MASTER THESIS

The relation between active word categorization and semantic brain activation

Modelling Cognitive Processing and Learning

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Abstract

The semantic system makes up an integral part of how we perceive and interact with the world, yet its structure and location in the brain are not clear. Recently, a semantic map of brain activation was presented, based on fMRI (Huth et al., 2016). In the map, the brain is divided into voxels, which are activated by different concepts and semantic categories. This thesis investigates how brain activation and categorization in this brain map relate to active word categorization. Data of 12 previous card sorting studies that looked into this connection were merged and analysed, to investigate the similarity between concept relations found in the brain map and those obtained with active word categorization. The results showed that active word categorization relates to the categories found in the semantic brain map, and also showed a link to within-voxel relations in the map. To confirm these results, a new card sorting study was performed. This study also investigated a possible geometrical structure of semantic space. In the new card sorting study, concept bridges between voxels were analysed based on the possible geometrical structure between concepts. Overall, the results connect to the hub-and-spoke model for semantic memory.

Keywords: semantic cognition, categorization, brain activation, voxel, card sorting, hub-and-spoke model, conceptual space, concept bridge

1. Introduction

Our brain's semantic system is central to our ability to describe the world and learn from our environment (Binder, Desai, Graves, & Conant, 2009). A great part of our conceptual knowledge is represented in language and is the foundation of our understanding of word meanings. By seeing and interacting with objects we gain knowledge about their characteristics such as shape, colour, taste, smell, movement etc. In other words, we infer and connect concepts based on experience. What is special here is that the acquired knowledge over time becomes independent of the circumstances in which we learned about those characteristics (Yee, Chrysikou, & Thompson-Schill, 2013). For example, we know that strawberries are red, but we generally do not link this knowledge to the time we first saw a strawberry. The learned features of an object become further interconnected in our brain so that we can specify which features an object has, and which it does not. This illustrates the great capacity our brain has for learning and storing knowledge about the world we live in.

However, it is not yet clear where the semantic system and its conceptual knowledge are located in the brain and how it is structured. An important theory in this respect is the hub-and-spoke theory, which provides one idea of how semantic memory could be structured in the brain (Patterson & Lambon Ralph, 2016). The theory assumes a multimodal semantic centre (hub) that has bidirectional connections to unimodal spokes. With the spokes being distributed across the cortex, the central hub integrates incoming modal-specific information into one general concept. For example, conceptual knowledge about the word "dog" entails modal-specific features such as its shape and colour, the feel of its fur, its movements, the sound of barking, and so forth.

The brain study conducted by Huth, de Heer, Griffiths, Theunissen, and Gallant (2016) could give more insights into whether the hub-and-spoke theory indeed fits the structure of the semantic system. In this study, participants listened to stories and their brain activity related to a large set of words in the stories was measured. On the basis of the brain activity related to these words, a semantic brain map was created, distributed over both hemispheres. This semantic map included 11 different word categories and further showed the brain divided into voxels (a small unit of the brain that can be understood as a 3-dimensional pixel (Torre, 2017)) related to the activation of a cluster of words. Furthermore, based on statistical analysis, each word could be assigned to one of the 11 word categories. Linking the hub-and-spoke theory to the results of Huth et al. (2016), it could be possible that voxels or categories from the brain map represent spokes as described in theory. That is, voxels could be related to spokes because voxels in the Huth map would typically be involved in processing information from the same modality (e.g., visual or auditory), which would enhance the possibility that the concepts they represent are related to each other in terms of these modalities. This corresponds to the observation that most words in a voxel belong to the same category in the Huth map. However, in Huth there are also different voxels that correspond with the same category. In terms of the hub-and-spokes theory, this would entail that all voxels that belong to the same category would be interconnected by a hub representation.

In this thesis, the relation between voxels and categories in the Huth map, and their interpretation in terms of the hub-and-spoke theory, will be investigated using the technique of card sorting. A further tool to analyse concept relations in a semantic map is provided by van der Velde (2015), who analyzed card sorting data based on creativity concepts in terms of geometrical conceptual spaces. The geometrical conceptual space describes a third way of representing information besides symbolic and neuronal representations and was introduced by Gärdenfors (2000) (as cited in Xiao et al., 2019). For the analysis, van der Velde used a distance function to investigate the relations between concepts within the maps. The results showed that the distance function could be applied to words within concept clusters but not to words between concept clusters. This finding could indicate that a semantic map could represent a collection of concept domains, as pointed out by van der Velde. These concept domains could relate to the spokes in the hub and spoke model. To investigate this, the distance function could be used to analyse Huth et al.'s (2016) semantic brain map, in particular, to see if the word categories or the word clusters in the voxels relate to the spokes (as further outlined below).

The present thesis is not the first study that investigated how Huth et al.'s (2016) semantic map and categories support the hub-and-spoke model. Up to now, 12 card sorting studies have been conducted to look into the link between Huth et al.'s brain activation results and active word categorization. In each of these studies, the Huth et al.'s brain map and word categories were investigated using card sorting data based on words from the map. In this respect, the use of a card sorting task is thought to actively elicit the participants' mental model of the concepts (as compared to the more passive listening task in the Huth et al. study). In this thesis, the 12 Jaccard score datasets obtained from the previous 12 card sorting studies will be used to investigate the difference of "within-voxel" and "between-voxel" concept relations.

To this end, a number of dedicated Python programs were developed to combine and analyse the data of all these studies. As noted, the focus was to compare the Jaccard scores of word relations between words that belong to the same voxel ("within-voxel" concept relations) with the Jaccard scores of word relations of words belonging to different voxels ("between-voxel" concept relations). A higher score for within-voxel concept relations could indicate that voxels can indeed be seen as belonging to spokes containing specific semantic categorical information, linking them to the spokes in the hub-and-spoke model. However, the Jaccard scores could correlate more with the 11 categories proposed by Huth et al., combined over different voxels. This would relate more to the combinations of hubs and spokes in the hub-and-spoke model. Furthermore, a Python program was developed to apply a distance function to the overall data set, in line with van der Velde (2015) to investigate if a geometrical structure is present at within-voxel or between-voxel level. In addition, a new card sorting study was performed to corroborate the findings of the analyses and to further investigate the relation between voxels and categories in the Huth map.

In the following, the hub-and-spoke model, Huth et al.'s (2016) research, and the use of a distance function in a semantic space will be explained in more detail. The three topics will be connected in a more detailed description of the aim of the current research.

1.1 Hub-and-Spoke model

One prominent theory about the structure and cerebral location of semantic memory is the hub-and-spoke model (Patterson & Lambon Ralph, 2016; Patterson, Nestor, & Rogers, 2007). As the name implies, the model hypothesizes that the basis of semantic memory can be described by a system of a central hub connected to various spokes. The hub is thought to be a multimodal representational resource that interacts with the unimodal spokes to form concepts in the brain. This is realized by the integration of different modal inputs (verbal, auditorial, somatosensory etc.) to produce a more abstract and generalizable representation of a concept. The hub mediates interactions between these inputs and encodes a deeper level of representation that merges modal specific information into the overarching concepts received from the spokes (Binney & Ramsey, 2020).

Figure 1 by Binney and Ramsey (2020) illustrates how the modality-specific cortex areas (spokes), distributed across the brain, are bidirectionally connected with the semantic hub in the bilateral anterior temporal lobes (ATL).

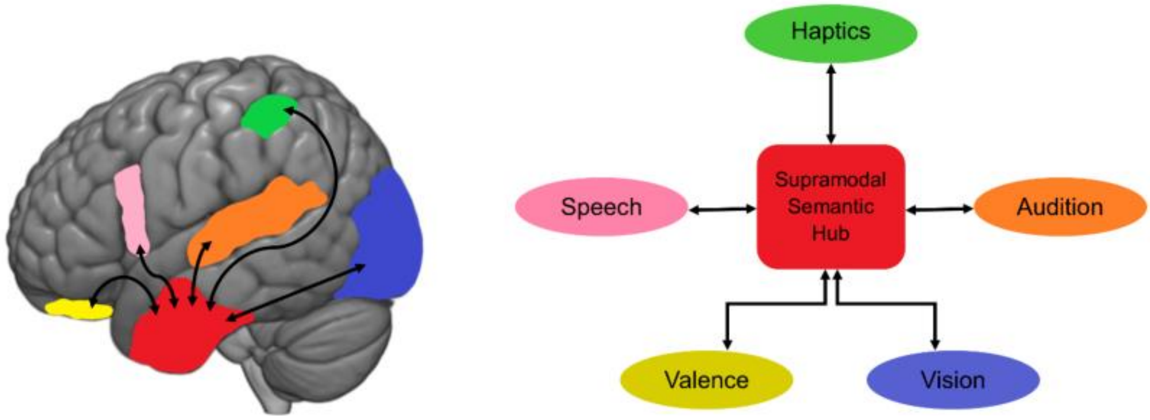

Figure 1. Hub-and-Spoke architecture (Binney & Ramsey, 2020). The left image part shows the location of the central hub (red) in the bilateral anterior temporal lobes and the spokes distributed over the cortex. The right image indicates the different modal inputs that reach the multimodal centre.

Till now neuropsychological research has accumulated extensive evidence for a central semantic hub at the ATL. Especially research into the disorder of semantic dementia (SD) has been valuable (Patterson & Lambon Ralph, 2016; Pobric, Jefferies, & Lambon Ralph, 2010). As described by Hoffman and Lambon Ralph (2011), SD impairs conceptual knowledge due to the atrophy of the ATL. In a further study, SD patients completed category learning tasks to investigate how ATL affects learning new concepts (Hoffman, Evans, & Lambon Ralph, 2014). The task included categorizing abstract visual stimuli into two groups. Because the groups conformed to family resemblance, the participants should have created concept representations incorporating multiple features instead of individual ones. The results showed that participants were not able to form the required comprehensive concept representations.

Further effects of this impairment, including verbal and non-verbal comprehension deficits, can be observed in persons during expressive and receptive semantic tasks that include speech, writing, motor coordination, olfaction, taste, and picture tasks (Binney & Ramsey, 2020; Bozeat, Lambon Ralph, Patterson, Garrard, & Hodges, 2000). Therefore, ranging across all modalities. This could confirm the neural location of the central hub, which takes in different modal information from the spokes to form a concept and its relations. Since SD causes damage to the ATL, resulting in defective conceptual knowledge, the existence of the central semantic hub at this location in the brain does seem plausible.

1.2 Huth et al. (2016): Semantic map across the cortex

In order to find out more about the semantic system and how it is spread across the cortex, Huth et al. (2016) aimed at creating a brain map that illustrates these locations. Furthermore, they analysed the semantic selectivity of the respective brain areas. The semantic map was created based on results from functional magnetic resonance imaging (fMRI), which recorded whole-brain blood-oxygen level-dependent (BOLD) responses of 7 participants. Participants listened to 10 narrative stories with a length of 10-15 minutes each during the recordings. The technique of voxel-wise modelling (VM) was applied to calculate the semantic selectivity of the cortex areas. With this, Huth et al. created a brain map divided into voxels, each containing a cluster of words indicating the semantic selectivity across the brain. The associated word clusters are thought to predict brain activation in the respective voxel they belong to.

Next to the voxel analysis, all included words were also categorized into 11 overall categories. These were named: “tactile”, “visual”, “number”, “outdoor”, “body part”, “place”, “violence”, “person”, “mental”, “time”, and “social”. The resulting map can be seen in figure 2. It turns out that the cluster of words that reliably activates a voxel typically belongs to the same overall category. However, an overall category activates more than one voxel. So, voxels and (overall) categories are related but not equivalent.

Huth et al.’s (2016) brain map suggests that the semantic system is well organized and seems to be consistent among humans. This might depict a brain structure innate to human beings. The found patterns indicate that different areas in the system stand for different semantic domains made up of related concepts - i.e., it suggests that the semantic system is domain-selective, with different brain areas responding selectively to specific categories of concepts.

As each voxel corresponds to a smaller group of words, which are thought to activate the voxel, it could be possible that they represent the spokes from the hub-and-spoke model. Similar to the voxels, each spoke stands for a specific information domain. Because both are similarly constructed, a resemblance might be found here. However, as noted, the group of words that reliably activate a voxel often belong to the same overall category, which underlines a correspondence between voxels and categories. Thus, there is a possibility that the proposed categories could stand for spokes instead, and that voxels are just a small part of it.

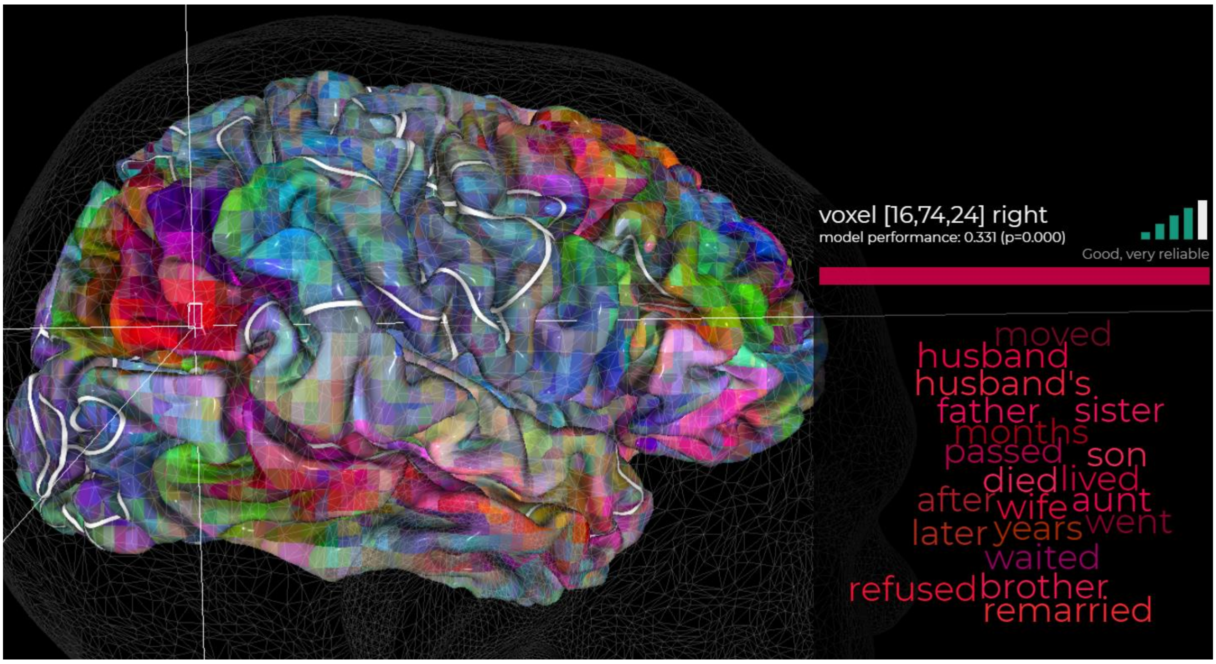

Figure 2. Semantic map across cortex (Gallantlab.org, n.d). Based on Huth et al.'s (2016) fMRI recordings, a brain map was created which was divided into voxels containing a group of words. Here, a voxel is selected to see its model performance and word cluster, which is of overall category "social" (red).

1.2.1 Studies based on Huth et al. (2016)

12 studies from the University of Twente have been conducted to look into the connection between Huth et al.'s (2016) results and manual (or 'active') word categorization. For this, card sorting tasks were given to participants using concepts (words) taken from Huth et al. Card sorting is a method in which participants sort a number of words into groups based on how they think they relate to each other. This method is used to investigate and understand a person's mental model (Nawaz, 2012). It is often used when information structures of websites are created, based on how participants would group information. An example of open card sorting can be seen in figure 3. Here, participants receive the concepts "grass", "airplane", "bus", "frogs", "train", and "leaf" which are then sorted based on similarities these words share. In open card sorting participants do not receive any group labels before sorting and are free to create groups however they see fit. Regarding the 12 previous studies, card sorting was used to compare participants' mental models to the 11-word categories proposed by Huth et al.

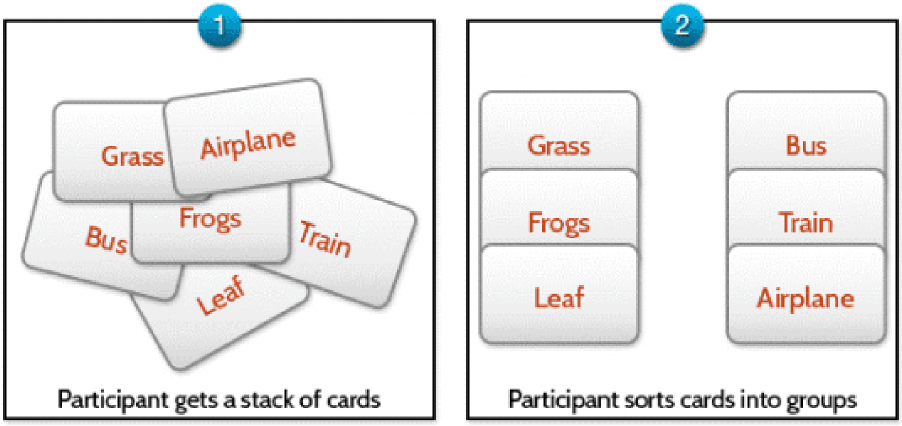

Figure 3. Open card sorting example (Interaction Design Foundation, 2016).

Overall, 348 participants were included, and 393 words have been categorized. Combining this amount of card sorting data would allow to further look into the Jaccard score differences with increased reliability. As previous studies only did comparisons between the card sorting clusters and Huth et al.'s (2016) categories, the current thesis will use their data to look further into voxel details. The goal here is to take all scores and analyse the differences in the card sorting data for within-voxel concepts (words coming from the same voxel) and between-voxel concepts (words picked from different voxels). This is done first to look if voxel location is indeed important, next to the Huth category, and adds to the observed word relations obtained from card sorting.

So, the main motivation of this work concerns whether the found word relations in the card sorting only correspond to Huth et al.'s (2016) categories or if belonging to the same voxel also has an (additional) influence. A stronger relation (i.e., higher Jaccard score) for within-voxel concepts might be observed as compared to same-category words between voxels. Furthermore, the card sorting data will be analysed in terms of a distance function related to a geometric concept description. Before presenting the research questions of this thesis, the distance function and its relation with a geometric concept description will be described below.

1.3 How to represent information: Semantic maps as geometrical spaces

Gärdenfors (2000) (as cited in Xiao et al., 2019) introduced geometrical spaces as a third way to represent concept relations. This approach has aimed to create a bridge between symbolic and connectionist representations, which are seen as the main approaches to represent concepts and their relations. Each of these will be discussed in the following.

1.3.1 Symbolic and connectionist representations

The symbolic approach to modelling information has traditionally shaped cognitive science and with that artificial intelligence (AI) (Smolensky, 1987). As the name implies, information is represented by symbols, which are manipulated based on pre-set rules (Gärdenfors, 1997; Xiao et al., 2019). The foundation to this approach is connected to Good Old Fashioned AI, which holds the assumption that human reasoning can be described explicitly by symbolic computation. Methods for achieving computations are logic formulas, theory of formal languages and discrete mathematics (Flasiński, 2016). Because of the use of specified rules, the symbolic approach of information representation excels in situations that require clear-cut methods, but not in situations where these methods are difficult to find. Xiao et al. note for example the process of perception or common-sense language use, which cannot be modelled by symbols since these are limited to logical reasoning and its set rules. Consequently, modelling knowledge in these situations becomes complex as the required (some even unknown) rules increase.

Here, the neuronal or connectionist approach could work more successfully when modelling knowledge in such situations. This approach proposes that human cognition is distributed, parallel and interactive (Zhao, 2017). Learning, information representation and processing are embedded in an interconnected network of various processing units working simultaneously (Clark, 1997; Xiao et al., 2019: Zhao, 2017). Most popular is the use of Artificial Neural Networks (ANN) that integrate layers of nodes as neurons to process input information (Bajada, 2019). The great benefit of a connectionist approach is that learning proceeds by observing or training with (unstructured) data. Interaction with such data then allows for the adaptation of network connections. Thus, no rules need to be given as the network finds them on its own in the data, making it easier to model knowledge. However, this comes with the downside of a lack of explanatory insights into the modelling process (Xiao et al., 2019). Thus, it is difficult to fully understand how the network works and arrives at its results.

