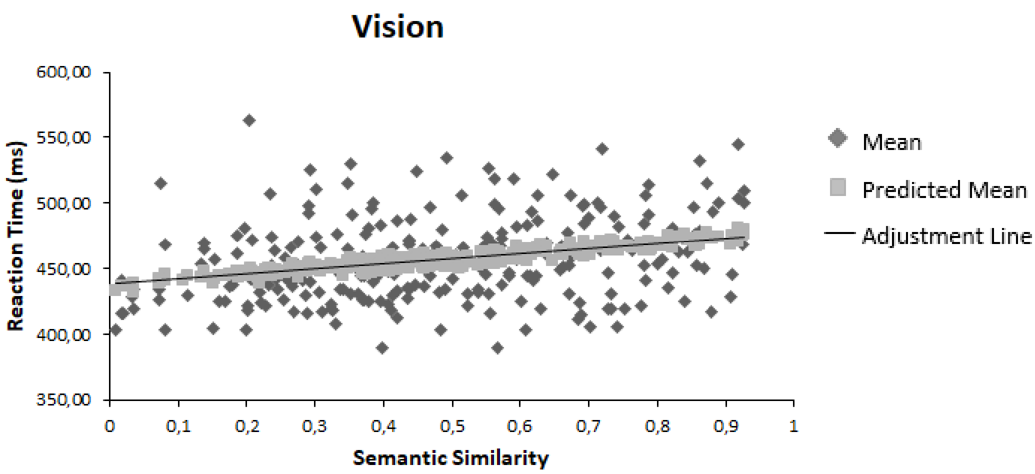


Figure 5

Response trend and predicted response in Vision



4. Discussion and Conclusion

The current study aimed to explore the relative contributions of distinct aspects of semantic information about objects in their representation. This was made through a behavioral task that consisted in distinguishing between different objects.

Based on the analysis of the data obtained in Model 2, the results showed that Vision had a significant effect, in which it was found that, at the vision level, the more features two objects share, i.e., greater semantic similarity, the slower we are to distinguish two objects. This result supports my hypothesis and reinforces the relevance of visual information processing during object recognition.

Furthermore, a trend, even if not significant, can also be observed in the information referring to Manipulation, placing it, in this case, as the second most relevant type of information, with a positive correlation between semantic similarity and reaction time. Finally, given the reasons mentioned above, the Function variable, both in the graphical representation and in the statistical analyses, proved to be less informative, and showed that semantic similarity and reaction time were negatively correlated.

In general, the correlation coefficients of the models obtained presented low values. However, regarding the comparison between the models obtained, the removal of All Features from the equation resulted in a big adjustment of the variance explanation of the results, since the power of variance explanation was distributed on the remaining coefficients. Observing in detail, while Manipulation's regression coefficient remained the same value in both models, Function gained much more explanatory power, becoming drastically more positive, but not significant. Concerning the coefficient of Vision, the value doubled for Model 2, and achieved a much more relevant significance level.

These results are important from a number of different perspectives. First, they present evidence for the relevance of using speaker-generated features to develop measures of semantic similarity (Vigliocco et *al*., 2002). They also offer supporting data that is consistent with the findings of McRae et *al*. (1997), who demonstrated, in the object domain, that semantic similarity (in terms of shared features) significantly predicted priming (in a semantic decision task). Therefore, this data adds to the reinforcement of similarity between stimuli as a strategy used by the brain to organise information.

A similar line of research, using functional neuroimaging studies, reported a numerical distance and numerical magnitude effects with the same pattern that was found in this study. It was concluded that numerical judgments became more difficult when the numerical distance between two values decreased. Additionally, this effect was amplified as their absolute magnitude increased, making it easier to distinguish between the two values presented (Ansari et *al*., 2006; Piazza et *al*. 2004, 2007). Furthermore, the same conclusions were obtained using words (Morgan et al., 2011; Siakaluk et *al*., 2003; Viganò et al., 2021) and pictures (Damian et *al*., 2001; Vigliocco et *al*., 2004).

Unpublished preliminary work in the lab already used these similarity values and, taking into consideration the dispersion of values, subdivided them into four experimental groups. Graphically, and using a similar paradigm to the current study, they verified statistically significant differences ($p < .05$) in the reaction times between each of these levels, with the exception of distant and super distant levels. This study has highlighted the relevance of exploring, in more detail, how our object recognition behaves along the whole spectrum of semantic similarity values (Valério et *al.*, in prep). Moreover, it was asked whether the best subdivision would have been the four-level one, since the response variance could be better explained by fewer or more levels. Thereby, I wanted to study the reaction times in a sample of object pairs, which would give us an approximation of the general picture, which would have been reached if all the couples had been employed. Graphically speaking, I could have found a diagram reflecting exponential, logarithmic or linear behavior.

Another aspect I could reflect on is the collinearity between dimensions. Namely, the fact that the All Features contained data that belonged to the Function and Vision dimensions contributed to the repetition of the information when I calculated the correlation between the dimensions, thus masking a value of explained variance that should result from independent variables. Although the initial aim was to rely on All Features for the delineation of the model, this limitation was significantly relevant in removing this dimension from the final equation.

The dispersion of semantic similarity values was restricted to the 250 pairs used, however, the non-addition of more pairs is justified by the possible effect of fatigue that would be caused in the participants, since the sessions would be much longer and would put at risk their adherence in the data collection process.

The kind of stimuli that were presented to the participants should also be considered. The class of objects presented a lot of variability of characteristics, so that it was easier to find differences than similarities between two objects. Other classes, like animals, usually include features that are more common to find in a larger number of animals, like for example "having fur", "having legs", which immediately encompasses a generous portion of animals. This individuality so salient in the class of objects caused a difficulty in creating groups that cohesively shared several characteristics. This difficulty was reflected in the similarity data obtained, as there were numerous objects that were used in different contexts and therefore received a value of zero, for example at the functional level, affecting the database in this dimension, as it caused a lower representativeness of values along the semantic similarity spectrum, making it difficult to clearly perceive the graph in better detail.

