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Exploring the connection between semantic similarity and spatial distance: Does *close in mind* mean *close in space*?

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“it seems they were all cheated of some marvelous experience
which is not going to go wasted on me which is why I’m telling you about it.”

Frank O’Hara, *Having a Coke with You* (1971)

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Perceptual experiences and interactions with the environment are assumed fundamental to the development of conceptual knowledge. For instance, the spatial arrangement of words can affect the perception of similarity between the concepts they represent, supporting theories which suggest that the neural systems involved in spatial cognition also contribute to structuring conceptual knowledge. At the same time, however, increasing evidence points to language as a powerful medium for learning, suggesting a close interaction between perceptual and linguistic experiences in structuring conceptual knowledge. That is, while studies have shown that spatial distance can influence semantic similarity, it remains unclear whether this process is reciprocal. In this context, the present study aims to explore this potential bidirectional relationship. To do so, we employed a Distributional Semantic Model to quantify the semantic similarity of a set of words and used these values as predictors in an explicit spatial judgment task. Specifically, we hypothesized that the spatial distance between word pairs would be perceived as shorter for semantically related pairs compared to unrelated ones, suggesting a "compression" in the perception of space induced by linguistic information. Although our results revealed only a subtle trend in the direction of our hypothesis, these findings contribute to the ongoing debate on conceptual processing, which has traditionally been divided between embodied and linguistic perspectives. We propose reconsidering traditional views on embodied cognition, which often separate sensory and language experience, as findings increasingly support their interconnected nature, with future research aimed at clarifying the intricate connection between spatial and linguistic processing.

Keywords: *spatial distance*, *semantic similarity*, *distributional semantics models*.

Abstract

Le esperienze percettive e le interazioni con l'ambiente sono considerate fondamentali per lo sviluppo della conoscenza concettuale. Ad esempio, la disposizione spaziale delle parole può influenzare la percezione di similarità tra i concetti che rappresentano, supportando così la teoria che i sistemi neurali coinvolti nella cognizione spaziale contribuiscano anche alla strutturazione della conoscenza concettuale. Allo stesso tempo, diverse evidenze identificano il linguaggio come un potente mezzo per l'apprendimento, proponendo una stretta interazione tra esperienze percettive e linguistiche nella strutturazione della conoscenza concettuale. Tuttavia, mentre diversi studi dimostrano che la distanza spaziale può influenzare la similarità semantica, rimane poco chiaro se questo processo sia reciproco. In questo contesto, il presente studio mira a esplorare questa potenziale relazione bidirezionale. Pertanto, abbiamo utilizzato un Modello di Semantica Distribuzionale per quantificare la similarità semantica di un insieme di parole, usando questi valori come predittori in un compito di giudizio spaziale esplicito. In particolare, abbiamo ipotizzato che la distanza spaziale tra coppie di parole fosse percepita come più breve per coppie semanticamente relate rispetto a quelle non relate, suggerendo una "compressione" nella percezione dello spazio indotta dalle informazioni linguistiche. Sebbene sia stata rilevata solamente una tendenza nella direzione della nostra ipotesi, questi risultati contribuiscono al dibattito in corso sul processamento concettuale, tradizionalmente diviso tra prospettive *embodied* e linguistiche. A questo proposito, proponiamo di riconsiderare le visioni tradizionali della cognizione *embodied*, che spesso separano esperienza sensoriale e linguistica, poiché sempre più studi supportano la loro natura interconnessa, con future ricerche volte a chiarire l'intricata connessione tra elaborazione spaziale e linguistica.

Parole chiave: *distanza spaziale*, *similarità semantica*, *modelli di semantica distribuzionale.*

1. Introduction

Over the last two decades, research has increasingly focused on semantic similarity: this interest is due to the fact that our ability to perceive similarity is closely connected to our capacity to generalize, create categories and distinguish between different concepts (Medin, Goldstone & Gentner, 1993; Casasanto, 2008). But what does *semantic similarity* stand for? Do we consider all semantically related items as *similar*? To answer these specific questions, we must specify that there is a substantial difference between two concepts that might seem interchangeable, but which are not: similarity and relatedness. While the first term refers to items which can be substituted in a given context without changing the underlying semantics (such as *cat* and *kitty*), the second one indicates items which are not substitutable, even if semantically correlated (such as *cat* and *tiger*; Navigli & Martelli, 2019).

When talking about similarity, people often refer to spatial distance: this occurs because in human perception, objects or concepts that share similarities across almost any aspect can be considered *close*, while those that differ significantly can be regarded as *far apart* (Casasanto, 2008). Namely, arranging words according to different spatial dispositions can influence our perception of the actual conceptual similarity between the words. Moreover, an important body of research supports the idea that the exploration of conceptual knowledge – that is, the ability to understand concepts, principles, theories, models, or classifications – relies on mechanisms originally deputed to navigate physical space (Rinaldi & Marelli, 2020; Bottini & Doeller, 2020; Bellmund et al., 2018). In other words, the neurocognitive system which allows us to map and explore objects in the physical world must have been recycled or sublimated in order to let us navigate and manipulate non-spatial information within our minds, giving structure to our conceptual knowledge (Buzsáki & Moser, 2013).

However, if on the one hand spatial mechanisms and computations can help us navigate conceptual knowledge, we must not forget that linguistic data itself can provide spatial orientation without relying on the previously described mechanisms (Rinaldi & Marelli, 2020). Indeed, despite being a debated topic, an increasing amount of research has shown that the language system is an ideal environment for learning, suggesting a close interaction between both perceptual and linguistic experiences in the organization of conceptual knowledge (Andrews, Vigliocco & Vinson, 2009; Davis & Yee, 2021). Furthermore, several pieces of evidence suggest that linguistic information can itself influence perception (Lupyan et al., 2020).

As mentioned before, someone could use alternatively the terms *similar* or *close* conveying the same meaning: for example, the sentence "these two options are close" would lead the listener to interpret it as referring to the similarity between the options rather than their physical proximity. These metaphorical expressions are not just linguistic devices. Rather, they reflect how people rely on their concrete sensory experiences when mentally representing abstract relationships (Pauels, Schneider & Schwarz, 2023; Barsalou, 2008; Lee & Schwarz, 2014), according to the *Conceptual Metaphor Theory* (Lakoff & Johnson, 1980, 1999). This mental association activates the concept of spatial closeness and makes it easier to process information about similarity (Pauels et al., 2023). For instance, when people see two similar geometric figures positioned near each other, they recognize their similarity quicker than when they are farther apart (Boot & Pecher, 2010). In the same way, when people observe objects that are positioned close to each other, they tend to judge them as more similar than when the same objects are spaced further apart (Guerra & Knoeferle, 2014).

The present work focuses on the association between space and semantic similarity. In particular, we question whether this relationship is bidirectional: if distance can influence similarity – as Casasanto (2008) demonstrated –, is it possible to assume the opposite? Does the semantic similarity of two objects affect the memory of their location in space? Is it true that the conceptual similarity between words can influence our concrete experience, and thus our perception of the physical distance between two objects?

In this first introductory chapter, we will discuss the constructs which are the basis of our research demand. Firstly, we will provide a detailed description of the theories on semantic similarity, with particular reference to the work of Harris (1954, 1970), and we will introduce Distributional Semantic Models, which will allow us to quantify the meaning of a set of words and calculate the semantic similarity between them during our experimental session. Moving forward, we will focus on the association between semantic similarity and the concept of spatial distance, once again presenting the theoretical foundations and offering a new perspective on the neural basis underlying these mechanisms. Afterwards, we will describe the methods, the experimental design and the tools used for testing our hypothesis. We will then present the results, which will be discussed thoroughly and framed in the reference literature in the fourth chapter, along with the limitations, implications, and future perspectives of the current study. At last, we will address our experimental hypothesis in the light of the obtained results, giving an answer to the long-awaited question: does *close in mind* mean *close in space*?

1.1. Semantic Similarity: The Representation of Meaning

Language allows us to express the vast internal landscape of our thoughts. But what is language? And how does language get its meaning? For centuries, disciplines such as psychology, linguistics and philosophy have focused on one question: that is, how meaning is represented and organized by the human brain. If we think about it: what does it mean to know what a *cat* is? To truly understand the meaning of the word “cat”, is it necessary to calculate an average of different exposures to individual cats? Or, instead, is it enough to collect certain characteristics that are typical of a cat (such as being small, striped, or whiskered) that are acquired through experience, and then stored and activated after encountering a cat? It is not surprising that substantial efforts have been devoted to understanding the processes involved in constructing meaning from experience, given that meaning plays a fundamental role in all cognitive functions (Kumar, 2021).

One of the earliest attempts to conceptualize how meaning is learned and represented was made by Osgood (1952), who proposed a combination of associational and scaling procedures: the *semantic differential* technique. Using this approach, Osgood collected feedbacks from multiple participants on various concepts (like *peace*) across different polar scales (such as *hot-cold* or *positive-negative*). He discovered that the ratings consistently aligned with three universal dimensions: evaluation (*good-bad*), potency (*strong-weak*), and activity (*active-passive*). By doing so, Osgood developed a practical method for exploring how semantic meaning is represented, challenging the notion of a localist representation and offering initial evidence that the meaning of a concept could be spread across multiple dimensions (Kumar, 2021). Another theory proposed by Harris (1954; 1970), one of the most significant contributors to the topic, is the *distributional hypothesis*. This hypothesis is often stated in terms such as "you shall know a word by the company it keeps" (Firth, 1957); "words which are similar in meaning occur in similar contexts" (Rubenstein & Goodenough, 1965); "a representation that captures much of how words are used in natural context captures much of what we mean by meaning" (Landauer & Dumais, 1997); and "words that occur in the same contexts tend to have similar meanings" (Pantel, 2005). Hence, the core idea behind this theory is that there is a correlation between distributional similarity and meaning similarity: as a result, we learn meaning by observing how words frequently appear together in natural language (Sahlgren, 2008; Kumar, 2021). For instance, the words *cat* and *whisker* may be connected because they often occur together, whereas the words *cat* and *tiger* may be linked because they co-occur with similar words. But how does *meaning* fit into the distributional paradigm? Firstly, Harris – following Bloomfield – rejects the use of meaning as an *explanans* in linguistics (Lenci, 2008):

> "As Leonard Bloomfield pointed out, it frequently happens that when we do not rest with the explanation that something is due to meaning, we discover that it has a formal regularity or explanation."[1]

Secondly, both Harris and Bloomfield shared a strong interest in linguistic meaning. Like Bloomfield, Harris recognized that his linguistic theory could not fully capture meaning in all its social dimensions. Despite this, Harris was confident in the effectiveness of his distributional method. He believed that if extralinguistic factors influenced linguistic events, there would always be a corresponding distributional pattern that could explain the event. Harris held the belief that linguistics, as a science, should focus solely on the internal structure of language, with everything within the language being subject to linguistic analysis, a process he called *distributional analysis*. According

[1] Harris, 1970, p. 785.

to this perspective, if meaning is purely linguistic (i.e. has a strictly linguistic dimension), it must be prone to distributional analysis (Sahlgren, 2008). Therefore, even though Bloomfield (1933) believed that meaning would lie outside the scope of linguistic research[2], Harris acknowledged that semantic analysis could also benefit from a strong empirical foundation through the distributional approach. Linguistics can account for meaning, at least in aspects that can be defined using the same methods applied to other linguistic entities: specifically, distributional analysis techniques (Lenci, 2008). Additionally, the distributional perspective asserts that linguistic meaning is fundamentally differential, not referential (since a referential view would require an extra-linguistic component): namely, meaning differences are mediated by distributional differences (Sahlgren, 2008). Hence, this approach allows us to measure the differences in meaning between linguistic entities and offers a method for identifying and determining semantic similarity between words:

> "…if we consider words or morphemes A and B to be more different in meaning than A and C, then we will often find that the distributions of A and B are more different than the distributions of A and C. In other words, difference of meaning correlates with difference of distribution."[3]

Another historically significant development in the study of meaning was the distinction between *episodic* and *semantic* memory, proposed by Tulving in 1952. Within long term memory structures, Tulving identified two kinds of declarative memory: *episodic* memory, a neurocognitive system that enables human beings to remember past experiences (Tulving, 2002), and *semantic* memory, the cognitive system where

[2] "The statement of meaning is therefore the weak point in language-study, and will remain so until human knowledge advances very far beyond its present state" Bloomfield (1933, p. 140); "the linguist cannot define meanings" (*ibidem*, p. 145).
[3] Harris, 1970, p. 786.

conceptual knowledge is stored (Borge-Holthoefer & Arenas, 2010). Respectively, episodic memory refers to the recollection of personal experiences that are tied to particular times and locations (as an example, remembering seeing a black cat on a roof last week), while semantic memory stores general knowledge about the world, including the meanings of verbal symbols (such as words), in a way that is not tied to any specific sensory modality (Gleason & Ratner, 1997; Kumar, 2021). For instance, semantic memory would hold information about what a cat is, what it looks like and similar facts, all represented through language. Moreover, this distinction was reinforced by early neuropsychological studies: notably, the article by O'Kane, Kensinger and Corkin (2004) investigates the differences between semantic memory and episodic memory through the case study of patient H.M., who suffered from profound amnesia following the removal of medial temporal lobe (MTL) structures. The researchers demonstrated that H.M. was able to acquire semantic knowledge through repeated exposure and practice, despite being unable to recall the specific episodes where the learning took place: as a result, we know that semantic and episodic memories are distinct functions, with episodic memory heavily dependent on the hippocampus and semantic memory relying on other cortical areas. Three methodologies have emerged in order to model the structure and organization of semantic memory from such findings: network-based approaches, feature-based models and distributional models (Kumar, 2021).

