

How the brain finds meaning: A representational similarity analysis of semantic similarity in EEG and pareidolia

Student: Marius Wolf

Matrikelnummer: 108015265856

Date: 13.05.2018

Degree program: Cognitive Science, M.Sc., Ruhr-Universität Bochum

Supervisor: Dr. Marie-Christin Fellner

2nd supervisor: Prof. Dr. Nikolai Axmacher

Table of Content

1. Introduction	p.1
2. Methods	p.5
3. Results	p.14
4. Discussion	p.25
Appendix	
References	
Eidesstattliche Erklärung	

Abstract

The thesis analyzes semantic processing in temporal generalization matrices of an EEG-signal in pareidolia. Pareidolia is the process of projecting meaning into abstract shapes (like seeing something meaningful in the clouds). Stimuli were abstract shapes that were rated by the subjects either as meaningless or meaningful. In the later case the subjects were asked to describe the stimuli briefly. The analyzes showed that the correlation between meaningful stimuli with each other is higher, than the correlation of meaningless stimuli with each other. Thus, the temporal generalization matrices of the EEG-signal encode the difference between meaningful and meaningless processing. This holds for frequencies lower than 30Hz but not higher than 30Hz. To assess whether the EEG does not only capture the difference between the meaningful and meaningless condition but as well fine-grained differences in meaning, a representational similarity analysis (RSA) was conducted between the similarity of the stimuli descriptions and temporal generalization matrices of the EEG-signal. The semantic similarity between the stimuli descriptions was assessed using two different measures: word2vec and the Normalized Google Distance (NGD). It showed that differences in meaning between the stimuli are encoded over the whole frequency spectrum of the EEG when NGD is used as a measure of semantic similarity but not when word2vec is used. This is surprising because the two measures of semantic similarity correlate with each other. Moreover, we discussed the finding that the encoding of differences in meaning are found in all frequencies, while in literature semantic processing is mostly related to frequencies below 30Hz.

1. Introduction

Research on how the brain processes semantic information has found different ways in which semantic similarity of words is encoded. EEG-studies identified several oscillatory networks that encode different semantic categories (Baroni 2009; Hald 2005; Behroozi 2015, Cichy 2016). Moreover, fMRI-studies could identify several regions related to the ventral stream that are particularly involved in encoding semantic similarity between words (Carota 2017; Fairhall 2013; Carlson 2014). Using single-cell recording, de Falco (2016) could show that semantic differences between words can as well be decoded from the single-cell level. The stimuli that were used in all aforementioned studies were either written or pictorial representations of real-world objects (e.g. human faces, animals or food).

This master thesis uses abstract minimalistic geometrical shapes known as squiggles as stimuli in order to analyze semantic processing. As de Falco (2016) argues, processing symbolic or iconic representations is affected by the familiarity and visual similarity of the stimuli. To avoid these confoundations and thus to capture semantic processing better, Voss (2009) suggested to use the squiggles as stimuli.

In a previous EEG-study (Bauer 2018) in which the data for this study was collected, the squiggles were shown to participants and they had to rate, whether they consider them to be

meaningful or not. If they rated a squiggle as meaningful they were asked to describe it in a few words. This can be compared to looking in to the sky and projecting meaning into the clouds. While some clouds do not evoke any meaningful association, into others one can project a meaning. The process of projecting meaning into meaningless shapes is called pareidolia.

As the results of Bauer (2018) and Voss (2009) show, the processing of meaning can be captured with the use of squiggles. Bauer (2008) showed that there is a significant decrease in power in α and β -bands when squiggles were rated meaningful compared to the meaningless condition. In addition, in γ -bands no change in power was found, while there was a slight increase in θ -bands. This is in accordance with studies that relate the processing of meaning to α and β -bands (Weiss 2012; Spironelli 2008; Klimesch 2001). Moreover, Voss (2009) showed that squiggles which are rated as meaningful induce conceptual priming while meaningless squiggles induce only perceptual priming.

While in the previous study and as well in Voss (2009) an univariate approach was used, in this study a multivariate pattern analysis is used (Hebart 2017; Kriegeskorte 2008). The multivariate framework of representational geometry is based on the concepts of representational space and representational distance. In a representational space the relation between any set of stimuli can be represented as a geometrical structure. The geometrical structure requires a distance measure that quantifies the relation between the stimuli. If the geometrical structures of a set of stimuli in two different spaces correlate with each other, it can be concluded that both structures represent the same properties of the stimuli. In terms of EEG-data and semantic similarity this means the following: If the relation between our stimuli as represented in a semantic space correlates with the relation of the stimuli as represented in the EEG-signal, it can be concluded that the EEG-signal encodes fine grained differences in meaning. An analysis based on representational geometry is called representational similarity analysis (RSA) (Kriegeskorte 2008).

Representational geometry has been widely used for research that is interested in the amount of mutual information between semantic stimuli and neuronal activation patterns, both using fMRI (Carota 2017; Fairhall 2013; Carlson 2014) and EEG (Cichy 2016). An advantage of the multivariate approach over the univariate approach is, that the former is able to analyze gradual differences in meaning on a fine-grained level, while the later can only distinguish between the meaningful and meaningless condition. In the multivariate approach the semantic distance between two words (e.g. “walk” and “run”) and the distance in neural activity as rec-

ordered by an EEG can be compared. Using a multivariate approach, Cichy (2016) found that the time-course of EEG signals carries information at the level of single objects and of object categories. The stimuli were either written or pictorial representation of real-world objects.

In my master thesis I investigate within the framework of representational geometry how semantic information in pareidolia is encoded in the time domain of an EEG signal. The thesis is based on data that was generated in a previous study by Bauer (2018). In that study each subject had to rate 120 squiggles on a 4-point scale from meaningful to meaningless. If a squiggle was rated as meaningful, the subject was requested to describe it verbally.

In order to assess the semantic similarity between the description of the squiggles two different measures were used: the Normalized Google Distance (NGD) (Cilibrasi 2007; de Falco 2016) and word2vec (Mikolov 2013). Both are based on the distributional approach of semantic meaning, that states that the meaning of a word can be derived by analyzing the context in which the word is used (Landauer and Dumais 1997).

Kriegeskorte (2013) argues that different measures of the representational geometry of the stimuli capture different properties of the stimuli and consequently correlate differently with the representational geometry of the neural code. While a measure might be more intuitive to humans or is more suitable for everyday applications, it can be that this measure is not correlating with the brain data. On the other hand, a measure that has worse results for everyday applications might still correlate high with the brain data, because it captures semantics in the way it is encoded in the brain. One measure can consider “hot” and “cold” to be very distant in a semantic space, because they mean the opposite. Another semantic measure can consider them to be highly similar because both are related to temperature. The same holds for the brain. One can assume that “hot” and “cold” elicit very different EEG-patterns, but it as well be reasonable to assume that they elicit similar patterns. Thus, finding a measure of the representational geometry of the semantic stimuli that matches the representational geometry of the brain is considered to be an advance (Kriegeskorte 2013).

First, we hypothesize that NGD and word2vec correlate with each other (**hypothesis 1**), since both are distributional measures of semantic similarity.

We expect as well to be able to find item-specific information in the time domain of the EEG-signal (**hypothesis 2**). Item-specific information is present when the EEG-patterns of trials that belong to the same meaningful squiggle correlate higher with each other, than with the

patterns of trials that belong to other meaningful squiggles. The presence of item-specific information would as well support the results of the univariate analysis (Bauer 2018), that there is a difference between the meaningful and meaningless condition. As in the univariate analysis (Bauer 2018), we expect to find the item-specific information in the α , β and θ -bands and not in the γ -bands (**hypothesis 3**).

The multivariate item-specific analysis remains on the same coarse grain level as the univariate analysis. It can only show us that the EEG-signal encodes meaning in some way, but it cannot answer the question if (and which) differences in meaning are encoded in the EEG-signal. Moreover, the item-specific analysis can be confounded with lower level cognitive processes (e.g. the mere recognition that there is something happening on the screen), eye-saccades (Yuval-Greenberg 2008) or most importantly other higher cognitive processes that are involved in pareidolia (such as imagination).

These problems can be solved all at once by conducting a multivariate analysis, that relates the representational space of semantic similarity of stimuli to the representational space of neuronal activation patterns. We therefore can test our main hypothesis, that differences in meaning are encoded in the time domain of the EEG-data (**hypothesis 4**). In the words of representational geometry, we test whether the structure of the representational geometry of the semantic similarity correlates with the structure of the representational geometry of the time domain of the EEG-data. We use two different measures of semantic similarity. Since both follow the distributional approach, we expect them to relate in a similar way to the representation of semantic meaning in the neural code (**hypothesis 5**). In accordance with the previous study we expect that the differences in meaning are encoded in α , β and θ -bands and not in the γ -bands (**hypothesis 6**).

2. Methods

2.1 Subjects

The master thesis made use of the data that was collected in a previous study (Bauer 2018). The study was approved by the Ethical Review Board of the Ruhr-Universität Bochum. Behavioral and electrophysiological data were collected from 20 Ruhr-Universität students (age 18-32, $M = 24.1$, $SD = 3.97$, five were male), after informed written consent was obtained (in accordance with the Declaration of Helsinki). The students received no monetary compensation, but research participation credits were offered. All participants were native German speakers, right-handed, had normal or correct-to-normal vision and reported no history of neurological or psychiatric diseases.

2.2 Materials

The visual stimuli consisted out of 240 minimalistic visual shapes (Fig. 1) known as “squiggles” (Voss 2011). They were created by freehand distortion out of the basic shapes of square, triangle and circle (Groh-Bordin 2006). Two experimental lists of 120 squiggles were created according to the relative frequency of meaningful ratings reported by Voss (2011). In each list the number of squiggles that were rate as meaningful with high frequency was balanced with those that were rated meaningful with low frequency. Each list was presented to half of the participants. Moreover, additional five squiggles were shown only in a training phase.

The squiggles were presented in the center of a computer monitor in white on black background. Each squiggle had a size of approximately 9 x 9 cm resulting in a visual angle of approximately 5 x 5°.



