A NEUROLINGUISTIC APPROACH TO NONCOMPOSITIONALITY AND ARGUMENT STRUCTURE

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A NEUROLINGUISTIC APPROACH TO NONCOMPOSITIONALITY AND ARGUMENT STRUCTURE

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Understanding the neural bases of language comprehension is to understand the implementation of language processing in the brain and how it affects language performance. Within a neurolinguistic study, we can examine the connection between linguistic competence and language performance at the cerebral level and whether the distinctions that we draw in linguistic theory map on to particular brain systems. Recently there has been an increase in psycholinguistic and neurolinguistic research using naturalistic stimuli following Willems's (2015) encouragement to investigate the neural bases of language comprehension with greater ecological validity. Along with naturalistic stimuli, applying tools from computational linguistics to neuroimaging data can help us gain further insight into naturalistic, online language processing as computational modeling makes it easier to study the brain responses to contextually situated linguistic stimuli. (Brennan 2016).

Utilizing this approach, in this dissertation I focus on two topics: noncompositional expressions (MWEs) and verbal argument structure. Across seven studies, I show how we can utilize various models and metrics from computational linguistics to operationalize cognitive hypotheses and help us better understand the neurocognitive bases of language processing. This dissertation is based on a large-scale fMRI dataset based on 51 participants listening to Saint-Exupéry's *The Little Prince* (1943), comprising 15,388 words and lasting over an hour and a half. While previous work has examined individual types of noncompositional expressions (such as idioms, compounds, binomials; see §3.2.1), this work combines this heterogeneous family of word clusters in a single analysis. Associa-

tion measures are metrics from corpus and computational linguistics to identify collocations. This research contributes a gradient approach to these noncompositional expressions by repurposing association measures and demonstrates how they can be adapted as cognitively plausible metrics for language processing, among other findings. This dissertation also investigates the neural correlates of argument structure and corroborates previous controlled, task-based experimental work on the syntactic and semantic constraints between a verb and its argument. Another finding is that the Precuneus, not traditionally considered a core part of the perisylvian language network, is involved in both processing noncompositional expressions and diathesis alternations for a given verb. Overall, based on this interdisciplinary approach, this dissertation presents empirical evidence through neuroimaging data, linking linguistic theory with language processing.

BIOGRAPHICAL SKETCH

Shohini Bhattasali is from Calcutta, India. She received her A.B. from Bryn Mawr College and graduated magna cum laude with a major in Linguistics (Hons) and minors in Computer Science and Chinese. She is graduating from Cornell University with a Ph.D. in Linguistics and a graduate minor in Cognitive Science. She applies computational models to brain data in order to understand the physical basis of language comprehension. This research brings together computational linguistics and neurolinguistics and it involves interfaces between linguistic theory, language processing, cognitive science, and neuroscience. She has presented her work at several international interdisciplinary conferences and also published in the *Language, Cognition and Neuroscience* journal.

This dissertation is dedicated to my parents, Shikha & Arunabha Bhattasali.

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Feeling gratitude and not expressing it is like wrapping a present and not giving it.

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I would also like to thank Roy Proper, the fMRI technician at Cornell who helped me run this study over the course of 18 months, and whose cheery presence always helped when we were running experiments all day in a basement. Special thanks to all those who assisted me with data collection: Adam Mahar, Skyler Yeatman, Jaelyn Moore, Jacob Collard, Katey Huddleston, Marissa Holl and Jixing Li. This material is based upon work supported by the National Science Foundation under Grant No. 1903783.

Last but not least, I could not have done all of this without my family and I am extremely grateful to them. Thank you to my parents, Shikha & Arunabha Bhattasali for always believing in me and teaching me the value of hard work and perseverance. Thank you to my brother, Arnab Bhattasali for always being there for me and making sure I sometimes have a life outside work. I'm also grateful to my nephews, Ognian & Nalin Bhattasali who are very proud of their aunt as a scientist-teacher (as they understand it) and always find endless ways to cheer me up and keep me going.

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CHAPTER 1

INTRODUCTION: NONCOMPOSITIONALITY AND ARGUMENT STRUCTURE IN THE BRAIN

Listening to stories is a common human experience. Not only are we hearing a spoken narrative, but we are simultaneously comprehending it. The goal of this dissertation is to examine different aspects of such an online language comprehension scenario. By applying computational models and metrics, word-by-word comprehension difficulty during online language processing can be estimated and these complexity metrics can be used to answer various research questions and operationalize cognitive hypotheses. The research presented here uses complexity metrics across different levels of linguistics analysis to study whether the distinctions that we draw in linguistic theory map on to particular brain networks. Through this interdisciplinary approach, I contribute empirical evidence through English neuroimaging data linking linguistic theory with language processing. Specifically, I address the following research questions:

- Do noncompositional expressions have different neural correlates compared to compositional expressions? Consequently, do the cognitive processes of composition and retrieval have distinct functional localizations?
- Can the differences in the grammatical category of noncompositional expressions be observed at the cerebral level? Is the brain sensitive to the internal structure of these "frozen" expressions?
- Can expressions be binarized as compositional and noncompositional or are there finer-grained distinctions along a continuum?
- Do the different components of argument structure (such as subcategorization, diathesis, selectional restrictions) have different neural substrates?
- How do the different components of argument structure influence online sentence processing?

1.1 fMRI Methodology sketch

In this section, I explain how we can use neuroimaging data to answer our research questions.

Utilizing complexity metrics, we can translate a linguistic question into a quantifiable measure which can be used as a predictor in a fMRI study. The linking hypothesis is between the observed neural activation and the convolved predictor (which represents an underlying cognitive process).

The General Linear Model (GLM) typically used in fMRI data analyses is a time series linear regression (Poldrack et al. 2011). It is a hierarchical model with two levels. At the first level, the data for each subject is modelled separately to calculate subject-specific parameter estimates and within-subject variance such that for each subject, a regression model is estimated for each voxel against the time series. The second-level model takes subject-specific parameter estimates as input. It uses the between-subject variance to make statistical inferences about the larger population.

The methodology described here is based on Brennan et al.'s (2012) approach to study the different operations that contribute to natural language comprehension, under relatively naturalistic conditions, without the potential confound of artificial experimental task demands. Their naturalistic experimental design was adapted and developed from a technique used to study visual processing while subjects watch a popular movie. Following Brennan et al. (2012) in using a spoken narrative as a stimulus, participants hear the story over headphones while they are in the scanner. The sequence of neuroimages collected during their session becomes the dependent variable in a regression against word-by-word predictors, derived from the text of the story, as seen in Figure 1. The predictors are convolved with the canonical HRF to create the estimated fMRI signal (BOLD), which is compared against the observed BOLD signal during passive story listening.

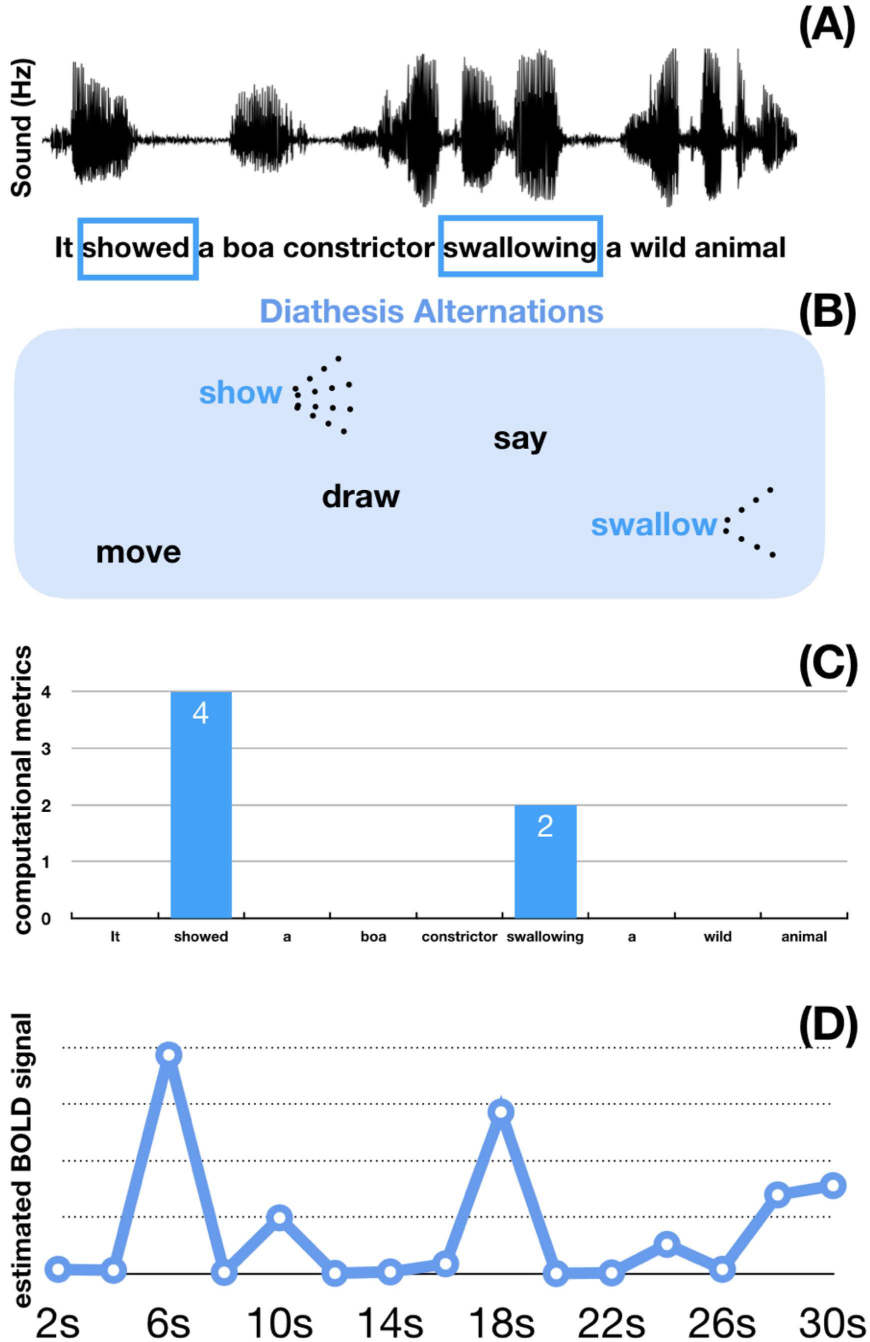

Figure 1: Deriving an expected BOLD signal for one sentence in a naturalistic text. (A) shows a segment of the spoken stimulus, with word boundaries in light blue. (B) illustrates a predictor for verbs, here diathesis alternations and the verbs in the sentence above are highlighted In (C) the value of these word-by-word predictors are shown together, where the verbs are annotated with the scores to reflect the number of diathesis alternations. Panel (D) shows the expected BOLD response, after these predictors are convolved with a haemodynamic response function (HRF).

1.2 Roadmap

Chapter 2 describes the fMRI dataset that will be used in the analyses described in the remaining chapters. It explains how the experiment was designed and presented, and how the data was collected and preprocessed, ending with a discussion about the advantages of such a naturalistic dataset.

In Chapter 3, I examine noncompositional expressions to shed light on memory retrieval and structure building processes, using neuroimaging evidence. I study these expressions grouped together along with breaking them down into smaller groups on the basis of grammatical category, such as verbal expressions versus other expressions. Chapter 4 follows up on Chapter 3 by further investigating alternate ways to study and classify these expressions by adapting different metrics from corpus and computational linguistics to illustrate the gradience within these noncompositional expressions. Chapter 5 extends the theme of verbal expressions from Chapter 3 and explores how different components of verbal argument structure play a role in sentence processing. Chapter 6 concludes with a discussion of the overall results against the architecture of several contemporary neurobioloigcal models of language processing and a summary of the main findings about noncompositionality and argument structure across the seven studies presented in this dissertation.

CHAPTER 2

NEUROIMAGING DATASET

2.1 Overview

The dataset created for this project comprises of fMRI images based on naturalistic stimulus. In this neuroimaging study, spoken narrative is used as a stimulus, following Brennan et al. (2012). Participants hear the story over headphones while they are in the scanner. The sequence of neuroimages collected during their session becomes the dependent variable in a regression against word-by-word predictors, derived from the text of the story. The set of these fMRI images is the dataset for all the subsequent data analyses in the following chapters. It will be referred to as the *Le Petit Prince* dataset (henceforth abbreviated as LPP).

2.2 Stimuli

The audio stimulus was a literary text, Antoine de Saint-Exupéry's *Le Petit Prince (The Little Prince)*, translated from French to English by David Wilkinson and read by Nadine Eckert-Boulet. The text constitutes a fairly lengthy exposure to naturalistic language, comprising 15,388 words and lasting over an hour and a half. There are 1,388 sentences in the story and it provides a variety of different constructions in an ecologically valid setting. The narrative consists of both direct and indirect speech along with extensive dialogue. Apart from English, the original French text has been translated multiple times across 300 languages (Earle 2018) which also makes it suitable for cross-linguistic comparisons.

2.3 Participants

Participants were fifty-one volunteers (32 women and 19 men, 18-37 years old) with no history of psychiatric, neurological, or other medical illness or history of drug or alcohol abuse that might compromise cognitive functions. All strictly qualified as right-handed on the Edinburgh handedness inventory (Oldfield 1971)[1]. They self-identified as native English speakers and gave their written informed consent prior to participation, in accordance with Cornell University IRB guidelines.

2.4 Presentation

After giving their informed consent, participants were familiarized with the MRI facility and assumed a supine position on the scanner gurney. The presentation script was written in PsychoPy (Peirce 2007). Auditory stimuli were delivered through MRI-safe, high-fidelity headphones (Confon HP-VS01, MR Confon, Magdeburg, Germany) inside the head coil. The headphones were secured against the plastic frame of the coil using foam blocks. Using a spoken recitation of the US Constitution, an experimenter increased the volume until participants reported that they could hear clearly.

Participants then listened passively to the audio storybook for 1 hour 38 minutes. The story had nine chapters and at the end of each chapter the participants were presented with a multiple-choice questionnaire with four questions (36 questions in total), concerning events and situations described in the story. These questions were used to confirm their comprehension and were viewed by the participants via a mirror attached to the head coil and they answered through a button box. Examples of comprehension questions designed for this study is given below in Fig. 2 and the layout of the answer choices corresponded to the orientation of the button box. The entire session lasted around two

[1]Complete list of questions provided in Appendix A

and a half hours. Overall, participants had a 90% accuracy (SD = 3.7%) and all 51 participants' quiz scores are listed in the Appendix A.

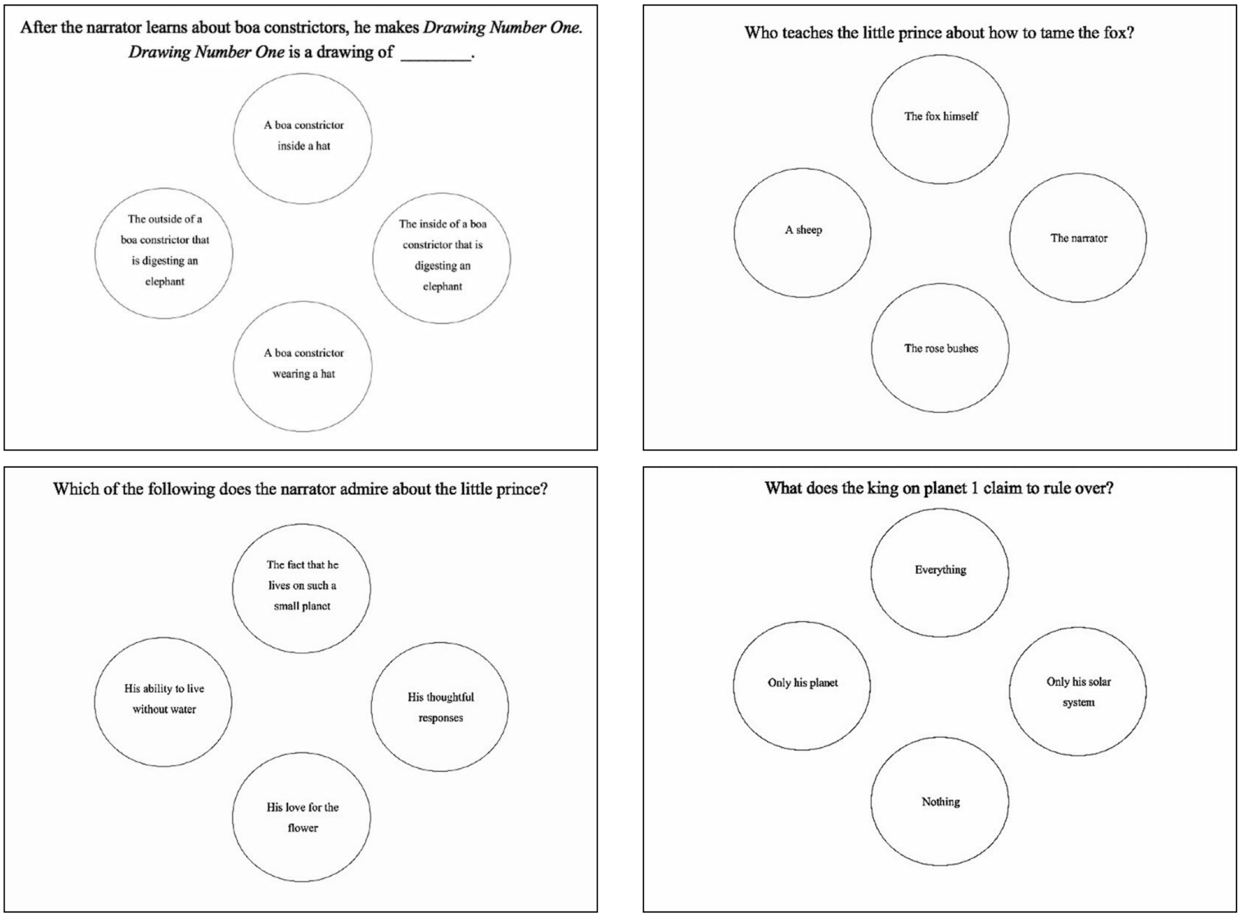

Figure 2: Four sample comprehension questions from the study. Full list of 36 comprehension questions used in the study given in Appendix A.

One of the central themes in the story is the difference between adults and children, especially the lack of imagination in the former. To make his point, the narrator uses the visual cues of different drawings to convey his message and these drawings are present in the original text. In the study, to help the participants understand this point, these visual cues were incorporated during the audio presentation for the first chapter and these are included below in Fig. 3.

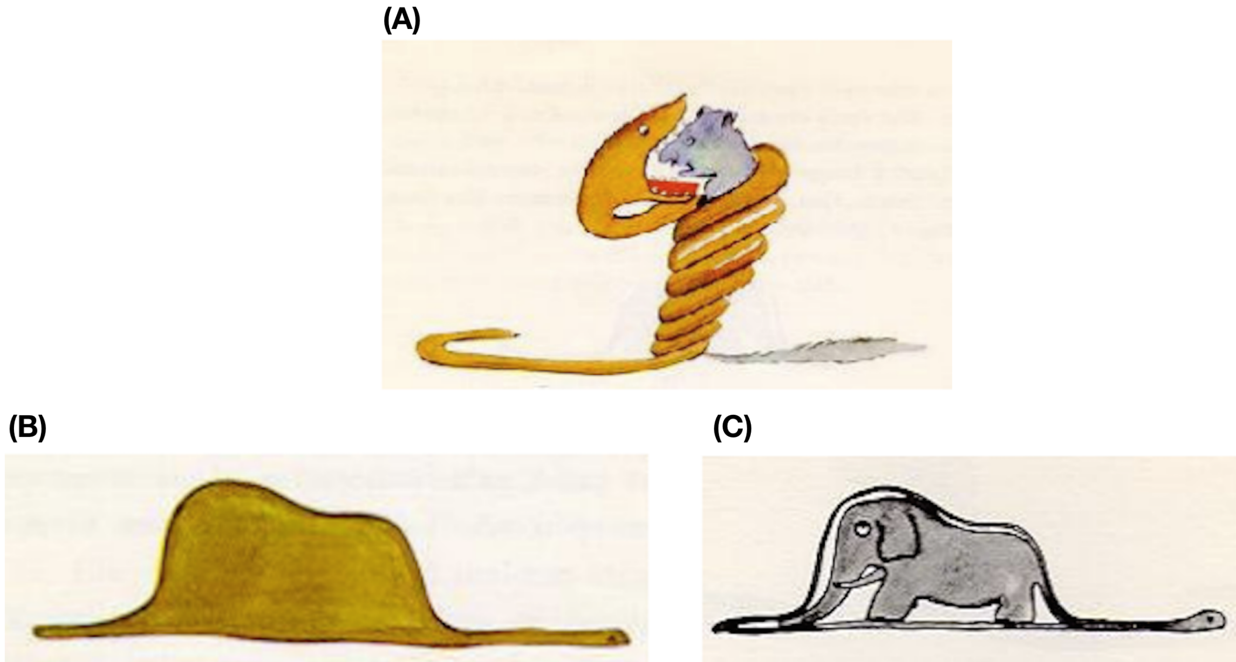

Figure 3: (A) Illustration of a boa constrictor swallowing its prey whole (B) Drawing One: Mistakenly assumed to be a hat (C): Drawing Two: Boa constrictor swallowing an elephant

2.5 Data Collection

Imaging was performed using a 3T MRI scanner (Discovery MR750, GE Healthcare, Milwaukee, WI) with a 32-channel head coil at the Cornell MRI Facility. Blood Oxygen Level Dependent (BOLD) signals were collected using a T2* -weighted echo planar imaging (EPI) sequence (repetition time: 2000 ms, echo time: 27 ms, flip angle: 77deg, image acceleration: 2X, field of view: 216 x 216 mm, matrix size 72 x 72, and 44 oblique slices, yielding 3 mm isotropic voxels). Anatomical images were collected with a high resolution T1-weighted (1 x 1 x 1 mm^3 voxel) with a Magnetization-Prepared RApid Gradient-Echo (MP-RAGE) pulse sequence.

2.6 Preprocessing

fMRI data is acquired with physical, biological constraints and preprocessing allows us to make adjustments to improve the signal to noise ratio. FSL's Brain Extraction Tool (Jenkinson et al. 2012) was used for skullstripping with a fractional intensity threshold setting of 0.5. Subsequent preprocessing steps were carried out using AFNI version 16 (Cox 1996). Anatomical and functional images were co-registered using the in-built AFNI function `3dseg`, images were normalised to the MNI–152 template, and images were resampled to 2mm isotropic voxels.

Multi-echo independent components analysis (ME-ICA) was used (Kundu et al. 2012, 2013) to improve the signal-to-noise ratio in these data. ME-ICA splits the T2* signal into BOLD-like and non BOLD-like components. Removing these non-BOLD components mitigates noise due to participants' head motion, physiology and scanner conditions such as thermal changes (Kundu et al. 2017). There were no exclusions based on degree of head movement. Nor was any high-pass filtering or smoothing applied at this stage.

2.7 Advantages of a naturalistic dataset

Traditionally, language processing has been studied in tightly controlled experimental designs due to concerns about replicability and reproducibility, and control of experimental stimuli, variables and confounds. However, as Kandylaki and Bornkessel-Schlesewsky (2019) point out, in addition to raising questions about the generalizability of such results to natural language use, these designs impose limitations on the types of research questions that can be examined.

Willems (2015) explains that the study of language in more ecologically valid conditions is possible in practice. He suggests ideas of bringing real-world complexity into experimental settings, free from artificial task demands. Furthermore, he argues that it is more advantageous, if the ultimate goal is to understand how the brain engages with discourse, dialogue and even literary texts, not only how it represents and processes words and sentences. The LPP dataset described in this chapter uses naturalistic stimuli and this kind of dataset offers several advantages.

Rich contextual settings of naturalistic stimuli provide an opportunity to investigate the comprehension of multiple linguistic levels of representation simultaneously. The levels of phonemes, syllables, words, phrases, sentences and discourse naturally unfold at different timescales and can be examined within a single dataset (Kandylaki and Bornkessel-Schlesewsky 2019). It creates new avenues for linking hypotheses between various linguistic representations and neurobiological architectures in the brain. Naturalistic experimental designs can also be used to complement and corroborate experimental approaches with controlled task-based designs. Apart from these benefits, naturalistic experimental designs also enable us to study language processing in populations for which more controlled experimental designs might not be feasible such as people with Autism Spectrum Disorder (ASD) or speakers of indigenous languages in remote locations through field-based experiments.

Lastly, naturalistic stimuli encourage Open Science practices of reproducability and reusability. With openly shared datasets, it is easy to rerun analyses on naturalistic stimuli without rerunning the entire experiment. Since the dataset is not task-specific, the nature of the stimuli opens up the possibility of multiple researchers testing out different research questions on the same dataset.

CHAPTER 3

NEURAL BASES OF NONCOMPOSITIONAL EXPRESSIONS

3.1 Introduction: Operationalizing compositionality and noncompositionality

This chapter provides a study on noncompositional expressions, often referred to as Multiword Expressions (MWEs) in the computational linguistics literature. While this term originates from computational linguistics, in this chapter these expressions are studied from a psycholinguistic perspective. Essentially, MWEs are word clusters or expressions formed by more than a single word. They are also referred to as *collocations, phraseology, formulaic language*, etc in the literature. While there has been a huge increase in research about multiword expressions or MWEs in recent years, there is no standard, universal definition for it. Some definitions are given below:

- "fixed and recurrent pattern of lexical material sanctioned by usage" (Grant and Bauer 2004)
- "sequences of words that acts as a single unit at some level of linguistic analysis" (Calzolari et al. 2002)
- "over-learned, literal and non-literal word clusters whose representations are stored in semantic memory" (Cacciari 2014)
- "expressions for which the syntactic or semantic properties of the whole expression cannot be derived from its parts" (Sag et al. 2002)

Siyanova-Chanturia (2013) provides examples of MWEs in English to illustrate the wide variety among these expressions:

An earlier version of this chapter appears in Bhattasali et al. (2019).

Linguistic phenomena	Examples
fixed phrases	*per se*, *by and large*
noun compounds	*black coffee*, *cable car*
verb compounds	*give a presentation*, *come along*
binomials	*heaven and hell*, *safe and sound*
complex prepositions	*in spite of*
idioms	*break the ice*, *spill the beans*

Table 1: A wide variety of linguistic phenomena that are considered to be MWEs.

What unifies cases of MWEs is the absence of a compositional linguistic analysis. Based on the examples from the LPP dataset below, MWEs (in bold) loosely groups a wide variety of expressions including idioms, conventionalized greetings and personal titles:

(1) So I thought **a lot** about the adventures of the jungle and **in turn**, I managed with a **coloured pencil** to make my first drawing.

(2) My **little fellow**, I don't know how to draw anything except **boa constrictors**, closed and open.

(3) When I drew the baobabs, I was spurred on by a **sense of urgency**.

(4) 'What are you doing there?', he said to the drinker who he found sitting **in silence** in front of **a number** of empty bottles and **a number** of full bottles.

(5) You must **see to it** that you regularly **pull out** the baobabs as soon as they can be told **apart from** the rose bushes to which they look very similar to when they are young.

(6) "**Good morning**", said the **little prince** politely, who then turned around, but saw nothing.

MWEs raise an important theoretical question about language processing, namely the balance between productivity and reuse (Goldberg 2006; Jackendoff 2002; O'Donnell 2015). If MWEs indeed lack internal structure, then perhaps their comprehension proceeds through a single, unitary memory retrieval operation, rather than some kind of multistep composition process. Proceeding from this hypothesis, through the lens of MWEs, this study investigates whether the cognitive processes of composition and retrieval evoke different patterns of activation by providing a functional localization. Furthermore, this study also investigates if the differences in the grammatical category of MWEs affect its processing and whether it is observable at the neuronal level.

3.2 Background

3.2.1 Previous MWE Processing studies

MWE comprehension has been shown to be distinct from other kinds of language processing. For instance, it is well-established at the behavioral level that MWEs are produced and understood faster than matched control phrases due to their frequency, familiarity, and predictability (Siyanova-Chanturia and Martinez 2014), in accordance with incremental processing (Hale 2006). This would follow if MWEs were remembered as chunks, in the sense of Miller (1956) that was later formalized by Laird et al. (1986); Rosenbloom and Newell (1987).

Eye-tracking and EEG work further documents this processing advantage across a wide range of MWE sub-types, e.g.

- Binomials (Siyanova-Chanturia et al. 2011b),
- Phrasal verbs (Yaneva et al. 2017),
- Complex prepositions (Molinaro et al. 2013, 2008),
- Nominal compounds (Molinaro and Carreiras 2010; Molinaro et al. 2012),
- Lexical bundles (Tremblay and Baayen 2010; Tremblay et al. 2011),
- Idioms (Underwood et al. 2004; Siyanova-Chanturia et al. 2011a; Strandburg et al. 1993; Laurent et al. 2006; Vespignani et al. 2010; Rommers et al. 2013).

For example, Siyanova-Chanturia et al. (2011b), found their eye-tracking results illustrate that binomial MWEs such as *bride and groom* are processed faster that the reversed three-word phrase *groom and bride*, due to the high-frequency nature of the former expression.

However, previous work has focused on a particular subtype of MWEs and none of them have implemented a fMRI study of MWEs within a naturalistic text to either study them collectively as a single group of expressions or contrast between different categories of MWEs.

3.3 Computational Models and Methodology

3.3.1 Identifying MWEs

Within the LPP text, 669 unique MWEs were identified using a transition-based MWE analyzer Al Saied et al. (2017), as illustrated in Figure 4, for a total of 1292 attestations in the stimulus text. Al Saied et al. use unigram and bigram features, word forms, POS tags and lemmas, in addition to features such as transition history and report an average F-score 0.524 for this analyzer across 18 different languages which reflects robust cross-linguistic performance. Al Saied and Matthieu Constant trained the analyzer on examples from the Children's Book Test, CBT (Hill et al. 2015) from the Facebook bAbI project to keep the genre consistent with our literary stimulus. This corpus consists of text passages that are drawn from the Children's section of Project Gutenberg, a free online text repository. External lexicons were used to supplement the MWEs found with the analyzer. The external lexicons included the Unitex lexicon (Paumier et al. 2009), the SAID corpus (Kuiper et al. 2003), the Cambridge International Dictionary of Idioms (White, 1998), and the Dictionary of American Idioms (Makkai et al. 1995).

