TRAINING AND PROBING LANGUAGE MODELS FOR DISCERNING BETWEEN SPEECH OF PEOPLE WITH APHASIA AND HEALTHY CONTROLS

by

NARINDER SINGH GHUMMAN

(Under the Direction of John Hale)

ABSTRACT

In recent years, machine learning based computational methods have been applied for automatically discerning between speech of a special population with language impairment - people with dementia - and healthy controls. The more successful of these methods employ a paired language model based approach where the diagnosis is based on perplexities of two models — one trained on speech samples of people with dementia and the other on healthy control samples. This work applies that approach to another special population with language impairment — people with post stroke aphasia — and asks whether (1) this approach still works — as measured by improvement over a baseline classifier that simply returns the majority class from training data as the output, and (2) if input from a single testing dimension — language production — is enough to improve significantly; since a clinical diagnosis is based on assessment along three dimensions - production, comprehension and repetition. Next, this work probes these language models to find out what is driving the difference in perplexity — the metric that underlies the classification decision. A word level analysis of difference in surprisals between the language models revealed that (1) for Broca's aphasia, the models were most sensitive to closed class lexical elements, (2) for Wernicke's aphasia, the models appeared to be sensitive to the main elements expected from a typical healthy response (e.g. the word 'bread' in a task that asks 'how to make a PB&J Sandwich?'), (3) for Anomic Aphasia, the models were found to be sensitive to filled pauses ('um' and 'uh') taken during the discourse and (4) for Conduction aphasia, the models were sensitive to phonemic paraphasias and main elements of a response.

INDEX WORDS: Natural Language Processing, Computational Linguistics, Neural Sequence Models, Artificial Neural Networks, Deep Learning, Aphasia, Information Theory, Machine Learning, Data Science, Big Data, Recurrent Neural Networks, Long Short Term Memory Networks.

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CHAPTER 1

INTRODUCTION

§ 1.1 Background Research

The subject of the present study is building and probing diagnostic models for language of people with post stroke aphasia, across all its syndromes [1]. To our knowledge, previous work on automated diagnosis of people with aphasia is rare but the general problem of making an automated diagnostic model for classifying between speech of a special population with a language impairment — like for instance Dementia— and healthy controls has, however, been studied and has a literature.

Evidence that it is possible to perform automated diagnosis based on language samples alone was presented early on in the last decade for many special populations. For instance, Fraser et al., 2012 recruited 40 participants consisting of healthy controls and people with Primary Progressive Aphasia (PPA) — which is a separate disorder from post stroke aphasia; PPA is a dementia syndrome [2], and addressed the problem of classifying between two PPA subtypes and healthy controls, taken any two at a time (binary classification). They showed that a significant improvement over the baseline could be achieved from relatively short speech samples using a set of 58 manually engineered features to train Support Vector Machines (SVMs). In a subsequent study, Fraser et al., 2014 studied automated diagnosis in post stroke aphasia — the subject of the present study — by considering a new set of 39 participants (transcripts) consisting of healthy controls and people with agrammatic aphasia - also called Broca's aphasia. They demonstrated that using similar methodology, albeit a different feature set and learning algorithm (Naive Bayes), a cross validation accuracy score of 97% could be achieved. However, hand engineering large feature sets on small datasets without explicitly holding out a validation set doesn't leave behind any truly unseen data, and

[1] The various aphasia syndromes are described in section 2.1

[2] PPA is caused by progressive deterioration of brain tissue associated with language functions and a steady decline in language competence over time

this can lead to over-engineered (overfitting) models. As admitted by the authors, while the results were encouraging, the dataset used was rather small and testing on a bigger dataset was required. The study also considered only a single discourse task for eliciting the speech sample and called for examining the effect of narrative task on the classification accuracies. The study also called for considering aphasia types other than Broca's aphasia. The major impairment in Broca's aphasia is syntactic in nature while other aphasia syndromes present semantic deficits which presents a different kind of challenge. These are some of the concerns that are addressed in the current study.

The methodology used in present study, however, comes from work done on a different special population — people with Alzheimer's Disease (AD). Early on, Kathleen C. Fraser and Rudzicz, 2016 showed that a high degree of classification accuracy — 81% cross-validated across 264 participants — could be achieved on this task using similar methodology as before but employing two different sources of features this time - audio files and text transcripts. A grand total of 370 linguistic and acoustic features were computed per discourse transcript and computing this grand feature set required the use of a range of different computational linguistics tools (parsers, part-of-speech taggers etc.). More recently, however, there has been a shift away from elaborately engineered feature sets in favor of purely statistical approaches. Beginning with Wankerl et al., 2017, where a pair of n-gram language models were presented — one trained on speech transcripts of healthy controls and the other on the transcripts of people with AD — and a classification decision was arrived at by the two models by using the difference in perplexity[3] of the two models on a speech transcript as the sole feature for discrimination. This technique achieved an accuracy of 77.1% and had the advantage of being language agnostic. This was soon followed by another work - Fritsch et al., 2019 that replaced the n-gram models of the previous work with neural sequence models [4] and achieved an accuracy of 85.6%. A parallel work Klumpp et al., 2018 inquired into the possibility of addressing this task based on a scheme that used a bag-of-words representation only and experimented with using a frequency distribution vector and feeding it directly all at once into a fully connected neural network instead and found that an accuracy of 84.4% could still be achieved. It showed that deep learning methods outperformed conventional machine learning methods in any case, with the neural sequence