Fig. 1: Three examples of the 240 squiggles

2.3 Behavioral paradigm

In the previous study 20 people participated (aged between 18 and 32, $M=24.1$, $SD=3.97$, five were male). One list with 120 squiggles was presented to one half of the participants, the other list to the other half. The experiment consisted of six rating blocks and one naming block.

In each of the six rating block the participants had to rate every squiggle on a 4-point scale where 1 indicated meaningless and 4 meaningful. In the rating blocks 120 squiggles were presented in a randomized order. Each trial began with a fixation cross for a randomized time interval of 1500 and 2000ms. Afterwards a squiggle was presented for 1000ms, followed by another fixation cross for 500ms. The trial ended with a rating screen that was shown for 1000ms.

In the naming block all 120 squiggles were presented in a pre-randomized order to each participant. Each trial started with the presentation of a fixation cross for a randomized time interval of 1000-1500ms, followed by the presentation of a squiggle for 1500ms. Then a fixation cross was presented for 500ms, followed by a question mark for 10s. In these 10s the participants were asked to name or describe the squiggle briefly (Figure 2).

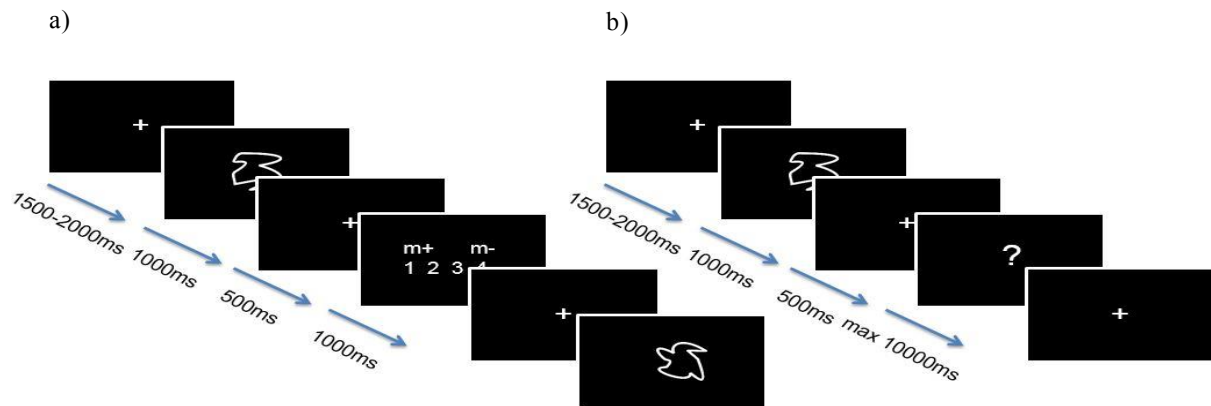


Fig. 2: A) Exemplified trial of the rating task (120 squiggles x 6 blocks)

B) Exemplified trial of the naming task (120 squiggles x 1 block)

Adapted from Bauer (2018). Adapted with permission.

2.4 Human EEG recordings and data preprocessing

A 64-channel Standard Brain Cap with Multitrodes (EasyCap GmbH, Hersching, BAV, Germany) was used to record the electrophysiological data. The Ag/AgCl centered electrodes were placed on the scalp on a 10-20 extended montage. The electrooculogram (EOG) was recorded by one electrode placed below the right eye. The recordings were referenced online

to FCz and re-referenced to average reference offline. Impedances were maintained below 30k Ω . The signals were sampled at 500Hz and amplified between 0.1 and 1000Hz.

Data preparation and EEG preprocessing was done in MATLAB (Release 2016b, The MathWorks, Inc., Natick, Massachusetts, United States) by using the Fieldtrip toolbox (Oostenveld et al. 2011) and customized MATLAB scripts.

The continuous EEG-signal was segmented into epochs of 6s, starting 2s before stimulus onset and ending 4s after stimulus onset. 50Hz line noise was removed from the segmented data by applying a notch filter. Artefact correction consisted out of three steps. First, in a visual inspection, epochs with short and severe muscle or movement artefacts were rejected. Epochs with EOG artefacts were kept, unless the duration of the blink (or eye movement) and the proximity to the stimulus presentation indicated that the participant might not have been engaged in the task. Second, independent sources of variance were isolated by using an Independent Component Analysis (ICA). Isolated components that contained EOG artefacts, sustained muscle artefacts or drift artefacts (based on time courses, topographies and frequency spectra) were removed from the signal (Jung et al. 2000). An average of 4.3 (range: 1-8) identified artefact components were discarded. Third, in a visual inspection, epochs with residual artefacts in a time window between -1s to 2s around stimulus onset were rejected. By calculating a weighted average of all neighbor electrodes, faulty electrodes or missing channels were interpolated.

2.5 Measures of semantic similarity

In order to assess the semantic similarity between the description of the stimuli, two models of semantic relatedness were implemented: the normalized google distance (NGD) and word2vec. Both models follow the distributional hypothesis of semantic meaning, which states that the meaning of a word is generated by its usage in society (Landauer and Dumais 1997). The models try to derive the meaning of a word by analyzing the frequency and context of occurrence of the word in large text corpora.

For each measure of semantic similarity the distance between all pairs of stimuli descriptions are calculated. From that a representational dissimilarity matrix (RDM) is constructed for each distance measure (Fig. 4b). Each entry of a RDM is a scalar value that quantifies the distance between a pair of stimuli according to the semantic measure (Fig. 4c) (Carlson et al 2014). In terms of representational geometry, the RDMs form the geometrical structures, that are compared with each other. The semantic RDMs are later compared to the RDM of the

EEG-signal. If they correlate with each other one can conclude that the EEG-signal encodes differences in meaning (see chapter 2.7).

The descriptions of the squiggles were either single words ('dog') or compounds of words ('brown dog, that barks'). While NGD is able to analyze the similarity of compounds, word2vec is not. To make the results of the NGD and word2vec comparable, we created a decoding schema and decoded all compounds into single words (see the appendix for more details about the decoding schema). After decoding a total of 225 different search terms remained.

2.5.1 NGD

The NGD (Cilibrasi 2007) makes use of the world-wide-web, which is the largest database on earth, in order to collect the information about the context in which a word is used. The basic notion is that if two words are used frequently on the same webpage, then they are likely to be similar. In order to calculate the NGD for two search terms, the frequency of the joint occurrence ("hits") of two search terms on a web page has to be related to the hits of each single search term by following formula:

$$\text{NGD}(x, y) = (\max\{\log f(x), \log f(y)\} - \log f(x, y)) / (\log N - \min\{\log f(x), \log f(y)\})$$

$f(x)$ and $f(y)$ denotes to the number of pages containing x and y respectively. $f(x,y)$ denotes the number of pages containing both x and y . N denotes the total number of pages indexed by Google. Since the formula is scale-invariant w.r.t. to N , one can replace it with any normalization constant bigger than the highest number of hits of either $f(x)$, $f(y)$ or $f(x,y)$. As suggested by Cilibrasi (2007), we choose $N=35200e+09$.

The RDM for the 225 search terms (25425 pairs of terms in total) was created with MATLAB (Release 2018b, The MathWorks, Inc., Natick, Massachusetts, United States) over several days on several computers, because Google allows only a maximum of around 500 search queries per IP-address per day. Bing or other search engines are not an alternative to Google, because they have an upper limit on the number of results per query and therefore the results for search terms with a lot of results are distorted.

2.5.2 word2vec

The word2vec model was developed by Mikolov (2013) and is an efficient algorithm for

learning word embeddings. The notion of word embeddings follows the distributional hypothesis of meaning but in a different way than the NGD does. While the NGD is purely count-based in the sense that it counts only the co-occurrence of words in a whole document (webpage), word2vec only considers the direct environment of the word, that means those words, that are directly left or right to it in the text. In order to do so, a neural network analyzes a large text corpus and learns the embedding for each word. Once the neural network has learned the embedding for all words in the text corpora of interest, one can use them to assess semantic similarity between them.

Since training a neural network for word embeddings can take several days or even weeks we used a pretrained neural network from Müller (2015) (it can be downloaded from: <https://github.com/devmount/GermanWordEmbeddings>, Retrieved April 25, 2018). The neural network is implemented in Python, therefore the semantic dissimilarity matrix was constructed in Python (Python, Anaconda 3) and then converted to MATLAB for further analysis.

2.5.3 Statistical significance and clustering

We correlated the RDM of word2vec and of NGD with each other to see if they are related. **(hypothesis 1)**. For correlation we used Kendalls Tau (Kriegeskorte 2008). To check statistical significance a permutation test was applied (Kriegeskorte 2008). The labels of one RDM were shuffled randomly and then the two RDMs were correlated again. Repeating this 1000 times creates a null-distribution of correlation values that simulate the null hypothesis, that the RDM are not correlated. For a significance level of 0.05, we can reject the null hypothesis, if the original correlation value is bigger than 950 out of 1000 shuffled correlation values.

2.6 Representational similarity analysis: Item-specific

We hypothesize that there is item-specific information in the EEG-signal (**hypothesis 2**), that means we expect that the EEG-pattern of trials that belong to the same stimulus correlate higher with each other, then with trials that belong to a different stimulus. We were interested in the time-domain of the EEG-signal and therefore constructed a temporal generalization matrix (Dehaene 2014) for each subject and then analyzed them in the multivariate framework of representational similarity analysis (RSA) (Kriegeskorte et al. 2008). Within the framework

of RSA a temporal generalization matrix can serve as a representational dissimilarity matrix (Dehaene et al. 2014).

Following the temporal generalization method, the EEG-signal of each trial is split into small time bins with the size of a few hundred milliseconds. Every time bin of every trial is correlated with every other time bin of every other trial. Thus, the first time bins of all trials are correlated with each other and form the first entry in the temporal generalization matrix (Fig. 3). Then the first time bins of all trials are correlated with the second time bins of all trials and form the second entry of the temporal generalization matrix (Fig. 3) and so on.

