Distinctive Phonological Feature Representation for Decoding Brain Activation

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Abstract

There is an increase in evidence that neural brain activity associated to nouns is possible to predict using various association techniques, such as lexical word embedding or story-related features. To further the increase in understanding of word associations in the brain there is yet another aspect to be examined which is a phonetic feature representation of brain activation. The action of producing words as segments of sound comes naturally, however, processes that govern the phonetic patterns in the human brain are still not well understood. In this thesis I aim to discover whether it is possible to predict and decode the brain activity associated with the phonological characteristics of words. This thesis uses the same 60 word data-set used by Mitchell et al., (2008) and is subdivided in two major tasks. Firstly, an extended study on the correct extraction of distinctive phonological feature vectors is performed that respects the composition and sound characteristics of words. Secondly, two models are approached that predict neural activity patterns based on the compared similarity values of a pair of stimulus words. The results presented in this research indicate that a distinctive approach of phonological feature vectors is not a good representation of neural activity to predict brain activation patterns. This thesis presents important insights on phonological representation of words, claiming a distinctive approach of phonological characteristics to be inaccurate and too simple for the prediction of neural activity patterns in a human brain. Further studies of phonological word-compositions and prediction of neural activity should learn form the accurately annotated steps and choices taken in this research to improve methods for the extraction of complex sound patterns in words.

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Part I

Thesis

Chapter 1

Introduction

1.1 Progress in the Field of Neuroscience

Studies in the field of neural science are gradually merging with computer science, thereby facilitating the analysis of distinct spatial patterns of functional magnetic resonance imaging (fMRI) activity. In particular, the field of Machine Learning has made a considerable contribution to further improve the understanding of how the human brain represents and organizes conceptual knowledge. Studies that are currently being conducted to illuminate knowledge gaps and uncertainties about the human brain put emphasis on the analogical link to memory and the role of associations in predictions (Bar, 2007).

Early studies that are using word embedding to predict activation patterns in brains showed that, using association rules in different semantic categories, it is possible to predict word probability from activation patterns inside a fMRI scan. These studies provided evidence for a direct, predictive relationship between the statistics of word co-occurrence in text and the neural activation associated with thinking about word meanings (Mitchell et al., 2008). Further research has performed well on the predictions of neural representations using diverse story features (Wehbe et al., 2014), which also signifies that the human brain organizes concepts and words using multiple associative techniques.

Further research in this area conducted by Bulat et al (2017) correlates semantic models with conceptual representation in the brain with the same dataset that Mitchell (2008) used for evaluating the similarity between actual fMRI images and model-predicted fMRI images. They concluded that association-based semantic models are a promising direction in computational semantics research and recommended that understanding how individual variations in participants can impact decisions in modelling would be of a great value to the computational semantics community. Recently, neural word embedding models have been identified to exhibit the best performance; specifically the Glove and dependency-based Word2Vec models which are considered to be valuable in this field of research (Abnar et al., 2018).

1.2 Brain Prediction with Phonological Feature Encoding

To further our understanding of word associations in the brain there is yet another aspect to be examined which is a phonetic feature representation of brain activation. Previous studies have already demonstrated the representation of speech sounds, such as whether local neural encoding is specific for phonemes (Mesgarani, 2014). Furthermore, as phonemes contain verbal information that can be stored in working memory, it is highly acceptable to assume that this information can be captured and used to predict neural activity. Previous research on phonetic priming, whether a word is recognized faster if it has similar phonetic properties, has shown that stimulus input activates a set of acoustic-phonetic patterns in memory. This indicates that the organization of words and concepts includes phonological structures (Luce, 2000).

A phoneme is considered to be an acoustic-phonetic segment of a word that consists of multiple features which are able to create its own unique sound pattern. Phonetic feature encoding of different languages have been important to construct a universal phonetic alphabet from which the sound representation of a word can be defined by its phonetic segments. The sequential combination of these features create a sound pattern that defines a word (Chomsky, 1968; Bloomfield, 1933; McCarthy, 2001). A great deal of time and study will be preserved for the extraction and encoding of feature vectors to increase the predictive power of the model.

There are, however, comments on a distinctive approach of phonetic features and the view that words are stored using segmental units such as consonants and vowels. Studies of linguistic and phonology argue that abstract descriptions of phonological characters do not resemble the form of words in memory (Coleman, 2002; Port, 2007). Still, this research follows the traditional view, mainly focusing on the transcriptions of the International Phonetic Association (IPA, 1999; IPA; 2018) and Hall & Clemant (1983) to validate whether a distinctive approach is sufficient to predict neural activity from fMRI images.

This study will elaborate on the data-set used by Mitchell et al., (2008), thereby predicting human brain activity associated with the phonetic properties of nouns. The aim is therefore to prove whether there exists a similarity between the phonetic structure of a word and the neural activity patterns in a human brain when hearing the word. The main challange is therefore,

> *Can the phonetic properties of words be used to predict and decode the brain activity associated with the set of nouns, used by Mitchell et al., (2008), based on their phonological characteristics?*

Following up, this paper is subdivided into two major tasks, namely,

(i) How can we compute phonetic vector representations of words that can be used in brain prediction and decoding experiments? This study on phonetics will include the correct extraction of a phonetic feature representation of words, taking into account the various conversions between phonetic transcripts.

(ii) How can we predict and decode brain activation's associated with words based on phonological vector representations of those words? This will be conducted with a linear regression model, thereby validating the predictive ability of the model with a feature vector based on the sound characteristics of words.

After an elaborate study on different phonetic languages and features, which is considered a non-trivial task, the general particulars of the linear regression model will be explained. The model used in this paper resembles the model that is used in the paper of Mitchell et al., (2008) due to the apparent certainty that it has a significant predictive ability when predicting brain activity associated with the meanings of nouns. A recent replication and extension on this paper by Abnar et al., (2018) has provided a linear regression model which has proven to be equally effective in this field. Finally, this paper will be evaluate whether the assumption that neural activity information can be captured with phonetic sound characteristics of words holds for a distinctive approach of phonological characters.

Chapter 2

Phonological Feature Encoding

This chapter provides a detailed study on phonological feature encoding to answer the first sub-question in this research, namely: *how can we compute phonetic vector representations of words that can be used in brain prediction and decoding experiment*. The first section transfers the reader with most important knowledge about phonology and will provide historical background of the discussions between phonologists and linguistics on different phonological representations of sound waves produced when expressing a word. This will be followed with the definitions of features used to comprise all sound characteristics that can be expressed with the word-nouns used in Mitchell's data-set. At last, a extensive study on phonological feature extraction gives the reader an explanation of decisions and choices with the specific conversion techniques to substantiate the the validity of the distinctive phonological feature vectors.

2.1 Theoretical Foundations of Phonetics

A phoneme of a language or dialect is an abstraction of a speech sound, used to identify the phonetic structures of a specific word. Every word has specific characteristics, thereby providing its unique properties that define it. There can, therefore, be stated that every word has a unique phonological structure, consisting of a sequence of characteristic features. Phonological feature encoding has been a field of research since the construction of the International Phonetic Alphabet(IPA) in the late 19th century to the inception of the phonological analysis of distinctive features of phonemes (Chomsky et al., 1968). The IPA and distinctive feature encoding have been adjusted and adapted over time which currently let to a general agreement in which a distinctive sound can be captured inside one or two characters from the phonetic alphabet. These phonetic characters then, according to the distinctive feature theory, can be represented as a set of distinctive features (Hall et al., 1983). Two specific areas of study within the field of phonetics are defined below (Trask, 1996):

Articulatory phonetics The branch of phonetics which studies the organs of speech and their use in producing speech sounds.

Acoustic phonetics The branch of phonetics which deals with the physical characteristics of the sound waves which carry speech sounds between mouth and ear, from the speaker to the listener.

This paper will primarily focus on the acoustic phonetics of a word. However, knowledge about the articulatory and auditory phonetics can prove itself useful to a more comprehensive understanding of phonetics in general. Still, as the articulatory characteristics are necessary to define the physical characteristics of the sound waves of a word, they are indispensable in this research and will be described in the following section. Although the phonetic features are considered to be useful inside the phonetic and linguistic communities, many of the features are defined loosely in phonetic terms. The current field of phonology has established highly abstract representations to grasp sound characteristics. Nevertheless, if phonology is to be related to the actual pronunciation of words, the features are considered indispensable to have a partial understanding of speech sounds. Therefore, the distinctive articulatory features are a necessity as speech sounds should at least have some phonetic basis to them (Hall et al.,1983).