[3] Perplexity is a kind of likelihood estimate. see Section 3.3 for details.
[4] See Section 3.2 for more on neural sequence models.

models slightly outperforming the fully connected neural-net. All these works collectively demonstrated that purely statistical approaches were doing better than engineered feature sets, and these works were soon followed up by Cohen and Pakhomov, 2020 where these models were investigated for what they had learnt - which is a general interest in the field of Deep Learning. Artificial Neural Networks - unlike conventional statistical models - are opaque learners and do not lend their learned parameters to a direct interpretation. Cohen and Pakhomov tested the workings of the paired language models for a known language impairment in Dementia, namely the loss of access to rare words with disease progression, by passing deliberately created transcripts simulating higher and higher degree of said impairment to the models and looking at the effect on difference in perplexity - the one final feature that the method was basing the decisions on. They reported that the models were sensitive to these fabricated changes and the simulated progression of dementia was guiding the difference in perplexity feature on this small set of synthetic transcripts. A minor improvement in classification performance over Fritsch et al., 2019 of 1.6% was also reported by way of substituting a mixture model for the dementia group, positing the language models based classification method as the benchmark method once again.

§ 1.2 Present Study

The present study has two aims. First, we test the language models based (purely statistical) approach for people with aphasia. Aphasia, unlike AD, can present itself in a tremendous variety of ways, so clinicians and researchers have come up with a typing system that puts similar manifestations of this disorder in a group. The typing system, and the clinical diagnosis of a person with aphasia (PWA), is based on language competence analysis along three dimensions - production, repetition and comprehension. The present work, like the previous works [5], asks if a language production sample alone is enough to achieve a high degree of accuracy on the task. Out of all the aphasia syndromes considered in this study, Broca's aphasia presents with the most distinct production alteration; so this study asks if the method is most performant (as measured by classification accuracy) for this aphasia type for the language production sample should be the most informative of the three dimensions - repetition, production and comprehension. Contrast

[5] AD is also a complicated disorder with symptoms like memory impairment, other than language impairment

this with Conduction aphasia where the major symptom is inability to repeat words or phrases which is something that would reveal itself during the repetition testing. The question here would be that in absence of any data form the language repetition task, can participants with this syndrome still be accurately separated from controls?

In the second part of the study, these models were probed to find out what they had picked up on and if the things that they were picking up on were known linguistic features of the various aphasia types. In linguistics, there are multiple levels of analysis - phonetics, phonology, morphology, syntax, semantics and pragmatics. A word level language model looks at some preceding words in a document — a speech transcript in our case — and spits out a probability distribution over the dictionary for what it thinks the next word might be in the sequence, thus immediately lending itself to a word level analysis. The difference in surprisals between two models against each word was compared to find out what was enabling the model pairs (e.g. Broca vs Control) in reaching a correct decision. For instance, the presence of a paraphasia - which would reveal itself as an out of dictionary word in a transcript - was found to be much more surprising by the healthy control model than Broca's or Conduction aphasia model which makes perfect sense in light of the fact that normal healthy people don't go about inventing or mis-producing words.

§ 1.3 Contributions

The main contributions of this thesis are two fold,

(1) this study expands the scope and scale of work done on automated diagnosis of people with aphasia. Previous work on automated diagnosis of post-stroke aphasia such as Fraser et al., 2014 considered a small set of participants (39) with one transcript per participant and only one aphasia syndrome - Broca's aphasia - against healthy controls. This study considers a much larger dataset consisting of 2,635 transcripts from 546 participants, a major fraction of which (901 transcripts) was privately sourced through a collaboration and isn't part of any freely available database. The set of aphasia syndromes considered in this study were also expanded to include Wernicke's, Anomic & Conduction aphasia (Fraser et al., 2014 only considered Broca's aphasia), so that the question regarding possibility of automated diagnosis

could be assessed over a range of syndromes (the various syndromes were considered one at a time in a binary classification setting against healthy controls). The language model based classification method adopted from work on automated diagnosis of AD (Fritsch et al., 2019) was found to be effective in these new classification settings as well, leading to significant improvements over the majority baseline classifier as shown in confusion matrices of Chapter 5. As speculated in the previous section, performance improvement for Broca's aphasia was the highest across all discourse tasks. Another question that was addressed was if the kind of task used had an effect on the classification performance. It was found that the discourse task (language sample) chosen had an effect on the classification accuracy and that a type of procedural task - Sandwich task (Section 2.2.4) - was maximizing the classification performance across all classification settings (pushing above the 90% mark for all tasks).