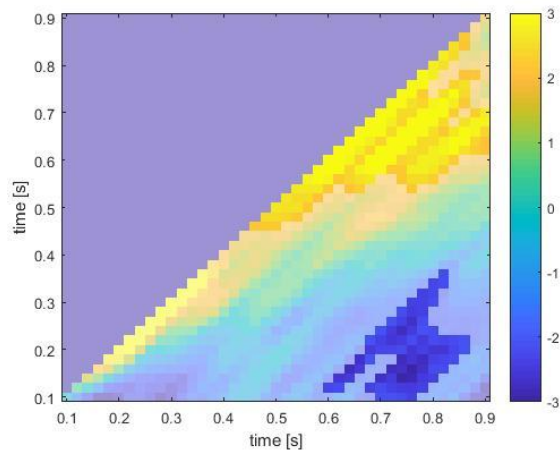


Fig 3: Example of a temporal generalization matrix. Yellow values indicate high correlation. Blue values indicate low correlation. Since temporal generalization matrices are always symmetric we only calculated one triangle of it.

The full temporal generalization matrix shows the temporal relations between all bins. The entries on the diagonal show if the same bins correlate with each other at the same point in time. In the example matrix in figure 3 there is high same bin correlation (yellow) close to the diagonal between 0.4 and 0.8s after stimulus onset. On the lower right there is negative correlation between 0.6 and 0.8s after stimulus onset. The correlation values on the off-diagonal are lower (blue) because they signify the correlations of different bins with each other. We can verify that there is item-specific information (hypothesis 3) if the correlation between values on the diagonal is significantly higher than the correlation of values on the off-diagonal.

Temporal generalization matrices are particularly useful for analyzing semantic processing. The time interval in which semantic processing occurs is to a certain degree variable. As Voss (2011) showed, it is influenced by priming effects. Showing a squiggle that was rated as meaningful a second or third time, might elicit semantic processing faster than at the first time. The temporal generalization method smoothes the temporal relations and is therefore to

a certain degree indifferent to the exact millisecond in which semantic processing occurs. This explains as well why not only the values that lay exactly on the diagonal of the temporal generalization matrix are high, but as well the values in proximity to the diagonal.

Creating the temporal generalization matrices

The temporal generalization matrices were created for each subject separately. The trials of each person were assigned into the groups of meaningless and meaningful according to following criteria: if a squiggle was named in the naming block, all trials of the six rating blocks in which the same squiggle was shown, were assigned to that name. All other trials were assigned to be meaningless. All further analysis was carried out on the group of meaningless and meaningful trials separately.

We resampled the data one time with 50Hz and another time with 100Hz, following the Nyquist-Shannon theorem (Shannon 1949). While resampling rate of 50Hz captures slowly varying signals better, 100Hz can extract information from faster changing signals. In order to reduce ERP-driven non-stimulus specific correlations, we z-transformed the data.

We defined the time of interest to be between 0 - 1 seconds after stimulus onset and restricted further analysis to that interval. This is in accordance with studies that suggest that semantic processing can be found in that time interval (Cichy 2017; Voss 2010).

The bins of the temporal generalization matrix were constructed with a sliding window of size 0.2 seconds and a slide of size 0.02 seconds on the full range of the EEG-signal. One entry in the temporal generalization matrix is constructed by correlating one sliding window over all trials with another sliding window over all other trials. Consequently, the whole matrix is constructed by correlating all sliding windows over all trials with each other. For correlation we used the Spearman's rank method. A fisher z-transformation was applied which allows us to calculate the mean over the correlation coefficients. Moreover, we excluded the correlations of the trials that were assigned to the same squiggle (to one squiggle a maximum of 6 trials – one out of each rating block - could be assigned). Since temporal generalization matrices are always symmetric, we calculated only one triangular of the matrices.

To check whether item-specific information can be found at specific frequencies (**hypothesis 3**), we applied band-path filters to the signal and constructed the temporal generalization matrices separately for lower bands (1-7Hz), α and β -bands (8-30Hz) and γ -bands (30Hz and above).

Item-specific analysis and statistical significance

To check for the item-specific information we compared across all subjects the on and off-diagonal entries of the temporal generalization matrices with each other with a t-test (significance level = 0.05).

To account for the multiple comparison problem and to test for statistical significance a cluster-based permutation test was used (Oostveld 2007; Jamalabadi 2016). The on and off-diagonal entries were shuffled randomly and then they were compared with each other with a t-test (significance level = 0.05). Repeating this 1000 times gives a matrix of test statistic values that simulates the null hypothesis that there is no difference between on and off diagonal entries. A cluster test was applied to the test statistic values of the shuffled t-test to check for clusters of significant t-values. It was clustered across coherent neighboring time bins. If the sum of the t-values of the cluster of the unshuffled t-test differs significantly (significance level = 0.05) from the sum of t-values of the clusters of the shuffled t-test, we can reject the null hypothesis that the EEG-patterns for the same stimuli correlate as much with each other as the EEG-patterns of different stimuli and therefore can conclude that there is item-specific information in the temporal generalization matrix.

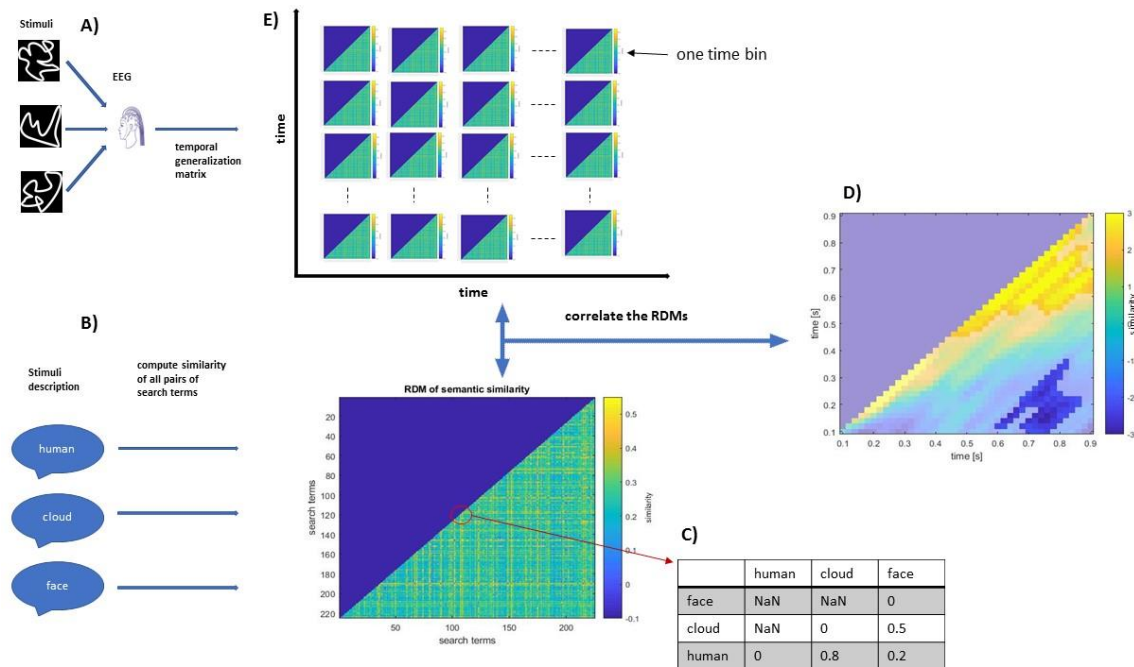


Fig. 4: Flowchart of the Representational Similarity Analysis (RSA). **A)** The stimuli elicit an EEG-response. Out of the EEG-data a temporal generalization matrix is created for each subject. **B)** The semantic similarity between all pairs of stimuli is calculated and saved into an RDM. **C)** Zoom into a part of the semantic RDM. Zero indicates that the two search terms are the same. Low values indicate that they are similar. High values indicate that they are the dissimilar. NaN=Not a Number, since the RDM is symmetric only one triangular is necessary and the rest can be NaNs **D)** The RDM of each subject is

correlated with the semantic RDM. Statistical significance is assessed across all persons with a cluster-based permutation test. **E)** At each time point of the temporal generalization matrix of the subject there is a time bin. Each time bin contains its correlation to all other time bins of the temporal generalization matrix.

2.7 RSA: semantic similarity with EEG-similarity

To analyze the relation between the semantic similarity matrix and the temporal generalization matrices of the subjects, we correlated the RDMs across all subjects with the corresponding semantic RDMs (**hypothesis 4**). The correlation values were transformed into t-values in order to test for statistical significance (Bortz 1999). On the t-map a two-sample dependent t-test (significance level = 0.05) was conducted. This was done one time for the NGD measure of semantic similarity and another time for word2vec (**hypothesis 5**).

To check whether specific frequencies of the EEG-signal correlate with the semantic similarity (**hypothesis 6**), we applied band-pass filters to the signal and constructed the temporal generalization matrices separately for lower bands (1-7Hz), α and β -bands (8-30Hz) and γ -bands (30Hz and above).

Statistical significance was validated with the same cluster-based permutation test (significance level = 0.05, 1000 permutations) as for the item-specific RSA (see chapter 2.6), only that this time the values of the semantic RDMs were shuffled to create the null distribution. If the sum of the t-values of the cluster of the unshuffled t-test differs significantly (significance level = 0.05) from the sum of the t-values of the clusters of the shuffled t-test, we can reject the null hypothesis that the temporal generalization matrices do not correlate with the semantic RDMs and therefore conclude that semantic differences are encoded in the EEG-signal.

3. Results

3.1 Results of the behavioral experiment and of preprocessing

In a first step we analyzed how many squiggles were named per subject and how many meaningful trials were kept after preprocessing. If a subject differed significantly from the others, it could be excluded from further analysis.

On average the subjects named 53.75 out of 120 possible squiggles (Fig. 5a). All subjects were within the range of the two standard deviations ($\text{std}=21,12$) and therefore no subject was excluded because of this criterion.

After preprocessing an average of 524 trials were kept with the range of two standard deviations of 214.444 ($\text{std}=107.222$). Subject 17 is with 313 trials slightly below the range (Fig. 5b).

An average of 230 trials out of the preprocessed trials was meaningful with the range of two standard deviations of 105.8 (Fig. 5c). Because subject 17 is with 167 meaningful trials well inside this range, we didn't exclude it from further analysis. Thus, all subjects were kept for further analysis.