A critical finding in these results was that each pair of objects had its own profile, and when compared to another, there may be identical characteristics, like "both are elongated" or "both are made of metal", however, they can also have fully different ways of being used. This type of pattern, where between two objects we found such extreme relationships, interfered with the data obtained.

Concerning the current study, despite the small sample size, preliminary results suggested a significant model, with predictors close to being strongly significant. Furthermore, to the development of future studies in this topic, it is recommended to add information in the function database, in order to complement the data deficit along the spectrum, since it will enable a better understanding of the relationship between similarity values and reaction times.

In this line of research, I intended to evaluate behavioral data, however, a methodological approach that includes neuroimaging data is being developed by Valério et *al*. (in prep). They want to compare the semantic accuracy values that were obtained from the study of Valério and Almeida (in prep) with the level of activation of the brain regions that are most related to each dimension.

This thesis served as an illustration of how cognitive neuroscience could be employed to study object recognition, providing ground space for the discussion of theoretically concerns about the way in which conceptual information is organized in the brain.

References

Almeida, J., Fintzi, A. R., & Mahon, B. Z. (2013). Tool manipulation knowledge is retrieved by way of the ventral visual object processing pathway. *Cortex*, *49*(9), 2334–2344. https://doi.org/10.1016/J.CORTEX.2013.05.004

Almeida, J., Mahon, B. Z., & Caramazza, A. (2010). The role of the dorsal visual processing stream in tool identification. *Psychological Science*, *21*(6), 772–778. https://doi.org/10.1177/0956797610371343

Almeida, J., Mahon, B. Z., Nakayama, K., & Caramazza, A. (2008). Unconscious processing dissociates along categorical lines. *PNAS*, *105*(39), 15214–15218. https://doi.org/10.1073/PNAS.0805867105

Almeida, J., Mahon, B. Z., Zapater-Raberov, V., Dziuba, A., Cabaço, T., Marques, J. F., & Caramazza, A. (2014). Grasping with the eyes: The role of elongation in visual recognition of manipulable objects. *Cognitive, Affective and Behavioral Neuroscience*, *14*(1), 319–335. https://doi.org/10.3758/S13415-013-0208-0/FIGURES/5

Amaral, L., Bergström, F., & Almeida, J. (2021). Overlapping but distinct: Distal connectivity dissociates hand and tool processing networks. *Cortex*, *140*, 1–13. https://doi.org/10.1016/J.CORTEX.2021.03.011

Ansari, D., Dhital, B., & Siong, S. C. (2006). Parametric effects of numerical distance on the intraparietal sulcus during passive viewing of rapid numerosity changes. *Brain Research*, *1067*(1), 181–188. https://doi.org/10.1016/J.BRAINRES.2005.10.083

Basso, A., Capitani, E., & Laiacona, M. (1988). Progressive language impairment without dementia: a case with isolated category specific semantic defect. *Journal of Neurology, Neurosurgery, and Psychiatry*, *51*(9), 1201. https://doi.org/10.1136/JNNP.51.9.1201

Bright, P., Moss, H. E., Stamatakis, E. A., & Tyler, L. K. (2005). The anatomy of object processing: The role of anteromedial temporal cortex. *The Quarterly Journal of Experimental Psychology*, *58*(3–4), 361–377. https://doi.org/10.1080/02724990544000013

Bruffaerts, R., Dupont, P., de Grauwe, S., Peeters, R., de Deyne, S., Storms, G., & Vandenberghe, R. (2013). Right fusiform response patterns reflect visual object identity rather than semantic similarity. *NeuroImage*, *83*, 87–97. https://doi.org/10.1016/J.NEUROIMAGE.2013.05.128

Capitani, E., Laiacona, M., Mahon, B., & Caramazza, A. (2003). What are the facts of semantic category-specific deficits? A critical review of the clinical evidence. *Cognitive Neuropsychology*, *20*(3–6), 213–261. https://doi.org/10.1080/02643290244000266

Caramazza, A. (1998). The interpretation of semantic category-specific deficits: What do they reveal about the organization of conceptual knowledge in the brain? *Neurocase*, *4*(4–5), 265–272. https://doi.org/10.1080/13554799808410627

Caramazza, A., Hillis, A. E., Rapp, B. C., & Romani, C. (1990). The multiple semantics hypothesis: Multiple confusions? *Http://Dx.Doi.Org/10.1080/02643299008253441*, *7*(3), 161–189. https://doi.org/10.1080/02643299008253441

Caramazza, A., & Mahon, B. Z. (2003). The organization of conceptual knowledge: The evidence from category-specific semantic deficits. *Trends in Cognitive Sciences*, *7*(8), 354–361. https://doi.org/10.1016/S1364-6613(03)00159-1

Caramazza, A., & Mahon, B. Z. (2006). The organisation of conceptual knowledge in the brain: The future's past and some future directions. *Cognitive Neuropsychology*, *23*(1), 13–38. https://doi.org/10.1080/02643290542000021

Caramazza, A., & Shelton, J. R. (1998). Domain-specific knowledge systems in the brain the animate-inanimate distinction. *Journal of Cognitive Neuroscience*, *10*(1), 1–34. https://doi.org/10.1162/089892998563752

Cree, G. S., McNorgan, C., & McRae, K. (2006). Distinctive features hold a privileged status in the computation of word meaning: Implications for theories of semantic memory. *Journal of Experimental Psychology: Learning Memory and Cognition*, *32*(4), 643–658. https://doi.org/10.1037/0278-7393.32.4.643

Cree, G. S., & McRae, K. (2003). Analyzing the factors underlying the structure and computation of the meaning of chipmunk, cherry, chisel, cheese, and cello (and many other such concrete nouns). *Journal of Experimental Psychology: General*, *132*(2), 163–201. https://doi.org/10.1037/0096-3445.132.2.163