One of the simplest methods to organize concepts, which also served as an inspiration for building computational network-based models of semantic memory, was the *Hierarchical model* (Collins & Quillian, 1969), presented in *Figure 1*. Collins and Quillian proposed that conceptual information is organized in a hierarchical tree, with general concepts (like “animal”) at the top and more specific concepts (like “canary”) at the bottom. Each concept is characterized equivalently by a set of features held within each concept node and by pointers connecting it to other nodes. Properties of concepts within a category are stored at the highest node in the hierarchy and are true for all concepts below (for example, the feature *has wings* is stored at the "bird" node, not the "animal" or "canary" nodes), implementing in this way a form of cognitive economy (Cree & Armstrong, 2012; Szymański & Duch, 2012).

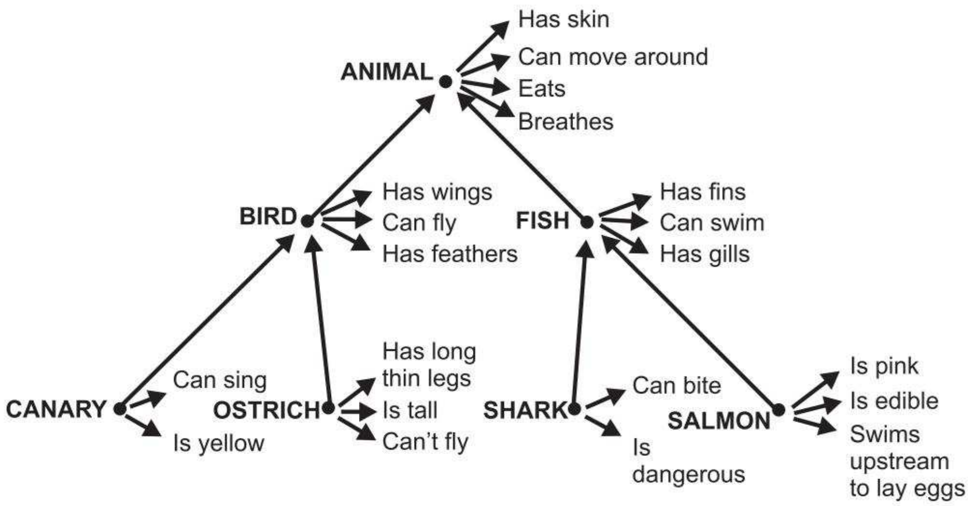

Figure 1. Hierarchical model of semantic memory (from Szymański & Duch, 2012). Original network proposed by Collins and Quillian (1969).

However, it is clear that semantic memory structures are not static. When we consider new relationships between two or more concepts that are distant from each other in the hierarchical structure, shortcuts or direct associations between these concepts are created: this specific process is something that this model could not fully explain (Szymański & Duch, 2012). A more realistic approximation to brain processes responsible for acquisition of new semantic knowledge was the *Spreading activation model* (Collins & Loftus, 1975), shown in *Figure 2*. This updated model arranged concepts in the form of a lexical network (Kumar, 2021), where links between nodes describe various relations, including semantic similarities between concepts stored in the network (Szymański & Duch, 2012). A concept that is analysed at a given moment (that is, a current thought) is considered to be active and symbolizes coordinated neural activity across multiple brain regions. This new framework was extensively applied to more general theories of language, memory, and problem solving (Anderson, 2000), albeit presenting some objective criticalities: in fact, the model failed to distinguish between different semantic relationships between concepts, treating all connections as equivalent (Rogers, 2008).

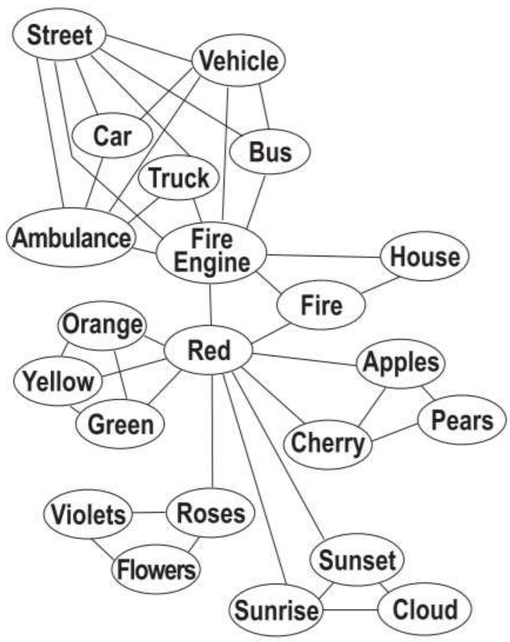

Figure 2. Spreading activation model of the semantic memory (from Szymański & Duch, 2012).

Around the same time, Smith, Shoben and Rips (1974) introduced an alternative representational format that relied on the notion of a set of semantic features representing concepts (a *cat* "has whiskers", "meows", "has a tail"), instead of an unanalyzable localist node within a network (Kumar, Steyvers & Balota, 2022). In this feature-based model, concepts had two types of semantic features: *defining* features shared by all concepts, and *characteristic* features specific to some exemplars only (Kumar, 2021). For instance, all cats *are mammals* (defining feature), but not all cats *are domestic* (characteristic feature). These early explorations highlight the importance of considering both the nature of the representation (network-based or feature-based) and the specific processes (spreading activation or feature comparison) that access these representations when explaining human behaviour (Kumar et al., 2022).

An important class of models in addition to feature-based and network-based models are Distributional Semantic Models (DSMs), also referred to as corpus-based semantic models, vector spaces, semantic spaces or word-space models, all of which are inspired by some version of the *distributional hypothesis* (Harris, 1954; Sahlgren, 2008; Baroni & Lenci, 2010; Rubinstein et al., 2015). As we have explained, this hypothesis is none other than a specification of the assumption that word meanings are acquired through experience (Günther, Marelli & Rinaldi, 2019). Indeed, as stated by Jenkins (1954), "intraverbal connections arise in the same manner in which any skill sequence arises, through repetition, contiguity, differential reinforcement" (p. 112). Although one could argue that DSMs date back to early work by Osgood (1952), these models have gained increasing success within the past decade and are nowadays considered the leading approach to lexical meaning representation in Natural Language Processing, Artificial Intelligence, and cognitive modelling (Lenci et al., 2022). This remarkable success is certainly due to the availability of large text databases and to the advancement of several machine learning algorithms (Kumar et al., 2022).

However, Sahlgren (2006) clearly states that it "cannot be stressed enough that the word-space model is a *computational* model of meaning, and *not* a psychologically realistic model of human semantic processing" (pp. 134-135) and that they represent "not the meanings that are in our heads, and not the meanings that are out there in the world, but the meanings that *are in the text*" (Sahlgren, 2008, p. 46; Günther et al., 2019a). Thus, while they may be highly beneficial for machine applications and artificial cognitive systems, DSMs are not as fitting as a psychological model for human semantic representations (for a demonstration see Niven & Kao, 2019; Günther et al., 2019a). Nevertheless, these objections can be addressed with both theoretical and empirical reasoning. From a theoretical point of view, corpus-based semantic models are seen as valuable tools for simulating how humans learn and use language and concepts based on the information they get from their surroundings (Landauer and Dumais, 1997; Baroni & Lenci, 2010; Mandera, Keuleers & Brysbaert, 2017; Hollis, 2017). As a matter of fact, distributional models are set up as a theory explaining how semantic representations are acquired (Lenci, 2008). Moreover, DSMs are rooted in the tradition of learning theories postulating that humans excel in capturing statistical patterns in their environments (Anderson & Schooler, 1991) and extracting information from them (see also Günther, Smolka & Marelli, 2019). From an empirical point of view, a significant amount of research shows that DSMs can effectively model and predict human behaviour in numerous semantic memory-related tasks, as we will further analyse and discuss in the next paragraph, paying particular attention on the functioning and the different types of these models.

1.2. Distributional Semantic Models (DSMs)

Distributional Semantic Models help us understand word meanings by analysing how words are used together, showing that meaning comes from context and relationships, not just definitions. As explained before, the concept behind DSMs is that words with similar meanings are employed in similar contexts (Harris, 1954; Mandera et al., 2017). As an example, when comparing the contexts in which the English nouns *car*, *train* and *table* appear, it is clear that the adjectives and verbs associated with *car* and *train* are much more alike than those for *table*. *Cars* and *trains* can be described as fast or air-conditioned, while *tables* cannot. Therefore, according to the *distributional hypothesis*, this provides empirical evidence that the meanings of *car* and *train* are more closely related to each other than they are to the meaning of *table* (Ježek, 2016).

DSMs implement this assumption by mapping each word computationally to a high-dimensional vector in a shared semantic space (Anceresi et al., 2024). The distance between these vectors, calculated using the cosine of the angle between them, is used as an indicator of how similar the meanings of the words are. Concretely, most DSMs represent the meaning of a word with a vector that records how frequently the word appears in various contexts within a corpus, such as documents or short passages. This vector-based representation allows DSMs to measure how closely related two words are by using geometric methods, particularly by calculating the angle between their vectors (Marelli & Baroni, 2015). Essentially, the closer two vectors are in this semantic space, the more similar the meanings of the words they represent are (Lenci, 2018). This concept is depicted in a simplified way in *Figure 3*.

	runs	wheels
automobile	1	4
car	2	4
horse	4	1

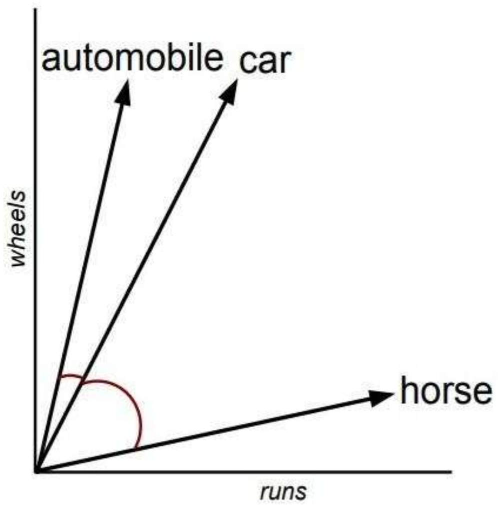

Figure 3. In this simplified example of a DSM, the words *automobile*, *car*, and *horse* are represented by vectors based on how often they appear with the context terms *runs* and *wheels* in a hypothetical dataset. The vectors for *automobile* and *car* – which share similar contextual patterns – form a smaller angle, indicating higher similarity in meaning. In actual DSMs, these vectors would be much more complex, with hundreds or even thousands of dimensions (from Marelli & Baroni, 2015).

Among the most famous word-vector models, a very influential one has been Latent Semantic Analysis (LSA; Landauer & Dumais, 1997), which counts the frequency of a word within a document or paragraph to build its vector representation (Mandera et al., 2017). Likewise, the Hyperspace Analogue to Language (HAL; Lund & Burgess, 1996) uses co-occurrence data to map out the relationships between words in a semantic space (Azzopardi, Girolami & Crowe, 2005; Bullinaria & Levy, 2007). These word-vector models have been effectively implemented across nearly all areas of cognitive science, including fields such as psycholinguistics (Jones, Kintsch & Mewhort, 2006), artificial intelligence (Turney & Pantel, 2010), computational psychology (Jones, Willits & Dennis, 2015), cognitive neuroscience (Mitchell et al., 2008), social psychology (Lenton, Sedikides & Bruder, 2009), education (Wade-Stein & Kintsch, 2004), psychiatry (Elvevåg et al., 2007) and biomedicine (Cohen & Widdows, 2009).

Recently, a new family of DSMs has emerged: Neural Language Models (Collobert et al., 2011; Mikolov et al., 2013a, 2013b), especially the one implemented in the word2vec library (Acquaviva et al., 2020), which have become increasingly successful, even surpassing their predecessors in number of citations (currently about 45.000 citations on Google Scholar, compared to the 9.000 of LSA; Günther et al., 2019a). These neural-network–based models generate vectors by training them to *predict* contextual patterns, instead of simply encoding the co-occurrences of words: this approach is necessary in order to identify closer connections between words based on the likelihood of them appearing together in different contexts (Marelli & Baroni, 2015).

An advantage of DSMs is that they can effectively induce and encode meaning representations for thousands or even millions of words which makes them highly useful for designing experiments and simulations (Marelli & Baroni, 2015). Moreover, since DSMs are based on associative learning models that are cognitively plausible (Günther et al., 2019a; Mandera et al., 2017), they can be understood as computational simulations of human semantic memory (Anceresi et al., 2024). In line with this perspective, DSMs have been shown to effectively predict human performance across several cognitive tasks, such as semantic priming (see Marelli, 2017; Günther, Dudschig & Kaup, 2016; Lapesa & Evert, 2013) and false memory paradigms (Gatti et al., 2023). Data from these models exhibit a strong correlation with human semantic similarity ratings (Baroni, Dinu & Kruszewski, 2014; Landauer & Dumais, 1997). Recently, DSMs have also been validated through neuroscientific approaches. The vector representations produced by DSMs have been found to closely align with brain activity patterns observed in neuroimaging studies (see Mitchell et al., 2008) and with electrical responses on the scalp (Murphy, Baroni & Poesio, 2009) during the processing of language. This suggests that DSMs not only model semantic relationships computationally but also mirror neural mechanisms involved in language comprehension (Marelli, 2017).