1.3.2 Geometrical conceptual spaces

Next to symbolic and connectionist/neural representations, Gärdenfors (2000) (as cited in Xiao et al., 2019) introduced geometrical conceptual spaces as a third approach. This is thought to be able to compensate for the difficulties of the symbolic and neural approaches when illustrating concept relations (van der Velde, 2015). Conceptual spaces define perceptual concepts and are based on "quality dimensions". As Gärdenfors explains, quality dimensions correspond to the way stimuli are judged to be similar or different. The geometrical structure of the space is given by a collection of quality dimensions for one or more domains (Raubal, 2014). The domains are made up of a set of unique dimensions distinct from other dimensions. The example of the domain colour is given here by Raubal, which is made up of the dimensions brightness, saturation, and hue. Furthermore, the conceptual space extends when new concepts are learned. Based on the learned content, new quality dimensions can be added to the space. Therefore, concept learning and modelling is aided by the geometrical structure of the space (Xiao et al., 2019). As every object has a specific point in the space, (dis)similarities can be represented by distance calculations between points. The structure of the space is thus linked to how distances between objects are calculated (van der Velde, 2015).

Gärdenfors' (2000) (as cited in Xiao et al., 2019) conceptual space offers an intermediate level between symbolic and neural representations. Semantic maps show a more linguistic form of representation but can also be localized in the brain (van der Velde, 2015). Huth et al. (2016) illustrate this with their semantic brain map created based on natural language. Because of these similarities, there is a possibility to apply distance calculations as found in Gärdenfors' geometrical conceptual space to semantic maps. Van der Velde (2015) investigated semantic maps related to creativity and applied such a distance metric to analyse the relations between concepts. The semantic maps were based on two card sorting studies and heatmaps were created to look into the word clusters. The used distance function $d(a,b)$ describes the distance between points a and b in a space.

A distance function is characterized by four properties (Hartenstein, 2014):

1. The distance between two points a and b has to be non-negative: $0 < d(a,b) < \infty$
2. The distance between the same point has to be zero: $d(a,a) = 0$
3. The distances from a to b and from b to a are equal (symmetric): $d(a,b) = d(b,a)$
4. The triangle inequality is fulfilled: $d(a,b) \leq d(a,c) + d(c,b)$

In Euclidian geometry, triangle inequality describes the property that in any triangle the length of one side does not exceed the sum of the lengths of the other two sides as given by $d(a,b) \leq d(a,c) + d(c,b)$ (Khamsi & Kirk, 2011). For a distance function this property needs to be fulfilled to have a meaningful metric and be able to analyse the different points in space.

Based on the heavily right-skewed heatmap scores obtained from the two card sorting studies, van der Velde (2015) applied the function:

$$d(a,b) = -log(x) \qquad for\ x = CST(a,b)/S$$

With *CST(a,b)* describing the card sort score for two concepts *a* and *b,* and *S* describing the maximum score, which equals the number of participants included in the card sorting task. (Also, in the card sorting data it is assumed that *CST(a,a) = S*.) This function fits the data as it is sensitive to differences in lower scores. Heatmap scores of 0 were substituted by 1 as log(0) is not defined. Property 1 and 2 are thus satisfied, and the distance scores range from *d(a,a)* = -*log(1)* = 0 to -*log(1/S).* The symmetry of the heatmap fulfills property 3. Van der Velde then looked further into violations of the triangle inequality (property 4). A violation of this property means that at least one of the distances between three concepts *a*, *b*, and *c* is larger than the sum of the other distances, which then does not fulfil $d(a,b) \leq d(a,c) + d(c,b)$. While violations were found by van der Velde, they only concerned scores between word clusters. Within a cluster, a geometrical structure was given but it diminishes beyond that. This finding could indicate that semantic maps are made up of several concept domains that each have a geometrical structure as compared to Gärdenfors' proposal. In turn, this could give more insights into how the semantic system is represented in the brain.

The ideas discussed above could be applied to the Huth map as follows. Huth et al.'s (2016) semantic map proposes 11 overall word categories and further shows the brain divided into voxels as word clusters. It could be assumed that voxels belong to spokes in the hub-and-spoke theory, with each voxel related to a category. However, a given category in Huth relates to multiple voxels. In terms of the hub and spoke theory, a category would then consist of multiple voxels (in the same or different spokes) interconnected by a hub representation. A question in this respect is the relative importance of individual voxels in the representation of a category. That is, whether word relations are stronger when the words belong to the same voxel, or whether word relations are influenced by category membership only. This question could also be investigated by using the distance function defined in van der Velde's (2015). In particular, these distance calculations might also show that triangle inequality violations occur only between voxels and not within.

1.4 The current research

Huth et al.'s (2016) semantic brain map gives an indication of how the semantic system is localized and structured in the brain. It seems to align with hub-and-spoke model that describes semantic memory in terms of various modal-specific spokes connecting to a central semantic hub. In addition to that, van der Velde's (2015) findings regarding distance calculations suggest that semantic maps entail a collection of concept domains. The analysis of Jaccard score data based on concepts from Huth et al. could give more insights into the question of whether the relations between words are influenced by belonging to the same voxel, or by just belonging to the same overall category. Since voxels are based on brain activation and Jaccard scores on manual categorization the relationship does not seem apparent at first. However, if belonging to the same voxel in general (compared over all categories) does result in a stronger relation, indicated by a higher Jaccard score, it would support Huth et al.'s map as a representation of semantic space. Meaning that, besides existing word categories, location in the brain would be an important factor for the strength of concept relations. So that concepts located close together (i.e., within the same voxel) have a stronger relation comparable to how a short distance between two words in a semantic space indicates a high semantic similarity between them. (Groups of) voxels would then represent own concept domains.

Furthermore, the investigation of whether relations among words coming from within the same voxel are stronger than other relations among words belonging to the same category would further show how categories are represented in terms of the hub-and-spoke theory. Thus, giving more insight into how the semantic system is structured in the brain. Therefore, this thesis poses the following main research questions:

1. Is active word categorization with card sorting related to word categorization based on brain activity during natural speech understanding, as found in Huth et al. (2016)?
2. Is active word categorization with card sorting different for within-voxel versus between-voxel concept relations of the same category in Huth et al. (2016)?
3. Are triangle violations as measured with the distance function different for within-voxel versus between-voxel concept relations of the same category in Huth et al. (2016)?

To answer these questions, two research phases will be conducted. In a first study, data from the 12 card sorting studies will be merged and analysed with the help of tools created in Python. The Jaccard scores for within-voxel and between-voxel concepts will be compared to see if participants' mental model shows similarities to Huth et al.'s (2016) brain map. This is done to see what the role of voxels is in the strength of word relations. Furthermore, the data will be analysed using distance calculations to check if violations of the triangle inequality occur for between-voxel concepts only. Secondly, a new card sorting study will be conducted to further investigate the difference between within-voxel word relations and word categories in Huth et al. to add to the first study. So, in the following the meta-analysis based on the 12 previous studies (Phase 1) will be presented first and after that the new card sorting study (Phase 2) will follow.

2. Phase 1: Meta-Analysis

2.1 Data analysis tools created with Python

In order to make use of the previously collected card sorting data, different tools were created for data processing and later analysis. For this, Python version 3.7 was used. Moreover, libraries "csv" and "numpy" were used when adding and transforming data. For illustrating the results, library "panda", "mathplot.lib.pyplot", and "math" were imported as well.

2.2 Merging datasets into one Mastertable

Before doing any analyses, the 12 CSV datasets containing Jaccard scores had to be added into one. As each Jaccard score corresponds to two concepts (e.g., "days" and "weekend"), the datasets can be compared to an unsorted heatmap in which each axis is labelled with the concept names. To ease data analysis, the used dataset format only included a first row with each concept name and no additional first column with concept names (i.e., no labelled y-axis). As a consequence of card sorting and the similarity to a heatmap, the datasets had to be symmetric at the diagonal so that each Jaccard score was noted twice. The diagonal score corresponded to the number of participants (N) per card sorting study. As the diagonal scores belong to one concept paired with itself (e.g., "days" and "days") it is assumed that the concept will have the highest possible relation with itself. Thus, the number of participants was taken since it represents the highest possible Jaccard score. Tables that included a relative Jaccard score (converted into scores between 0 and 1) were reconverted into the original raw score. This was done by multiplying the relative scores by the respective number of subjects (i.e., the diagonal score). The program created for this can be found in Appendix A.

When all datasets had the correct format, they were merged into one overall score table (see Appendix B for the program). When a concept already appeared in a previous table, the score was added into the previous cell instead of adding a new column with the concept label. Additionally, the diagonal subject score had to be added together as well. 0 was filled in for concept combinations that had no score. The final table was converted into relative scores to account for differences in participant numbers between studies and concepts. To this end, a subject table was created with the same format as the overall score table, but instead containing the number of participants per concept combination in each cell (Appendix C). This allowed to retrieve each subject number behind the Jaccard score of the overall score table. In this way, the raw Jaccard scores in the overall score table were divided by the respective subject number and all diagonal scores changed into 1 (highest score) as these represent a concept combination of the same word. Scores that were 0 stayed 0. This created the 'master table' used for analyses. Appendix D illustrates the program created here.

2.3 Creating a dataset with Voxel data

To later analyse the scores for within-voxel and between voxel concepts, a dataset containing voxel locations was created. The program for this (Appendix E) takes a table including all voxel coordinates per concept and based on that sorts the Jaccard scores from the master table into two lists, one for scores for two concepts belonging to the same voxel and one for scores for concepts coming from different voxels. Scores of 0 were only included if they were based on real scores, meaning the subject number for this had to be at least 1.

2.4 Calculating the distance function

Based on van der Velde (2015), the function $d(a,b) = -\log(x)$ (presented above) was used for calculating the distance function on the card sorting data. The program (Appendix F) applies this function to every relative Jaccard score. For real scores of 0 (subject number at least 1) the function used $-2*\log(0.0001)$ as $-\log(0)$ is not defined. This score gives a very large distance between concepts with card sorting score 0. Default zero scores, which are not based on any ratings by participants, were changed into -1 and ignored in further calculations. A specific aim of applying the function was to look into violations of the triangle inequality $d(a,b) \leq d(a,c) + d(c,b)$. All violations were collected in a list and saved into a text document.

3. Results

3.1 Jaccard score data analysis

3.1.1 Same-category vs different-category scores

In order to answer the first research question, the Jaccard scores were analysed for all concept relations within the same category and all concept relations between different categories. This was done to compare the relation strength between concepts in both conditions. If concepts from the same category show significantly stronger relations (higher Jaccard scores) it would show that participants frequently grouped these concepts together and perceive a similarity between them. Thus, if Huth et al.'s (2016) word categories based on brain activity can be replicated to a significant extent in card sorting tasks it would show that there exists a relation between both categorization procedures. If concepts from different categories show significantly stronger relations, therefore deviating from Huth et al.'s results, or if there is no difference found between the conditions, it would show that there is no relation between active categorization and categorization based on brain activity.

The results showed that the number of same-category concept relations amounted to 7,563 while for different-category relations this number was 45,386. Furthermore, the mean score for relations between concepts coming from the same category was 0.32 (SD = 0.29). For relations between concepts coming from different categories, the mean score was 0.05 (SD = 0.12), indicating a difference of 0.27 between both groups of concept relations. To test if this difference is statistically significant, an independent t-test was conducted in SPSS statistics 27. The result showed that there was a significant difference in scores with $t(8010.11) = -78.886$, $p < 0.001$.

To illustrate the results, histograms were created in Python and presented in figure 4. Here, the results indicate higher scores for same-category concept relations. Especially for scores above 0.1 the number of relations appear to be higher than for different-category ones. However, what needs to be noted is the difference in scales of the histograms. There are many more different-category concept relations than same-category concept relations. This makes it hard to compare the scores in the histograms and furthermore doesn't allow for a detailed analysis of the different-category data. So, in order to have a more useful comparison, the scores were converted into percentages relative to the total number of same- and different-category relations respectively (Figure 4a). This already shows the difference in distributions between both groups, with same-category scores being more spread between 0 and 1 while different-category scores centre around approximately 0.05. For more details, the histograms were also created only for Jaccard scores above 0.5 for each condition (Figure 4b). Especially for this range in scores, the difference between both conditions is underlined. The number of same-category relations peaks at about 1.76%. However, the number of different-category relations stays close to 0, which explains the large difference in mean Jaccard scores between the conditions.

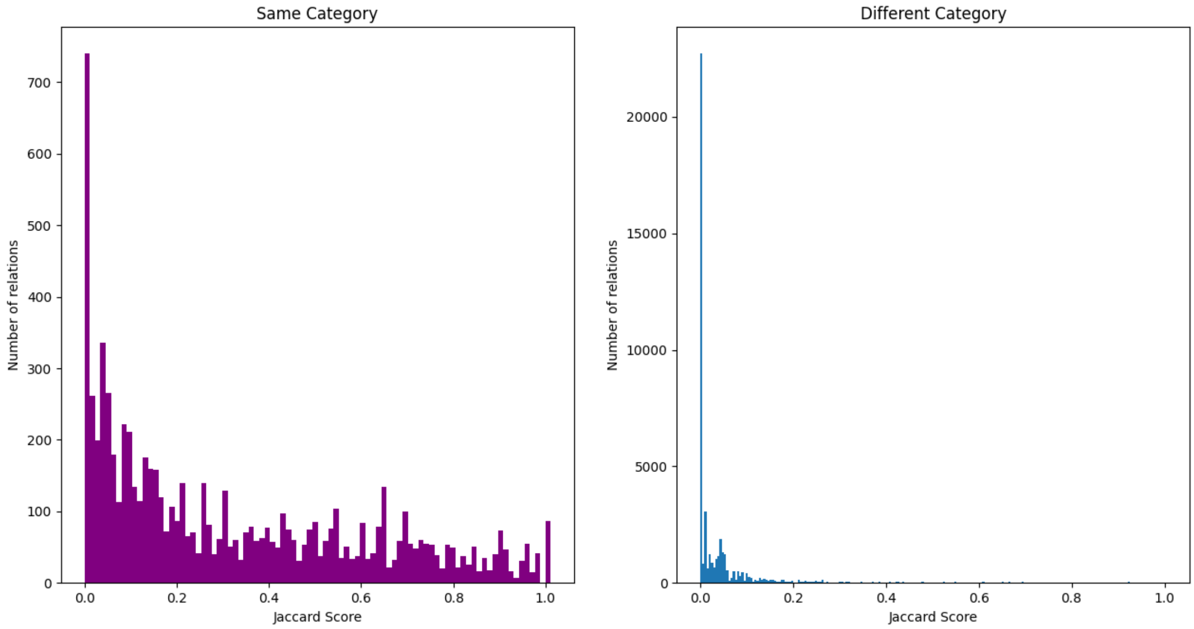

Figure 4. Jaccard scores illustrated for same- and different-category concept relations.

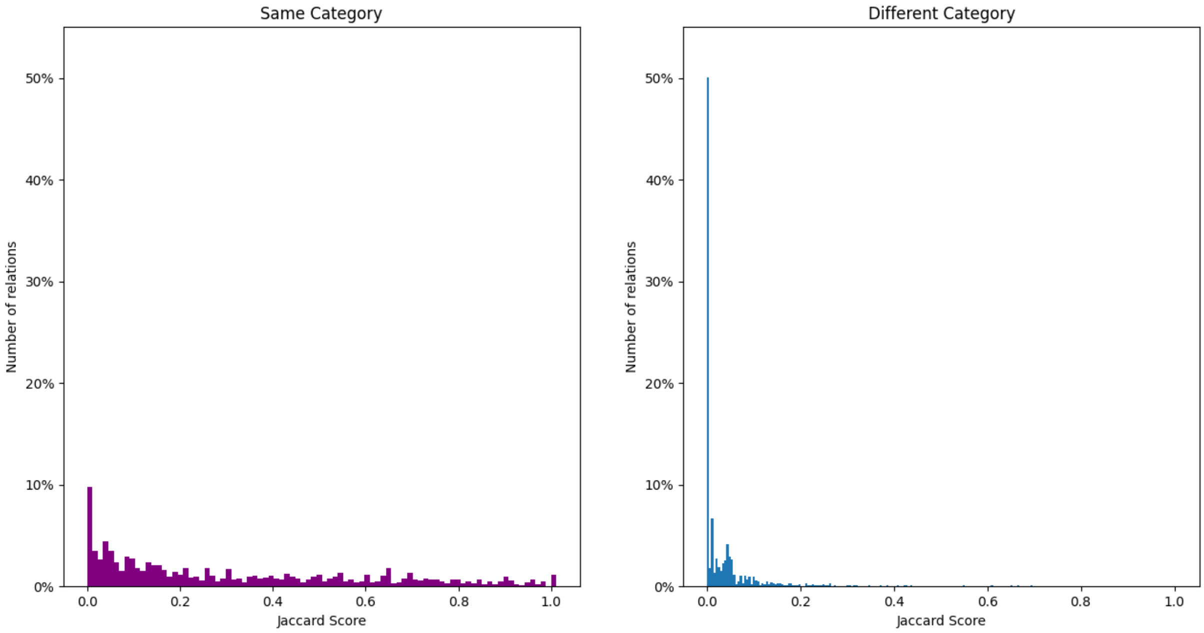

Figure 4a. Relative Jaccard scores illustrated for same- and different-category concept relations. The y-axis shows the percentage of relations relative to the total amount of relations per group.

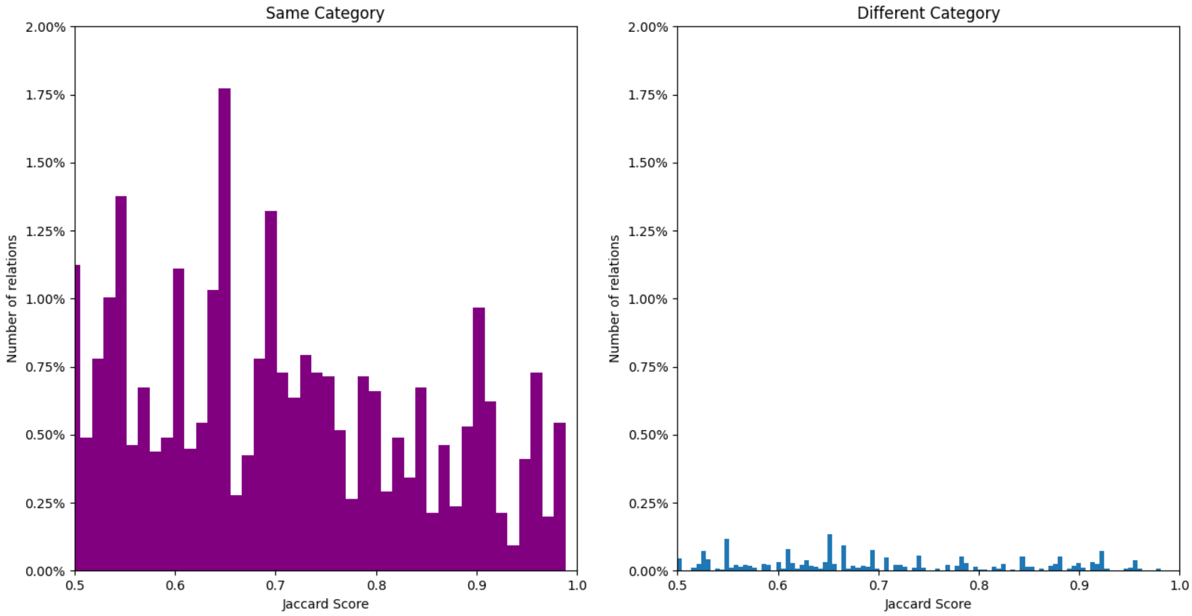

Figure 4b. Relative Jaccard scores above 0.5 illustrated for same- and different-category concept relations. The y-axis shows the percentage of relations relative to the total amount of relations per group.