(2) deep learning methods were used in this research which show that there is no need for manual feature engineering as in Fraser et al., 2014. Furthermore, this allowed the models to come up with their own feature representations regarding what the various aphasia types looked like; and through the language model probing method applied in Chapter 6, we were able to confirm that the language models had become sensitive to several well known clinical indicators of aphasia. For instance, while discriminating between healthy control transcripts and transcripts of people with Broca's aphasia, the language models were found to be most sensitive to the appearance of closed class lexical elements (e.g. pronouns, determiners), lack of production of which is a well known language impairment among clinicians for this type of aphasia. In the case of Anomic aphasia, the indicator that was picked up on was the use of filled pauses ('um') that people with this type of aphasia often take in face of word finding difficulties. In fact, the most influential token during classification was the filled pause ('um') for a majority of the discourse tasks (3/4) considered in this study. In the case of Wernicke's (or Conduction) aphasia and healthy controls, main elements of a discourses task (e.g. 'cinderella' in the Cinderella story re-tell task) were found to be the most influential tokens in arriving at the correct classification decision. These were also found to be asymmetrically distributed between healthy controls and people with Wernicke's (or Conduction) aphasia. In case of Wernicke's aphasia, this was interpreted to correspond to the bizarre semantics of people with this type of aphasia (Section 6.5), and in case of Conduction aphasia, this was interpreted as corre-

sponding to the difficulty that people with this type of aphasia have with semantically significant words (Section 6.7), both salient features of the two aphasia syndromes. These demonstrations served to show that the language models were sensitive to known language deficits of people with aphasia. This probing method could further be pursued to identify other aspects of language production that the language models had become sensitive to, which could turn out to be new as yet unknown features of particular aphasia syndromes. Furthermore, while individual words or tokens were analysed in our work, language models condition the outputted probability distribution over the entire left context. So these models have the potential to uncover multiword features which is something that was not studied in Stark and Fukuyama, 2020.

CHAPTER 2

APHASIA

§ 2.1 Aphasia

Aphasia is a neurological disorder resulting from brain damage typically as a result of a stroke or some other form of head trauma which is to say it is an acquired impairment of language resulting from damage to the neural foundations of language. The specific language deficits that present after brain damage have been correlated with specific brain regions since very early on (Geschwind, 1970).

The impairments or deficits themselves are neither unidimensional nor an all or none proposition. On the language production front, deficits can vary from occasional word retrieval difficulties to complete inability at producing anything but a few select words or certain formulaic expressions. The language produced can even be hyper-fluent (more productivity than healthy control) but make no sense and contain nothing but made up words and phrases. On the language comprehension side of things, the deficit may range from inability to understand certain syntactically complex structures or the inability to make out certain similar sounding words to being completely unable to follow the topic of the conversation or any command or directive given to the individual.

There's a great deal of variation in symptoms and each individual with aphasia presents with their own set of language competencies and incompetencies but clinicians and researchers have come up with a general classification system that captures that variation into a small range of aphasia types or syndromes (a syndrome is a set of symptoms). These types reflect recurring patterns of symptoms and the said classification system is called Boston Classification and is associated with the Boston school of aphasia [1] and it proposes eight aphasia types based on whether or not each of the three competencies - production,

[1] There exist other taxonomies but this is the most widely used one and also the one used by clinicians for dataset considered in our study

comprehension and repetition were spared or impaired which although is a simplistic way of looking at the symptoms has proven to be quite useful to talk about aphasia. This also leads to bifurcation of the eights types from the perspective of each dimension - non-fluent vs fluent, impaired vs spared repetition, impaired vs spared comprehension. Not all aphasia types were considered in this study for lack of data pertaining to some of these but the following ones were. In total, one non-fluent aphasia - Broca's aphasia, and three fluent aphasias - Wernicke's, Anomic and Conduction were considered. A brief description of these various types with a focus on production deficits is presented below. These sketches are heavily based on a standard textbook on neuroscience of linguistics - Kemmerer, 2014.

§ 2.1.1 Broca's Aphasia

Broca's aphasia is typified by a marked impairment of language production abilities. The speech is produced in an effortful manner, is slow and lacks normal flow and rhythm. The utterances are short, lacking in grammar (closed class elements of speech), syntactically simple and sound telegraphic for the content words are there to draw the meaning but other aspects of fluent speech are missing. Patients are generally aware of their incompetencies and feel defeated or frustrated in their attempts at communicating. Patients often also resort to hand gestures and other kinds of actions in order to communicate. There's a marked deficiency in usage of function words, a condition known as agrammatism. Language comprehension is relatively spared although closer investigation reveals trouble with more syntactically complex forms. Patients with Broca's aphasia do have trouble repeating words and sentences spoken to them, so language repetition is impaired, although generally not to the degree that production is.

§ 2.1.2 Wernicke's Aphasia

Speech produced in patients with this type of aphasia is fluent - it has rhythm and flow of a healthy person but is semantically incoherent. The speech may even be hyper fluent and still not make much sense and the patient might not even be able to follow the topic of the conversation. In an extreme case, the speech might consist entirely of made up words. Furthermore, patients with this type of aphasia are often unaware of their own speech errors and not frustrated by their inability to communicate. The errors in speech are errors produced by substitution rather than omission (e.g. in Broca's) of words or morphemes. These mis-produced words by people with aphasia are called paraphasias. Language comprehension deficits are major in this type of aphasia - the patient is usually unable to follow any commands or directions or repetition tasks asked of them.