In summary, DSMs conceptualize meaning by representing words within a multidimensional semantic space. Each word is encoded as a vector, and the spatial relationship between these vectors – such as their proximity – serves as a measure of semantic similarity: words that occur in similar contexts are positioned closer together, reflecting their shared meanings. This spatial framework provides a geometric structure to semantic representation, which is primarily a methodological tool. Indeed, the real significance of these models lies in their connection to psychologically plausible learning mechanisms (Rinaldi & Marelli, 2020). Recent DSMs, particularly those based on prediction, reflect these associative learning models (Günther et al., 2019a) and perform impressively in tasks such as analogical reasoning. Hence, DSMs question the traditional emphasis on spatial mechanisms in organizing knowledge (Bottini & Doeller, 2020), showing that general-purpose associative learning is key to structuring conceptual understanding (Ekstrom, Harootonian & Huffman, 2020). Furthermore, some studies have shown that brain areas like the hippocampus and parietal cortex, often linked to spatial processing, are equally involved in associative learning – with neural responses aligning closely to patterns derived from DSMs (Wang et al., 2018; Rinaldi & Marelli, 2020). For instance, the posterior parietal cortex is linked to probabilistic reasoning more than it is to spatial processing (Wendelken, 2015). This highlights the broader cognitive impact of distributional semantics, suggesting that spatial reasoning may emerge from linguistic experience and associative processes rather than inherent spatial strategies. The deeply interconnected relationship between space and language experience is the intricate topic that will be examined in detail in the next section.

1.3. The Space of Words

Space is commonly used to convey similarity, as people often use terms such as *close* or *far apart* to refer to things that are either similar or dissimilar (Casasanto, 2008; Tuena et al., 2023). During childhood, humans develop implicit associations between spatial dimensions (such as length, size, position) and different non-spatial concepts, including emotional valence, number, and time (Pitt & Casasanto, 2022; Starr & Srinivasan, 2021; Casasanto & Henetz, 2012). Besides, according to *Construal Level Theory* (Trope & Liberman, 2010), people tend to form mental constructions of things that are psychologically distant – such as the past, the future or hypothetical scenarios. This mental process is closely connected to the spatial metaphor often used to describe similarity: as explained by Trope and Liberman (2010), psychological distance is considered as the subjective perception that something is *close* or *far away* from the self – here, and now – with the self being the main point of reference (Huang & Zhang, 2023). This distance can be manifested in different dimensions such as social distance, hypotheticality, time and space.

Therefore, we know that spatial metaphors are deeply-rooted in language: for instance, sentences like "His spirits were soaring" or "She is feeling low" indicate a clear example of a spatial metaphor that associates *up* with positive emotions and *down* with negative ones (Lakoff & Johnson, 1980; Pitt & Casasanto, 2022), which is the same implicit metaphor conveyed by gestures such as the thumbs-up sign or the corresponding "like" button. Certainly, these are not the only metaphors we encounter daily: most of these spatial metaphors connect several non-spatial domains to different spatial dimensions across three axes – lateral, vertical, and sagittal (Pitt & Casasanto, 2022). We refer to high and low numbers using *vertical* space, discuss political positions using *lateral* space (left and right), and describe time management with *sagittal* space (moving meetings forward or back in time). In addition, we use spatial terms to describe quantities as big or small, vacations as long or short, and relationships as close or distant.

As we have mentioned in this introductory chapter, metaphor theorists argue that metaphors are not merely linguistic tools but rather, they are fundamental to how we conceptualize abstract ideas (Lakoff & Johnson, 2008; Gibbs, 1994; Casasanto & Bottini, 2014). Indeed, we unconsciously activate spatial representations – height, size, proximity, and depth – whenever we think about abstract domains like numbers, questions, theories, or relationships, just as we would each time we perceive and distinguish physical objects in the real world. As Benjamin Whorf (2012) observed:

> "Physical shapes 'move, stop, rise, sink, approach' in perceived space; why not these other referents in their imaginary space? This has gone so far that we can hardly refer to the simplest nonspatial situation without constant resort to physical [spatial] metaphors. I "grasp" the "thread" of another's arguments, but if its "level" is "over my head" my attention may "wander" and "lose touch" with the "drift" of it, so that when he "comes" to his "point" we differ "widely," our "views" being indeed so "far apart" that the "things" he says "appear" "much" too arbitrary, or even "a lot" of nonsense!".[4]

The systematicity and prevalence of these metaphorical expressions led Lakoff and Johnson (1980) to propose two complementary conceptual mappings to describe the close relationship between space and similarity: spatial proximity as similarity and spatial distance as dissimilarity, or alternatively, similarity as spatial proximity and dissimilarity as spatial distance (Tuena et al., 2023). This concept is explained thoroughly in their theory, which will be discussed in the following paragraph.

[4] Whorf, 2012, p. 146.

1.3.1. The *Conceptual Metaphor Theory* (CMT)

The idea that abstract concepts rely on a few simpler concepts that are grounded in sensorimotor experience is frequently associated with linguist George Lakoff and philosopher Mark Johnson, who claimed that *Conceptual Metaphor Theory* (CMT) was one of "three major findings of cognitive science" (1999, p. 3; Casasanto, 2010). An example of this phenomenon is metaphors in language: indeed, expressions like "time is money" or "argument is war" reveal how we use concrete and familiar experiences to frame and encompass abstract concepts in a spatial manner (Lakoff & Johnson, 2020). These experiential concepts include a set of basic spatial relations (*up*/*down*, *front*/*back*), a set of basic actions (*eating*, *moving*) and a set of physical ontological concepts (*entity*, *container*). According to this perspective, any concept that does not directly derive from physical experience must be metaphorical (Boroditsky, 2000).

Nonetheless, at first, the belief that conventional metaphors in language could reflect the structure of abstract concepts was upheld almost solely by linguistic evidence, with additional support from a computational model that demonstrated, in theory, how the meanings of certain linguistic metaphors could be learned and represented (Narayanan, 1997; Casasanto, 2010). Without non-linguistic evidence, this idea remained "just an avowal of faith" among scientists who strongly believed that the mind could be explained as a product of natural selection, that is, an *exaptation*[5] (Pinker, 1997, p. 301).

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[5] The neologism "*exaptation*" was introduced for the first time by palaeontologists Stephen Gould and Elisabeth Vrba (1982) in order to describe two evolutionary mechanisms: (1) a functional shift in a Darwinian sense (such as the re-use by natural selection of a structure with previously different purposes); (2) a functional cooptation, that is, an evolutionary mechanism which is not entirely described as a process of standard adaptation because, at the beginning, a specific trait was not originally designed to serve that exact purpose (Pievani & Serrelli, 2011).

Lera Boroditsky (2000) was one of the first researchers to conduct behavioural experiments with the aim of testing *Conceptual Metaphor Theory*, offering a more rigorous empirical treatment of metaphorical representation. In particular, she exploited the fact that speakers must choose a specific frame of reference when talking about spatial or temporal sequences (Casasanto, 2010; Bundgaard, 2019). In daily life, some expressions we commonly use suggest that we are moving through time or space (such as *we're approaching Christmas*; *we're approaching Maple Street*). Conversely, other phrases suggest that objects or events are moving in relation to each other (*Christmas comes before New Year's*; *Maple Street comes before Elm Street*). In one experiment, Boroditsky showed that priming participants with spatial frames of reference helped them to interpret temporal sentences, but not vice versa. This asymmetry reflects a common linguistic pattern: people describe abstract concepts – such as time – in terms of more concrete ones, that is, space (Lakoff & Johnson, 1980). Based on these findings, Boroditsky proposed the *Metaphoric Structuring View*, which stated that (a) the domains of space and time are conceptually connected, and (b) spatial information can be helpful, though not essential, for thinking about time (Casasanto & Boroditsky, 2008).

As we said, in most of these conventional metaphors language from a concrete domain is used to talk about the more abstract domain (Lakoff & Johnson, 1980; Lakoff & Kovecses, 1987; Boroditsky, 2000). Moreover, these metaphors often reveal a particular source-to-target mapping, such as we can see in the common expressions "life is a journey", "mind is a container" and "ideas are food". For instance, to better illustrate the "ideas are food" schema, we propose this clarifying example: "if you really cannot wait to *sink your teeth* into the theory, you will have to wait until *the meaty part* of the paper." Typically, *source* domains are concrete and grounded in perception and physical actions, while *target* domains are purely abstract and can be experienced only through interoception[6] or introspection. A cross-domain mapping from a source domain to a target domain can be represented as "target is source" (for example, *similarity* is *proximity*), or, as an alternative, "source → target", as in "proximity → similarity" (Lakoff & Johnson, 1999; Casasanto, 2008; Denroche, 2024). In this pervasive metaphor, the abstract concept of similarity is represented by the concrete experience of spatial closeness (Casasanto, 2008; Boot & Pecher, 2010; Winter & Matlock, 2013; Pauels et al., 2023). Notably, the influence of the "similarity is proximity" metaphor on similarity judgments applies *only* to conceptual similarity. Casasanto (2008) has demonstrated that when participants were asked to judge tools on their similarity in use (hence, conceptual similarity), tools shown close together were seen as more similar than tools placed far apart. However, when participants were asked to focus on visual appearance, tools shown close together were judged as less similar than tools shown far apart. Altogether, these findings suggest that spatial relationships play a key role in shaping how we perceive abstract concepts. Still, an interesting question remains: does the mental association between proximity and similarity work both ways? In other words, could similarity also impact how we judge physical distance? In the next paragraph we emphasize the key points of *A Theory of Magnitude* (ATOM; Walsh, 2003; Bueti & Walsh, 2009), a theory which provides behavioural and neurocognitive evidence towards the assumption that space, time, and number are processed by a single cross-domain magnitude system in the brain. Afterwards, we will explore the hypothesis that the same neurocognitive system that appears to support spatial cognition is also used for the organization of conceptual knowledge (Bellmund et al., 2018; Bottini & Doeller, 2020).

[6] That is, the perception of the state of the body (Ceunen, Vlaeyen & Van Diest, 2016).

1.3.2. A *Theory of Magnitude* (ATOM)

Embodied cognition is the term used to describe how the individual sensorimotor experience contributes to conceptual knowledge, while also acknowledging the universal physical limitations of the human body (Fischer, 2012). For many years, studies inspired by embodied cognition have explored how concepts and language are rooted in sensorimotor and emotional systems (Pulvermüller, 1999; Barsalou, 1999; Gallese & Lakoff, 2005). The aim of these studies was to challenge the *language-of-thought* theory (Fodor, 1975) and the idea that sensorimotor experience would be converted in a semi-linguistic mental format (Borghi, 2020). Crucially, *A Theory of Magnitude* (Walsh, 2003; Bueti & Walsh, 2009) by itself does not falls under the embodied cognition framework, but simultaneously, ATOM gains valuable insights from the embodied cognition approach on how not only actions but general sensorimotor experiences can help shape conceptual knowledge. In his theory, Walsh suggests that magnitude is represented in a domain-general way, in which time, numbers and space are computed according to a common metric and they rely on the same neural resources (Fabbri, Cancellieri & Natale, 2012; Winter, Marghetis & Matlock, 2015). Indeed, the ATOM theory posits that a shared neural system for processing spatial, temporal, and numerical quantities provides adaptive advantages by allowing the coordination of information needed for actions such as grasping, pointing or running (Walsh, 2003; Bueti & Walsh, 2009). This system, located mainly in the parietal cortex, is activated to assess both spatial distances, numerical quantities or time intervals.

On the one hand, the ATOM model has garnered substantial behavioural evidence: for instance, a vast body of research suggests that the interaction between time and space reflects a metaphorical representation of time along a left-to-right spatial line (Casasanto & Boroditsky, 2008; Vallesi, Binns & Shallice, 2008; Frassinetti, Magnani & Oliveri, 2009; Merritt, Casasanto & Brannon, 2010; Fabbri et al., 2012). Typically, short durations of time are mentally placed on the left side of this line, while long durations are positioned on the right. As further confirmation, Ishihara et al. (2008) proposed the *Spatial–Temporal Association of Response Codes* (STEARC) *effect*: in their study, participants pressed one of two response keys depending on whether the timing of a stimulus occurred earlier or later than expected. The results revealed a consistent association between left-hand responses and earlier timings, and right-hand responses with later timings. This interaction between time and space supports the concept of a Mental Time Line (MTL), where shorter temporal intervals are mapped to the left side and longer intervals to the right in a left-to-right mapping (see Torralbo, Santiago, & Lupiáñez, 2006; Arzy, Adi-Japha & Blanke, 2009; Fabbri et al., 2012). Another fascinating behavioural evidence is that asking people to generate random numbers while walking affects their decision of turning left or right (Shaki & Fischer, 2014). In this study, the authors reported that when people generate a small number their probability of turning left becomes higher, while generating a larger number tends to result in a right turn. The same is true for the opposite direction of concept-motor interactions: a small number is more likely to be generated if the intention is to turn left, and a larger number is more likely to be generated if the intention is to turn right. Furthermore, neuroimaging studies show that the bilateral intra-parietal sulcus (IPS) and surrounding areas are activated when processing spatial and numerical magnitudes (Hubbard et al., 2005; Kaufmann et al., 2008; Pinel et al., 2004; Winter et al., 2015). The IPS is also involved in perceiving time, as seen in a functional magnetic resonance imaging (fMRI) study by Coull and Nobre (1998): in fact, an increased blood-oxygen-level-dependent (BOLD) signal in the left IPS was assessed during tasks requiring attention to temporal intervals. Furthermore, targeted disruptions of the posterior parietal cortex using transcranial magnetic stimulation (TMS) result in selective impairments in processing spatial, temporal, and numerical magnitudes (Sandrini & Rusconi, 2009). For example, TMS applied to the right IPS interferes with spatial and numerical processing (Andres, Seron & Olivier, 2005; Cohen Kadosh et al., 2007). In addition, studies on non-human primates – in particular, macaques – show that the areas equivalent to the human IPS are activated during the processing of temporal durations (Leon & Shadlen, 2003), numerical magnitudes (Sawamura, Shima & Tanji, 2002) and spatial extents (Stein, 1989). Nevertheless, Tudusciuc and Nieder (2007) have found that specific neuronal populations in apes are responsive both to spatial and numerical magnitudes, which can be considered one of the most conclusive pieces of evidence for a shared magnitude processing (Winter et al., 2015). It is worth to mention that while ATOM claims that the processing of space, time and number is based on common cortical circuits, it does not mean that these circuits are restricted to one specific area of the brain. Although the magnitude system is primarily situated in the parietal cortex, it involves –presumably – a distributed network of cortical areas which are also connected to the prefrontal cortex (Bueti & Walsh, 2009).