3.1.2 Within-voxel vs between-voxel scores

In regard to the second research question, the overall Jaccard scores were also compared for within-voxel concept relations and between-voxel concept relations. Similar to the previous section, this analysis was applied to compare the relation strength between concepts in both conditions, this time at voxel level. Finding a significantly stronger relation (higher Jaccard score) for concepts from within the same voxel would indicate that participants grouped these concepts together more often. This could indicate that voxel location in the brain influences the relation strength between concepts. A significantly stronger relation for concept relations between voxels or no difference between the conditions would show that location in the brain does not play a role in relation strength.

The results showed that the number of within-voxel relations was 1,000 and 51,949 for between-voxel relations. To analyse the difference in mean scores, an independent t-test was conducted. The results of Levene's test for Equality of Variances showed that the variances for within- and between voxel scores were not equal, F = 1039.70, $p < 0.001$. Therefore, the t-test results with equal variance not assumed were included. These showed that the Jaccard scores for within-voxel concept relations ($M = 0.40$, $SD = 0.29$) significantly differed from those for between-voxel concepts ($M = 0.08$, $SD = 0.17$) with $t(1012.72) = 33.83$, $p < 0.001$.

The Jaccard score distributions per voxel condition were transferred into histograms, presented in figure 5. For both histograms, the scores ranged from 0 to 1. One can see that for the two graphs the data is right-skewed, with 0 being the most frequent score. About 53 within-voxel and 23,000 between-voxel concept relations had a score of 0. Further, the within-voxel scores centre around 0.4 while between-voxel scores centre around approximately 0.1. Thus, the differences in overall score distributions would show generally higher scores for within-voxel concepts.

In figure 5a this difference can be further observed. Here, the scores were converted into percentages relative to the total number of relations per group. Especially the zero scores are prominent, showing that about 44% of between-voxel relations had a score of 0 while for within-voxel relations this amount was below 10%. Furthermore, the distribution of within-voxel relations is more consistently spread up to the highest score of 1. For between-voxel relations it seems the higher the Jaccard scores get the closer the number of relations gets to 0%. Figure 5b was therefore added to give a more detailed view of the relative scores showing a range from 0.5 to 1. This clearly shows the difference in scores between both groups as between-voxel scores in the area above 0.5 never amount to more than 0.3%, while within-voxel scores here reach up to 3.3% of the total amount of relations.

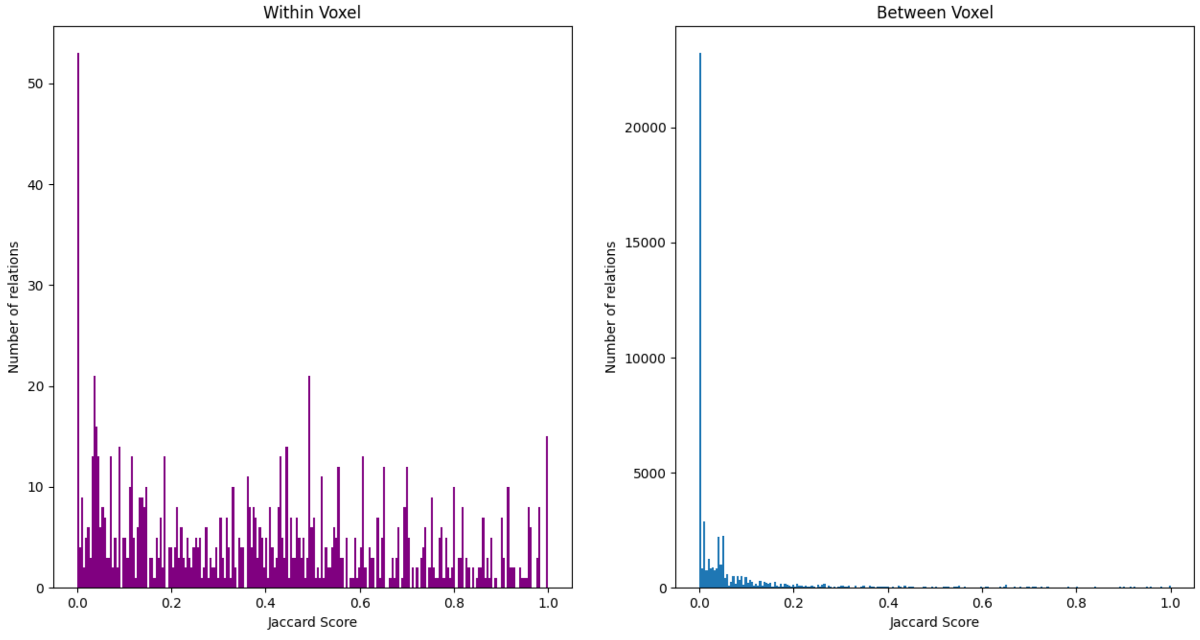

Figure 5. Histograms per voxel location illustrating Jaccard score distributions.

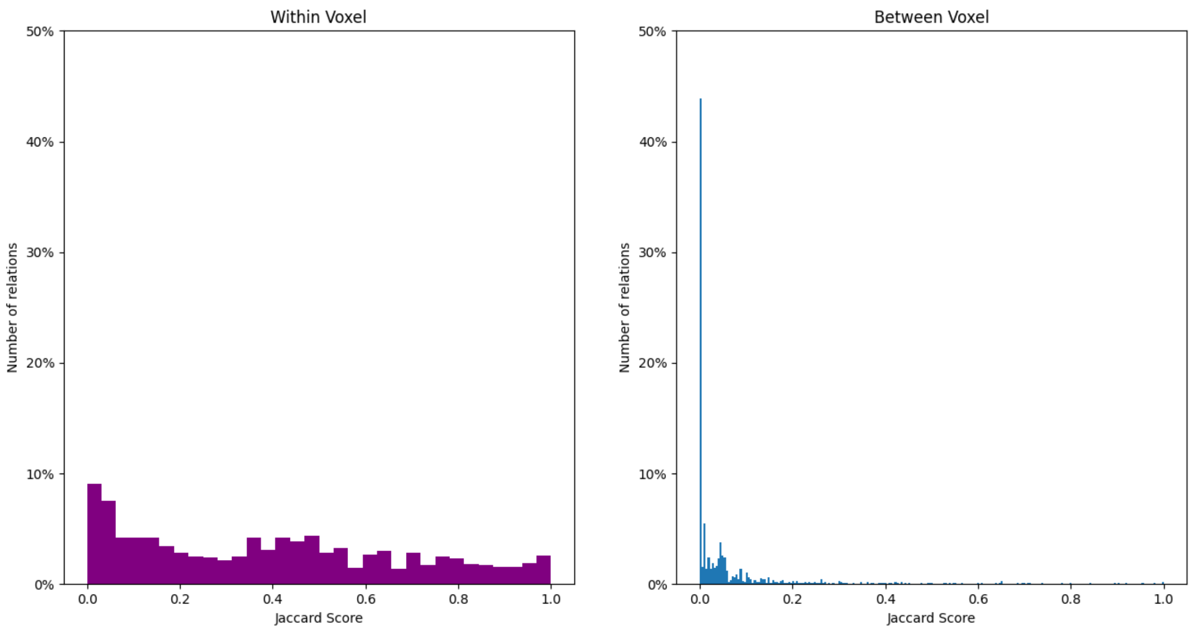

Figure 5a. Histograms per voxel location illustrating relative Jaccard scores. The y-axis shows the percentage of relations relative to the total amount of relations per group.

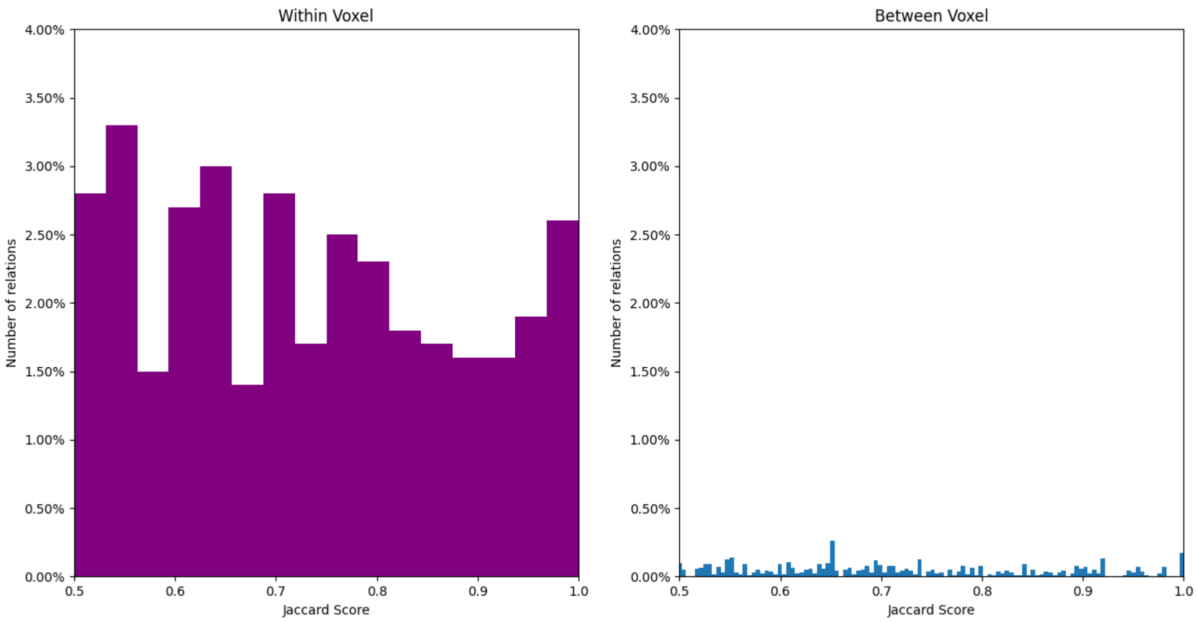

Figure 5b. Histograms per voxel location illustrating relative Jaccard scores only above 0.5. The y-axis shows the percentage of relations relative to the total amount of relations per group.

3.1.3 Same-category: Within-voxel vs between-voxel scores

As noted in section 1.4, voxels and categories are closely related in the Huth map. In particular, most words within a voxel come from the same category. But a given category is distributed over multiple voxels. Therefore, in order to complement the previous analysis, the difference in Jaccard scores per voxel location was also investigated for concept relations only coming from the same category. Within-voxel relations only from the same category amounted to 948, while same-category between-voxel ones amounted to 6,615. The mean scores here were 0.40 (SD = 0.29) for within-voxel relations and 0.31 (SD = 0.29) for between-voxel ones. In comparison to the between-voxel scores for all relations (M = 0.08), noted in section 3.1.2, the between-voxel mean score for only same-category concept pairs was about 0.23 higher. Despite this increase, the independent samples t-test again showed that the strength of within-voxel relations was significantly higher than for between-voxel ones with $t(7561) = -9.972$, $p < 0.001$.

Histograms presented in figure 6 show the overall scores for both groups. As only same category concepts were included the number of zero scores is greatly decreased to about 750 for between-voxel relations. Moreover, figure 6a provides the results converted to percentages. These showed that the percentage of within-voxel relations with scores higher than 0.2 is about twice the number of between-voxel relations within the same category. Figure 6b illustrates the results again for scores ranging from 0.5 to 1. What can be clearly observed is that overall, within-voxel relations show higher scores than between-voxel ones, even when coming from the same category.

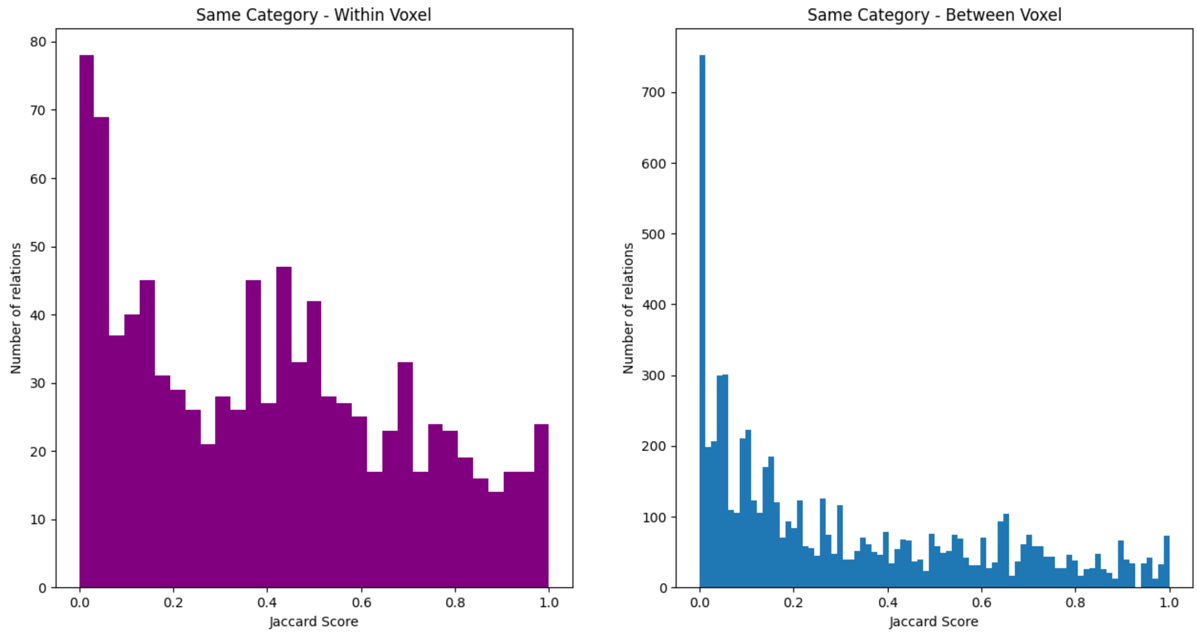

Figure 6. Histograms showing same category Jaccard scores for within-voxel and between-voxel relations.

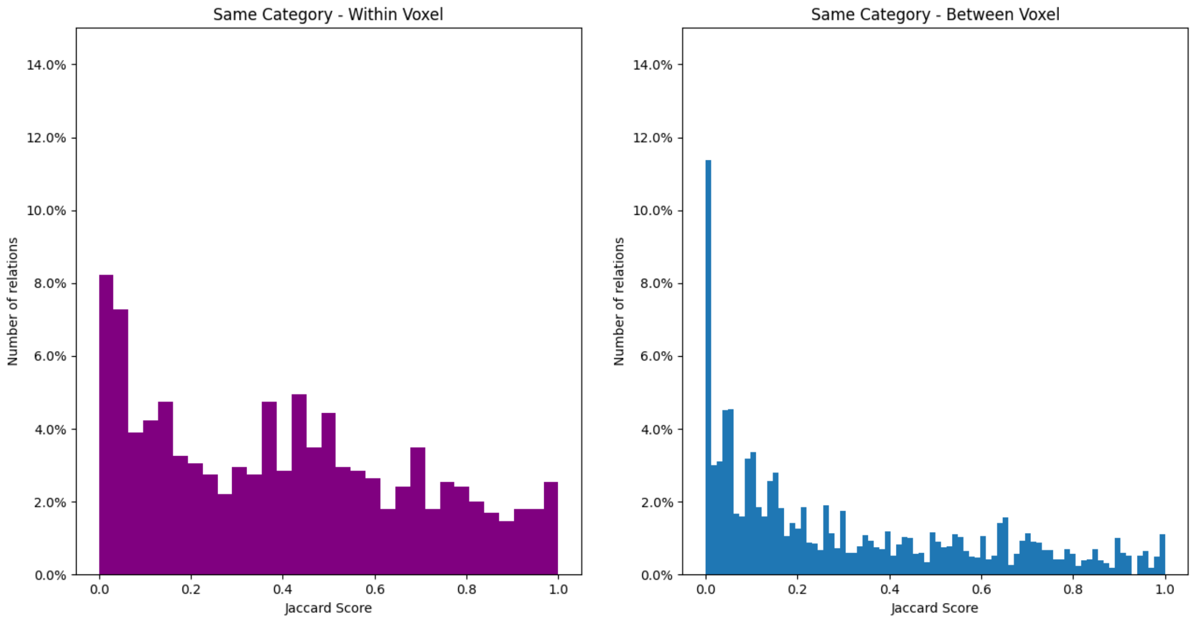

Figure 6a. Histograms showing relative same category Jaccard scores for within-voxel and between-voxel relations. The y-axis shows the percentage of relations relative to the total amount of relations per group.

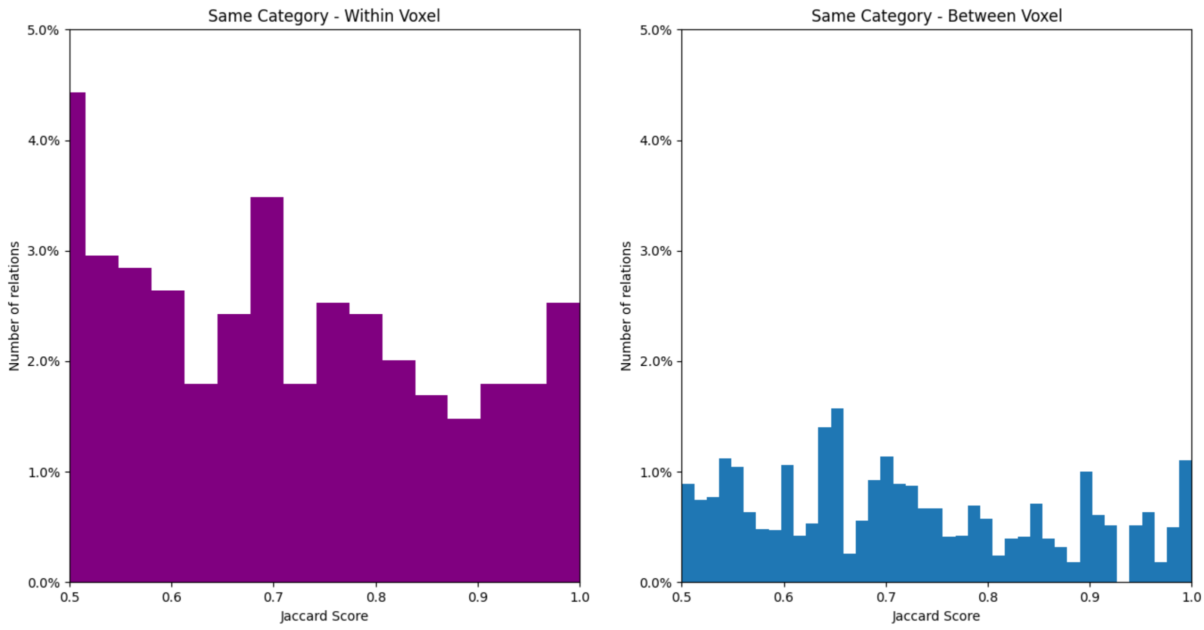

Figure 6b. Histograms showing relative same category Jaccard scores above 0.5 for within-voxel and between-voxel relations. The y-axis shows the percentage of relations relative to the total amount of relations per group.

3.1.4 Between voxel: Same category vs different category scores

Furthermore, the above between-voxel scores for same category relations can also be compared to between-voxel scores for concepts only coming from different categories. The number of between-voxel relations coming from the same category was 6,615 and it was 45,334 for relations coming from different categories. Here, the between-voxel mean score for different-category concepts was about 0.26 lower with 0.05 (SD = 0.21) than the mean score for same-category concepts with 0.31 (SD = 0.29). The independent samples t-test showed that this difference in scores was statistically significant with t(6956,813) = -71,073, p < 0.001. Figure 7 illustrates the distribution of Jaccard scores for both groups. Again, the scores were converted into percentages relative to the total number of relations per condition to have a more useful comparison which can be seen in Figure 7a. In general, it can be observed that between-voxel scores within the same category show fewer zero scores and are more spread up to the highest score of 1. Which explains the higher mean score in comparison to between-voxel relations from different categories. In figure 7b this difference can be further investigated when displaying the relative Jaccard scores above 0.5. While the number of between-voxel for same-category concept pairs reaches up to approximately 1.6%, the number for different-category ones stays below 0.13%.