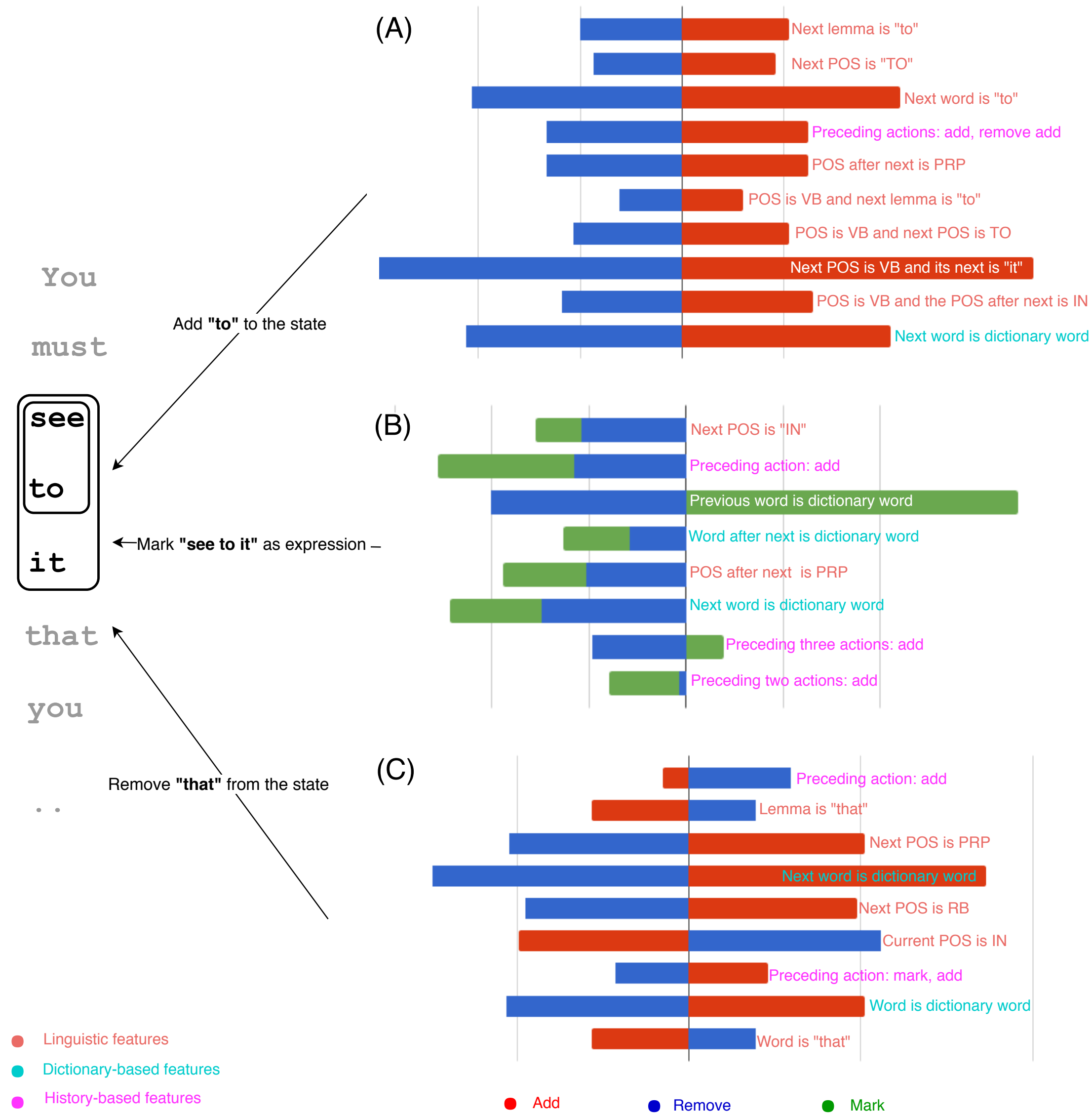

Figure 4: Tagging the multiword expression *see to it* using feature templates to help the classifier choose the right actions (Bhattasali et al. 2019). Figure created by Hazem Al Saied.

3.3.2 Bottom-up Parsing as Structure Building

In contrast to MWEs, other expressions are less likely to have been explicitly memorized and therefore call for some degree of structural composition, in comprehension. This sort of processing can be formalized using parsing algorithms (Hale 2014). The intermediate states of this parsing algorithms quantify the amount of structure-building work that

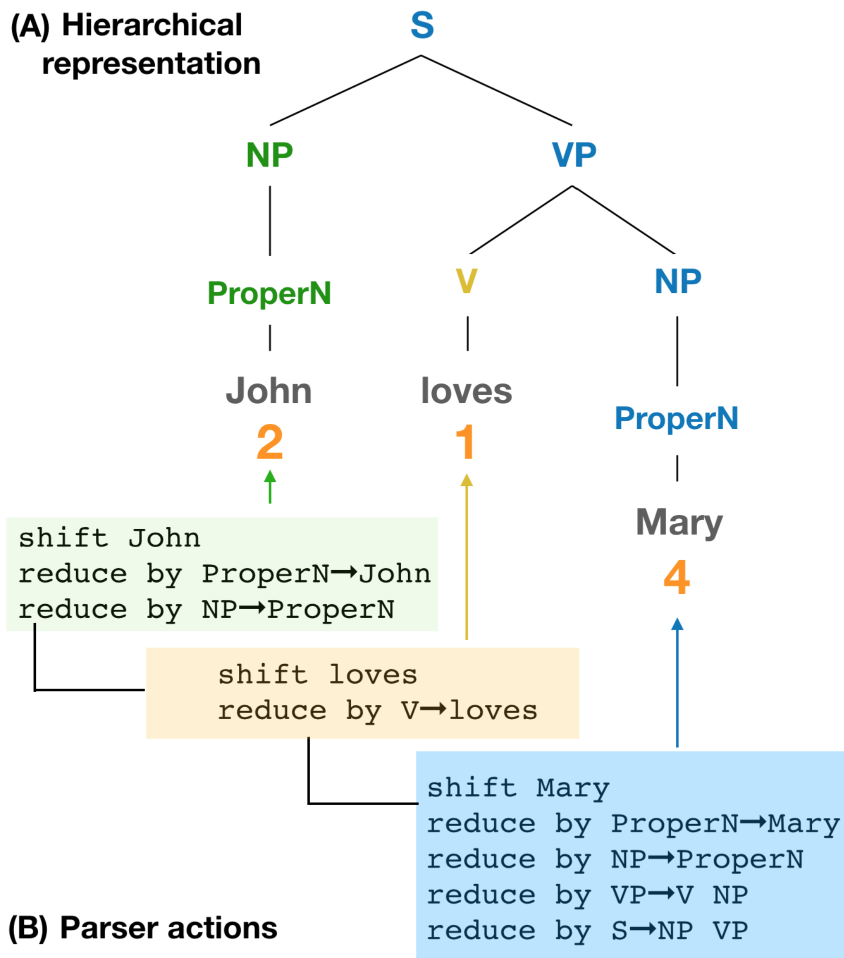

Figure 5: Panel (A) depicts hierarchical structure for *John loves Mary* to be recognized via processes of syntactic composition with the word-by-word parser action counts given in orange. Panel (B) shows the sequences of parser actions (i.e. `shift` and `reduce`) that would build the color-coded tree nodes during bottom-up parsing. Figure created by John Hale and Murielle Fabre.

an idealised system would do, in the course of processing the naturalistic stimulus.

In this study, a bottom-up parsing algorithm was used. Bottom-up parsing amounts to a repeated cycle of choice: whether to `shift` to the next word or `reduce` a sequence of transient elements held in memory. As shown in Figure 5 `reduce` actions are individuated by particular grammar rules. The number of parser actions required at each word defines an incremental complexity metric, also seen in Figure 6. Following Brennan et al. (2012); Brennan (2016), the analyses reported below both use this complexity metric to quantify structure-building effort in the brain.

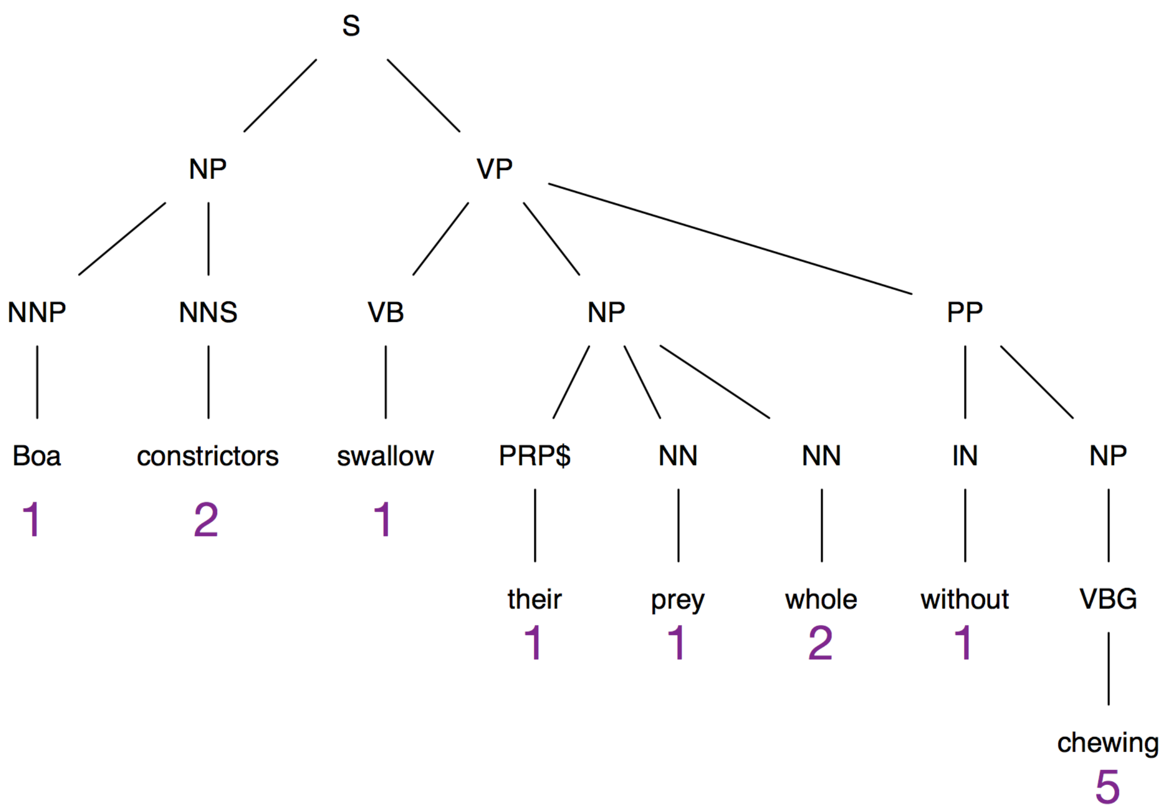

Figure 6: Phrase structure tree with bottom-up parser action counts in purple, as determined by the Stanford parser (Klein and Manning 2003).

3.4 Analysis

3.4.1 Analysis 1: Presence of MWEs

This analysis comprised of six word-by-word regressors in the GLM along with six regressors to account for the visual stimuli (as discussed in §2.4 and explained further below) for a total of 12 regressors.

The word-by-word predictors described below in were regressed against fMRI timecourses recorded during passive story-listening in a whole-brain analysis. For each of the 15,388 words in the story, their timestamps were estimated using Praat TextGrids (Boersma 2002). Along with the parser action count and MWE indicators of theoretical interest, four “nuisance” variables of non-interest were entered into the GLM analysis. These serve to improve the sensitivity, specificity and validity of activation maps (Bullmore et al. 1999; Lund et al. 2006).

Bottom-up parser action count

This predictor formalizes structure-building using a standard bottom-up parsing algorithm, as explained in §3.3.2. The number of `reduce` actions that an incremental, bottom-up parser would be required to take, word-by-word, to build the correct phrase structure tree as determined by the Stanford parser (Klein and Manning 2003) was calculated and taken as an index of structure-building effort.

Categorical MWE predictor

This predictor formalizes memory retrieval by marking MWEs in the text (identification outlined in §3.3.1). As mentioned previously, an underlying assumption is that since MWE are not compositional, their processing probably does not involve structure-building, but rather proceeds via memory retrieval.

The final word of the MWEs was annotated with a 1 while the non-final words of the MWEs and the other words were annotated with a 0. This coding scheme expresses the idea that a different process occurs at the end of multiword expressions, and this provisionally assumes a very conservative approach to the Configuration Hypothesis (Cacciari and Tabossi 1988; Tabossi et al. 2009). While the Configuration Hypothesis is given for idioms, this idea is adopted in this study and extended for all MWEs. Full list of 669 MWEs is provided in Appendix B.

Word rate

Based on the Praat TextGrids, this predictor marks the offset of each spoken word in time.

Lexical Frequency

This predictor represents the log-frequency of the individual word in movie subtitles taken from SUBTL spoken-language database (Brysbaert and New 2009) and is added in the model to control for lexical frequency effects.

f0

This predictor represents the fundamental frequency of the narrator's voice, which reflects pitch and is in the model to control for acoustic effects.

RMS Amplitude

This predictor represents the Root Mean Square Amplitude of the narrator's voice, which reflects intensity, an acoustic correlate of volume. Similar to f0, this predictor is also in the model to control for acoustic effects.

Apart from these six predictors, three "picture events" conditions and "picture blocks" conditions are also included in the analysis to account for the visual stimuli presented to participants, described in §2.4, and its associated neural activation. The "picture events" occur at the 10 second, 35 second, and 60 second timepoints in the first section of the story while the "picture blocks" also occur at the 10 second, 35 second, and 60 second timepoints in the first section and last for 15 seconds, 20 seconds, and 15 seconds respectively. These conditions match the presentation and duration of the visual stimuli and the mention of particular plot points in the narrative.

3.4.2 Analysis 2: Verbal MWEs vs Non-verbal MWEs

Analysis 2 uses the same 12 predictors as in Analysis 1, except that the categorical indicators for MWEs are further subdivided into the presence/absence of verbal expressions for a total of 13 regressors in this analysis. The Stanford POS tagger and the NLTK POS tagger were used to annotate the words within the MWEs with their grammatical categories (Bird and Loper 2004; Manning et al. 2014).

Bottom-up parser action count

As explained in in Analysis 1 (§3.4.1), this predictor operationalizes structure-building.

Verbal MWE predictor

56% of the MWEs were tagged as verbal (375 MWEs) and these consist of verb participle constructions, light verb constructions, and verb nominal constructions among others. Similar to Analysis 1, the last word of the MWE was marked with 1 to indicate presence of verbal MWE. Full list of verbal MWEs provided in Appendix B.

Non-verbal MWE predictor

The remaining 44% of MWEs were tagged as non-verbal (294 MWEs) and these consist of nominal compounds, greetings, personal titles, character names, and complex prepositions. Similar to Analysis 1, the last word of the MWE was marked with 1 to indicate presence of non-verbal MWE. Full list of non-verbal MWEs provided in Appendix B.

Word rate

Same as in Analysis 1 (§3.4.1).

Lexical Frequency

Same as in Analysis 1 (§3.4.1).

f0

Same as in Analysis 1 (§3.4.1).

RMS Amplitude

Same as in Analysis 1 (§3.4.1).

3.4.3 Group-level Analysis

In the second-level group analysis, each contrast was analysed separately at the group-level. An 8 mm FWHM Gaussian smoothing kernel was applied on the contrast images from the first-level analysis to counteract inter-subject anatomical variation. All the group-level results reported in the next section underwent FWE voxel correction for multiple comparisons which resulted in T-scores > 5.3.

3.5 Results

All whole-brain effects reported survived a $p < 0.05$ Family-Wise-Error threshold at the voxel level. These results were surface rendered in Mango (Lancaster and Martinez 2006) using the Colin-27 template (Holmes et al. 1998).

3.5.1 Analysis 1: Presence of MWEs

Results for Composition

Table 2 shows the significant clusters of activation for bottom-up parser action count and peak activation voxels, using brain region labels from the Harvard-Oxford Cortical Structure Atlas.

Bottom-up parser action count shows a broad activation pattern both in right and left hemisphere. The peak activation is right lateralised in the anterior temporal lobe within a main cluster of activation which extends through the middle and superior temporal gyri. While anterior temporal activation is bilateral, both middle temporal gyrus and posterior superior temporal gyrus are only right lateralised. The second strongest cluster of increased activation is observed in the left inferior frontal gyrus stretching over pars orbitalis and triangularis and extending to the anterior insula and the putamen. A similar increased activation is observed in the right inferior frontal gyrus.

3.5.1.1 Results for MWE Presence

The categorical MWE predictor gives rise to two clusters of activation both in the right precuneus cortex, as seen in Table 3 and Figure 7. Brain region labels from the Harvard-Oxford Cortical Structure Atlas were used.

3.5.2 Analysis 2: Verbal MWEs vs Non-verbal MWEs

Analysis 2 serves to provide further insight into noncompositional expressions by dividing them across grammatical categories to observe if they are processed differently. Table 4 shows the significant clusters of activation for verbal and non-verbal MWEs and peak activation voxels, using brain region labels from the Harvard-Oxford Cortical Structure

Regions for Bottom-up Parser Action Count	Cluster size (in voxels)	MNI Coordinates x	y	z	p-value (corrected)	T-score (peak level)
R Anterior Temporal	4816	52	6	-20	0.000	13.20
R Middle Temporal Gyrus		50	-20	-10	0.000	11.31
R Supramarginal Gyrus/Superior Temporal Gyrus		60	-40	-10	0.000	10.11
L IFG Orbitalis/Triangularis (BA47) & Anterior Insula	2461	-36	18	-14	0.000	10.40
L Temporal Pole		-50	6	-26	0.000	8.30
L Putamen		-30	8	-4	0.000	6.99
R Supplementary Motor Area/Superior Frontal Gyrus (BA9)	6495	10	18	62	0.000	9.35
R Medial Superior Frontal Gyrus (BA9)		12	58	32	0.000	8.62
L Superior Frontal Gyrus		-8	18	66	0.000	8.24
L Cerebellum – Crus I/II	448	-24	-74	-30	0.000	8.96
R Cerebellum – Crus I/II	941	26	-74	-36	0.000	8.15
R Cerebellum		36	-60	-32	0.021	5.16
L Middle Occipital Gyrus/Fusiform Gyrus	1084	-34	-78	12	0.000	7.59
L Fusiform Gyrus/Temporal Occipital Cortex		-30	-58	-10	0.000	7.19
L Occipital Fusiform Gyrus		-28	-70	-14	0.010	5.85
R Precentral Gyrus	159	42	0	48	0.000	7.57
L Supramarginal Gyrus/Parietal Lobe (BA40)	665	-54	-56	30	0.000	7.35
L Parietal Lobe		-48	-66	50	0.032	5.45
L Supramarginal Gyrus		-52	-58	50	0.036	5.41
R Temporal Occipital Cortex/Fusiform Gyrus (BA19)	164	30	-50	-10	0.001	6.75
L IFG Orbitalis/Frontal Pole (BA11)	252	-44	46	-12	0.001	6.61
L Frontal Pole		-36	60	-6	0.013	5.75
L Middle Frontal Gyrus (BA9)	252	-42	24	44	0.001	6.49
L Precuneus	154	-10	-52	38	0.003	6.25
R Middle Occipital Gyrus	160	28	-72	22	0.003	6.19
L Caudate	54	-14	16	10	0.005	6.07
R/L Anterior Cingulate Gyrus (BA24)	49	0	22	22	0.011	5.82
L Cerebellum	21	-6	-58	-40	0.018	5.64
L Superior Parietal Lobule (BA7)	5	-32	-58	62	0.024	5.54
R Lateral Occipital Cortex (BA19)	12	40	-64	-8	0.027	5.51
R Cerebellum – Vermis 4-5	6	4	-48	-8	0.038	5.39
R Putamen	3	32	-8	-6	0.041	5.37

Table 2: Significant clusters of increasing activation for bottom-up parser action count after FWE voxel-correction for multiple comparisons with $p < 0.05$. Peak activation is given in MNI Coordinates and p-values are reported at peak-level after voxel-correction.

Atlas.

Whole-brain contrasts show that these two types of MWEs activate different brain re-

Regions for Multiword Expression	Cluster size (in voxels)	MNI Coordinates x	y	z	p-value (corrected)	T-score (peak level)
R Precuneus	209	6	-70	56	0.000	7.15
R Precuneus	18	6	-48	50	0.019	5.63

Table 3: Significant clusters of increasing activation for multiword expressions after FWE voxel correction for multiple comparisons with $p < 0.05$. Peak activation is given in MNI Coordinates and p-values are reported at peak-level after voxel-correction.

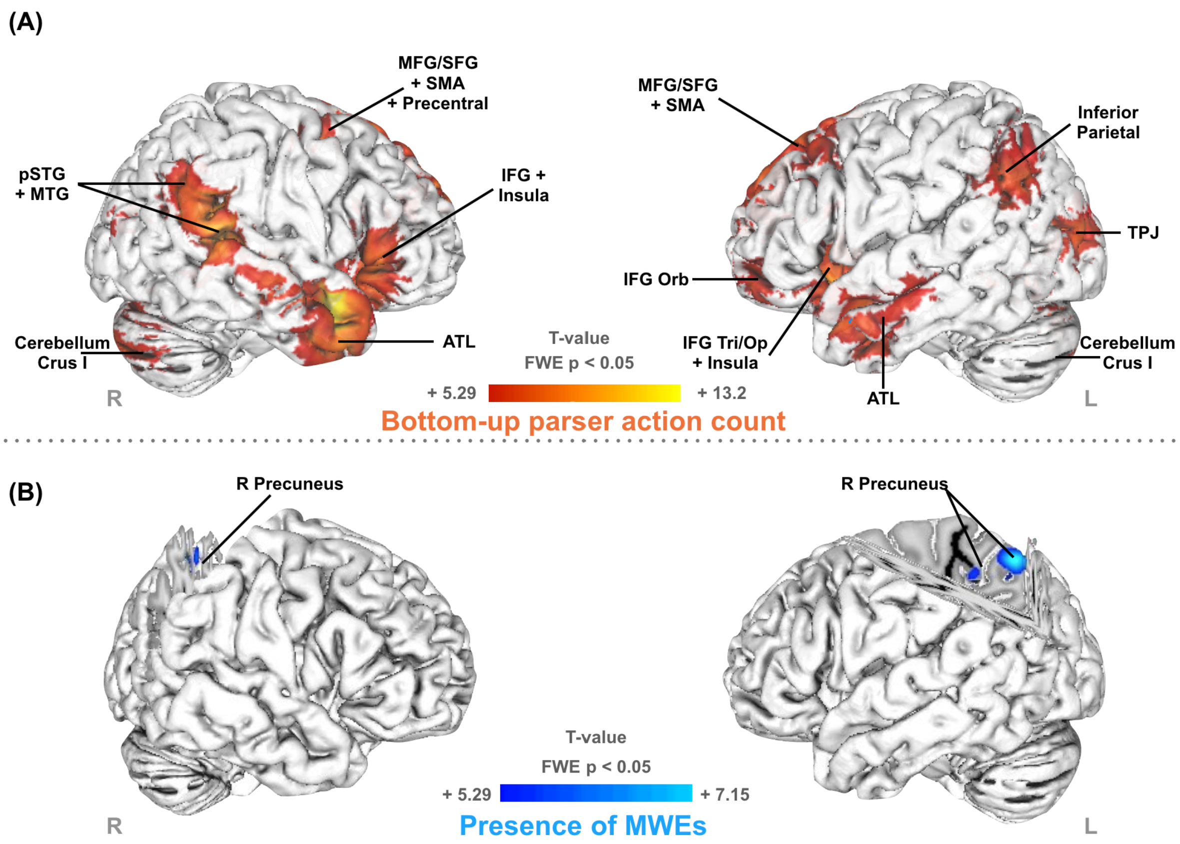

Figure 7: Whole-brain images with significant group-level activation clusters. Panel (A) shows the significant clusters for Bottom-up parser action count in orange; Panel (B) shows the significant clusters for Multi-word Expressions in blue. All images underwent FWE voxel correction for multiple comparisons with $p < 0.05$. .

gions with no overlap. Verbal MWEs appear right-lateralized compared to non-verbal ones in IPL and in IFG triangularis (Fig. 8). The opposite contrast yielded a mostly right-lateralized and wider pattern of activation, including bilateral Supramarginal Gyrus extending to STG and right SMA together with smaller activation clusters in Pars Opercularis and MTG (Fig. 8). Contrasts were inclusively masked with the main effect of all MWEs from Analysis 1.

Regions	Cluster size (in voxels)	MNI Coordinates x	y	z	p-value (corrected)	T-score (peak level)
VERBAL MWES >NON-VERBAL MWES						
R IFG Pars Triangularis	71	46	36	14	0.000	7.38
R Inferior Parietal Lobule	57	50	-40	52	0.002	6.38
NON-VERBAL MWES >VERBAL MWES						
R Angular Gyrus	585	56	-42	14	0.000	9.43
R Supplementary Motor Area	235	12	20	60	0.000	8.91
L Cerebellum	58	-22	-72	-30	0.002	7.85
L Supramarginal Gyrus	32	-60	-50	34	0.001	6.50
R IFG Pars Triangularis/Opercularis	28	56	22	8	0.001	6.51

Table 4: Significant cluster for contrasts between verbal MWEs and non-verbal MWEs after FWE voxel correction for multiple comparisons with $p < 0.05$. Peak activation is given in MNI Coordinates and p-values are reported at peak-level after voxel-correction.

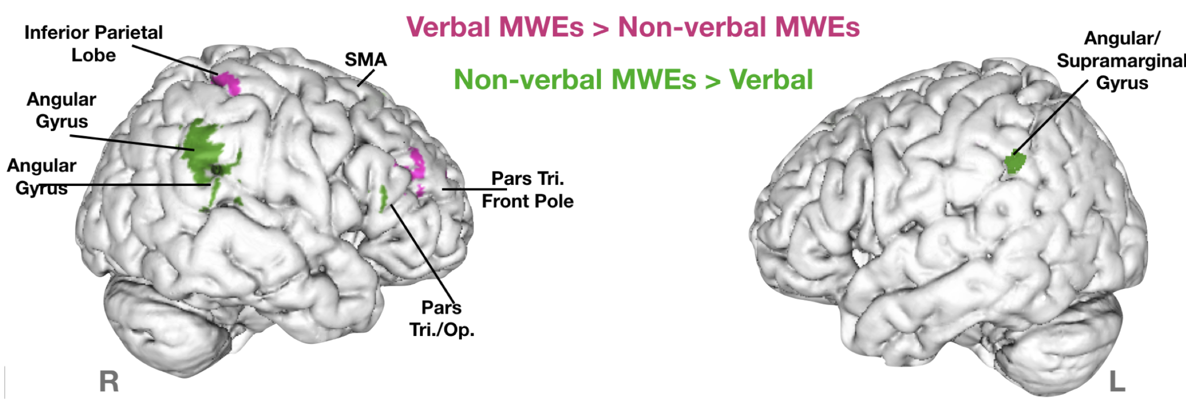

Figure 8: Whole-brain contrast images with significant clusters for [Verbal MWEs > Non-verbal MWEs] in pink and for [Nonverbal MWEs > Verbal MWEs] in green. All images underwent FWE voxel correction for multiple comparisons with $p < 0.05$.

3.6 Discussion

3.6.1 Brain areas involved in composition and noncompositionality

Processing MWEs evokes a pattern of activation that is spatially distinct from the pattern evoked by compositional processes. The results for MWEs and parser action counts in Analysis 1 supports a dissociation between Temporal and Parietal brain structures and anterior Frontal regions such as IFG and ATL, as respectively sub-serving the retrieval of memorized expressions and structure-building processes. These findings are broadly consistent with the proposals of Hagoort (2016), Friederici and Gierhan (2013) and Ullman (2015)[2]. Overall, these results suggest that retrieval and composition are localized to different brain regions and thus, they are two separate cognitive processes recruiting different neural substrates.

Precuneus

The Precuneus has been implicated in larger memory networks such as for verbal material (Halsband et al. 2002). The Precuneus also plays an important role in the Default Network, situated within the dorsal-medial subsystem. This subsystem supports story comprehension and other aspects of self-generated thought (Andrews-Hanna et al. 2014). While the Precuneus also has been designated as part of the Protagonist's Perspective Interpreter Network (Mason and Just 2006) and implicated in naturalistic reading by Wehbe et al. (2014), the Precuneus activation observed in the study cannot be due to reference to story characters since less than 2% of the MWEs in the stimuli are names of story characters.

Within the Precuneus, a functional subdivision has been proposed between anterior and posterior portions, for higher-order cognitive functions (Cavanna and Trimble 2006). Successful retrieval from episodic memory is linked to more posterior localisation, whereas Default Network-related activation and self-centered imagery was observed in more anterior portion of Precuneus, together with theory of mind and mental tasks like navigation.

Furthermore, the postero-medial portion of the parietal lobe has already linked to processing of complex lexical information by previous studies. e.g., argument structure (Shetreet et al. 2007) and sentential embeddings (Shetreet et al. 2010a). Although the Precuneus is not part of the traditional perisylvian language network, these studies col-

[2]The models proposed by them are discussed further in §6

lectively suggest that the Precuneus is a language-relevant region.

Anterior Frontal and Anterior Temporal Regions

Word-by-word syntactic structure-building effort, quantified in terms of bottom-up parser actions, correlates in Analysis 1 with a highly bilateral pattern across several areas in the language network. Frontal regions encompassing different sub-parts of IFG and anterior Insula are commonly attributed a role in composition and structure-building processes (Friederici and Gierhan 2013; Snijders et al. 2009; Zaccarella and Friederici 2015).

While there is disagreement about the role of ATL in sentence comprehension, some studies do report bilateral activation of ATL in sentence comprehension (Rogalsky and Hickok 2009). The structure-building effect observed bilaterally in anterior temporal lobe is consistent with previous work on syntactic processing in naturalistic narrative (Brennan et al. 2012). It confirms and extends results on two-word structure-building (Bemis and Pylkkänen 2011), as well as findings reporting anterior temporal sensitivity to parametric variation of constituent size (Pallier et al. 2011). This result highlights the involvement of anterior Temporal Lobe in basic composition processes.

3.6.2 Brain areas involved in processing verbal and nonverbal MWEs

Broca's area and IPL

Significant clusters for verbal and non-verbal MWEs illustrate spatially distinct patterns of activation and a dorso-ventral gradient is observed in Broca's area for verbal versus non-verbal MWEs. Activation patterns for verbal MWEs suggest that verbal argument structure relations in these noncompositional expressions implicate right hemisphere activity in Brocaś area and IPL. In the case of non-verbal MWEs, we do not make a strong conclusion since it is a mixed bag of nominal compounds, complex prepositions, greetings, personal titles among other types. We did not contrast between verbal and nominal

MWEs since our dataset is skewed towards verbal MWEs and we have very few attestations of nominal MWEs in the text ($< 10\%$).

Overall, our results point to a spatial differentiation between verbal MWEs and non-verbal MWEs since they localize to different areas of the brain. Crucially, these findings also suggest that the brain is sensitive to the grammatical category of noncompositional expressions and more generally, the internal structure of these "frozen" expressions. Traditionally, all noncompositional expressions are regarded as a homogeneous group of "frozen" expressions but the results suggest otherwise. Finer-grained metrics are needed to investigate the heterogeneity and gradience amongst these expressions. Such metrics will be discusses in the next chapter (§4).

3.6.3 Future Work

Another approach to follow up and verify the results reported above would be to compare a compositional expression like a VP against a noncompositional verbal MWE (e.g. *kick the ball* vs. *kick the bucket*. Morphosyntactically, these would be structurally similar yet they should be processed differently if our hypothesis about the neurocognitive mechanisms underlying language processing is correct. Based on our prediction, the neuroimaging data should illustrate a spatial dissociation between compositional VPs and noncompositional verbal MWEs.

Additionally, overall we can observe a surprisingly right-lateralized network in both sets of results reported for Analysis 1 and Analysis 2. This could be due to the semantic richness of MWEs (Price et al. 2015) or due to the naturalistic stimuli used in the study. In the case of the latter, Wehbe et al. (2014) also find unexpected right-laterlization during naturalistic reading and they attribute it to the contextual richness of the naturalistic stimuli. This suggests that the way the human brain processes linguistic stimuli within a contextually rich setting, one more similar to the everyday language environment, shows a strongly bilateral involvement of the language network. Future work that parametrically varies contextual richness, from more isolated to more naturalistic stimuli, could investigate the bilaterality further and may shed light on this speculation.

CHAPTER 4

NONCOMPOSITIONAL EXPRESSIONS: GRADIENT APPROACH

4.1 Introduction: Capturing heterogeneity within MWEs

In the previous chapter, the heterogeneous family of MWEs was discussed as one group and also as differentiated by grammatical category. However, as seen through previous examples in the LPP text, MWEs exhibit more gradience and cannot be strictly binarized as compositional and non-compositional or just categorized verbal and non-verbal. These expressions can be differentiated based on various aspects e.g., they can fall along a graded spectrum of compositionality. To capture this graded nature of MWEs on a neural level, two different gradient metrics are utilized, explained below. Utilizing these quantitative measures to qualitatively describe MWEs and the different ways to express their association sheds further light on the subprocesses of MWE comprehension and language processing in general.