Because of these abstract representations there can be discussed whether the representation of the feature vectors is sufficient to predict neural activity. The early developed segment of English phonology by Chomsky Hall (1968) is, even according to the authors, inaccurate in 'certain respects, perhaps in fundamental respects'. Therefore, to extract phonetic features, it is of great importance to be precise and conduct an extended study between phonetic similarities and differences between languages. Although there exists disagreement within the field of linguistics and phonetics (Port, 2007), there is sufficient literature that has proven distinctive phonetic features to be an effective technique to capture sound patterns. This paper, therefore, follows the hypothesis that a distinctive phonological representation of words contains adequate information to make predictions about neural activity (Handbook of IPA, 1999; Bloomfield, 1933; Chomsky & Halle, 1968; Saussure, 1916).

In order to validate the use of the theory of distinctive phonetic features in this research, it should be noted that a distinctive approach is considered to be the most efficient way of reducing the phoneme inventory of a language. Secondly, it can be argued that most phonological oppositions are binary in nature (e.g. that sounds are produced either oral or nasal) (Chomsky & Halle, 1968; George, 2010). The features used to represent phonetic words are defined according to Hall & Clemant (1983), as has been described in their book 'Problem Book in Phonology', who believed this set of features to be 'sufficient to define and distinguish the great majority of speech sounds used in the languages of the world'. These features are also adopted, however slightly adjusted, by Mortensen et al., (2016) inside the PanPhon, a database relating over 5000 IPA segments to 21 subsegmental articulatory features.

2.2 The Articulatory Correlates of the Distinctive Features

Before providing the descriptions of the different feature characteristics inside this research there is one ambiguity to be clarified, which is the difference between phonetic and phonological features. Discriminating one from another clarifies which is used for defining the feature tables and which are the sub characteristics of the predefined speech sounds.

Phonetic features : These features are a specific articulatory or acoustic characteristic and define the physical movement of speech organs to produce sound waves. It therefore deals with the production of sounds by human, without prior knowledge to the language being spoken (Chomsky & Halle, 1968; Hall et al., 1983).

Phonological Feature : All information necessary to define a segment of a word is contained inside a phonological feature. A phonological feature can often be defined by multiple phonetic features. It therefore deals with the pattern of sound which will be used to define the distinctive features in this paper (Chomsky & Halle, 1968).

The phonological component is to derive the phonetic representation of an utterance, thereby grasping all necessary information about the produced sound patterns. A phonological feature may be realized by more than one articulatory or acoustic feature, eg. anterior [ant] is realized by labial, dental and alveolar (Chomsky, 1968). The following descriptions show the phonological features which are defined by its articulatory or acoustic features. To increase the chance that the model can generalize on the feature set, a wide variety of phonological representations is used. It is subdivided into two major parts, namely, a complete set of all possible articulatory and acoustic characteristics of sound patterns, consisting of 43 features, and a subset, consisting of 20 features. The latter, as mentioned in the last section, is considered to contain all necessary characteristics to distinguish between speech sounds, providing each word with a unique set of phonological items.

2.2.1 Complete set of Distinctive Phonological Features and its abbreviations

```
alv = 'alveolar'          lao = 'labiodental'       plo = 'plosive'
app = 'approximant'       lat = 'lateral'           pro = 'protruded'
bac = 'back'              lax = 'lax'               pul = 'pulmonic'
bil = 'bilabial'          mid = 'mid'               rnd = 'rounded'
cen = 'central'           nas = 'nasal'             sib = 'sibilant fricative'
clo = 'close'             nec = 'near-close'        stp = 'stop'
cmi = 'close-mid'         nef = 'near-front'        trl = 'trill'
com = 'compressed'        neo = 'near-open'         unr = 'unrounded'
con = 'consonant'         occ = 'occlusive'         uvu = 'uvular'
den = 'dental'            ong = 'ong'               vel = 'velar'
fri = 'fricative'         opn = 'open'              voi = 'voiced'
fro = 'front'             opm = 'open-mid'          vol = 'voiceless'
glo = 'glottal'           ora = 'oral'              vow = 'vowel'
lab = 'labialized velar'  pal = 'palatal'
lai = 'labio-palatal'     pav = 'palatal-alveolar'
```

2.2.2 Sub-set of Distinctive Phonological Features and its definitions

syllabic / non-syllabic [syll] :
[+syll] refers to vowels and to syllabic consonants
[-syll] refers to all non-syllabic consonants (including semi-vowels).

consonantal / non-consonantal [cons] :
[+cons] refers to all consonants except for semi-vowels (which often have resonant stricture).
[-cons] refers to vowels and semi-vowels.

sonorant / obstruent [son] :
[+son] refers to vowels and approximants (glides and semi-vowels).
[-son] refers to stops, fricatives and affricates.

coronal / non-coronal [cor] : This feature is intended for use with consonants only.
[+cor] refers to dentals (not including labio-dentals) alveolars, post-alveolars, palato-alveolars, palatals.
[-cor] refers to labials, velars and uvulars.

anterior / posterior [ant] : This feature is intended to be applied to consonants.
[+ant] refers to labials, dentals and alveolars.
[-ant] refers to post-alveolars, palato-alveolars, retroflex, palatals, velars and uvulars.

labial / non-labial [lab] : Labial sounds involve rounding or constriction at the lips.
[+lab] refers to labial and labialised consonants and to rounded vowels.
[-lab] refers to all other sounds.

distributed / non-distributed [distr] :
[+distr] refers to sounds produced with the blade or front of the tongue, or bilabial sounds.
[-distr] refers to sounds produced with the tip of the tongue. This feature can distinguish between palatal and retroflex sounds, between bilabial and labiodental sounds, between lamino-dental and apico-dental sounds.

high / non-high [high] :
[+high] refers to palatals, velars, palatalised consonants, velarised consonants, high vowels, semi-vowels.
[-high] refers to all other sounds.

mid / non-mid [mid] :
[+mid] refers to vowels with intermediate vowel height.
[-mid] refers to all other sounds.

low / non-low [low] :
"Low sounds are produced by drawing the body of the tongue down away from the roof of the mouth; nonlow sounds are produced without such a gesture."
[+low] refers to low vowels, pharyngeal consonants, pharyngealised consonants.

back / non-back [back] :
[+back] refers to Velars, uvulars, pharyngeals, velarised consonants, pharyngealised consonants, central vowels, central semi-vowels, back vowels, back semi-vowels.
[-back] refers to all other sounds.

front / non-front [front] :
To describe the central vowels of Australian English its necessary to define them as [-back, -front].

continuant / stop [cont] :
[+cont] refers to vowels, approximants, fricatives.
[-cont] refers to nasal stops, oral stops.

lateral / central [lat] :
[+lat] refers to lateral approximants, lateral fricatives, lateral clicks.
[-lat] refers to all other sounds.

nasal / oral [nas] :
[+nas] refers to nasal stops, nasalised consonants, nasalised vowels.
[-nas] refers to all other sounds.

tense / lax [tense] :
[+tense] refers to tense vowels or long vowels.
[-tense] refers to lax vowels or short vowels.

sibilant / non-sibilant [si] :
[+sib] refers to [s z ʃ and ʒ].
[-sib] refers to all other sounds.

spread glottis / non-spread glottis [spread] :
[+spread] refers to aspirated consonants, breathy voiced or murmured consonants, voiceless vowels, voiceless approximants.
[-spread] refers to all other sounds.

constricted glottis / non-constricted glottis [constr] :
[+constr] refers to ejectives, implosives, glottalized or laryngealised consonants, glottalized or laryngealised vowels.
[-constr] refers to all other sounds.

voiced / voiceless [voice] :
[+voice] refers to all voiced sounds.
[-voice] refers to all voiceless sounds.

2.3 A comprehensive study on phonetic feature extraction

An ideal feature vector should contain the right characteristics that resembles the information enclosed inside the data, thereby enabling the model to make unambiguous predictions about the data. Therefore, it is of great importance to create and select the appropriate set of features to make accurate predictions (Viszlay, 2010).

Inside this paper there will be attempted to capture the physical characteristics of the sound waves of words inside a feature vector which is able to contain all necessary information to predict neural activity. Much attention should be given to the conversion of words to both a phonetic- and phonological feature vector to comprise all necessary information. Therefore, an elaborate study on various techniques to extract and construct a phonological feature vector will be provided.