On the other hand, ATOM has been challenged by the idea that biases in magnitudes, particularly space and time, may be a result of the linguistic labels we assign to them and how we conceptualize these dimensions at a linguistic rather than at a perceptual level (Togoli et al., 2024). As we have seen in the previous paragraph, this concept is known as *Metaphoric Structuring View* (Casasanto & Boroditsky, 2008). For example, the above-mentioned STEARC effect is compatible with a conceptual metaphor in which times are conceptualized as spatial locations (Lakoff & Johnson, 1999; Winter et al., 2015). In regard to this, alternative theories propose that magnitudes interact at a more cognitive level rather than at a perceptual one, as a response bias (Yates, Loetscher & Nicholls, 2012), or as a working memory interference (Cai et al., 2018). However, as mentioned above and as already proposed by Bueti and Walsh in 2009, recent neuroimaging data suggests that this interaction could derive from the processing of different dimensions in partially overlapping cortical maps, without necessarily involving a shared neural code (Harvey et al., 2015; Tsouli et al., 2022; Fortunato, Togoli & Bueti, 2023; Togoli et al., 2024; Hendrikx et al., 2022, 2024).

In conclusion, as far as we have seen both CMT and ATOM share a common explanatory target: the interaction between space, time, and number. Together, ATOM and CMT demonstrate how the interweaving of space, time and number in the human mind may create a framework that supports cognitive processes, from low-level perception to the development of complex concepts (for reviews, see Núñez & Cooperrider, 2013; Bender & Beller, 2014; Winter et al., 2015). Nonetheless, neither of the two theories suggests that the neural or mental representation of these domains is fully explained by their areas of overlap. Indeed, ATOM and CMT have been compared based on how much they predict “asymmetries” in cross-domain interactions – that is, whether one domain has a greater influence on another than the reverse. These asymmetries have to be further investigated: only a few scientific papers have begun to address the study of the neural mechanisms underlying these asymmetries (Gijssels et al., 2013) and to investigate this interaction in more depth (Reali, Lleras & Alviar, 2019; Nourouzi Mehlabani, Sabaghypour & Nazari, 2020). For now, we will focus on CMT and, in particular, on the neural correlation between spatial and linguistic processing.

1.3.3. Spatial Codes for Human Thinking

Neuropsychological research on amnesic patients (Scoville & Milner, 1957; Kensinger & Giovanello, 2005) and recent neuroimaging experiments (Eichenbaum, 2004) have shown that the hippocampal formation – including the proper hippocampus and surrounding cortices – is essential for memory formation and retrieval (Bottini & Doeller, 2020). However, along with the medial prefrontal cortex (mPFC), these brain regions also play a fundamental role in our ability to represent and navigate the physical environment (O'Keefe & Nadel, 1978; Viganò & Piazza, 2020).

Two primary types of neurons are crucial for spatial navigation: place cells (O'Keefe & Dostrovksy, 1971) and grid cells (Hafting et al., 2005), as shown in *Figure 4*. Place cells, located in the hippocampus, fire when an animal moves through a particular spot in its surroundings. In contrast, grid cells – in the entorhinal cortex (EC) – fire at multiple locations arranged in a distinct hexagonal grid that creates a map-like representation of the local environment. Notably, grid cell activity can be detected through the BOLD signal decoded from fMRI when participants navigate virtual reality environments (Viganò & Piazza, 2020). In a study by Doeller, Barry and Burgess (2010), participants navigated a virtual arena, collecting and repositioning objects. The researchers used fMRI to monitor the BOLD signal, which reflects changes in blood oxygenation and can therefore indicate neural activity, while spatial memory accuracy was assessed based on how closely objects were repositioned to their original locations. They focused on an anatomical region of interest, the EC, and analysed movements, direction and speed of the participants: the results revealed consistent activation of grid cells in the right EC during fast movements, while the left EC exhibited similar but less reliable patterns.

Together with other spatially tuned neurons in the hippocampal formation, place and grid cells are believed to form the navigation system of the brain (Moser, Rowland & Moser, 2015; Bush, Barry & Burgess, 2014; Bottini & Doeller, 2020). This navigation system also encompasses head direction cells conveying information about head direction in animals (Cullen & Taube, 2017), speed cells sensitive to running speed (Kropff et al., 2015), goal and goal direction cells signalling egocentric directions to navigational goals (Hok et al., 2005; Sarel et al., 2017), and border (Savelli, Yoganarasimha & Knierim, 2008; Solstad et al., 2008) or boundary vector cells (Lever et al., 2009) responding to borders in the environment.

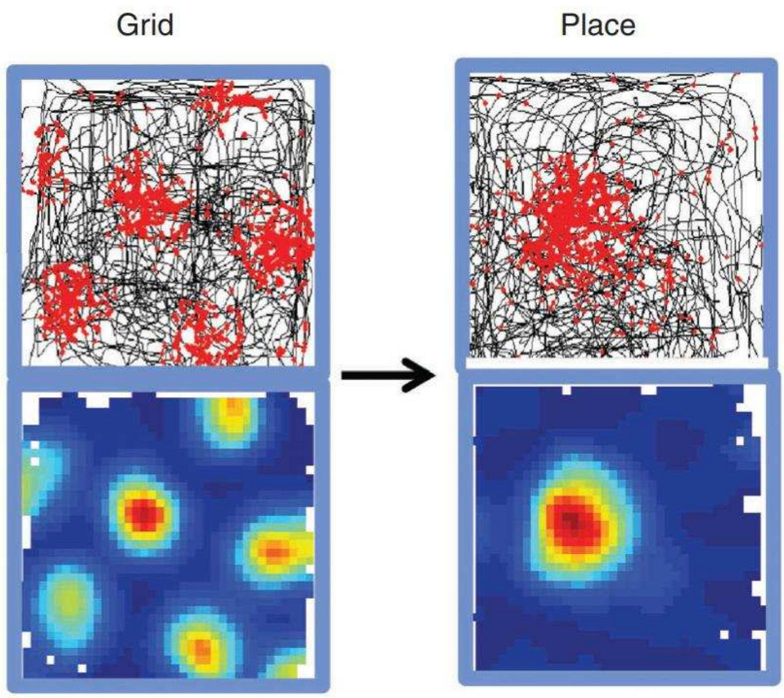

Figure 4. Firing of a grid cell (left) and a place cell (right) recorded from the rat hippocampus and entorhinal cortex, respectively (from Moser et al., 2015). In the upper panel, pike locations (red dots) are shown on the animal's path (black line) through a square enclosure. In the lower panel, autocorrelation firing fields reveal the regular hexagonal field of grid cells (left) and the unique spatial field of place cells (right).

Grid-like activity has been observed not only within the hippocampal formation but also in cortical areas usually associated with conceptual representation and advanced cognition – such as the precuneus and, as we said before, the mPFC. The presence of grid cells in the entorhinal and medial prefrontal cortices, along with place cells in the hippocampus, has been validated through single-cell recordings in implanted epileptic patients (Jacobs et al., 2013; Ekstrom et al., 2003; Bottini & Doeller, 2020). Grid cells are also active during tasks with minimal resemblance to physical navigation, such as imagined spatial navigation (Horner et al., 2016; Bellmund et al., 2016), exploration of visual scenes (Nau, Julian & Doeller, 2018), and the processing of morphing visual objects (Constantinescu, O'Reilly & Behrens, 2016) and odours (Bao et al., 2019). Moreover, grid cells also contribute to encoding gaze location during free viewing of visual stimuli, a function observed in both humans (Nau et al., 2018; Julian et al., 2018) and primates (Killian, Jutras & Buffalo, 2012).

The role of the hippocampal formation in spatial perception has also been evidenced by neuropsychological studies showing that amnesic patients with hippocampal damage struggle to recognize scenes more than faces, objects, or colours (Lee et al., 2005a). These patients exhibit notable impairments in processing multiple spatial relationships (Lee et al., 2005b) or in integrating information gathered from several fixations into a wholesome and coherent perception (Lee, Yeung & Barense, 2012; Erez, Lee & Barense, 2013). Altogether, the hippocampal formation, particularly the hippocampal-entorhinal system, seems to offer a world-centered and relational map of the surrounding environment (Doeller et al., 2010) and perceptual landscapes, supporting both navigation and visual exploration (Bottini & Doeller, 2020).

A recent proposal suggests that the same place- and grid-like organization is used to support internal representations ("cognitive maps"[7]) of nonspatial memories and experiences (Viganò & Piazza, 2020; Bottini & Doeller, 2020; Zheng et al., 2024). In a recent study, Aronov, Nevers and Tank (2017) trained rats to distinguish between different sound frequency levels in order to get little food rewards. The researchers showed how hippocampal place cells responded for specific frequencies, while grid cells in the EC responded to multiple frequencies (mirroring the role of place and grid cells in spatial environments, where place cells activate for specific locations and grid cells for multiple locations). Notably, in a follow-up experiment where rats navigated a physical enclosure, the very same cells activated by sound frequencies also fired for particular spatial locations. This demonstrates that place and grid cells are involved in encoding both spatial and non-spatial information.

In addition, research shows that the hippocampal-entorhinal circuit can arrange nonspatial experiences into a metric and relational configuration, extended to several cognitive domains: statistical regularities of events (Garvert, Dolan & Behrens, 2017), their temporal duration and succession (Bellmund, Deuker & Doeller, 2019; Buzsáki & Tingley, 2018; Eichenbaum, 2014), concepts in abstract feature spaces (Theves, Fernandez & Doeller, 2019), the structure of episodes in complex narratives (Collin, Milivojevic & Doeller, 2015), the relationship between characters in social interactions (Tavares et al., 2015), and finally, semantic relationships (Solomon et al., 2019). Essentially, evidence indicates that nonspatial conceptual knowledge could be structured

[7] In 1948, Tolman collected evidence to demonstrate that rodents could create detailed maps of their surroundings, which would enable them to engage in flexible goal-directed behaviour, i.e. finding shortcuts. Tolman coined the term "cognitive map" and speculated how these maps could support several psychological functions (Bellmund et al., 2018).

into low-dimensional cognitive maps, similar to the spatial representations used for navigating the physical world (Bellmund et al., 2018; Bottini & Doeller, 2020).

In their paper, Bottini and Doeller (2020) highlight another aspect: the "curse of dimensionality". As we know, objects in the physical world – just like concepts in our minds – vary widely along multiple dimensions (Binder et al., 2016; Borghesani & Piazza, 2017). To embrace this extensive variety of concepts, semantic memory might rely on high-dimensional representational spaces (Kriegeskorte & Kievit, 2013), where each concept is represented as a vector with coordinate values across the various dimensions that define that space. Indeed, high-dimensional geometries have been shown to predict neural activity associated with semantic processing (Binder et al., 2016; Fernandino et al., 2016), even allowing predictions at the single-item level (Pereira et al., 2018). However, high-dimensional geometries are often impractical for organizing and manipulating relevant patterns in conceptual knowledge: accordingly, in some instances relevant similarities might be overlooked due to an overwhelming number of dimensions. This phenomenon, known as the "curse of dimensionality" (Ganguli & Sompolinsky, 2012), is the reason why information becomes sparse, and patterns get lost as the number of high-dimensional spaces grows. For example, assessing a possible similarity between any animal and a cat is easy if we consider few traits, such as size or behaviour; however, it becomes nearly impossible if we take into account a dozen of different traits. Low-dimensional topological configurations, such as cognitive maps and image spaces, reduce this complexity by focusing on fewer relevant dimensions: therefore, similarities and differences become clear, and patterns appear. For instance, to understand the analogy "my job is a jail", we must ignore the numerous differences between jobs and jails and instead focus on similarities, such as lack of freedom or loneliness (Gentner, 1983).

Hence, low-dimensional cognitive maps might be essential to draw connections between seemingly unrelated experiences and objects (Gentner et al., 2001; Bottini & Doeller, 2020). Moreover, low-dimensional image spaces can significantly support the formation of primary conceptual metaphors (Grady, 1997, 1999, 2005) that underlie several abstract domains – time, numbers, and emotions – on the basis of grounded sensorimotor experience (Lakoff & Johnson, 1999; Casasanto & Bottini, 2014; Bottini & Doeller, 2020). For example, metaphors such as "You have a bright future in front of you" (*time* is *space*) illustrate intuitive metaphorical schemas rooted in spatial experience. These schemas often emerge from dimensions linked to spatial movement (such as *I move through time while I move through space*; Clark, 1973) or those that share a recognizable, iconic resemblance to sensorimotor experiences. Therefore, on the one hand, primary metaphors like "knowing is seeing", "more is up", and "bad is down" are effectively supported by image spaces due to their direct experiential correlations (Gibbs Jr, Lima & Francozo, 2004). On the other hand, more complex metaphors, such as "love is a journey" or "old age is like winter", which require a multidimensional analogical structure, may depend on the additional use of cognitive maps to facilitate their understanding (Bottini & Doeller, 2020). Although the precise neural mechanisms responsible for these processes are not yet completely understood, an extensive body of research gives substantial evidence that the parahippocampal and inferior parietal areas are involved in the production and comprehension of new metaphors (Rapp, Mutschler & Erb, 2012; Benedek et al., 2014). As a matter of fact, both the hippocampus and the inferior parietal lobule seem to play a major role in relational thinking and transitive inference (Dusek & Eichenbaum, 1997; Waechter et al., 2013), which support the structure of analogical mapping (Gentner et al., 2001; Wendelken & Bunge, 2010; Bottini & Doeller, 2020).