4.2 Background

4.2.1 Association Measures

Association Measures are a family of common metrics in corpus linguistics and computational linguistics and more informative than raw attestation counts. While these measures are commonly used in computational linguistics to identify MWEs since ngrams with higher scores are likely to be MWEs (Evert 2008), in this study they are repurposed as a gradient predictor to describe the MWEs within the text.

An earlier version of this chapter appears in Bhattasali et al. (2019).

Krenn (2000) suggests that PMI and Dice are better-suited to identify high-frequency collocations whereas other association measures such as log-likelihood are better at detecting medium to low frequency collocations. Since MWEs are inherently high-frequency collocations, these two association measures were chosen to describe the strength of association between these word clusters.

Pointwise Mutual Information

The first measure is called Pointwise Mutual Information (PMI) (Church and Hanks 1990). Intuitively, its value is high when the word sequence under consideration occurs more often together than one would have expected, based on the frequencies of the individual words (Manning et al. 1999). More formally, PMI is a log-ratio of observed and expected counts:

$$\text{PMI} = log_2 \frac{c(w_n^1)}{E(w_n^1)} \tag{4.1}$$

MWEs that receive a higher PMI score are seen as more conventionalized, as we can see in Table 5 which provides examples of 10 MWEs from the LPP dataset with the highest PMI scores associated with it.

MWE	PMI
heart skipped a beat	10
have nothing to do with	9.104284373
forehead with a handkerchief	8.290288776
burst into tear	8.26368970
once upon a time	7.942578059
boa constrictor	7.934566291
peal of laughter	7.5182748424
at the same time	7.226966969
gust of wind	7.18210107
rumble like thunder	7.054874199

Table 5: 10 MWEs from the LPP dataset with the highest PMI values. Full list of MWEs with their corresponding Association Measures are given in Appendix B.

Dice's Coefficient

The second measure used in this study is Dice's Coefficient (Dice 1945; Sørensen 1948). Dice's coefficient is used to identify rigid MWEs with strong association (Evert 2008; Smadja et al. 1996). It is the ratio of the frequency of the sequence over the sum of the unigram frequency of the words in the sequence. E.g., for a bigram the two ratios are averaged by calculating their harmonic mean. The harmonic mean only assumes a value close to 1 (the largest possible Dice score) if there is a strong prediction in both directions, from `w1` to `w2` and vice versa. The association score will be much lower if the relation between the two words is asymmetrical.

This measure takes into account the length of the MWEs and the value ranges between 0 and 1:

$$\text{Dice} = \frac{n \times c(w_n^1)}{\Sigma_{i=1}^{n} c(w_i)} \tag{4.2}$$

A higher value for the Dice Coefficient indicates that the two tokens do not occur together by chance. Since Dice coefficient focuses on cases of very strong association rather than the comparison with independence, it can be interpreted as a measure of predictability. Table 6 provide examples of 10 MWEs from the LPP dataset with the highest Dice's coefficient associated with it.

MWE	Dice
boa constrictor	10
fairy tale	6.422389807
volcanic eruption	4.566947869
you know	3.382710888
look at	3.079620739
each other	2.705594598
come back	2.475590017
at least	2.320820589
no longer	2.307564864
year old	2.285531715

Table 6: 10 MWEs from the LPP dataset with the highest Dice values. Full list of MWEs with their corresponding Association Measures are given in Appendix B.

4.2.2 Linking Association Measures with Cognitive Processes

While existing work has focused on individual types of MWEs, this study investigates the cognitive processes underlying the comprehension of heterogeneous MWEs differing along the lexical association of the words that compose them. Specifically, it is expected that different association measures would map onto different cognitive aspects of MWEs, such as how predictable they are, how cohesive they are, how conventionalized they are, how frozen they are etc.

MWE	PMI	Dice
boa constrictor	7.934948602	10
fairy tale	6.16476593	6.422385484
coloured pencil	6.545610815	1.925855827
heart skipped a beat	10	0.0006670005821
gesture of weariness	5.124696746	0.00000002229179732
object of curiosity	5.096267996	0.00009852974441
a dirty trick	5.603255371	0.0002759423777
united states	1.859726247	0.004874108327
against all odds	6.011525024	0.01272124699
sense of urgency	6.255194902	0.004011177732
christmas tree	4.484999817	1.233571486
good morning	3.782589879	1.432966049
find out	3.479684666	1.24034032
come into	3.066762622	0.6832262366

Table 7: Example of MWEs with two Association Measures: Pointwise Mutual Information and Dice's Coeffecient. Full list of MWEs with their corresponding Association Measures are given in Appendix B.

Thus, these association measures are adapted and used to describe different facets of MWEs. PMI is taken to quantify the degree of conventionalization within these MWEs. Dice is taken to represent the degree of predictability of these MWEs. In Table 7, we can compare these measures. For example, expressions like *object of curiosity*, *gesture of weariness*, and *heart skipped a beat* would be considered highly conventionalized given their high PMI score but not predictable, given their low Dice score. As per these metrics, both *boa constrictor* and *fairy tales* are highly conventionalized and highly predictable whereas expressions like *united states* and *come into* are neither highly conventionalized nor highly predictable.

If we visually compare these scores for all 669 MWEs, as in Figure 9 below, we can also notice an interesting pattern. The values for PMI are spread across the axis and thus, the expressions are along a graded spectrum of conventionalized and have more fine-grained distinctions. On the other hand, since Dice is used to identify rigid MWEs, it tends to cluster the expressions around each end of the spectrum.

4.3 Computational Models and Methodology

669 MWEs were tagged as described in §3.3 and annotated with their respective association measures. Both association measures are based on corpus frequency counts from the Corpus of Contemporary English (COCA, Davies 2008), and were calculated using `mwetoolkit` (Ramisch et al. 2010; Ramisch 2012) and the formulas given above. COCA is a large, genre-balanced corpus of American English and contains contains more than 560 million words of text, equally divided among spoken, fiction, popular magazines, newspapers, and academic texts.

4.4 Analysis

4.4.1 Analysis 3: Pointwise Mutual Information

Similar to GLM analyses described in §3.4.1 and §3.4.2, there were 12 regressors in total with one regressor of interest: Pointwise Mutual Information, taken to represent the degree of conventionalization within noncompositional expressions. To keep the analyses comparable and account for sentence-level compositional processes, a regressor formalizing syntactic structure building, based on a bottom-up parsing algorithm, was included.

Additionally, there were the same four regressors of non-interest from previous studies: word rate, lexical frequency, f0, rms. As in previous analyses, the last word of the MWE was marked with the corresponding Pointwise Mutual Information, all other words were marked with a 0.

4.4.2 Analysis 4: Dice's Coefficient

Similar to GLM analyses described in §3.4.1 and §3.4.2, there were 12 regressors in total with one regressor of interest: Dice's Coefficient, taken to represent the degree of predictability within noncompositional expressions. To keep the analyses comparable and account for sentence-level compositional processes, a regressor formalizing syntactic structure building, based on a bottom-up parsing algorithm, was included. Additionally, there were the same four regressors of non-interest from previous studies: word rate, lexical frequency, f0, rms. As in previous analyses, the last word of the MWE was marked with the corresponding Dice's coefficient, all other words were marked with a 0.

4.4.3 Group-level Analysis

In the second-level group analysis, each contrast was analysed separately at the group-level. An 8 mm FWHM Gaussian smoothing kernel was applied on the contrast images from the first-level analysis to counteract inter-subject anatomical variation. All the group-level results reported in the next section underwent FWE voxel correction for multiple comparisons which resulted in T-scores > 5.3.

4.5 Results

All whole-brain effects reported survived a $p < 0.05$ Family-Wise-Error threshold at the voxel level. These results were surface rendered in Mango (Lancaster and Martinez 2006) using the Colin-27 template (Holmes et al. 1998).

4.5.1 Analysis 3: Pointwise Mutual Information

Increasing MWE conventionalization, as seen through the positive correlation with PMI, yields a single cluster in the right Precuneus.

Left-lateralised activity in superior frontal gyrus, angular gyrus, pars triangularis, posterior middle temporal gyrus, and frontal pole was observed in proportion to decreasing conventionalization, as seen through the negative correlation with PMI scores. These are detailed in Table 8 and in Figure 10.

Regions for PMI	Cluster size (in voxels)	MNI Coordinates x	y	z	p-value (corrected)	T-score (peak level)
CORRELATED WITH INCREASING CONVENTIONALIZATION						
R Precuneus	244	6	-68	56	0.000	7.33
CORRELATED WITH DECREASING CONVENTIONALIZATION						
L Superior Frontal Gyrus	2039	-18	32	52	0.000	8.39
L Precentral Gyrus (BA9)		-44	8	40	0.000	7.26
L Middle Frontal Gyrus		-38	22	46	0.000	6.89
L Angular Gyrus	688	-42	-58	34	0.000	7.27
L Inferior Parietal Lobule (BA40)		-48	-46	50	0.012	5.76
L Posterior Middle Temporal Gyrus	320	-60	-44	-4	0.000	7.25
L IFG Pars Triangularis (BA46)	211	-46	30	18	0.002	6.41
L IFG Pars Triangularis		-46	34	10	0.002	5.41
L Anterior Middle Temporal Gyrus	152	-56	0	-32	0.001	6.49
L Anterior Inferior Temporal Gyrus		-54	-8	-32	0.009	5.85
L Frontal Pole/Medial Frontal Gyrus (BA10)	50	-6	64	-20	0.009	5.88
R Superior Frontal Gyrus	33	14	52	28	0.004	6.15
L IFG orbitalis	27	-38	48	-18	0.023	5.55
R Anterior Inferior Temporal Gyrus/Fusiform Gyrus	21	58	-10	-32	0.012	5.78
R Superior Frontal Gyrus/ SMA (BA6)	14	12	24	58	0.007	5.94

Table 8: Significant clusters for PMI after FWE voxel-correction for multiple comparisons with $p < 0.05$. Peak activation is given in MNI Coordinates and p-values are reported at peak-level after voxel-correction.

4.5.2 Analysis 4: Dice's Coefficient

Increasing MWE predictability, as seen through the positive correlation with Dice, correlates with bilateral activation in the Precuneus along with right-lateralized activation in

Middle Frontal Gyrus/Precentral, Superior Temporal Gyrus, and IFG.

Left-lateralized activation in the Anterior temporal regions, Superior Frontal Gyrus, Medial Frontal Gyrus along with a cluster in the right Inferior Temporal gyrus was observed in proportion to decreasing MWE predictability, as seen through the negative correlation with Dice scores. These are detailed in Table 9 and in Figure 11.

Regions	Cluster size (in voxels)	MNI Coordinates x	y	z	p-value (corrected)	T-score (peak-level)
CORRELATED WITH INCREASING PREDICTABILITY						
L Precuneus (BA 7)	254	-10	-66	40	0.000	7.89
R Middle Frontal Gyrus/Precentral Gyrus	96	42	6	48	0.001	6.58
R Superior Temporal Gyrus	82	52	-42	16	0.006	6.04
R Precuneus (BA 7)	37	10	-62	30	0.011	5.83
R Inferior Frontal Gyrus	36	50	22	24	0.021	5.60
R IFG Triangularis		46	24	12	0.023	5.58
R IFG Orbitalis/Triangularis	16	2	-74	50	0.022	5.59
CORRELATED WITH DECREASING PREDICTABILITY						
L Anterior Middle Temporal Gyrus	237	-58	-4	-24	0.000	7.07
L Superior Frontal Gyrus/Medial Frontal Gyrus	306	-10	44	46	0.001	6.65
R Inferior Temporal Gyrus	11	56	-8	-34	0.001	5.69
L Superior Frontal Gyrus	237	-10	56	30	0.001	5.51

Table 9: Significant clusters for Dice after FWE voxel-correction for multiple comparisons with $p < 0.05$. Peak activation is given in MNI Coordinates and p-values are reported at peak-level after voxel-correction

4.6 Discussion

4.6.1 Association Measures as Cognitively Plausible Metrics

The noncompositional, lexicalized expressions discussed in this chapter have a frequency aspect that generative grammar cannot capture. Traditionally, all these expressions would simply be classified as noncompositional expressions. However, our findings show that there is a gradability to these expressions and they cannot simply be binarized as compositional or noncompositional. Results from Analysis 3 and Analysis 4 confirm that using two Association Measures, Pointwise Mutual Information and Dice's coefficient, we can quantify different aspects of noncompositional expressions such as conventionalization and predictability of these expressions. Furthermore, since these metrics are calculated based on corpus frequency counts, as seen in §4.2.1, these measures also capture the frequency aspect of these expressions, while being more informative than raw attestation counts. Based on these two metrics, we observed two different patterns of activation in the brain, mapping onto two different cognitive subprocesses. The former involved processing noncompositional expressions and implicates the Precuneus in its retrieval process while the latter suggests that the less conventionalized and predictable expressions might not actually be retrieved from memory. Thereby, this study demonstrates how metrics from computational linguistics can be adapted into a cognitively plausible measure and in this way, shed light on cognitive processes at the cerebral level.

Precuneus and Noncompositionality

Analysis 3 and Analysis 4 extend the results of Analysis 1 and corroborate the centrality of the Precuneus in processing noncompositional MWEs. It suggests that only truly lexicalized linguistic expressions rely on this areas rather than traditional left-lateralized frontal and temporal nodes of the language network. As discussed in §3.6, the functional characterization of the precuneus as part of a network sub-serving memory tasks has been reported for different memory-based processes, such as verbal memory, spatial memory, episodic memory, and memory-related imagery. Taken together, this suggests that the Precuneus is involved in memory-related tasks, along with a linguistic functionalization.

Perisylvian Areas and Composition

Less conventionalized and less predictable MWEs evoke a pattern of activation that illustrates the core language areas in the perisylvian language network. The regions that show sensitivity to the decreasing MWE conventionalization are the left superior frontal gyrus along with the left inferior frontal gyrus, or Broca's area (pars triangularis and pars orbitalis), and also anterior and posterior regions of the left temporal gyrus. There is relatively less negative activation in the case of decreasing predictability and the areas that are significantly correlated to it form a subset of the first group of perisylvian regions reported above.

4.6.2 Future Work

While these two metrics described above are used to represent the gradience in the degree of conventionalization and degree of predictability within these noncompositional expressions, there are other aspects of MWEs that can be captured with other measures. Apart from an association measure like PMI and Dice, there are alternate approaches to describes MWEs such as word space models (based on distributional semantics) which could also serve as a metric of compositionality for these noncompositional word clusters. This type of metric would utilize the distributional patterns of words collected over large text data to represent semantic similarity between words in terms of spatial proximity (Sahlgren 2006). However, in the current study we were not trying to model the semantic opacity of these expressions but this could be an area to explore in the future to investigate another facet of MWEs.

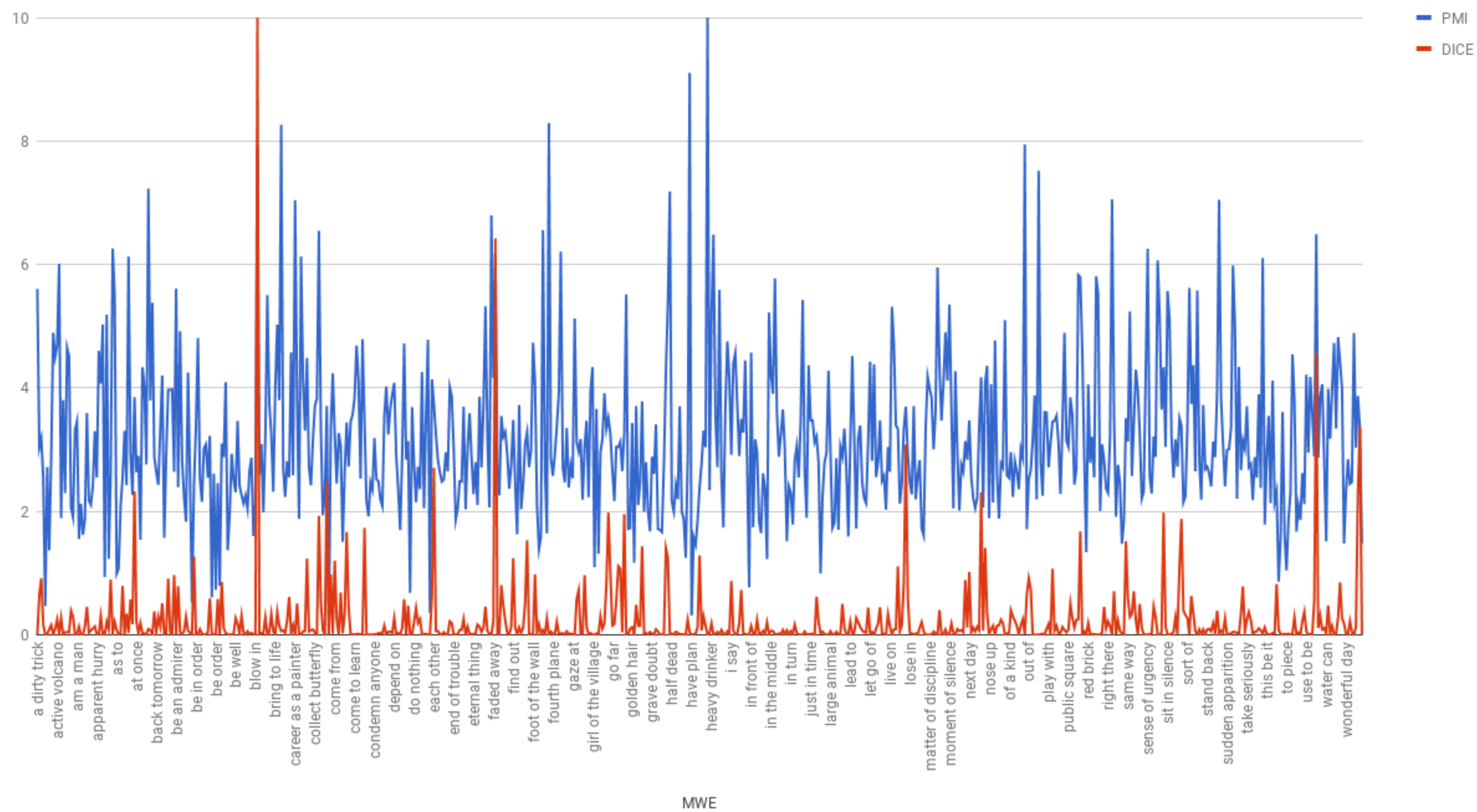

Figure 9: Comparing PMI (in blue) and Dice's Coefficient (in red); scaled up for visual purposes

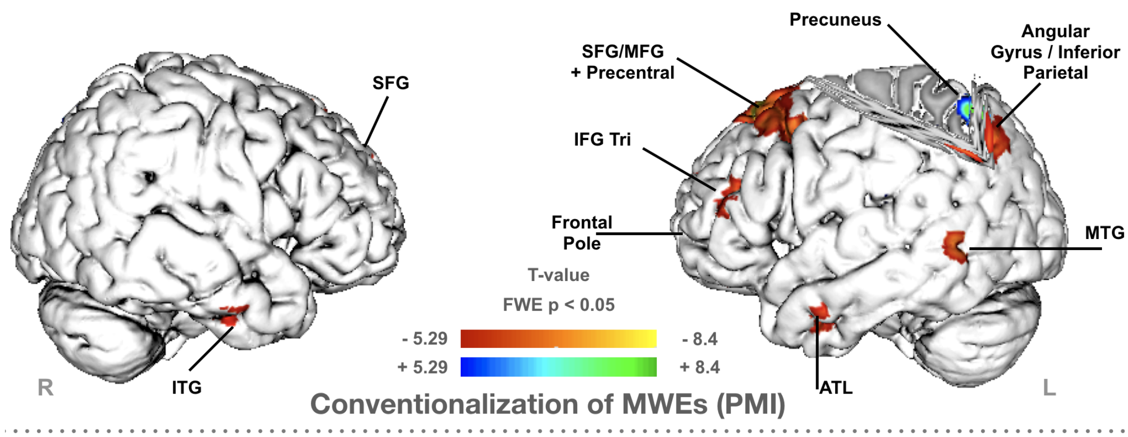

Figure 10: Significant cluster for the increasing and decreasing conventionalization of MWEs after FWE voxel correction for multiple comparisons with $p < 0.05$. Increasing conventionalization represented in blue and decreasing conventionalization represented in orange. Peak activation is given in MNI Coordinates.

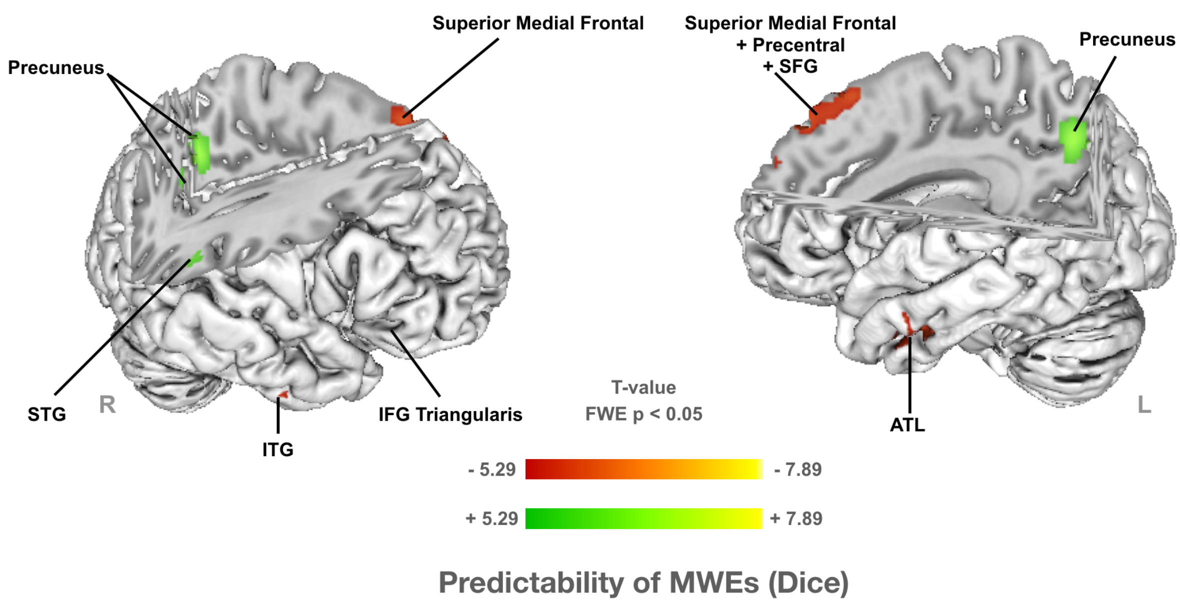

Figure 11: Significant cluster for the increasing and decreasing predictability of MWEs after FWE voxel correction for multiple comparisons with $p < 0.05$. Increasing predictability represented in green and decreasing predictability represented in orange. Peak activation is given in MNI Coordinates.

CHAPTER 5

VERBAL ARGUMENT STRUCTURE AND SENTENCE PROCESSING

5.1 Introduction: Role of verbs in sentence processing

In this chapter, the goal is to investigate how verbal argument structure plays a role in sentence processing using computational metrics and fMRI data. Sentence processing is more than decoding linear strings of words. There are hierarchical structures and relationships which affect language comprehension and verbal argument structure is one such example. As Boland (1993) explains, verbs provide the interface between lexical access and sentence processing. Furthermore, they also illustrate the integration of syntactic and semantic representations since they impose syntactic and semantic constraints on its arguments. When verbs precede their arguments (e.g., in SVO languages), knowledge associated with the verb, such as its semantic roles, subcategorization, or selectional restrictions can help the listener anticipate upcoming arguments and prime their expectations. Conversely, when verbs follow their arguments (as in head-final languages), this implicit information about the verb's argument structure could confirm earlier interpretations or introduce new knowledge that might cause a reinterpretation. Thus, in this way verbs play a central role in sentence processing.

This study examines different components of argument structure, such as diathesis alternations, subcategorization, and selectional restrictions in English and investigates whether they have differing neural substrates across three analyses. Furthermore, another related question is how these different components of argument structure of a verb affect prediction and uncertainty about the rest of the sentence during natural language comprehension and thereby, influence real-time sentence processing.

An earlier version of this chapter appears in Bhattasali and Hale (to appear).

5.2 Background

5.2.1 Argument Structure: Behavioral and Theoretical Perspectives

Psycholinguistic studies have shown that argument structure information is accessed and used during real-time sentence processing e.g. Boland (2005, 1993); Ferretti et al. (2001); Friedmann et al. (2008); MacDonald et al. (1994); Trueswell and Kim (1998); Trueswell et al. (1993) among others. In a lexical decision task setting, Shapiro et al. (1991, 1987) illustrated that reaction times to visual stimuli was longer after hearing verbs like *hear* with multiple subcategorization options in comparison to a verb like *hit* with a single option. Similarly, Gorrell (1991) found a difference in reaction times between transitive verbs like *hit* and intransitive verbs like *sneeze*. Thus, these results indicate that once a verb is encountered, its argument structure properties are activated and the processing time is directly related to the complexity of these properties, accounting for delays in concurrent visual lexical decision (Thompson and Meltzer-Asscher 2014).

These experimental findings are consistent with a lexicalist view. As per Chomsky (1981), the lexical information associated with a verb consists of a list of the thematic roles that the verb assigns, as well as subcategorization frames. This lexical information associated with verbs determines the syntactic structure in which the verb appears, as well as the interpretation of its accompanying arguments. This account follows the traditional linguistic approach to argument structure, as exemplified in Jackendoff (2002); Williams (1981); Levin and Hovav (1995); Reinhart (2003); Horvath and Siloni (2011) to name a few. While this study does not probe into the lexical representation of argument structure in the lexicon, the assumption is that when a verb is heard in the narrative, the tacit information about the verb's argument structure is available to the listener and employed in real-time sentence processing.

5.2.2 Previous Neurolinguistic Work

Prior neuroimaging studies with healthy participants have investigated activation patterns by examining specific aspects of argument structure complexity. Argument structure complexity can be captured and quantified along various dimensions. Previous studies have demonstrated the role of verbal lexical information and its corresponding syntactic and semantic information by utilizing the subcategorization frames of a given verb, the number of arguments, and varying thematic roles for a verb (theta grid) e.g., Ben-Shachar et al. (2003); Shetreet et al. (2007, 2009b, 2010a,b); Thompson et al. (2007, 2010); Meltzer-Asscher et al. (2013, 2015); den Ouden et al. (2009) (see Thompson and Meltzer-Asscher 2014 for review). Generally, all these studies taken together suggest that posterior brain regions comprising the left posterior superior temporal sulcus, supramarginal gyrus, and angular gyrus are involved in processing argument structure, along with MFG and other temporal regions.

Ben-Shachar et al. (2003) conducted an auditory study in Hebrew and found increased bilateral superior temporal sulcus (STS) activation as the number of arguments in the sentence increased, which suggests that these areas are relevant for verbal argument structure processing in sentences. In order to investigate theta roles, Newman et al. (2010) manipulated the semantic relatedness within English sentences by varying the semantic associations of the sentence constituents. The theta role violations correlated with activation in left IFG and posterior STS. Shetreet et al. (2007) altered the number of thematic options, subcategorization options, and number of verbal complements in a Hebrew auditory study. They observed increased activation in the the right Precuneus and right anterior Cingulate for the number of verbal complements and the left STG and IFG for the other two conditions, indicating that these regions are part of the neural circuitry for argument structure processing. Through lexical decision tasks in English, Thompson et al. (2007, 2010) illustrated differential activation patterns associated with verbs with different number of arguments and they suggest that posterior perisylvian regions, specifically the bilateral Angular Gyrus, is important for processing verbs with more arguments compared to verbs with fewer arguments.

In order to investigate the processing of verbs with multiple thematic options and subcategorization options, Shetreet et al. (2009b,a, 2010b,a) have carried out auditory fMRI studies in Hebrew and have shown a left hemisphere network which includes the left STG, IFG, MFG, SFG, MTG, indicating their relevance for processing verbal argument structure. den Ouden et al. (2009) conducted a verb naming task based on pictures and videos in English and found that for increased number of arguments, clusters were observed in left IFG, Angular Gyrus, and Supramarginal Gyrus. In a study comparing alternating transitives with simple transitives, Meltzer-Asscher et al. (2013) discovered increased activation in bilateral Angular Gyrus and MFG. They argue that the posterior activation reflects processing associated with the greater number of thematic roles associated with the transitive reading of alternating verbs whereas the frontal activation reflects the processing of lexical ambiguity arising from the multiple thematic options for the alternating verbs. In a follow-up study, Meltzer-Asscher et al. (2015) found that unaccusativity correlated with increased activation in left IFG.

Fabre (2017) investigated argument structure processing in French and through probing multiple conditions such as unaccusative verbs with additional locative argument compared to simple transitive verbs, or one argument unaccusatives compared to transitives among others, they found a brain network, which includes anterior STS, MFG, SFG, bilateral Precuneus, IPL, and Supramarginal Gyrus. These areas are consistent with earlier studies in other languages and confirms the centrality of these areas in processing of argument structure. In an fMRI reading study in English, Malyutina and den Ouden (2017) found increased activation in left SFG and MTG with greater number of subcategorization options and increased activation in left IFG with greater number of thematic options. In a recent study, Matchin et al. (2019) tested whether areas like the Angular gyrus, STS, and IFG were relevant for processing argument structure or general structural relations by matching VPs with lexically-matched NPs as a contrast. They found that only STS and IFG showed increased activation for VPs relative to NPs.

While these studies give us an overview of the brain network implicated in argument structure processing, all of these are controlled, task-based designs and often test specific constructions such as unergative vs. unaccusative. In this study, similar research questions are asked about verbs but in a broader manner and in an ecologically valid setting to study whether similar activation patterns are observed. Furthermore, selectional restrictions have not been specifically investigated in a neuroimaging study and in §5.3.2, I explain how this component of argument structure is leveraged in our study.

5.2.3 Verbs in LPP

There are 2,948 verbs in total which were tagged with the NLTK toolkit and Stanford POS tagger. Excluding modals, auxiliaries, gerunds, adjectival verbs and negation contractions (e.g., *shouldn't* and *wouldn't*), there are 1,970 verbs attested in the story with 401 unique verb types. Many of the verbs occur frequently in the story and a wide variety of verb-argument structural relations are attested. For example, one can compare the examples of two verbs *come* and *drink* below. Although both of them are attested several times in the story, the former appears in varied different subcategorizations frames (as seen in (7–13), while the latter appears only in three (as seen in (14–18).

(7) So you also **come** from the sky?

(8) He replied, "Oh, **come** on!"

(9) It could **come** in useful sometimes.

(10) She did not want to **come** out all rumpled like the poppies.

(11) Let them **come**.

(12) So the little prince, despite the good will of his love, had soon **come** to doubt her.

(13) The information **came** slowly as his thought wandered.

(14) You could take one pill a week and and you no longer felt the need to **drink** anything.

(15) I have nothing left to **drink**.

(16) All the stars will pour out fresh water for me to **drink**.

(17) I had hardly enough water to **drink** for a week.

(18) I **drank** the last drop of my water supply.

5.3 Computational Models and Methodology

In this study, three computational metrics are used to formalize diathesis alternations, selectional restrictions, and subcategorization, as described in the sections below.