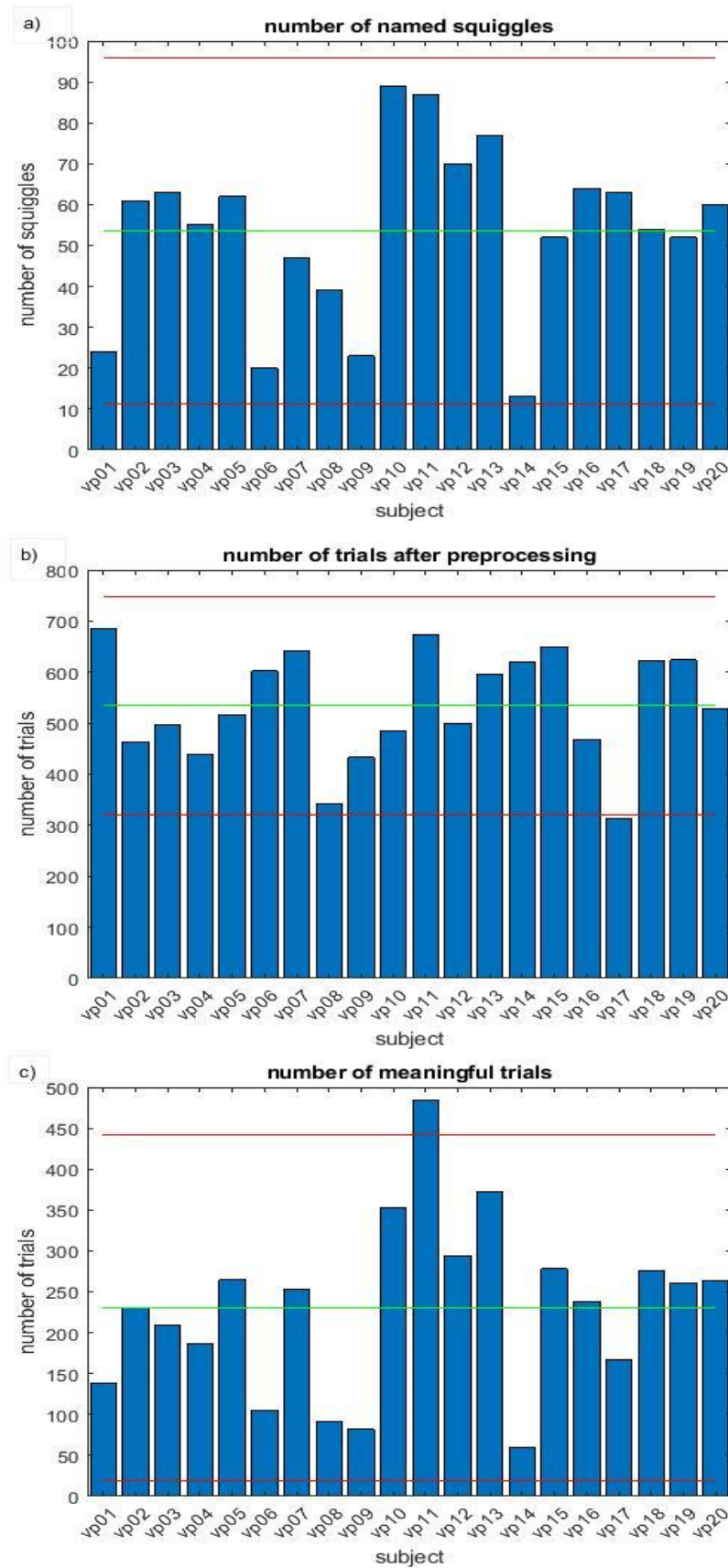


Fig 5: **a)** number of named squiggles per subject out of 120 possible squiggles **b)** number of trials out of 720 that were kept after preprocessing per subject. **c)** number of trials out of the preprocessed trials, in which a meaningful squiggle was shown. The green lines indicate the mean. The red lines indicate two times the standard deviation

3.2. Results of the semantic analysis

The representational geometries of different measures of semantic similarity relate differently to the way meaning is represented in the EEG-signal. Before comparing the measures directly with the EEG-data (see chapter 3.4.), we compared them with each other. Because both follow the distributional approach of semantic meaning, we expected high positive correlation (**hypothesis 1**). We used Kendalls Tau as a measure of correlation (Kriegeskorte 2008) and evaluated significance with a permutation test (significance level=0.05, number of permutations=1000).

As expected there is a positive correlation between the two RDMs ($r=0.1737$), that is significant according to the permutation test (number of permutations= 1000) (Fig. 6).

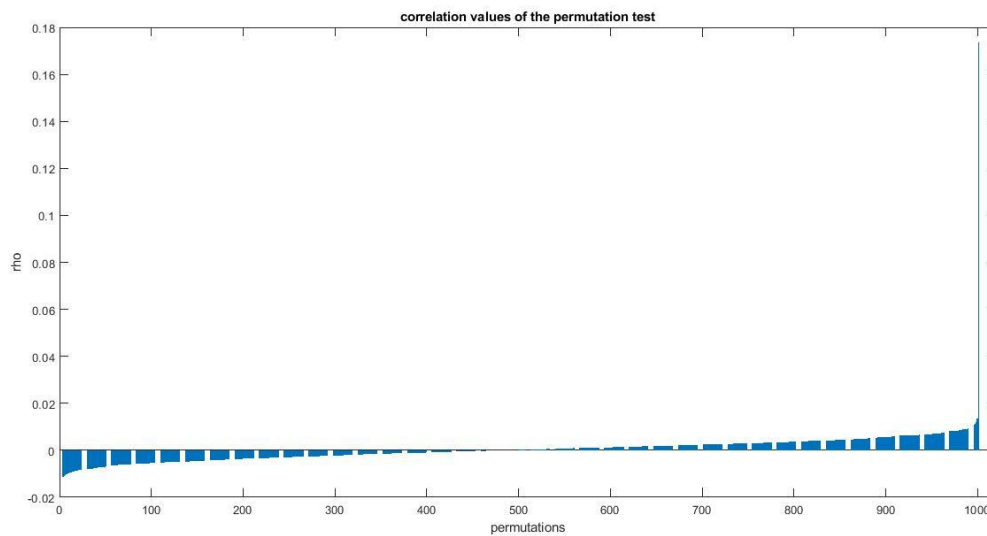


Fig. 6: The blue bars indicate the ordered correlation values for one of the 1000 shuffled tests. The high blue bar at the very right is the value for the original correlation ($\rho=0.1737$). It clearly is much higher than the 50 highest correlation values of the shuffled test.

As the scatter plot (Fig. 7b) shows some values of the NGD are below zero, although the scale is only supposed to range from 0 (similar) to 1 (dissimilar). As Cilibrasi (2007) states, a value below 0 is unlikely but in general possible. In the RDMs (Fig. 7a) each entry is one of the search terms and the degree of similarity between search terms is illustrated by the colors. As one can see, some search terms seem to be dissimilar to almost all other search terms as the strong yellow lines indicate. The histograms (Fig. 7c) show that most of the values of the NGD lay between 0 and 0.5 while the values for word2vec lay between 0.5 and 1.

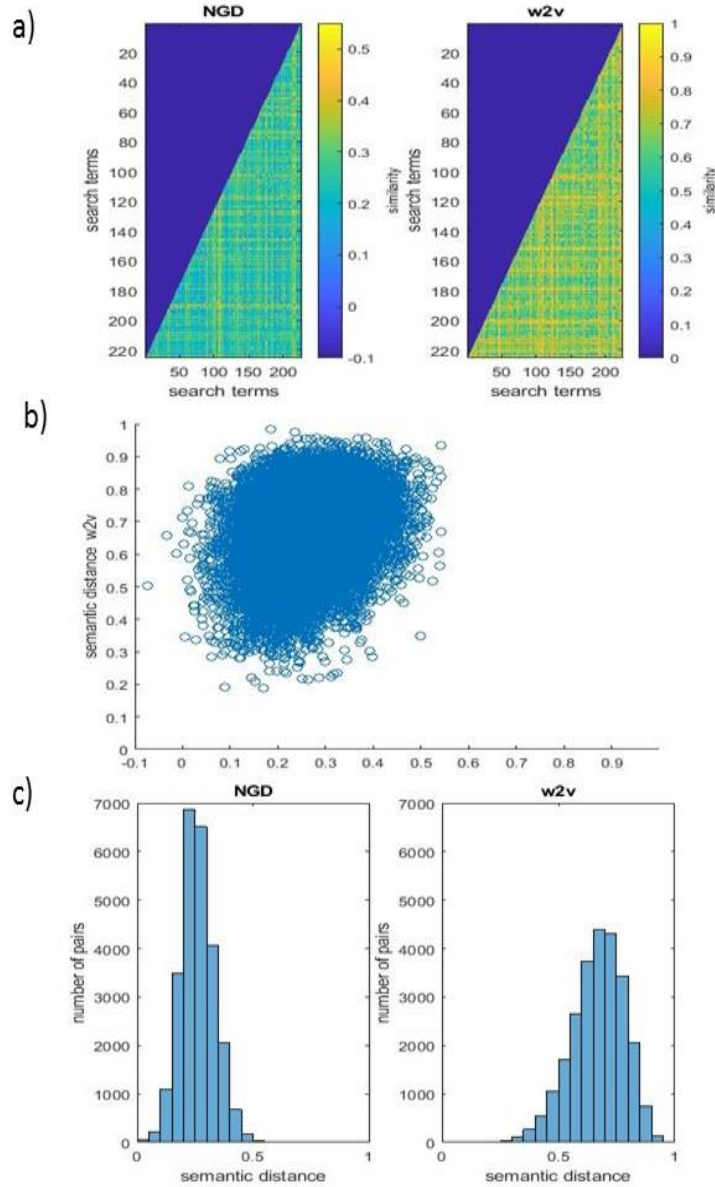


Fig. 7: **a)** TheRDM for NGD and word2vec for 225 search terms. Only one triangular is shown, because the matrices are symmetric. Each entry is one search term. Low values indicate high similarity and vice versa. **b)** Scatterplot for the semantic distance of all word pairs in NGD and word2vec. **c)** Histogram of semantic distances of NGD and word2vec.