In conclusion, investigating low-dimensional representational spaces within the hippocampal and parietal cortex could provide significant insights into the neural mechanisms underlying analogy and metaphor, thereby enhancing our understanding of these cognitive functions (Bottini & Doeller, 2020). Currently, we know that the brain creates distinct, parallel representations of different relational structures rather than combining them into one compositional map (Spiers, 2020). It is likely that these parallel representations of separable maps facilitate generalization and adaptation in dynamic environments where the relevance of stimulus dimensions can shift rapidly (Zheng et al., 2024). These cognitive processes enable the hippocampus to flexibly adapt based on task demands (Garvert et al., 2023) and to direct focused behaviour in response to new challenges (Whittington et al., 2020; Zheng et al., 2024). Then, if the hippocampal-entorhinal circuitry can represent abstract knowledge structures similarly to spatial environments, then semantic proximity (or similarity) might also be processed as spatial closeness. Fundamentally, this would mean that related concepts could be "mapped" closer together within this cognitive space, influencing our spatial perceptions. This observation is thoroughly consistent with findings from behavioural studies, such as those conducted by Casasanto (2008), which demonstrated that individuals frequently employ spatial language to describe conceptual relationships. Findings from Bellmund et al. (2018) further support this idea by demonstrating that the hippocampal formation organizes both spatial and non-spatial information in a structured manner. Based on these premises, we expect a reciprocal relationship: that is, not only does closeness influence our perception of similarity, but similarity also affects how we remember distances. This issue will be explored further in the next section.

1.4. Similarity and Distance

The significance of space for the representation of similarity is supported by a substantial body of evidence, particularly within the semantic domain. First and foremost, this relationship was studied by Casasanto (2008). In his study, participants were asked to rate the similarity of pairs of abstract nouns, faces and object pictures, which were displayed on a computer screen at different spatial distances (*close*, *medium*, or *far apart*). In particular, they were asked to evaluate the similarity of the items based on their meanings (for abstract nouns), their functional uses (for objects), or their visual characteristics (for both objects and faces). Stimuli appeared at each spatial distance the same number of times for all participants. The spatial location of the stimuli on the computer screen had a systematic impact on participants: indeed, their similarity ratings were affected by spatial proximity, although not always in line with the predictions of spatial metaphors in language. Specifically, when the participants made perceptual judgments about face pairs and object pictures (visual appearance), stimuli presented closer together were judged to be less similar than stimuli presented farther apart. Otherwise, when the participants made conceptual judgments about abstract nouns and object pictures, stimuli presented closer together were judged to be more similar than stimuli presented farther apart, consistent with predictions based on linguistic metaphors linking similarity to physical closeness (Lakoff & Johnson, 1999).

Guerra and Knoeferle (2014) demonstrated that spatial distance between objects can modulate real-time semantic interpretation of abstract sentences. When noun pairs (such as *joy* and *euphory*) were displayed close together on a computer screen with a sentence that indicated similarity (“Joy and euphory are almost similar”), participants had quicker reading times for the adjective ("similar"), compared to when the nouns were presented farther apart (Tuena et al., 2023). Conversely, when the noun pairs were displayed at a distance, reading times for the adjective were faster in sentences that expressed dissimilarity. Boot and Pecher (2010), instead, examined whether the distance between two coloured squares influenced performance in a colour similarity decision task. They found that participants reacted faster to similar-coloured squares when the squares were spatially close to each other, compared to when they were spatially far away from each other. Interestingly, participants also responded faster to dissimilar colours that were presented far than to those near each other. Such findings suggest that the relationship between similarity and proximity should be asymmetrical. However, these results contrast with those from Casasanto (2008) and Breaux and Feist (2008), who showed that stimuli were rated as less similar when presented close together compared to when they were further apart. This discrepancy might be due to the fact that Boot and Pecher (2010) presented a very clear distinction between similar and dissimilar stimuli; furthermore, in their study, participants were asked to respond with binary choices rather than using a scale. In another research, participants saw a scenario in which two characters were close to each other or far from each other in physical space (Winter & Matlock, 2013). In this experimental condition, they judged characters positioned close to each other in space to be more similar in political ideals: these results challenge the assumption of an asymmetrical relationship since they suggest a bidirectional mapping – that is, from source to target domain and from target to the source domain.

As we have mentioned, the concept of asymmetry in metaphorical mappings seems to be consistent in literature: for instance, it has been confirmed that spatial information often influences temporal judgments, but time rarely affects spatial judgments (see

Boroditsky, 2000; see also Casasanto & Boroditsky, 2008), reflecting asymmetry in the metaphor "time is space". Nonetheless, some findings corroborate the opposite idea: for example, perceiving numbers impacts spatial responses ("more is up" or "more is right"; Fischer et al., 2003), whereas emotional state ("happy is up") influences vertical spatial perceptions (Meier & Robinson, 2004) and perceived room temperature (Zhong & Leonardelli, 2008). Moreover, Wang, Liu and Wang (2021) explored whether the spatial distance between words in the mental lexicon affects time perception. Participants were shown two words in succession and were asked to judge the temporal gap between them as either long or short. Word pairs varied in semantic or phonological similarity, representing either close or distant associations (Hillinger, 1980; Rouibah, Tiberghien & Lupker, 1999; Zhou & Marslen-Wilson, 2000). Using a temporal bisection task (Li et al., 2021), participants were trained with "short" and "long" intervals before judging intermediate test intervals. They discovered that the perceived temporal distance between two successively presented words was shorter when the words were semantically or phonologically close in the mental lexicon, compared to when they were more distantly related. Hence, lexical proximity influences perceived temporal proximity: in their paper, Wang et al. (2021) refer to this phenomenon as the "*lexical Kappa effect*", alluding to the original *Kappa effect*[8] (Cohen, Hansel & Sylvester, 1953; Price-Williams, 1954).

Further, indirect evidence for bidirectionality of "similarity is proximity" could be the "social distance is physical distance" metaphor, since social similarity is consistently related to social distance, and both are associated with physical distance (Christakis & Fowler, 2009; Winter & Matlock, 2013). In line with this claim, Matthews and Matlock

[8] This phenomenon occurs while presenting two short flashes in succession at different locations: if the spatial distance between the flashes is increased during the experimental session, people will perceive a longer temporal distance between the two flashes (Cohen et al., 1953; Price-Williams, 1954).

(2011) demonstrated that when asked to draw paths on a map, people drew paths closer to characters labelled as “friends” than to characters described as “strangers”.

One last perspective that does not emphasize asymmetry is *Conceptual Integration Theory* (Fauconnier & Turner, 1998; Turner & Fauconnier, 2002): in this approach metaphorical domains are seen as two input spaces that combine in a “blended” cognitive space rather than existing as distinct mappings. Nevertheless, “blending” is not capable of accounting for primary metaphors (see Grady, Oakley & Coulson, 1999) as they are deeply rooted, and their mappings have evolved from repeatedly perceiving environmental correlations in the world (Winter & Matlock, 2013). In this regard, Kövecses (2013) argues that these metaphors might be better understood as metonymies (“proximity for similarity”); thus, language that refers to proximity can be seen as a way to metonymically refer to similarity within the same domain (Winter & Matlock, 2013).

So far, the most compelling evidence was given by Pauels and colleagues (2023). In their paper, the researchers presented six studies in which they investigated the relationship between the “similarity is proximity” metaphor and spatial bias. In all studies, participants were shown two objects of the same category (two dogs or two food items) that differed in similarity, judged how similar these objects were to one another, and then indicated where they thought the objects had been located when they saw them. Overall, their findings show that perceived similarity reliably influences how people remember spatial distances between stimuli and speak in favour of a reciprocal relationship between distance and similarity. These lines of research suggest an intricate relationship between judgments of similarity and distance with potential implications for spatial thinking (Pauels et al., 2023).

On these grounds, we aim to demonstrate that semantic cues can influence spatial perception, gathering further evidence for a bidirectional relationship between semantic similarity and perceived spatial proximity. Specifically, we hypothesize that the distance between words will be perceived as shorter in a semantically close condition (e.g., “doctor – physician”) than in a semantically distant condition (e.g., “doctor – dog”), suggesting that semantic similarity between the two words can “compress” the perception of space. To accomplish this, DSMs will be implemented to calculate the semantic similarity between the words used. All linguistic stimuli collected for our experiment are sourced from the Italian databases provided by Montefinese and colleagues (2014) and by Crepaldi and colleagues (2015), which are called, respectively: ANEW (*Affective Norms for English Words*) and SUBTLEX-it, both available in the OSF repository.

In the experimental task of the current study, participants will be asked to judge the spatial distance between pairs of words manipulated along two specific dimensions: semantic similarity (i.e., similar and dissimilar words) and spatial distance (i.e., words positioned at different distances on the computer screen). After presenting each pair of nouns, participants will indicate whether they perceive the spatial distance between the words as “short” or “long”, similarly to the aforementioned study by Wang et al. (2021). Materials and methods will be explained in detail in the second chapter of this work.

2. Materials and Methods

2.1. Participants

For this study, the participants involved were 68 (specifically, 53 females and 15 males) ranging from 20 to 32 years of age [mean age (SD) = 23.60 ± 2.44 years]. Sample size was determined *a priori* based on Brysbaert and Stevens' (2018) indication that, in order to achieve properly power, an experiment should have at least 1.600 observations per cell of the design (i.e., per condition tested), that is at least 40 stimuli for 40 participants. Participants were recruited via institutional email advertisements and via social media. All participants were native Italian speakers, with normal or corrected-to-normal vision and were naive to the purpose of the study. In addition, no previous history of learning disorders was recorded. For the current study, each participant was assigned a unique subject code to ensure anonymity during data collection and analysis. All participants provided informed consent before participating in the study. Finally, the study protocol was approved by the ethical committee of the University of Pavia (Department of Brain and Behavioural Sciences) and all participants were treated in accordance with the guidelines outlined in the Declaration of Helsinki.

2.2. Distributional Semantic Model

The DSM we used here was *fastText*, originally proposed by Schütze in 1993 and realized computationally by Joulin and colleagues (2016) and Bojanowski and colleagues (2017). Words and pseudowords vectors were retrieved from the Italian pre-trained vectors (Grave et al., 2018). To do this, we relied on a pre-trained *fastText* model (specifically for the Italian language), which is called "wiki.it.bin": the model was trained using the Continuous Bag of Words (CBoW) method, an approach originally proposed by Mikolov and colleagues (2013a), with 300 dimensional vectors, character n-grams of up to length 5, and a window of size 5. The model was trained on the Italian Wikipedia corpus with 730.748.126 tokens (hence "wiki.it" in the name).

When using CBoW, the obtained vector dimensions capture the extent to which a target element is reliably predicted by the linguistic contexts in which it appears, where "context" is represented as the words contained in a fixed size window around the target word (Gatti, Marelli & Rinaldi, 2023; Anceresi et al., 2024). Specifically, the CBoW model will induce a representation for a given target w_0 based on context words:

$$w_{-n}, \dots, w_{-1}, w_1, \dots, w_n$$

2.3. Stimuli

We selected 210 two-syllable words (with five letters) for the experiment, paired together into 100 pairs. The remaining 10 words were paired with a pseudoword, that is, a made-up term that follows the phonological and morphological rules of a language (Stark & McClelland, 2000; Arndt, Lee & Flora, 2008). The 10 pseudowords used were also composed of five letters and were all readable. These couples constituted the filler items and were used to assess the attention of the participants during the experimental task: hence, if participants were actually reading the stimuli. Stimuli were additionally balanced for valence, arousal, frequency and Levenshtein distance (LD; Levenshtein, 1996). Additionally, each letter string, whether a word or a pseudoword, appeared only once in the entire set of stimuli.

We selected words from the ANEW Italian database by Montefinese and colleagues (2014), developed from translations of the 1.034 English words present in the *Affective Norms for English Words* (Bradley & Lang, 1999) and from words selected from Italian semantic norms (Montefinese et al., 2013). In this dataset, all the words were rated according to six measures (valence, arousal, dominance, familiarity, imageability, and concreteness). For the purpose of this study, we considered only *valence* and *arousal* ratings. We then selected another dataset containing additional words, the SUBTLEX-it (Crepaldi et al., 2015), an Italian word frequency database created by analyzing movie subtitles. The reason we chose SUBTLEX-it is that it contains a much larger number of words, offering a broader range of possibilities for matching in terms of word length, frequency, and LD. This measure is often referred to as "edit distance" and can be defined as the minimum cost of transforming one string into another through a sequence of weighted edit operations (Yujian & Bo, 2007). For instance, the LD between the words *cat* and *bat* is 1 because it would take one letter (*c* instead of *b*) to transform *cat* into *bat*. Alternatively, the LD between *kitten* and *smitten* is 2 because it involves one substitution (*m* instead of *k*) and one insertion at the beginning of the word (*s*).

All the analyses were performed with R-Studio (RStudio Team, 2015). At first, we developed a script by taking into account *only* valence and arousal values for our linguistic stimuli. As mentioned above, we extracted 300-word vectors from the ANEW dataset loading a pre-trained *fastText* model ("wiki.it.bin"). We estimated two linear model formulas (*form_val* and *form_aro*) where the 300-dimensional word vectors were used as predictors for both valence and arousal. Our aim was to determine whether these numerical representations generated by *fastText* could accurately predict *valence* and *arousal*: the results showed that these vectors successfully predicted both dimensions.