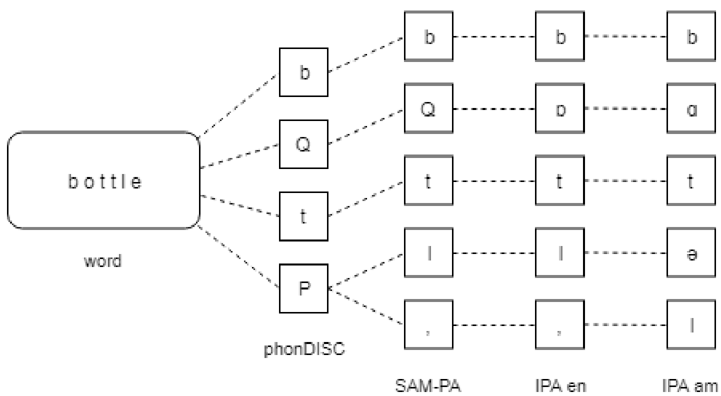

Figure 2.1: The conversion of one of the words from the data set of Mitchell (2008) from word to phonDISC to SAM-PA to English IPA to American IPA

We have assumed that features are binary (a segment is either nasal or it is not) following the original formulation of distinctive feature theory of Jakobsons (1941) which was later adopted in Sound Pattern of English by Chomsky & Halles (1968) and revised by multiple studies (Hall & Clemant, 1983; IPA, 1999). Firstly, to obtain distinctive phonetic features, the original set of words was converted to a phonetic transcription that contains the segmented characteristics of the sound patterns of the words. Subsequently, for each segment of the word there exists a set of characteristics which are saved and stored inside the feature table of the word (figure 2.1 and figure 2.2). Therefore, for each segment of the phonetic transcript, a feature table is constructed which displays the sound characteristics necessary to pronounce the word.

This paper applies three distinct alphabets, namely, the phonDISC, SAM-PA (an abbreviation for Speech Assessment Methods Phonetic Alphabet) and the earlier mentioned IPA. The alphabets phonDISC and SAM-PA are primarily used to identify similarities between phonetic languages and to obtain insights on the properties of word-segments. The IPA is consulted for the extraction of phonetic features as it is considered to be universally applicable and because of its strong foundations within the field of phonology (IPA, 1999; Mortensen, 2016; Burnage, 1990).

With the objective to extract the phonetic properties of the 60 nouns from Mitchell's data set, firstly the phonDISC phonology is used. phonDISC is a phonetic alphabet made up from distinct single characters in which a phonetic segment of a word can be contained inside a single character. This is in contrast to other phonetic alphabets that use extra characters for long vowels such as affricates and diphthongs, which makes it easy to comprehend the sequential sound patterns of the word (Wells, 1987). These phonemes are then converted to SAM-PA, a widely-agreed computer-readable phonetic character set which is employed according to the transcription schemes for phonemes, constructed by the Centre for Lexical Information (Burnage, 1990).

Subsequently the phonetic SAM-PA words are converted to IPA. Both SAM-PA and IPA are used to identify the features to reduce the chance of false classifications inside the feature table. This study follows the phonetic feature chart from the newly revised IPA chart (Appendix A), containing all phonetic characters and its features, as well as a transcription conversion from SAM-PA to IPA and its features (Wells, 1997).

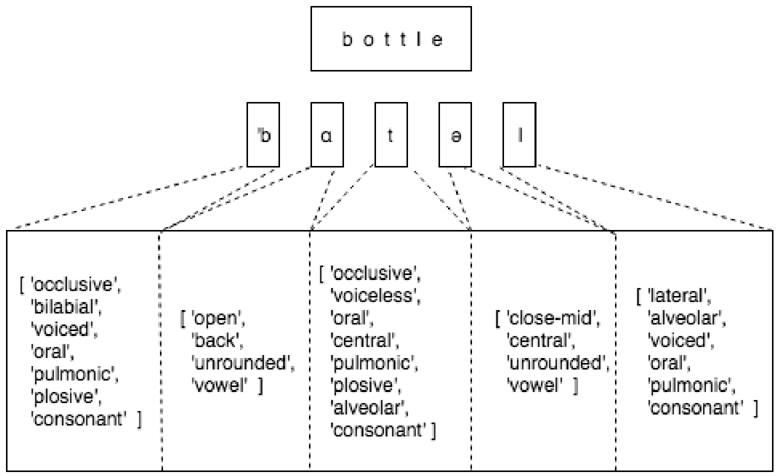

Figure 2.2: The conversion from word to IPA and from IPA to phonetic feature characteristics

Conversions from phoneme to phonetic feature are presented inside a table in Appendix B, which consists of the articulatory and acoustic characteristics of all phonemes from the IPA. For both phonological feature sets, four different conversions are used which are listed below. All feature tables are constructed according to the IPA:

1. Distinctive feature table, taken from the English phonetic dictionary, with the assumption that the phonetic information of a word can be captured by a binary articolatory feature table without taking into account the sequential order of the phonetic segments.

2. Distinctive feature table, taken from the American phonetic dictionary. As previously mentioned, the experiment from Mitchell is done with American participants which makes this feature table presumably more effective.

3. Distinctive feature table with only the first letter. There can be hypothesized that most information about words are contained inside the first letter because it is expressed first, thereby inducing more attention to the brain for memorizing words.

4. Distinctive feature table with only the features of the stressed letters of the word. There can be hypothesized that most information lies here, due to the assumption that most information is captured and memorized within the stressed tones of a word.

The techniques described in this section allows for the automatic conversion from orthographic texts to sequences of articulatory and acoustic feature vectors. One example word is provided below to visualize the activation of the complete set of phonological features, created for all 60 nouns from the dataset.

alv	app	bck	bil	cen	clo	cmi	com	con	den	fri	fro	glo	lab	lai	lao	lat
1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0
lax	mid	nas	nec	nef	neo	occ	ong	opn	opm	ora	pal	pav	plo	pro	pul	rnd
0	0	0	0	0	0	1	0	1	0	1	0	0	1	0	1	1
sib	stp	trl	unr	uvu	vel	voi	vol	vow								
0	0	0	0	0	0	1	1	1								

Table 2.1: Active articolatory and acoustic characteristics of the phonological feature vector for the word ’bottle’, constructed from the American phonetic alphabet.

Following is the phonological feature table (table 2.2) with the phonological characteristics as presented in the previous section. This feature set is considered to contain all necessary characteristics to define a word of a language (Hall, 1983). It would therefore be valuable to know if there are differences in accuracy between a complete phonological representation of specific words and a subset of such a phonological representation. Multiple representation techniques are used to grasp the information of phonemes as they are organized in the human brain.

ant	back	cons	constr	cont	cor	distr	front	high	lab
1	1	0	0	0	1	1	0	0	0
lat	low	mid	nas	si	son	spread	syll	tense	voice
1	0	1	0	1	1	1	0	1	0

Table 2.2: Active articolatory and acoustic characteristics of the phonological feature vector for the complete set of segments of the word ’bottle’, constructed from the American phonetic alphabet.

The conversion from orthographic texts to sequences of articulatory and acoustic feature vectors is a complex task with a great deal of variations and techniques. The feature vectors retrieved from the 60 words is constructed according to the IPA. Both phonological representations are empirically validated whether the vectors contain the right characteristics associated to the words. The vectors are considered to be accurate and contain sufficient information to predict brain activity from fMRI images.

Chapter 3

Prediction and Decoding of Brain Activation

This chapter provides the methods of predicting and decoding brain activation patterns from fMRI images in attempt to answer the question: *how can we predict and decode brain activation's associated with words based on phonological vector representations of those words?* This study implemented two models, a linear regression model and a similarity based decoding model, to grasp neural information contained in the fMRI images. These are explained after a short notice on the fMRI data and a general view on the design and procedure of the methods used. The results of the experiments are provided in chapter 4.

3.1 fMRI Data from Participants

The data used in this research has been acquired from the study of Mitchell et al (2008) which consists of fMRI data from nine college-age participants who viewed 60 different word-picture pairs presented six times each. To reduce the error and prevent noise in the data, the participants viewed these words six times each, after which the mean fMRI response was created over its six presentations. The 60 stimuli words are randomly collected in pairs of 5 for each of 12 semantic categories (animals, body parts, buildings, building parts, clothing, furniture, insects, kitchen items, tools, vegetables, vehicles, and other man-made items) for a wide variation of concepts.

The participants are American students (of which 6 women) with the age between 18 and 32. When a word was presented, the task of the participants was to think about the properties of the object. Furthermore, the image of the word was presented for 3 seconds in which the fMRI image was taken, meaning that the overall neural activity was obtained within a range of 3 second per stimulus word.

3.2 Design and procedure

Now the form representation of the words is complete, there can be attempted to predict neural activity. There are multiple representations of words, contained inside a phonetic feature vector, that are validated to detect similar patterns between neural fMRI images and phonetic characteristics of words. Although some representations are ambiguous in a sense that it contains very little information that is substantial enough to predict neural activity, there can still be surprising results and they will, therefore, be included in the experiments. Besides the pre-made feature vectors, the brain voxel data from the set of Mitchell et al. (2008) is available, containing the observed neural activity.