5.3.1 PropBank: Formalizes diathesis alternations

PropBank (Kingsbury and Palmer 2002) is a lexical resource that consists of all the sentences from the Penn Treebank annotated with semantic roles. Based on the annotation, each verb is tagged with all the various semantic roles it can assign and the variations in meaning associated with it, if any. For example, the verb *hang* has the following 8 entries in PropBank and is assigned a score of 8:

- hang, *suspend, suspending*
- hang, *exist, be*
- hang_on ,*wait*
- hang_on, *maintain possession of*
- hang_up, *terminate a phone call*

- hang_up, *stuck on*
- hang_out, *spend time socially*
- hang, *execution*

This score can be used to estimate the cardinality of a given verb's set of semantic role labels and formalize diathesis alternations. Diathesis alternations are "changes in the argument structure of a verb that are sometimes accompanied by changes in meaning" (Levin 1993). This diathesis score is used as a predictor where higher score indicates more diathesis alternations. Some verbs from *The Little Prince* annotated with their diathesis scores from PropBank are in Table 13. These PropBank scores are thus taken to represent the diathesis alternations for a given verb. Out of the 401 unique verbs in LPP, 397 are given a score based on PropBank annotations since 4 of the verbs are missing from PropBank.

Verb	PropBank Score
take	33
come	30
get	30
go	28
make	23
break	20
pass	20

Verb	PropBank Score
disappear	1
inflict	1
laugh	2
sleep	5
write	7
bring	8
pull	9

Table 10: Example of LPP verbs with PropBank scores to represent diathesis alternations. Full list of verbs with the scores are given in Appendix C.

The intuition behind this metric is that the diathesis score should be directly proportional to the uncertainty about the remaining sentence after the verb since higher the number of diathesis alternations, there are more possibly ways for the sentence to be completed. On the other hand, this score is inversely related to the prediction strength of the verb since if the score is low, then there are minimal alternations and based on the verb, the listener can better predict the upcoming portion of the sentence.

5.3.2 Selectional Preference Strength: Formalizes selectional restrictions

Another component of argument structure is the selectional restrictions imposed by a verb on the semantic class of its arguments. For example, some verbs require animate arguments, some verbs require physical locations as arguments, etc. Resnik (1996) proposes a selectional association model where he defines selectional preference strength as "the amount of information a verb can tell us about the semantic class of its arguments". The formula is given below and it is based on estimating verb-direct object pairs from a corpus and then calculating the number of different WordNet (Miller 1995) semantic classes a given verb's direct objects falls into and the final scores is the inverse of that. Higher selectional restrictions scores indicate the verb is more particular about the kinds of arguments it takes as its direct object.

$$\mathrm{Pr}(v,c) = \frac{1}{N} \sum_{n \in \mathrm{words}(c)} \frac{1}{|\mathrm{classes}(n)|} \mathrm{freq}(v,n) \tag{5.1}$$

{*act, action, activity*}	{*natural object*}
{*animal, fauna*}	{*natural phenomenon*}
{*artifact*}	{*person, human being*}
{*attribute, property*}	{*plant, flora*}
{*body, corpus*}	{*possession*}
{*cognition, knowledge*}	{*process*}
{*communication*}	{*quantity, amount*}
{*event, happening*}	{*relation*}
{*feeling, emotion*}	{*shape*}
{*food*}	{*state, condition*}
{*group, collection*}	{*substance*}
{*location, place*}	{*time*}
{*motive*}	

Figure 12: The 25 noun semantic classes in WordNet (Miller 1995)

Originally Resnik calculated the selectional preference strength for a limited set of verbs across different corpora, such as the Brown corpus (Francis and Kucera 1964). However, these scores only covered 27 of the 401 verb types in LPP (6.73%). In order to analyze all the verbs in LPP, these scores were recalculated by estimating verb-direct object pairs from the Gigaword (Ferraro et al., 2014) and WaCkypedia (Baroni et al., 2009) corpora and then calculating their distribution across the 25 different WordNet semantic classes, as illustrated in Fig 12. Some sample verbs with their selectional preference strength are provided in Table 11. For example, a verb like *pour* has a high score since it is quite particular about the semantic class of its argument (typically some kind of liquids). In contrast, a verb like *find* is quite flexible and can accept arguments from most semantic classes and thus, has a relatively low score.

Verb	Selectional Preference Strength	Verb	Selectional Preference Strength
pour	4.8	bring	1.33
drink	4.38	show	1.39
eat	3.51	hear	1.7
hang	3.35	want	1.52
pull	2.77	find	0.96

Table 11: Example of LPP verbs with their selectional preference strength to represent the selectional restrictions between the verb and its direct object. Full list of verbs with the scores are given in Appendix C.

In terms of uncertainty about the rest of the sentence, the selectional preference strength is inversely related to it since higher scores narrow down the semantic class of the verb's argument and thus, lower the uncertainty. Selectional preference strength is directly related to the prediction strength of the verb since low scores are uninformative about the semantic class of the verb's complement and thus, do not help inform the listener's expectation about the remaining sentence as much whereas higher scores does help prime the listener's expectation and are more predictive.

5.3.3 SCF Entropy: Formalizes syntactic subcategorization

While the first two metrics formalized semantic constraints, Subcategorization Frame (SCF) Entropy operationalizes the syntactic constraint of subcategorization present in argument structure. Furthermore, this measure incorporates frequency into the subcategorization frame metric, as suggested by Hale (2003).

The subcategorization frame entropy (SCF entropy) is a measure indexing uncertainty about the syntactic constituent following a verb. The entropy of the subcategorization frame distribution is a combined measure of the number of possible syntactic frames of a verb and the extent to which their distribution is balanced, reflecting the degree of uncertainty about the syntactic category of the verb's complement. As formalized by Linzen et al. (2013), if a verb *X* has *n* possible frames, and the probability of the *i*-th frame is p_i, its subcategorization frame entropy will be as follows:

$$\mathrm{H(X)} = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{5.2}$$

The SCF entropy values were initially from Sharpe et al. (2019), which are based on Linzen et al. (2013). Their entropy values were calculated using the formula above and subcategorization distribution from VALEX databse Korhonen et al. (2006) which includes subcategorization frame and frequency information for English verbs. However, this only covered 100 of the 401 verb types in LPP. In order to supplement these scores, the SCF entropy for the remaining verbs was calculated using the subcategorization distribution provided in Gahl et al. (2004), as per Linzen's formula mentioned above, which covered 56% of the verb attestations in LPP. The remaining verbs could not be tagged since apart from these two databases, the other verb subcategorization resources have limited coverage, limited ecological validity, and divergent coding criteria. Table 12 gives some examples of verbs in LPP with their SCF entropy. Higher entropy indicates more uncertainty about the syntactic constituent following the verb.

SCF entropy is directly proportional to the uncertainty about the rest of the sentence since it represents the uncertainty about the upcoming syntactic constituent. Similar to PropBank, this score is inversely related to the prediction strength of the verb since if the score is low, then there is less uncertainty about syntactic category of the verb's complement and the listener can better predict the remaining portion of the sentence.

5.4 Analysis

The three components of argument structure discussed above, lend themselves to three separate analyses.

5.4.1 Analysis 5: Diathesis Alternations

Comparable to GLM analyses described in earlier chapters, there 11 regressors in total with one regressor of interest: diathesis alternations, as represented through the PropBank scores. Additionally, there were the same four regressors of non-interest from previous studies: word rate, lexical frequency, f0, rms. Each verb was marked with its PropBank score (described in §5.3.1), otherwise it was marked with a 0.

5.4.2 Analysis 6: Selectional Restrictions

Similar to Analysis 5, Analysis 6 has all the same 11 regressors except instead of diathesis alternations, this analysis has Resnik's selectional preference strength as the predictor which formalizes selectional restrictions between a verb and its direct object. Addition-

Verb	Subcategorization Frame Entropy	Verb	Subcategorization Frame Entropy
bring	3.036947593	disappear	0.1539041273
break	2.893574237	cause	0.6457729254
advise	2.820062941	solve	0.7784798323
appear	2.795889371	attempt	0.8048097562
warn	2.779808611	kill	0.9286728433
learn	2.772242084	rise	1.012193608

Table 12: Example of LPP verbs with their subcategorization frame entropy to represent the subcategorization between the verb and its direct object. Full list of verbs with the scores are given in Appendix C.

ally, there were the same four regressors of non-interest from previous studies: word rate, lexical frequency, f0, rms. Each verb was annotated with its selectional preference strength (described in §5.3.2), otherwise it was marked with a 0.

5.4.3 Analysis 7: Syntactic Subcategorization

Analysis 7 has the SCF entropy as a predictor to operationalize subcategorization subprocess of argument structure. It also the same four regressors of non-interest from previous studies: word rate, lexical frequency, f0, rms and six regressors for the visual stimuli (§2.4), for a total of 11 regressors in the GLM. Each verb was tagged with its subcategorization frame entropy (described in §5.3.3), otherwise it was marked with a 0.

5.4.4 Group-level Analysis

In the second-level group analysis, each contrast was analysed separately at the group-level. An 8 mm FWHM Gaussian smoothing kernel was applied on the contrast images from the first-level analysis to counteract inter-subject anatomical variation. All the group-level results reported in the next section underwent FWE voxel correction for multiple comparisons which resulted in T-scores > 5.3.

5.5 Results

All whole-brain effects reported survived a $p < 0.05$ Family-Wise-Error threshold at the voxel level. These results were surface rendered in Mango (Lancaster and Martinez 2006) using the Colin-27 template (Holmes et al. 1998).

5.5.1 Analysis 5: Diathesis Alternations

Table 13 shows the significant clusters of activation for diathesis alternations and peak activation voxels, using brain region labels from the Harvard-Oxford Cortical Structure Atlas.

The largest clusters for diathesis alternation was observed in the bilateral Precuneus, the Supramarginal gyrus, Middle Temporal gyrus, Middle Frontal gyrus, and Superior Frontal gyrus on the right and the Middle Occipital on the left, as seen in Fig. 13 in green.

Regions	Cluster size (in voxels)	MNI Coordinates x	y	z	p-value (corrected)	T-score (peak-level)
Precuneus (bilateral)	2416	8	-56	44	0.000	10.92
L Precuenus		-8	-62	54	0.000	7.47
R Supramarginal Gyrus	2037	56	-44	30	0.000	10.65
R Middle Temporal Gyrus		50	-50	18	0.000	8.46
R Middle Occipital Gyrus		44	-64	26	0.000	7.01
R Middle Frontal Gyrus	1080	24	28	44	0.000	8.70
R Superior Frontal Gyrus		18	12	60	0.000	7.10
R Superior Frontal Gyrus		22	26	58	0.000	6.06
R Medial Frontal Gyrus/Anterior Cingulum	523	10	50	14	0.000	7.38
R Superior Medial Frontal Gyrus		10	54	6	0.000	7.28
R Medial Frontal Gyrus (BA 10)		6	56	-6	0.000	5.92
L Middle Occipital	102	-40	-76	34	0.002	6.37
L Cuneus/Precuneus	45	-12	-62	24	0.006	6.03
R Middle Temporal Gyrus (BA 21)	63	56	-8	-16	0.006	6.01
R Mid Cingulum	19	4	-20	40	0.008	5.92
R Superior Frontal Gyrus (BA 10)	36	16	66	22	0.017	5.66
R Superior Frontal Gyrus (BA 10)		22	62	12	0.022	5.57

Table 13: Significant clusters for diathesis alternations after FWE voxel correction. Peak activation is given in MNI coordinates and p-values are reported at peak-level after voxel-correction.

5.5.2 Analysis 6: Selectional Restrictions

Table 14 shows the significant clusters of activation for selectional restrictions and peak activation voxels, using brain region labels from the Harvard-Oxford Cortical Structure Atlas. Three main clusters of right-lateralized activation can be observed in Fig. 13 (in blue): Supplementary Motor Area, Inferior Frontal gyrus Pars Orbitalis/Triangularis, and Superior Temporal gyrus.

Regions	Cluster size	MNI Coordinates			p-value	T-score
	(in voxels)	x	y	z	(corrected)	(peak-level)
R Superior Temporal Gyrus	1442	52	-38	12	0.000	8.56
R IFG Orbitalis/Triangularis	367	52	26	-6	0.000	7.05
R Supplementary Motor Area	200	6	12	66	0.004	6.13

Table 14: Significant clusters for selectional restrictions after FWE voxel correction. Peak activation is given in MNI coordinates and p-values are reported at peak-level after voxel-correction.

5.5.3 Analysis 7: Syntactic Subcategorization

Table 15 shows the significant clusters of activation for subcategorization and peak activation voxels, using brain region labels from the Harvard-Oxford Cortical Structure Atlas. Largest clusters are observed in Medial Frontal gyrus on the right and Inferior Parietal Lobule on the left, as seen in Fig. 13 in orange.

Regions	Cluster size (in voxels)	MNI Coordinates x	y	z	p-value (corrected)	T-score (peak-level)
R Middle Temporal Gyrus	800	50	-20	-10	0.000	8.13
R Superior Temporal Gyrus		58	-36	12	0.018	5.66
R Middle Temporal Gyrus (BA 21)	598	52	6	-24	0.000	7.27
R Inferior Temporal Gyrus		50	6	-36	0.000	7.17
R Superior Medial Frontal Gyrus	334	6	56	12	0.001	6.47
R Superior Medial Frontal Gyrus		12	58	24	0.002	6.36
R Superior Frontal Gyrus (BA 9)		14	58	34	0.012	5.80
R Superior Frontal Gyrus	43	10	24	60	0.003	6.21
R Superior Temporal Gyrus/Inferior Parietal Lobule	33	58	-42	22	0.020	5.62
R IFG Orbital/Triangularis	6	54	24	-4	0.029	5.49

Table 15: Significant clusters for syntactic subcategorization after FWE voxel correction. Peak activation is given in MNI coordinates and p-values are reported at peak-level after voxel-correction.

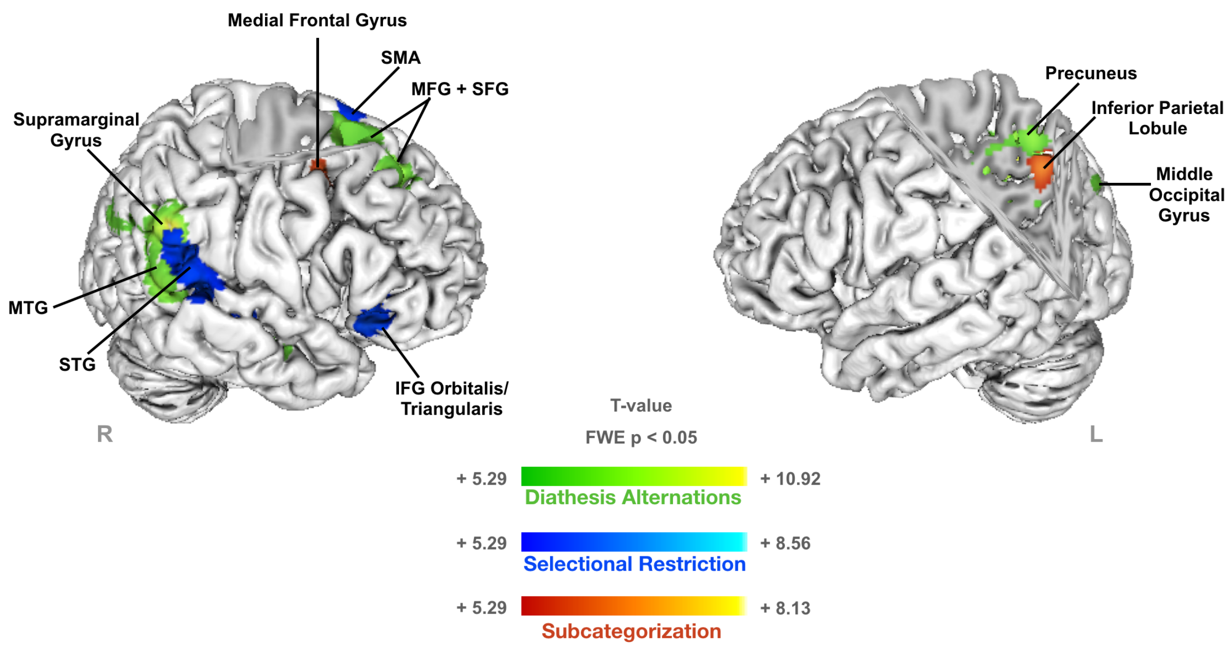

Figure 13: Whole-brain contrast images with significant clusters for diathesis alternations in green, for selectional restrictions in blue, and for subcategorization in orange. All images underwent FWE voxel correction for multiple comparisons with $p < 0.05$.

5.6 Discussion

5.6.1 Brain network involved in argument structure

This section examines the different brain areas that were significantly activated across Analysis 5, Analysis 6, and Analysis 7. For the most part, our results corroborate existing work and the relevant brain areas reported. This is notable since prior neuroimaging studies were controlled, task-based designs, and often included lexical decision tasks. However, this study differs in that the neural bases of argument structure was investigated in an ecologically valid setting within a naturalistic language comprehension study and we found comparable results.

Precuneus

Significant bilateral Precuneus activation is observed for diathesis alternations in Analysis 5, which is consistent with previous studies. Examining verb processing at the sentence level, Shetreet et al. (2007) found significant activation in medial Precuneus and the anterior cingulate cortex. Similarly, Shetreet et al. (2010a) also found the medial Precuneus while investigating the effect of the numner of complements on brain activations. Furthermore, in den Ouden et al. (2009), the precuneus was implicated in verb production. Thus, this suggests that the Precuneus is involved in processing argument structure, as well as processing noncompositional expressions, as discussed in §3.6 and §4.6.

Supramarginal

The Supramarginal gyrus is one of the largest clusters observed for diathesis alternations in Analysis 5. Thompson et al. (2007) also find bilateral activation in Supramarginal gyrus while conducting a lexical decision task with intransitive, transitive, and ditransitive verbs. Bilateral Supramarginal gyrus activation was also observed in verb production (den Ouden et al. 2009).

Inferior Parietal Lobule

Activation in the IPL is observed in Analysis 7, correlated with SCF entropy. Thompson et al. (2007) also identifies the IPL as a region implicated in processing argument structure. The IPL is also involved in the processing of verbs with multiple thematic options (Meltzer-Asscher et al. 2013). Also, Wernicke's aphasic individuals do not exhibit normal sensitivity to subcategorization options and this suggests that this knowledge and perhaps knowledge about argument structure in general involves the IPL (along with posterior temporal regions), since these areas are often damaged in this population (Dronkers et al. 2004b; Kertesz and Lesk 1977; Kertesz et al. 1979). This area is implicated within the eADM model (Bornkessel-Schlesewsky and Schlesewsky 2013)[3] as relevant to the processing of information related to sequential order. SCF entropy formalizes the sequential relationship between a verb and its syntactic constituent and thus, sequential information processing situates this region within Bornkessel-Schlesewsky and Schlesewsky's model.

Superior Frontal Gyrus and Middle Frontal Gyrus

Significant clusters are observed in SFG and MFG across Analysis 5 and Analysis 7, correlated with diathesis alternations and SCF entropy respectively. MFG is implicated both in verb processing (Shetreet et al. 2007) and verb production (den Ouden et al. 2009). In their study on verbs with alternating transitivity, Meltzer-Asscher et al. (2013) found activation in bilateral Superior Frontal gyrus (BAs 8 and 9). They suggest that this activation is due to ambiguity associated with alternating verbs since MFG and SFG are also implicated in processing lexical ambiguity of nouns (Chan et al. 2004; Mason and Just 2007). This is consistent with the results presented above since both diathesis alternations and SCF entropy involve processing ambiguity in terms of semantic and syntactic constraints

[3]This model is discussed further in §6.

respectively.

Inferior Frontal Gyrus

Significant activation is observed in the right IFG in Analysis 6 with selectional restrictions. In most previous work on argument structure, the left IFG is implicated e.g., Shetreet and Friedmann (2014); Friederici (2012) but we do not observe any activation in that region. Furthermore, there are no prior neuroimaging work looking at selectional restrictions between a verb and its argument. However, this pattern of activation is consistent with other neuroimaging studies related to lexical-semantic processing and semantic ambiguity (Kuperberg et al. 2000; Zempleni et al. 2007).

Superior Temporal Gyrus and Middle Temporal Gyrus

Significant clusters were observed in posterior Temporal regions namely, STG and MTG across Analysis 4 and Analysis 5 for diathesis alternations and selectional restrictions respectively. Ben-Shachar et al. (2003) found increased bilateral superior temporal sulcus activation as the number of arguments in the sentence increased as a function of the number of thematic roles associated with a verb, similar to Shetreet et al. (2007)'s finding. Hadar et al. (2002) also reports STG and MTG activation associated with verbs. Evidence from Wernicke's aphasia mentioned above also indicates that these posterior temporal regions are implicated in argument structure processing (Dronkers et al. 2004a; Kertesz and Lesk 1977; Kertesz et al. 1979).

Posterior MTG has often been associated with lexical processes, such as the retrieval of words and their associated features as formulated by Hickok and Poeppel (2007) and Hagoort and Indefrey (2014). In a study examining argument structure complexity, Meltzer-Asscher et al. (2015) suggests that MTG is involved in representation of lexical-semantic information, which is consistent with our selectional restrictions results.

Furthermore, Friederici (2012) states that the MTG is engaged for retrieval of argument structure information. Thompson et al. (2007) concurs that these regions are engaged for processing argument structure information associated with verbs, especially information referring to the number of thematic roles. This corroborates our finding of posterior temporal activation with diathesis alternations.

5.6.2 Neurocognitive Models of Sentence Processing

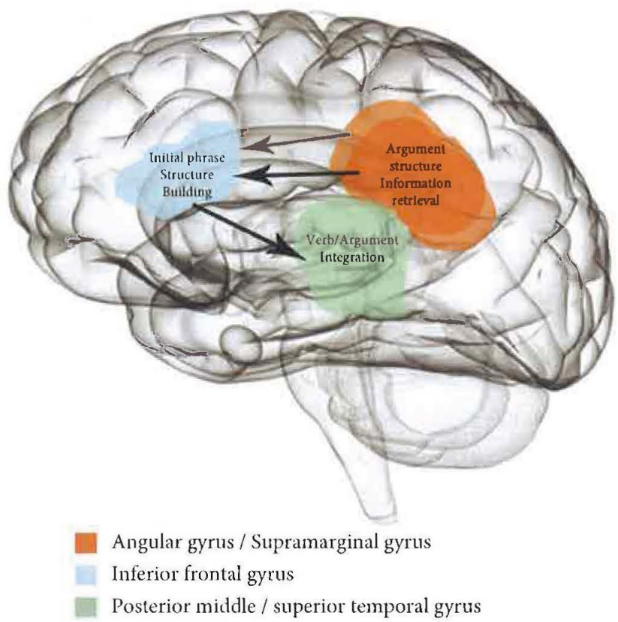

Figure 14: Neurocognitive model of verb argument structure processing proposed by Thompson and Meltzer-Asscher (2014)

Thompson and Meltzer-Asscher (2014) propose a neurocognitive model of argument structure processing, based on the existing work investigating the neural substrates of verb processing. They posit that initial syntactic parsing and structure building involves the left IFG. Once verbs are encountered, the bilateral angular/supramarginal gyri are activated to support retrieval of associated argument structure information. This information, along with the initial structure, is transmitted to posterior temporal regions (MTG and STG) for sentence-level semantic and syntactic integration. This model is represented in Fig. 14. While no left IFG activation is observed in our results for processing argument structure, our results do map onto the areas they propose for argument structure information retrieval (Supramarginal gyrus) and verb-argument integration (posterior MTG and STG).

Thompson and Meltzer-Asscher's model is comparable to the model for sentence processing proposed in Friederici (2012). Friederici's model consists of left-lateralized networks involving the temporal cortex and the inferior frontal cortex, which are shown to support syntactic processes, whereas less lateralized temporo-frontal networks subserve semantic processes[4]. While we do not observe a left-lateralized network, we do see a right-lateralized pattern of activation in the temporo-frontal regions which would subserve the semantic subprocesses of argument structure processing according to this model.

5.6.3 Future Work

Incorporating morphology

All the analyses described in §5.4 are based on verb lemmas. Verb lemmas entail both syntactic and semantic information but are not specified for phonological form (Thompson and Meltzer-Asscher 2014). Thus, verb lemmas can include argument structure information such as diathesis alternations, selectional restrictions, and SCF entropy. As a result of using verb lemmas, all the forms of a given verb receive the same score and verbal morphology is not accounted for in this study. But given the number and diversity of our tokens along with the relative lack of rich English verbal morphology, the contribution of morphology to the overall statistical result would be minimal and would possibly be averaged out.

However, verbal morphology can also be a predictive cue and can help the listener infer the semantic role assignment or the upcoming syntactic constituent. For example,

[4]This model is discussed more in detail in §6

if a verb has passive morphology, we know it is likely that the syntactic constituent will be a prepositional phrase (*by* phrase), a verbal participle, or no constituent, even if these options are not the most frequent subcategorization frame for that verb, given corpus distribution information. Similarly, passive morphology would also prime our expectation that the semantic role assignment following the verb would be an THEME or GOAL, with an optional AGENT after it. In future analyses, I would like to leverage verbal morphology as a predictive cue for processing argument structure alongside the existing metrics and investigate its overall contribution.

Collostruction strength

According to Wiechmann (2008), collostruction strength is the degree of attraction that a word C_j exhibits to a construction C_k. It can be used to estimate the degree of attraction between a verb and its complementation patterns. In a way, this extends the idea of association measures (discussed in §4.2.2) and applies it to argument structure. However, rather than estimating the lexical association within a collocation, it abstracts away from words and provides a gradient metric to reflect the association between verbs and its syntactic frames.

Wiechmann tests 47 different association measures against human reading times, behavioural measure to index processing cost. He discovers that the metric of minimum sensitivity (Pedersen and Bruce 1996) is the most predictive of the reading times and thus the most cognitive plausible metric to estimate collostruction strength. In order to follow-up the current analyses on argument structure presented in this chapter, implementing an analyses with collostruction strength, especially minimum sensitivity will help us gain further insight into argument structure and language processing in general.

Whole brain model comparison

The three analyses described in this chapter employs the standard GLM analysis in SPM12 (described in §1.1) and is quite commonly used to provide functional localization of various cognitive processes. As seen above, the group-level results in each of the three studies gives us neural correlates of the different components of argument structure processing.

Although this helps us gain further insight into brain areas implicated in processing argument structure during real-time sentence processing, it does not answer one of the initial questions that I had proposed in §1: how do the different components of argument structure influence real-time sentence processing? The answer to this question goes beyond the scope of a GLM localization analysis. It would require a whole brain model comparison analysis which is not readily available through standard neuroimaging data analysis software packages. Earlier work by Li et al. (2016) used fMRI timecourses in specific ROIs to compare different complexity metrics by implementing a regression analysis in R. However, this study uses whole brain fMRI timecourses and picking certain ROIs would not be informative enough to answer our question.

Currently, Christophe Pallier at INSERM is developing a new methodology to implement a statistical test which would allow us to do this sort of comparison. In this analysis, known as a R2 analysis, we can test how much each regressor contributes to the fMRI signal variance. In this way, we can test regressors within the same model e.g., f0 and RMS if we wanted to compare the effect of these acoustic parameters; or we can test regressors from different models e.g., we can compare diathesis alternations, selectional restrictions, and SCF entropy and check how much each regressor contributes to the overall signal variance. Based on such an analysis, we can infer which regressor, and thus the cognitive process it formalizes, is more influential during online sentence processing in certain brain regions.

CHAPTER 6

DISCUSSION & CONCLUSION

This chapter discusses the key findings across the seven studies presented and situates the results presented in earlier chapters within the framework of several contemporary neurobiological models of language processing. It concludes with an overview of the main contributions of this dissertation.

6.1 General Discussion

Overall, across seven studies presented in §3 - §6, these are the key findings summarized below:

- Noncompositional expressions have different neural substrates compared to phrases built compositionally. The former mainly implicates the Precuneus while the latter involves areas such as Anterior Temporal and Anterior Frontal regions, which have been involved in studies related to syntax. Furthermore, these two expressions were taken to represent the cognitive processes linked to memory retrieval and composition and consequently, in this study the results suggest that these processes have distinct functional localizations. Thus, language productivity (as exemplified through composition) and language reuse (exemplified through memory retrieval) were shown here to implicate different brain networks.
- The differences in the grammatical category of noncompositional expressions is observable at the cerebral level, which shows that the brain sensitive to the internal structure of these "frozen" noncompositional expressions, especially the inherent argument structure of verbal expressions. This suggests that these noncompositional expressions are not as "frozen" as traditionally assumed or there is a gradient spectrum of frozenness along which these expressions can be situated.

- Expressions cannot be strictly binarized as compositional and noncompositional. There are finer-grained distinctions that can be captured by using a gradient approach, such as the ones suggested in §4 by adapting different metrics from corpus and computational linguistics to reflect the degree of conventionalization and degree of predictability within this MWEs. Furthermore, while highly conventionalized and highly predictable MWEs are plausibly retrieved from memory and involved the Precuneus, less conventionalized and less predictable MWEs are possibly not retrieved, and instead processed compositionally, as evidenced through their neural correlates highlighting the perisylvian language network.
- The different components of argument structure such as diathesis alternations, selectional restrictions, and SCF entropy have distinct neural correlates, which indicates that different subprocesses map onto different brain areas to illustrate a network relevant for processing argument structure. Furthermore, these results corroborate findings from previous controlled, task-based experimental designs.
- Based on the results for noncompositional expressions and argument structure, the Precuneus is implicated in two different areas of language processing. Thus, this suggests that the language network extends beyond the traditional perisylvian regions and should include the Precuneus.

Based on the findings from these studies, we can examine connections between linguistic competence and language performance at the cerebral level. For example, in Analysis 1 structure-building effort is taken to be part of competence. However, the retrieval of memorized elements during real-time language comprehension reflects language performance at the brain level. Analysis 2, Analysis 3, and Analysis 4 offer similar examples since they all deal with MWE retrieval in various ways. Analysis 5 with diathesis alternations offers a slightly different perspective. The diathesis alternations for a given verb is abstract, tacit knowledge and therefore, can be counted as competence. However, this tacit knowledge is leveraged during sentence processing and thus, also instantiates language performance. Selectional restrictions in Analysis 6 and SCF entropy in Analysis 7 both reflect linguistic competence in terms of the abstract linguistic knowledge they encapsulate. However, both of them also incorporate a frequency distribution, either in terms of semantic classes or syntactic constituents, and thus exemplify an instantiation of language performance at the brain level during natural language comprehension.

6.2 Neurobiological Models of Language Processing

In this section, I discuss some of the contemporary neurobiological models of language processing and situate my work within those.

6.2.1 Friederici's Model of Language Comprehension

Friederici (2012) proposes a model of language comprehension with two dorsal and two ventral streams relevant for language. The two dorsal pathways support auditory-to-motor mapping and the processing of syntactically complex sentences, respectively. The two ventral pathways subserve semantic and basic syntactic processes, respectively (Friederici and Gierhan 2013).

The findings for different components of argument structure such as diathesis alternation, selectional restrictions, and SCF entropy, are consistent with Friederici's model with a caveat. In the ventral semantic stream, lexical-semantic information is retrieved from the MTG and transferred via anterior temporal regions to anterior IFG, whereas dorsal route connects the posterior IFG to posterior temporal regions and is involved in complex syntactic computation (e.g. movement) and verb-argument integration. However, this is in line with our results from Analysis 5 - 7 if do not assume a strict left-lateralization since most of the significant clusters we report for argument structure processing is in the right hemisphere.