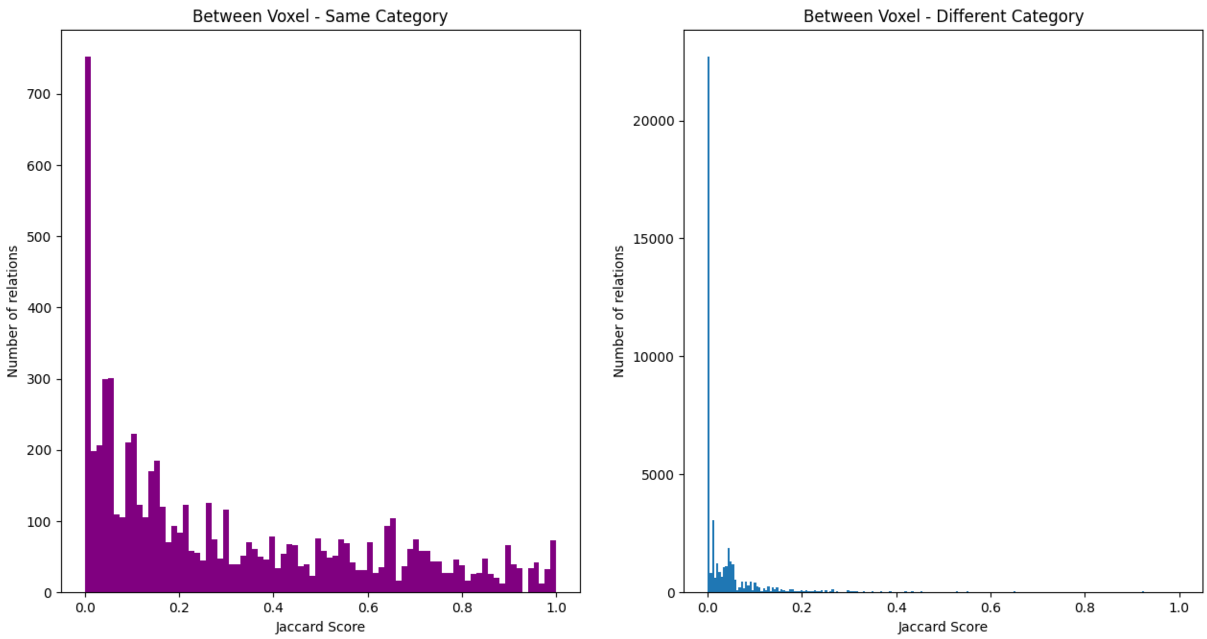

Figure 7. Histograms showing between-voxel Jaccard scores for same category and different category concept relations.

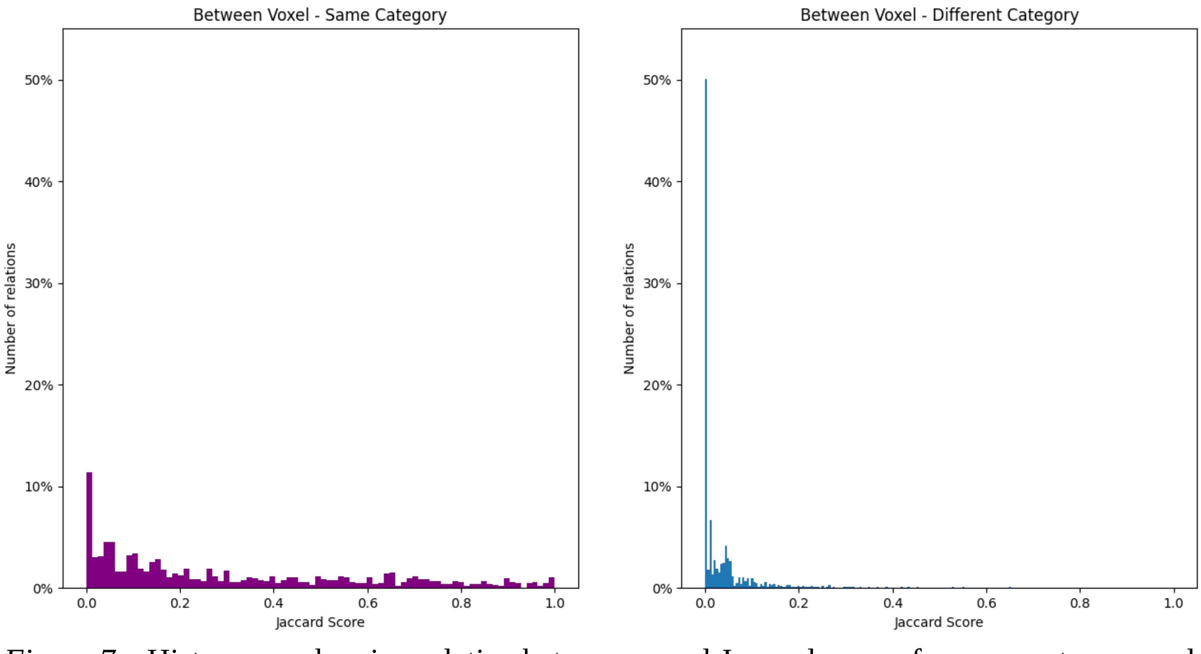

Figure 7a. Histograms showing relative between-voxel Jaccard scores for same category and different category concept relations.

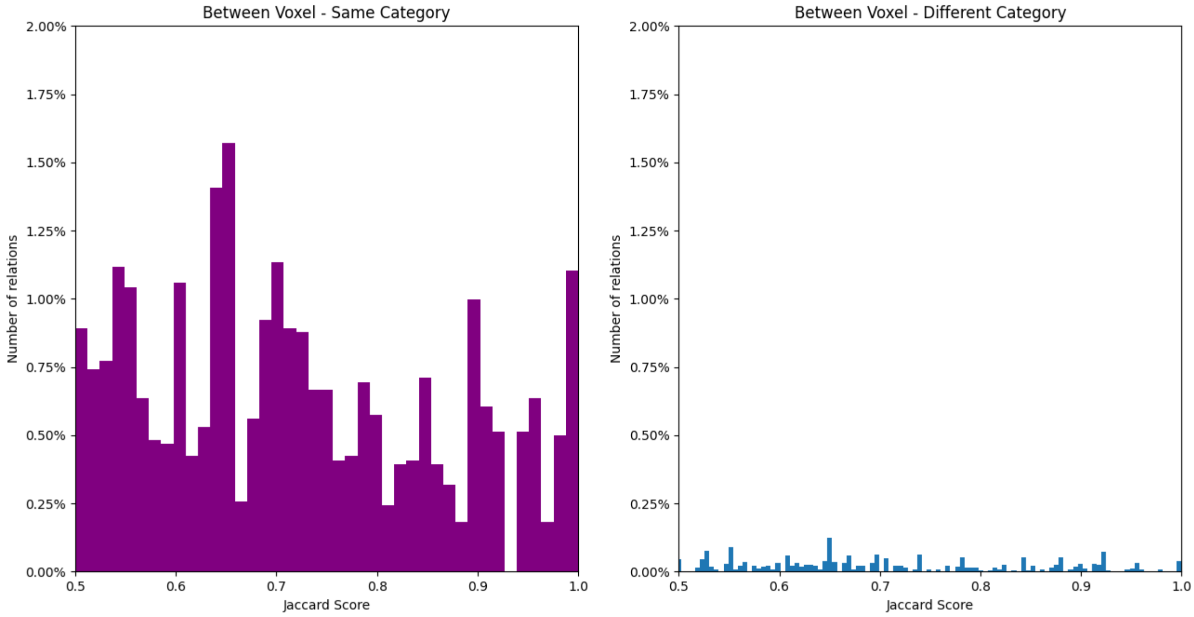

Figure 7b. Histograms showing relative between-voxel Jaccard scores above 0.5 for the same category and different category concept relations. The y-axis shows the percentage of relations relative to the total amount of relations per group.

3.1.5 Scores per category and voxel location

Besides for the overall Jaccard scores, the differences between within-voxel scores and between-voxel scores were also analysed for each of the categories separately. Here, all 11 categories from Huth et al. (2016) were present, namely “tactile”, “visual”, “number”, “outdoor”, “body part”, “place”, “violence”, “person”, “mental”, “time”, and “social”. Table 1 shows the mean Jaccard scores per voxel level for each category. For each, an independent samples t-test was executed to test if the differences at voxel level are statistically significant. In addition to that, table 1a provides a detailed overview of the t-test results for each category. The results show that for the categories “place”, “person”, “visual”, “number”, “mental”, “time”, and “tactile” the Jaccard score was significantly higher for within-voxel concept relations. The difference in relation strength for these concepts ranged from 0.1 to 0.18. Only for the category “violence” the between-voxel concept relations were stronger. No statistically significant differences in scores were seen for categories “outdoor”, “body part”, and “social”.

Table 1

Mean Jaccard Scores per Category and Voxel Location. Underlined values indicate a higher score at within-voxel level.

Category	Within voxel		Between voxel		
	M	*SD*	*M*	*SD*	*t-test*
place	.48	.29	.30	.24	$p < 0.001$
violence	.40	.22	.53	.21	$p < 0.001$
person	.41	.28	.27	.29	$p < 0.001$
visual	.35	.28	.20	.21	$p < 0.001$
number	.62	.30	.44	.33	$p < 0.001$
mental	.34	.23	.16	.17	$p < 0.001$
time	.38	.34	.25	.31	$p < 0.001$
tactile	.41	.25	.31	.24	$p < 0.001$
outdoor	.19	.20	.25	.24	ns
body part	.45	.32	.42	.34	ns
social	.34	.33	.35	.33	ns

Table 1a

Detailed Results Independent Samples T-Test per Category. Underlined categories indicate a higher score at the within-voxel level.

Category	*F*	*t*	*df*	Sig. (2-tailed)
place	6,795	-5,32	101,411	.000
violence	,116	3,51	391	.000
person	3,433	-6,00	1595	.000
visual	11,429	-3,07	39,712	.000

number	7,336	-5,19	129,714	.000
mental	21,986	-7,58	136,656	.000
time	1,613	-3,07	827	.000
tactile	,445	-4,92	1077	.000
outdoor	3,407	1,88	666	.061
body part	4,544	-.672	68,237	.504
social	1,642	.296	827	.767

3.2 Violations regarding triangle inequality

Based on van der Velde (2015), distance calculations were applied to the Jaccard score data. More specifically, the function d(a,b) = -log(x) was used to look into violations of the triangle inequality given by d(a,b) ≤ d(a,c) + d(c,b) (Table 2). The violations were compared for within-voxel and between voxel concept relations to test if voxels have an additional role in the formation of categories, as indicated in the results presented above. As suggested by van der Velde's findings, triangle inequality violations would then occur more with between-voxel concept relations compared to within-voxel concept relations.

For the 393 concepts, 710,280 "real" relations of the kind d(a,b) vs d(a,c) + d(c,b) (with a, b, and c being different concepts) were calculated. "Real" here means that all distances between the concepts had to have a real Jaccard score given by at least 1 subject. Filler Jaccard scores of 0 (standing for subject number of 0) were filtered out. Out of the 710,280 relations, 76,688 violations of the triangle inequality were found. That corresponds to 10.8% of the total relations. Further, within-voxel relations amounted to 1,422 out of the overall 710,280 relations. Here, 141 violations were found (about 9.8% of within-voxel relations). For the remaining between-voxel relations 76,547 violations occurred (about 10.8% of between-voxel relations), indicating 1% more violations than for within-voxel relations.

As argued by van der Velde (2015), in particular "significant" violations, for which d(a,b) – (d(a,c) + d(c,b)) ≥ 1, would be informative to assess differences in concept relations. Table 2a shows the results for significant violations only. Here, 67,409 significant violations were found overall, making up 9.5% of the total relations. For within-voxel relations, 72 significant violations were found out of the 1,422 relations, which amounts to 5.1%. At the between-voxel level 67,337 significant violations were found. As this corresponds to 9.5%, between-voxel relations showed about 4.4% more significant violations than within-voxel concept relations.

Table 2

Relations and triangle inequality violations per Voxel

Voxel	*Relations*	*Violations*	*%*
Overall	710,280	76,687	10.8
Within	1,422	140	9.8
Between	708,858	76,547	10.8

Table 2a

Relations and triangle inequality violations (D ≥ 1) per Voxel

Voxel	*Relations*	*Violations*	*%*
Overall	710,280	67,409	9.5
Within	1,422	72	5.1
Between	708,858	67,337	9.5

4. Discussion

Table 3 provides an overview of the type of results of the current study and relates these to the research questions and the respective sections in the text.

Table 3

Overview of the results. Type of analysis describes which groups were compared; M Jaccard Scores describe the mean Jaccard score per group while N gives the number of word relations per group.

Research Question	Section	Type of Analysis	Results *M* Jaccard Scores*	*N*
RQ1	3.1.1	Same-category vs. different-category	0.32 vs. 0.05	7,563 vs. 45,386
RQ2	3.1.2	Within-voxel vs. between-voxel	0.40 vs. 0.08	1,000 vs. 51,949
RQ1/2	3.1.3	Same-category: Within-voxel vs. between-voxel	0.40 vs. 0.31	948 vs. 6,615
RQ1	3.1.4	Between-voxel: Same-category vs. different-category	0.31 vs. 0.05	6,615 vs. 45,334
RQ2	3.1.5	Scores per category and voxel location		
RQ3	3.2	Triangle inequality violations		

Note. * indicates $p < 0.001$ for all results.

4.1 Answering Research Question 1

Is active word categorization with card sorting related to word categorization based on brain activity during natural speech understanding, as found in Huth et al (2016)?

Regarding the first research question, the present results indicated that there is a relationship between Jaccard scores based on active word categorization and the categories proposed by Huth et al. (2016). This was observed in section 3.1.1 which showed the significant difference in mean scores between same-category and different-category scores. Meaning that participants grouped concepts from the same category more often together, therefore aligning with Huth et al.'s results. Here, concept relations within the same category were rated about 6.4 times stronger by participants than concept relations between different categories. The effect of category membership was also found in sections 3.1.3 and 3.1.4. The findings showed that concepts coming from the same category have an increased relation strength, regardless of voxel location. Additionally, while same-category concept pairs between voxels were significantly weaker than those at within-voxel level (section 3.1.3), the same set of scores showed a large difference in strength when compared to different-category concept pairs between voxels (section 3.1.4). This supports the fact that different-category concept relations overall had the weakest strength and further illustrates the link between active word categorization and Huth et al.'s categorization results.

What needs to be highlighted is that the method of card sorting applied in the studies included in the current meta-analysis appears to have no direct connection to the fMRI recordings in Huth et al. (2016). Huth et al.'s brain recordings were based on narrated stories that participants listened to while the current thesis' results were based on manual (active) word categorization in which the words were presented without additional context of their use. This underlines the lack of connection between both methods. Furthermore, the majority of the current participants were European with English as a second language. Despite these substantial differences with Huth et al.'s study, a similarity between both results was present, which is a remarkable finding.

4.2 Answering Research Question 2

Is active word categorization with card sorting different for within-voxel versus between-voxel concept relations of the same category in Huth et al. (2016)?

Looking into voxel differences only, the results in section 3.1.2 showed that generally within-voxel concept relations had a significantly higher Jaccard score compared to between-voxel ones. To answer the second research question, this difference was further investigated in section 3.1.3 for concept relations coming from the same category. While the score difference between within-voxel and between-voxel relations decreased for this condition, within-voxel scores remained significantly higher. In addition to that, this result was also found for 7 out of the 11 word categories proposed by Huth et al. (2016), analysed in section 3.1.5.

When comparing the results of sections 3.1.1, 3.1.2, and 3.1.3 the highest strength between relations is given for within-voxel concept relations, also on top of category membership. This illustrates the link of voxel location and Jaccard scores. Further, the similarity in means between sections 3.1.2 and 3.1.3 can be explained by the taken sets of scores. The sample difference was only minimal since most within-voxel concepts also come from the same category, which therefore results in a similar mean Jaccard score giving an additional insight into the effect of voxel location besides category membership.

Together these findings indicate an influence of voxel location on the strength of relations between concepts, which provides an answer to how Jaccard scores relate to voxel differences within the same category. So, not only did Jaccard scores obtained from card sorting relate to the categories from Huth et al. (2016), but these also showed a relation within-voxel concepts inside these categories.

4.3 Discussing Research Question 3

Are triangle violations as measured with the distance function different for within-voxel versus between-voxel concept relations of the same category in Huth et al. (2016)?

For the violations of triangle inequality (section 3.1.2), one can see that there was a small difference of 1% between within-voxel concepts and between-voxel ones. However, for significant violations this difference increased to more than 4%, meaning the violations for between-voxel relations were nearly twice as high as for those at within-voxel level. This finding gives a first answer to the third research question and corresponds to van der Velde's (2015) results suggesting higher violations for relations between concept domains which would relate voxels to an own domain. Since the number of concept relations in this study was quite large it was not feasible to look into these violations at a more detailed level. Therefore, the third research question cannot be answered completely. Therefore, another analysis will be performed in the study presented below.

4.4 Limitations

One relevant restriction of the given data was the unequal number of concepts per voxels and categories. As the current results showed an influence of voxels on concept relations, an additional study with equal concept sample sizes could further support this result regarding the question whether active categorization also relates to voxels or just to Huth et al.'s (2016) categories. Moreover, testing with an equal number of concepts per voxels and category will give more insights into the effect of categories and allows for a more detailed analysis of differences.

5. Phase 2: Supporting card sorting study

Purpose of the study

The analyses of the results obtained in the 12 previous studies show that concept relations, as given by Jaccard scores, are higher for within voxel relations compared to between voxel relations (over all categories), even for relations in the same category. The present study again investigated whether even in the same category concept relations are higher within voxels compared to between voxels. In contrast to the sample of the meta-analysis in phase 1, the number of concepts per voxel and category are now the same which allows for looking into triangle inequality violations for each. Furthermore, using a lower number of concept relations makes this analysis, in general, more feasible. And, as explained above, the results would answer the research question whether categorization relates to Huth et al.'s (2016) categories only or (also) to within-voxel word relations. For this, a card sorting task was chosen. The included words were taken from the previous 12 studies based on Huth et al. to build on the above results.

5.1 Method

5.1.1 Design

The card sorting was presented online (see below), so the task was executed in one round, meaning that the created word-groups by participants were not further split up in subgroups. The dependent variable was the relation between concepts, measured by Jaccard scores obtained from card sorting. The independent variables were category and voxel location with two levels, consisting of "within-voxel" and "between-voxel". This distinction was made to test if participants' sorting aligns more with voxel locations or just with the category of the concepts. More specifically, the aim was to investigate whether the scores for within-voxel words are higher than for between-voxel words that belong to the same category.

If so, this could indicate an influence of voxel location on concept relations besides belonging to category.

The concepts in this study came from 6 different categories with two different voxels per category. Per voxel either 3 or 4 concepts were chosen, with an equal amount for the two voxels for the same category. A more detailed description is given in the Materials section.

5.1.2 Participants

In the study, 45 participants participated, with 14 being male and 31 being female. The average age was 21.53 years (*SD* = 3.48). One person had a master's degree, 8 participants had a bachelor's degree, and 36 had a high school diploma as highest completed level of education. The requirement for this study was a sufficient level of English which was noted as an eligibility requirement on the website of the study before signing up. Sona was used for collecting participants, with that course credits were given as a reward for participation. Furthermore, participants in the subject pool provided by Sona came from English-language studies of the University of Twente which should fulfil the language requirement. This research was reviewed and approved by the BMS Ethics Committee of the University of Twente. All participants gave informed consent (see Appendix G for the consent form used).