As stated before, this paper follows the same metric as performed by Mitchell (2008) and Abnar et al., (2018) which will be further explained in the following section. The model has performed well

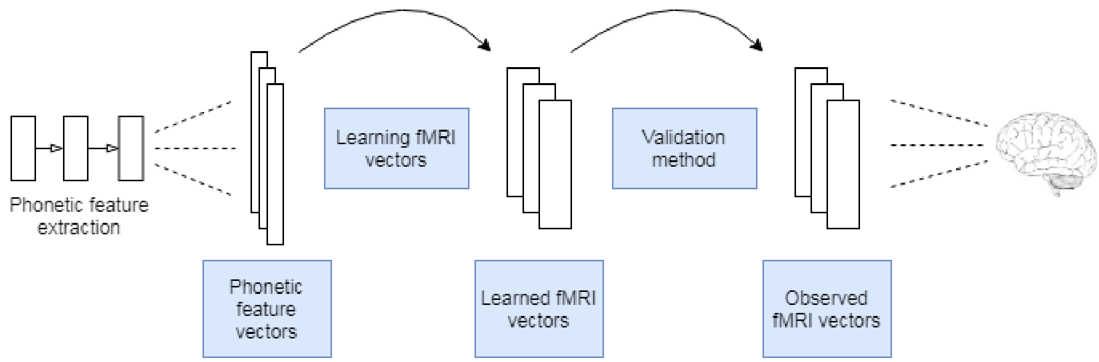

Figure 3.1: The general flow of the project with the main goal to extract a phonological form of words that resembles the neural activity of a human brain.

on the prediction of neural activity related to the distributional properties of the stimulus words in a broadly based text corpus. It is therefore not necessary to relate all the details of the model as it is a close copy to the effective regression model used in earlier research. The following sections will provide a brief explanation of the different similarity metrics.

3.3 Similarity metrics

3.3.1 Matching neural similarity onto semantic similarity

Learning neural activity patterns to synthesize a predicted neural activity pattern is considered an interesting task. Still, learning them implicates complications such as a high cost training time and a chance of inducing errors such as over-fitting. The major challenge is to understand the patterns of neural activity and to see if there is a correlation between neural activity and the phonological properties of nouns. Therefore, instead of learning neural activity, all that is necessary is to compute the similarity between them.

This method is introduced by Andrew et al., (2016), who implemented their model on the data-set of Mitchell (2008) with the original set of semantic-feature vectors. They discovered that their similarity-encoding method is able to make accurate predictions about the neural representations of concrete-nouns. This research has proven this metric to be robustly enough to predict neural activity and, as there is no need to fit a model, it is extremely low cost.

There is no need to go in depth, as this metric is proven to effectively predict neural activity. Below, a replicate of the most important steps is shown to provide a general idea of the method. For further analysis of the model, this paper refers to the research of Andrew (2016).

Appendix C shows the pair-wise similarity matrix of the neural activity taken from the fMRI images. Also it shows the pair-wise similarity matrices of the phonological representations. This allows for an empirical measurement of the correlations between the observed fMRI images and the generated phonological feature vectors.

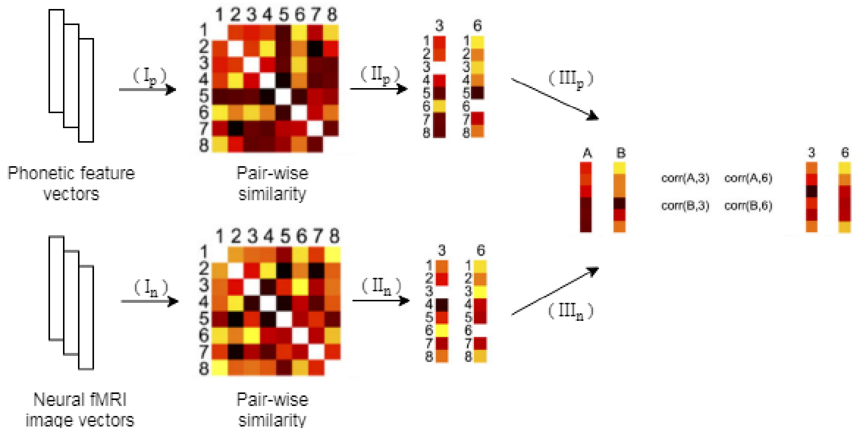

Figure 3.2: This figure has been reconstructed from the research of Andrew (2016) to visualize the procedure of the similarity based decoding algorithm. First (I), for both the phonetic feature vectors (I_p) and the neural fMRI images (I_n), a pair-wise similarity 60 x 60 matrix is computed (for visual clarity illustrated as a 8 x 8 matrix). Following, for each existing stimulus pair $(60 + 59 + 58...)$, the degree of match between two stimulus vectors (both phonetic (II_p and III_p) and neural (II_n and III_n) is computed, classifying the vectors according to their correlated score.

3.3.2 Learning neural activity patterns

A linear regression model was used to learn the fMRI vectors from the phonetic feature vectors. As for the evaluation method, there is made use of a cross validation approach, in which the model was repeatedly trained using only 58 of the 60 stimulus word vectors and the associated fMRI images. Following, each trained model was evaluated by means of a 'leave-two-out' approach. Each trained model was tested by requiring that it first predict the fMRI images for the two held-out words and then match these correctly to their corresponding held-out fMRI images.

Therefore, on each iteration, the two predicted and the two observed fMRI images are matched, trying to predict which of the two novel images was associated with which of the two novel words. This was determined by computing the cosine similarity and selecting the matched pair with the highest similarity score. The cosine similarity score is based on their co-occurrence values, therefore the total cosine similarity of both matches is taken and compared to a greater then statement, thereby either correctly or incorrectly classifying the predicted and observed fMRI-images. These were evaluated over the 500 image voxels with the most stable responses across training presentations.

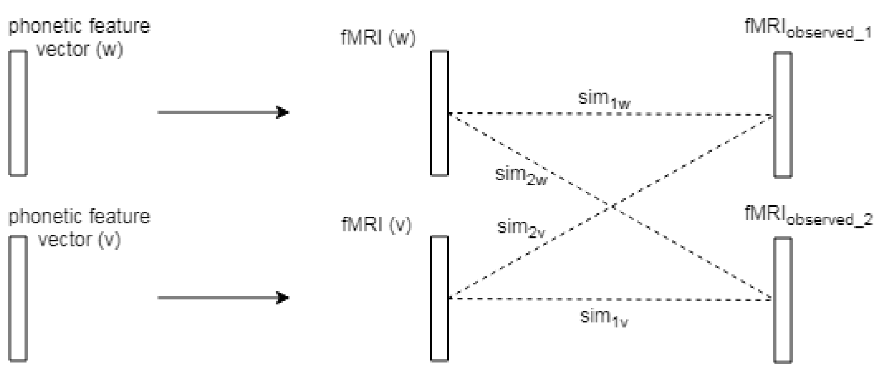

Figure 3.3: The process of training on the phonetic feature vectors and predicting the fMRI images for word (w) and word (v) which is directly followed by the validation, based on their co-occurrence value of the cosine similarity score.

$$f(x) = \begin{cases} \text{match(fMRI(w), fMRI(observed-1))}, & \text{if sim(1w) + sim(1v) > sim(2v) + sim(2w)} \\ \text{match(fMRI(v), fMRI(observed-2))} & \\ & \\ \text{match(fMRI(w), fMRI(observed-2))}, & \text{otherwise} \\ \text{match(fMRI(v), fMRI(observed-1))} & \end{cases}$$

If the phonological feature vector does not represent the neural activity measured inside the voxel data, then the expected accuracy of matching the left-out words to their left-out fMRI images is 0.50. In this case, the model performs at chance levels, as no effective pattern or structure can be learned from the feature vectors. According to Mitchel et al (2008), an accuracy of ’0.62 or higher for a single model trained for a single participant is determined to be statistically significant relative to chance’. This is based on the empirical distribution of accuracy’s for randomly generated null models which they calculated for their study.

Chapter 4

Experiments

4.1 Similarity based decoding

The similarity based decoding has been conducted with 12 different phonological feature tables, consisting of both sets of phonological features of either the American or English phonology. The accuracy of the model is computed according to the same formulas as used by Andrew et al., (2016), who did a binary classification based on the highest correlated value of two feature pairs and two neurological fMRI vectors associated to one of the 60 words from Mitchell's data-set. Then for every pair in the set of 60 words, the correct and incorrect similarity predictions are counted, according to the formula below.

b$_{N+1} = \frac{1}{C} * \sum_{i=1}^{N} b * corr(s_{N+1}, s_i)$

C = $\sum_{i=1}^{N} corr(s_{N+1}, s_i)$

b indicates the accuracy of the binary classification of the 'leave-two-out' method in which the correlated value is computed for each two pairs of stimulus words. To correlated value is between two phonetic feature vector and two neural fMRI brain activity vectors that are associated with the stimulus pair. Then, the pair is classified according to the correlated value between phonetic and neural vectors, which will be labeled as true or false, judging their right or wrong classification. C indicates the total amount of pairs that are classified. With the semantic vector used by Abnar et al., (2018) with which they obtained an accuracy of 76 % it is possible to predict a 86.44 % with the similarity based decoding. This proves that the similarity based decoding is a substantial metric and can be adopted to a phonetic feature vector as well.