6.2.2 Declarative/Procedural Model

The declarative/procedural model posited by Ullman (2001) is based on upon a distinction that contrasts memory-related with non-memory-related processing. In this model, the ventral stream is tied to declarative memory while the dorsal stream is tie to procedural memory. Ullman (2015) links rule-based mechanisms to frontal regions and subcortical structures, while memory for words is supported by medial temporal regions. In this model subcategorization is linked to declarative memory, which is supported by MTL and this is tied to prediction. This fits in with the results from the current study where the MTG is implicated in both diathesis alternation and SCF entropy for a given word. Ullman also claims that the IFG, specifically BA 45/47 seems to be involved verbal working memory but no similar pattern of activation was observed in this study.

6.2.3 Extended Argument Dependency Model (eADM)

The eADM (Bornkessel-Schlesewsky and Schlesewsky 2009, 2013) divides up language processing in a different way. In this model sequential information (for instance about word order) is handled by a dorsal stream, while dependency information (as expressed through case-marking) is handled by a ventral stream. If MWE comprehension is sequential processing in this sense, then structures along this dorsal stream, including the Inferior Parietal Lobule, should be involved. On the other hand, structure-building should activate temporal regions along the ventral stream. Our results from Analysis 1 consistent with this view.

However, this model is "category-neutral" and words are not designated as nouns or verbs. Instead there are unification operations and these take place within the temporal (and parietal) regions that form part of the dorsal and ventral streams. Argument structure involves both sequential ordering and dependency information, so according to this model, our results from Analysis 5 - 7 would map onto both temporal regions of the dorsal stream and parietal regions of the ventral stream.

6.2.4 Memory, Unification, and Control (MUC)

In this framework structure-building falls under the scope of the Unification operation and is assigned to frontal areas. Regarding the Memory aspect of their model, Hagoort and colleagues agree partly with Ullman, associating that function (among others) to posterior temporal regions (Hagoort and Indefrey 2014; Hagoort 2009). Recruitment of the posterior language network for verb argument structure processing is also in line with this model of language processing. This model suggest that entries in the mental lexicon are associated with syntactic properties, such as grammatical class and in the case of verbs, syntactically relevant sub-categorization frames.

6.2.5 Dual Streams Model

The Dual Streams model (Hickok and Poeppel 2007) locates the Lexical Interface, where individual words would be processed, to posterior Middle Temporal Gyrus. Syntactic phrases would be composed, part-by-part, by a Combinatorial Network in the Anterior Temporal Lobes. Furthermore, they state that verbal working memory is a special case of auditory–motor integration, and involve Broca's area and STG. While we do not find the former in our study, Analysis 6 - 7 implicate STG.

6.3 Conclusion: Noncompositionality and Argument Structure from a Neurolinguistic Perspective

In conclusion, this dissertation brings together neurolinguistics and computational linguistics to focus on two topics: noncompositional expressions (MWEs) and verbal argument structure. Across seven studies, I show how we can utilize various models and metrics from computational linguistics to operationalize cognitive hypotheses and help us better understand the neurocognitive bases of language processing. I present a large-scale fMRI dataset based on 51 participants listening to Saint-Exupéry's *The Little Prince* (1943), comprising 15,388 words and lasting over an hour and a half in §2. While previous work has examined individual types of noncompositional expressions (such as idioms, compounds, binomials), I unify this heterogeneous family of word clusters in a single analysis in §3 and illustrate that they are processed differently from compositional phrases. In this way, memory retrieval and composition are shown to have different neural correlates. This research also contributes a gradient approach to these noncompositional expressions by repurposing association measures (from computational linguistics) and demonstrates how they can be adapted as cognitively plausible metrics for language processing in §4. Furthermore, this gradient approach also suggests that highly conventionalized and highly predictable MWEs are retrieved from memory while less conventionalized and less predictable MWEs are processed compositionally. This dissertation also probes the neural correlates of argument structure and corroborates previous controlled, task-based experimental work on the syntactic and semantic constraints between a verb and its argument in §5 to illustrate a network of brain areas implicated in processing argument structure and its different linguistic subprocesses. Another finding is that the Precuneus, not traditionally considered a part of the core perisylvian language network, is involved in both processing noncompositional expressions and diathesis alternations for a given verb. Overall, based on this interdisciplinary approach, this dissertation presents empirical evidence through neuroimaging data, linking linguistic theory with language processing.

APPENDIX A

QUIZ COMPREHENSION QUESTIONS AND PARTICIPANTS' SCORES

This appendix consists of experimental materials used in the study, along with information about the participants. The list below gives the exclusion criteria used in the study based on handedness. Figures 15 – 23 illustrate the comprehension questions presented to participants at the end of each section. Table 16 contains each participant's gender and age information, as provided by them, and their quiz scores.

The following questions, adapted from the Edinburgh inventory (Oldfield 1971), were uses to assess handedness in the study. Anyone who answered *left* to more than two questions were excluded from the study.

What hand do you prefer to use when:

- Writing?
- Drawing?
- Throwing?
- Using Scissors?
- Using a Toothbrush?
- Using a Knife (without a fork)?
- Using a Spoon?
- Using a Broom(upper hand)?
- Striking a match?
- Opening a box (holding the lid)?
- Which foot do you prefer to kick with?
- Which eye do you use when only using one?

Subject number	Gender	Age	Quiz score
57	F	20	34
58	M	22	33
59	F	21	33
61	F	25	36
62	M	23	36
63	M	22	36
64	M	19	33
65	F	21	31
66	F	19	33
67	F	21	35
68	M	19	33
69	F	21	34
70	F	20	34
72	F	18	34
73	F	19	36
74	F	18	34
75	M	18	35
76	M	20	30
77	M	22	35
78	F	19	27
79	F	21	35
80	F	22	34
81	F	22	35
82	F	28	33
83	F	20	36

Table 16 continued from previous page

Subject number	Gender	Age	Quiz score
84	F	22	32
86	M	19	33
91	M	20	21
92	M	21	32
93	F	20	31
94	F	21	30
95	F	20	35
96	F	18	30
97	F	21	32
98	F	24	31
99	F	37	24
100	F	19	35
101	M	23	30
102	F	18	30
103	F	19	34
104	F	19	18
105	M	20	34
106	F	19	30
107	M	21	35
108	M	18	32
109	M	19	34
110	F	21	33
111	F	20	23
113	F	21	31

Table 16 continued from previous page

Subject number	Gender	Age	Quiz score
114	M	20	33
115	F	20	27

Table 16: List of participants in the LPP study with their respective gender, age, and quiz scores.

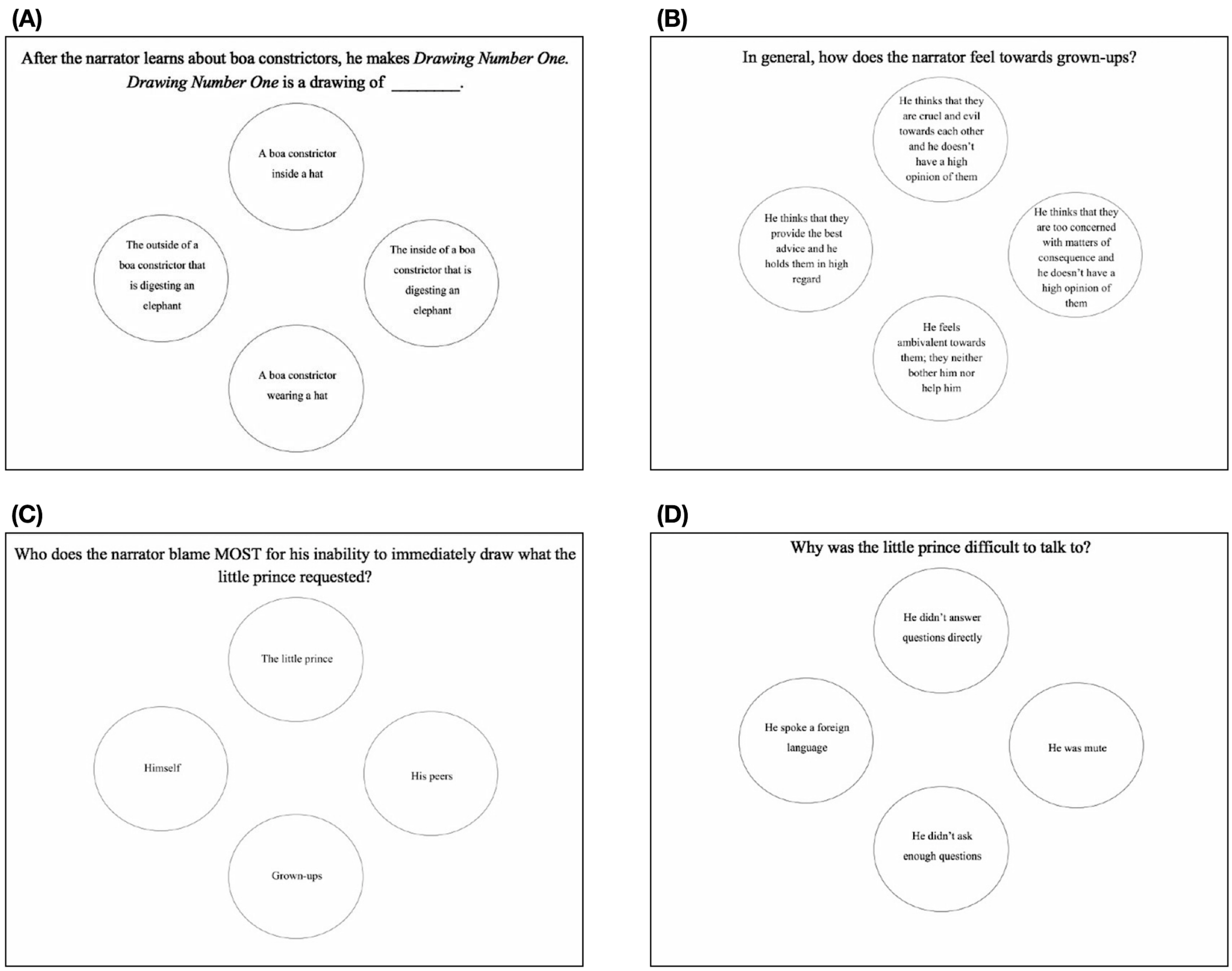

Figure 15: Comprehension questions based on section 1 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

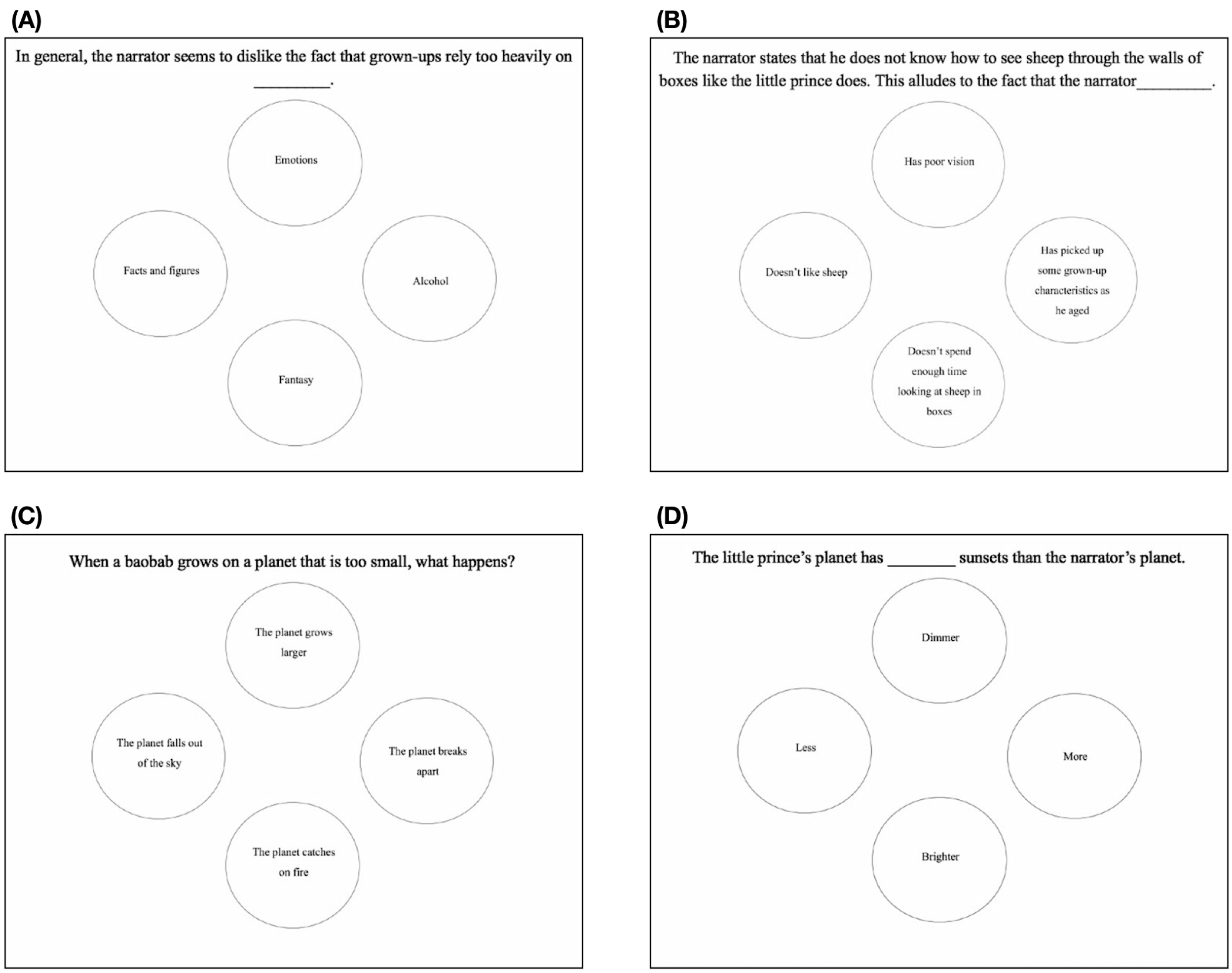

Figure 16: Comprehension questions based on section 2 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

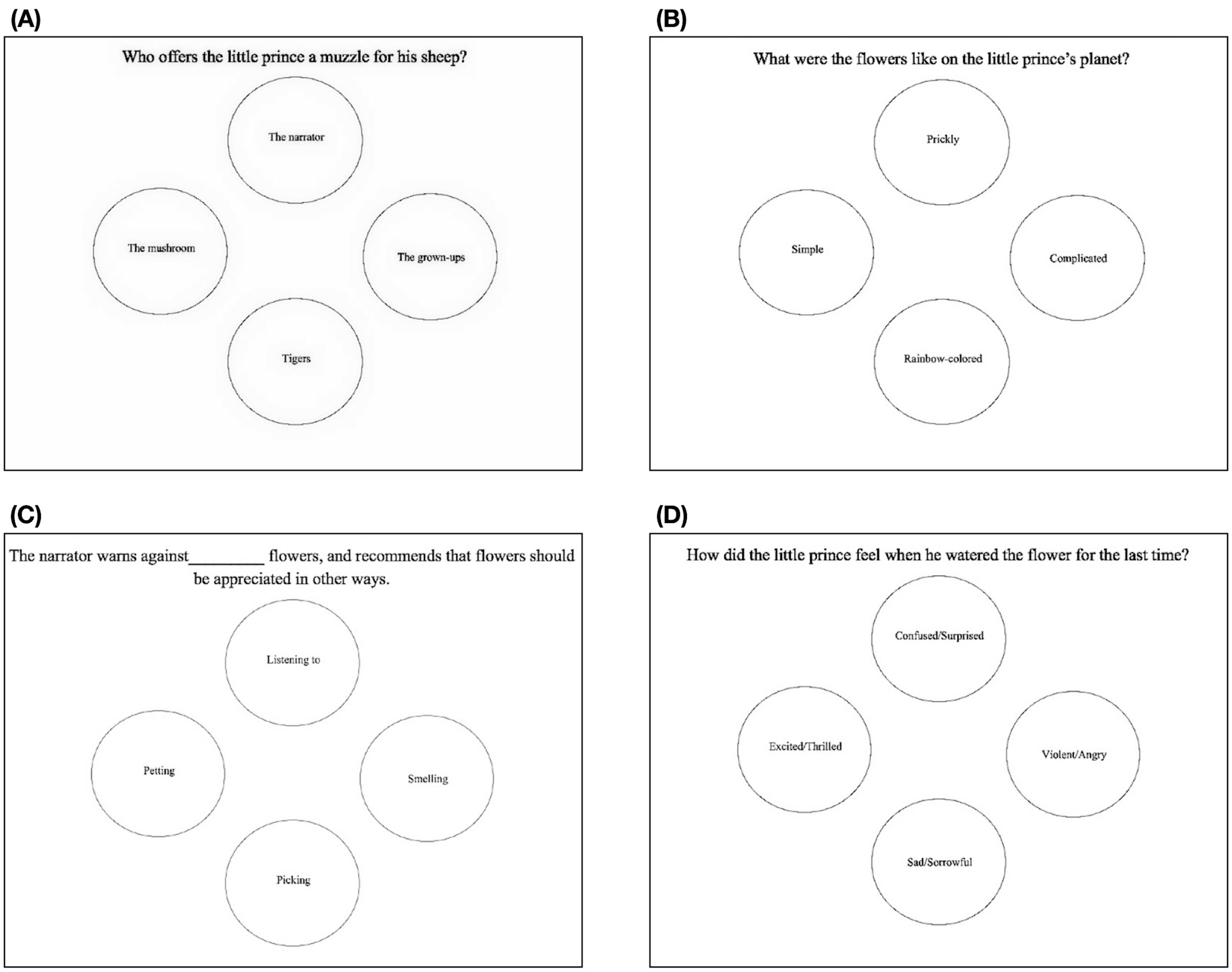

Figure 17: Comprehension questions based on section 3 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

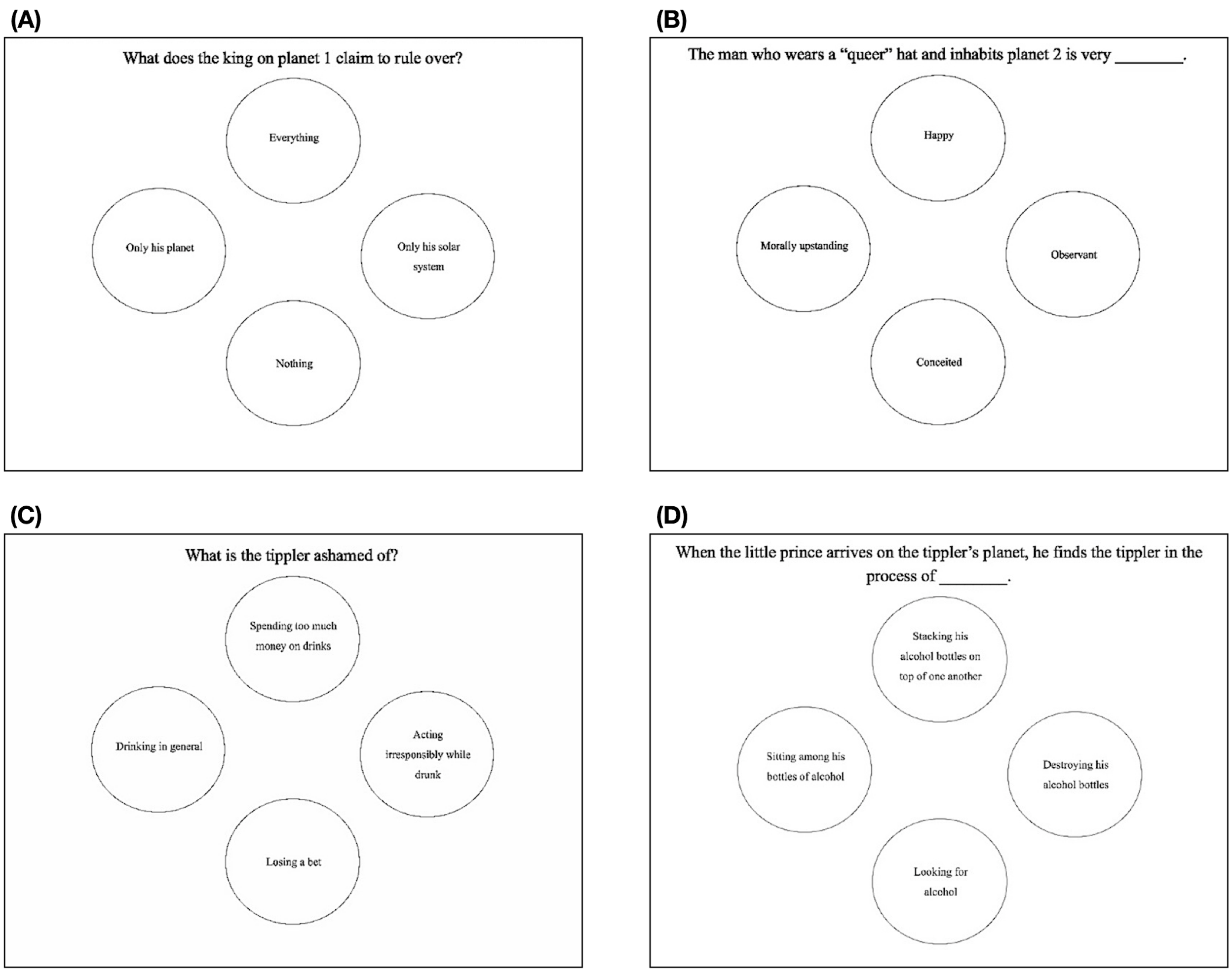

Figure 18: Comprehension questions based on section 4 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

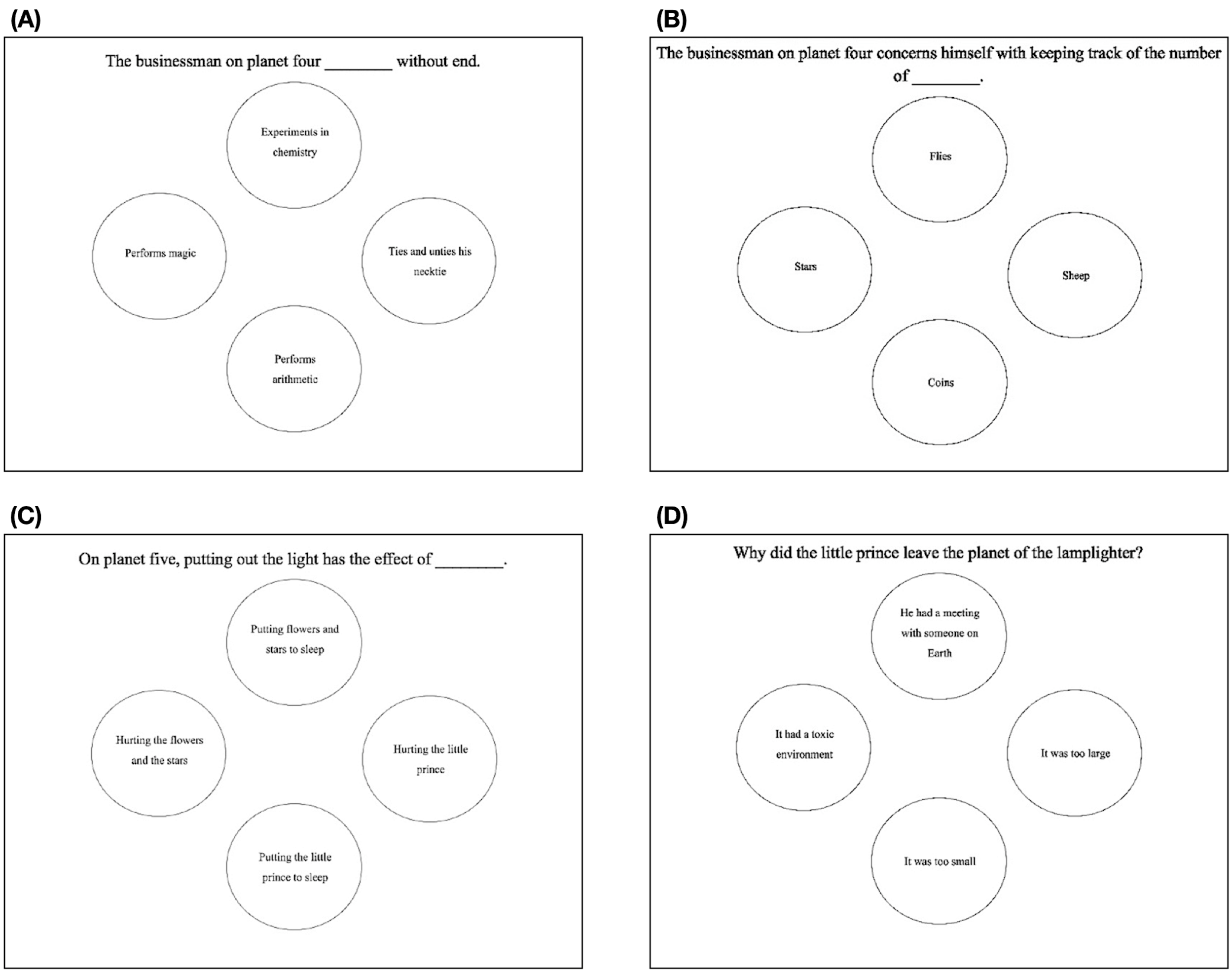

Figure 19: Comprehension questions based on section 5 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

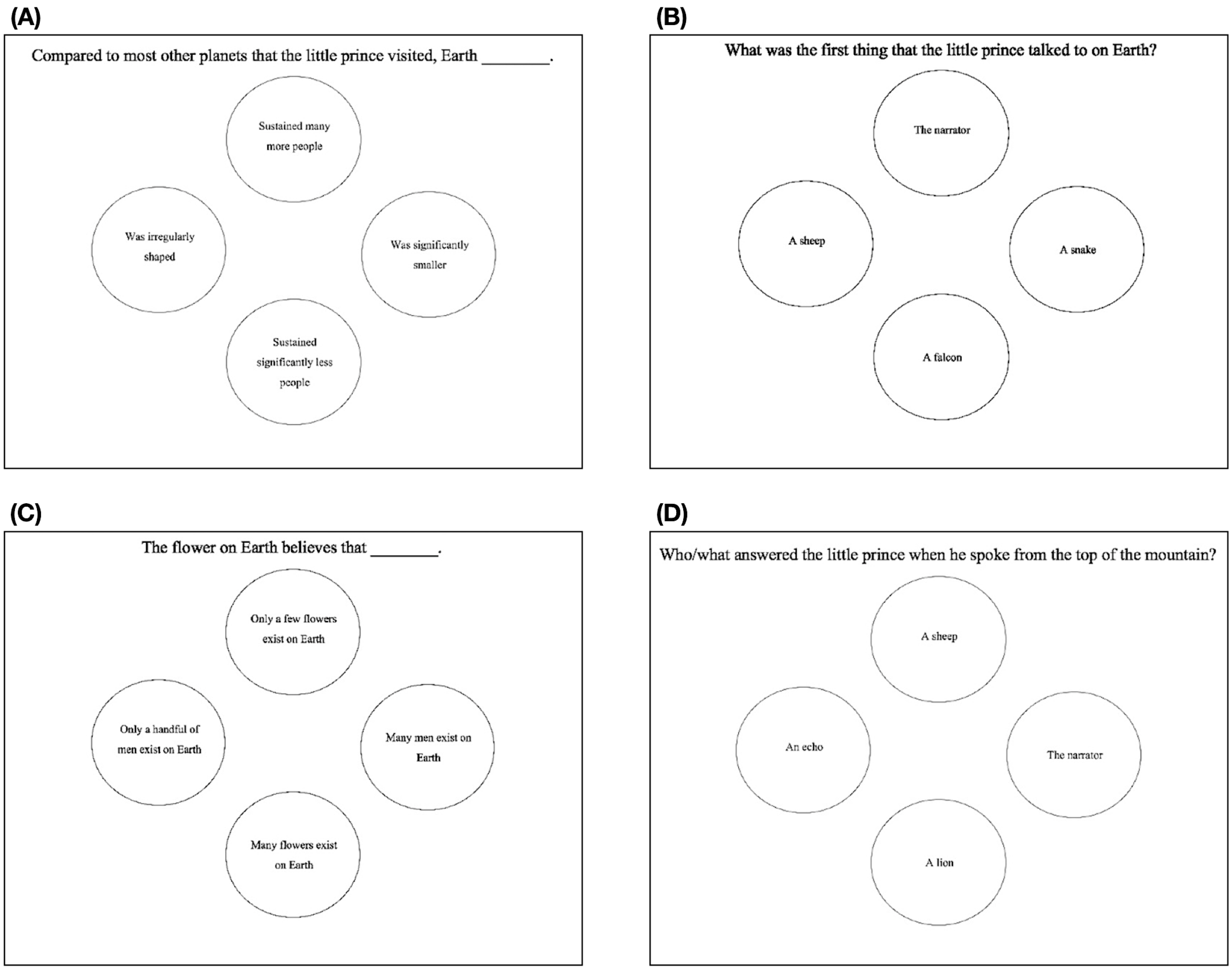

Figure 20: Comprehension questions based on section 6 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

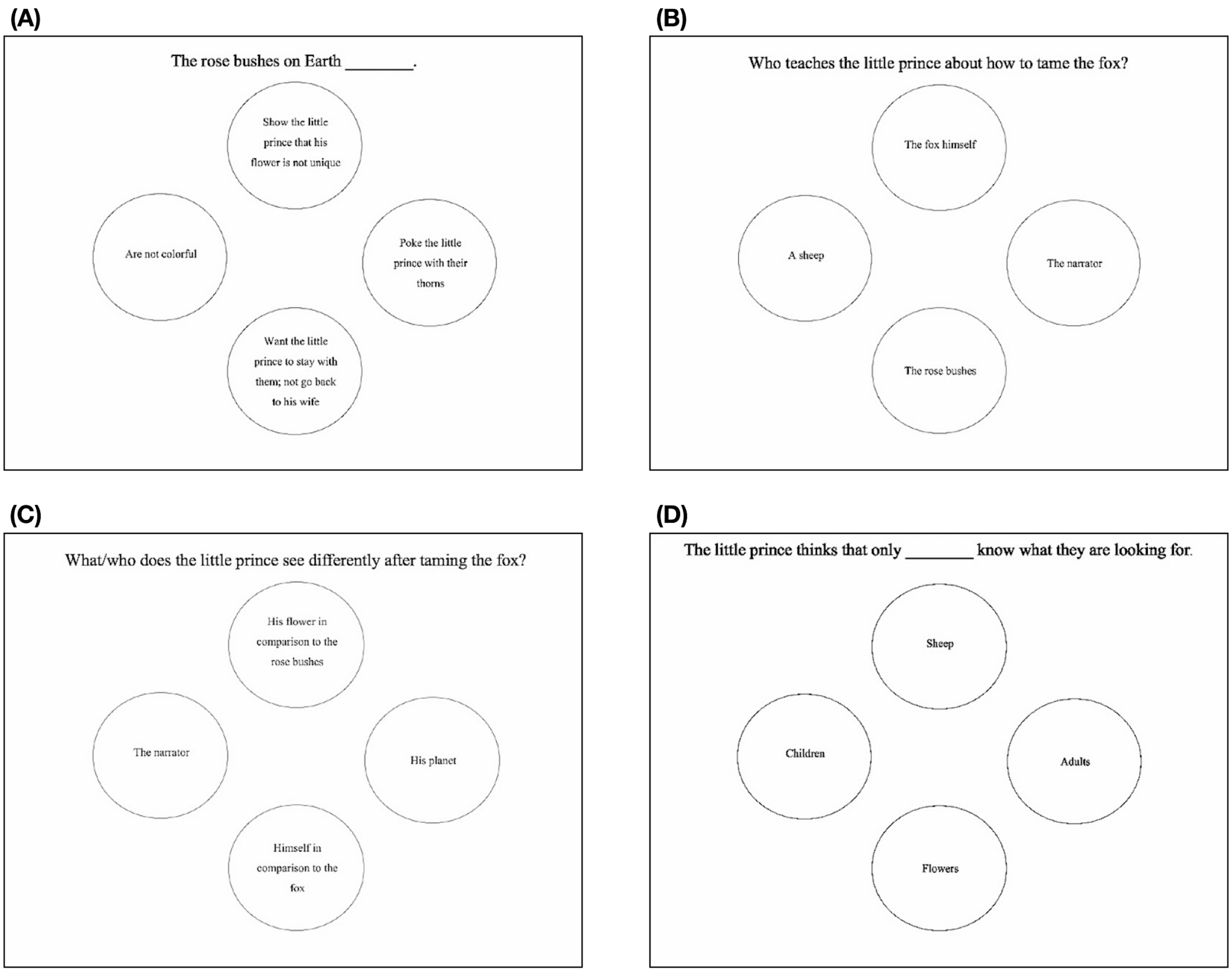

Figure 21: Comprehension questions based on section 7 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