§ 2.1.3 Conduction Aphasia

Speech is fluent for patients with this type of aphasia but there is difficulty with getting the phonetic structure of a word right due to the severed connections between Broca's and Wernicke's area - the two main regions of the brain where language competence is centered. Conduction aphasiacs are aware of their errors and make repeated attempts at correction in event of a paraphasia. Language comprehension is generally preserved and patients do not have trouble with any comprehension based tasks. Language repetition is however damaged and in fact, that is the key symptom in patients with this type of aphasia. The difficulty is more pronounced for sentence level repetition tasks than word level.

§ 2.1.4 Anomic Aphasia

This type of aphasia is typified by excessive word retrieval difficulties. Like conduction aphasics, speech of people with anomic aphasia is largely fluent but still abnormal. The speech is filled with pauses stemming from word retrieval difficulties. Patients with this type of aphasia don't do so well on object naming task for it directly strikes at their key inability. The impairment may further be more severe for certain categories of words (e.g. nouns, proper-nouns) than others. Language repetition and comprehension abilities are well preserved for patients with this type of aphasia.

§ 2.2 Tasks

Discourse elicitation is thought to be an ecologically valid (naturalistic) way of assessing a patient's language ability. Monologic discourse elicitation tasks are used (1) across diagnostics (e.g., aphasia severity, linguistic impairment), (2) to identify appropriate therapy (e.g., word finding treatment), and as well as (3) for therapy (discourse-specific treatment), and (4) measuring improvement post intervention. The kind of discourse elicitation task used has an impact on the kind of language produced (Stark and Fukuyama, 2020). Language varies between tasks because each task has a specific ask (e.g., "tell me how would you ...", "describe what's going on here ..."), and draws upon different organizational, cognitive, contextual and linguistic processes (Leaman and Edmonds, 2021). Different tasks tax an individual's cognitive-linguistic system in different ways. Consider a picture description (expositional) task (e.g. the Broken Window task described below), the examiner is already aware of what the individual with aphasia is attempting to describe for there's a one rather unambiguous description of the scene in such a task. With set expectations, errors and missing information are easy to catch and compare between individuals. At the perception level, the individual with aphasia has visual input in front of them for the entire duration of the task, which may be helpful for lexical retrieval. In contrast, a fictional narrative task like Cinderella (described below) presents an individual with a wordless picture book of Cinderella for a brief amount of time before it is taken away, and the subsequent retelling without any visual cues heavily taxes an individual's semantic memory. This heavy reliance on semantic memory wasn't the case in an expositional task. Contrast this again to an autobiographical narrative (talking about oneself. e.g. important Event task below). Autobiographical memory is very different from semantic memory. This again provides a change in pace with respect to the underlying cognitive processes involved. Multiple tasks provide multiple points of testing and analysing the linguistic system. For this reason, a variety of tasks across different discourse genres were considered in this study. The following task administration scripts are from the official protocol used for data collection.

§ 2.2.1 Important Event (Genre: Personal Narrative)

Examiner: "Thinking back, can you tell me a story about something important that happened to you in your life? It could be happy or sad or from any time – from when you were a kid or more recently.". If not response in approx. 10 seconds, prompt: "For instance, you could tell me about a trip you took or something about your family or your work – anything."

§ 2.2.2 Broken Window (Genre: Expositional; Picture Description)

Examiner: "Now I'm going to show you these pictures. Take a little time to look at these pictures. They tell a story. Take a look at all of them, and then I'll ask you to tell me the story with a beginning, a middle, and an end. You can look at the pictures as you tell the story.". If no response in approx. 10 seconds, prompt: 'Take a look at this picture (point to first picture) and tell me what you think is happening.' If needed, point to each picture sequentially, giving the prompt: "And what happens here?" For each panel, if no response, provide the prompt: "Can you tell me anything about this picture?" Figure 2.1 shows the pictures associated with this task.

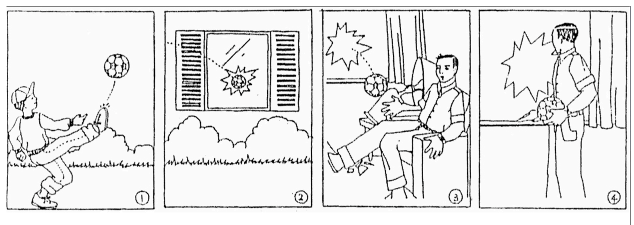

Figure 2.1: Broken Window

§ 2.2.3 Cinderella Story (Genre: Expositional Narrative)

Examiner: "I'm going to ask you to tell a story. Have you ever heard the story of Cinderella? Do you remember much about it? These pictures might remind you of how it goes. Take a look at the pictures and then I'll put the book away, and ask you to tell me the story in your own words." Allow participant to look through the book (assist with page turning if needed) and then, if necessary, prompt: "Now tell me as much of the story of Cinderella as you can. You can use any details you know about the story, as well as the pictures you just looked at." If participant gives a response of fewer than three utterances, or seems to falter, allow 10 seconds, then prompt: "What happened next?" or "Go on." Continue until participant concludes story or it is clear s/he has finished. Figure 2.2 shows the storybook that is presented as part of this task.