Experiment	Complete word	First segment	Stressed segment
Similarity based decoding American phonology	41.86%	56.49%	50.50%
Similarity based decoding English phonology	35.98%	53.65%	47.83%

Table 4.1: Results of the complete phonological feature set

All predictions are close to 50 %, signifying that the binary classification has performed according to chance. Therefore, no true similarity between the phonological feature vectors and the fMRI neural data is expected to exist. There is, however, a consistently higher score for the American phonology.

No real difference is measured between the two feature sets, which implies that neither one contains evident information about neural activity. There exists a clear consistency between feature sets, as the accuracy between the complete word, first segment and stressed segment is closely related between both feature sets, besides that the accuracy of the subset features is slightly lower (table 3.1 and 3.2).

Experiment	Complete word	First segment	Stressed segment
Similarity based decoding American phonology	45.27%	59.04%	49.74 %
Similarity based decoding English phonology	30.96%	56.16%	47.36%

Table 4.2: Results of the sub-set of phonological features

Appendix C presents the pair-wise similarity matrices. It can be observed that the similarity matrices of the complete words are mostly yellow, which implies that the overall similarity between word-vectors is high. The high pair-wise similarity values are correlated with low accuracy values when predicting the correct combination of phonological vectors and neural fMRI vectors. Low similarity matrices, such as the first segment of words or the stressed segments, intend to have higher prediction accuracy's as well.

4.2 Binary classification

The binary classification experiments are run on a total of 12 phonological feature vectors for all 60 words and its associated fMRI-images. These are represented in the tables below (table 3.2), the first presenting the results of the complete characteristic set of 43 features and the second presenting a sub set of characteristics of 20 features. The model is first run with a semantic feature vector, consisting of the co-relation of 25 verbs and the 60 nouns of the data-set of Mitchell (2018). This feature vector attained an accuracy of 76.5, which demonstrates the validity of the model. Parallel to the similarity based decoding, the binary classification of the learned fMRI images shows an overall accuracy of chance without evident outliers that perform consistent right, or wrong, classifications.

Experiment	Complete word	First segment	Stressed segment
Word to Brain American Brain to Word American	52.3% 50.1%	46.3% 49.7%	50.2% 49.3%
Word to Brain English Brain to Word English	48.4% 39.5%	55.5% 43.3%	46.5% 48.8%

Table 4.3: Results of the complete phonological feature set

Experiment	Complete word	First segment	Stressed segment
Word to Brain American Brain to Word American	54.5% 44.5%	46.6% 37.2%	50.0 % 48.9 %
Word to Brain English Brain to Word English	34.8% 37.1%	49.6% 39.6%	51.4% 43.5%

Table 4.4: Results of the sub-set of phonological features, still being computed

There can be observed that the predictions conducted with the American phonology is slightly higher then those conducted with the English phonology. The two metrics show similar accuracy values, inclining that both methods are robust when predicting neural activity.

Chapter 5

Discussion, Conclusion and Further Research

5.1 Discussion

In this work, there is attempted to predict neural activity associated with phonological feature set, based on the sound characteristics of spoken words, thereby proving a correlation between neural activity and phonological patterns of sound waves. Previous research has proven the semantic correlation towards neural activity, though the relation of the phonological properties of nouns remain obscure. This research failed to show a clear similarity between brain fMRI images and distinctive phonological features of words. Both metrics have shown to accurately predict neural activity using association rules in different semantic categories. Therefore, the major limitation lies within the structure of the phonological feature sets. These findings indicate that a distinctive approach of phonological characteristics is not able to grasp the full particulars of phonological properties as it is organized and memorized in a human brain. A few points are enumerated that are apparent to have a negative effect on the predictive ability of the model.

At first, these findings suggest that words are not memorized as a complete set of characteristics that are contained in every segment of the word, without taking into account the sequential order of segments. Although attempts have been made to efficiently comprise phonetic information, such as the emphasis on the first segment or the stressed segments of words, no significant similarity was observed. As mentioned in the start of this paper, distinctive phonological features are considered to be too abstract descriptions of speech sounds that do not resemble the form of words in memory. This study has thereby proven the assumption that neural activity, captured by fMRI images, does not resemble a distinctive approach of phonological words. Besides the imperfections of distinctive phonological features, the sequential order of segments has been fully neglected within this research. There should, therefore, be attempted to capture the sequential information of segments, instead of assuming characteristics to be expressed simultaneously, which they (needless to say) do not.

Furthermore, the participants were confronted with the symbolic representation of words, while other activation patterns might be active when hearing or seeing a word. This implies that no similarity could be detected between the two feature vectors due to the fact that the neural activity was collected when the participants saw the word instead of hearing it. This research is done with the assumption that the neural activity patterns can be matched with the phonological properties of words. However, if the data is collected while the participants see a symbolic representation, other neural activity is presumable to be active. This would indicate that the phonological feature set is not necessarily in-able to comprise phonological information of words. The current distinctive feature sets should be tested on neural fMRI data from participants when hearing the word, to assure whether there is a similarity between a distinctive approach of phonological characteristics and the way the human brain organizes the vocal characteristics of words.

The traditional view that words are stored in memory using segments units, however intuitively it seems, is too abstract to capture complex sound patterns. The phonological features could be learned from a large data-set of speech sounds, collected for each stimulus word with its associated brain fMRI image. This way, more complex sound characteristics can be captured, taking into account the phonetic characteristics as well.

At last there should be a revision on the conversion between phonetic languages and on the extraction of phonological features. Though this has been done with a great deal of care, there are inevitably mistakes made or ill-considered decisions. However this should only have slightly reduced accuracy predictions while the predictive ability of both metrics lies between chance, implying that such mistakes are not the main cause.

5.2 Conclusion

After the analysis of the results, there can be concluded that the model was not able to generalize on the distinctive feature sets that was constructed for this research. For all different representations, the neural network predicted with an accuracy close to chance, mostly within the borders of 38% and 62% which was considered to be the range of chance.

There is also no clear distinction between the complete feature set and the subset, implicating that a distinctive approach does not contain sufficient information for the model to make good predictions. Also no significant distinctions is observed between the American and the English phonological features. Due to their difference in phonetic properties and the fact that the participants are natural American speakers, a difference in accuracy would have been expected to be observed. However, no such assumptions can be made as the model performs at chance level and, therefore, the predictive outcome is necessarily unsubstantiated.

This study therefore concludes that with a distinctive approach of phonological features it is not possible to predict neural activity. There can, therefore, be further deduced that a human brain does not organize or memorize words and concepts based on the distinctive phonological characteristics. This does not exclude the assumption that phonology participates the organization and memorization of words and concepts. Further studies will have to invent different approaches to grasp the phonological properties of words, thereby investigating the probable relation of phonology and neural activity.

5.3 Further Work

This research has conducted a comprehensive study on a correct distinctive phonological feature set, thereby proving the dissimilarity between the constructed features and neural fMRI activity patterns. Further research should conduct different approaches to comprise correct characteristics of word sound patterns. There are several new directions possible from the results of this thesis.

Firstly, it would be interesting to include the sequential information of sound waves produced when speaking a word. The sequential order is able to represent a phonetic characteristics more effectively. Phonetic transcription is a complex task and it is important to take into account such things as inferences about unseen articulatory patterns and relations between sounds in a particular language's phonology. Furthermore, attention should be given to words with similar phonetic properties. It would be valuable to know if there is a consistence misclassification with words that have related sound characteristics, such as 'shirt' and 'skirt'.

It is also of great interest to train on specific brain voxels that are more inclined to have phonological information stored. When training on such a region of the brain, the model might be able to generalize better or compute higher similarity scores as the neural activity matches the phonological characteristics associated to words.

Subsequently, the phonological features have to be learned from a large data-set of speech sounds, collected for each stimulus word with its associated brain fMRI image. There could be attempted to automatically learn a phoneme representation. This has already been conducted by Kane et al., (2013) who used a multi-layer perceptron (MLP) for the extraction of phonetic features. Other research by Cernak (2017) presented a PhonVoc toolkit which learns phonological feature representations from spoken words.

The feature set should be trained on neural fMRI data which is collected from participants while speaking the word instead of seeing the word. Perhaps the Open fMRI data-set contains valuable data for further research. I hope this work informs further research into the nature of phonological composition in the human brain.

