Diathesis Alternations and Selectional Restrictions: A fMRI Study

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1 Introduction

Verbs play a crucial role in sentences as they have their corresponding argument structure information, which is deployed during sentence processing. Thompson & Meltzer-Asscher (2014) propose a neurocognitive model of argument structure processing, based on existing work investigating the neural underpinnings of verb processing. They posit that once verbs are encountered, its associated argument structure information is retrieved and utilized for sentence-level semantic and syntactic integration. In this paper, we revisit some of the same questions to examine how different components of verbal argument structure are used as predictive cues during sentence processing.

The naturalistic language comprehension study described here explores various aspects of argument structure, such as diathesis alternations and selectional restrictions in English and probes whether they have differing neural substrates. Using computational metrics and fMRI data, the goal of this study is to investigate how argument structure plays a role in sentence processing.

In §2, we provide an overview of previous behavioral, theoretical, and neurolinguistic work relevant to the study. §3 describes the fMRI study, including the overall methodology, and the metrics used. In §4 we explain how the neuroimaging data was analyzed while in §5 we present our results. §6 consists of a discussion of the brain areas implicated in our study. Our results illustrate that diathesis alternations and selectional restrictions evoke different patterns of activation and confirm the brain regions involved in processing argument structure.

2 Background

2.1 Behavioral and Theoretical Perspectives on Argument Structure

Prior studies have provided behavioral and psycholinguistic evidence to demonstrate that argument structure information is accessed and used during real-time sentence processing e.g. Boland 2005; Boland 1993; Ferretti *et al.* 2001; Friedmann *et al.* 2008; MacDonald *et al.* 1994; Trueswell & Kim 1998; Trueswell *et al.* 1993 among others. These experimental findings are consistent with a lexicalist view, initially proposed by Chomsky (1970), and further exemplified in Jackendoff 2002; Williams 1981; Levin & Hovav 1995; Reinhart 2003; Horvath & Siloni 2011

Thanks to Murielle Fabre, Christophe Pallier, John Whitman, Miloje Despic, and Wen-Ming Luh for their feedback. This material is based upon work supported by the National Science Foundation under Grant Number 1607441.

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.

2.2 Previous Neurolinguistic Work

Earlier 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; Shetreet *et al.* 2009; Shetreet *et al.* 2010a; Shetreet *et al.* 2010b; Thompson *et al.* 2007; Thompson *et al.* 2010; Meltzer-Asscher *et al.* 2013; Meltzer-Asscher *et al.* 2015; den Ouden *et al.* 2009; Fabre 2017; Malyutina & den Ouden 2017 (see Thompson & Meltzer-Asscher 2014 for review for a subset of these). 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.

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 sense and in an ecologically valid setting to study whether similar activation patterns are observed.

3 fMRI Study

3.1 Method

We follow 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.

3.2 Dataset

The English audio stimulus was Antoine de Saint-Exupéry's *The Little Prince*, translated by David Wilkinson and read by Nadine Eckert-Boulet. It constitutes a fairly lengthy exposure to naturalistic language, comprising 19,171 tokens; 15,388 words and 1,388 sentences, and lasting over an hour and a half.

There are 2,948 verbs in total which were tagged with the NLTK toolkit (Bird & Loper 2004) and Stanford POS tagger (Manning *et al.* 2014) and the labels were hand-checked for accuracy. 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. In this study two different computational metrics are used to formalize diathesis alternations and selectional restrictions, as described below. While both of these metrics operationalize different aspects of verbal argument structure within a sentence, they also formalize a degree of constraint in terms of sentence processing. While one reflects the degree of constraint in terms of thematic roles and structural relations, the other metric reflects the degree of constraint in terms of selectional restrictions and the semantic categories. Both of these gradient measures are thus taken as indices of degrees of constraint and correlated with brain activity.

3.2.1 PropBank: Formalizes diathesis alternations

PropBank (Kingsbury & 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 1. 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.