5.1.3 Materials

Due to the Covid-19 situation, the card sorting task was created in Qualtrics as an online version administered to participants. The task included 46 words taken from the previous studies analysed above. Criteria for choosing the words were a voxel model performance of "Good, very reliable" or "Excellent". A lower performance would mean that the voxel is not reliable in its selectivity, consequently these were not included. Further, the aim was to use more abstract categories to avoid concepts that are too straightforward and thus too easy to categorize. For example, this includes concepts from category "Number" such as "zero" or "forty" which are quite direct in their meaning. Hence, six categories were chosen from Huth et al. (2016). These are: "tactile", "outdoor", "violence", "mental", "time", and "social". Important here was that words from each category had to come from two different voxels/brain locations, to be able to compare scores at within- and between-voxel level per category. An example are the words "moonlight" and "waves" from category outdoor, "moonlight" comes from the left hemisphere with voxel number [18,82,57] while "waves" was taken from the right hemisphere with voxel number [15;17;29]. The complete list including all voxel locations is presented in Appendix H.

5.1.4 Procedure

Participants received general information about the study and were informed that they could withdraw at any time. Before starting the experiment, participants were asked to give informed consent. After that, demographic questions had to be answered and the card sorting task followed. Participants had to drag and drop the concepts into group slots the way it made most sense to them. It was not required to rank the words or name the groups. This took about 10-20 minutes. When finished, the participants were thanked for their participation.

5.1.5 Data Analysis

For each participant, a Jaccard score table was created. The Jaccard score describes the relation between 2 concepts (Schmettow & Sommer, 2016) and is created based on which words are grouped together. The chosen 46 words represented both columns and rows of the table. For the cells either a 1 or 0 was added if the respective words were members of the same group or not. In the end all tables were added together into one. A vector analysis of clusters was used to create an organized heatmap in R, which can be seen in figure 8. Appendix I shows the R script for this analysis.

Moreover, the within- and between-voxel Jaccard scores were compared per category to see if there was a significant difference in results and to test the influence of voxel location compared to category membership. For this a Mann-Whitney test was chosen and conducted in SPSS as the overall scores were skewed to the right. This was done for all within- and between-voxel scores and then per word category.

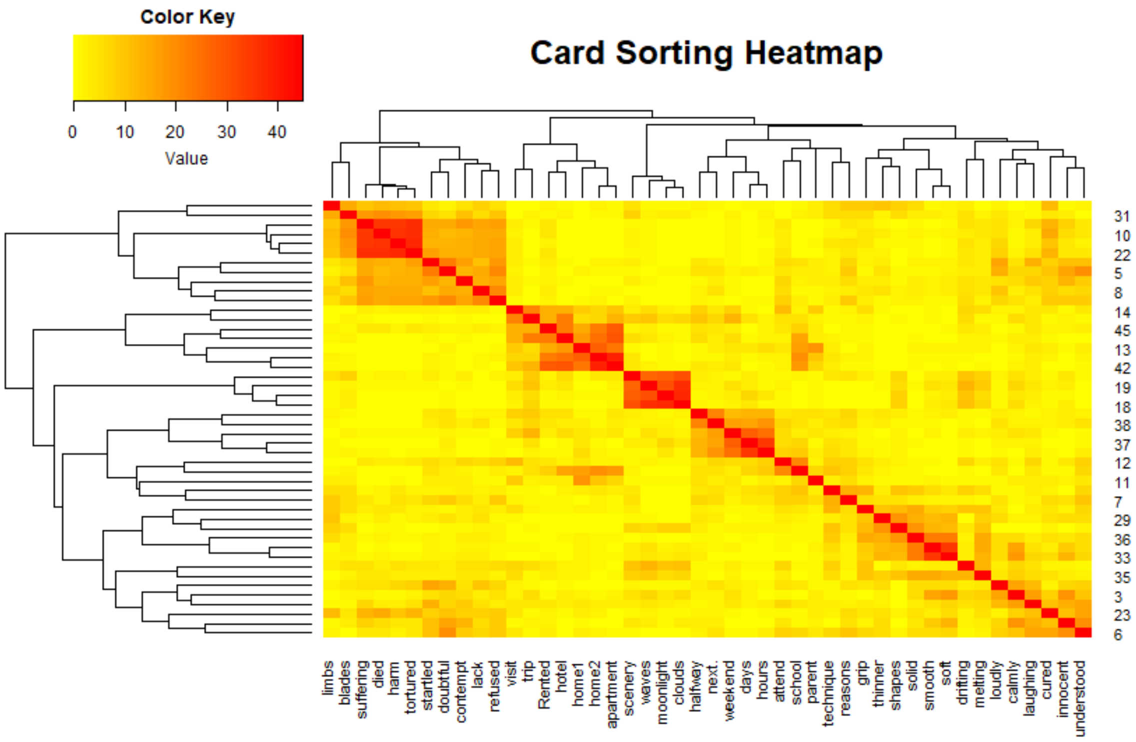

Figure 8. Heatmap created from all collected card sorting data.

6. Results card sorting study

6.1 Jaccard score data analysis

6.1.1 Overall scores: Within-voxel vs. between-voxel

Table 4 shows the mean Jaccard scores and standard deviations for all within-voxel and all between-voxel data. In this study the number of within-voxel relations amounted to 70 while between-voxel relations amounted to 965. Generally, within-voxel scores were higher as compared to between voxel scores with 0.33 (SD = .21) and 0.09 (SD = .12) respectively. The Mann-Whitney test indicated that this was a statistically significant difference in scores, $U(N_{\text{within-voxel}} = 70, N_{\text{between-voxel}} = 965) = 8823$, $z = -10.42$, $p < .001$. Figure 9 displays the scores as histograms for comparison, showing the large number of 0 scores for between-voxel relations. To provide a more useful comparison figure 9a shows the Jaccard scores relative to the number of relations per voxel level. Based on percentages, the majority of within-voxel relations have a score above 0 while the opposite is the case for between-voxel relations. This difference becomes especially clear in figure 9b when limiting the relative scores to above 0.5 for each voxel level. Here, the percentage of within-voxel relations reaches up to 8.5% however the number of between-voxel relations barely reaches 0.4% in this range.

Table 4

Mean Jaccard Scores per Voxel for all Scores

	Within Voxel		Between Voxel	
	M	*SD*	*M*	*SD*
All Scores	.33	.21	.09	.12

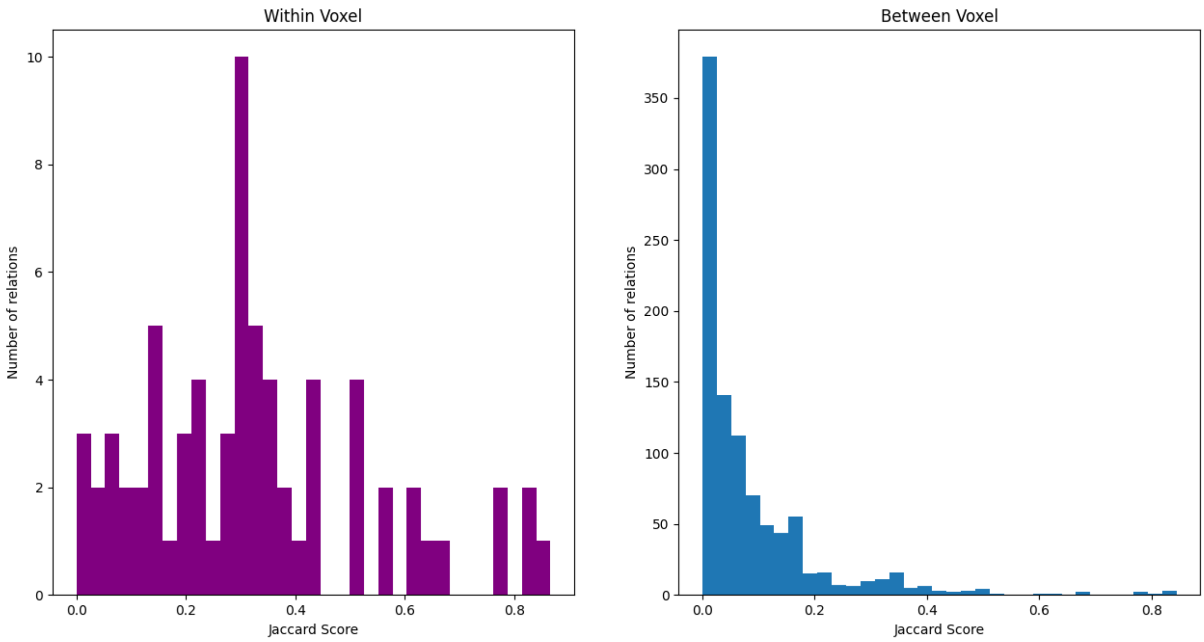

Figure 9. Histograms per voxel location illustrating Jaccard score distributions.

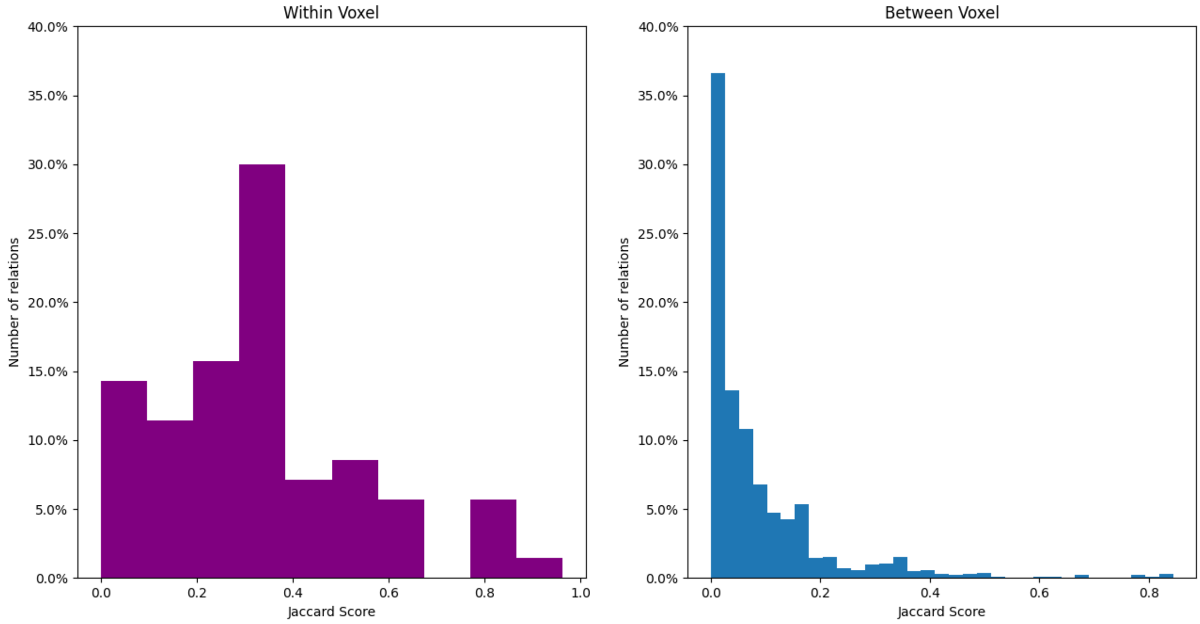

Figure 9a. Histograms per voxel location illustrating relative Jaccard score distributions. The y-axis shows the percentage of relations relative to the total amount of relations per group.

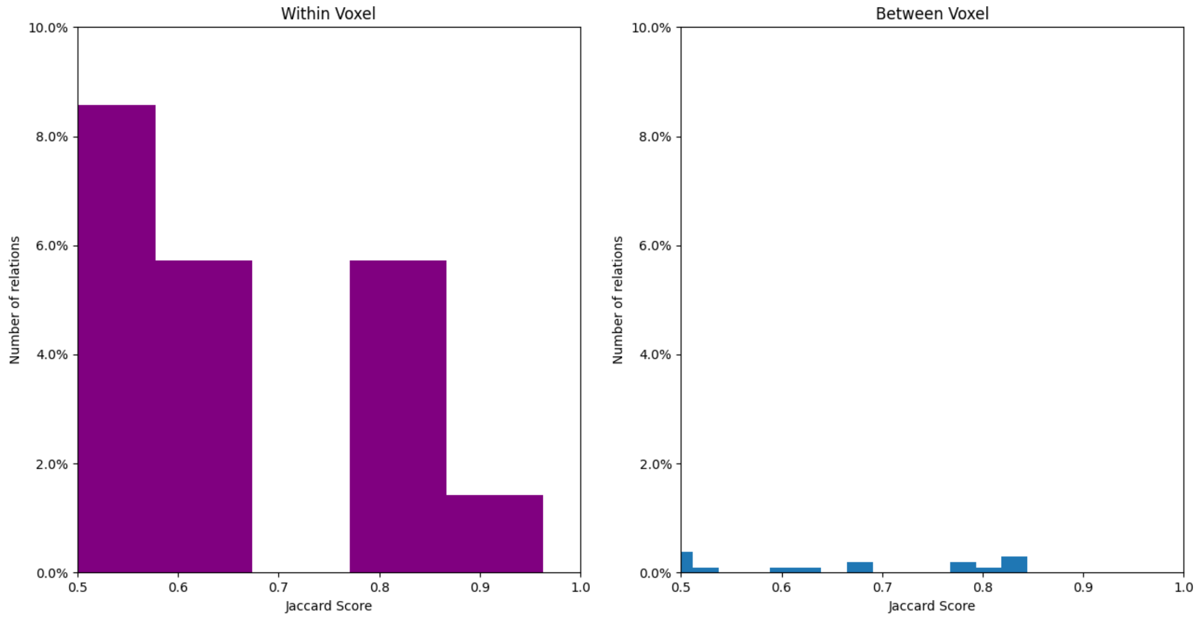

Figure 9b. Histograms per voxel location illustrating relative Jaccard scores only above 0.5. The y-axis shows the percentage of relations relative to the total amount of relations per group.

6.1.2 Same-category: Within-voxel vs between-voxel scores

Moreover, the Jaccard scores were compared further to look for differences at the two voxel levels despite coming from the same category. The number of within-voxel relations stayed 70 since all within-voxel concepts also came from the same category. For between-voxel relations only from the same category the number was reduced to 93. When comparing the overall within-voxel scores with the between-voxel scores only for same-category relations, the latter scores are 0.1 higher than when also taking different-category relations into account (Table 5 vs Table 4). Despite that difference the Mann-Whitney test showed that within-voxel relations still had a significantly higher score, $U(N_{\text{within-voxel}} = 70, N_{\text{between-voxel}} = 93) = 1808$, $z = -4{,}857$ $p < .001$. Figure 10 and 10a display these differences as histograms with figure 10a showing the relative scores. For between-voxel relations zero scores were again higher than at within voxel level. A difference to the overall between-voxel relations in section 5.1.1 is that the distribution is more spread up to a score of 0.9. Especially for the range of approximately 0.02 to 0.4 the frequency increased, which explains the difference in mean scores to overall between-voxel relations. Regardless of that within-voxel relations remained significantly stronger which can also be seen in figure 10b, illustrating relative Jaccard scores above 0.5. For this range within voxel concept were nearly three times as high as between-voxel ones.

Table 5

Mean Jaccard Scores per Voxel for Same-Category Relations

	Within Voxel		Between Voxel	
	M	*SD*	*M*	*SD*
Same Category	.33	.21	.19	.19

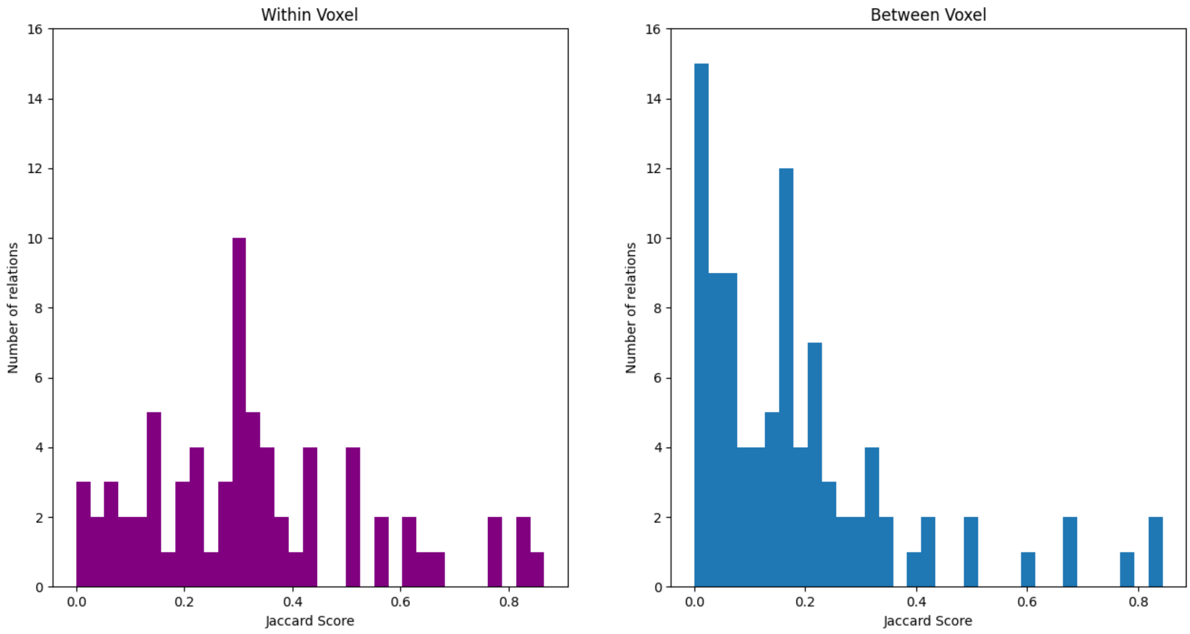

Figure 10. Histograms per voxel location illustrating same-category Jaccard score distributions.

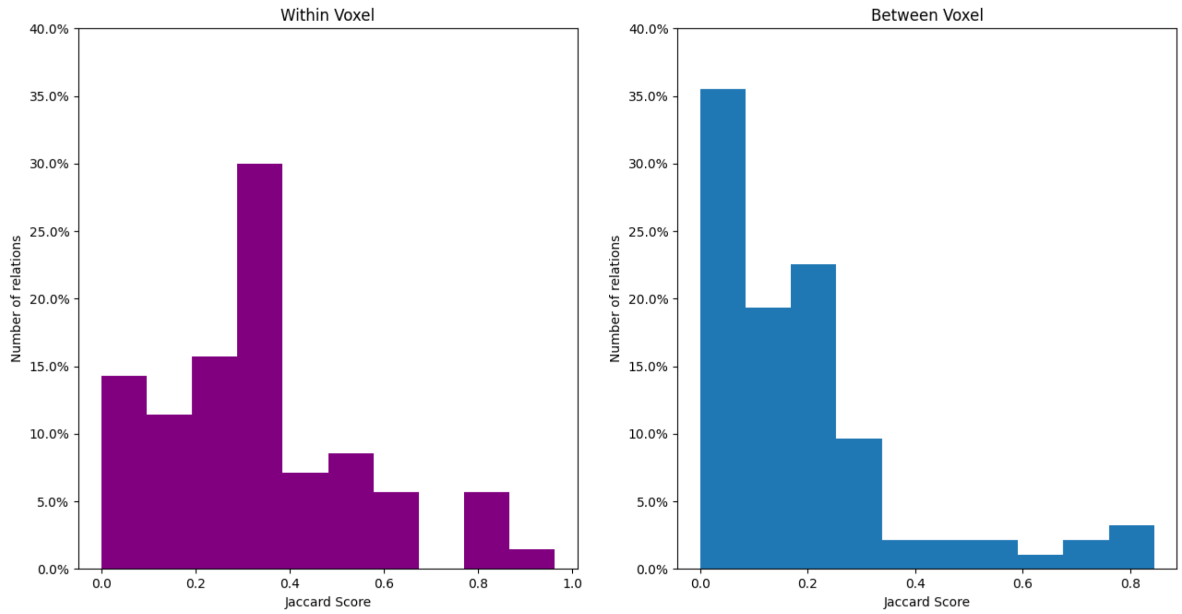

Figure 10a. Histograms per voxel location illustrating relative same-category Jaccard score distributions. The y-axis shows the percentage of relations relative to the total amount of relations per group.