To further validate the models, we employed a "Leave-One-Out" (LOO) cross-validation method. This approach ensured that our predictive models for valence and arousal were not simply memorizing the data but were evaluated based on how well they generalized to new words. Since the model was trained on nearly the entire dataset in each iteration (just one word was left out), we could examine how well the model performed on each specific instance. For example, if the model can accurately predict the valence and arousal for a left-out word, it indicates that the word vectors contain meaningful information about these dimensions. In contrast, if the model struggles to make accurate predictions for a left-out word, it may indicate that the vector does not capture sufficient information or that the model fails to learn the relationship between the vectors and the associated ratings. Consequently, the word vectors were merged with the original ANEW database, creating a unified dataset.

Afterwards, we prepared another data frame containing the additional Italian words taken from the SUBTLEX-it dataset. An "anti-join" operation was performed to exclude words that had already been evaluated in the ANEW, ensuring that only new words were analysed. In the script, a linear model was executed for each word in a loop, processing one word at a time. After each iteration, the results were combined using the *rbind* function to create a cumulative data set. Once all words were processed, we calculated the cosine distance between words: the cosine is typically taken as a proxy for semantic similarity (Günther et al., 2019a). The higher the cosine value, the more semantically related the words are expected to be.

We then focused on balancing pairs of words to form both related and unrelated couples. These pairs were carefully balanced according to different factors: word frequency, emotional dimensions such as arousal and valence, and the Levenshtein distance. In particular, by setting LD > 1, we guaranteed that the words in each pair were sufficiently different, requiring at least two-character edits (insertions, deletions, or substitutions) to transform one word into the other. Finally, we created 200 different Excel files containing related, unrelated, and filler words, already randomized and ready to be used for the experimental task.

2.4. Experimental Design and Procedure

The experiment was programmed and executed using PsychoPy (Peirce, 2007, 2009; Peirce & MacAskill, 2018; Peirce et al., 2019), a Python-based software for the creation of experiments in behavioural science (psychology, neuroscience, linguistics) with precise spatial control and timing of stimuli. The experimental task was conducted through the Pavlovia platform, created for the wide community of researchers in the behavioural sciences to run, share, and explore experiments online. Participants were required to use the Google Chrome browser, ensuring compatibility with PsychoPy running on Pavlovia. After agreeing to the informed consent, participants went through the experimental condition in the same session. Upon accessing the experiment link, participants were presented with a digital form to input their unique subject code. Before starting, participants were given on-screen instructions that explained the task requirements.

2.4.1. Explicit Spatial Judgment Task

This study employed an explicit spatial judgement task to examine the perceived spatial distance between pairs of words manipulated along two specific dimensions: semantic similarity (similar and dissimilar words) and spatial distance (words positioned at different distances on the computer screen). This task included a training phase followed by a testing phase. In the training phase, participants were initially exposed to two anchors: a "short" standard and a "long" standard (from 0.1 to 0.5 normalised display units). Specifically, the units represent percentages of the screen space, meaning the actual physical distance depends on the size of the display being used. For all units, the centre of the screen is represented by coordinates (0,0), negative values mean down/left, positive values mean up/right. In normalized units, the display window ranges from -1 to +1 along both the x and y axes; thus, the top-right corner of the window has coordinates (1,1), and the bottom-left corner has coordinates (-1,-1)[9]. This configuration aimed to prevent participants from focusing excessively on the center of the screen when making spatial judgments. Participants practiced categorizing distances as either "short" or "long" based on the anchor distances, ensuring they could distinguish between the two standards. This phase was important to ensure that participants understood the task requirements before proceeding to the main experiment. In the testing phase, each trial began with a fixation (+) at the center of the screen for 500 ms, followed by a blank screen for 500 ms. After that, two words were successively presented at different spatial distances (0.1, 0.2, 0.3, 0.4 and 0.5 display units) for 1500 ms (see *Figure 5).* All the selected word pairs appeared on the screen aligned along the vertical axis.

Participants were asked to judge whether the spatial distance between the pairs of words was closer to the "long" or "short" anchor interval, pressing the "A" key on the keyboard for the "short" distance and the "L" key for the long distance. Following the main spatial judgement task, an attention trial was included: in this condition, one of the two presented words in the couple was a pseudoword. This trial was a control measure used to assess the attention of the participants to the words, verifying that they were genuinely reading and understanding their meaning rather than merely calculating the

[9] Note that setting a stimulus height to 1.0 would represent half the window's height, rather than the full height, as the total range in height is 2 (from -1 to +1). Additionally, specifying equal values for width and height does not necessarily produce a square stimulus unless the display window itself is square. For example, on a 1024x768 window, a stimulus with size parameters (0.75,1) would result in a square due to the aspect ratio of the window.

spatial distance between them. Whenever the participants saw the pseudoword, they were required to press the spacebar instead of the two previously indicated keys. Therefore, as previously stated, the stimuli were 210 two-syllable words, with 10 additional pairs of real words and pseudowords serving as fillers, for a total of 110 trials. Trial order was randomized across participants.

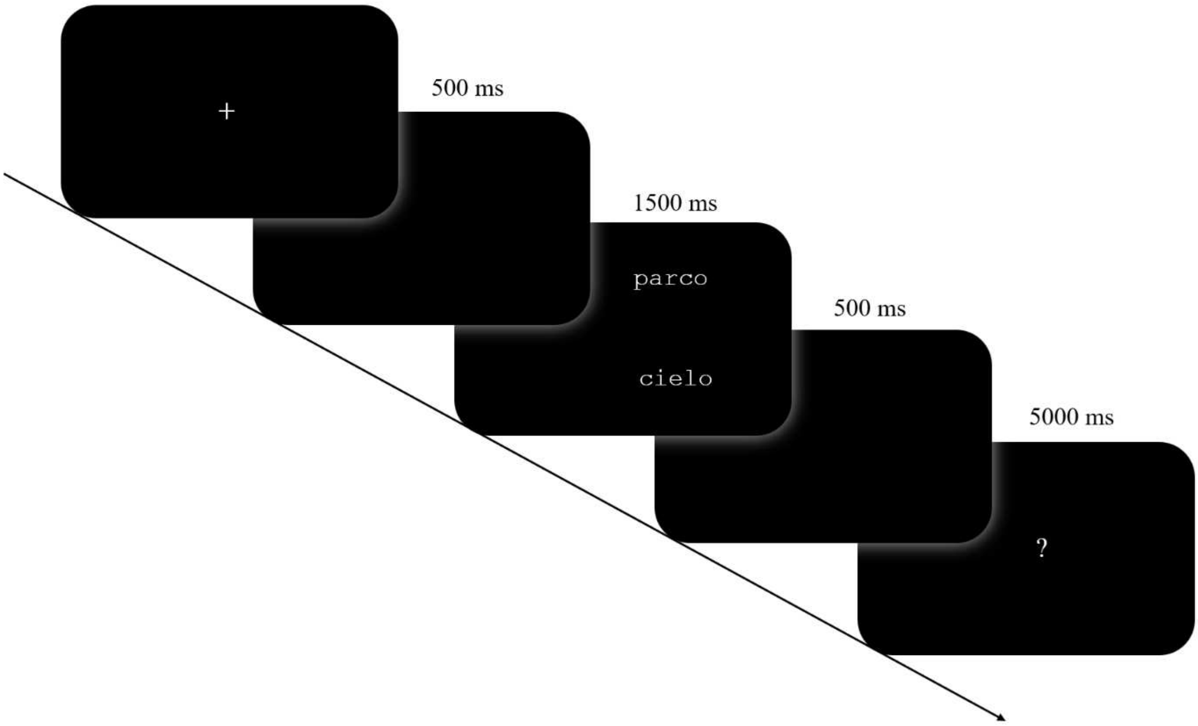

Figure 5. Schematic representation of the trial structure for the experiment (long distance). The font used for the task was Courier New: in all the pairs, each letter filled the same space on the screen.

2.5. Data Analysis

Data were collected using PsychoPy and exported as CSV files. Data cleaning, preprocessing, and final analysis were conducted using RStudio (R-Studio Team, 2015). Generalized linear mixed models (Cox, 1958; Knoblauch & Maloney, 2012) – henceforth, GLMMs – were run using the *lme4* R package (Bates et al., 2015; Kuznetsova, Brockhoff & Christensen, 2015). Our dependent variables were the correct *responses* given by the participants, which were analyzed using GLMMs fitted on a binomial family distribution ("short" answers were computed as 1 and "long" answers as 0), while *type* (related, unrelated) was our categorical predictor, with participants and trials set as random intercepts. The experimental pipeline consisted of several steps.

In the initial data processing, we imported the CSV files on RStudio and used a *for* loop to merge each file into a single, comprehensive master data frame. We isolated the catch trials, that is, the specific trials we implemented in the experiment to assess the attention of the participants to the stimuli. In these attention trials, participants were instructed to press the spacebar: consequently, we checked whether they followed this instruction or not. We calculated the average accuracy for each participant by assessing the proportion of correctly completed catch trials. Participants who demonstrated an accuracy below 60% on these trials were considered inattentive, and the script filtered them out, leaving only participants who passed this threshold. This resulted in the removal of data from 8 participants. After the dataset was filtered to keep only those participants who demonstrated high accuracy on the catch trials, we removed all the fillers from the dataset in order to focus on the meaningful results. Moreover, we filtered out any cases where the response column contained unexpected key presses, retaining only entries where responses were either “a” or “l”. We encoded the “a” response as 0 (indicating a “short” response) and “l” as 1 (indicating a “long” response). This step was crucial to ensure that subsequent analyses could accurately identify the different types of responses from participants.

Mean accuracy was calculated for each participant. For “short” responses, if the response was “a” and the distance value was less than 0.25, the accuracy was coded as 1 (correct); otherwise, it was marked as 0 (incorrect). Similarly, for “long” responses, if the response was “l” and the distance was greater than 0.35, the accuracy was 1; otherwise, it was set to 0. At this point, using the *ddply* function (contained in the *plyr* package), the dataset was filtered in order to exclude all instances where the distance (*dist*) was equal to 0.3. Participants with an average accuracy greater than 0.70 were retained in a subset. In contrast, those with an average accuracy below 0.69 were stored in a different subset, indicating a reduction in the participant pool from 60 to 56 individuals.

Finally, using the *lme4* R package, we estimated a GLMM. Specifically, in the *lme4* syntax the model estimated was:

$$resp \sim type\ +\ (1|ID) +\ (1|trial)$$

To prepare for the GLMM analysis, the variables *ID* (participant identity) and *trial* (each specific trial in the experiment) were converted into factors. This allowed for their inclusion as random intercepts in the subsequent statistical models, accounting for individual differences among participants and potential variations across trials. In the next section, we report the results of this estimated model.

3. Results

In the current study, a GLMM was employed using the *glmer* function to analyze the data. The model consisted of 1.030 observations with the dependent variable *resp* representing the type of response provided by participants. The independent variable *type* was included as a fixed effect (thus, it was expected to influence the *resp* variable).

In the first place, *Table 1* shows that distance (*dist*) significantly predicted correct "long" response probability, confirming that the task worked as intended in detecting distance-related effects. In particular, the coefficient for the *dist* variable (32.83644) indicates that for each one-unit increase in the distance between words, the estimated *log-odds*[10] of the response variable being in the 1 category ("long") increased by approximately 32.83644 units. In simpler terms, as the spatial distance between words grows, the probability of a "short" response decreases, while the likelihood of a "long" response significantly increases. This relationship is visually clear in *Figure 6*, where the logistic curve shows the typical S-shape of binary response data. The curve reflects a sharp transition from "short" to "long" judgments around a certain distance, with participants making confident "short" judgments at low distances and vice versa.

Table 1. Fixed Effect Table revealed by the GLMM and their *p*-values.

Fixed Effect	***Estimate***	***Standard Error***	***z-value***	***p-value***
(Intercept)	-8.46189	0.48034	-17.61662	<0.00001
Distance (*dist*)	32.83644	1.31245	25.01918	<0.00001

[10] *Log-odds* are the logarithm of the odds of an event occurring, used in statistics to express probabilities in logistic regression, where positive values indicate a higher likelihood of the event and negative values indicate a lower likelihood (Norton & Dowd, 2018).

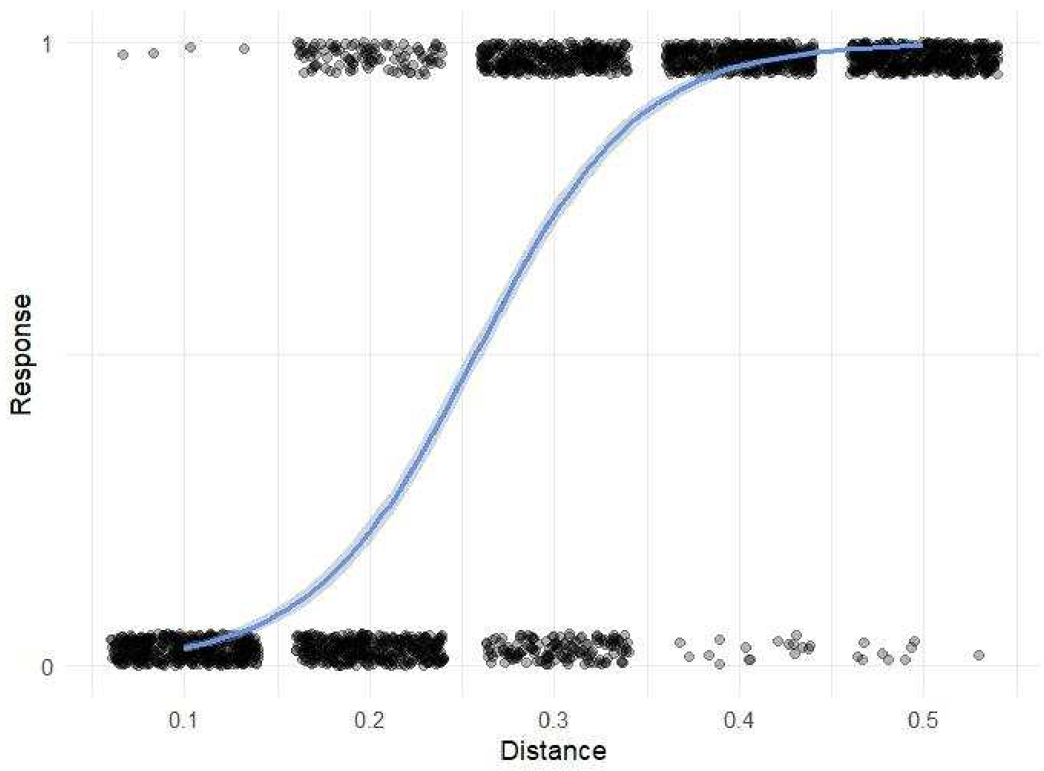

Figure 6. Positive relationship between distance and “long” judgments in participants.