The intuition behind this metric is that the diathesis score should reflect the uncertainty about the remaining sentence and in a way, quantifies the ambiguity the listener is resolving during sentence processing. Verbs with higher number of diathesis alternations are more ambiguous since there are more possible ways for the sentence to be completed. In comparison, verbs with low diathesis scores are less ambiguous about the rest of the sentence.

3.2.2 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 an-

Verb	PropBank Score
take	33
come	30
get	30
go	28
make	23
break	20
pass	20
disappear	1
inflict	1
laugh	2
sleep	5
write	7
bring	8
pull	9

Table 1: Example of LPP verbs with PropBank scores to represent diathesis alternations. Full list of verbs with the scores are given in Appendix C.

imate 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 (c.f. equation 1) 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.

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

Originally Resnik calculated the selectional preference strength for a limited set of verbs across different corpora, such as the Brown corpus (Francis & 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 (David & Cieri 2003) and WaCkypedia (Baroni *et al.* 2009) corpora and then calculating their distribution across the 25 different WordNet semantic classes. Some sample verbs with their selectional preference strength are provided in Table 2. 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.

Selection preference strength reflects the prediction strength of a verb i.e., the verb helps the listener make predictions about the semantic class of its direct object and this metric quantifies the ease or difficulty of making this prediction. Verbs with 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 verbs with higher scores does help prime the listener's expectation and are more predictive.

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

Table 2: 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.

3.3 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). They self-identified as native English speakers and gave their written informed consent prior to participation, in accordance with Cornell University IRB guidelines.

3.4 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 served to confirm participants' comprehension. They were viewed via a mirror attached to the head coil and answered through a button box. The entire session lasted around 2.5 hours.

3.5 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.

4 Data Analysis

4.1 Preprocessing

fMRI data is acquired with physical, biological constraints and preprocessing allows us to make adjustments to improve the signal to noise ratio. Primary preprocessing steps were carried out in AFNI version 16 (**?**) and include motion correction, coregistration, and normalization to standard MNI space. After the previous steps were completed, ME-ICA (Kundu *et al.* 2012) was used to further preprocess the data. ME-ICA is a denoising method which uses Independent Components Analysis to split the T2*-signal into BOLD and non-BOLD components. Removing the non-BOLD components mitigates noise due to motion, physiology, and scanner artifacts (Kundu *et al.* 2017).

4.2 Statistical Analysis

The General Linear Model (GLM) typically used in fMRI data analysis is a hierarchical model with two levels (Poldrack *et al.* 2011). 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 research questions presented above in §**??** motivate two statistical analyses. The first analysis in Model 1 probes the neural correlates of diathesis alternations, formalized by PropBank scores and the second analysis in Model 2 investigates the neural correlation of selectional restrictions, formalized by Selectional preference strength.

4.2.1 Model 1

We regressed the word-by-word predictors described below 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). Each of the 1,970 verbs in the story were annotated with its corresponding PropBank scores. Additionally, we entered four regressors of non-interest into the GLM analysis (SPM12): word-offset, lexical frequency, pitch, intensity which serve to improve the sensitivity, specificity and validity of activation maps Bullmore *et al.* 1999; Lund *et al.* 2006. These predictors were added to ensure that conclusions about argument structure processing would be specific to the cognitive processes they were taken to instantiate, as opposed to more general aspects of speech perception.

4.2.2 Model 2

Model 2 is similar to Model 1 and uses the same predictors. However, instead of PropBank scores, the verbs were annotated with their corresponding Selectional preference strength, calculated as described in §3.2.2.

4.2.3 Group-level Analysis

In the second-level group analysis, each contrast was analyzed 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 Results

Behavioral results of the comprehension task showed attentive listening to the auditory story presentation. Across 51 participants, average accurate responses to the comprehension questions was 90% (SD = 3.7%).

5.1 Model 1: Diathesis Alternations

Table 3 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, and Middle Frontal gyrus, as seen in Fig. 1.

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 3: 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.