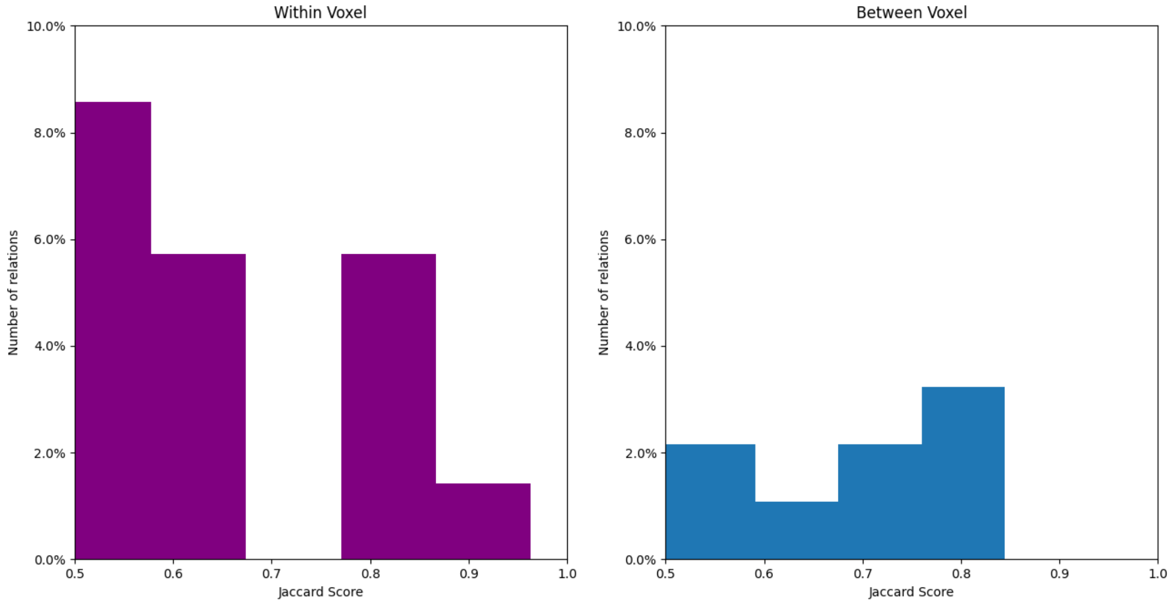

Figure 10b. Histograms per voxel location illustrating relative same-category Jaccard scores above 0.5. The y-axis shows the percentage of relations relative to the total amount of relations per group.

6.1.2.1 Scores per category and voxel location

Looking further into category difference one can see that a higher within-voxel score is also true for 4 out of 6 categories namely “mental”, “social”, “tactile”, and “time” (Table 6). Exceptions to this are categories “outdoor” and “violence”, scores here were similarly high for both voxel conditions with scores of above .30. The Mann-Whitney test conducted for each category only indicated a statistically significant difference in scores for categories “tactile” and “time”. Regarding category “tactile”, the within-voxel score was .29 (SD = .17), while the between-voxel added up to .17 (SD = .11), $U(N_{\text{within-voxel}} = 20, N_{\text{between-voxel}} = 25) = 136$, $z = -2.62$, $p < .01$. For category “time”, the within-voxel score (M = .44, SD = .22) was about 4 times higher than for the between-voxel condition (M = .11, SD = .12), $U(N_{\text{within-voxel}} = 20, N_{\text{between-voxel}} = 25) = 43$, $z = -4.74$, $p < .001$.

Table 6

Mean Jaccard Scores per Category and Voxel.

Category	Within Voxel		Between Voxel	
	M	*SD*	*M*	*SD*

mental	.27	.12	.19	.12
social	.15	.14	.11	.14
outdoor	.34	.32	.38	.33
violence	.35	.25	.36	.27
tactile	.29	.17	.17	.11
time	.44	.22	.11	.12

6.1.3 Scores excluding same category between-voxel data

Lastly, within-voxel scores were also compared with between-voxel scores excluding same-category concepts discussed in the previous section. That means the current between-voxel scores are only noted for relations between concepts coming from different categories, which amounted to 872 relations. Table 7 presents the mean Jaccard scores and shows that when taking out same-category relations, the mean score for between-voxel relation is decreased by 0.01 (see Table 4). Again, a Mann-Whitney test showed that within-voxel scores were significantly higher than between voxel scores, $U(N_{\text{within-voxel}} = 70, N_{\text{between-voxel}} = 872) = 7015$, $z = -10{,}840$ $p < .001$. Histograms were created for the scores once more and are illustrated in figure 11 and figure 11a with relative scores for comparison. The score distributions are similar to those in section 6.1.1 since the sample of different-category between-voxel relations was only lowered by 93 instances. Again, the strength of within-voxel relations can especially be seen when only taking scores above 0.5, shown in figure 11b. A small difference to section 6.1.1 is that less between-voxel relations received a score above 0.5 thus never showing more than about 0.2% in this range.

Table 7

Mean Jaccard Scores per Voxel for all Scores

	Within Voxel		Between Voxel	
	M	*SD*	*M*	*SD*
All Scores	.33	.21	.08	.10

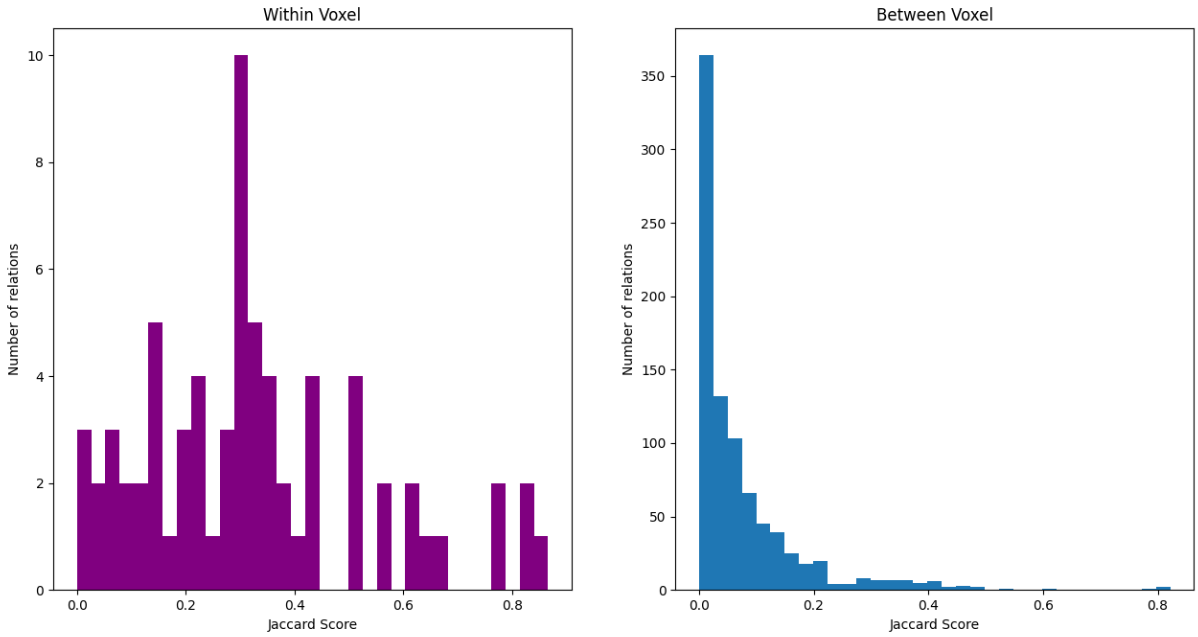

Figure 11. Histograms per voxel location illustrating Jaccard score distributions. Between voxel scores are shown for different-category concept relations.

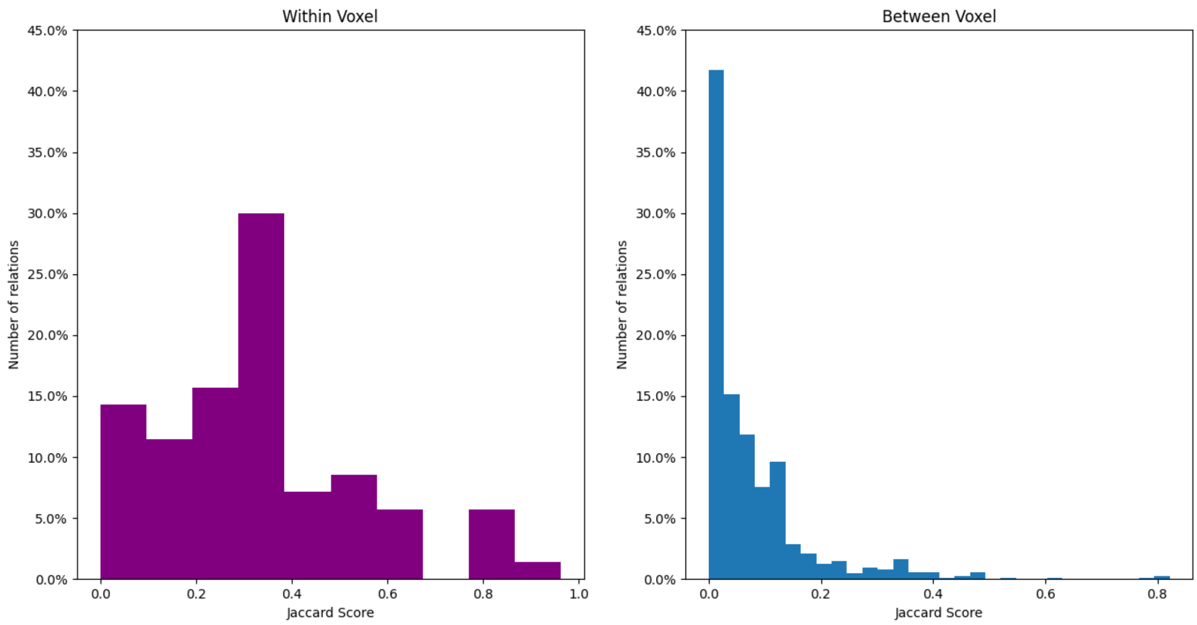

Figure 11a. Histograms per voxel location illustrating relative Jaccard scores. Between voxel scores are shown for different-category concept relations. The y-axis shows the percentage of relations relative to the total amount of relations per group.

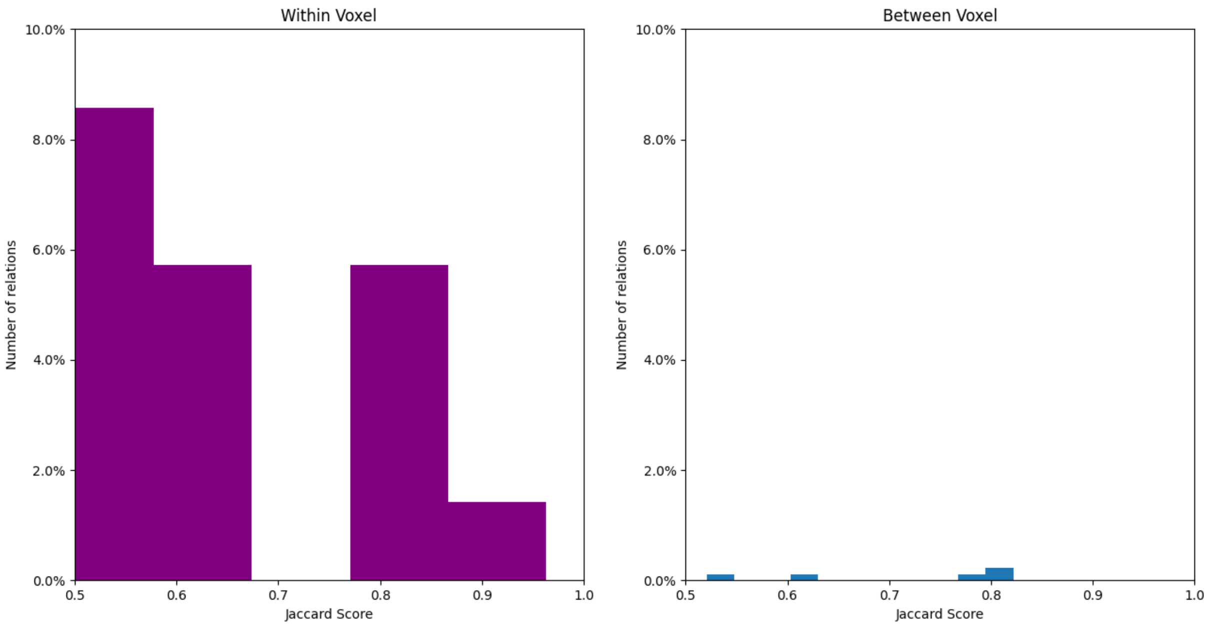

Figure 11b. Histograms per voxel location illustrating relative Jaccard scores above 0.5. Between voxel scores are shown for different category concept relations. The y-axis shows the percentage of relations relative to the total amount of relations per group.

6.2 Violations regarding triangle inequality

The same distance function that was used for the analysis of the data collected in the previous 12 studies was applied for the current card sorting. Violations of the triangle inequality $d(a,b) \leq d(a,c) + d(c,b)$ per category and voxel are listed in table 8. A violation of the triangle inequality entails that the concept pair a-b is not strongly related even though the concept pairs a-c and c-b are. This could suggest that the concepts a and b do not belong to the same concept domain (or at least are not often used as a relation). But the strong indirect relation between them could be an indication of the existence of 'concepts bridges' between the domains to which they belong (see below).

Table 8 gives the number of triangle relations (in the columns "Relations") for within voxels (summed over both voxels) and for between voxels for each category. For example, in the category "social" there are 3 concepts per voxel (see Appendix H). This gives 3 triangle relations per voxel and thus 6 summed over two voxels. Likewise, in the category "time" there are 5 concepts per voxel. This gives 30 triangle relations per voxel and 60 with two voxels. The number of relations for between voxels is calculated in a similar manner by taking all possible triangle relations in which at least two concepts belong to two different voxels per category.

For the categories “social”, “outdoor”, and “violence” only one violation for within-voxel concept relations was found. Violations for between-voxel relations ranged from 4-7 here (7.4-13%). Thus, based on percentages between-voxel relation show less violations. However, the low numbers of relations for these categories do not give too much information and could make this result rather unreliable.

Further, the within-voxel relations for category “mental” had 2 violations (8.3%). In turn the between-voxel relations showed 8 violations (5.5%). This shows 2.8% more violations for within-voxel relations in category “mental”. Category “tactile” had the lowest number of violations with 1 (1.6%) at within-voxel level. And, moreover, had 22 violations (7.3%) at between-voxel level. Here the violations at within-voxel level were 5.7% lower than at between-voxel level. Lastly for category “time” the within-voxel violations were lower by 2% with 9 violations and 51 violations for between-voxel concept relations. A Mann-Whitney test for every category showed that these differences were not significant.

However, of all categories, “tactile” and “time” have significantly higher Jaccard scores for within-voxel relations (see Table 6). This could point to individual concept domains within the voxels for these categories. Also, these categories have the most within and between-voxel relations and with it the most triangle violations (in absolute terms, not in percentages). Therefore, it interesting to look at concept bridges that could exist between the voxels for each of these categories.

Table 8
Triangle Inequality Violations per Category and Voxel

Category	Within-Voxel			Between-Voxel		
	Relations	*Violations*	*%*	*Relations*	*Violations*	*%*
mental	24	2	8.3	144	8	5.5
social	6	1	16.6	54	7	13
outdoor	6	1	16.6	54	4	7.4
violence	6	1	16.6	54	7	13
tactile	60	1	1.6	300	22	7.3
time	60	9	15	300	51	17

6.3 Concept bridges

The categories “tactile” and “time” showed a higher number of violations for between-voxel relations than for within-voxel, while not statistically significant it is still interesting to look further into concept bridges that could exist. A concept bridge describes one concept that forms a bridge between two other concepts that seem rather unrelated (van der Velde, 2015). So, the bridge concept shows a moderate to strong relation with both other concepts while these have only a weak relation between them. For example, the word “apple” could be a concept bridge between the concepts “computer” and “fruit”. Because apple is a fruit it will have a high relation with the concept “fruit”, but apple is also computer brand which would show a high relation with “computer” as well. However, fruit and computer alone seem rather unrelated and would have a low relation. In this way the word apple connects two unrelated concepts. Below the concept bridges for categories “tactile” and “time” are summed for all violations, both within- and between-voxel.

6.3.1 Category tactile

Regarding the card sorting data, for category “tactile” overall 23 violations of the distance rule were found (Table 8). It is in particular interesting to look at 'significant' violations, defined by the rule $d(a,b) - (d(a,c) + d(c,b)) \geq 1$ (van der Velde, 2015). Of the overall 23 violations, 6 violations were found in which the bridge concept had significantly stronger relations than the two unrelated concepts, given by this rule. These bridges were only found between concepts that came from different voxels. One example here is given by the concepts “limbs” from voxel [19;67;77] and “melting” from voxel [21;67;25]. The direct relation between these concepts is low with a score of 0. Figure 12 shows that there are 5 indirect relations, given by significant concept bridges as defined above. Three of these are formed by concepts in voxel V1, and two are formed by concepts in voxel V2. A detailed overview including the Jaccard scores and distances per relation are found in table 9 for voxel 1 [19;67;77] and table 10 for voxel 2 [21;67;25].

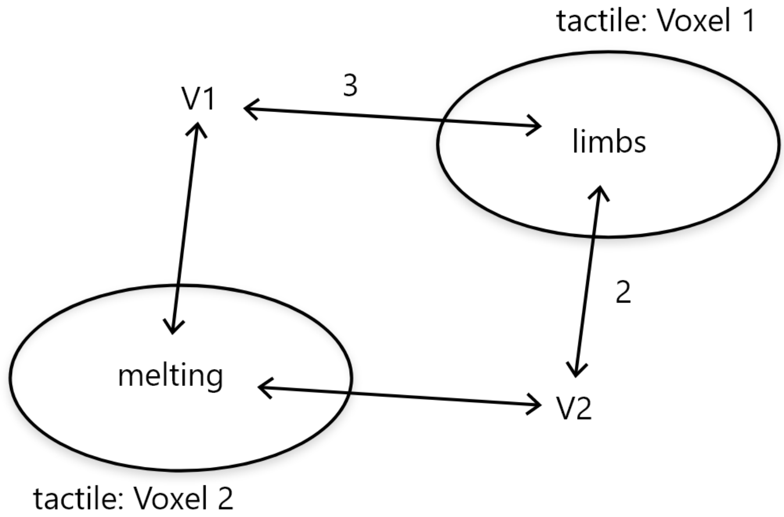

Figure 12. Indirect relations (bridges) between the concept “limbs” from voxel 1 ([19;67;77]) and “melting” from voxel 2 ([21;67;25]) of category tactile. V1 and V2 stand for voxel 1 and 2 from category tactile.