§ 2.2.4 Peanut Butter & Jelly (Genre: Procedural Description)

Examiner: "Let's move on to something a little different. Tell me how you would make a peanut butter and jelly sandwich." If no response in 10 seconds, give second prompt: "If you were feeling hungry for a peanut butter and jelly sandwich, how would you make it?"

Figure 2.2: Some pictures from the Cinderella Picturebook

CHAPTER 3

LANGUAGE MODELS

The human brain makes predictions about all kinds of things all the time. This is very true when it comes to our language ability When someone utters a sentence like, "I really like my new shoes, they're super ______"; before they even get to the last word, one has already made reasonable predictions about what it might be. A word like "comfy" or "cute" may be at top of one's mind and words like "tasty" or "Antarctica" would not even be close to top. A Language Model mimics this predictive ability by calculating probability distributions over the dictionary for what it thinks the next word might be given some preceding set of words (Goldberg, 2017). More formally, given some preceding set of words $w_1 \ldots w_{n-1}$, language models estimate the conditional probability $P(w_n|w_1...w_{n-1})\forall w_n \in$ Dictionary. The next sections build up to neural sequence models and then present some mathematical background necessary for subsequent chapters.

§ 3.1 N-gram Models

The simplest way of estimating said probabilities is to simply look at the frequency distribution of various words in a corpus. A uni-gram model does exactly that, estimating the probability of a word that occurs k times in a corpus as $\frac{k}{n}$, where n is the total number of words in the corpus. The predictions from such a model can only be so good however. For a sentence like the one mentioned in the first paragraph, it would be proposing elements of lexical categories such as nouns or verbs with a high probability - for they have a high frequency in a natural language corpus, but an element of such a category clearly can not fit in the given context. Conditioning the probabilities on some preceding context, however, can and does improve these estimates. By looking at bi-grams instead of uni-grams, information about usage patterns of "super" can be factored in and adjectives can be proposed with a greater probability than before for the conditional $P(w_n|super)$ would narrow down on the possibilities. One might start to capture the syntax at that point but to make semantically even more plausible predictions, one needs to look even farther back since it's the phrase "my new shoes" that is guiding the usage of the adjective at the end. Language is full of such long range dependencies and capturing these long range dependencies is essential to the language modeling task (Chomsky, 1956). Increasing the gram size however, doesn't present a scalable solution. The amount of possibilities increase exponentially with increase in gram size, asking for very specific conditioning contexts and putting unrealistic demands on corpus. Neural Sequence models can, however, circumvent these issues and are briefly described next.

§ 3.2 Neural Sequence Models

A family of neural networks called Recurrent Neural Networks (RNNs) (Rumelhart et al., 1985) are able to capture long range dependencies in time-series data like language by maintaining an internal state that is a function of all the inputs leading up to a time step t, for all time steps. Mathematically at each time step,

$$h_t = f(h_{t-1}, x_t; W) \tag{3.1}$$

where h_t is the hidden state at time step t, x_t is the input vector at time step t and W is the set of weights in the network. The input vectors are word embeddings and in Vanilla RNNs, the set of weights correspond to two weight matrices that multiply out with the hidden state and the input vector respectively. The equation is a recursive formulation in terms of f and unrolling the recursion reveals that the current computation references all the prior inputs,

$$
\begin{aligned}
h^t &= f(h^{t-1}, w^t) \\
h^{t-1} &= f(h^{t-2}, w^{t-1}) \\
h^{t-2} &= f(h^{t-3}, w^{t-2}) \\
h^{t-3} &= f(h^{t-4}, w^{t-3}) \\
&\dots \\
h^1 &= f(h^0, w^1)
\end{aligned}
$$

The output probability distribution at time step t is simply a function of the hidden state as,

$$\hat{y}_t = f(h_t; W) \tag{3.2}$$

The set of weights could be, for instance, associated with a fully connected neural network terminating in a softmax layer that is outputting a probability vector the size of the dictionary. Long Short Term Memory Networks (LSTMs) (Hochreiter and Schmidhuber, 1997), a variety of RNNs, were used for the work presented here. LSTMs are better able to capture long range dependencies in time-series data by regulating flow of information into the hidden state.

§ 3.3 Perplexity

While language models assign probabilities to sentences (or documents), raw probability masses aren't used in practice and one reason for doing so is that the probability mass assigned to a longer sentence would invariably be smaller because of the multiplications involved in the computation of joint probability. A length invariant measure of likelihood is hence desirable and Perplexity (denoted as PP) presents itself to be one such metric (Jurafsky and Martin, 2020). Perplexity of a language model on a piece of text is defined as the n^{th} root of the inverse probability of that piece of text. Because of this inverse relation, higher probability values are associated with lower perplexities, and minimizing perplexity leads to maximizing probability and vice-versa. The formula for Perplexity (PP) is,

$$PP(D) = \frac{1}{P(w_1...w_n)}^{\frac{1}{n}} \tag{3.3}$$

where D is a document containing words w_1 through w_n.