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Part II

Appendix

A

THE INTERNATIONAL PHONETIC ALPHABET (revised to 2018)

CONSONANTS (PULMONIC)

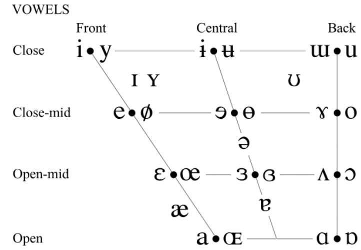
	Bilabial	Labiodental	Dental	Alveolar	Postalveolar	Retroflex	Palatal	Velar	Uvular	Pharyngeal	Glottal
Plosive	p b			t d		ʈ ɖ	c ɟ	k ɡ	q ɢ		ʔ
Nasal	m	ɱ		n		ɳ	ɲ	ŋ	ɴ		
Trill	ʙ			r					ʀ		
Tap or Flap		ⱱ		ɾ		ɽ					
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	h ɦ
Lateral fricative				ɬ ɮ							
Approximant		ʋ		ɹ		ɻ	j	ɰ			
Lateral approximant				l		ɭ	ʎ	ʟ			

Symbols to the right in a cell are voiced, to the left are voiceless. Shaded areas denote articulations judged impossible.

CONSONANTS (NON-PULMONIC)

Clicks	Voiced implosives	Ejectives
ʘ Bilabial	ɓ Bilabial	ʼ Examples:
ǀ Dental	ɗ Dental/alveolar	pʼ Bilabial
ǃ (Post)alveolar	ʄ Palatal	tʼ Dental/alveolar
ǂ Palatoalveolar	ɠ Velar	kʼ Velar
ǁ Alveolar lateral	ʛ Uvular	sʼ Alveolar fricative

VOWELS



Where symbols appear in pairs, the one to the right represents a rounded vowel.

OTHER SYMBOLS

- ʍ Voiceless labial-velar fricative
- w Voiced labial-velar approximant
- ɥ Voiced labial-palatal approximant
- ʜ Voiceless epiglottal fricative
- ʢ Voiced epiglottal fricative
- ʡ Epiglottal plosive
- ɕ ʑ Alveolo-palatal fricatives
- ɺ Voiced alveolar lateral flap
- ɧ Simultaneous ʃ and x

Affricates and double articulations can be represented by two symbols joined by a tie bar if necessary. t͡s k͡p

SUPRASEGMENTALS

- ˈ Primary stress ˌfoʊnəˈtɪʃən
- ˌ Secondary stress
- ː Long eː
- ˑ Half-long eˑ
- ̆ Extra-short ĕ
- | Minor (foot) group
- ‖ Major (intonation) group
- . Syllable break ɹi.ækt
- ‿ Linking (absence of a break)

DIACRITICS Some diacritics may be placed above a symbol with a descender, e.g. ŋ̊

̥	Voiceless	n̥ d̥	̤	Breathy voiced	b̤ a̤	̪	Dental	t̪ d̪
̬	Voiced	s̬ t̬	̰	Creaky voiced	b̰ a̰	̺	Apical	t̺ d̺
ʰ	Aspirated	tʰ dʰ	̼	Linguolabial	t̼ d̼	̻	Laminal	t̻ d̻
̹	More rounded	ɔ̹	ʷ	Labialized	tʷ dʷ	̃	Nasalized	ẽ
̜	Less rounded	ɔ̜	ʲ	Palatalized	tʲ dʲ	ⁿ	Nasal release	dⁿ
̟	Advanced	u̟	ˠ	Velarized	tˠ dˠ	ˡ	Lateral release	dˡ
̠	Retracted	e̠	ˤ	Pharyngealized	tˤ dˤ	̚	No audible release	d̚
̈	Centralized	ë	̴	Velarized or pharyngealized	ɫ			
̽	Mid-centralized	e̽	̝	Raised	e̝ (ɹ̝ = voiced alveolar fricative)			
̩	Syllabic	n̩	̞	Lowered	e̞ (β̞ = voiced bilabial approximant)			
̯	Non-syllabic	e̯	̘	Advanced Tongue Root	e̘			
˞	Rhoticity	ɚ a˞	̙	Retracted Tongue Root	e̙			

TONES AND WORD ACCENTS

LEVEL			CONTOUR		
e̋ or	˥	Extra high	ě or	˩˥	Rising
é	˦	High	ê	˥˩	Falling
ē	˧	Mid	e᷄	˦˥	High rising
è	˨	Low	e᷅	˩˨	Low rising
ȅ	˩	Extra low	e᷈	˧˦˧	Rising-falling
ꜜ		Downstep	↗		Global rise
ꜛ		Upstep	↘		Global fall

Typefaces: Doulos SIL (metatext); Doulos SIL, IPA Kiel, IPA LS Uni (symbols)

IPA	alv	app	bck	bil	cen	clo	cmi	com	con	den	fri	fro	glo	lab	lai	lao	lat	lax	mid	nas	nec	nef	neo	occ	ong	opn	opm	ora	pal	pav	plo	pro	pul	rnd	sib	stp	trl	unr	uvu	vel	voi	vol	vow
n	-	-	-	-	+	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	+	-	-	-	+	-	-	+	-	+	-	-	-	-	-	-	+	-	+	-
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Figure 5.1: IPAlphabet with phonetic features, containing the phonological properties of the 60 words of Mitchell's dataset, considering the English phonology (IPA, 1999; IPA chart, 2018)

B

201 Introduction to Linguistics: Features of Sounds

The International Phonetic Alphabet (IPA)

Consonants

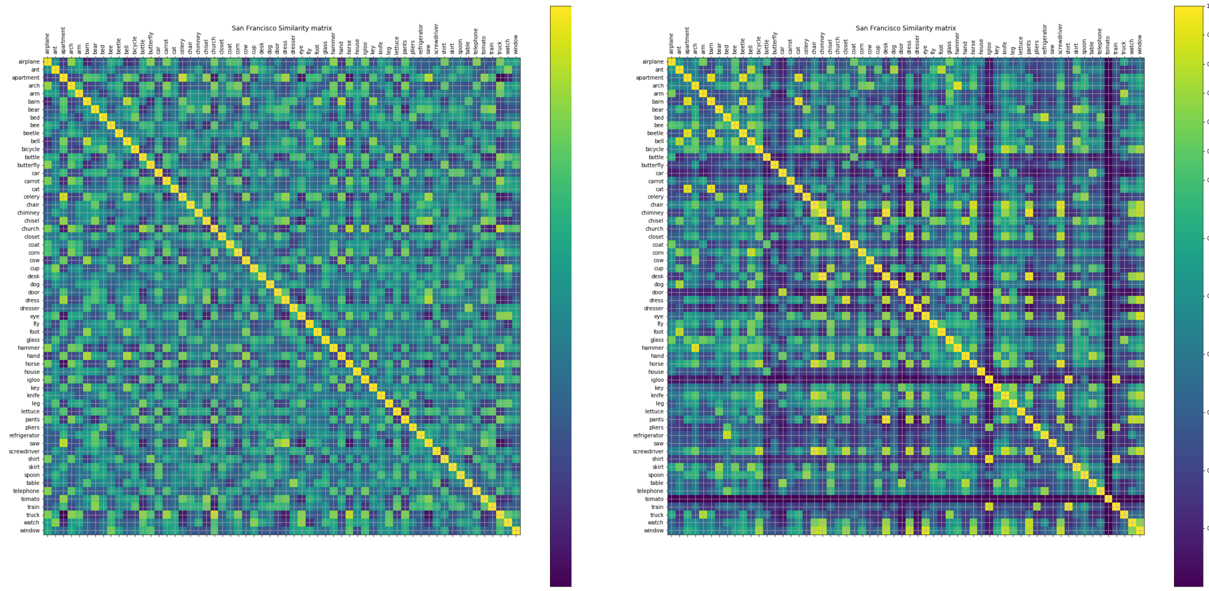
Symbol	**Description in Terms of (a Subset of) Their Features**
p	[+labial, +bilabial, -voiced, -nasal, -continuant]
b	[+labial, +bilabial, +voiced, -nasal, -continuant]
m	[+labial, +bilabial, +voiced, +nasal, -continuant, +sonorant]
w	[+labial, +labiovelar, +voiced, -nasal, +continuant, +approximant, +sonorant]
ʍ	[+labial, +labiovelar, -voiced, -nasal, +continuant, +approximant]
f	[+labial, +labiodental, -voiced, -nasal, +continuant]
v	[+labial, +labiodental, +voiced, -nasal, +continuant]
θ	[+coronal, +dental, -voiced, -nasal, +continuant]
ð	[+coronal, +dental, +voiced, -nasal, +continuant]
t	[+coronal, +alveolar, -voiced, -nasal, -continuant]
d	[+coronal, +alveolar, +voiced, -nasal, -continuant]
n	[+coronal, +alveolar, +voiced, +nasal, -continuant, +sonorant]
s	[+coronal, +alveolar, -voiced, -nasal, +continuant, +strident]
z	[+coronal, +alveolar, +voiced, -nasal, +continuant, +strident]
l	[+coronal, +alveolar, +voiced, -nasal, +continuant, +approximant, +sonorant]
tʃ	[+coronal, +post-alveolar, -voiced, -nasal, -continuant, +strident]
dʒ	[+coronal, +post-alveolar, +voiced, -nasal, -continuant, +strident]
ʃ	[+coronal, +post-alveolar, -voiced, -nasal, +continuant, +strident]
ʒ	[+coronal, +post-alveolar, +voiced, -nasal, +continuant, +strident]
r	[+coronal, +retroflex, +voiced, -nasal, +continuant, +approximant, +sonorant]
j	[+dorsal, +palatal, +voiced, -nasal, +continuant, +approximant, +sonorant]
k	[+dorsal, +velar, -voiced, -nasal, -continuant]
g	[+dorsal, +velar, +voiced, -nasal, -continuant]
ŋ	[+dorsal, +velar, +voiced, +nasal, -continuant, +sonorant]
ʔ	[+glottal, -voiced, -nasal, -continuant]
h	[+glottal, -voiced, -nasal, +continuant]