Table 9

Jaccard scores and distances for concept bridges in Voxel 1 [19;67;77]

a	b	c	*CST(a,b)*	*CSTd(a,c)*	*CST(c,b)*	*d(a,b)*	*d(a,c)*	*d(c,b)*
		grip		10	9		1.50	1.61
melting	limbs	thinner	0	8	10	18.42	1.73	1.50
		technique		6	6		2.01	2.01

Table 10

Jaccard scores and distances for concept bridges in Voxel 2 [21;67;25]

a	b	c	*CST(a,b)*	*CSTd(a,c)*	*CST(c,b)*	*d(a,b)*	*d(a,c)*	*d(c,b)*
melting	limbs	shapes	0	10	8	18.42	1.50	1.73
		solid		15	6		1.10	2.01

6.3.2 Category time

For the category “time” 60 violations were found, as can be seen in table 8. Here, for 12 violations the rule $d(a,b) - (d(a,c) + d(c,b)) \geq 1$ was valid. 1 out of the 12 bridges was found between concepts within the same voxel. In this case the word “weekend” presented a bridge between “trip” and “hours” from voxel [6;41;23]. The calculated distance given by $d(a,b) = -\log(x)$ was 3.1 for “trip” and “ hours”. The distance between “trip” and “weekend” was 1.2 and 0.6 for “hours” and “weekend”. This shows that weekend seems to work as a bridge within its own voxel (Figure 13). The remaining 11 bridges were formed between concepts coming from different voxels. Prominent here were the combinations "apartment-days" and "rented-days", which both had 4 indirect relations each, as can be seen in Figure 14. Here, for both 3 bridges were formed with concepts from voxel [6;41;23] (V1) and 1 bridge from voxel [15;75;44] (V2). Furthermore, table 11 presents the Jaccard scores and distances between “apartment” and “days” and the found bridges. Table 12 shows these values for bridges between “rented” and “days”.

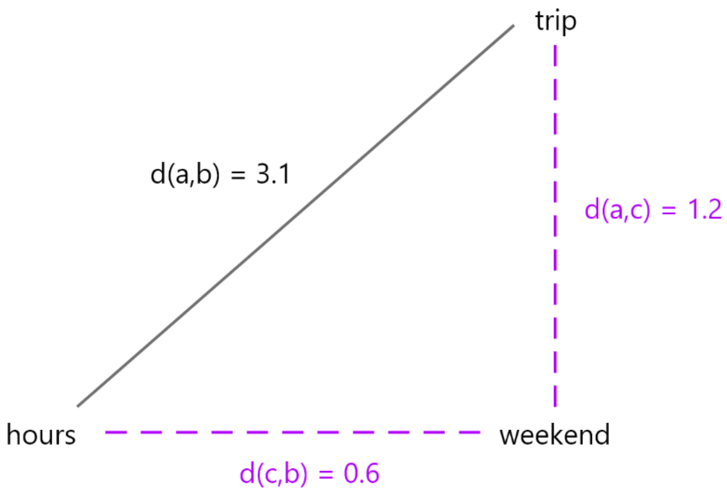

Figure 13. Calculated distances between the concepts “trip”, “hours”, and “weekend” from voxel [6;41;23] of category time. This highlights the bridge function of “weekend” within its own voxel.

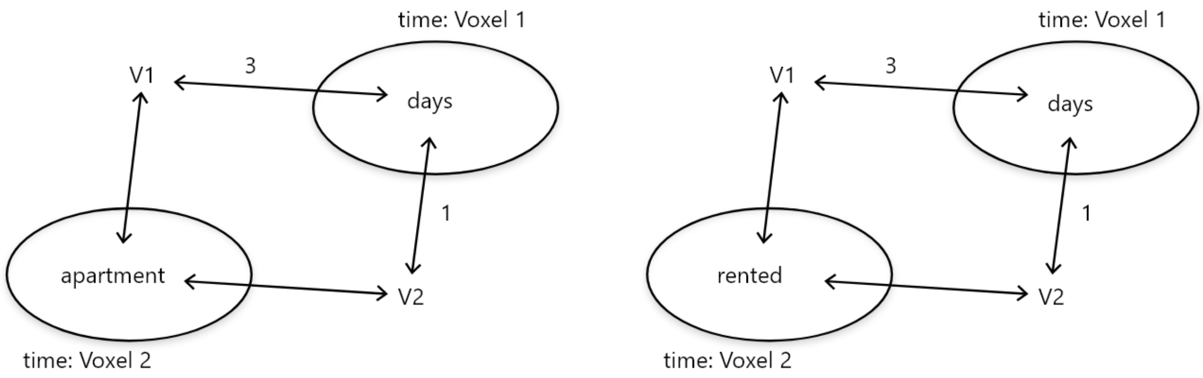

Figure 14. Indirect relations between “apartment” and “days” (left), and “rented” and “days” (right) from different voxels each in category time.

Table 11

Jaccard scores and distances for concept bridges between “apartment” and “days”. Concept “school” marks the singular bridge from voxel 2 [15;75;44].

a	b	c	*CST(a,b)*	*CSTd(a,c)*	*CST(c,b)*	*d(a,b)*	*d(a,c)*	*d(c,b)*
apartment	days	next	0	3	16	18.42	2.71	1.03
		weekend		4	28		2.42	0.47
		trip		13	5		1.23	2.20
		school		18	7		0.92	1.86

Table 12

Jaccard scores and distances for concept bridges between “rented” and “days”. Concept “school” marks the singular bridge from voxel 2 [15;75;44].

a	b	c	*CST(a,b)*	*CSTd(a,c)*	*CST(c,b)*	*d(a,b)*	*d(a,c)*	*d(c,b)*
rented	days	next	0	4	16	18.42	2.42	1.03
		weekend		3	28		2.71	0.47
		trip		14	5		1.17	2.20
		school		8	7		1.73	1.86

7. Discussion card sorting study

7.1 Further answering Research Question 2

Is active word categorization with card sorting different for within-voxel versus between-voxel concept relations of the same category in Huth et al. (2016)?

The present results add further to the findings of the first study in regard to the second research question. Section 6.1.1 showed again that within-voxel relations were significantly stronger than between-voxel relations. More specifically, this result was also found for concept pairs of the same category in section 6.1.2. Between-voxel concept pairs of the same category further showed a stronger relation than when coming from different categories (Section 6.1.3). When looking at the individual categories it was found that not for all within-voxel relations were rated significantly stronger. Here, only categories “time” and “tactile” had a significant difference in relation strength per voxel location. Interestingly, categories “social”, “outdoor”, and “violence” did also not show significantly higher rated within-voxel relations in the meta-analysis, which was analysed in section 3.1.5. A reason for this overlap in results could be the higher degree of abstractness of concepts from these categories. Because of that, the effect of voxel location could be reduced when using the card sorting method since concepts are presented without context. In this case, it might only be possible to have general active categorization based on the respective categories. Despite this additional result, the finding of a relation between Jaccard scores and within-voxel concept relations cannot be rejected.

7.2 Answering Research Question 3

Are triangle violations as measured with the distance function different for within-voxel versus between-voxel concept relations of the same category in Huth et al. (2016)?

Section 6.2 illustrated that for categories “tactile” and “time” the triangle inequality violations were higher for between-voxel relations. The found differences were not statistically significant but could give some indication for individual concept domains for these voxels, based on van der Velde’s (2015) research. Moreover, the missing difference in violations for categories “social”, “outdoor”, and “violence” overlaps with the result that within-voxel relations were not significantly stronger either for these groups (Section 3.1.5 and 6.1.2.1). Because of that, the effect of triangle inequality violations could look different when including all categories with significantly stronger within-voxel relations. Furthermore, the number of triangle relations at within-voxel level were quite small, which could also affect the results. So, while between-voxel concept relations generally showed more violations (Section 3.2) the same result was only found in two cases for concepts of the same category which were also not statistically significant. Therefore, it could be further studied taking larger samples (that still allow for a feasible analysis) and looking at other categories from Huth et al. (2016), specifically those that had stronger within-voxel relations.

Furthermore, concept bridges were analysed for the categories that showed higher (significant) triangle violations (> 1) at between-voxel level. The results in section 6.3 showed that, apart from one relation in category “time”, all significant bridges were formed between the voxels of the same category. The voxel differences found for category “tactile” and “time” could thus indicate that voxels relate to spokes with their own concept domain as described in the hub-and-spoke theory. Such that the concepts represented by voxels in a specific area are related in terms of the respective modality. This is supported by stronger relations for within-voxel concept pairs as compared to between-voxel pairs coming from opposite locations. The found concept bridges between voxels would further illustrate the hub connection between both.

This result suggests the importance of individual voxels which add something to the relation strength between concepts, besides category membership. A word category would then consist of an interconnection of various voxels in different spokes by a central hub, in which word relations are stronger when belonging to the same voxel. This can also be seen in Huth et al.’s (2016) brain map where the different categories are distributed over the brain. Furthermore, one concept can also be found in different voxels, which adds to the description of different modality specific areas (spokes) responding to the same concept.

This finding provides more information about how and where semantic knowledge could be stored and aligns Huth et al. (2016) results with the hub-and-spoke theory. However, since the concept bridges of only two categories were investigated there is still a need for future research to look into the other categories proposed by Huth et al.

8. General Discussion

The semantic system makes up an integral part of how we perceive and interact with the world, yet its structure and location in the brain are not clear. Because of that, the current thesis aimed at creating a better image of how conceptual knowledge is represented in the brain. For this, it was investigated how brain activity based on natural speech understanding relates to active word categorization. More specifically it was looked into how word categorization relates to categories and individual voxels as taken from Huth et al.'s (2016) brain map and what this tells about the semantic system in the brain. The hub-and-spoke model was included as a basis for a possible structure of the semantic system since it shares similarities with Huth et al.'s proposed map.

The present results showed a strong relation between active word categorization by participants and the categories from Huth et al. (2016). Overall, the relations for concepts from the same category were approximately 6.4 times stronger than concepts from different categories. This gives a clear positive answer for the first research question and shows that there exists a relation between active word categorization and Huth et al.'s categories. This finding is especially outstanding since the methods used in both studies were vastly different. The current study used card sorting data based on grouping of singular words with no context while Huth et al. measured brain activity of participants listening to stories containing the selected concepts. Despite this significant difference, a large overlap was found between both results.

Secondly it was investigated if active word categorization differs for within-voxel and between-voxel concept relations of the same category in Huth et al. (2016). Here, the results of both the meta-analysis and supporting card sorting study showed that active word categorization significantly relates more to within-voxel concept relations than to between-voxel ones. This shows that besides category membership voxel location adds to the relation strength between different words. Overall, concepts coming from the same category and the same voxel showed the strongest relations between all conditions.

Lastly, it was looked into if triangle inequality violations differ for within-voxel and between-voxel concept relations of the same category in Huth et al. (2016). This was based on van der Velde's (2015) research which applied the distance function to Jaccard score data. The current results of the meta-analysis indicated more significant violations for different-voxel concept relations. However, in the supporting card sorting study that analysed these differences for selected categories of Huth et al., no statistically significant differences were found between the voxel levels. Categories "time" and "tactile" showed notably more violations for different-voxel concept pairs, which were then further analysed with regard to concept bridges. This analysis further added to the previous results as all but one bridge was formed between concepts from different voxels. Despite that it needs to be acknowledged that the findings for each category were not statistically significant. Therefore, the third research question cannot be answered confidently and only an indication for future research can be given. Currently, it is suggested that different-voxel relations show more violations depicting (groups of) voxels as own concept domains, which would align with van der Velde's results.

The current results give a first indication that voxels on top of category membership play a role in active word categorization and in turn could show how the semantic system is structured. The hub-and-spoke model illustrates the semantic system as being composed of different modal areas (spokes) that are linked through a multimodal hub. The present findings in connection to Huth et al.'s (2016) brain map support this theory. The different concepts were not only related because of the overall category they come from but additionally also based on their voxel. Furthermore, the majority of concept bridges were created between different voxels and not within. Based on that, semantic categories could then be made up of different voxels representing the spokes from the theory which are interconnected by the central hub. What adds to that is the overall distribution of categories over the brain, as seen in Huth et al.'s map, and the fact that concepts activate several voxels at different locations. This could illustrate a network of different modal aspects of a concept that are elicited when encountering the respective word. Besides modal aspects, relations to other concepts are also present since a voxel is not only activated by a singular concept but a cluster of words. This is similar to Zhang, Han, Worth, and Liu's findings (2020). Like Huth et al. their study used fMRI results from participants listening to narrated stories. The authors highlight that their semantic categories and relations are not represented by a singular cortical region. The results rather suggest that individual categories are represented by overlapping spatially distributed cortical networks. Each network is thought to connect different attributes of a domain by linking the regions that encode these attributes. This overlaps with the present results in which a category would encompass various interconnected voxels that are distributed over the hemispheres. However, one difference in Zhang et al.'s semantic system was the connection of different multimodal areas, therefore deviating from the hub-and-spoke model in which a multimodal hub connects modality-specific areas.

Another different approach to studying semantic cognition was applied by Jackson, Rogers, and Lambon Ralph (2021) and adds to the current results. In this article, reverse-engineering was used to uncover the most favourable structure that best supports the semantic system’s functions. A number of neural networks with different types of connections were tested. The used connections included were: Direct Spoke Connections, Bimodal Hubs Connections, Multimodal Hub Connections and Shortcut Connections. The results showed that a network with a shared multimodal hub was the best to learn a cross-modal semantic structure, which is in line with the hub-and-spoke model that was also suggested in the present thesis (Rogers & Lambon Ralph, 2022).

In summary, the results answer the first two research questions and are able to provide a direction regarding the last question. Active word categorization relates to the categories proposed by Huth et al. (2016) and further also showed a relation to within-voxel relations. Triangle violations and concept bridges between voxels could depict different facets of a category that are connected through hub relations. However, this needs to be studied further since this finding was not significant. One reason for that could be that the number of concept relations per category were too small to gain reliable results. The choice of selecting only 3-5 concepts per voxel was made to have a feasible analysis of triangle violations but it could also reduce the precision and reliability of the findings. This marks a limitation of the current research.

8.1 Limitations and future research

As mentioned above the number of concept relations for some categories were too small for a reliable data analysis when comparing triangle inequality violations. Therefore, it is essential to choose an appropriate number of concepts per voxel in further research to avoid that. Besides the main findings, a smaller result was that categories “social”, “outdoor”, and “violence” had no significant differences in concept relation strength between voxel locations. This was found for both studies. One reason for this result could be that these categories specifically were more abstract than the other ones, which made it more difficult to categorize their concepts in a card sorting task. In comparison to Huth et al.’s (2016) listening task, card sorting misses context information and is therefore not able to add nuances to the respective concepts. Because the selected words were not presented in a sentence, participants can have different interpretations about the same concept and thus apply it in a different way. However, increasing the number of concepts that need to be sorted and providing additional information on how the word is used in a sentence greatly increases the time and effort participants need to put in the task. Therefore, administering a card sorting task might not be fitting anymore and another method needs to be chosen.

Since this thesis was not able to answer the third research question regarding triangle inequality violations, future research could look into this again, also for categories from Huth et al. (2016) that were not included in the second study. This could give more insights into the geometrical structure of the conceptual domains as indicated by van der Velde (2015). Especially for categories “social”, “outdoor”, “violence”, and “mental”, which were more abstract, it was not possible to thoroughly analyse the geometrical structure within these categories. Therefore, it is not clear if the small sample size or the abstractness of the categories explains the result of less violations for between-voxel relations. Furthermore, Zhang et al. (2020) hypothesize that the brain encodes semantic relations as vector fields in a continuous semantic space. Since their study was similar to Huth et al.’s this gives an additional reason for looking into the geometrical structure in Huth et al.’s brain map as a semantic space.

8.2 Overall conclusion

The aim of the present thesis was to find out how brain activity relates to active word categorization to gain more insights into the structure of the semantic system in the brain. This was analysed by looking into how card sorting results related to the categories and voxels from Huth et al.’s (2016) brain map. The results were then applied to the hub-and-spoke model to analyse the structure of the semantic system. The findings indicated that besides category membership voxel location plays an important role in the relation strengths between concepts. This could illustrate the structure of semantic categories as being made up of multiple voxels in different spokes interconnected by a central hub as given by the hub-and-spoke model.

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10. Appendices

Appendix A

Python Code Converting Decimal Jaccard Scores

```
"""
03.2021

Program for converting a table with jaccard score decimal fractions into
raw scores

Note: csv tables have to be symmetrical at the diagonal and only the first
row should contain labels (no column)

Author: Pia Elsasser
"""



import csv
import numpy as np


def csv_to_lists(filename):
    infile = csv.reader(open(filename))
    table = []
    for row in infile:
        table.append(row)
    for r in range(1, len(table)):
        for c in range(len(table[0])):
            table[r][c] = float(table[r][c])
    return table


tableDec = csv_to_lists("path/filename.csv")



data = {"column header": tableDec[0],  # concept names from table1
        "array": np.array(tableDec[1:])}  # jaccard scores from table1



participants = 30 # needs to be adjusted for the respective table



for concept in data["column header"]:
    cIndex = data.get("column header").index(concept)
    for secConcept in data["column header"]:
        cIndexSec = data.get("column header").index(secConcept)
        if concept == secConcept:
            data["array"][cIndex][cIndexSec] = participants
        else:
            data["array"][cIndex][cIndexSec] =
round(data["array"][cIndex][cIndexSec]*participants, 2)
```

```
### write data into new csv file

outfile = open("converted_file.csv", "w", newline='')
writer = csv.writer(outfile)


# turn "data" dictionary into list of lists

finalTable = data["array"].tolist()
finalTable.insert(0, data["column header"])


for row in finalTable:
    writer.writerow(row)
outfile.close()
```

Appendix B

Python Code Merging CSV Tables

```
"""
02.2021

Program for combining different csv tables into one mastertable
Note: csv tables have to be symmetrical at the diagonal and only the first
row should contain labels (no column)

The program is used for tables that contain jaccard scores of different
concept combinations. From each table these
values are added into a mastertable twice (mirrored), for the diagonal
score the value is only added once as it is only
one cell that has the value.

Author: Pia Elsasser
"""

import csv
import numpy as np


### read csv data into a table(list of lists) and change values from type
string to float

def csv_to_lists(filename):
    infile = csv.reader(open(filename))
    table = []
    for row in infile:
        table.append(row)
    for r in range(1, len(table)):
        for c in range(len(table[0])):
            table[r][c] = float(table[r][c])
    return table
```

```
# create tables from csv files
table1 = csv_to_lists("path/filename.csv")
table2 = csv_to_lists("path/filename.csv")
table3 = csv_to_lists("path/filename.csv")
table4 = csv_to_lists("path/filename.csv")
table5 = csv_to_lists("path/filename.csv")
table6 = csv_to_lists("path/filename.csv")
table7 = csv_to_lists("path/filename.csv")
table8 = csv_to_lists("path/filename.csv")
table9 = csv_to_lists("path/filename.csv")
table10 = csv_to_lists("path/filename.csv")
table11 = csv_to_lists("path/filename.csv")
table12 = csv_to_lists("path/filename.csv")

# put all tables into a list which can be iterated later
allTables = [table1, table2, table3, table4, table5, table6, table7,
table8, table9, table10, table12]


# create start data which takes all data from the first given file, later
data from other files will be added
data = {"column header": allTables[0][0],  # concept names from table1
        "array": np.array(allTables[0][1:])}  # jaccard scores from table1


### add tables together into one

# iterate through all tables starting at the second one (first was already
read into the "data" variable)
for table in allTables[1:]:

    # go through the concept names, index 0 always entails a list of
concepts in our tables
    for concept in table[0]:
        # if the concept is not in "data" yet add a new column + row
        if concept.lower() not in data["column header"]:
            data.get("column header").append(concept.lower())  # add new
concept to "data"
            data["array"] = np.pad(data.get("array"), ((0, 1), (0, 1)),
                                   "constant")  # create new column and row
filled with zeros

    # iterate through concept names, per concept add all jaccard scores to
"data"
    for concept in table[0]:
        cIndex = data.get("column header").index(concept.lower())  # get
index of first concept in "data"

         # iterate again through concepts to get scores, with each new loop
skip already added scores
        for secConcept in table[0][table[0].index(concept):]:
            cIndexSec = data.get("column header").index(secConcept.lower())
# get index of second concept in "data"
            cellBoth = table[table[0].index(concept) + 1][
                table[0].index(secConcept)]  # cell in table with score
between 2 concepts

            # add jaccard score of two concepts, done twice at different
positions (if second concept is different)
            data["array"][cIndex][cIndexSec] += cellBoth  # add jaccard
score
            if concept != secConcept: # avoid adding own jaccard score
```

```
twice when concept and secConcept are the same
                data["array"][cIndexSec][cIndex] += cellBoth  # add score
again at opposite cell in "data"



### write data into new csv file

outfile = open("#ConceptMastertable.csv", "w", newline='')
writer = csv.writer(outfile)

# turn "data" dictionary into list of lists
finalTable = data["array"].tolist()
finalTable.insert(0, data["column header"])

for row in finalTable:
    writer.writerow(row)
outfile.close()
```