As an example of computing perplexity, consider rolling a fair 6-sided die. After n rolls of such a die, the probability of observing a given outcome is $\frac{1}{6}^n$, while the perplexity of any outcome is 6 regardless of n. The underlying reason for this is that the average branching factor (uncertainty) remains the same at each step in the probability tree. Like probability, perplexity has no units.

§ 3.4 Surprisal (Self-Information)

Surprisal or self-information is simply the log of inverse probability (Attneave, 1959). Figure 3.1 shows surprisal as a function of probability. For a completely certain event, probability is 1 and surprisal is 0 and as uncertainty regarding an event increases so does the surprisal. The self-information or surprisal of a coin flip is 1 bit. Perplexity (PP) can also be written out in terms of surprisals as,

$$s(w_i) = log_2(\frac{1}{P(w_i)}) \tag{3.4}$$

$$PP(D) = 2^{\frac{1}{n}\sum_1^n s(w_i)} \tag{3.5}$$

This view of perplexity as mean surprisal over the words in a document is used for probing language models in 6

§ 3.5 Cross-Entropy

Cross Entropy is the loss function that was used in this work for computing losses while training language models (Charniak, 1993). The formula for cross-entropy is written out as,

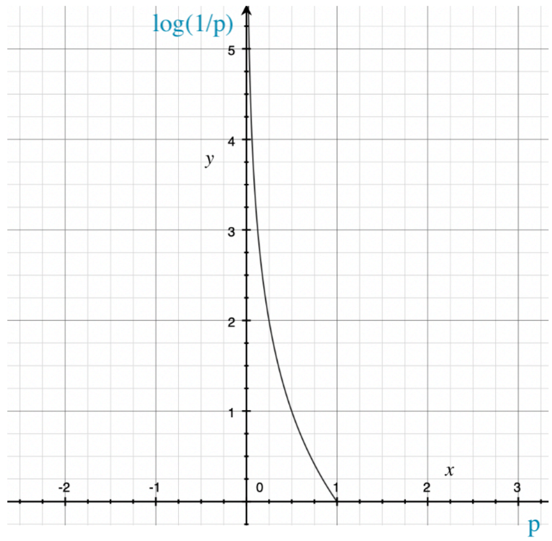

Figure 3.1: Surprisal as a function of probability

$$H(p,q) = -\sum_{x \in \chi} p(x) \cdot log(q(x)) \tag{3.6}$$

where p is the true probability distribution and q is the distribution outputted by a model. For the task of training a language model, p would correspond to the true distribution for the next word in any corpus, and q would correspond to the distribution outputted by the language model. Since the true distribution is unknown, cross-entropy can not directly be calculated. Instead, an estimate is calculated by setting $p(x)$ to be a one hot vector where the probability of each word in the distribution is set to 0 except for the actual next word in the training corpus τ - which has its probability set to 1. This reduces the equation above to $-log(e)$ where e is the probability assigned to the next word in τ by the model. Computed in this manner, cross-entropy loss with one hot target distributions seeks to minimize the mean surprisal (and hence, perplexity; see Equation 3.4) on the training data, and doing so is equivalent to maximizing the probability of the training corpus (τ).

CHAPTER 4

DATA & MODELING

The data for this study fundamentally consisted of hand transcribed speech of people with aphasia and their clinical diagnosis. The final dataset compiled for this study came from two sources - one public[1] and the other private; details follow.

§ 4.1 AphasiaBank

AphasiaBank is a curated datasource of multimedia interactions with people with aphasia (PWA) and healthy controls (MacWhinney et al., 2011). PWA are primarily individuals whose aphasia resulted from a stroke that was verified through neuro-imaging or a clear medical diagnosis. It is the largest data resource of its kind assembled through a collaborative effort across many institutions - academic research labs and aphasia centers. The data was collected at the collection sites using a standardized protocol [2]. The protocol describes the inclusion criteria for participants, sets the examination material (e.g. a script for examiner to administer a discourse task, the exact copy of Cinderella picture-book to be used etc.) and some sets guidelines related to audio/video recordings. The participant responses are recorded for audio and video and transcribed into a dedicated speech transcription format called CHAT format by a human transcriber. The utterances are temporally linked to the video in the CHAT transcript through timestamps. This database was pulled for transcripts on discourse tasks outlined in the previous chapter. Only participants with one of the following aphasia syndromes were considered: Broca, Wernicke, Anomic & Conduction, along with healthy controls. The specific sub-corpora used are laid out in Tables 4.1 & 4.2 . The exact set of transcripts pulled are listed in Appendix .