C

```
{
60 words from Mitchell et al (2008)

"words": {
    'airplane', 'ant', 'apartment', 'arch', 'arm', 'barn',
    'bear', 'bed', 'bee', 'beetle', 'bell', 'bicycle',
    'bottle', 'butterfly', 'car', 'carrot', 'cat',
    'celery', 'chair', 'chimney', 'chisel', 'church',
    'closet', 'coat', 'corn', 'cow', 'cup', 'desk', 'dog',
    'door', 'dress', 'dresser', 'eye', 'fly', 'foot',
    'glass', 'hammer', 'hand', 'horse', 'house', 'igloo',
    'key', 'knife', 'leg', 'lettuce', 'pants', 'pliers',
    'refrigerator', 'saw', 'screwdriver', 'shirt', 'skirt',
    'spoon', 'table', 'telephone', 'tomato', 'train',
    'truck', 'watch', 'window'}
}
```

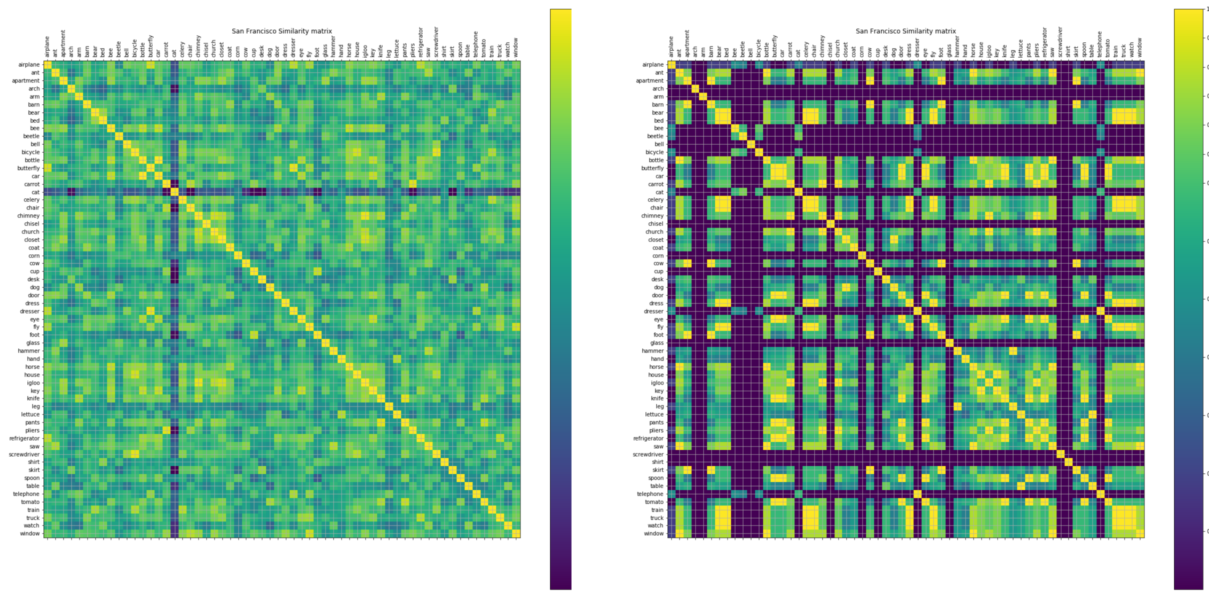
The following pages are reserved for the pair-wise similarity matrices of the neural fMRI image and the 12 phonological feature tables.



(a) Neural activity of fMRI image

(b) F25 semantic vector

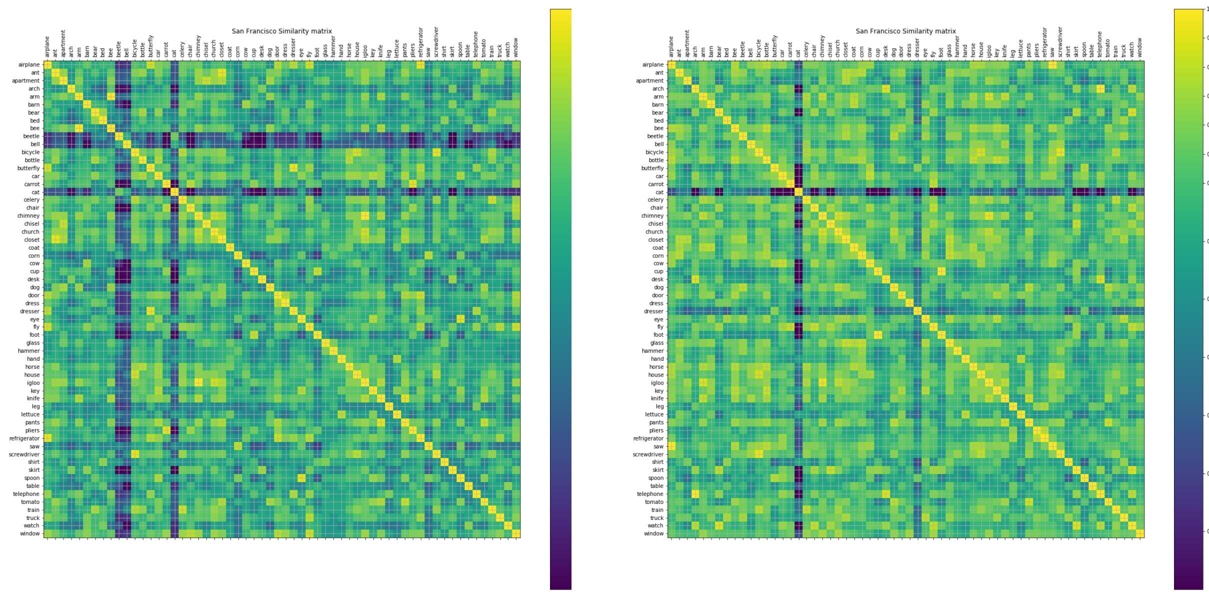
Figure 5.2: Plots of pair-wise similarity representations of the neural activity patterns of fMRI image and semantic representation of word-associations.



(a) Complete word

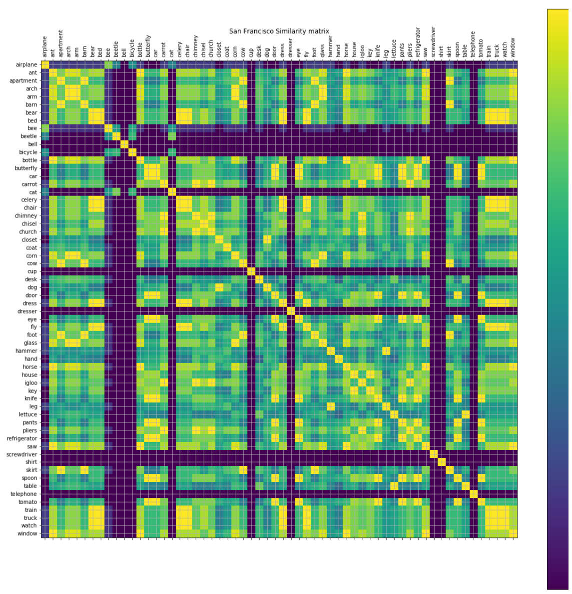
(b) First segment

Figure 5.3: Plots of pair-wise similarity representations of the American phonology, using the complete feature-set