3.3 Results of the item-specific RSA

First, we were interested in item-specific information in the time domain of the EEG-signal. **(hypothesis 3)**. Item-specific information is present, when the EEG-patterns of trials that belong to the same meaningful squiggle, correlate higher with each other, then trials that belong to another meaningful squiggle. We assessed the item-specific information by comparing across all subjects the on and off-diagonal entries of the temporal generalization matrices with each other with a t-test (significance level = 0.05).

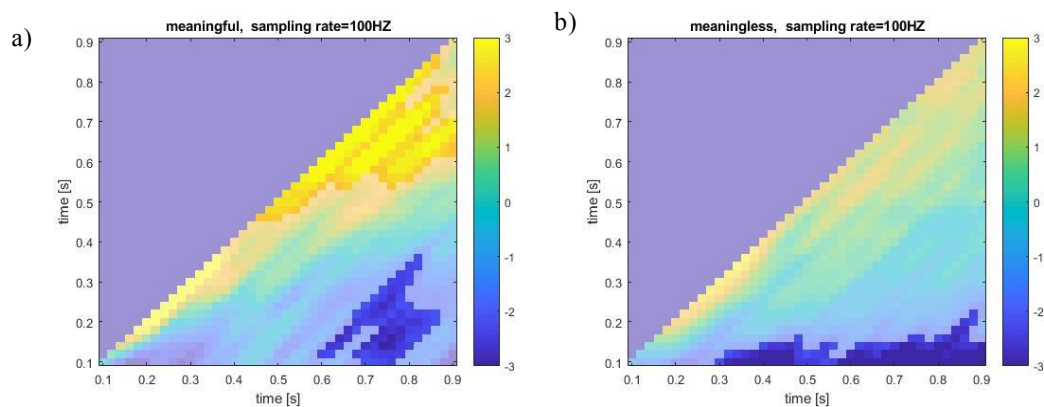
Statistical significance was evaluated with a cluster-based permutation test (significance level=0.05, number of permutations=1000). The analysis was conducted with 100Hz and with 50Hz on the groups of meaningful and meaningless squiggles separately.

For a sampling rate of 100Hz and meaningful trials a positive (p -value=0.008) and a negative cluster (p -value=0.043) was found between 0.6 and 1 seconds after stimulus onset (Fig. 8a). For the sampling rate of 50Hz and meaningful trials a positive cluster (p -value= 0.017) was found in the same interval (Fig. 8c). In comparison, for meaningless trials and both sampling rate no significant positive clusters was found (see table 1). This verifies the hypothesis that the EEG-signal encodes semantic information.

Tab.1: Results of the item-specific RSA over the whole frequency spectrum

	50Hz		100Hz	
	<i>p-value positive cluster</i>	<i>p-value negative cluster</i>	<i>p-value positive cluster</i>	<i>p-value negative cluster</i>
meaningful trials	0,0170*	0.0590	0,0080*	0.0430*
	0.1640			
meaningless trials	0,3220	0.0380*	0,2530	0.0034*

significance level=0.05, significant p-values are marked with an asterisk ()*



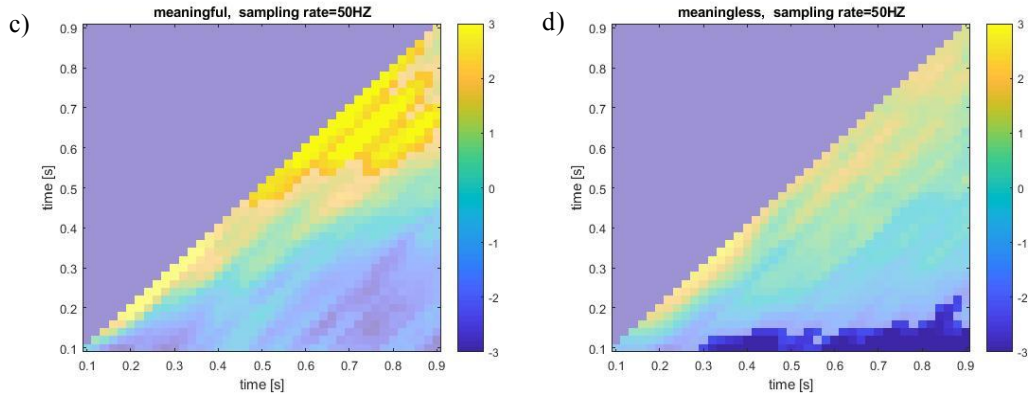


Fig. 8: The RDMs show the correlation between the trials across all subjects in the time course of 0 – 1 seconds after stimulus onset. Bright yellow or bright blue clusters indicate significant correlations. **a and c)** only meaningful trials. **b and d)** only meaningless trials.

As suggested by the previous univariate study (Bauer 2018) we expected semantic processing to occur more in the frequency bands below 30Hz (**hypothesis 3**). To check for that we split the data into different frequencies using a bandpass filter and then analyzed the different frequencies separately. We conducted this analysis only with 100Hz sampling rate because following the Nyquist-Shannon theorem, a sampling rate of 50Hz cannot capture higher γ -bands.

In accordance with our hypothesis, in the meaningful condition significant positive clusters were found in α and β -bands (7-30Hz, p -value=0.0040) and in frequencies below 7Hz (p -value=0.003) (Fig. 9). Above 30Hz no cluster was found. In the meaningless condition only one significant positive cluster was found in the frequencies below 7Hz (see table 2).

Tab. 2: Results of the item-specific RSA over different frequencies

	meaningful trials		meaningless trials	
	P-VALUE POSITIVE CLUSTER	P-VALUE NEGATIVE CLUSTER	P-VALUE POSITIVE CLUSTER	P-VALUE NEGATIVE CLUSTER
0-7Hz	0,0030*	0.0420*	0,0130*	0.3390
	0.1810			
8-30Hz	0,0040*	0.1500	0,2346	0.1590
+30HZ	NO CLUSTER	NO CLUSTER	NO CLUSTER	NO CLUSTER

significance level=0.05, significant p -values are marked with an asterisk (*)

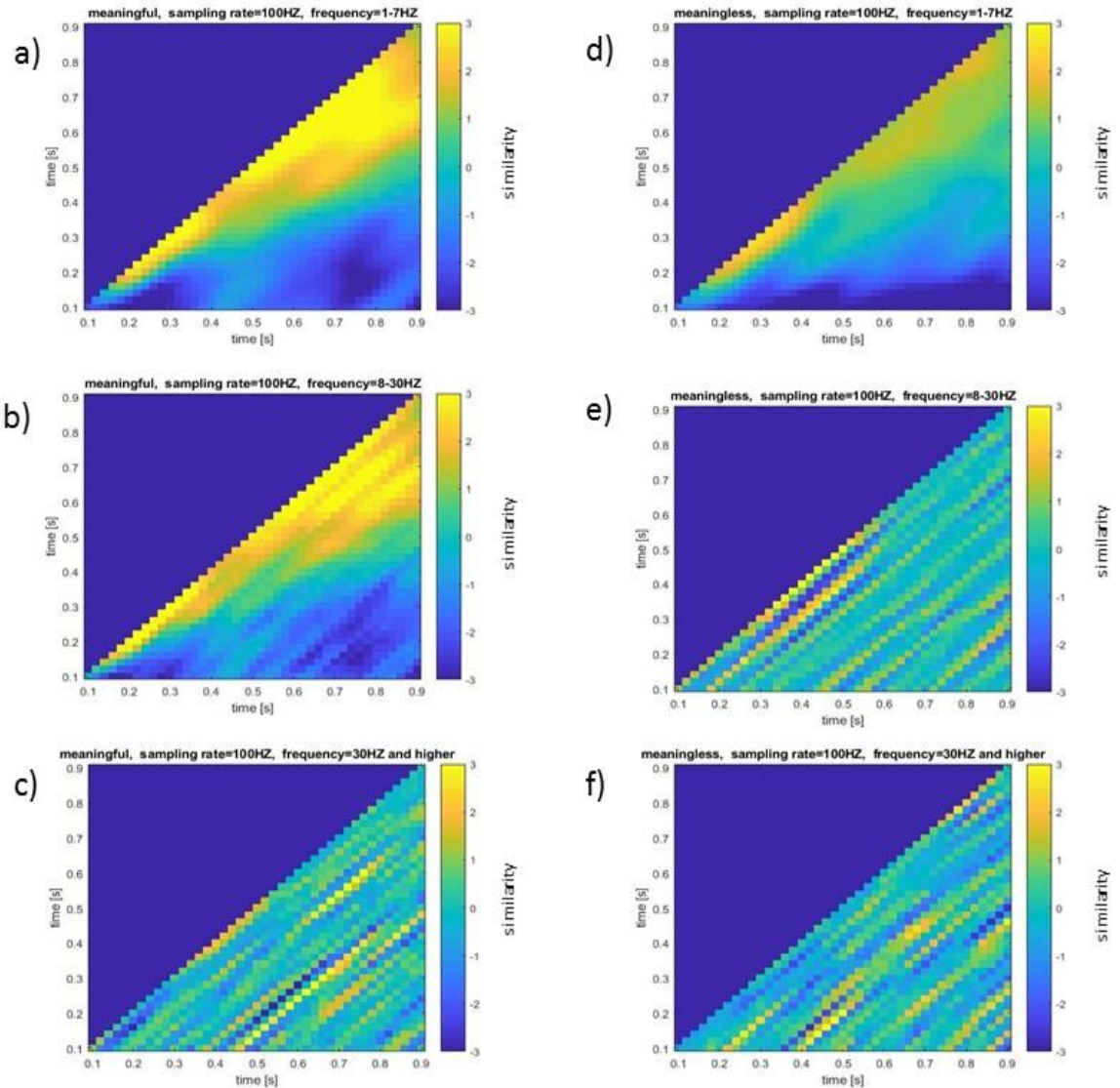


Fig. 9: The RDMs show the correlation between the trials across all subjects in the time course of 0 – 1 seconds after stimulus onset. Bright yellow or bright blue clusters indicate significant correlations. The meaningful condition is on the left side (a, b, c) and the meaningless condition on the right side (e, f, g). First row (a, d) shows it for 1-7Hz. Second row shows it for 8-30Hz (b, e). Third row for 30Hz and higher (c, f).