However, while showing some positive trend (as we can see in *Figure 8*), the variable *type* does not reach statistical significance in this model. An analysis of variance for deviance tests[11] (Nelder & Wedderburn, 1972) was conducted to evaluate the significance of *type* in predicting the response variable. The Chi-squared value for *type* is 2.5 with 1 degree of freedom (p = 0.11). This *p*-value is above the conventional significance level of 0.05, indicating that *type* is not statistically significant at the 5% level. Nevertheless, it is worth noting that it is relatively close to this threshold, suggesting a potential trend towards significance. Hence, although not statistically significant, it might warrant further investigation with an alternative trials structure to determine whether this trend could become significant under different conditions.

[11] Deviance serves as a measure of how well the model fits the data; lower values indicate a better fit.

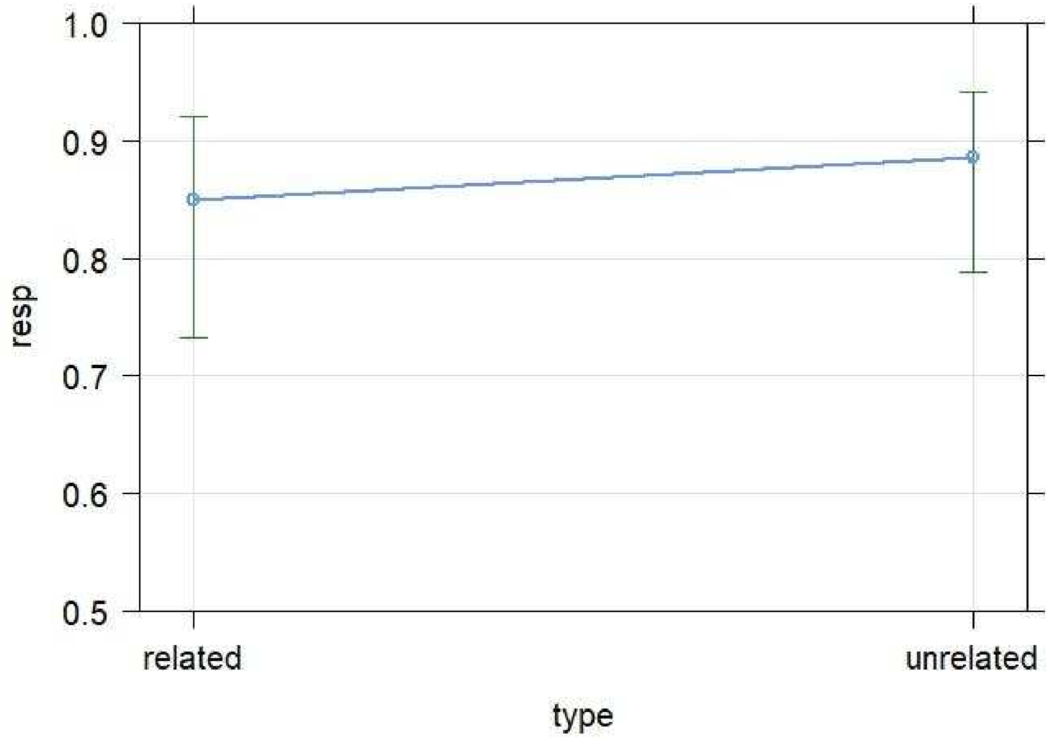

Figure 7. The plot shows a slight increase in *resp* between the related and unrelated conditions, suggesting that participants may have perceived a slight difference in spatial distance based on the semantic similarity of the words, but this difference is not significant (p = 0.11).

As additional check, we ran a GLMM to analyze how the variables distance (*dist_f*) and *type* (related/unrelated) affected the response (*resp*) variable. In this case, the *lme4* syntax of the estimated model was:

$$resp \sim dist\_f \ * \ type \ + \ (1 \mid ID)$$

This model predicts *response* as a function of *distance*, *type*, and their interaction, while (1 | *ID*) specifies a random effect with an intercept for each level of *ID*, allowing for individual variations in the model. As shown in *Figure 8*, at a distance of 0.3 (regardless of whether the word pairs are related or unrelated), participants tend to choose the "long" condition over the "short" one. This observation suggests that the "short" anchor in the task could be so pronounced that, when in doubt, participants are inclined to respond with the "long" condition. Consequently, the task appears to be unbalanced in terms of stimulus presentation, leading to a bias toward the "long" condition.

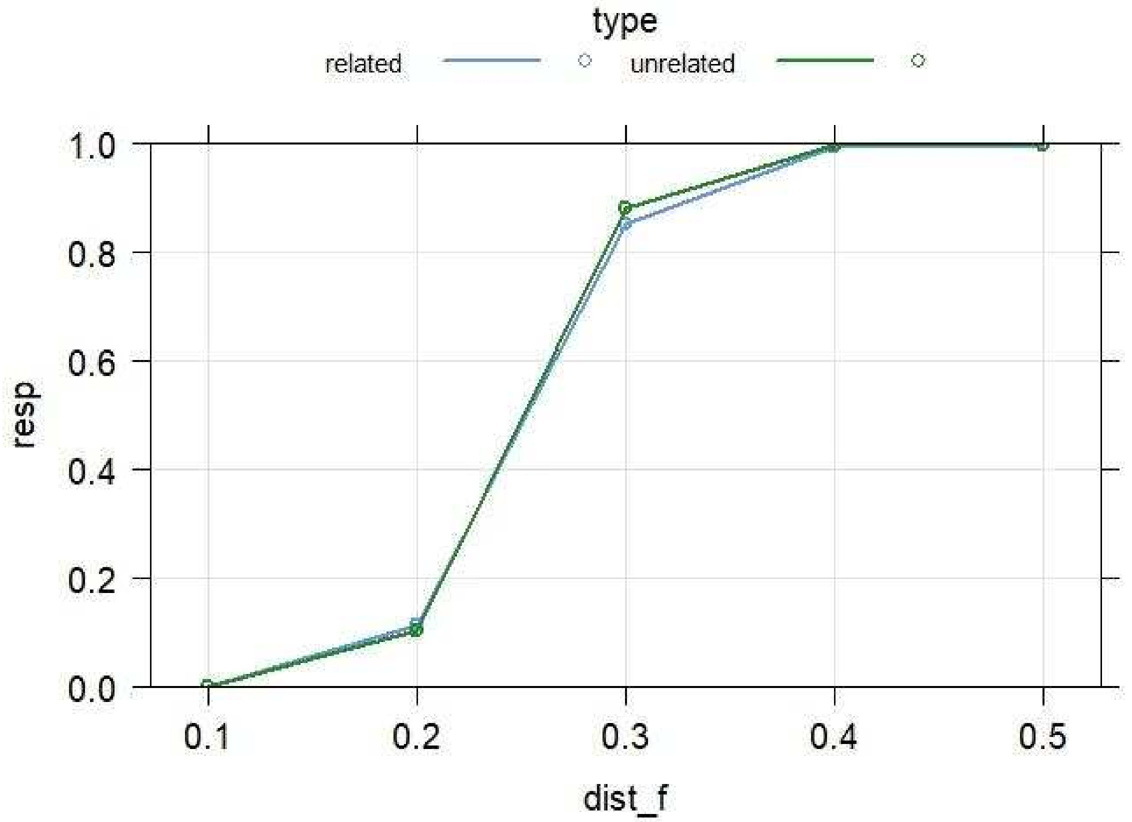

Figure 8. Graphical representation of the interaction model *resp ~ dist_f*type + (1|ID)*. As distance increases, particularly at 0.3, there is a noticeable bias toward the "long" condition.

Given the psychophysical nature of this task, it is worth noting that we additionally estimated the *Point of Subjective Equality* (henceforth, PSE) for each participant as a further measure of response accuracy. The PSE represents the point at which participants perceive two stimulus intensities as subjectively equivalent, or ambiguous, with a 50% probability of choosing either response. To estimate the PSE, we fit a psychometric curve using the *quickpsy* function, which models the relationship between stimulus intensity and response probability across conditions. Additionally, the model calculates a slope parameter, which can be used to derive the *Just Noticeable Difference* (JND), a measure of sensitivity to changes in stimulus intensity (Moscatelli, Mezzetti & Lacquaniti, 2012).

To ensure the reliability of our findings, we calculated the mean and standard deviation (SD) of PSE values within each participant and condition, and we then filtered out participants whose PSE values deviated more than 2 SDs from the mean. *Figure 9* shows the plot of the fitted psychometric curves across conditions and participants. This cleaning procedure led to participant exclusion outcomes which closely aligned with those described in the previous method. Note that the psychometric curve was fitted solely as an additional check on participant performance. Indeed, due to the imbalances previously mentioned, the data showed a response bias that limited the precision of a PSE-based analysis. Therefore, we chose not to pursue this approach further and opted for the GLMM analysis instead.

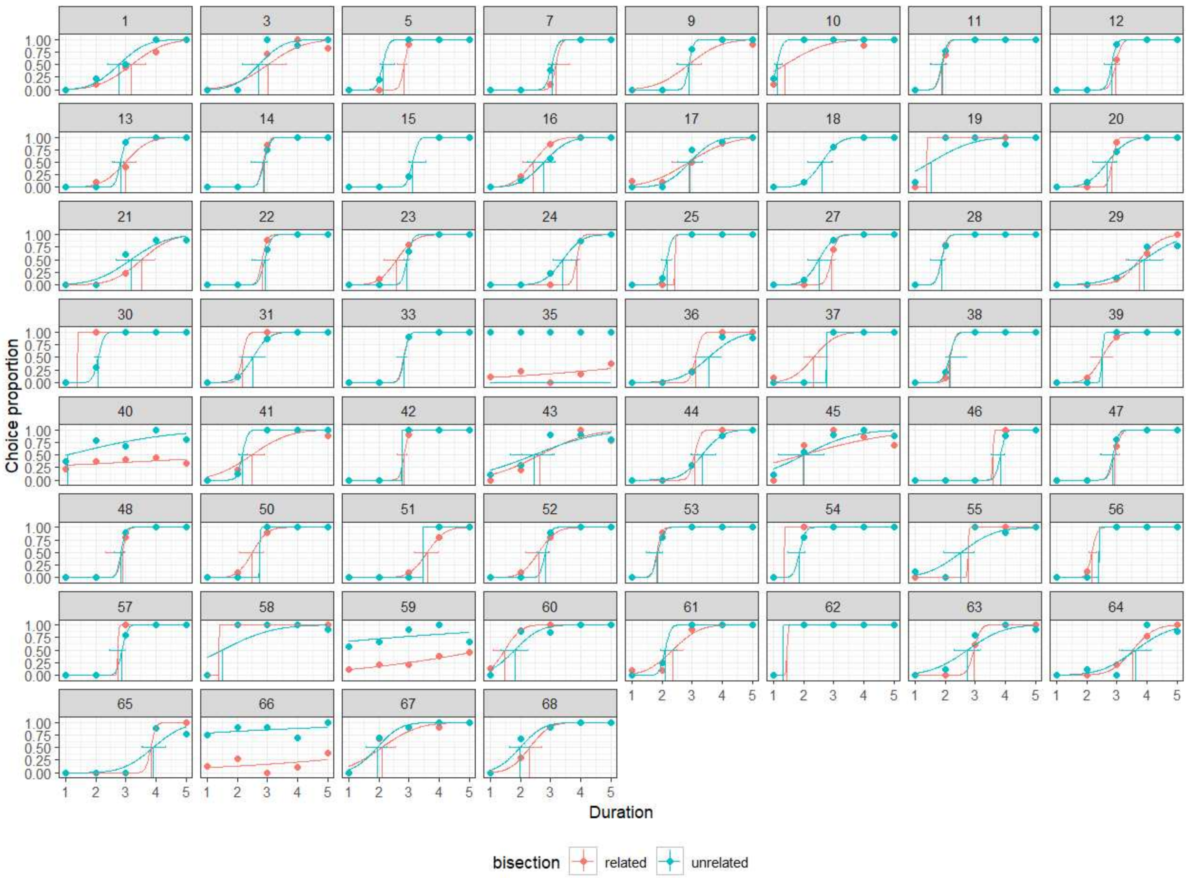

Figure 9. Point of Subjective Equality (PSE) for each participant in the related and unrelated conditions.

4. Discussion

In the present study, we gathered a sample of sixty-eight participants to investigate whether semantic similarity could influence the accuracy of remembered distance. In particular, we hypothesized that spatial distance between words would be perceived as shorter for semantically related pairs compared to unrelated pairs. Our research demand was initially inspired by Casasanto (2008), who demonstrated in a series of behavioural studies that spatial proximity could affect similarity judgments. Besides his findings, prior research has explored the impact of distance on perceived similarity (Winter & Matlock, 2013), as well as its effects on choice (Boot & Pecher, 2010; Schneider et al., 2020) and categorization (Lakens et al., 2011; Schneider & Mattes, 2022). Conversely, we were interested in whether an abstract information, such as semantic similarity, could influence the perception of a more concrete attribute, such as spatial distance. Supported by positive results in literature (see Pauels et al., 2023) which proved that perceived similarity can reliably shape spatial memory, we took advantage of a DSM to explore this potential reciprocal relationship.