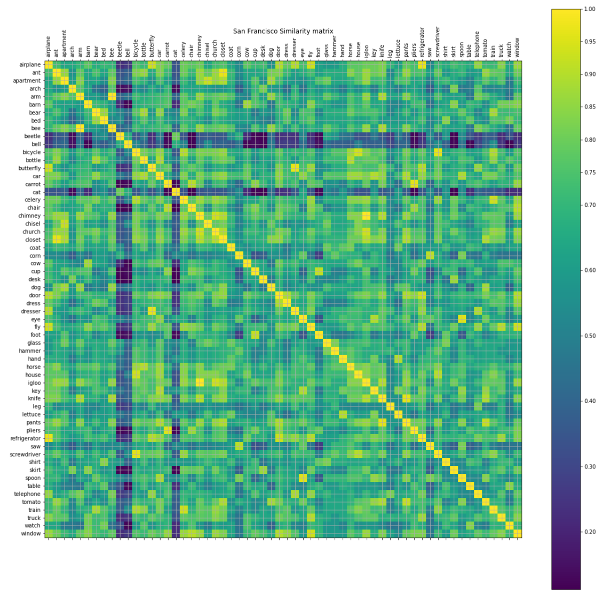


(a) Stressed segment (b) Complete word

Figure 5.4: Plots of pair-wise similarity representations of the English (left) and American (right) phonology, using the complete feature-set

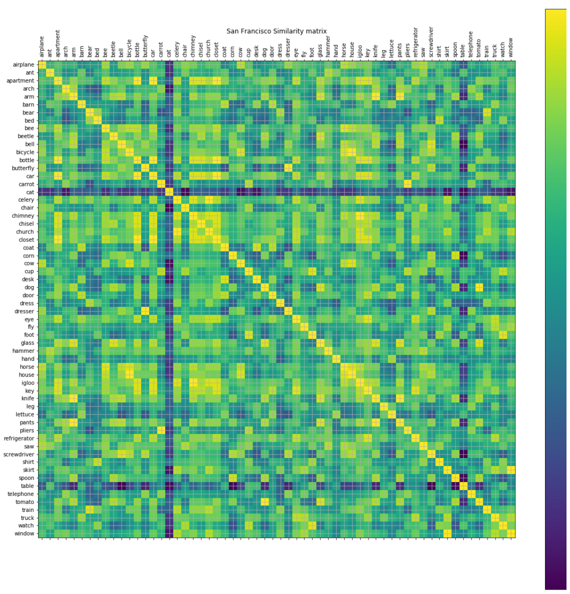


(a) First segment

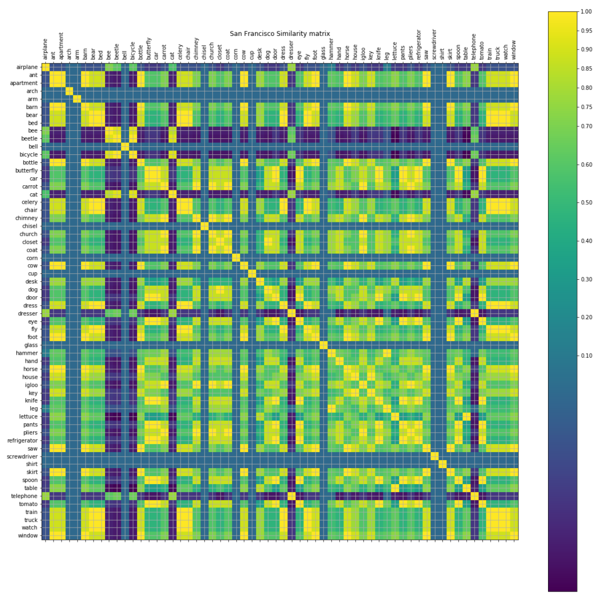


(b) Stressed segment

Figure 5.5: Plots of pair-wise similarity representations of the English phonology using the complete feature-set

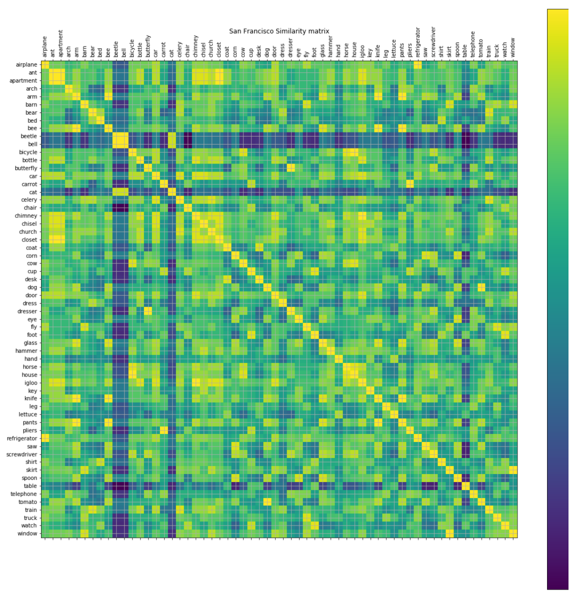


(a) Complete word

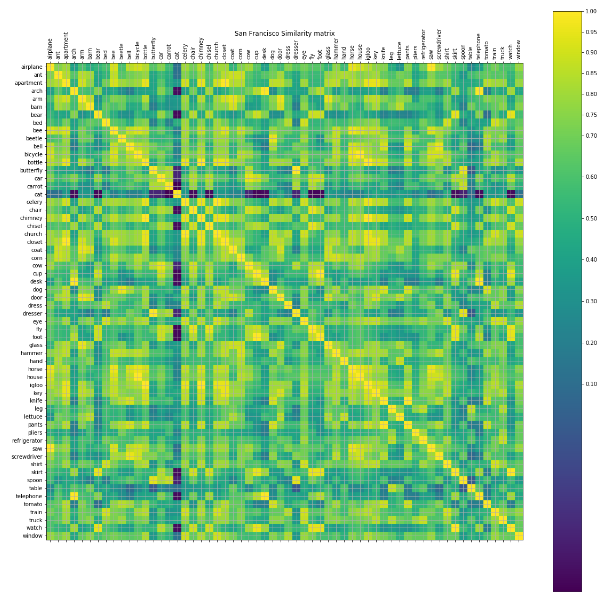


(b) First segment

Figure 5.6: Plots of pair-wise similarity representations of the American phonology using the subset of words

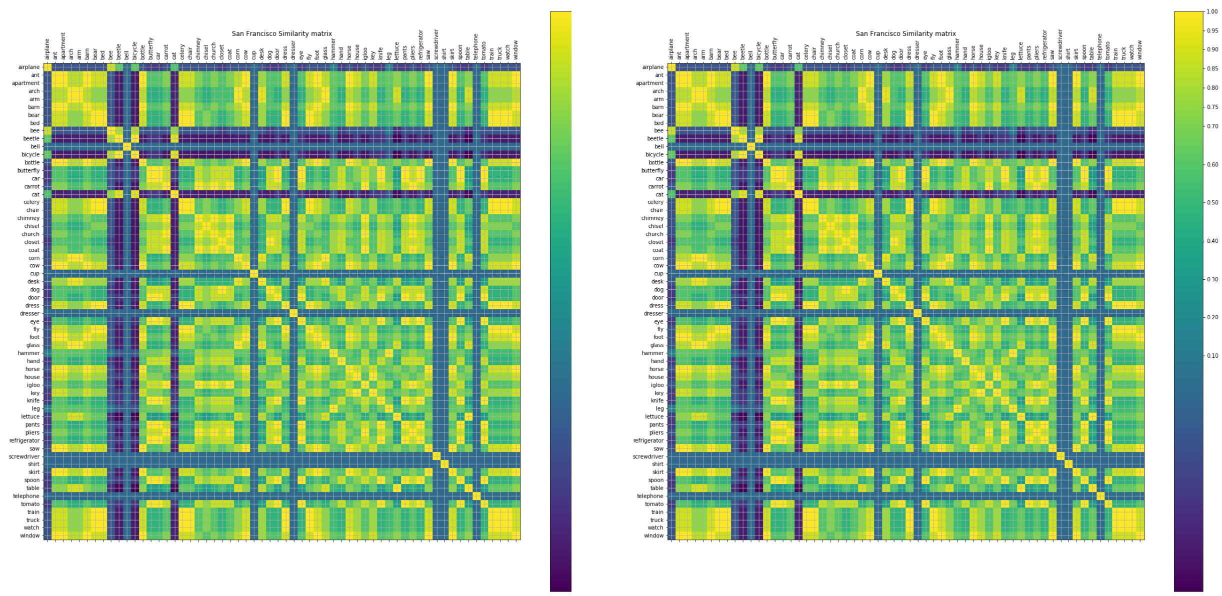


(a) Stress segment



(b) Complete word

Figure 5.7: Plots of pair-wise similarity representations of the English (right) and American (left) phonology using the subset of words



(a) First segment

(b) Stress segment

Figure 5.8: Plots of pair-wise similarity representations of the English phonology using the subset of words