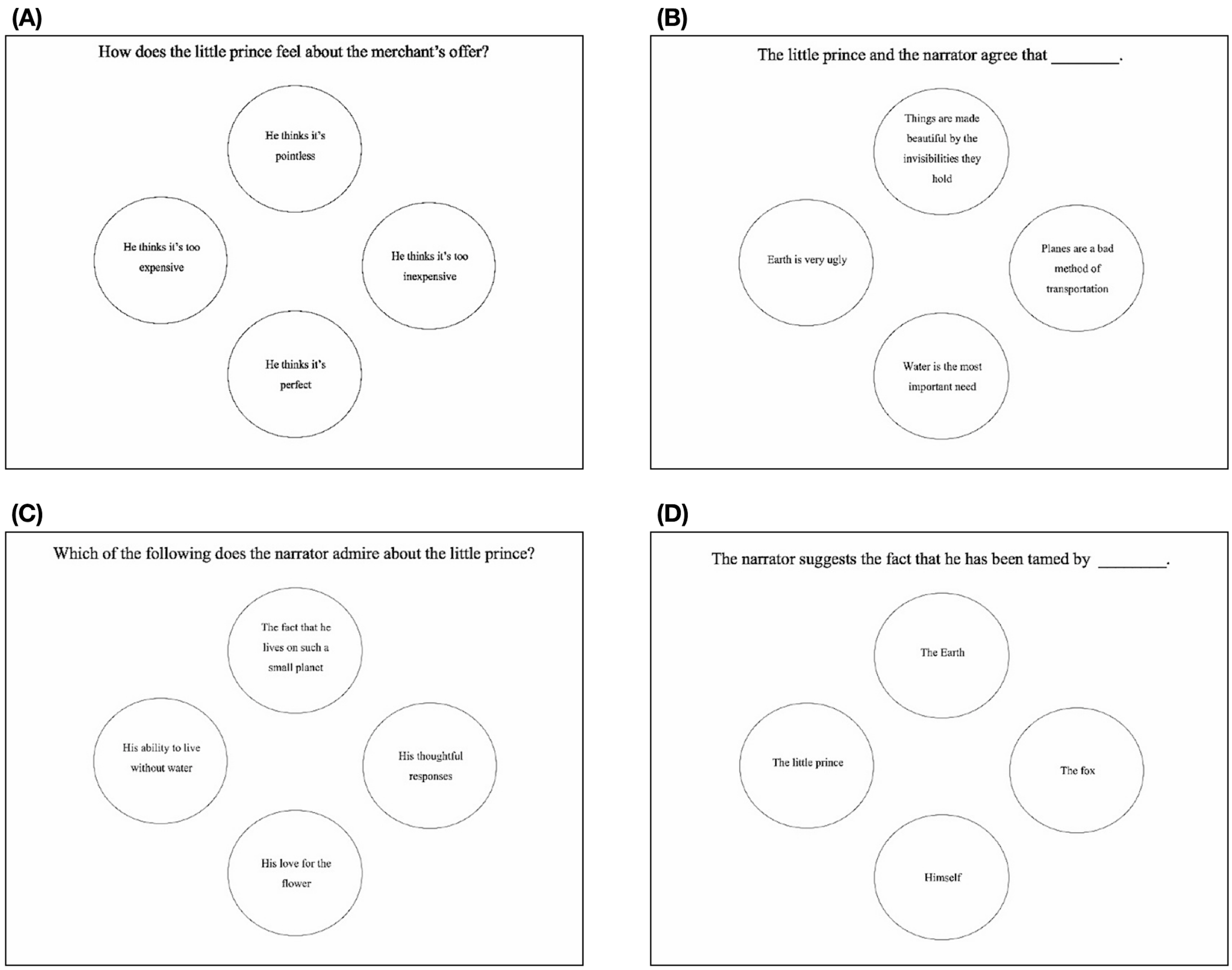

Figure 22: Comprehension questions based on section 8 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

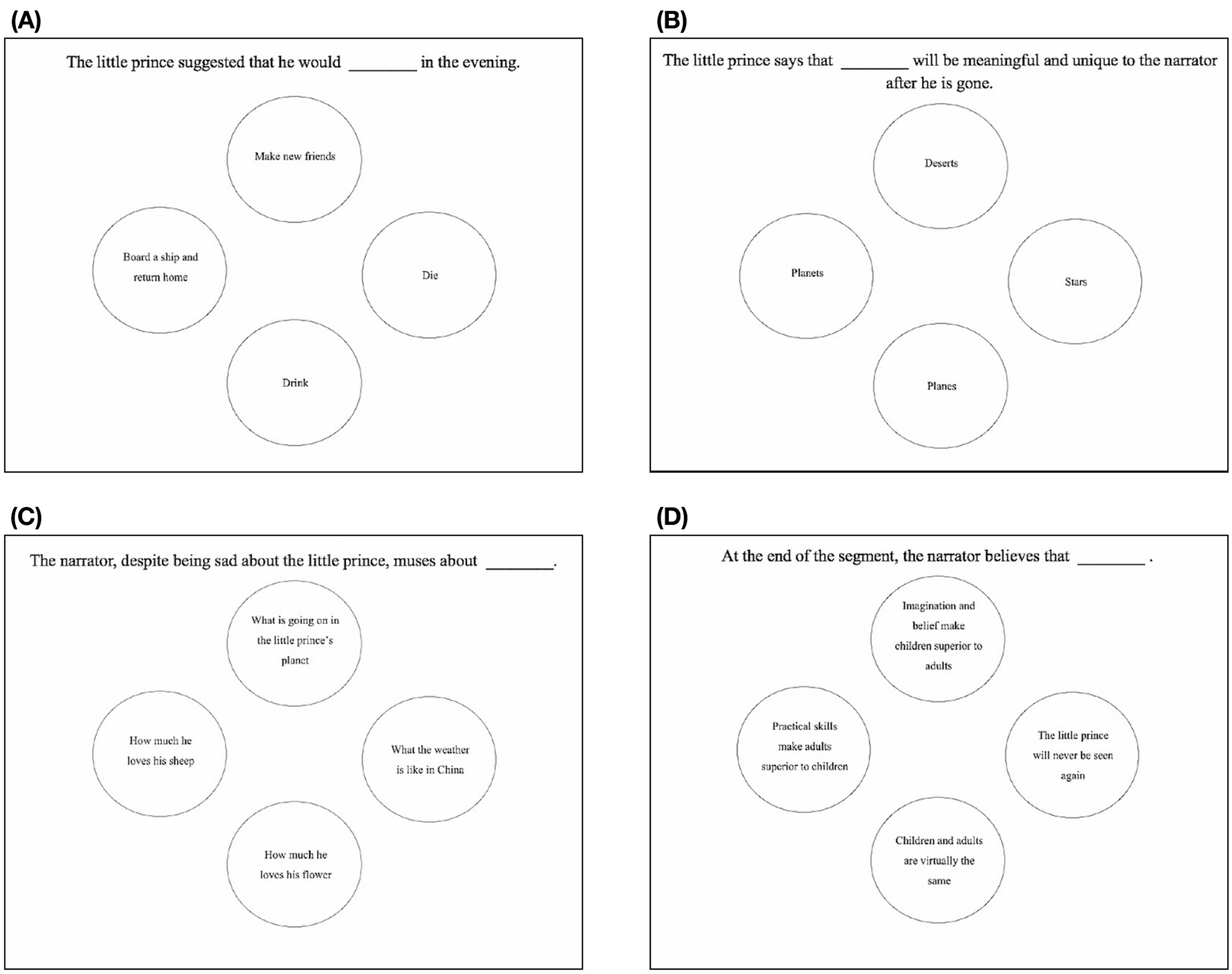

Figure 23: Comprehension questions based on section 9 of LPP. (A): Question 1 (B): Question 2 (C): Question 3 (D): Question 4

APPENDIX B

LIST OF MWES IN LPP

This appendix consists of the list of MWEs used in the study. Table 17 lists all 669 MWEs in LPPand each are marked as verbal or non-verbal expressions while Table 18 lists all the MWEs that are also verb particle constructions. Table 19 also lists all the MWEs in LPP along with their two respective Association Measures: Pointwise Mutual Information (PMI) and Dice's Coefficient (Dice).

MWE	Non-Verbal	Verbal
a dirty trick	✓	
a few	✓	
a lot	✓	
a number	✓	
a well	✓	
abandoned shell	✓	
about to	✓	
above all	✓	
absence of reproach	✓	
absolute monarch	✓	
active volcano	✓	
against all odds	✓	
agree with		✓
air of authority	✓	
all alone	✓	
all at once	✓	
all kind of	✓	
all of	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
all the	✓	
all the same	✓	
am a man		✓
and all	✓	
and all day	✓	
and all road	✓	
and how	✓	
answer question		✓
answer to		✓
any day	✓	
anything but	✓	
apart from	✓	
apparent hurry	✓	
appear on earth		✓
apple tree	✓	
arrive on earth		✓
as best can	✓	
as far as	✓	
as for	✓	
as if	✓	
as long as you	✓	
as soon as	✓	
as to	✓	
ask of		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
ask yourselves		✓
at all	✓	
at all afraid	✓	
at first	✓	
at first glance	✓	
at home	✓	
at last	✓	
at least	✓	
at once	✓	
at random	✓	
at that	✓	
at that moment	✓	
at the moment	✓	
at the other	✓	
at the same time	✓	
at the time	✓	
attack of rheumatism	✓	
back home		✓
back tomorrow		✓
back up		✓
bad dream	✓	
bad luck	✓	
bad plan	✓	
bad seed	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
base on		✓
be a man		✓
be a scholar		✓
be about		✓
be an admirer		✓
be at		✓
be at risk		✓
be eleven		✓
be everything		✓
be for		✓
be good for		✓
be guide		✓
be hundred		✓
be in		✓
be in order		✓
be in the wrong		✓
be inside		✓
be king		✓
be like fire		✓
be like music		✓
be nobody		✓
be nothing		✓
be object		✓
be on one		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
be order		✓
be out		✓
be problem		✓
be something		✓
be subject		✓
be sure to		✓
be thank		✓
be traveler		✓
be twenty-two		✓
be wealthy		✓
be well		✓
be worried		✓
beautiful drawing	✓	
because of	✓	
big book	✓	
big presentation	✓	
big time	✓	
bit lonely	✓	
bit sad	✓	
bit wrong	✓	
blow in		✓
boa constrictor	✓	
boring job	✓	
bother anyone		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
break in		✓
break into		✓
breakfast in the morning	✓	
breathed easily		✓
bring back		✓
bring to		✓
bring to life		✓
brisk pace	✓	
burst into		✓
burst into tear		✓
buy thing		✓
by chance	✓	
call out		✓
can do		✓
can do anything		✓
care for		✓
career as a painter	✓	
carry out		✓
catch out		✓
catch sight of		✓
cause havoc		✓
chase after		✓
christmas tree	✓	
clean out		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
close up		✓
closed eye	✓	
collect butterfly		✓
color of honey	✓	
coloured pencil	✓	
come across		✓
come as		✓
come at just		✓
come back		✓
come come		✓
come down		✓
come down on		✓
come from		✓
come in		✓
come in useful		✓
come into		✓
come now		✓
come on		✓
come out		✓
come to		✓
come to doubt		✓
come to know		✓
come to learn		✓
come to mind		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
come to see		✓
come to that		✓
come to visit		✓
come up		✓
complete tour		✓
complicated flower	✓	
conceited man	✓	
conceited people	✓	
condemn anyone		✓
confuse everything		✓
cool night	✓	
cover in		✓
cover with		✓
cry out		✓
danger of death	✓	
dear fellow	✓	
deep sadness	✓	
demand obedience		✓
depend on		✓
die for you		✓
die of		✓
difficult repair	✓	
difficult thing	✓	
dirty trick	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
discovery in question	✓	
do anything		✓
do calculation		✓
do no good		✓
do nothing		✓
do with		✓
do you know		✓
down on		✓
down to earth	✓	
draw anything		✓
dreadful noise	✓	
dress in purple		✓
drink anything		✓
drinking water		✓
each other	✓	
eat bread		✓
eat everything		✓
eat flower		✓
eat shrub		✓
eat up		✓
eat weed		✓
eighth day	✓	
emerge from		✓
empty bottle	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
end of trouble	✓	
enormous book	✓	
enough exercise	✓	
enough room	✓	
enough water	✓	
enter into		✓
entire plane	✓	
entire world	✓	
entry on stage	✓	
establish bond	✓	
eternal thing	✓	
european fashion	✓	
even as	✓	
exact spot	✓	
explain thing		✓
express train	✓	
extinct volcano	✓	
extraordinary thing	✓	
eye to		✓
eye toward the sky	✓	
faded away		✓
fairy tale	✓	
false idea	✓	
familiar task	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
far away	✓	
feel good		✓
few step	✓	
fifth day	✓	
fifth plane	✓	
find nothing		✓
find out		✓
first came	✓	
first drawing	✓	
first glance	✓	
first moment	✓	
first night	✓	
first thing	✓	
first time	✓	
first traveller	✓	
fond of		✓
foot of the wall	✓	
for example	✓	
for fun	✓	
for it	✓	
for once	✓	
for the first time	✓	
for the world	✓	
for you	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
forehead with a handkerchief	✓	
fourth day	✓	
fourth plane	✓	
fragile treasure	✓	
fresh water	✓	
from afar	✓	
from time to time	✓	
full bottle	✓	
funny animal	✓	
funny hat	✓	
funny idea	✓	
gather in		✓
gaze at		✓
gesture of weariness	✓	
get away		✓
get back		✓
get impatient		✓
get lose		✓
get out		✓
get stuck		✓
get to it		✓
get to know		✓
girl of the village	✓	
give explanation		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
give it to		✓
give name		✓
give way		✓
given names	✓	
glance at		✓
go away		✓
go back		✓
go down		✓
go far		✓
go for		✓
go off		✓
go on		✓
go out		✓
go round		✓
go to		✓
god know where	✓	
golden bracelet	✓	
golden curl	✓	
golden hair	✓	
golden thing	✓	
good evening	✓	
good for	✓	
good look	✓	
good morning	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
good plan	✓	
good reputation	✓	
good seed	✓	
good will	✓	
grave doubt	✓	
great consequence	✓	
great difficulty	✓	
great mystery	✓	
great prince	✓	
green chamber	✓	
grow thorn		✓
grow up		✓
grown ups	✓	
gust of wind	✓	
half dead	✓	
hammer in		✓
happen on		✓
have friend		✓
have get old		✓
have gun		✓
have horn		✓
have idea		✓
have nothing		✓
have nothing to do with		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
have plan		✓
have star		✓
have thing		✓
have time		✓
have to		✓
hear anyone		✓
hear anything		✓
hear nothing		✓
heart skipped a beat		✓
heavy body	✓	
heavy drinker	✓	
herd of elephant	✓	
here and there	✓	
high mountain	✓	
hint of sadness	✓	
hold it		✓
home today	✓	
hour in silence	✓	
human habitation	✓	
hundred of other	✓	
i say	✓	
i tell you	✓	
idea of the size	✓	
imminent disappearance	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
important point	✓	
important thing	✓	
impose on		✓
in a hurry	✓	
in case of	✓	
in circles	✓	
in front of	✓	
in hand	✓	
in midair	✓	
in order	✓	
in peace	✓	
in question	✓	
in response	✓	
in silence	✓	
in that	✓	
in the form of	✓	
in the middle	✓	
in the past	✓	
in the same way	✓	
in the sand	✓	
in the way	✓	
in the wind	✓	
in the world	✓	
in the wrong	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
in time	✓	
in time to	✓	
in turn	✓	
inside of	✓	
instead of	✓	
intelligent man	✓	
international astronomy	✓	
intoxicate man	✓	
it be not for the	✓	
judge by		✓
judge someone		✓
just for fun	✓	
just in time	✓	
just like that	✓	
just the same	✓	
kind of	✓	
know anything		✓
know of		✓
know someone		✓
lamp light	✓	
land of tear	✓	
landscape in the world	✓	
large animal	✓	
large mountain	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
large plane	✓	
large stone	✓	
last drop	✓	
last for day	✓	
last time	✓	
laugh at		✓
lazy man	✓	
lead life		✓
lead to		✓
lead up to		✓
lean on		✓
lean over		✓
learn something		✓
leave aside		✓
leave for		✓
leave in		✓
leave to		✓
let go		✓
let go of		✓
lie in		✓
life of leisure	✓	
life story	✓	
light up		✓
little boy	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
little fellow	✓	
little prince	✓	
little sheep	✓	
live in		✓
live on		✓
lock of hair	✓	
locomotive engineer	✓	
long journey	✓	
long time	✓	
long while	✓	
look after		✓
look around		✓
look at		✓
look for		✓
lose in		✓
lose on		✓
lot of space	✓	
love anyone		✓
magnificent career	✓	
make friend		✓
make mistake		✓
make of		✓
man of consequence	✓	
matter of consequence	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
matter of discipline	✓	
matter of life	✓	
mental effort	✓	
metallic sound	✓	
middle of the ocean	✓	
mile wide	✓	
million of star	✓	
million of year	✓	
miraculous apparition	✓	
moment of regret	✓	
moment of silence	✓	
moral character	✓	
move about		✓
much less charming	✓	
much trouble	✓	
much work	✓	
my eye	✓	
my foot	✓	
my life	✓	
new friend	✓	
next day	✓	
next evening	✓	
next to	✓	
no end	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
no good	✓	
no harm	✓	
no longer	✓	
no use	✓	
north america	✓	
north pole	✓	
nose up	✓	
not at all	✓	
not much	✓	
nothing in the universe	✓	
nothing like	✓	
now that	✓	
number one	✓	
number two	✓	
object of curiosity	✓	
occur to		✓
of a kind	✓	
of course	✓	
of its	✓	
old day	✓	
old house	✓	
old monarch	✓	
on earth	✓	
on top	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
once upon a time	✓	
one day	✓	
out of	✓	
out there	✓	
pacific isle	✓	
pain of death	✓	
passer by	✓	
peal of laughter	✓	
peculiar sense	✓	
perfect order	✓	
person of consequence	✓	
pile up		✓
play with		✓
pluck up		✓
point out		✓
pour out		✓
prepare for		✓
pretend to		✓
pretty thing	✓	
previous page	✓	
primeval forest	✓	
provide proof		✓
public square	✓	
pull out		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
pull up		✓
put down		✓
put out		✓
quench thirst		✓
rag doll	✓	
raise in salute		✓
real purpose	✓	
reasonable order	✓	
red brick	✓	
reflective silence	✓	
reign over		✓
reply to		✓
rest of the day	✓	
rest of the night	✓	
reveal to		✓
rid of		✓
right here	✓	
right place	✓	
right there	✓	
rise up		✓
rumble like thunder		✓
run away		✓
sad life	✓	
same day	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
same moment	✓	
same one	✓	
same star	✓	
same time	✓	
same way	✓	
sand dune	✓	
say about		✓
say anything		✓
say goodbye		✓
say in response		✓
say nothing		✓
see through		✓
see to it		✓
sense of grief	✓	
sense of urgency	✓	
sensible man	✓	
serious look	✓	
set off		✓
set out		✓
sheet of paper	✓	
sigh of regret	✓	
silent meditation	✓	
sit down		✓
sit in		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
sit in silence		✓
size of the earth	✓	
sketch out		✓
sleep on		✓
small child	✓	
so as to	✓	
so far	✓	
so much	✓	
so that	✓	
so what	✓	
sort of	✓	
sound of the wind	✓	
south america	✓	
south pole	✓	
speak for		✓
speak in riddle		✓
speak to		✓
special festival	✓	
spin round		✓
spur on		✓
stand back		✓
start off		✓
stay in		✓
step back		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
stir in		✓
stone wall	✓	
strike by lightning		✓
subtle gesture	✓	
succeed in		✓
such a	✓	
sudden apparition	✓	
sweep out		✓
swell up		✓
take advantage of		✓
take away from		✓
take heart		✓
take it away		✓
take out		✓
take over		✓
take pleasure		✓
take seriously		✓
take up		✓
talk to		✓
tell apart		✓
tell lie		✓
thanks to		✓
that be all	✓	
the idea	✓	

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
the other side of	✓	
think of		✓
this be it		✓
time of day	✓	
tire of		✓
to be sure		✓
to bed	✓	
to do		✓
to it	✓	
to light		✓
to my mind	✓	
to order		✓
to piece		✓
to rest		✓
to the eye		✓
tolerate insubordination		✓
tomorrow evening	✓	
travel in		✓
turn to		✓
united states	✓	
up against	✓	
up to	✓	
use to be		✓
use to know		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
use to say		✓
veritable army	✓	
very well		✓
volcanic eruption	✓	
wait for		✓
wake up		✓
wander off		✓
watch over		✓
water can	✓	
water supply	✓	
weak creature	✓	
wheat field	✓	
white as snow	✓	
whole herd	✓	
wide eyed	✓	
wild animal	✓	
wild bird	✓	
with it	✓	
wonderful day	✓	
wonderful spectacle	✓	
work out		✓
worth it	✓	
worth the effort	✓	
write about		✓

Table 17 continued from previous page

MWE	Non-Verbal	Verbal
year old	✓	
you know		✓
young judge	✓	

Table 17: List of MWEs in LPP split into verbal and non-verbal expressions.

Verb particle MWEs
agree with
answer to
ask of
back up
base on
blow in
break in
break into
bring back
bring to
burst into
call out
care for
carry out
catch out
chase after
clean out
close up

Table 18 continued from previous page

Verb particle MWEs
come back
come down
come in
come into
come on
come out
come to
come up
cover in
cover with
cry out
danger of death
depend on
die of
do with
down on
eat up
emerge from
enter into
faded away
find out
fond of
foot of the wall
gather in

Table 18 continued from previous page

Verb particle MWEs
gaze at
get away
get back
get out
glance at
go away
go back
go down
go off
go on
go out
go to
grow up
hammer in
happen on
have to
hold it
impose on
judge by
know of
laugh at
lead to
lean on
lean over

Table 18 continued from previous page

Verb particle MWEs
leave aside
leave for
leave in
leave to
let go
lie in
light up
live in
live on
look after
look around
look at
look for
lose in
lose on
make of
move about
occur to
pile up
play with
pluck up
point out
pour out
prepare for

Table 18 continued from previous page

Verb particle MWEs
pretend to
pull out
pull up
put down
put out
reign over
reply to
reveal to
rid of
rise up
run away
say about
set off
set out
sit down
sit in
sketch out
sleep on
speak for
speak to
spin round
spur on
stand back
start off

Table 18 continued from previous page

Verb particle MWEs
stay in
step back
stir in
succeed in
sweep out
swell up
take out
take over
take up
talk to
tell apart
thanks to
think of
tire of
travel in
turn to
wait for
wake up
wander off
watch over
work out
worth it
write about

Table 18: List of 137 MWEs in LPP which are also verb particle constructions.

MWE	PMI	Dice
a dirty trick	5.603255371	0.0002759423777
a few	3.032724651	0.6356183935
a lot	3.181476617	0.9144775916
a number	2.530413226	0.1580497945
a well	0.4663553966	0.006027426043
abandoned shell	2.717490489	0.007867680275
about to	1.369079386	0.08876049899
above all	2.873667492	0.154997287
absence of reproach	4.892815597	0.00000002229179732
absolute monarch	4.49911388	0.0931259473
active volcano	4.685132224	0.2457447529
against all odds	6.011525024	0.01272124699
agree with	3.398989544	0.2695830127
air of authority	3.800706225	0.0001905948676
all alone	2.294427813	0.03781463912
all at once	4.650977219	0.04352637912
all kind of	4.510631127	0.03799290727
all of	2.057417795	0.3871219338
all the	1.906837324	0.2938203479
all the same	3.310298804	0.005154528828
am a man	3.455299324	0.0008153414073
and all	1.551042223	0.1298666856
and all day	2.118132377	0.0004702267422
and all road	1.61844799	0.00003477520391
and how	1.867929885	0.1377558097

Table 19 continued from previous page

MWE	PMI	Dice
answer question	3.591418736	0.4509127932
answer to	2.172468711	0.03083720815
any day	2.106931694	0.06943989265
anything but	2.404057242	0.0983273307
apart from	3.297275157	0.132646763
apparent hurry	2.546209713	0.004862557389
appear on earth	4.599369837	0.0005599959462
apple tree	4.071819355	0.2999517239
arrive on earth	5.025841789	0.0004473017258
as best can	0.933714636	0.00000918422052
as far as	5.185718323	0.2102030106
as for	1.228174727	0.09232110644
as if	2.611567099	0.8895607549
as long as you	6.258122852	0.02424815746
as soon as	5.484284784	0.2079170603
as to	0.987709617	0.07659012023
ask of	1.071313459	0.004285167043
ask yourselves	3.625349106	0.0184454865
at all	2.542034404	0.7908373563
at all afraid	3.304162419	0.0004213627349
at first	2.422941424	0.3400003452
at first glance	6.128653731	0.03229187974
at home	2.940224379	0.5700293486
at last	2.266632365	0.1686845689

Table 19 continued from previous page

MWE	PMI	Dice
at least	3.849968621	2.320740627
at once	2.633064695	0.2030255396
at random	2.896447512	0.02253424705
at that	1.53872565	0.186334989
at that moment	4.333430064	0.0269337661
at the moment	4.013977341	0.01726722981
at the other	2.75921054	0.007633000284
at the same time	7.227143048	0.09205983012
at the time	3.793228065	0.07299293145
attack of rheumatism	5.378732163	0.000004480651273
back home	2.878539938	0.3779895889
back tomorrow	2.636000069	0.03950236347
back up	2.428569156	0.2838684532
bad dream	3.322739047	0.1342686068
bad luck	4.200911265	0.5102535819
bad plan	1.569669961	0.005790346869
bad seed	2.924575131	0.02150352161
base on	3.967920376	0.9077802402
be a man	3.968810001	0.03799842273
be a scholar	3.974433769	0.0007939237277
be about	2.64018876	0.9651733027
be an admirer	5.608242329	0.001541578025
be at	2.390079904	0.7835056651
be at risk	4.919796144	0.03938775706

Table 19 continued from previous page

MWE	PMI	Dice
be eleven	2.830805121	0.01322464092
be everything	2.233055428	0.05790157
be for	1.831509425	0.2903584748
be good for	4.249078982	0.07011986088
be guide	2.570358328	0.02675987835
be hundred	0.5210398012	0.0004280269658
be in	2.412160271	1.266708361
be in order	3.357419243	0.003171556125
be in the wrong	4.806747075	0.001251888834
be inside	2.531205187	0.08779013705
be king	2.15463678	0.02134599062
be like fire	3.014364983	0.0003772689513
be like music	3.081963508	0.0007636688765
be nobody	2.545632829	0.03851193138
be nothing	3.222114047	0.5847096751
be object	0.6044661994	0.0002970258277
be on one	2.608766541	0.005038873243
be order	0.7279066576	0.001837747417
be out	2.456118986	0.5784753892
be problem	0.7908014451	0.002901099739
be something	3.096628559	0.8531870379
be subject	2.880442448	0.1032479318
be sure to	4.092248017	0.0254832437
be thank	1.367740531	0.007440723681

Table 19 continued from previous page

MWE	PMI	Dice
be traveler	1.941273774	0.0007048553827
be twenty-two	2.931756616	0.004506166551
be wealthy	2.506177041	0.00863152184
be well	2.309279896	0.2698862184
be worried	3.46591264	0.181745522
beautiful drawing	2.411106528	0.01026833684
because of	2.261606475	0.3059329781
big book	2.128594099	0.0308918776
big presentation	2.255583808	0.005089845529
big time	2.045580485	0.05480063201
bit lonely	2.65512056	0.008697149808
bit sad	2.866827865	0.02915570285
bit wrong	1.600581022	0.00515602617
blow in	2.152337371	0.006251391408
boa constrictor	7.934948602	10
boring job	2.596664282	0.006376821942
bother anyone	3.088198492	0.02654374585
break in	1.981506581	0.02134344234
break into	3.211546505	0.2811606732
breakfast in the morning	5.501763034	0.00007423168527
breathed easily	3.736112681	0.0382615587
bring back	3.24194958	0.3333634577
bring to	2.316339114	0.05137360442
bring to life	3.991437903	0.001992216203

Table 19 continued from previous page

MWE	PMI	Dice
brisk pace	5.024040944	0.3703415459
burst into	3.800739567	0.1473233088
burst into tear	8.263764682	0.05852311616
buy thing	2.708026825	0.06777500963
by chance	2.232642726	0.02897101252
call out	2.811567979	0.2339401296
can do	2.552520306	0.6109804529
can do anything	4.575346176	0.02185449024
care for	2.58348581	0.150337751
career as a painter	7.040508411	0.0001154715104
carry out	3.835140188	0.5045344552
catch out	1.87700713	0.006634726343
catch sight of	6.126202332	0.005121940936
cause havoc	4.131722746	0.05427842963
chase after	3.308298774	0.05714850168
christmas tree	4.484999817	1.233571486
clean out	2.715463178	0.0513100131
close up	2.420781124	0.07190285939
closed eye	3.169917038	0.084237673
collect butterfly	3.705356663	0.03102948629
color of honey	3.826388756	0.00005350031371
coloured pencil	6.545610815	1.925855827
come across	3.342719683	0.527987544
come as	1.934481682	0.07457660891

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MWE	PMI	Dice
come at just	2.277288466	0.0003116760709
come back	3.705900007	2.475595177
come come	0	0.0006282068071
come down	3.324489833	0.9732215442
come down on	4.235328479	0.01394988401
come from	3.23999946	1.199771269
come in	2.452111449	0.245243706
come in useful	3.265456864	0.00009429430291
come into	3.066762622	0.6832262366
come now	1.507171053	0.02297411519
come on	2.629979024	0.3400249803
come out	3.440524829	1.663744497
come to	2.725312069	0.4474018142
come to doubt	3.44712491	0.0001647363826
come to know	3.565151303	0.006309517176
come to learn	3.838642618	0.0009943580381
come to mind	4.685477857	0.01019076319
come to see	4.103473386	0.01363218712
come to that	2.528456208	0.003871079443
come to visit	4.789180567	0.005906858447
come up	3.462097051	1.732337711
complete tour	2.16520491	0.006587988471
complicated flower	1.917493601	0.001469866864
conceited man	2.466332084	0.0001125735768