Cree, G. S., McRae, K., & McNorgan, C. (1999). An attractor model of lexical conceptual processing: Simulating semantic priming. *Cognitive Science*, *23*(3), 371–414. https://doi.org/10.1207/S15516709COG2303_4

Damian, M. F., Vigliocco, G., & Levelt, W. J. M. (2001). Effects of semantic context in the naming of pictures and words. *Cognition*, *81*(3), B77–B86. https://doi.org/10.1016/S0010-0277(01)00135-4

Devereux, B. J., Clarke, A., & Tyler, L. K. (2018). Integrated deep visual and semantic attractor neural networks predict fMRI pattern-information along the ventral object processing pathway. *Scientific Reports 2018 8:1*, *8*(1), 1–12. https://doi.org/10.1038/s41598-018-28865-1

Devlin, J. T., Gonnerman, L. M., Andersen, E. S., & Seidenberg, M. S. (1998). Category-specific semantic deficits in focal and widespread brain damage: A computational account. *Journal of Cognitive Neuroscience*, *10*(1), 77–94. https://doi.org/10.1162/089892998563798

Downing, P. E., Jiang, Y., Shuman, M., & Kanwisher, N. (2001). A cortical area selective for visual processing of the human body. *Science*, *293*(5539), 2470–2473. https://doi.org/10.1126/SCIENCE.1063414

Epstein, R., Harris, A., Stanley, D., & Kanwisher, N. (1999). The parahippocampal place area: Recognition, navigation, or encoding? *Neuron*, *23*(1), 115–125. https://doi.org/10.1016/S0896-6273(00)80758-8

Garcea, F. E., Almeida, J., Sims, M. H., Nunno, A., Meyers, S. P., Li, Y. M., Walter, K., Pilcher, W. H., & Mahon, B. Z. (2019). Domain-specific diaschisis: Lesions to parietal action areas modulate neural responses to tools in the ventral stream. *Cerebral Cortex*, *29*(7), 3168–3181. https://doi.org/10.1093/CERCOR/BHY183

Goodale, M. A., & Milner, A. D. (1992). Separate visual pathways for perception and action. *Trends in Neurosciences*, *15*(1), 20–25. https://doi.org/10.1016/0166-2236(92)90344-8

Hillis, A. E., & Caramazza, A. (1991). Category-specific naming and comprehension impairment: A double dissociation. *Brain, 114*(5), 2081–2094. https://doi.org/10.1093/BRAIN/114.5.2081

Hummel, J. E. (2013). Object recognition. In D. Reisburg (Ed.) *Oxford Handbook of Cognitive Psychology* (pp. 32-46), Oxford, England: Oxford University Press. https://psycnet.apa.org/doi/10.1093/oxfordhb/9780195376746.013.0003

Humphreys, G. W., & Riddoch, M. J. (1987). On telling your fruit from your vegetables: a consideration of category-specific deficits after brain damage. *Trends in Neurosciences*, *10*(4), 145–148. https://doi.org/10.1016/0166-2236(87)90040-3

Kanwisher, N., McDermott, J., & Chun, M. M. (1997). The fusiform face area: A module in human extrastriate cortex specialized for face perception. *Journal of Neuroscience*, *17*(11), 4302–4311. https://doi.org/10.1523/JNEUROSCI.17-11-04302.1997

Kristensen, S., Garcea, F. E., Mahon, B. Z., & Almeida, J. (2016). Temporal frequency tuning reveals interactions between the dorsal and ventral visual streams. *Journal of Cognitive Neuroscience*, *28*(9), 1295–1302. https://doi.org/10.1162/JOCN_A_00969

Lee, D., Mahon, B. Z., & Almeida, J. (2019). Action at a distance on object-related ventral temporal representations. *Cortex*, *117*, 157–167. https://doi.org/10.1016/J.CORTEX.2019.02.018

Magri, C., Konkle, T., & Caramazza, A. (2021). The contribution of object size, manipulability, and stability on neural responses to inanimate objects. *NeuroImage*, *237*. https://doi.org/10.1016/J.NEUROIMAGE.2021.118098

Mahon, B. Z., & Caramazza, A. (2003). Constraining questions about the organisation and representation of conceptual knowledge. *Cognitive Neuropsychology*, *20*(3–6), 433–450. https://doi.org/10.1080/02643290342000014

Mahon, B. Z., & Caramazza, A. (2011). What drives the organization of object knowledge in the brain? *Trends in Cognitive Sciences*, *15*(3), 97–103. https://doi.org/10.1016/J.TICS.2011.01.004

Mahon, B. Z., Kumar, N., & Almeida, J. (2013). Spatial frequency tuning reveals interactions between the dorsal and ventral visual systems. *Journal of Cognitive Neuroscience*, *25*(6), 862–871. https://doi.org/10.1162/JOCN_A_00370

Mahon, B. Z., Schwarzbach, J., & Caramazza, A. (2010). The representation of tools in left parietal cortex is independent of visual experience. *Psychological Science : A Journal of the American Psychological Society / APS*, *21*(6), 764–771. https://doi.org/10.1177/0956797610370754

Marques, J. F., Raposo, A., & Almeida, J. (2013). Structural processing and category-specific deficits. *Cortex*, *49*(1), 266–275. https://doi.org/10.1016/J.CORTEX.2011.10.006

McRae, K., & Cree, G. S. (2002). Factors underlying category-specific semantic deficits. In E. M. E. Forde & G. W. Humphreys (Eds.), *Category-specificity in brain and mind* (pp. 211–249). East Sussex, England: Psychology Press.