[1] restricted access but freely available to researchers upon request

[2] The complete protocols are available on the AphasiaBank website. The control protocol can be found here: https://aphasia.talkbank.org/protocol/materials-control/, and the Persons with aphasia (PWA) protocol can be found here: https://aphasia.talkbank.org/protocol/materials-aphasia/

Table 4.1: Participant and Transcript counts for AphasiaBank Corpuses used (Aphasia Protocol)

Corpus Name	Participants	Transcripts
Aphasia Center of West Texas (ACWT) Corpus (Kitty Binek, 2021)	7	24
Adler Aphasia Center Corpus (Szabo, 2021)	20	77
Boston University Corpus (Hoover, 2021)	11	37
Carnegie Mellon University Corpus (MacWhinney, 2021)	1	4
Elman Corpus (Aphasia Center of California) (Elman, 2021)	14	50
Fridriksson Corpus (University of South Carolina)[a] (Elman, 2021)	10	39
Garrett Corpus (Garrett, 2021)	2	4
University of Kansas Corpus (Jackson, 2021)	19	63
Kempler Corpus (Kempler, 2021b)	3	12
Kurland Corpus (Kurland, 2021)	24	95
Montclair State University Corpus (Boyle, 2021)	7	19
SCALE Corpus (McCall, 2021)	29	104
STAR Corpus (Corwni, 2021)	1	3
Triangle Aphasia Project Corpus (Silverman, 2021)	17	55
Texas Christian University Corpus (Munoz, 2021)	5	18
Thompson Corpus (Thompson, 2021)	13	50
Aphasia Center of Tucson Corpus (Kruse, 2021)	15	57
University of New Hampshire Corpus (Ramage, 2021)	8	32
Whiteside Corpus (Whiteside, 2021)	18	70
Williamson Corpus (Williamson, 2021)	17	66
Wozniak Corpus (Wozniak, 2021)	6	22
Wright Corpus (Wright, 2021b)	7	27
Grand Total	**254**	**928**

[a] from the same place as private dataset but is a different corpus that is public

Table 4.2: Participant and Transcript counts for AphasiaBank Corpuses used (Control Protocol)

Corpus Name	Participants	Transcripts
Capilouto Control Corpus (Capilouto, 2021)	74	292
Montclair State University Control Corpus (Boyle, 2021)	9	56
Kempler Control Corpus (Kempler, 2021a)	1	4
Richardson Control Corpus (Richardson, 2021)	57	168
Wright Control Corpus (Wright, 2021a)	97	286
Grand Total	**238**	**806**

Table 4.3: Participant and Transcript counts for POLAR (UofSC) data

Corpus Name	Participants Count	Transcript Count
POLAR Project Corpus	53	901

§ 4.2 POLAR (UofSC)

The second piece of data for this work came from a collaboration [3] at the University of South Carolina (UofSC). The participants for this dataset were recruited by the Center for Study of Aphasia Recovery (C-STAR) at UofSC - headed by Dr. Julius Fridriksson - as part of an ongoing multi-year research project called POLAR. The data made available to us is not publicly posted but will be post completion in accordance with NIH data sharing policy [4]. This data — unlike AphasiaBank — had many more repeat administrations of task. A total of 53 participants contributed 901 transcripts (see Table 4.3).

Table 4.4: Total Data Distribution across the entire dataset

Aphasia Type	Cinderella	Broken Window	Important Event	Sandwich
Broca	224	231	73	203
Conduction	119	123	53	110
Wernicke	39	42	24	31
Anomic	155	158	98	146
Control	245	247	73	241

The combined dataset had a grand total of 546 participants and 2,635 transcripts which makes it the largest study of its kind known to us, made possible by all the contributors mentioned above.

§ 4.3 Data Extraction

The speech transcripts were transcribed is a special speech transcription format called CHAT format (MacWhinney, 2000). CHAT format has a numerous amount of provisions for describing the interaction beyond just words. It has, for instance, provisions for writing down non-linguistic events like laughing or pointing at an object. It has provisions for writing down phonological fragments (partial word

[3]Our collaborator being Dr. William Matchin of the Arnold School of Public Health

[4]policy: https://grants.nih.gov/grants/policy/data _ sharing/index.html

Table 4.5: Neural Model vocabulary sizes for different tasks

Broken Window	2016
Cinderella	4711
Important Event	3788
Sandwich	1719

utterances) using IPA (International Phonetic Alphabet), it has provisions for encoding pauses in an utterance, adding timestamps to an utterance to align with the corresponding video resource etc. Since the purpose of this work was to study language of people with aphasia, almost all of this special information was deleted in favor of raw language content. For those in the know of the format, the steps taken are described next in brief. Time markers were deleted and interactional markers (‡ and „) were replaced with a single ','. All other special punctuations were also replaced with their English counterparts appropriately. Filled pauses (`um and uh`) were left in for they seemed indicative of hesitations and word finding difficulties and could be presenting useful information to the models. Unfilled pauses (`e.g., (...)`) were deleted and so were non-linguistics events (`e.g. &=laughs, &=coughs etc.`). Paraphasias were replaced with intended target wherever the transcriber had made the annotation and all unfixed paraphasias were replaced by symbol "x". The symbol "x" with the neologism tag "@n" is used in the dataset to also denote paraphasia where the transcriber couldn't make out the intended target - this was also reduced to just "x". In this manner, all the paraphasias were reduced to single special token. Word repetitions and re-tracings (denoted by [//]) were preserved so all the speech content was there as said by the participant, with no alterations. Partial utterances and other disfluencies (`for e.g. "&cin" and "&cinder" in "&cin &cinder cinderella"`) were however deleted for they were getting at the subword level and would've blown up the output vocabulary of the models with no real utility. This led to three model architectures, one for each discourse task.