5.2 Model 2: Selectional Restrictions

Table 4 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. 1: Supplementary Motor Area, Inferior Frontal gyrus Pars Orbitalis/Triangularis, and Superior Temporal gyrus.

Regions	Cluster size (in voxels)	MNI Coordinates x	y	z	p-value (corrected)	T-score (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 4: 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.

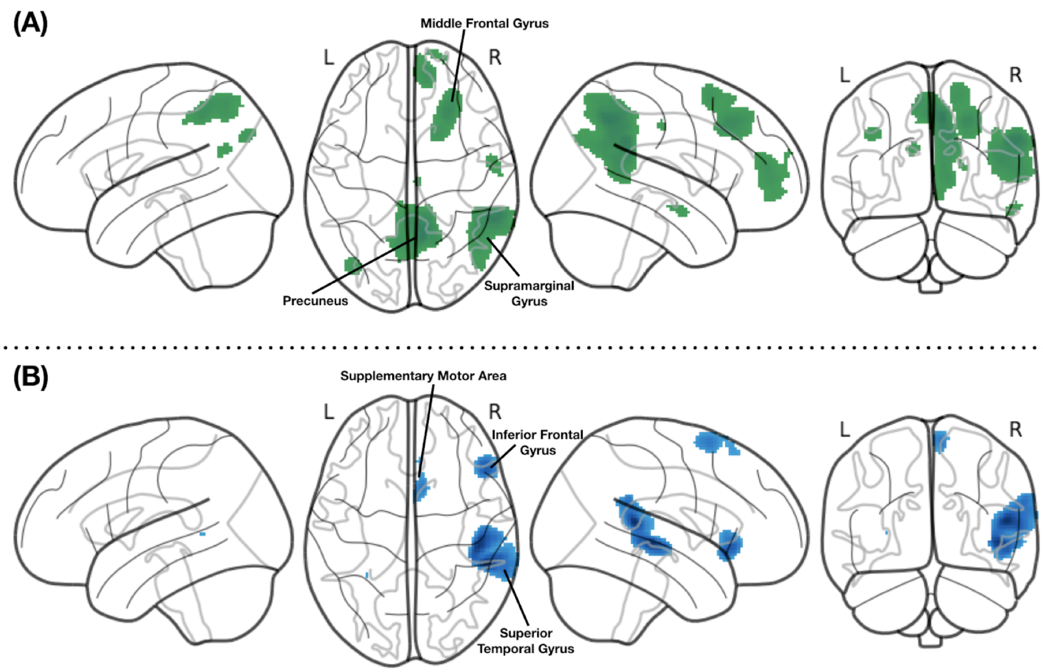

Figure 1: (A): Whole-brain contrasts for diathesis alternations in green
(B): Whole brain contrasts for selectional restriction in blue

6 Discussion

This section provides a brief overview of the different brain areas that were significantly activated in the study.

Diathesis alternations results corroborate previous neuroimaging studies related to semantic roles. Significant bilateral Precuneus activation is observed for diathesis alternations in Model 1 and this area has also been implicated in prior work on verb processing by Shetreet *et al.* 2007; Shetreet *et al.* 2010a; den Ouden *et al.* 2009. Consistent with Thompson *et al.* 2007; den Ouden *et al.* 2009, there is significant activation in the Supramarginal gyrus. The Middle Frontal gyrus is another area implicated in our study and Shetreet *et al.* 2007; den Ouden *et al.* 2009 also found similar patterns of activation in their studies.

Although there have been no specific studies examining the neural bases of selectional restrictions, our results from Model 2 are consistent with other neuroimaging studies related to lexical–semantic processing and semantic ambiguity (Kuperberg *et al.* 2000; Zempleni *et al.* 2007).

7 Conclusion

The results in this study illustrate a network of brain areas involved in processing argument structure. Diathesis alternations and selectional restrictions evoke differing patterns of activation.

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. Overall, we provide further evidence to demonstrate that argument structure information is accessed and used during language comprehension and confirm the brain areas reported in previous literature.

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