3.4 Results of the RSA of semantic similarity with EEG-similarity

While the item-specific analysis revealed high similarity of EEG-patterns for meaningful trials and thus indicated semantic processing, the analysis remains on a very coarse level. It only tells us that there is a difference between meaningful and meaningless trials. By comparing the representational space of the EEG-signal with the representational space of the semantic space, we can answer the more fine-grained question if differences in meaning are

encoded in the EEG-signal (**hypothesis 4**). In addition, the item specific-analysis is blind to confounding with eye-saccades (Yuval-Greenberg 2008) and lower or higher-level cognitive processes that are involved in pareidolia (such as imagination). In contrast, the RSA with semantic similarity captures only cognitive processes that are related to semantic processing. Since both measures of semantic similarity follow the distributional approach, we moreover expect that they relate similarly to the EEG-signal (**hypothesis 5**).

We correlated all temporal generalization matrices of all subjects with their corresponding RDMS of either word2vec or NGD. Statistical significance was evaluated across all subjects with a cluster-based permutation test (significance level=0.05, number of permutations=1000). The analysis was conducted for a sampling rate of 100Hz and 50Hz separately.

For NGD with both sampling rates (100Hz and 50Hz) one strongly significant positive cluster was found ($p\text{-value}=1e^{-3}$) between roughly 0.4 and 0.7 seconds after stimulus onset (Fig. 10 b and d). In addition, for NGD and 50Hz a slightly significant negative cluster ($p\text{-value}=0.037$) between 0.1 and 0.4 seconds after stimulus onset was found. For word2vec and both sampling rates no significant positive cluster was found (Fig. 10 a and c). A significant negative cluster was found for word2vec and 100Hz sampling rate ($p\text{-value}=0.02$) (see table 3).

While the results support the hypothesize that semantic meaning as measured by NGD relates to the EEG-signal, surprisingly this is not true for word2vec. Even though word2vec and NGD correlate with each other, word2vec has no relation to the temporal generalization matrices of the EEG-signal.

Tab. 3: Results of the RSA of semantic similarity with EEG-similarity over the whole frequency spectrum

	50Hz		100Hz	
	<i>p-value positive cluster</i>	<i>p-value negative cluster</i>	<i>p-value positive cluster</i>	<i>p-value negative cluster</i>
word2vec	1	0.0940	0,3930	0.0200*
NGD	$1e^{-3}$ *	0,0370	$1e^{-3}$ *	0.055
	0,2890		0.1599	

significance level=0.05, significant p-values are marked with an asterisk ()*

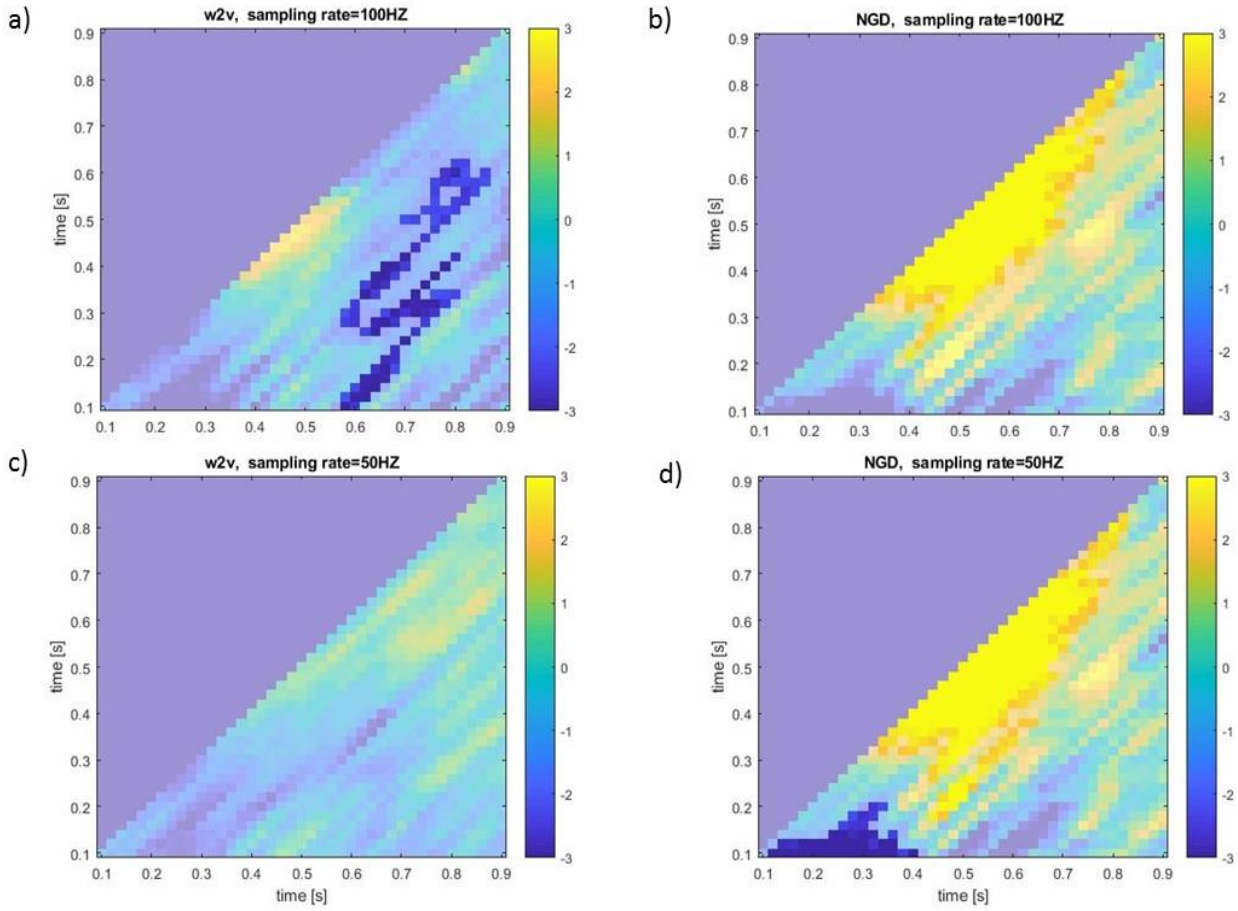


Fig. 10: The RDMs show the correlation between the semantic similarity and all meaningful trials across all subjects in the time course of 0 - 1second after stimulus onset. Word2vec is on the left side (a, c) and NGD on the right side (b, d).

As suggested by our previous univariate study (Bauer 2018) and other studies bands (Weiss 2012; Spironelli 2008; Klimesch 2001) that relate the processing of meaning to α and β -bands, we hypothesize that semantic processing occurs in frequency bands below 30Hz (**hypothesis 6**). To check for that we split the data into different frequencies using a bandpass filter and then analyzed the different frequencies separately. Since the word2vec measure did not give any significant results, we used the NGD measure and analyzed different frequencies separately. The sampling rate was again 100Hz because following the Nyquist-Shannon theorem, a sampling rate of 50Hz cannot capture higher γ -bands (Shannon 1949).

In contrast to our hypothesis in all frequency bands strongly significant positive clusters were found with a p-value $1e^{-3}$. In addition, in the frequencies above 30Hz two more significant clusters were found (p-value=0.002 and 0.018) (Fig. 11). Moreover, significant negative clusters were found in all frequency bands (see table 4).

The analysis shows that fine-grained differences in meaning are encoded over the whole frequency spectrum of the EEG. It is particularly surprising that the strongest significant clusters were found in frequencies above 30Hz, because the item-specific analysis suggested that these frequencies do not encode the difference between meaningful and meaningless processing.

Tab. 4: Results of the RSA of semantic similarity with EEG-similarity over different frequencies

NGD		
	<i>p-value positive cluster</i>	<i>p-value negative cluster</i>
0-7Hz	1e ⁻³ *	0.0050*
	0.3270	
8-30Hz	1e ⁻³ *	0.0420*
	0,1930	
+30Hz	1e ⁻³ *	0.005*
	0.0020*	
	0.0180*	
	0.0470*	
	0.2080	

significance level=0.05,

significant p-values are marked with an asterisk ()*

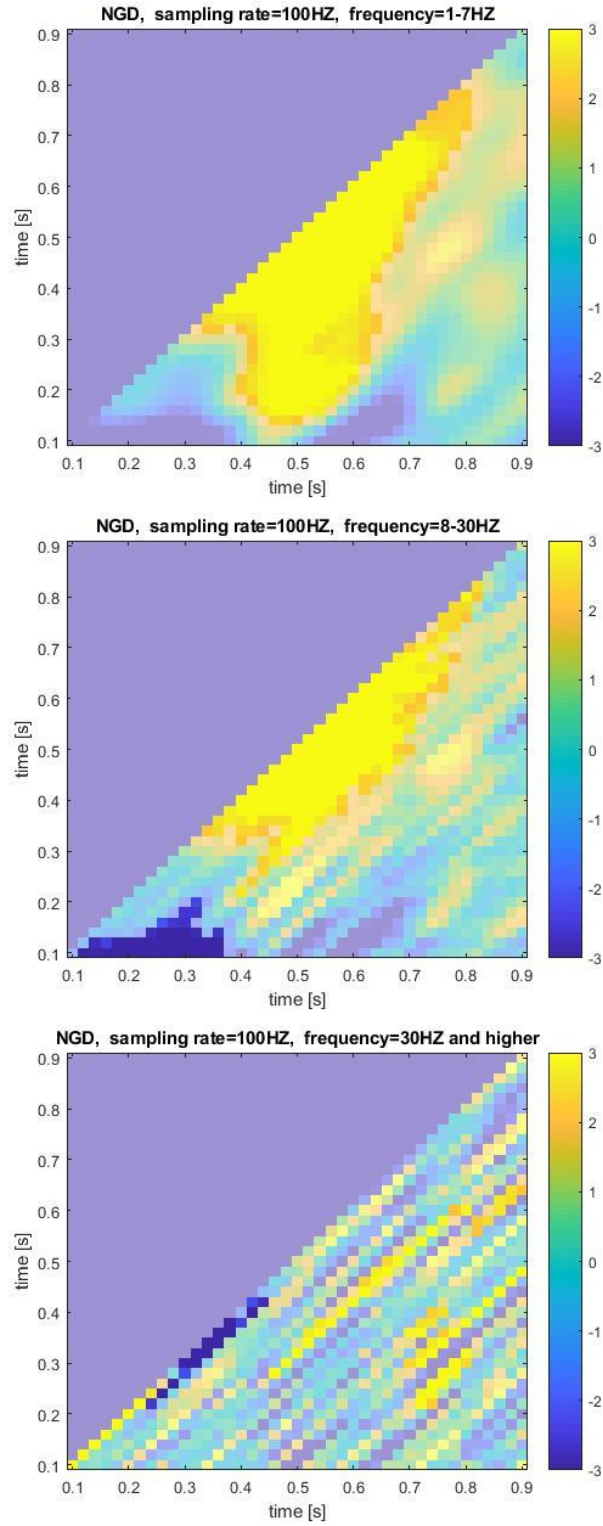


Fig. 11: The RDMs show the correlation between all meaningful trials (NGD) across all subjects in the time course of 0 – 1 second after stimulus onset. Bright yellow or bright blue clusters indicate significant correlations.