To begin with, semantic similarity is central to many fundamental processes in human cognition, such as categorization (Nosofsky, 1986; Hampton, 1998), memory recall and recognition (Baddeley, 1966; Montefinese, Zannino & Ambrosini, 2015), and language processing (Raveh, 2002; Wingfield & Connell, 2023). Consequently, the study of semantic similarity is indelibly connected to theories of conceptual processing and representation. For instance, theories that organize the conceptual system as a taxonomic hierarchy (see Collins & Quillian, 1969) often derive measures of semantic similarity from distance metrics within hierarchical databases (Wingfield & Connell, 2023). By contrast, according to the distributional hypothesis (Firth, 1957; Harris, 1954), linguistic distributional measures of semantic similarity can be obtained by extracting statistical patterns from large natural language corpora, as seen in Latent Semantic Analysis (Landauer & Dumais, 1997) and the Continuous Bag of Words approach (Mikolov et al., 2013a). Finally, within a grounded cognition framework (Barsalou, 1999; Connell & Lynott, 2014), it is plausible to assume that similarity between concepts corresponds to similarity in sensorimotor experiences. However, embodied and distributional accounts of semantic memory have traditionally been seen as opposing views, largely due to the fact that DSMs rely solely on linguistic input without incorporating sensorimotor experience (Glenberg & Robertson, 2000; Glenberg & Kaschak, 2002; Borghesani & Piazza, 2017; Munoz-Rubke, Kafadar & James, 2018; Sadoski, 2018; Günther et al., 2019a). This contrast may also be due to limited cross-disciplinary communication, which has constrained opportunities to integrate insights from both approaches (Davis & Yee, 2021). Nonetheless, they are not fundamentally distinct, as both rely on mechanisms that process and integrate associations over time.

As a matter of fact, Andrews and colleagues (2009) effectively demonstrated the potential of combining linguistic and embodied data by integrating both types in a unified model, creating a joint distribution of linguistic and perceptual feature-based data (also see Steyvers, 2010; Davis & Yee, 2021). The resulting semantic representations matched human behaviour better than those created using each data type independently: hence, the interaction between sensorimotor and linguistic data seems to be rather crucial for developing more human-like semantic knowledge (Andrews et al., 2009; Louwerse & Zwaan, 2009; Louwerse, 2011). In particular, this model can essentially perform inference, a crucial feature to the "grounding problem" for words encountered purely through language. For instance, if we have substantial sensorimotor experience with coffee – and we know it as typically dark-coloured, hot, and often served in a mug – we develop a grounded representation of coffee. If the word "coffee" and "tea" happen to occur in similar contexts, the model can then infer and assign attributes to "tea" based on its association with the already grounded representation of coffee, even without direct experience with tea (Davis & Yee, 2021). More recent efforts in hybrid computational modelling have made this inference process more explicit (Hoffman, McClelland & Lambon Ralph, 2018). For example, Johns and Jones (2012) designed a global memory model that integrates linguistic distributional data (word co-occurrence vectors from large text corpora) with proxies for sensory-perceptual data, such as feature norms (Vinson & Vigliocco, 2008) and modality exclusivity norms (Lynott & Connell, 2009). In this context, the linguistic model faces a limitation: that is, not every word in the linguistic corpus has an associated sensory-perceptual representation. Therefore, the model infers sensory-perceptual qualities for words based on their similarity to words with established perceptual information: in this way, more abstract concepts can acquire sensory-perceptual associations (Davis & Yee, 2021).

Building on these developments, evidence from a growing number of studies converges in suggesting that perception is affected by language, further emphasizing our previous points: in the *symbol-interdependency hypothesis*[12], Louwerse and Zwaan (2009) posit that language and sensorimotor experience are inherently intertwined, suggesting that linguistic data alone can encode considerable information about the physical world. In some of their studies, they demonstrated that distributional vectors

[12] The *symbol-interdependency hypothesis* is not a new concept; it draws directly from Deacon's (1998) hierarchy of signs, which itself is rooted in Peirce's (1923) foundational theories of semiotics.

contain surprising amounts of real-world information. For instance, when city names are represented through distributional vectors, their spatial relationships in a model correspond to their actual geographic locations (Louwerse & Zwaan, 2009; Recchia & Louwerse, 2016), and even hold true within fictional worlds such as Middle-earth from *The Lord of the Rings* (Louwerse & Benesh, 2012; Günther et al., 2019a). Moreover, it has been demonstrated that distributional vectors can represent a large range of sensorimotor information: indeed, these vectors capture the vertical location of objects in the world (Hutchinson & Louwerse, 2013), different perceptual modalities (such as *visual*, *auditory*, *olfactory*, *gustatory*, and *haptic*; Louwerse & Connell, 2011), and affective dimensions (including *dominance*, *valence*, and *arousal*; Hollis & Westbury, 2016). That is to say, distributional models are able to capture enough world structure to mimic some aspects of embodied knowledge, albeit not comprehensively.

As previously discussed in the *Spatial Codes for Human Thinking* section, the cognitive map theory (Tolman, 1948; O'Keefe & Nadel, 1978) and more recent theories (Behrens et al., 2018; Bellmund et al., 2018; Bottini & Doeller, 2020; Stoewer et al., 2022, 2023) propose that the brain mechanisms responsible for spatial orientation in mammals can also be engaged to represent more abstract conceptual spaces, suggesting that spatial and nonspatial knowledge might share common representational systems (Viganò et al., 2024). An explanatory framework can be described as follows: highly processed sensory information from our sensory organs is directed to the hippocampal-entorhinal complex, which supports spatial navigation and forms cognitive maps of the environment (O'Keefe & Dostrovksy, 1971). Within this complex, information is contextualized and associated with past experiences (Opitz, 2014). Grid and place cells generate map-like codes, which are suggested to contribute to these cognitive maps, thereby supporting the processing of memories, emotions, and navigation (Stoewer et al., 2022). In line with embodied theories of cognition, this perspective gives priority to the perceptual and motor origins of cognitive maps (Barsalou, 2008; Gallese & Lakoff, 2005). Nevertheless, as discussed above, additional evidence suggests that the development of cognitive maps may not depend solely on specialized spatial computations (Friedman & Brown, 2000; Friedman & Montello, 2006; Louwerse & Zwaan, 2009; Louwerse, 2018; Gatti et al., 2022). First of all, experimental evidence has already demonstrated that the hippocampal-entorhinal complex is involved in language processing (Covington & Duff, 2016; Piai et al., 2016). In the second place, Shrager, Kirwan and Squire (2008) demonstrated that patients with lesions in the hippocampal and entorhinal cortex could accurately track reference locations and estimate distances, performing in a similar way to healthy controls. Although this study used short paths, which could be retained in working memory, this evidence challenges the view that spatial computations are entirely responsible for developing mental representations of the environment (Gatti et al., 2024).

In light of these considerations, it is plausible that both perceptual and linguistic experiences contribute to the formation of cognitive maps[13]. Moreover, we know that studies exploiting Distributional Semantic Models have shown that spatial information can be inferred from the statistical structure of natural language (Louwerse, 2018; Rinaldi & Marelli, 2020; Gatti et al., 2022, 2024). If this were the case, then language should influence our perception of space in the same way that space influences our perception of words. In particular, concepts that are semantically similar could be mentally represented

[13] It is crucial to mention that the extent to which linguistic and perceptual information contributes to this process depends on several factors, including the experimental task, the type of stimuli, and the domain assessed (Louwerse et al., 2015; Gatti et al., 2022).

as being “closer” together within an abstract cognitive space, which could influence our perception, our memory of physical distances and the relationships between concepts. Casasanto (2008) was one of the first researchers to provide evidence of this connection through behavioural studies, demonstrating that people often use spatial language to describe abstract relationships (“close friends” or “distant relatives”). Then, Pauels and colleagues (2023) demonstrated that similarity influences distance memory, as in the case for many conceptual metaphors.

Here, we exploited a distributional semantic model – specifically, *fastText* – to further investigate the possibility of a bidirectional relationship between semantic similarity and perceived spatial distance. Despite the inherent limitations of our task outlined in the previous section, the results showed a slight trend: indeed, participants tended to choose the “short” anchor when the proposed word pairs were semantically close. However, the Chi-squared value for the variable *type* (whether word pairs were semantically related or unrelated) was 2.5 with 1 degree of freedom ($p = 0.11$), which is above the commonly accepted *p*-value of 0.05. Given this proximity to the conventional significance threshold, it is worth considering the possibility that under a modified experimental structure, the trend observed in this analysis might become significant.

In addition to the primary analysis, a GLMM was employed to further examine how *distance* and *type* affected the *response* variable: the model showed a tendency for participants to favour the “long” condition at a distance of 0.3, regardless of whether the word pairs were related or unrelated. At this point, it becomes evident how the “short” anchor in the task was overly pronounced, leading participants to gravitate toward the “long” condition in cases of uncertainty. Similarly to Boot and Pecher (2010), this outcome highlights a flaw in the task design: in their study, in fact, the very clear distinction between similar and dissimilar stimuli might have made the task more straightforward for the participants.

Furthermore, as we can see in *Figure 9*, some of our participants appear to have not fully understood the instructions of the task: this misunderstanding led to inconsistent or unexpected responses, affecting the overall validity of our data. The direction of the psychometric curve provides a critical insight as it reflects how participants are interpreting the intensity of the stimuli: in this specific case, it is a crucial indication that some of our participants (for instance, 35, 59 or 66) were perceiving or responding in a opposite manner to what was intended by the experimental design. Despite the data cleaning procedures we applied, the complex instructions of the task and the imbalance in the stimuli may have influenced the performance of the entire sample, not just that of the participants excluded after data cleaning. Therefore, it is important to consider that the performance we observed in the current study might not be entirely representative of how participants would respond under more controlled or optimized conditions.

In summary, our findings could be considered as preliminary data, supporting further research on the bidirectional association between spatial perception and semantic similarity. In particular, the dominant perspectives aligned with embodied accounts of cognition (Barsalou, 2008; Gallese & Lakoff, 2005; Gatti et al., 2024) should be challenged by future research, since we have significant evidence that language and sensory experience are not separate entities (Louwerse & Zwaan, 2009) and that similarity not only reflects our abstract understanding of the world, but also has direct implications for our spatial perception (Pauels et al., 2023).

5. Conclusion

In this study, we explored whether semantic similarity between words could influence perceived spatial distance, hypothesizing that semantic similarity could "compress" the perception of space. Although the results of the current study show only a subtle trend, this minor evidence is coherent with theoretical views which suggest that linguistic and perceptual experiences work together in shaping mental representations (Louwerse, 2018) and is consistent with recent behavioural insights by Pauels and colleagues (2023). Moreover, this trend is also in line with previous research by von Hecker, Hahn and Rollings (2016), which showed that when two elements appear more coherent or logically related, they are perceived and judged as closer in space.

On the one hand, the theoretical basis of this study included the *Conceptual Metaphor Theory*, which proposes that abstract ideas are grounded in more basic, sensorimotor experiences (Lakoff & Johnson, 1999), a concept also highlighted in *A Theory of Magnitude* (Walsh, 2003; Bueti & Walsh, 2009). However, the semantic distance of words is not a magnitude in the same sense as physical stimuli: then, if the perception of spatial distance can be distorted by semantic similarity, this effect cannot be explained by ATOM. In this regard, Louwerse (2007, 2011) offers an alternative perspective with the *symbol-interdependency hypothesis*, which argues that perceptual relationships are encoded within the language system. Two decades ago, Barsalou (1999) predicted that "whatever approach ultimately does succeed will similarly attempt to integrate representation, statistical processing, and embodiment" (p. 652), while Landauer and Dumais (1997) stated that "the same process [of higher-order co-occurrences] would presumably be used to reach agreement on similarities between words and perceptual inputs and between perceptual inputs and each other” (p. 215; Louwerse, 2018). Today, an integrated perspective on symbolic and embodied cognition has gained considerable support (Louwerse, 2007; Barsalou et al., 2008; Andrews et al., 2009; Bruni, Tran & Baroni, 2014), challenging traditional views which favour specialized spatial computations (Bellmund et al., 2018; Bottini & Doeller, 2020; Derdikman & Moser, 2010).

On the other hand, our empirical basis draws from several research: notably, we mention a study by Casasanto (2008), which showed that when items are semantically or conceptually close (whether in meaning or usage), people often perceive them as physically closer, albeit spatially separated. Other studies, such as those by Boot and Pecher (2010) and Winter and Matlock (2013), suggested a possible bidirectional association between similarity and proximity. Pauels and colleagues (2023) further supported this reciprocal relationship, demonstrating that perceived similarity shapes memory for spatial distance.

In conclusion, despite its limitations, this work contributes to the growing understanding of how language and perceptual experiences interact to shape cognitive representations of space. Future research should address these limitations, proposing a task with simpler instructions, ensuring a thorough understanding of the guidelines by the participants. Moreover, the task appeared to be unbalanced in terms of stimulus presentation, introducing a bias toward the “long” condition. To address this issue, the task could be adjusted by rebalancing the stimulus presentation or modifying the anchors to minimize such bias. Hence, we cannot still answer exhaustively to our initial question: semantic similarity seems to influence spatial perception, but future studies are needed to enrich our understanding of this intricate connection.

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[V]

The Happy Years

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