McRae, K., Cree, G. S., Seidenberg, M. S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behavior Research Methods 2005 37:4*, *37*(4), 547–559. https://doi.org/10.3758/BF03192726

McRae, K., de Sa, V. R., & Seidenberg, M. S. (1997). On the nature and scope of featural representations of word meaning. *Journal of Experimental Psychology*. *General*, *126*(2), 99–130. https://doi.org/10.1037//0096-3445.126.2.99

Miceli, G., Fouch, E., Capasso, R., Shelton, J. R., Tomaiuolo, F., & Caramazza, A. (2001). The dissociation of color from form and function knowledge. *Nature Neuroscience*, *4*(6), 662–667. https://doi.org/10.1038/88497

Morgan, L. K., MacEvoy, S. P., Aguirre, G. K., & Epstein, R. A. (2011). Distances between real-world locations are represented in the human hippocampus. *Journal of Neuroscience*, *31*(4), 1238–1245. https://doi.org/10.1523/JNEUROSCI.4667-10.2011

Moss, H. E., & Tyler, L. K. (2000). A progressive category-specific semantic deficit for non-living things. *Neuropsychologia*, *38*(1), 60–82. https://doi.org/10.1016/S0028-3932(99)00044-5

Moss, H., Tyler, L. K., & Devlin, J. T. (2002). The emergence of category-specific deficits in a distributed semantic system. In E. M. E. Forde & G. W. Humphreys (Eds.), *Category specificity in brain and mind* (pp.115–147). New York: Psychology Press.

Moss, H. E., Tyler, L. K., Durrant-Peatfield, M., & Bunn, E. M. (1998). 'Two eyes of a see-through': Impaired and intact semantic knowledge in a case of selective deficit for living things. *Neurocase*, *4*(4–5), 291–310. https://doi.org/10.1080/13554799808410629

Neely, J. H. (1991). Semantic priming effects in visual word recognition: A selective view of current findings and theories. In Besner D., & Humphreys, G. (Eds.), *Basic processes in reading: Visual word recognitio*n (pp. 264 –336). Hillsdale, NJ: Erlbaum.

Ni, L., Liu, Y., & Yu, W. (2019). The dominant role of functional action representation in object recognition. *Experimental Brain Research*, *237*(2), 363–375. https://doi.org/10.1007/S00221-018-5426-9/FIGURES/6

Padberg, J., Franca, J. G., Cooke, D. F., Soares, J. G. M., Rosa, M. G. P., Fiorani, M., Gattass, R., & Krubitzer, L. (2007). Parallel evolution of cortical areas involved in skilled hand use. *Journal of Neuroscience, 27*(38), 10106–10115. https://doi.org/10.1523/JNEUROSCI.2632-07.2007

Piazza, M., Izard, V., Pinel, P., le Bihan, D., & Dehaene, S. (2004). Tuning curves for approximate numerosity in the human intraparietal sulcus. *Neuron*, *44*(3), 547–555. https://doi.org/10.1016/J.NEURON.2004.10.014

Piazza, M., Pinel, P., le Bihan, D., & Dehaene, S. (2007). A magnitude code common to numerosities and number symbols in human intraparietal cortex. *Neuron*, *53*(2), 293–305. https://doi.org/10.1016/j.neuron.2006.11.022

Ruttorf, M., Kristensen, S., Schad, L. R., & Almeida, J. (2019). Transcranial direct current stimulation alters functional network structure in humans: A graph theoretical analysis. *IEEE Transactions on Medical Imaging*, *38*(12), 2829–2837. https://doi.org/10.1109/TMI.2019.2915206

Santos, L., & Caramazza, A. (2002). The domain-specific hypothesis: A developmental and comparative perspective on category-specific deficits. In E. Forde & G. Humphreys (Eds.). *Category Specificity in Brain and Mind* (pp. 1-23). New York: Psychology Press.

Schwarzbach, J. (2011). A simple framework (ASF) for behavioral and neuroimaging experiments based on the psychophysics toolbox for MATLAB. *Behavior Research Methods*, *43*(4), 1194–1201. https://doi.org/10.3758/S13428-011-0106-8/TABLES/1

Schwarzlose, R. F., Baker, C. I., & Kanwisher, N. (2005). Separate face and body selectivity on the fusiform gyrus. *The Journal of Neuroscience*, *25*(47), 11055–11059. https://doi.org/10.1523/JNEUROSCI.2621-05.2005

Shelton, J., & Caramazza, A. (2001). The organization of semantic memory. In B. Rapp (Ed.), *Handbook of Cognitive Neuropsychology: What deficits reveal about the human mind* (pp. 423-443). New York: Psychology Press.

Siakaluk, P. D., Buchanan, L., & Westbury, C. (2003). The effect of semantic distance in yes/no and go/no-go semantic categorization tasks. *Memory & Cognition 2003 31:1*, *31*(1), 100–113. https://doi.org/10.3758/BF03196086

Silveri, M. C., & Gainotti, G. (1998). Interaction between vision and language in category-specific semantic impairment. *Cognitive Neuropsychology*, *5*(6), 677–709. https://doi.org/10.1080/02643298808253278

Tyler, L. K., Marslen-Wilson, W. D., Randall, B., Wright, P., Devereux, B. J., Zhuang, J., Papoutsi, M., & Stamatakis, E. A. (2011). Left inferior frontal cortex and syntax: Function, structure and behaviour in patients with left hemisphere damage. *Brain*, *134*(2), 415–431. https://doi.org/10.1093/BRAIN/AWQ369

Tyler, L. K., & Moss, H. E. (1997). Functional properties of concepts: Studies of normal and brain-damaged patients. *Cognitive Neuropsychology*, *14*(4), 511–545. https://doi.org/10.1080/026432997381466

Tyler, L. K., & Moss, H. E. (2001). Towards a distributed account of conceptual knowledge. *Trends in Cognitive Sciences*, *5*(6), 244–252. https://doi.org/10.1016/S1364-6613(00)01651-X

Tyler, L. K., Moss, H. E., Durrant-Peatfield, M. R., & Levy, J. P. (2000). Conceptual structure and the structure of concepts: A distributed account of category-specific deficits. *Brain and Language*, *75*(2), 195–231. https://doi.org/10.1006/BRLN.2000.2353

Tyler, L. K., Stamatakis, E. A., Bright, P., Acres, K., Abdallah, S., Rodd, J. M., & Moss, H. E. (2004). Processing objects at different levels of specificity. *Journal of Cognitive Neuroscience*, *16*(3), 351–362. https://doi.org/10.1162/089892904322926692

Valério, D., & Almeida, J. (in prep). Features importance for the recognition of manipulable objects: Norms and feature verification task.