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MWE	PMI	Dice
conceited people	2.349868285	0.00008649217383
condemn anyone	3.187080317	0.008220791273
confuse everything	2.519380299	0.001754194466
cool night	2.488089078	0.02715216434
cover in	2.194883762	0.02388120603
cover with	2.085564181	0.01865781091
cry out	3.542465101	0.1467854588
danger of death	4.020961276	0.0001511383862
dear fellow	3.244951389	0.04486769888
deep sadness	3.663782727	0.04912267466
demand obedience	3.890166957	0.02860683107
depend on	4.08202221	0.2683176186
die for you	2.904930981	0.0005319899778
die of	2.347620992	0.02623551094
difficult repair	1.695840755	0.001307020418
difficult thing	2.87971906	0.1113827345
dirty trick	4.720905491	0.575574878
discovery in question	2.837895746	0.000008136506043
do anything	3.136998914	0.4688710406
do calculation	0.6777397466	0.00004257733299
do no good	3.686242775	0.006686122929
do nothing	2.760040654	0.2099558399
do with	2.14707799	0.4305243569
do you know	4.593179968	0.1901475333

Table 19 continued from previous page

MWE	PMI	Dice
down on	2.358368015	0.2521719027
down to earth	4.254878034	0.003087280801
draw anything	2.046938322	0.006700054085
dreadful noise	3.520235676	0.01433745634
dress in purple	4.778708072	0.00009786099049
drink anything	0.3545607889	0.000204415782
drinking water	4.136754766	0.6148612078
each other	3.739906925	2.705545791
eat bread	3.257295141	0.06084981137
eat everything	2.83745831	0.0610643678
eat flower	2.635270522	0.00931901255
eat shrub	2.481895193	0.0007840376114
eat up	2.516785904	0.0400627577
eat weed	2.954462086	0.007484745172
eighth day	2.645366166	0.008410350723
emerge from	4.012968029	0.2167821034
empty bottle	3.867268161	0.1894031741
end of trouble	3.014517033	0.00006598372024
enormous book	1.863263568	0.003841855191
enough exercise	2.042132314	0.009203907492
enough room	2.485704312	0.07665031827
enough water	2.482595673	0.07773622943
enter into	3.69313297	0.2518827888
entire plane	2.032648721	0.005919697205

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MWE	PMI	Dice
entire world	3.039840858	0.1285644094
entry on stage	3.588820871	0.00001232736395
establish bond	2.855687611	0.01373206547
eternal thing	2.278100768	0.002481163953
european fashion	2.793560301	0.02421194595
even as	2.101694591	0.1641713882
exact spot	3.854847665	0.1328628747
explain thing	2.710797853	0.04446253407
express train	3.710505936	0.1087428615
extinct volcano	5.320513901	0.4535895102
extraordinary thing	3.220521381	0.05666056349
eye to	2.062473995	0.01676296228
eye toward the sky	6.795327612	0.0000153367566
faded away	4.161558006	0.2182951302
fairy tale	6.16476593	6.422385484
false idea	2.673758958	0.01722495461
familiar task	2.258577284	0.008173950215
far away	3.544036621	0.8023207029
feel good	3.208196867	0.4753203459
few step	3.285208485	0.2290200528
fifth day	2.925439931	0.03295395105
fifth plane	2.36725683	0.006665982292
find nothing	2.747617019	0.1285383087
find out	3.479684666	1.24034032

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MWE	PMI	Dice
first came	2.443110894	0.1185035648
first drawing	1.626846072	0.002571548845
first glance	3.722813418	0.1184983883
first moment	2.032862472	0.02888010428
first night	2.42059295	0.1095790168
first thing	3.09414536	0.5006711851
first time	3.279392631	1.530334581
first traveller	2.714041087	0.0006455013277
fond of	2.984914086	0.008830049152
foot of the wall	4.73183441	0.00001094527251
for example	4.081873901	0.978636213
for fun	2.101960771	0.01617263373
for it	1.386242756	0.1671058257
for once	1.589449203	0.02189264307
for the first time	6.554962969	0.07283111991
for the world	2.681821683	0.004920993833
for you	1.64178101	0.2606417871
forehead with a handkerchief	8.290292687	0.00010231935
fourth day	2.865885451	0.04938865533
fourth plane	2.573124955	0.01445214957
fragile treasure	2.929128682	0.006393060021
fresh water	3.375852602	0.2090902108
from afar	3.90321081	0.01897637418
from time to time	6.207466472	0.02097889017

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MWE	PMI	Dice
full bottle	2.712043783	0.02114358248
funny animal	2.470273617	0.01061508839
funny hat	3.347827004	0.05353760586
funny idea	2.383819007	0.01299632089
gather in	2.73851285	0.01641345246
gaze at	2.537342764	0.01132269285
gesture of weariness	5.124696746	0.00000002229179732
get away	3.128842823	0.5772950956
get back	2.968513729	0.7200689363
get impatient	3.171401753	0.01114760748
get lose	2.188025582	0.0170896806
get out	2.980898489	0.9629909736
get stuck	3.467764827	0.1321862031
get to it	2.229575636	0.003061860154
get to know	3.946934938	0.0265093568
girl of the village	4.335540517	0.000003254602417
give explanation	1.094115262	0.0005843154772
give it to	3.659263687	0.0198551429
give name	1.312684792	0.004924919613
give way	2.951966441	0.2985556812
given names	3.176471754	0.09920940946
glance at	3.91285267	0.1810548888
go away	3.335462958	0.8209580432
go back	3.510676021	1.979029396

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MWE	PMI	Dice
go down	3.256757066	1.00237732
go far	2.667560692	0.1494024836
go for	2.165125718	0.1701668768
go off	3.043653531	0.5533021918
go on	3.041634968	1.109177983
go out	3.124580916	1.069711111
go round	2.65189028	0.03905603862
go to	3.260720381	1.954144147
god know where	5.516392881	0.006818914214
golden bracelet	3.418145061	0.01266041168
golden curl	4.311143703	0.09874368047
golden hair	3.428859187	0.1218660999
golden thing	1.167042978	0.001062525079
good evening	3.704551873	0.4839170019
good for	2.101736271	0.1434207861
good look	2.465932151	0.1434650806
good morning	3.782589879	1.432966049
good plan	1.990681484	0.02271279924
good reputation	2.798029336	0.02399086636
good seed	1.995814036	0.003106548516
good will	1.673622084	0.04294446545
grave doubt	2.883799275	0.01400021262
great consequence	2.607690959	0.007823507824
great difficulty	3.407218392	0.08711234967

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MWE	PMI	Dice
great mystery	3.191133516	0.05034607291
great prince	1.823596564	0.003039458715
green chamber	1.665238486	0.001415803402
grow thorn	2.747451776	0.001005011996
grow up	4.269095263	1.399913951
grown ups	5.343016936	1.243712494
gust of wind	7.182176689	0.002773719787
half dead	2.156000266	0.01812249111
hammer in	1.993349801	0.001948938551
happen on	2.420436558	0.04709846688
have friend	2.197564566	0.03276712782
have get old	3.702460787	0.003568590306
have gun	1.999346325	0.01078558478
have horn	1.87070406	0.001359215011
have idea	1.247365302	0.00583257603
have nothing	2.81518278	0.2423281845
have nothing to do with	9.104273128	0.03574023782
have plan	0.3117009522	0.0006996037645
have star	1.573965306	0.005923440981
have thing	1.45997231	0.01836253577
have time	1.856172197	0.12128986
have to	2.39541939	1.284723645
hear anyone	2.770566968	0.06426629546
hear anything	3.307818455	0.2968778166

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MWE	PMI	Dice
hear nothing	2.979447355	0.1466836385
heart skipped a beat	10	0.0006670005821
heavy body	2.342995254	0.01934397703
heavy drinker	5.159568003	0.1846389819
herd of elephant	6.484894025	0.0002646913335
here and there	3.542044418	0.01530182281
high mountain	2.714271326	0.04484570037
hint of sadness	5.58830429	0.00007177958756
hold it	2.591723924	0.07726975322
home today	1.736100073	0.02061996257
hour in silence	3.620753037	0.00004636693855
human habitation	4.752990201	0.05389668773
hundred of other	4.154646069	0.002531042485
i say	2.914655335	0.8713794504
i tell you	4.389692374	0.06819122437
idea of the size	4.561946248	0.00002831058267
imminent disappearance	3.723778034	0.02139064641
important point	2.895991824	0.180866171
important thing	3.496656008	0.7237224839
impose on	3.274364634	0.02877805883
in a hurry	4.444439906	0.006759687534
in case of	2.736803603	0.004196729121
in circles	0.7688882893	0.0001921552934
in front of	4.571344073	0.1410503348

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MWE	PMI	Dice
in hand	1.739716803	0.02764103728
in midair	3.167388019	0.003045242573
in order	2.958795048	0.2373677072
in peace	1.837599963	0.01017873124
in question	1.644335574	0.02024691385
in response	2.613707675	0.06202073087
in silence	2.366079748	0.016710451
in that	1.225440492	0.199901885
in the form of	5.220900007	0.0142367731
in the middle	4.205543139	0.06156290437
in the past	3.903870165	0.05961747605
in the same way	5.77551218	0.00797109032
in the sand	3.597446499	0.003400369174
in the way	2.885982252	0.02049025911
in the wind	3.253177053	0.003814557791
in the world	3.649375503	0.07602671186
in the wrong	2.988109035	0.004160781825
in time	1.514468219	0.07175729746
in time to	2.404463457	0.008399138796
in turn	2.301351281	0.06001709648
inside of	1.784823225	0.01810698016
instead of	2.823355115	0.1616562097
intelligent man	3.053338329	0.02416070121
international astronomy	2.546973577	0.005068879906

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MWE	PMI	Dice
intoxicate man	3.480584061	0.0002296586263
it be not for the	5.423699237	0.0006254934337
judge by	2.646026268	0.05272944838
judge someone	1.895065658	0.007648065683
just for fun	4.363663805	0.004815961068
just in time	3.469116515	0.01223540788
just like that	3.470130576	0.01413775835
just the same	3.118827189	0.002290695649
kind of	3.210798104	0.6150896013
know anything	2.792764372	0.2037621118
know of	0.9925532534	0.02391929703
know someone	2.246438057	0.05042430738
lamp light	2.791730248	0.008734129994
land of tear	2.945465878	0
landscape in the world	4.276002218	0.00001246111473
large animal	2.962470825	0.0569123645
large mountain	1.730874223	0.004906415093
large plane	1.815820475	0.004727231566
large stone	2.861211194	0.04604365098
last drop	1.70028168	0.004269225136
last for day	3.04118593	0.0009649213229
last time	2.88675194	0.5001432906
laugh at	3.341583447	0.1127416403
lazy man	2.703048803	0.005314177948

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MWE	PMI	Dice
lead life	1.590850646	0.006878844467
lead to	3.085548758	0.2089979129
lead up to	4.514606159	0.01440986166
lean on	3.195067059	0.03619284301
lean over	4.130840391	0.2705976096
learn something	3.190769893	0.2028505255
leave aside	3.389424201	0.12411859
leave for	2.465052844	0.06977735537
leave in	2.207333548	0.04044153299
leave to	2.130362964	0.03433766415
let go	3.127294421	0.438471666
let go of	4.423860268	0.01393600418
lie in	2.819694168	0.04480822278
life of leisure	4.380833367	0.0002053074539
life story	2.553330458	0.09814860548
light up	2.802492099	0.1780336643
little boy	3.471832158	0.4422242248
little fellow	2.494109015	0.02096298741
little prince	2.572624488	0.01577296155
little sheep	2.025644802	0.002260715834
live in	3.040895013	0.3326912235
live on	2.641081586	0.1370140691
lock of hair	5.314451867	0.0009847358164
locomotive engineer	4.698509828	0.08579075913

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MWE	PMI	Dice
long journey	3.392109538	0.08976747035
long time	3.3356009	1.107518452
long while	2.12491929	0.05830294202
look after	2.456587337	0.1538377018
look around	3.341662695	0.8320850534
look at	3.694922457	3.079694239
look for	2.921077757	0.6050248553
lose in	2.475049144	0.0337879239
lose on	2.273249694	0.02166690346
lot of space	3.705272256	0.0007520952693
love anyone	2.194213175	0.02191408516
magnificent career	2.562904113	0.004358042433
make friend	2.82664923	0.1124827526
make mistake	3.642724333	0.2043534275
make of	1.607167664	0.05228729501
man of consequence	3.341818593	0.00003499812188
matter of consequence	4.18148472	0.00005795867319
matter of discipline	3.989903937	0.00007133375161
matter of life	3.842812595	0.001316327637
mental effort	3.002575024	0.05010689762
metallic sound	3.60987029	0.02261147894
middle of the ocean	5.951409996	0.0001997345045
mile wide	4.261477531	0.3980779257
million of star	3.46769228	0.0001852448362

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MWE	PMI	Dice
million of year	4.079367074	0.004970916632
miraculous apparition	4.897362808	0.08383197595
moment of regret	4.11579404	0.00006219411469
moment of silence	5.352119272	0.003668280138
moral character	3.642889139	0.1793403177
move about	2.047582606	0.03025638779
much less charming	4.269003283	0.00008560050193
much trouble	2.955286606	0.09154108575
much work	2.010043571	0.0612884682
my eye	2.753877391	0.07189159949
my foot	2.644255314	0.03902091484
my life	3.137502238	0.8859157529
new friend	2.835328119	0.117485422
next day	3.471774368	1.015913787
next evening	2.56026444	0.03795332812
next to	2.211673618	0.111774512
no end	2.053314797	0.05144907987
no good	2.214187977	0.1282703101
no harm	3.372726811	0.07328707252
no longer	4.173859407	2.307561393
no use	2.059612402	0.06555882982
north america	4.072234927	1.406126414
north pole	4.357144519	0.3460098128
nose up	1.889316515	0.005411735962

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MWE	PMI	Dice
not at all	4.059502006	0.08601389282
not much	2.143569505	0.1453373128
nothing in the universe	4.766164061	0.00001469029447
nothing like	2.615085428	0.1450389825
now that	1.882726227	0.1526043952
number one	2.775963997	0.2422156495
number two	2.710321455	0.1845578993
object of curiosity	5.096267996	0.00009852974441
occur to	2.581575101	0.02037702345
of a kind	2.541133267	0.0026816697
of course	2.957322985	0.394376427
of its	2.231965861	0.2915336273
old day	2.808528176	0.2243270519
old house	2.64370899	0.1414119247
old monarch	2.357863094	0.00102689941
on earth	3.010492921	0.1496627989
on top	2.867751381	0.2480147293
once upon a time	7.942508837	0.00889952184
one day	2.95786375	0.6409495156
out of	2.519642804	0.9125969675
out there	2.66108908	0.7395072851
pacific isle	3.152718509	0.00479539466
pain of death	3.877766972	0.0002440216759
passer by	2.194804365	0.000387663869

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MWE	PMI	Dice
peal of laughter	7.518600302	0.0003676957661
peculiar sense	2.801178773	0.007568836604
perfect order	2.251788167	0.01521347187
person of consequence	3.605030112	0.00002229179738
pile up	3.602475464	0.09329449315
play with	2.712464812	0.1726016778
pluck up	3.118798169	0.0030770497
point out	3.452387534	1.066232245
pour out	3.467669549	0.06701773786
prepare for	3.546654554	0.1429601616
pretend to	3.10982652	0.02112833158
pretty thing	2.281363047	0.03105892627
previous page	3.394269416	0.1247584089
primeval forest	4.892318394	0.07533369474
provide proof	3.144488036	0.03791048429
public square	3.047086538	0.08182269371
pull out	3.845723864	0.5039390449
pull up	3.555874129	0.269014919
put down	2.431407821	0.1124884287
put out	2.679234273	0.2397139985
quench thirst	5.826876395	0.2490540112
rag doll	5.793841592	1.67447644
raise in salute	4.591876127	0.00001471258627
real purpose	2.879827511	0.05323966954

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MWE	PMI	Dice
reasonable order	1.338419875	0.0009452063969
red brick	4.054846036	0.1863819434
reflective silence	2.783329897	0.005078880711
reign over	3.204454794	0.01231993572
reply to	2.549035076	0.006492422121
rest of the day	5.805949305	0.002221136644
rest of the night	5.520923677	0.0007068554631
reveal to	2.006046121	0.004688516093
rid of	3.083759038	0.03620121215
right here	2.826830913	0.4505440519
right place	2.368610391	0.104411141
right there	2.298219957	0.2121805305
rise up	3.207215256	0.1342883493
rumble like thunder	7.055179693	0.0003470398445
run away	3.573764578	0.7032970012
sad life	1.911824819	0.004242617582
same day	2.753965304	0.2257941678
same moment	2.450023841	0.06015173885
same one	1.475144694	0.02108292315
same star	1.863645702	0.009503250376
same time	3.507739678	1.5138162
same way	3.133065499	0.592126085
sand dune	5.235359606	0.2884897356
say about	2.569437437	0.3356464756

Table 19 continued from previous page

MWE	PMI	Dice
say anything	3.416582883	0.7040290726
say goodbye	4.294414308	0.2398794168
say in response	3.972229343	0.001585228932
say nothing	3.250188076	0.4960428243
see through	2.203986171	0.1088299316
see to it	2.318430215	0.003080673876
sense of grief	4.27523655	0.0001112360689
sense of urgency	6.255194902	0.004011177732
sensible man	2.572484611	0.004041873078
serious look	2.288303545	0.02740411094
set off	3.212926451	0.456795329
set out	2.881634875	0.2859508207
sheet of paper	6.06589467	0.006238120384
sigh of regret	5.172373741	0.00002697307483
silent meditation	3.647455747	0.03180985914
sit down	4.334426948	1.979437294
sit in	3.04341742	0.1334873899
sit in silence	5.568721165	0.00257891622
size of the earth	5.116590476	0.0000552836575
sketch out	3.211888345	0.01573328365
sleep on	2.544918367	0.04021685818
small child	3.165511138	0.2867348069
so as to	2.724048025	0.01126489619
so far	3.507690927	1.098097836

Table 19 continued from previous page

MWE	PMI	Dice
so much	3.382515256	1.878592443
so that	2.147130371	0.3954525343
so what	2.242583586	0.3176759387
sort of	3.349305234	0.2722219817
sound of the wind	5.618518399	0.0001669655624
south america	3.738238239	0.6264152016
south pole	4.366750296	0.3490972922
speak for	2.646817307	0.05964027819
speak in riddle	5.578483222	0.00009763807252
speak to	2.809850734	0.08558545783
special festival	2.189766081	0.005680419921
spin round	3.722926329	0.08491997872
spur on	2.682086982	0.00308094146
stand back	2.722848638	0.08187593014
start off	2.612221294	0.09471629094
stay in	2.401199155	0.05650810942
step back	3.130666134	0.1869385621
stir in	2.878870703	0.0295036896
stone wall	3.956716147	0.3888747084
strike by lightning	7.047734352	0.007257692616
subtle gesture	3.812471469	0.06422304779
succeed in	3.082549116	0.0326329108
such a	2.404651981	0.2643269275
sudden apparition	2.992383027	0.001820424634

Table 19 continued from previous page

MWE	PMI	Dice
sweep out	3.007067751	0.01418326383
swell up	3.33271793	0.0140145442
take advantage of	5.984307699	0.04863729478
take away from	5.016008014	0.040789751
take heart	2.204367808	0.03323947308
take it away	4.33954971	0.01088245715
take out	2.666188665	0.3293104859
take over	3.146285007	0.781258114
take pleasure	3.015016497	0.05020916324
take seriously	3.70098418	0.2417780323
take up	2.717991861	0.3659274372
talk to	2.766578937	0.2384396199
tell apart	2.180536817	0.01054882926
tell lie	2.877102357	0.04501865354
thanks to	2.544792973	0.05442275707
that be all	3.895167001	0.1026376395
the idea	2.377027943	0.07015077131
the other side of	6.10436462	0.01760589289
think of	1.785040699	0.1172068954
this be it	2.836115842	0.01468117038
time of day	3.545373713	0.006356808638
tire of	2.131278264	0.00244222973
to be sure	4.116520623	0.02685701626
to bed	2.152197089	0.02582683101

Table 19 continued from previous page

MWE	PMI	Dice
to do	2.316509343	0.8199469254
to it	0.8583825127	0.08395111562
to light	1.549317374	0.01302610311
to my mind	3.608675708	0.003214284628
to order	1.631539532	0.01349100912
to piece	1.041260803	0.001832254807
to rest	1.866863701	0.01690506178
to the eye	2.306480008	0.000755481973
tolerate insubordination	4.542204862	0.01672889191
tomorrow evening	3.786383119	0.2817223244
travel in	1.669702428	0.005417591509
turn to	2.089235047	0.03806539286
united states	1.859726247	0.004874108327
up against	2.618741764	0.2210102601
up to	2.11577394	0.3710324851
use to be	4.211901237	0.05489372541
use to know	2.951210622	0.00136878783
use to say	4.176366672	0.01166017646
veritable army	3.590376102	0.009239454005
very well	2.888744935	0.5484268571
volcanic eruption	6.489699932	4.566901775
wait for	2.867838806	0.108250239
wake up	3.845229757	0.3021724304
wander off	4.058031267	0.08535031684

Table 19 continued from previous page

MWE	PMI	Dice
watch over	2.81834068	0.1059749826
water can	1.514348579	0.01660761283
water supply	3.982592907	0.4729411087
weak creature	3.175833505	0.02178404083
wheat field	3.992351338	0.1393318602
white as snow	4.725672969	0.001266103159
whole herd	3.338859338	0.02062702153
wide eyed	4.822948382	0.2749177319
wild animal	4.417466407	0.8481148292
wild bird	3.991297767	0.2643018131
with it	1.47751073	0.1811882223
wonderful day	2.324328266	0.01731327127
wonderful spectacle	2.843457385	0.005322684764
work out	2.446310859	0.2167248312
worth it	2.476426763	0.03805905263
worth the effort	4.887670367	0.001230974593
write about	3.032207379	0.125241063
year old	3.868517062	2.285485688
you know	3.340663447	3.382701932
young judge	1.483068992	0.003370410035

Table 19: List of MWEs in LPP with their respective Pointwise Mutual Information and Dice's Coefficient, as explained in §4.2.1

APPENDIX C

LIST OF VERBS IN LPP

This appendix consists of all the verbs in LPP tagged with its PropBank scores (in Table 20), its SCF entropy (in Table 21), and its selectional preference strength (in Table 21).

Verb Root	PropBank score
abandon	3
abash	1
acclaim	1
accommodate	1
add	5
administer	1
admire	1
adore	1
advise	1
agree	1
allow	3
annoy	1
answer	1
apologize	1
appear	2
apply	4
arouse	1
arrange	1
arrive	1
ask	4

Table 20 continued from previous page

Verb Root	PropBank score
astonished	1
astounded	1
attempted	1
avoid	1
based	2
become	3
beg	1
begin	2
believe	1
belong	1
bends	2
bite	1
blame	1
blow	13
blush	1
born	8
break	20
breathe	2
bring	8
burn	4
burst	4
bury	1
buy	6
call	17

Table 20 continued from previous page

Verb Root	PropBank score
care	4
carry	5
cast	4
catch	7
cause	1
change	2
chasing	1
chewing	2
choose	1
chuckle	1
clap	1
clean	4
climb	2
collect	1
come	30
comforted	1
command	2
concluded	2
condemn	1
confessed	1
confuse	1
conserve	1
considers	2
consulted	1

Table 20 continued from previous page

Verb Root	PropBank score
continued	2
convinced	1
coughed	3
count	4
covered	5
created	1
crossed	5
cry	5
dance	2
daydream	1
decided	1
decorated	1
defend	1
demand	1
depend	1
describe	1
despised	1
destroy	1
detest	1
die	5
digesting	1
disappear	1
disappointed	1
discouraged	1

Table 20 continued from previous page

Verb Root	PropBank score
discover	1
dismantling	1
dispatch	1
disturbed	1
doubt	1
draw	5
dreaming	3
dress	3
drifted	1
drink	3
dug	4
eat	3
elongates	1
emerge	2
empties	2
endure	1
enquired	1
enter	2
establish	1
examining	1
exclaimed	1
excuse	1
exist	1
explain	1

Table 20 continued from previous page

Verb Root	PropBank score
eyed	1
facing	2
faded	1
fall	11
fasten	1
fear	1
feel	6
fill	8
find	3
fit	3
flow	1
fly	5
follow	7
forbid	1
forced	3
forget	1
forgive	1
freeze	3
frighten	3
fumble	1
gathered	3
gazed	1
get	30
give	15

Table 20 continued from previous page

Verb Root	PropBank score
glanced	1
go	28
greet	1
grieve	1
groomed	2
grow	4
guess	1
hang	7
happen	3
hastened	1
hear	1
heating	2
help	3
hesitate	1
hides	2
hoisted	1
hold	16
humble	1
Humiliated	1
hunt	1
hurrying	2
imagine	1
imply	1
imposed	1

Table 20 continued from previous page

Verb Root	PropBank score
improved	2
infested	1
inflict	1
inhabited	1
inquired	1
insisted	1
interesting	1
interrupted	1
irritated	1
judge	1
jumped	8
keep	7
kill	4
knock	10
know	6
lack	1
landed	2
lasted	4
laugh	2
lead	5
lean	1
leap	3
learn	1
leave	13

Table 20 continued from previous page

Verb Root	PropBank score
let	6
like	3
linger	1
listen	1
live	6
lock	6
look	11
loosened	3
lost	6
love	2
maintain	1
make	23
manage	2
matter	1
mean	2
meet	5
missed	3
mix	3
moaned	1
moistened	1
move	6
need	1
neglected	1
nurse	2

Table 20 continued from previous page

Verb Root	PropBank score
obey	1
objected	1
observe	2
occurred	1
open	3
order	2
overwhelmed	1
own	2
panted	2
pardon	2
pass	20
perfumed	1
pick	12
picture	1
pierces	1
piled	4
played	9
please	1
plucked	1
plummeting	1
plunged	2
point	2
postponing	1
pour	2

Table 20 continued from previous page

Verb Root	PropBank score
prefer	1
prepared	2
press	3
pretend	1
produce	2
proposed	1
protect	1
proves	1
provide	1
pull	9
put	15
puzzled	1
quench	1
questioned	2
raise	3
reach	4
read	3
readied	1
realised	2
reassure	1
received	1
recognise	2
record	1
recount	1

Table 20 continued from previous page

Verb Root	PropBank score
redo	1
redraw	1
regretting	1
regulated	1
reign	1
rejected	1
remained	1
remarked	1
remember	1
remind	1
repair	1
repeat	1
replied	1
require	1
respected	1
responded	1
rest	2
restrain	1
retorted	1
return	4
revealed	1
reviving	1
rise	2
rocked	4

Table 20 continued from previous page

Verb Root	PropBank score
rubbed	1
rule	3
rumbling	1
rumpled	2
run	15
rush	1
said	2
saluted	1
sank	1
satisfied	2
save	4
saw	2
search	1
seek	2
seem	1
seized	3
sell	4
send	4
served	4
set	16
sharpened	1
shatter	1
shelter	1
shine	2

Table 20 continued from previous page

Verb Root	PropBank score
shock	1
shook	3
show	4
shrug	3
shut	6
sighed	2
simplified	1
sit	8
sketched	2
skipped	3
skirting	2
sleep	5
slipped	4
smelled	2
smiled	2
snapped	8
solve	1
sort	2
sound	4
speak	5
spend	4
spins	4
sponged	2
spotted	2

Table 20 continued from previous page

Verb Root	PropBank score
sprouted	1
spurred	1
sputtered	1
squashing	1
stand	10
stared	2
start	9
starved	1
stay	4
stirred	4
stop	7
stroll	1
struck	10
studied	2
stunned	1
succeed	3
suffer	1
suffice	1
suggested	2
surprise	1
swallow	2
sweep	5
swell	1
take	33

Table 20 continued from previous page

Verb Root	PropBank score
talk	3
tame	1
tell	3
tended	2
think	4
throw	7
thundered	2
tie	6
tire	3
tolerate	1
torment	1
touch	8
travel	1
trembled	1
trust	2
try	5
turn	18
understand	1
unscrew	1
use	4
visit	2
wait	3
wake	3
walk	5

Table 20 continued from previous page

Verb Root	PropBank score
wandered	1
want	1
warn	1
waste	1
watch	4
watered	3
weeping	2
weigh	4
wish	1
witnessed	1
wonder	2
wore	6
work	12
worry	2
wrapped	4
write	7
yawn	1

Table 20: List of verbs in LPP annotated with its PropBank scores, taken to represent diathesis alternations on a verb.

Verb root	SCF entropy
add	2.025611588
administer	1.936478702
advise	2.820062941
agree	2.758439766
allow	2.042284812
answer	2.141467586
appear	2.795889371
apply	1.653004892
arrange	2.440029381
ask	2.089743356
attempted	0.8048097562
beg	2.612133791
believe	2.584110404
belong	1.424861368
bends	1.651732164
bite	1.83106486
blow	2.295778691
blush	1.921031952
break	2.893574237
breathe	2.022416487
bring	3.036947593
burst	2.03261976
buy	2.334690203
call	1.715089656
carry	2.029573649

Table 21 continued from previous page

Verb root	SCF entropy
cause	0.6457729254
change	1.703585131
chasing	1.317683616
chewing	2.244586848
choose	1.772625398
chuckle	1.435195974
clean	2.251431924
climb	1.879765685
collect	1.828385685
comforted	2.057107657
confessed	2.365421466
confuse	1.858979167
continued	2.071387431
convinced	1.924870545
covered	1.897957074
crossed	2.002677836
cry	1.224527958
dance	1.749000651
decided	2.00976869
describe	1.637707353
disappear	0.1539041273
discover	2.079502792
disturbed	1.970794121
doubt	1.981416015

Table 21 continued from previous page

Verb root	SCF entropy
draw	2.275223139
drifted	1.893253379
drink	1.27872856
eat	1.863167257
empties	2.058016941
establish	1.410785734
faded	1.410785734
fall	2.122700877
fear	1.979153575
fill	1.878055415
find	2.174790373
fit	2.205001345
fly	1.616539736
follow	2.185669242
forget	2.345669829
freeze	1.974559633
frighten	1.559957581
gathered	2.430471309
grieve	1.697999793
grow	1.941427008
guess	1.849323628
hang	2.134334628
happen	1.975201575
hear	2.022983298

Table 21 continued from previous page

Verb root	SCF entropy
heating	1.814622557
help	2.121489805
hesitate	1.090467314
hides	1.862017003
hold	2.284681063
humble	1.904141096
hunt	2.487592776
hurrying	2.749207394
imply	2.538951206
improved	1.663017051
judge	2.559765011
jumped	2.063062858
keep	2.025696016
kill	0.9286728433
knock	2.388016142
know	2.232102266
laugh	1.430050119
lean	2.322103467
leap	2.023797893
learn	2.772242084
leave	2.260871102
listen	1.48878289
live	1.717690929
lock	2.436025707

Table 21 continued from previous page

Verb root	SCF entropy
lost	1.595307789
maintain	1.445450308
manage	2.600086285
mix	2.43521842
moaned	1.992435937
move	1.147317835
need	1.85729974
neglected	1.793100526
objected	1.638874549
observe	1.58204139
order	2.580537333
pass	2.032557647
pick	2.724715148
pierces	1.755727678
played	2.192600024
point	2.281754193
prepared	1.924033922
proposed	2.300156211
proves	2.767345558
pull	2.358760792
puzzled	1.689539631
read	1.447255865
readied	1.752503776
realised	1.290108357

Table 21 continued from previous page

Verb root	SCF entropy
recognise	2.303401432
regretting	2.168139868
remember	2.311055064
require	2.374060802
rest	1.092234274
revealed	1.815482794
rise	1.012193608
rubbed	2.44144125
rush	2.195903164
said	1.19750379
save	1.994317439
saw	1.912678707
seem	2.017194354
sell	2.448491131
shatter	1.733222538
shrug	1.939104841
shut	2.109925175
sighed	1.449140195
sit	1.858709304
sketched	2.43270294
slipped	2.461464591
smiled	2.461464591
snapped	2.098010845
solve	0.7784798323

Table 21 continued from previous page

Verb root	SCF entropy
spend	2.01254596
spins	2.337617431
stand	1.72449208
stared	1.44386808
start	2.725627603
stay	2.109508326
stop	1.809812822
struck	1.981151985
studied	1.318761723
suffer	1.737870904
suggested	2.233158896
swallow	1.200495563
sweep	2.338916458
swell	1.869306718
talk	2.146330418
tame	1.666490279
tell	1.801050439
think	2.247217965
throw	2.364540997
tie	2.402085383
tire	1.861728855
touch	1.919501485
travel	1.918814722
try	1.08662064

Table 21 continued from previous page

Verb root	SCF entropy
understand	1.956087539
visit	1.216397757
wait	1.365982811
walk	1.871008515
want	1.732613869
warn	2.779808611
watch	1.886337937
weigh	2.159213457
wore	1.827404627
worry	2.169653646
wrapped	2.325535016
write	2.666174274

Table 21: List of verbs in LPP annotated with its SCF entropy taken to represent the syntactic constraint between a verb and its upcoming argument.