4. Discussion

The study examined if the organization of semantic knowledge is reflected in the time-domain of an EEG-signal. More precisely, we conducted a representational similarity analysis to examine whether the semantic relations between words corresponds to the encoding of semantic relations in the temporal generalization matrix of an EEG-signal. Processing symbolic, iconic or written representations of real-world objects can be confounded with familiarity and visual similarity. To avoid that, we made use of the human capacity of pareidolia, that is to project meaning into abstract meaningless shapes. Therefore, we used abstract geometrical squiggles as stimuli (Voss 2009) and asked the subjects to describe them briefly. To assess the semantic similarity between the stimuli descriptions we used two different measures, namely word2vec and the Normalized Google Distance (NGD).

The main finding is that differences in meaning are encoded in temporal generalization matrices when NGD is used as a measure of semantic similarity. The semantic processing occurred within 1 second after stimulus onset. This is in accordance with studies on event-related potentials (particularly N400), that find semantic processing in that time-frame (Kutas 2014).

The differences in meaning are encoded over the whole frequency spectrum, which is surprising for two reasons. First, because other studies suggest that semantic processing is related only to α and β -bands and not to γ or θ -bands (Weiss 2012; Spironelli 2008; Klimesch 2001). Second, a previous univariate study (Bauer 2018) and our item-specific analysis (see chapter 3.3) showed that the difference between meaningful and meaningless squiggles is encoded in frequencies below 30Hz. Our finding can be interpreted in four different ways.

1) The difference between meaningful and meaningless trials could be encoded in frequencies below 30Hz, while frequencies above 30Hz encode the more fine-grained semantic difference between meaningful words. Although this is possible in theory other studies showed, that difference between semantic categories can be decoded from frequencies between 20-30Hz from the phase and power domain of an EEG-signal (Behroozi 2016).

2) It is as well possible that the univariate analysis and the item-specific RSA on the EEG-data do not capture meaning but are confounded with other processes such as eye-saccades (Yuval-Greenberg 2008), while the RSA of the EEG-data and semantic similarity can capture - by the way it is designed - nothing else then meaningful processing. That would mean that

the significant clusters in frequencies below 30Hz, are due to confoundations with eye-saccades, while the actual encoding of meaning is happening in higher frequencies. This opposes the position of Weiss (2012) that α and β -bands are involved in semantic processing.

3) While there is a lot support for the relation between α and β -bands and semantic processing (Weiss 2012; Spironelli 2008; Klimesch 2001), some studies on semantic processing show that as well γ -bands are involved, in particular when it comes to expecting the upcoming words in an expression (Lam 2016) and the violation of this expectation (Penolazzi 2009). This suggests that the term semantic processing actually captures a variety of processes that can be analyzed separately. Further analysis could try to dissociate the processes underlying semantic processing, to see which process elicits which frequency bands.

Since we analyzed α and β -bands (8-30Hz) together in a further study it could be interesting to analyze them separately and to see if they relate to different aspects of semantic processing.

4) Another line of interpretation is based on the fact, that we used abstract squiggles and pareidolia. When written or pictorial representations of real-world objects are used as stimuli, the processing of meaning could be confounded with visual similarity or familiarity (Voss 2009). While these studies (Cichy 2017, Behroozi 2016) indeed can decode different semantic categories (e.g. animate vs. inanimate) from the EEG-signal, this might not be because of semantic differences between the stimuli but between visual difference between living or dead objects.

On the other hand, one could argue that pareidolia can be confounded with other cognitive processes such as imagination. While using an RSA of semantic similarity and EEG-data strongly suggests that we captured semantic processing, it cannot be completely ruled out that semantic processing in pareidolia differs fundamentally from semantic processing without pareidolia. In this case the frequencies below 30Hz would capture as expected semantic processing, while the frequencies above 30Hz would capture semantic processing confounded with imagination or other cognitive processes involved in pareidolia. This thought is close to the line of reasoning of argument 3, that states that semantic processing is a technical term that can be split into different processes.

Moreover, a study by Rodriguez (1999) offers interesting findings for the discussion of the relation of different frequency bands, pareidolia and semantic processing. In the study “Mooney” faces were shown to the subjects. These are black and white drawings that are usually recognized as faces when they are in the upright position but are categorized as

meaningless shapes when they are presented upside down. The study found that when a drawing is recognized as meaningful (usually upright position) there is significant activity in the γ -bands, while there is no such activity when the drawing is considered to be meaningless. The process of recognizing the faces does not capture pareidolia to the same extent as our study, but it certainly is related. The subjects were primed to search for faces but still in around 25% of the cases they were not able to recognize the face in the upright stimuli. Moreover, in around 25% of the cases where no face was shown, the subjects saw a face. This failure of the subjects shows that recognizing the faces was not that easy and involves cognitive abilities that are related to pareidolia (projecting meaning into abstract shapes). The study differs from our study because they did not ask the subjects to describe the stimuli with words. This difference should not make a big impact since we only asked the subjects to describe the stimuli in the last presentation block, while the 6 blocks before were only about perception.

The findings of Rodriguez (1999) for the two conditions (meaningful and meaningless) oppose the results of our item-specific analysis, that shows that there is no significant activity in γ -bands neither in the meaningful nor in the meaningless condition. It supports the results that γ -oscillations are involved in the task. It could be understood as a support of our results that γ -bands are involved in the task of our experiment. Strangely, we found a change in γ -bands only using the semantic analysis – but semantic analysis is not what Rodriguez (1999) did. Concluding, their results challenge our item-specific analysis because they state that γ -bands are involved in perceiving something abstract as meaningful. Still, their results can not be easily taken as support for our finding, that γ -bands are involved in semantic processing in pareidolia because we conducted a semantic analysis while they did not.

While there are many possible explanations for the relation between pareidolia, semantic processing and γ -oscillations, there are as well many studies that oppose these explanations. Thus, the subject remains elusive and requires further research.

Another surprise is that both measures of semantic similarity (word2vec and NGD) are based on the distributional concept of semantic meaning and correlate with each other, while they relate in a different way to the EEG-signal. While there is no literature that compares NGD and word2vec directly, word2vec and other measures that use neural networks to analyze the close surrounding of a word (word embeddings), seem to be the most promising when it comes to semantic similarity (Mikolov 2013). It could be that word2vec captures semantic

meaning in a more fine-grained way that fits better to human understanding of the words, but still older distributional measures that capture semantic meaning more coarsely-grained, fit better to how meaning is encoded in our brains or at least to our ability to decode it from brain data. This is supported by other studies that found relations between older distributional measures of meaning (such as LSA (Landauer 1997)) and fMRI data (Carota 2017, Carlson 2014). Moreover, this is supported by De Falco (2016) who showed that there is a relation between data from single-cell recordings and NGD (although de Falco used a slightly different formula and Bing instead of Google).

There are several ways for further analyses. One could investigate if it makes a difference if the full-length stimuli description (compounds) are used instead of the one-word form into which we decoded the descriptions. While the Normalized Google Distance is in principle able to analyze compounds (Cilibrasi 2007), more recent studies state that there are several obstacles in compound semantics that have not been overcome yet (Baroni 2014; Mitchell 2010).

Moreover, analyses on the level of semantic categories instead of single items are promising. Several studies (Kaneshiro 2015, Behroozi 2015) showed that semantic categories such as “animate” and “inanimate” could be decoded from brain data. The classification of the stimuli description into broader semantic categories could be done by human raters or by the use of cluster algorithms. We applied two clustering algorithms to both semantics RDMS without finding any promising results. In a further analysis other clustering algorithm could be tested on our data. (We tested the following algorithms: 1. The Hierarchical Cluster algorithm of MATLAB (Release 2018b, The MathWorks, Inc., Natick, Massachusetts, United States). It is a standard clustering algorithm for distance matrices such as the RDM (Hierarchical Clustering, 2018). 2. The Louvain Community Detection algorithm (Blondel 2008). It was used as well by de Falco (2016) on RDMS in a representational similarity analysis. We used an implementation from Scherer (2010)).

Moreover, one could change the assignment of trials to the meaningful and meaningless condition. We considered all trials of the 6 ratings blocks to be meaningful in which a squiggle was shown that was considered to be meaningful in the naming block (last block). This allows for the possibility that a squiggle that was consistently rated as meaningless on the 4-point scale in the six rating blocks, is considered to be meaningful if it is named in the naming block. In a further analysis, a criterion could be developed that assigns the trials in a

different way to the meaningful or meaningless condition (e.g. the trials of a named squiggle are only included if they are rated as meaningful on average over the 6 ratings blocks. Another possibility is to include only those of the 6 trials of a named squiggle that were rated as meaningful on the 4-point scale).