Valério, D., Peres, A., Bergström, F., Seidel, P., & Almeida, J. (in prep). Tuning curves for the manipulable object’s similarity: Behavioral and neural findings.

Victoria, L. W., Pyles, J. A., & Tarr, M. J. (2019). The relative contributions of visual and semantic information in the neural representation of object categories. *Brain and Behavior*, *9*(10). https://doi.org/10.1002/BRB3.1373

Viganò, S., Rubino, V., Soccio, A. di, Buiatti, M., & Piazza, M. (2021). Grid-like and distance codes for representing word meaning in the human brain. *NeuroImage*, *232*, 117876. https://doi.org/10.1016/J.NEUROIMAGE.2021.117876

Vigliocco, G., Vinson, D. P., Damian, M. F., & Levelt, W. (2002). Semantic distance effects on object and action naming. *Cognition*, *85*(3), B61–B69. https://doi.org/10.1016/S0010-0277(02)00107-5

Vigliocco, G., Vinson, D. P., Lewis, W., & Garrett, M. F. (2004). Representing the meanings of object and action words: The featural and unitary semantic space hypothesis. *Cognitive Psychology*, *48*(4), 422–488. https://doi.org/10.1016/J.COGPSYCH.2003.09.001

Walbrin, J., & Almeida, J. (2021). High-level representations in human occipito-temporal cortex are indexed by distal connectivity. *Journal of Neuroscience*, *41*(21), 4678–4685. https://doi.org/10.1523/JNEUROSCI.2857-20.2021

Warrington, E. K. (1981). Neuropsychological studies of verbal semantic systems. *Philosophical Transactions of the Royal Society of London. B, Biological Sciences*, *295*(1077), 411–423. https://doi.org/10.1098/RSTB.1981.0149

Warrington, E. K., & McCarthy, R. A. (1983). Category specific access dysphasia. *Brain*, *106*(4), 859–878. https://doi.org/10.1093/BRAIN/106.4.859

Warrington, E. K., & McCarthy, R. A. (1987). Categories of knowledge. Further fractions and an attempted integration. *Brain*, *110*(5), 1273–1296. https://doi.org/10.1093/BRAIN/110.5.1273

Warrington, E. K., & Shallice, T. (1984). Category-specific semantic impairments. *Brain*, *107*, 829–854. https://doi.org/10.1093/NEUCAS/8.3.193-A

Zannino, G. D., Perri, R., Pasqualetti, P., Caltagirone, C., & Carlesimo, G. A. (2006a). (Category-specific) semantic deficit in Alzheimer's patients: The role of semantic distance. *Neuropsychologia*, *44*(1), 52–61. https://doi.org/10.1016/J.NEUROPSYCHOLOGIA.2005.04.008

Zannino, G. D., Perri, R., Pasqualetti, P., Caltagirone, C., & Carlesimo, G. A. (2006b). Analysis of the semantic representations of living and nonliving concepts: A normative study. *Cognitive Neuropsychology*, *23*(4), 515–540. https://doi.org/10.1080/02643290542000067

Zannino, G. D., Perri, R., Pasqualetti, P., Paola, M. di, Caltagirone, C., & Carlesimo, G. A. (2006). The role of semantic distance in category-specific impairments for living things: Evidence from a case of semantic dementia. *Neuropsychologia*, *44*(7), 1017–1028. https://doi.org/10.1016/J.NEUROPSYCHOLOGIA.2005.11.006

Annexes

Table A

List of pairs presented, their similarity values in all dimensions and obtained means

Pair	Adaptor	Deviant	All Features	Function	Manipulation	Vision	Mean (ms)
1	abre-caricas	buzina	0,076	0,000	0,631	0,421	452,73
2	abre-caricas	carrinho de compras	0,176	0,000	0,262	0,456	473,60
3	abre-caricas	chávena	0,187	0,019	0,671	0,242	475,38
4	abre-caricas	copo	0,167	0,015	0,830	0,206	433,33
5	abre-caricas	parafuso	0,389	0,000	0,406	0,807	477,43
6	abre-caricas	pinça	0,456	0,225	0,394	0,857	421,54
7	abre-caricas	quebra nozes	0,298	0,000	0,624	0,890	444,29
8	abre-caricas	ralador	0,379	0,000	0,651	0,880	518,72
9	abre-caricas	rolha	0,309	0,016	0,753	0,137	471,86
10	afia-lápis	apito	0,276	0,000	0,331	0,782	445,92
11	afia-lápis	borrifador	0,157	0,000	0,337	0,583	446,27
12	afia-lápis	corta-unhas	0,194	0,000	0,334	0,550	436,25
13	afia-lápis	moedor de pimenta	0,139	0,000	0,878	0,412	443,31
14	agrafador	alicate	0,250	0,000	0,925	0,594	440,29
15	agrafador	carimbo	0,404	0,000	0,742	0,187	412,79
16	agrafador	clip	0,752	0,641	0,490	0,907	427,22
17	agrafador	furador	0,537	0,010	0,970	0,918	445,14
18	agrafador	prego	0,265	0,174	0,521	0,688	463,16
19	agrafador	tesoura	0,313	0,000	0,409	0,583	441,79
20	agulha	clip	0,253	0,000	0,863	0,673	440,99
21	agulha	dardo	0,284	0,033	0,810	0,486	444,79
22	agulha	faca	0,188	0,000	0,483	0,348	418,60
23	agulha	garfo	0,258	0,078	0,617	0,408	425,58
24	agulha	taco de golfe	0,182	0,000	0,213	0,384	449,67
25	agulha	tesoura	0,258	0,083	0,838	0,421	489,76
26	alicate	balde	0,335	0,030	0,673	0,618	490,61
27	alicate	borracha	0,166	0,000	0,590	0,169	509,06
28	alicate	descascador	0,357	0,153	0,666	0,571	405,71
29	alicate	esfregona	0,303	0,000	0,297	0,573	496,43
30	alicate	leque	0,179	0,000	0,465	0,152	468,93
31	alicate	martelo	0,436	0,070	0,741	0,570	434,01
32	alicate	pá	0,466	0,067	0,448	0,728	467,52
33	alicate	varinha mágica	0,302	0,076	0,618	0,396	480,55
34	apagador	borracha	0,598	0,880	0,898	0,203	419,22