Appendix C

Python Code Creating Subject Table

```
"""
04.2021

Program for making a subject file

Note: csv tables have to be symmetrical at the diagonal and only the first
row should contain labels (no column)

The program is used for tables that contain jaccard scores of different
concept combinations. From each table only the diagonal subject score is
taken and filled in for each concept combination twice (mirrored). If one
of the two concepts in the combination has a smaller subject number, the
smaller number is filled in.

The resulting file helps later when calculating distance functions.

Author: Pia Elsasser
"""


import csv
import numpy as np



### read csv data into a table(list of lists) and change values from type
string to float


def csv_to_lists(filename):
    infile = csv.reader(open(filename))
    table = []
    for row in infile:
```

```
        table.append(row)
    for r in range(1, len(table)):
        for c in range(len(table[0])):
            table[r][c] = float(table[r][c])
    return table



# create tables from csv files

table1 = csv_to_lists("path/filename.csv")
table2 = csv_to_lists("path/filename.csv")
table3 = csv_to_lists("path/filename.csv")
table4 = csv_to_lists("path/filename.csv")
table5 = csv_to_lists("path/filename.csv")
table6 = csv_to_lists("path/filename.csv")
table7 = csv_to_lists("path/filename.csv")
table8 = csv_to_lists("path/filename.csv")
table9 = csv_to_lists("path/filename.csv")
table10 = csv_to_lists("path/filename.csv")
table11 = csv_to_lists("path/filename.csv")
table12 = csv_to_lists("path/filename.csv")




# put all tables into a list which can be iterated later

allTables = [table1, table2, table3, table4, table5, table6, table7,
table8, table9, table10]



# create start data which takes all data from the first given file, later
data from other files will be added

data = {"column header": allTables[0][0],  # concept names from table1
        "array": np.array(allTables[0][1:])}  # jaccard scores from table1


data["array"][data["array"] != 0] = 0   # keep the size of the array but
change all values to 0


for table in allTables: # go through all tables and add the subject numbers
to "data"


    # go through the concept names, index 0 always entails a list of
concepts in our tables


    for concept in table[0]:
        # if the concept is not in "data" yet add a new column + row
        if concept.lower() not in data["column header"]:
            data.get("column header").append(concept.lower())   # add new
concept to "data"


            data["array"] = np.pad(data.get("array"), ((0, 1), (0, 1)),
                                   "constant")
```

```
    for concept in table[0]:
        cIndex = data.get("column header").index(concept.lower())   # get
index of first concept in "data"


         # iterate again through concepts to get scores
        for secConcept in table[0]:
            cIndexSec = data.get("column header").index(secConcept.lower())
# get index of second concept in "data"


            # get subject number of first concept in table
            subjects1 = table[table[0].index(concept) + 1][
                table[0].index(concept)]


            # get subject number of second concept in table
            subjects2 = table[table[0].index(secConcept) + 1][
                table[0].index(secConcept)]



            if subjects1 < subjects2:    # always add the smaller subject
number for a concept combination


                data["array"][cIndex][cIndexSec] += subjects1
            else:
                data["array"][cIndex][cIndexSec] += subjects2




### write data into new csv file


outfile = open("#VoxelSubjectTable.csv", "w", newline='')
writer = csv.writer(outfile)


# turn "data" dictionary into list of lists
finalTable = data["array"].tolist()
finalTable.insert(0, data["column header"])


for row in finalTable:
    writer.writerow(row)
outfile.close()
```

Appendix D

Python Code Converting Raw Jaccard Scores

```
"""
03.2021

Program for converting a table with raw jaccard scores into decimal
fractions

Note: csv tables has to be symmetrical at the diagonal and only the first
row should contain labels (no column)

Takes 2 tables: Raw score table and subject table

Values are divided by number of participants. Values of 0 stay 0, diagonal
scores are changed to 1

Author: Pia Elsasser
"""


import csv
import numpy as np


### read csv data into a table(list of lists) and change values from type
string to float


def csv_to_lists(filename):
    infile = csv.reader(open(filename))
    table = []
    for row in infile:
        table.append(row)
    for r in range(1, len(table)):
        for c in range(len(table[0])):
            table[r][c] = float(table[r][c])
    return table



filename_concepts = "#VoxelCardSortingSum.csv"
filename_subjects = "#VoxelSubjectTable.csv"
tableRaw = csv_to_lists(filename_concepts)
subjectTable = csv_to_lists(filename_subjects)


data = {"column header": tableRaw[0],  # concept names from tableRaw
        "array": np.array(tableRaw[1:])}  # jaccard scores from tableRaw

### convert values

# iterate through concepts


for concept in data["column header"]:
    cIndex = data.get("column header").index(concept)
```

```
    # iterate again through concepts to get scores, with each new loop skip
already converted scores

    for secConcept in data["column header"]: #[data.get("column
header").index(concept):]:
        cIndexSec = data.get("column header").index(secConcept)  # get
index of second concept in "data"
        nParticipants = subjectTable[subjectTable[0].index(concept) + 1][
                subjectTable[0].index(secConcept)]   # number of subject
for concept combination


        if nParticipants == 0: # keep value of 0
            continue


        # convert values by dividing them by the respective number of
participants


        else:
            data["array"][cIndex][cIndexSec] =
round(data["array"][cIndex][cIndexSec] / nParticipants, 4)





### write data into new csv file

outfile = open("#VoxelDecimal.csv", "w", newline='')
writer = csv.writer(outfile)


# turn "data" dictionary into list of lists

finalTable = data["array"].tolist()
finalTable.insert(0, data["column header"])


for row in finalTable:
    writer.writerow(row)
outfile.close()
```

Appendix E

Creating data set with voxel locations

```
"""
05.2021

Program for making a file that contains the location/voxel for concept
combinations and their score
Note: csv tables have to be symmetrical at the diagonal and only the first
row should contain labels (no column)
Voxeltable has to consist of 2 rows, header with labels and second row with
voxels

The program sorts concept combinations into 2 lists based on if their
locations are the same or not. Concept names,
voxels and scores are collected.
Additionally a list is created that denotes each combination with either 0
or 1 and their respective jaccard score.
This is done to be able to use the data in spss.


Author: Pia Elsasser
"""

import csv
import itertools as itt
import matplotlib.pyplot as plt


### read csv data into a table(list of lists) and change values from type
string to float

def csv_to_lists(filename):
    infile = csv.reader(open(filename))
    table = []
    for row in infile:
        table.append(row)
    for r in range(1, len(table)):
        for c in range(len(table[0])):
            table[r][c] = float(table[r][c])
    return table


filename_concepts = "#VoxelDecimal.csv"
filename_subjects = "#VoxelSubjectTable.csv"
filename_voxel = "#CardSortVoxelTable.csv"
tableRaw = csv_to_lists(filename_concepts)
subjectTable = csv_to_lists(filename_subjects)
voxelList = []

# read voxelTable and keep type string
infile = csv.reader(open(filename_voxel))
for row in infile:
    voxelList.append(row)


sameList = [[],[],[]]        # collect concept combinations with same
location and their scores
diffList = [[],[],[]]        # collect concept combinations with differing
locations and their scores
```

```
voxelCategory = [[],[]]      # notes either a 1 or 0 if combinations have
the same location or not, also collects scores
                            # -> can later be used for a dataset in spss

conceptCategory = []

betweenVonlyCategory = []

betweenVinterCategory = []


### sort combinations into the respective list

index1 = 0     # counter used as index for first concept, avoids instances
where a concept is missed because it appears
              # more than once in voxelList (but with different location)

# iterate through concepts in voxelList
for concept in voxelList[0]:

    index2 = 0 # counter used as index for second concept, resets every
loop

    cVoxel = voxelList[1][index1] # get voxel of first concept

    # iterate again through concepts to get scores, with each new loop skip
already covered concepts
    for secConcept in voxelList[0][index1:]:
        cVoxelSec = voxelList[1][index1:][index2]  # get voxel of second
concept
        #nParticipants = 41
        nParticipants = subjectTable[subjectTable[0].index(concept.lower())
+ 1][
               subjectTable[0].index(secConcept.lower())]    # number of
subjects for concept combination
        cellBoth = tableRaw[tableRaw[0].index(concept.lower()) + 1][
                tableRaw[0].index(secConcept.lower())]   # cell in table
with score between 2 concepts

        if nParticipants != 0:    # only use real scores, subject number
above 0

            if concept.lower() != secConcept.lower():  # skip concept
paired with itself, e.g apple-apple

                if cVoxel == cVoxelSec:    # if voxel locations are the same
append concepts to sameList

                    sameList[0].append(concept + "-" + secConcept) #
concepts names
                    sameList[1].append(voxelList[1][index1])       # voxel
                    sameList[2].append(cellBoth)                   #
jaccard score

                    voxelCategory[0].append(1)                     # note a
1 if the location is the same
                    voxelCategory[1].append(cellBoth)              #
jaccard score
                    conceptCategory.append(voxelList[2][index1])   # add
category name
```

```
                else:    # if voxel locations are different append concepts 
to diffList

                    diffList[0].append(concept + "-" + secConcept)
                    diffList[1].append(voxelList[1][index1]+ "-" + 
voxelList[1][index1:][index2])
                    diffList[2].append(cellBoth)

                    voxelCategory[0].append(0)                      # note a 
0 if location is different
                    voxelCategory[1].append(cellBoth)

                    if voxelList[2][index1] == 
voxelList[2][index1:][index2]:  # if word category is the same
                        conceptCategory.append(voxelList[2][index1]) 
# add category name
                        betweenVonlyCategory.append(cellBoth)
                    else:
                        conceptCategory.append(0) 
# add 0 if categories are different
                        betweenVinterCategory.append(cellBoth)

        index2 += 1
    index1 += 1



### write data into new csv file

outfile = open("VoxelLocationDataExtra2.csv", "w", newline='')
writer = csv.writer(outfile)
header = ["CSameLocation", "SVoxel", "SJaccardScore", "CDifferentLocation",
          "DVoxel", "DJaccardScore", "Category", "allScores", "Group", 
"betweenVonlyCategory", "betweenVinterCategory"]

writer.writerow(header)

# zip lists so that they appear as columns in the csv file
rows = itt.zip_longest(sameList[0], sameList[1], sameList[2], diffList[0],
                       diffList[1], diffList[2], voxelCategory[0], 
voxelCategory[1], conceptCategory,
                       betweenVonlyCategory, betweenVinterCategory)

for row in rows:
    writer.writerow(row)

outfile.close()
```

Appendix F

Calculating the distance function

```
"""
Created 29-3-2021

Program for calculating distance function on card sorting data
Distance function: d(a, b) = -log(x)
NB: log(x) = ln(x)
x = relative (weigthed) Jaccard score for (a, b)
Zero Jaccard score for (a, b):
Real zero scores:
d(a, b) = -2*log(0.0001)

Default zero score (no data available):
Ignore d(a, b)
"""

import numpy as np
import pprint


N = 343  # number of words in card sorting

DM = np.zeros((N,N))                 # distance between items in card sorting

Result = [] # list that collects results

# read cardsorting data
data = np.genfromtxt('#ConceptMastertableDecimal.csv', delimiter = ",")
# read data file
data = np.asarray(data[1:])     # only use jaccard scores, ignore first row
with concepts
card_sort = data.copy()

subjectData = np.genfromtxt('#SubjectTable.csv', delimiter = ",")      #
read subject data file
subjectData = np.asarray(subjectData[1:])
subjects = subjectData.copy()

# Real zero distance (a, b) = 0:
D_zero  = -2*np.log(0.0001)        # Value distance if  x = 0


# Distance based on: -ln(x)  with x = relative score card sorting,
# check if score is real (based on an actual jaccard score)
# If not: mark distance (a, b) in DM. E.g. DM(a, b) = - 1. These scores can
be ignored later on
for i in range(N):
    for j in range(N):
        if subjects[i, j]== 0:  # indicates no data for the word
combination
            DM[i,j] = -1
        elif card_sort[i, j]== 0:  # actual jaccard score of 0 in the table
            DM[i,j] = D_zero
        else:
            DM[i,j] = -np.log(card_sort[i, j])
```

```
# Search for violations of rule d(a,b) <=  d(a,c) + d(c,b)
# Needs adapting: use only real jaccard scores for all three distances
(none of them = -1)

Distance = 0.0
Sum = 0.0
Score = 0
Count = 0


for i in range(N-1):
    k = i + 1
    for j in range(N):
        if j < k:            #DM is symmetrical. Search in lower triangle
of matrix
            Distance = DM[k,j]
            if Distance == -1:   # a score of -1 is not used
                continue

            for p in range(N):
                if DM[k,p] == -1 or DM[p,j] == -1:  # a score of -1 is not
used
                    continue

                if p!=k and p!=j:
                    Count = Count + 1
                    Sum = DM[k,p] + DM[p,j]

                    if Distance > Sum:
                        Result.append([])
                        Result[Score].append(k)
                        Result[Score].append(j)
                        Result[Score].append(p)
                        Result[Score].append(DM[k,j])
                        Result[Score].append(DM[k,p])
                        Result[Score].append(DM[p,j])
                        Result[Score].append(Sum)
                        Result[Score].append(Distance - Sum)
                        Score = Score + 1


outfile = open('Distance violations.txt', 'w')

outfile.write(" %6s "  % "a")
outfile.write(" %6s "  % "b")
outfile.write(" %6s "  % "c")
outfile.write(" %12s "  % " d(a,b)")
outfile.write(" %12s "  % " d(a,c)")
outfile.write(" %12s "  % " d(c,b)")
outfile.write(" %19s "  % " d(a,c) + d(c,b)")
outfile.write(" %28s "  % " d(a,b) - (d(a,c) + d(c,b))")
outfile.write("\n" * 2)


for i in range(Score):
    outfile.write(' %6d '  % Result[i][0])
    outfile.write(' %6d '  % Result[i][1])
    outfile.write(' %6d '  % Result[i][2])
    outfile.write(' %12.4f '  % Result[i][3])
    outfile.write(' %12.4f '  % Result[i][4])
    outfile.write(' %12.4f '  % Result[i][5])
    outfile.write(' %14.4f '  % Result[i][6])
```

```
    outfile.write(' %22.4f '  % Result[i][7])
    outfile.write('\n')

outfile.close()
```

Appendix G
Informed Consent Form

Informed Consent

Dear participant,

This study aims to gain information about how concepts and conceptual spaces are learned. Therefore, it involves a card sorting task in which you will sort different words into groups. This will take about 10-20 minutes. You can withdraw at any time.

If you have any questions or concerns about this study, you can contact me at p.l.elsasser@student.utwente.nl

All data is kept anonymously and personal information will not be passed on to third parties under any condition. Under no circumstances will any personal data or identifying information be included in the report of this research. Nobody, except the researcher and the supervisor will have access to the anonymized data in its entirety. Participation in this study is voluntarily and you can withdraw at any time. This research project has been reviewed and approved by the BMS Ethics Committee.

Appendix H

Concept List

Table Voxel Selection

Nr	Words	Category	Voxel	Brain area	Reliability
1	loudly	mental	[22,20,42]	right, prefrontal cortex	Good, very reliable
2	laughing	mental	[22,20,42]	right, prefrontal cortex	Good, very reliable
3	calmly	mental	[22,20,42]	right, prefrontal cortex	Good, very reliable
4	startled	mental	[22,20,42]	right, prefrontal cortex	Good, very reliable
5	doubtful	mental	[15,32,75]	Left ventrolateral frontal cortex	Good, very reliable
6	understood	Mental	[15,32,75]	Left ventrolateral frontal cortex	Good, very reliable
7	reasons	Mental	[15,32,75]	Left ventrolateral frontal cortex	Good, very reliable
8	lack	Mental	[15,32,75]	Left ventrolateral frontal cortex	Good, very reliable
9	refused	social	[15,80,27]	right, parietal cortex	Good, very reliable
10	died	social	[15,80,27]	right, parietal cortex	Good, very reliable
11	parent	social	[15,80,27]	right, parietal cortex	Good, very reliable
12	attend	social	[15,86,67]	Left occipital lobe	Excellent, extremely reliable
13	home	social	[15,86,67]	Left occipital lobe	Excellent, extremely reliable
14	visit	social	[15,86,67]	Left occipital lobe	Excellent, extremely reliable
15	Halfway	Outdoor	[18,82,57]	Left occipital lobe	Good, very reliable

16	Moonlight	Outdoor	[18,82,57]	Left occipital lobe	Good, very reliable
17	Scenery	Outdoor	[18,82,57]	Left occipital lobe	Good, very reliable
18	clouds	outdoor	[15,17,29]	right, prefrontal cortex	Good, very reliable
19	waves	outdoor	[15,17,29]	right, prefrontal cortex	Good, very reliable
20	drifting	outdoor	[15,17,29]	right, prefrontal cortex	Good, very reliable
21	suffering	violence	[9,49,21]	Right temporal lobe	Good, very reliable
22	tortured	violence	[9,49,21]	Right temporal lobe	Good, very reliable
23	cured	violence	[9,49,21]	Right temporal lobe	Good, very reliable
24	Innocent	violence	[24,25,54]	Frontal lobe, left	Good, very reliable
25	Contempt	violence	[24,25,54]	Frontal lobe, left	Good, very reliable
26	Harm	violence	[24,25,54]	Frontal lobe, left	Good, very reliable
27	grip	tactile	[19, 67, 77]	LH	Excellent
28	limbs	tactile	[19, 67, 77]	LH	Excellent
29	thinner	tactile	[19, 67, 77]	LH	Excellent
30	technique	tactile	[19, 67, 77]	LH	Excellent
31	blades	tactile	[19, 67, 77]	LH	Excellent
32	smooth	tactile	[21,67,25]	right, parietal cortex	Good, very reliable
33	soft	tactile	[21,67,25]	right, parietal cortex	Good, very reliable
34	shapes	tactile	[21,67,25]	right, parietal cortex	Good, very reliable
35	melting	Tactile	[21,67,25]	right, parietal cortex	Good, very reliable
36	solid	tactile	[21,67,25]	right, parietal cortex	Good, very reliable
37	days	Time	[6,41,23]	RH, temporal lobe	Good, very reliable
38	next	Time	[6,41,23]	RH, temporal lobe	Good, very reliable
39	weekend	Time	[6,41,23]	RH, temporal lobe	Good, very reliable

40	hours	Time	[6,41,23]	RH, temporal lobe	Good, very reliable
41	trip	Time	[6,41,23]	RH, temporal lobe	Good, very reliable
42	Apartment	Time	[15, 75, 44]	RH	Excellent
43	Home	Time	[15, 75, 44]	RH	Excellent
44	Hotel	Time	[15, 75, 44]	RH	Excellent
45	Rented	Time	[15, 75, 44]	RH	Excellent
46	school	Time	[15, 75, 44]	RH	Excellent

Appendix I

R Script for Vector Analysis of Clusters

```
# R script to generate a heatmap
# Call these libraries. They need to be installed as packages
library(gplots)
library(RColorBrewer)

# Read the data file
data <- read.csv("path/filename")

# Transform data in numerical format
mat_data <- data.matrix(data[,1:ncol(data)])

# Define colors of heatmap: red for high numbers
my_palette <- colorRampPalette(c("yellow","red"))(n = 393)

# Call heatmap function (from gplots), with these arguments
# See:
https://www.rdocumentation.org/packages/gplots/versions/3.0.1/topics/heatmap.2
# Note: argument 'main=' gives name of plot
heatmap.2(mat_data, col = my_palette, density.info="none", trace="none", revC = TRUE,
main="Name")
```