Finally, it would be interesting to conduct a source location on the EEG-data. fMRI-studies could identify several regions related to the ventral stream that are particularly involved in encoding semantic similarity between words (Carota 2017; Fairhall 2013; Carlson 2014). In a further analysis it could be checked if there is particularly high activity in electrodes that capture these areas of the brain.

Appendix:

Decoding Scheme

All stimuli descriptions were decoded into a one-word form according to the following schema:

1. All propositions were decoded to the subject of the sentence (e.g. “man that walks through a door” → “man”).
2. Compounds (e.g. “brown dog” → “dog”) were decoded to the subject.
3. Expressions containing “somebody” were decoded to “person”.
4. single letters like “Z”, “U” or “T” were decoded to “letter”.
5. if two mutually exclusive descriptions were given it was decoded to the first (“human or house” → “human”)
6. if two different descriptions were given, while one is the category term of the other (“animal, maybe a dog” the category term was eliminated and it was decoded to the more specific term (“animal, maybe a dog” → “dog”).
7. some descriptions were not part of the word2vec text corpus. These words were decoded to similar words (“Phantasiefisch” → “Fisch”)

References:

Bauer M (2018) *How the brain generates meaning: Neuronal oscillatory differences of conceptual vs. perceptual processing*. Unpublished Manuscript, Ruhr-Universität Bochum, Institut für Kognitive Neurowissenschaft.

Baroni M, Murphy B, Poesio M, (2009) *EEG responds to conceptual stimuli and corpus semantics*. Proceeding EMNLP '09 Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 2 – Volume 2, p. 619-627

Baroni M, Bernardi R, Zamparelli R (2014) *Frege in Space: A Program for Compositional Distributional Semantics*. LiLT Volume 9, Perspectives on Semantic Representations for Textual Inference.

Behroozi M, Daliri MR, Shekarchi B (2015) *EEG phase patterns reflect the representation of semantic categories of objects*. Med Biol Eng Comput (2016) 54:205–221

Blondel VD, Guillaume JL, Lambiotte R, Lefebvre E (2008) *Fast unfolding of communities in large networks*. J. Stat. Mech. (2008) P10008

Bortz (1999) *Statistik*. Auflage 5, Springer Verlag, Berlin Heidelberg

Carlson TA, Simmons RA, Kriegeskorte N, Slevc LR (2014) *The Emergence of Semantic Meaning in the Ventral Temporal Pathway*. Journal of Cognitive Neuroscience 26:1, pp. 120–131

Carota F, Kriegeskorte N, Nili H, Pulvermüller F, (2017) *Representational Similarity Mapping of Distributional Semantics in Left Inferior Frontal, Middle Temporal, and Motor Cortex*. Cerebral Cortex, 2017; 1–16

Cichy RM, Pantazis D (2017) *Multivariate pattern analysis of MEG and EEG: a comparison of representational structure in time and space*. NeuroImage (2017); 158:441–454

Cilibrasi RL, Vitanyi PMB (2007) *The Google Similarity Distance*. IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, VOL. 19, NO 3, MARCH 2007, 370–383
1

De Falco E, Ison JM, Fried I, Quiroga QR (2016) *Long-term coding of personal and universal associations underlying the memory web in the human brain*. NATURE COMMUNICATIONS | DOI: 10.1038/ncomms13408

Dehaene S, King JR (2014) *Characterizing the dynamics of mental representations: the temporal generalization method*. Trends in Cognitive Sciences, April 2014, Vol. 18, No. 4

Fairhall SL, Caramazza A (2013) *Brain Regions That Represent Amodal Conceptual Knowledge*. The Journal of Neuroscience, June 19, 2013 • 33(25):10552–10558

Yuval-Greenberg S, Tomer O, Keren AS, Nelken I, Deouell LY (2008) *Transient Induced Gamma-Band Response in EEG as a Manifestation of Miniature Saccades*. *Neuron*, Volume 58, Issue 3, 8 May 2008, Pages 429-44

Groh-Bordin C, Zimmer HD, Ecker UK (2006) *Has the butcher on the bus dyed his hair? When color changes modulate ERP correlates of familiarity and recollection*. *Neuroimage* 32, 1879–1890.

Hald LA, Bastiaansen CM, Hagoort P (2005) *EEG theta and gamma responses to semantic violations in online sentence processing*. *Brain and Language*, Volume 96, Issue 1, January 2006, Pages 90-105

Hebart MN, Baker CI, (2017) *Deconstructing multivariate decoding for the study of brain function*. *Neuroimage*. PMID 28782682 DOI: 10.1016/j.neuroimage.2017.08.005

Jamalabadi H, Alizadeh S, Schönauer M, Leibold C, Gais S (2016) *Classification Based Hypothesis Testing in Neuroscience: Below-Chance Level Classification Rates and Overlooked Statistical Properties of Linear Parametric Classifiers*. *Human Brain Mapping* 37:1842–1855 (2016)

Jung TP, Makeig S, Humphries C, Lee TW, McKeown MJ, Iragui V, Sejnowski TJ (2000) *Removing electroencephalographic artifacts by blind source separation*. *Psychophysiology*, 37, 163–178. doi: 10.1111/1469---8986.3720163

Kaneshiro B, Guimaraes MP, Kim HS, Norcia AM, Suppes P (2015) *A Representational Similarity Analysis of the Dynamics of Object Processing Using Single-Trial EEG Classification*. *PLoS ONE* 10(8): e0135697

Kutas M, Federmeier KD (2014) *Thirty years and counting: Finding meaning in the N400 component of the event related brain potential (ERP)*. *Annu Rev Psychol*. 2011; 62: 621–647.

Klimesch W, Doppelmayr M, Wimmer H, Gruber W, Röhm D, Schwaiger FH, Hutzler F

(2001) *Alpha and beta band power changes in normal and dyslexic children*. Clinical Neurophysiology 112 (2001) 1186±1195

Kriegeskorte N, Mur M, Bandettini P (2008) *Representational similarity analysis –connecting the branches of systems neuroscience*. Frontiers in Systems Neuroscience published: 24 November 2008, doi: 10.3389/neuro.06.004.2008

Kriegeskorte N, Kievit RA (2013) *Representational geometry: integrating cognition, computation, and the brain*. TICS-1216

Landauer TK, Dumais ST. (1997) *A solution to Plato's problem: the latent semantic analysis theory of the acquisition, induction, and representation of knowledge*. Psychol Rev. 104:211–240

Maris E & Oostenveld R (2007) *Nonparametric statistical testing of EEG- and MEG-data*. Journal of Neuroscience Methods, 164, 177–190. doi:10.1016/j.jneumeth.2007.03.024

Mitchell J, Lapata M (2010) *Composition in Distributional Models of Semantics*. Cognitive Science 34 (2010) 1388–1429

Mikolov T, Sutskever I, Chen K, Corrado G, Dean J (2013) *Distributed Representations of Words and Phrases and their Compositionality*. arXiv:1310.4546v1, 16 Oct 2013

Müller A (2015) *Analyse von Wort-Vektoren deutscher Textkorpora*. Unpublished manuscript. Technische Universität Berlin, Institut für Softwaretechnik und Theoretische Informatik. (for download: <https://github.com/devmount/GermanWordEmbeddings>, Retrieved April 25, 2018)

Lam NHL, Schoffelen JM, Uddén J, Hultén A, Hagoort P (2016) *Neural activity during sentence processing as reflected in theta, alpha, beta, and gamma oscillations*. NeuroImage 142 (2016) 43–54

Oostenveld R, Fries P, Maris E, Schoffelen JM (2011) *FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data*. Computational

Penolazzi B, Angrilli A, Job R, (2009) *Gamma EEG activity induced by semantic violation during sentence reading*. Neuroscience Letters 465 (2009) 74–78

Scherer A, (2010) *Matlab / C++ implementation of community detection algorithm*. École Normale Supérieure Lyon (for download: <https://github.com/jblocher/matlab-network-utilities/tree/master/Louvain> , Retrieved April 25, 2018,)

Shannon CE (1949) *Communication in the Presence of Noise*. Proceedings of the IRE Volume: 37, Issue: 1, Jan. 1949

Spironelli C, Penolazzi B, Angrilli A (2008) *Dysfunctional hemispheric asymmetry of theta and beta EEG activity during linguistic tasks in developmental dyslexia*. Biological Psychology 77 (2008) 123–131

Su L, Fonteneau E, Marslen-Wilson W, Kriegeskorte N (2012) *Spatiotemporal Searchlight Representational Similarity Analysis in EMEG Source Space*. Pattern Recognition in NeuroImaging (PRNI), 2012 International Workshop on

Voss JL, Schendan HE, Paller KA (2009) *Finding meaning in novel geometric shapes influences electrophysiological correlates of repetition and dissociates perceptual and conceptual priming*. NeuroImage 49 (2010) 2879–2889

Voss JL, Federmeier KD, Paller KA (2011) *The Potato Chip Really Does Look Like Elvis! Neural Hallmarks of Conceptual Processing Associated with Finding Novel Shapes Subjectively Meaningful*. Cerebral Cortex October 2012;22:2354±2364

Weiss S, Muelle HM (2012) *“Too many betas do not spoil the broth”: the role of beta brain oscillations in language processing*. Frontiers in Psychology, doi: 10.3389/fpsyg.2012.00201

Online sources:

Hierarchical Clustering (2018, April 26) Retrieved from:
<https://de.mathworks.com/help/stats/hierarchical-clustering.html>

Eidesstattliche Erklärung

„Hiermit erkläre und versichere ich, dass ich die vorliegende Arbeit selbständig verfasst und - einschließlich eventuell beigefügter Abbildungen, Zeichnungen und Skizzen - keine anderen als die angegebenen Quellen und Hilfsmittel verwendet habe. Dies gilt in gleicher Weise für gedruckte Quellen wie für Quellen aus dem Internet. Die Stellen der Arbeit, die anderen Werken dem Wortlaut oder dem Sinn nach entnommen sind, sind unter Angabe der Quelle als Zitat kenntlich gemacht worden.“

Bochum, den 13.05.2018

Marius Wolf