35	apagador	colher	0,106	0,000	0,612	0,269	439,81
36	apagador	desentupidor	0,181	0,008	0,456	0,437	434,18
37	apagador	lápis	0,209	0,000	0,566	0,556	466,21
38	apagador	pá	0,169	0,016	0,347	0,414	452,23
39	apagador	rolo da massa	0,203	0,000	0,248	0,572	434,20
40	apito	clip	0,257	0,000	0,854	0,733	481,54
41	apito	moedor de pimenta	0,155	0,000	0,184	0,505	451,20
42	apito	pá	0,198	0,000	0,172	0,374	478,79
43	apito	peso	0,134	0,058	0,519	0,361	452,06
44	balde	borrifador	0,366	0,156	0,450	0,659	411,12
45	balde	castiçal	0,215	0,449	0,834	0,228	473,52
46	balde	desentupidor	0,330	0,023	0,624	0,523	505,85
47	balde	esfregona	0,395	0,245	0,559	0,609	442,58
48	balde	martelo	0,236	0,052	0,642	0,395	455,47
49	balde	saco de pasteleiro	0,243	0,196	0,609	0,453	498,90
50	batedeira manual	carrinho de compras	0,175	0,000	0,245	0,420	424,97
51	batedeira manual	colher	0,501	0,082	0,466	0,763	456,81
52	batedeira manual	colher de pau	0,442	0,401	0,958	0,137	457,47
53	batedeira manual	esfregona	0,208	0,000	0,271	0,468	446,45
54	batedeira manual	jarro	0,159	0,000	0,587	0,267	456,55
55	batedeira manual	ralador	0,456	0,048	0,461	0,685	495,23
56	batedeira manual	rolo da massa	0,366	0,047	0,385	0,216	464,63
57	batedeira manual	secador	0,114	0,000	0,598	0,276	472,01
58	batedeira manual	tigela	0,345	0,053	0,514	0,306	459,94
59	batedeira manual	varinha mágica	0,448	0,068	0,914	0,447	454,34
60	berbequim	broca	0,743	0,952	0,784	0,372	434,52
61	berbequim	dardo	0,083	0,000	0,462	0,245	415,32
62	berbequim	secador	0,199	0,000	0,563	0,591	450,37
63	boia	bola de basquetebol	0,210	0,000	0,756	0,414	449,53
64	boia	tigela	0,227	0,000	0,878	0,694	430,35
65	bola de basquetebol	dardo	0,170	0,505	0,430	0,010	507,57
66	bola de basquetebol	peão	0,213	0,581	0,901	0,209	464,55
67	bola de basquetebol	raquete	0,233	0,622	0,664	0,019	433,90
68	bola de basquetebol	remo	0,134	0,325	0,659	0,036	472,79

69	bola de basquetebol	taco de golfe	0,189	0,528	0,584	0,020	477,18
70	bola de basquetebol	tigela	0,170	0,000	0,785	0,353	417,88
71	borracha	castiçal	0,037	0,000	0,669	0,201	468,29
72	borracha	isqueiro	0,132	0,000	0,397	0,549	437,66
73	borracha	lima das unhas	0,131	0,000	0,924	0,460	500,08
74	borrifador	jarro	0,322	0,100	0,479	0,309	466,05
75	borrifador	saco de pasteleiro	0,200	0,039	0,569	0,639	468,84
76	broca	canivete	0,289	0,077	0,789	0,543	429,86
77	broca	chave	0,186	0,000	0,680	0,822	433,82
78	broca	chave inglesa	0,341	0,052	0,766	0,831	424,58
79	broca	descascador	0,155	0,016	0,669	0,366	426,16
80	broca	faca	0,207	0,075	0,772	0,435	453,14
81	broca	lima das unhas	0,160	0,000	0,538	0,660	487,28
82	broca	ralador	0,242	0,027	0,631	0,671	498,18
83	broca	tesoura	0,223	0,077	0,662	0,502	418,93
84	broca	varinha mágica	0,194	0,008	0,734	0,323	466,11
85	buzina	cabide	0,013	0,000	0,627	0,175	444,14
86	buzina	quebra nozes	0,074	0,000	0,853	0,367	457,08
87	cabide	castiçal	0,052	0,000	0,939	0,399	426,12
88	cabide	secador	0,058	0,000	0,796	0,364	445,98
89	cana de pesca	peso	0,086	0,035	0,524	0,255	480,86
90	cana de pesca	remo	0,217	0,066	0,723	0,302	446,38
91	cana de pesca	taco de golfe	0,197	0,037	0,791	0,563	424,71
92	canivete	descascador	0,406	0,206	0,726	0,787	476,31
93	canivete	parafuso	0,371	0,000	0,586	0,625	451,01
94	canivete	seringa	0,168	0,000	0,518	0,241	452,90
95	canivete	taco de golfe	0,218	0,000	0,235	0,390	518,53
96	carimbo	desentupidor	0,169	0,000	0,787	0,234	444,36
97	carimbo	faca	0,167	0,000	0,719	0,283	500,62
98	carimbo	martelo	0,175	0,000	0,909	0,267	514,77
99	carrinho de compras	pá	0,243	0,105	0,768	0,406	438,04
100	castiçal	copo	0,226	0,411	0,781	0,434	457,56
101	castiçal	jarro	0,380	0,716	0,899	0,482	441,79
102	castiçal	lanterna	0,180	0,279	0,867	0,438	459,82
103	chave	clip	0,257	0,000	0,650	0,910	414,79
104	chave	colher	0,231	0,000	0,592	0,718	458,20
105	chave	garfo	0,236	0,000	0,514	0,573	467,46
106	chave	manípulo da porta	0,507	0,318	0,736	0,854	429,29
107	chave	parafuso	0,363	0,000	0,874	0,872	450,13