APPENDIX D

CORRELATION MATRICES

This appendix consists of all the correlation matrices based on the design matrices for the analyses. Figure 24 – 30 illustrates the correlation between the regressors in Analysis 1 – 7 respectively while Table 22 – 28 shows the variance inflation factors in these analyses. Figure 31 compares the correlations between all the convolved regressors related to argument structure and Table 29 shows the variance inflation factors between the argument structure convolved regressors.

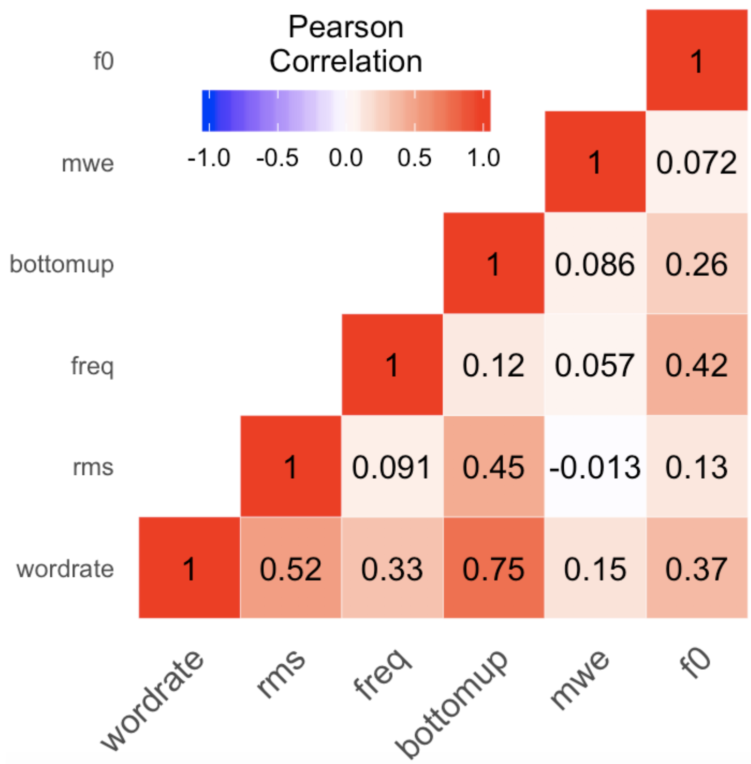

Figure 24: Correlation matrix (Pearson's r) of the convolved regressors included in the GLM model reported in Analysis 1

wordrate	rms	freq	bottomup	mwe	f0
3.056824	1.409968	1.337956	2.411014	1.034463	1.314458

Table 22: Variance Inflation Factors in Analysis 1.

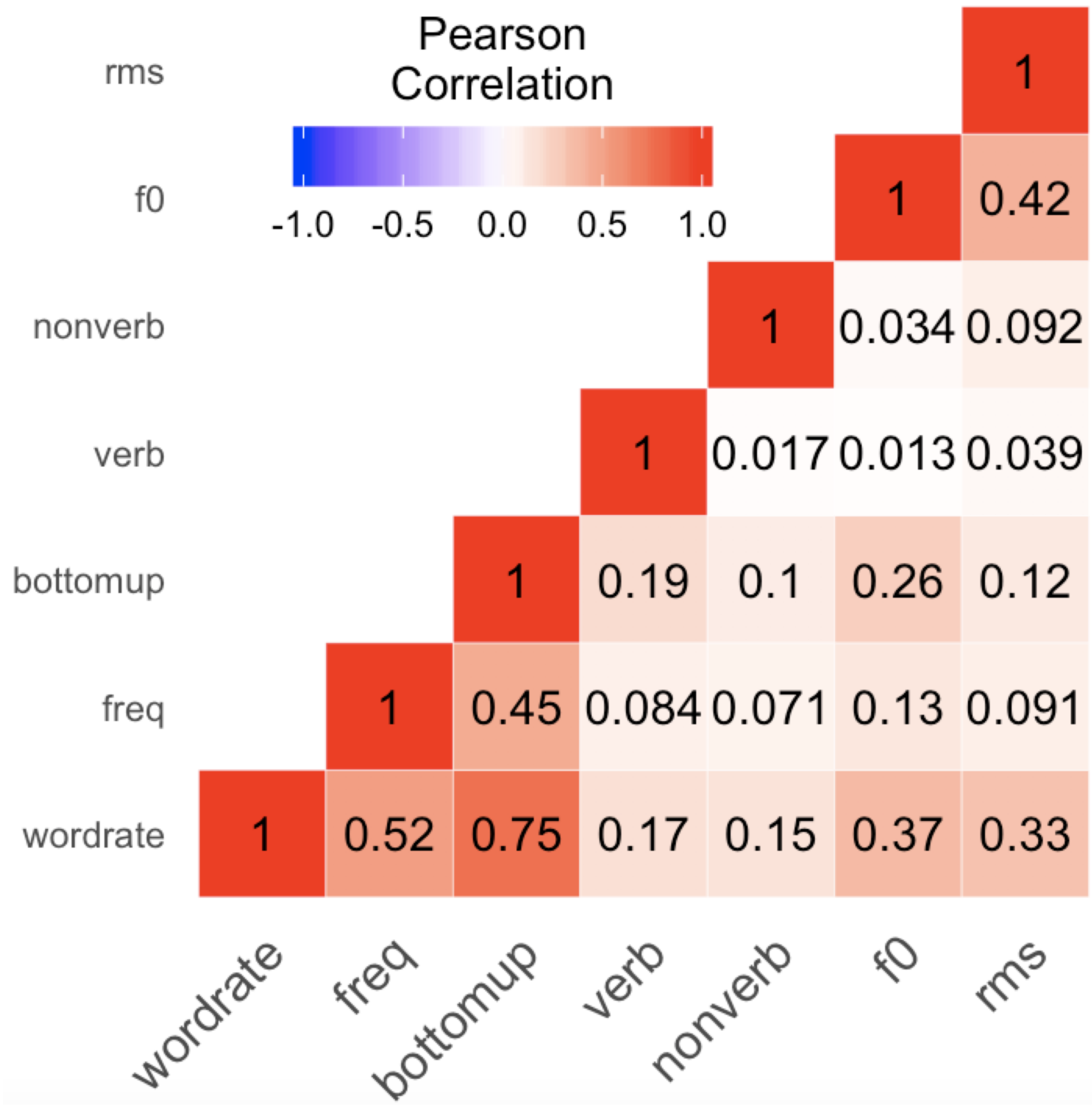

Figure 25: Correlation matrix (Pearson's r) of the convolved regressors included in the GLM model reported in Analysis 2

wordrate	freq	bottomup	verb	nonverb	f0	rms
3.035677	1.395752	2.431785	1.042754	1.028455	1.320799	1.341813

Table 23: Variance Inflation Factors in Analysis 2.

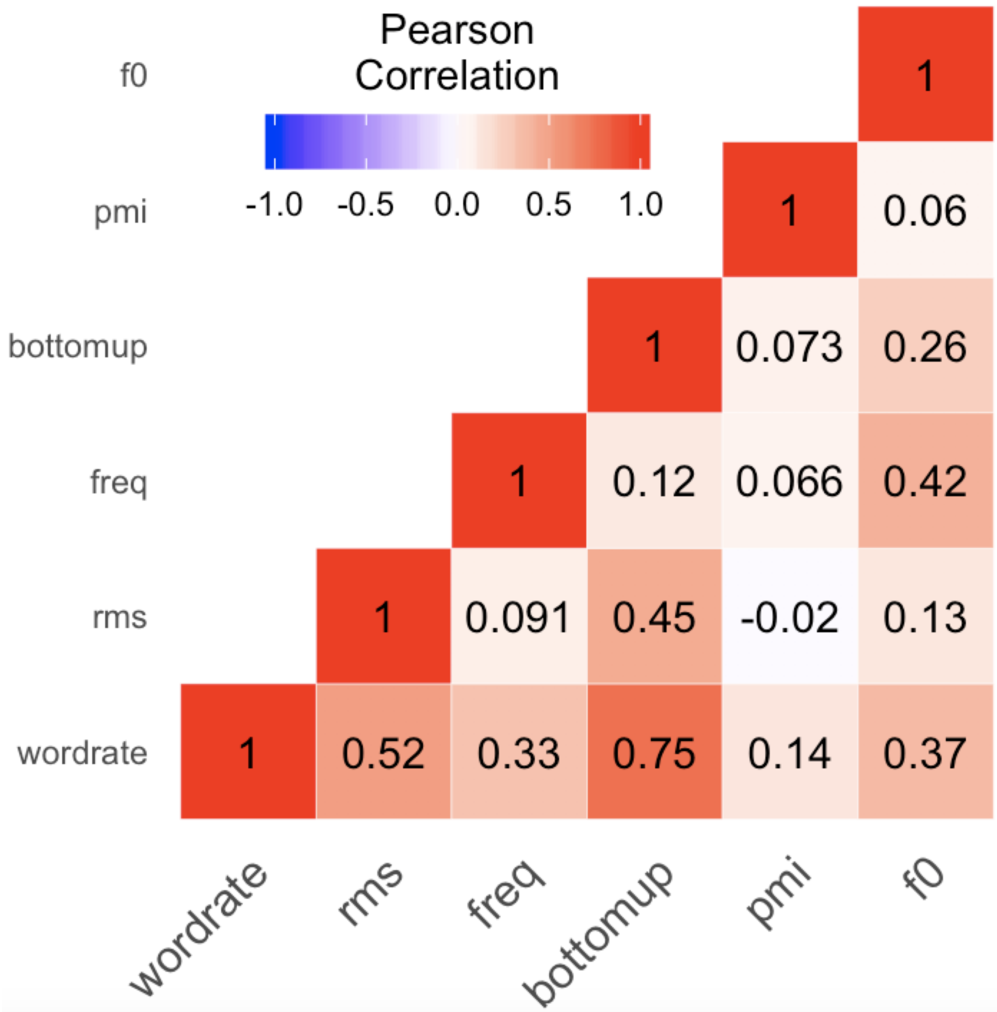

Figure 26: Correlation matrix (Pearson's r) of the convolved regressors included in the GLM model reported in Analysis 3

wordrate	rms	freq	bottomup	pmi	f0
3.053261	1.409882	1.337797	2.411620	1.031445	1.314141

Table 24: Variance Inflation Factors in Analysis 3.

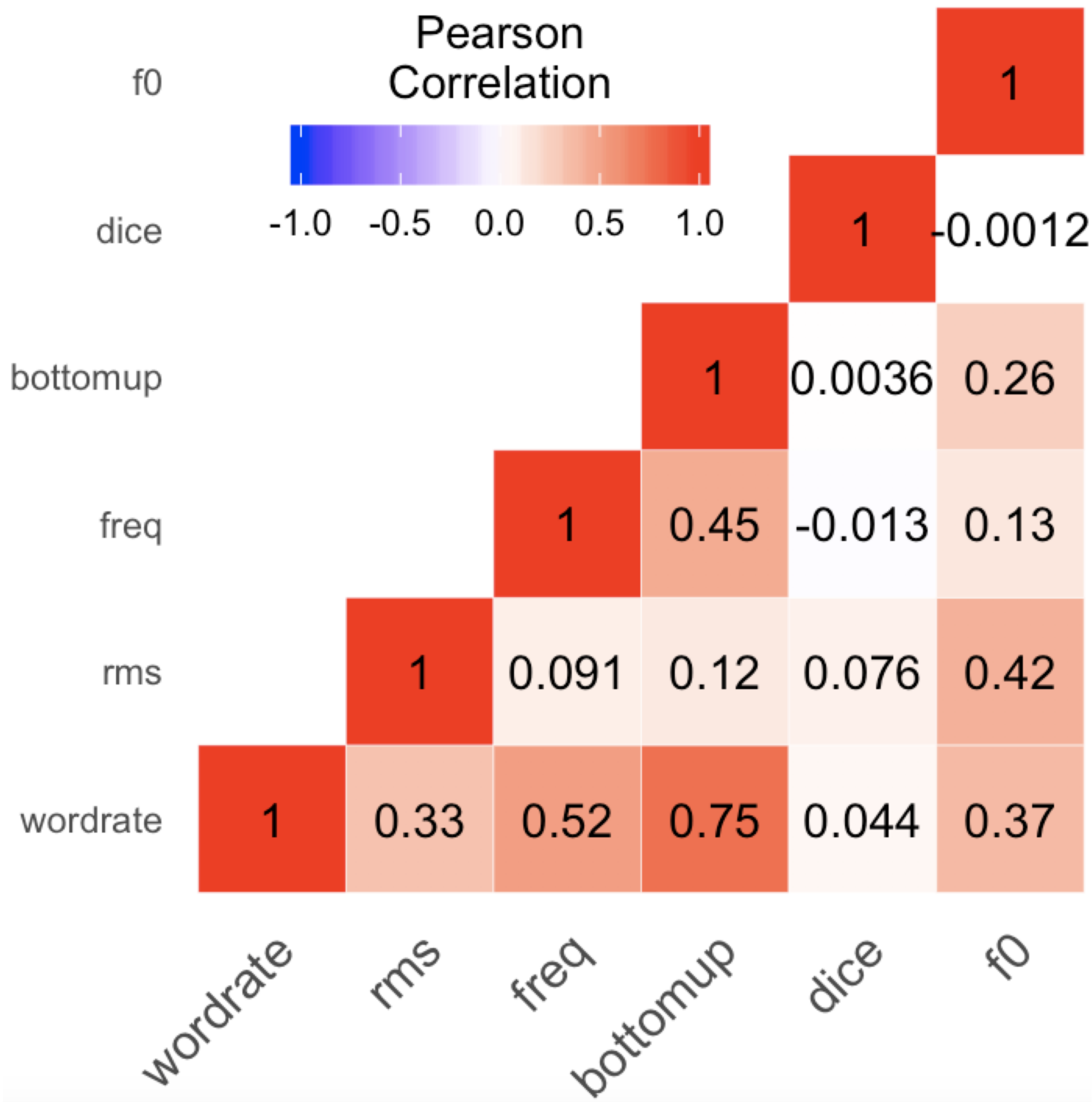

Figure 27: Correlation matrix (Pearson's r) of the convolved regressors included in the GLM model reported in Analysis 4

wordrate	rms	freq	bottomup	dice	f0
3.006189	1.343616	1.396924	2.410851	1.010121	1.316597

Table 25: Variance Inflation Factors in Analysis 4.

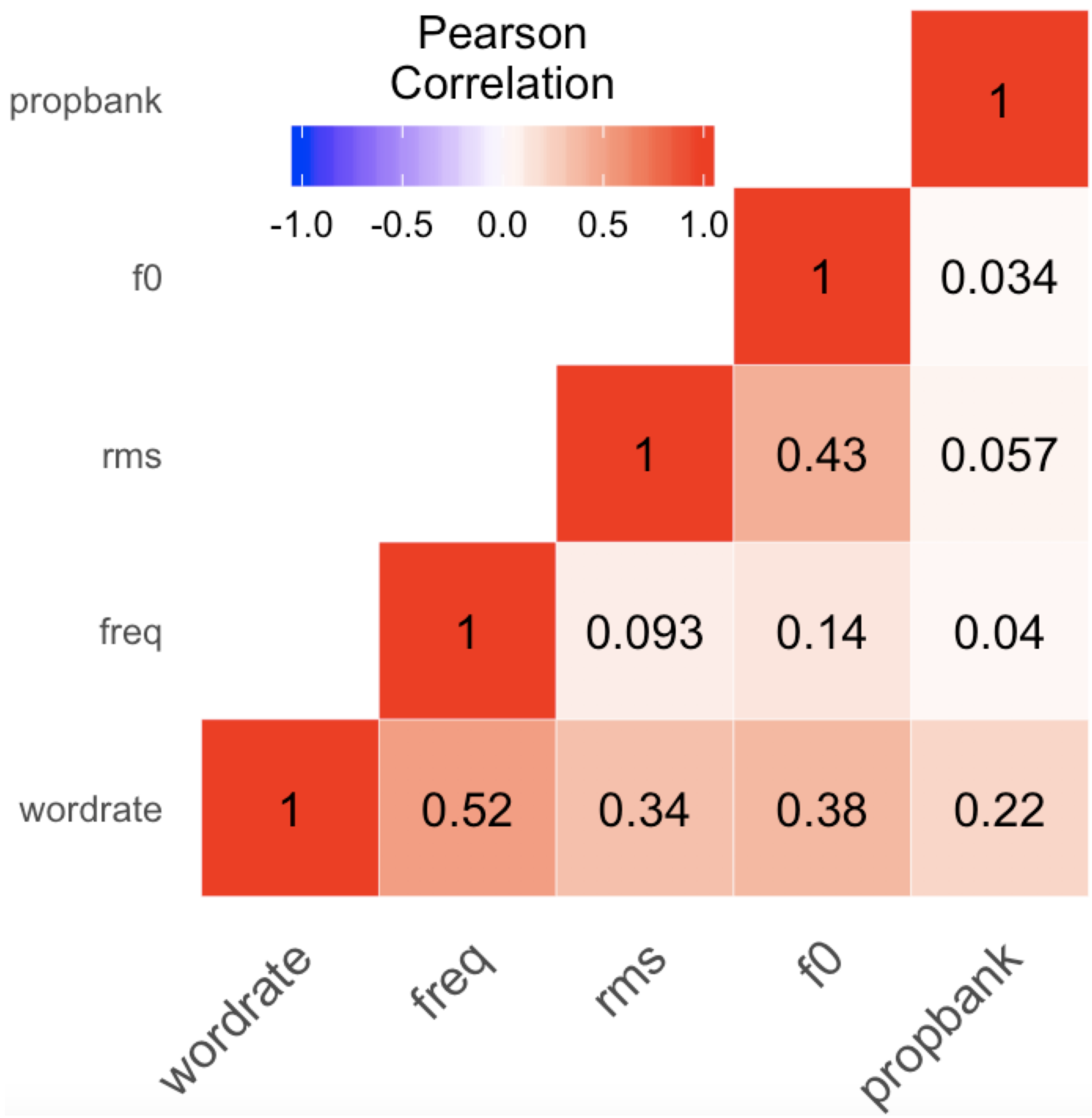

Figure 28: Correlation matrix (Pearson's r) of the convolved regressors included in the GLM model reported in Analysis 5

wordrate	freq	rms	f0	propbank
1.754218	1.400773	1.325511	1.285971	1.065054

Table 26: Variance Inflation Factors in Analysis 5.

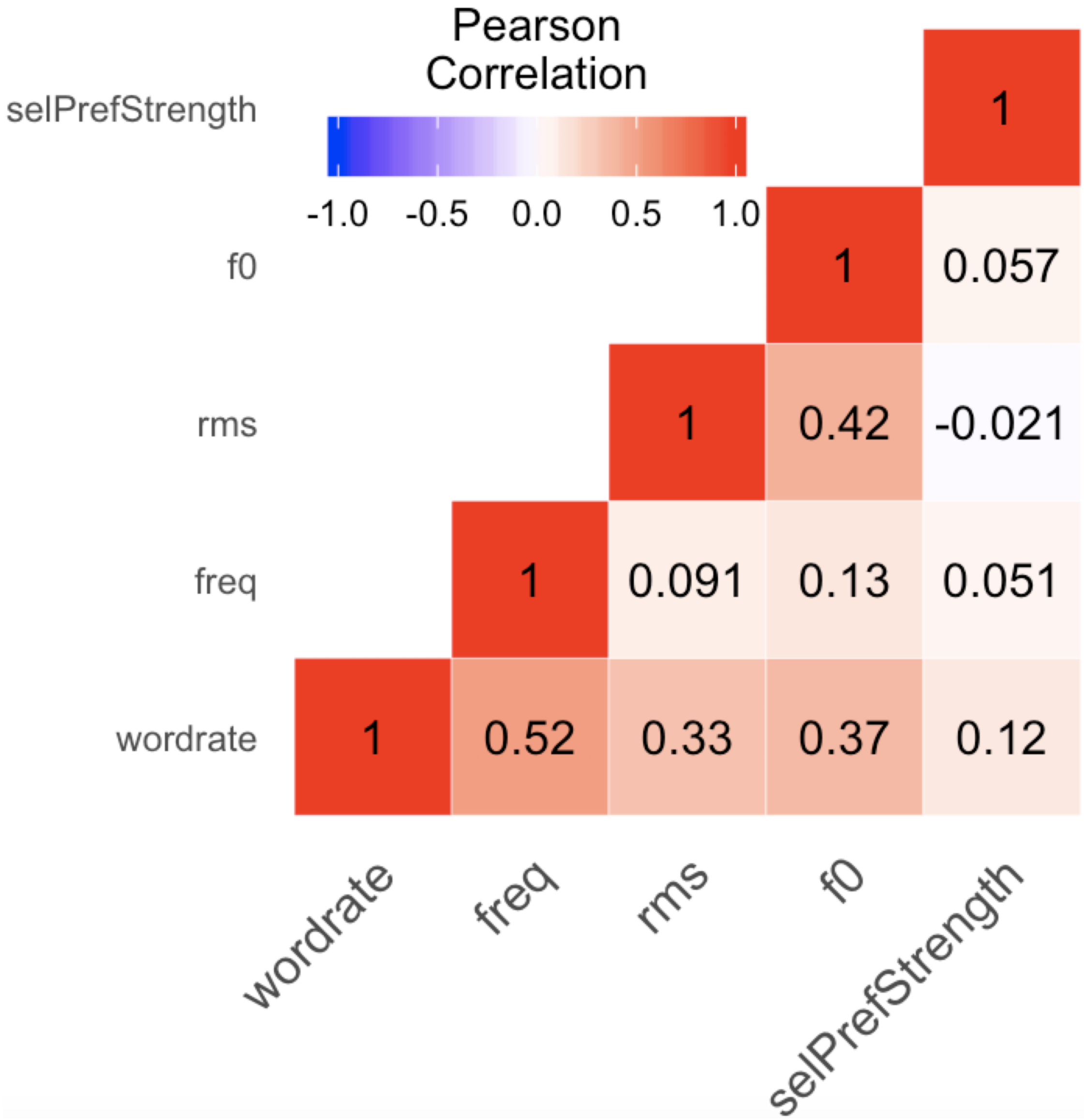

Figure 29: Correlation matrix (Pearson's r) of the convolved regressors included in the GLM model reported in Analysis 6

wordrate	freq	rms	f0	selPrefStrength
1.662559	1.385525	1.311345	1.287662	1.021331

Table 27: Variance Inflation Factors in Analysis 6.

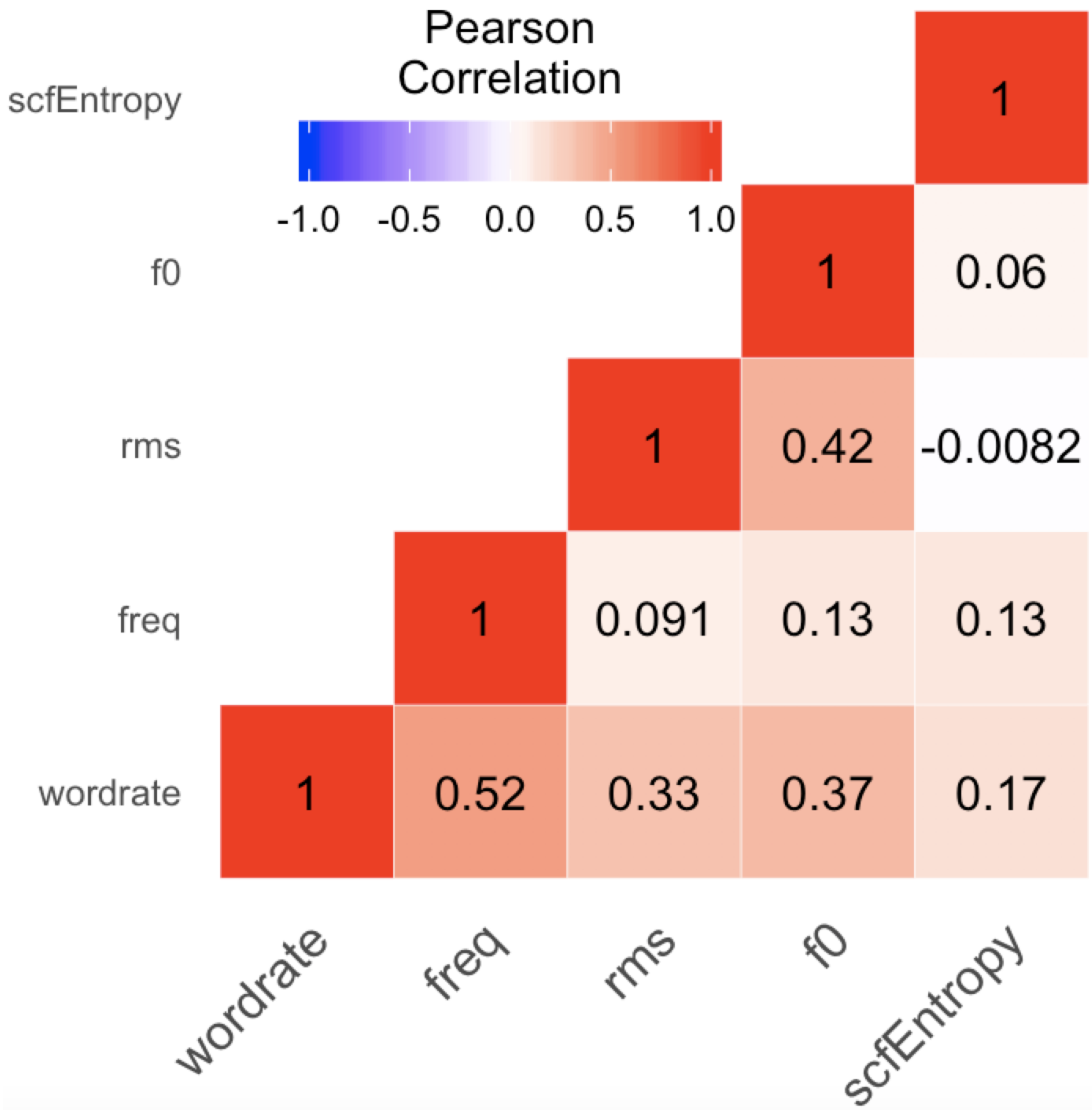

Figure 30: Correlation matrix (Pearson's r) of the convolved regressors included in the GLM model reported in Analysis 7

wordrate	freq	rms	f0	scfEntropy
1.667823	1.387466	1.310313	1.286459	1.037694

Table 28: Variance Inflation Factors in Analysis 7.

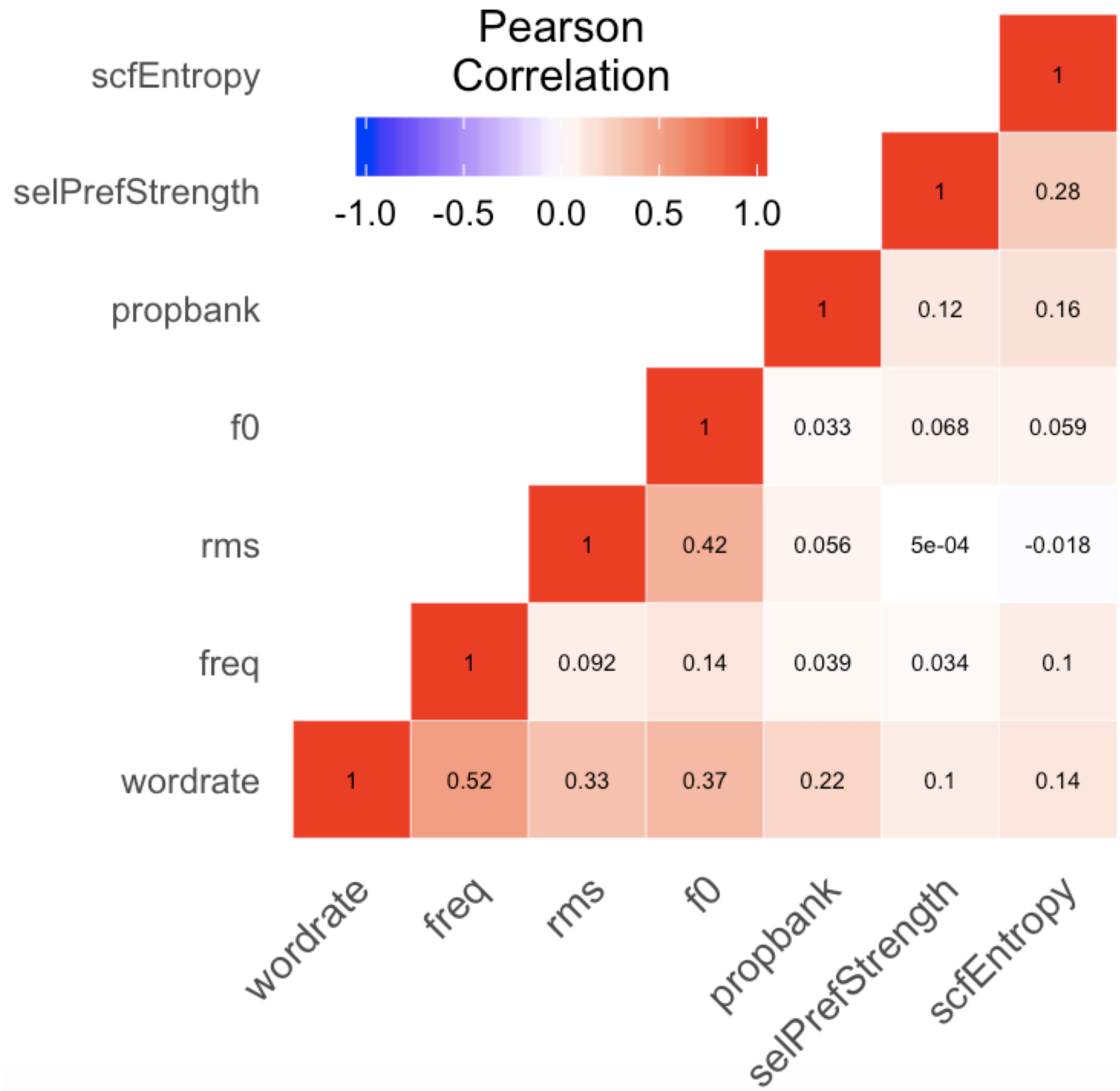

Figure 31: Correlation matrix (Pearson's r) to compare between the convolved regressors related to argument structure

wordrate	freq	rms	f0	propbank	selPrefStrength	scfEntropy
1.760379	1.404015	1.323452	1.290478	1.090372	1.099160	1.123143

Table 29: Variance Inflation Factors to compare between the convolved regressors related to argument structure.

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