108	chave	pinça	0,318	0,000	0,610	0,868	425,08
109	chave	quebra nozes	0,203	0,000	0,318	0,856	436,77
110	chave	seringa	0,116	0,000	0,504	0,272	483,75
111	chave	tampa de garrafa	0,178	0,097	0,962	0,352	403,27
112	chave inglesa	manípulo da porta	0,156	0,000	0,881	0,717	424,88
113	chave inglesa	martelo	0,357	0,078	0,651	0,449	466,81
114	chave inglesa	prego	0,399	0,094	0,554	0,669	430,35
115	chave inglesa	tesoura	0,304	0,000	0,438	0,618	390,14
116	chávena	colher	0,281	0,010	0,936	0,408	510,44
117	chávena	copo	0,544	0,884	0,800	0,366	486,79
118	chávena	garrafa	0,397	0,560	0,712	0,325	418,33
119	clip	pinça	0,322	0,000	0,897	0,841	496,96
120	clip	prego	0,363	0,281	0,889	0,639	497,27
121	clip	quebra nozes	0,196	0,000	0,337	0,783	524,01
122	colher	descascador	0,422	0,010	0,749	0,605	422,82
123	colher	faca	0,525	0,134	0,635	0,800	419,79
124	colher	jarro	0,194	0,010	0,569	0,337	465,25
125	colher	pá	0,351	0,000	0,363	0,743	407,39
126	colher	ralador	0,480	0,017	0,641	0,732	453,32
127	colher	raquete	0,275	0,000	0,557	0,622	513,75
128	colher	vassoura	0,275	0,000	0,227	0,496	489,36
129	colher de pau	descascador	0,396	0,038	0,601	0,133	424,23
130	colher de pau	espremedor	0,255	0,000	0,680	0,071	430,25
131	colher de pau	faca	0,406	0,000	0,644	0,411	419,20
132	colher de pau	moedor de pimenta	0,448	0,132	0,643	0,671	440,04
133	colher de pau	pá	0,335	0,000	0,291	0,595	492,00
134	colher de pau	quebra nozes	0,192	0,000	0,457	0,019	422,09
135	colher de pau	remo	0,350	0,000	0,358	0,918	434,92
136	colher de pau	rolo da massa	0,558	0,063	0,315	0,784	469,06
137	colher de pau	taco de golfe	0,205	0,000	0,190	0,369	442,76
138	colher de pau	tigela	0,391	0,071	0,573	0,080	514,97
139	colher de pau	varinha mágica	0,442	0,111	0,899	0,081	480,59
140	copo	escova de dentes	0,166	0,000	0,595	0,331	483,70
141	copo	ralador	0,187	0,000	0,633	0,179	458,55
142	copo	tampa de garrafa	0,320	0,000	0,432	0,585	451,27
143	copo	varinha mágica	0,192	0,000	0,592	0,254	532,33
144	corta-unhas	mola da roupa	0,127	0,000	0,868	0,292	527,05
145	corta-unhas	pinça	0,386	0,000	0,869	0,927	416,74

146	dardo	lima das unhas	0,160	0,000	0,446	0,385	506,42
147	dardo	prego	0,464	0,000	0,765	0,738	443,01
148	descascador	esponja	0,161	0,000	0,581	0,160	458,76
149	descascador	faca	0,527	0,201	0,726	0,776	422,99
150	descascador	garfo	0,416	0,010	0,670	0,448	534,10
151	descascador	ralador	0,489	0,086	0,773	0,476	486,89
152	descascador	varinha mágica	0,415	0,033	0,623	0,377	456,87
153	desentupidor	escova de dentes	0,260	0,039	0,417	0,437	464,87
154	desentupidor	mola da roupa	0,215	0,000	0,198	0,409	440,98
155	desentupidor	vassoura	0,549	0,075	0,485	0,786	416,46
156	enxada	esfregona	0,348	0,000	0,689	0,701	402,87
157	enxada	faca	0,388	0,000	0,329	0,791	470,30
158	enxada	lápis	0,190	0,000	0,278	0,439	465,91
159	enxada	martelo	0,530	0,000	0,669	0,927	490,60
160	enxada	pincel	0,341	0,000	0,130	0,648	562,77
161	escova de cabelo	escova de dentes	0,367	0,000	0,624	0,926	465,59
162	escova de cabelo	esfregona	0,310	0,000	0,269	0,687	448,67
163	escova de cabelo	vassoura	0,386	0,000	0,254	0,702	443,29
164	escova de dentes	esponja	0,302	0,627	0,944	0,231	447,23
165	escova de dentes	guardanapo	0,214	0,394	0,826	0,114	421,26
166	escova de dentes	lanterna	0,169	0,000	0,740	0,553	515,04
167	escova de dentes	pá	0,234	0,073	0,542	0,467	492,97
168	escova de dentes	pincel	0,284	0,000	0,651	0,720	428,17
169	esfregona	esponja	0,341	0,690	0,352	0,036	456,35
170	esfregona	faca	0,332	0,000	0,435	0,727	441,46
171	esfregona	guardanapo	0,426	0,890	0,557	0,152	505,55
172	esfregona	jarro	0,136	0,000	0,537	0,293	500,06
173	esfregona	lupa	0,229	0,000	0,205	0,459	466,97
174	esfregona	pá	0,457	0,164	0,601	0,757	470,91
175	esfregona	pincel	0,384	0,000	0,256	0,790	521,85
176	esfregona	raquete	0,247	0,000	0,348	0,523	437,15
177	esponja	guardanapo	0,348	0,528	0,847	0,197	472,12
178	esponja	lanterna	0,098	0,000	0,796	0,385	424,22
179	esponja	peso	0,071	0,000	0,421	0,221	476,78
180	espremedor	lupa	0,156	0,000	0,327	0,371	460,53
181	espremedor	peão	0,155	0,000	0,665	0,290	425,67
182	espremedor	rolha	0,088	0,000	0,688	0,332	421,68
183	espremedor	seringa	0,163	0,000	0,223	0,489	440,24

184	espremedor	tesoura	0,193	0,000	0,281	0,484	431,57
185	faca	lima das unhas	0,145	0,000	0,804	0,349	462,61
186	faca	manípulo da porta	0,121	0,000	0,706	0,471	498,36
187	faca	maquina de barbear	0,360	0,805	0,735	0,189	434,48
188	faca	tesoura	0,750	0,963	0,492	0,692	505,71
189	faca	varinha mágica	0,374	0,100	0,602	0,439	429,72
190	fósforo	isqueiro	0,488	0,865	0,386	0,218	460,72
191	fósforo	prego	0,178	0,000	0,852	0,291	476,40
192	fósforo	rolo da massa	0,294	0,000	0,304	0,547	434,41
193	furador	quebra nozes	0,152	0,000	0,892	0,816	430,65
194	furador	secador	0,058	0,000	0,700	0,416	469,43
195	furador	seringa	0,109	0,000	0,553	0,371	437,46
196	garfo	pinça	0,335	0,091	0,601	0,517	461,85
197	garrafa	lanterna	0,185	0,000	0,899	0,630	442,20
198	guardanapo	secador	0,042	0,000	0,727	0,201	402,83
199	guardanapo	vassoura	0,306	0,758	0,725	0,032	404,99
200	isqueiro	lanterna	0,190	0,065	0,568	0,753	428,23
201	isqueiro	parafuso	0,224	0,000	0,379	0,567	500,29
202	isqueiro	rolha	0,080	0,000	0,509	0,265	483,76
203	lanterna	pincel	0,109	0,000	0,710	0,263	545,01
204	lanterna	rato de computador	0,220	0,000	0,732	0,559	495,63
205	lápis	manípulo da porta	0,067	0,000	0,579	0,223	437,36
206	lápis	moedor de pimenta	0,163	0,000	0,200	0,610	483,22
207	lápis	prego	0,182	0,000	0,828	0,353	415,44
208	lápis	taco de golfe	0,172	0,000	0,212	0,402	431,15
209	leque	lima das unhas	0,157	0,000	0,518	0,289	449,45
210	leque	moedor de pimenta	0,165	0,000	0,155	0,538	431,68
211	lima das unhas	taco de golfe	0,176	0,000	0,161	0,516	444,80
212	lupa	manípulo da porta	0,115	0,000	0,570	0,379	415,71
213	lupa	pinça	0,169	0,010	0,494	0,236	468,90
214	maquina de barbear	quebra nozes	0,064	0,000	0,422	0,235	435,65
215	maquina de barbear	varinha mágica	0,263	0,085	0,672	0,845	498,99
216	martelo	pá	0,563	0,119	0,633	0,882	463,33
217	martelo	remo	0,331	0,000	0,535	0,692	441,04
218	martelo	rolo da massa	0,362	0,000	0,323	0,610	431,24
219	martelo	vassoura	0,504	0,000	0,304	0,823	450,03

220	moedor de pimenta	pinça	0,157	0,000	0,170	0,341	425,03
221	moedor de pimenta	ralador	0,578	0,755	0,466	0,277	463,73
222	moedor de pimenta	rolo da massa	0,383	0,046	0,661	0,729	503,82
223	moedor de pimenta	saco de pasteleiro	0,212	0,048	0,546	0,256	444,23
224	moedor de pimenta	varinha mágica	0,586	0,770	0,740	0,337	525,29
225	mola da roupa	pinça	0,200	0,000	0,926	0,410	479,68
226	mola da roupa	remo	0,193	0,000	0,157	0,539	454,46
227	mola da roupa	secador	0,142	0,082	0,414	0,601	452,60
228	pá	raquete	0,346	0,051	0,730	0,615	467,87
229	pá	remo	0,325	0,000	0,680	0,674	541,03
230	pá	taco de golfe	0,347	0,047	0,785	0,625	436,63
231	pá	vassoura	0,620	0,139	0,784	0,862	402,73
232	parafuso	quebra nozes	0,278	0,000	0,287	0,781	431,35
233	parafuso	ralador	0,311	0,000	0,372	0,662	445,56
234	peão	raquete	0,230	0,508	0,729	0,286	404,27
235	pincel	remo	0,241	0,000	0,179	0,562	389,56
236	pincel	rolo da massa	0,277	0,000	0,087	0,509	529,74
237	pincel	vassoura	0,510	0,000	0,342	0,863	415,64
238	prego	taco de golfe	0,287	0,000	0,184	0,554	464,11
239	ralador	rolo da massa	0,238	0,022	0,479	0,072	473,84
240	ralador	vassoura	0,157	0,000	0,497	0,200	493,41
241	rato de computador	varinha mágica	0,137	0,000	0,607	0,303	451,99
242	remo	vassoura	0,345	0,000	0,664	0,713	482,32
243	rolha	secador	0,029	0,000	0,703	0,187	455,73
244	rolha	tampa de garrafa	0,758	0,970	0,807	0,513	403,01
245	rolo da massa	saco de pasteleiro	0,232	0,023	0,513	0,075	444,72
246	rolo da massa	tigela	0,293	0,025	0,516	0,324	418,94
247	rolo da massa	varinha mágica	0,271	0,019	0,478	0,107	430,79
248	taco de golfe	vassoura	0,273	0,000	0,844	0,492	419,01
249	tesoura	varinha mágica	0,284	0,101	0,381	0,742	445,19
250	tigela	varinha mágica	0,423	0,022	0,642	0,311	417,21