§ 4.4 Model Vocabulary

The discourse elicitation tasks provide for a controlled experimental environment for eliciting speech. The vocabulary used by a participant is constrained by the discourse task used and so the output vocabulary of a language model was also constrained. It could not be set to the entire English dictionary for almost virtually all of the words in the output would then remain unseen during training in that case. The input and output vocabulary of a model was set to the union of all the words in all the transcripts for the corresponding discourse task. The resulting vocabulary sizes are shown in Table 4.5

§ 4.5 Language Model Architecture

The language models employed a recurrent architecture as shown in Figure 4.1. The architecture uses randomly initialized trainable word embeddings of length 200 for representing words. This vector representation is passed through two LSTM cells with different output vector dimensions - 200 and 800. The output of the second cell is linked to a linear layer and the Softmax function generating a probability distribution over the dictionary. The architecture is very similar to the one used in (Cohen and Pakhomov, 2020). This architecture was adopted after a fair bit of experimentation. Using vanilla RNN cells and/or a single recurrent layer was not found to be as effective as well as using 2 LSTM layers.

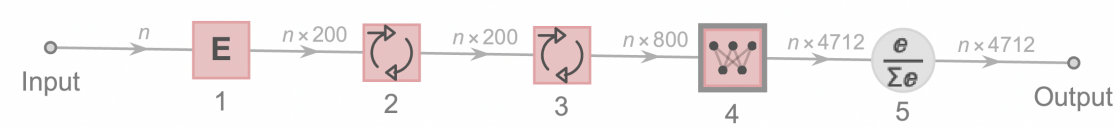

Figure 4.1: Language model architecture for the Cinderella task. There are five layers in the network: Layer 1 is the word embedding layer. Layers 2 & 3 are Recurrent Layers. Layer 4 is a Linear Layer and Layer 5 is a softmax function outputting a probability distribution.

§ 4.6 Training Examples & Hyper-parameters

The language models were trained on full length transcripts (as opposed to finite length examples drawn form transcripts). Batch size was set at 32 and the models were trained using cross-entropy loss functions described in previous chapter for 10 epochs. At the end of each epoch, training loss was recorded and the best epoch was picked at the end.

CHAPTER 5

CLASSIFICATION

This chapter presents the language models created using methods described in the previous chapter and subjects them to a classification task. The task tests their ability to discriminate between healthy control speech transcripts and transcripts pertaining to an aphasic group.

§ 5.1 Method

There are five participant groups in this study: Broca's aphasics, Wernicke's aphasics, Conduction aphasics, Anomic aphasics and Healthy controls, and there are four discourse tasks as outlined in Section 2.2 - Cinderella, Window, Sandwich & Event. A range of classification scenarios were constructed each pitting a model trained on transcripts from individuals with aphasia against the control model trained on the same discourse task and the paired models were subject to their training data as test data yielded via a leave one out cross validation scheme. Against each transcript, the less perplexed model was taken to be representing the test transcript's group and allowed to assign its label to the transcript. This method was called the lower perplexity method and it varies slightly from the works presented in introduction (Cohen and Pakhomov, 2020, Wankerl et al., 2017, Fritsch et al., 2019) in that they used the difference in perplexity between the two models as a single feature for classification while this one sees perplexities as likelihood estimates directly. In this manner, automated diagnoses using language models were arrived at for all transcripts. The specific cross validation scheme that was used here is called leave one participant out cross validation (James et al., 2021). Under this scheme, all the transcripts pertaining to a single participant are separated out of the training data during each run. This takes care of the fact that each participant could have contributed multiple transcripts (through multiple visits) and the participant in its entirety remains unseen to the models.Leave one out cross-validation, although allows for maximal use of the available data, is computationally very expensive. A grand total of 1,886 models had to trained for this study. All the results presented in this work were derived using this scheme, never was any table or plot drawn from already seen data. The GPU time needed for training models and computing results for this entire study was of the tune of 5-7 days on an NVIDIA Tesla V100 GPU. This is mentioned to advise anyone wishing to replicate these results.

§ 5.1.1 Baseline

The baseline model is set to be the null model i.e., a model that ignores the input and simply outputs the majority class from the training set. This sets the minimum expectations (accuracy) from a model and also gives an idea of how hard the problem is. A good way of characterizing a model's performance is as percent improvement over the baseline.

§ 5.1.2 Confusion Matrix

A confusion matrix shows the classification results from the cross-validation, comparing the neural network's output to the clinician's diagnosis. The correct predictions (agreement between the neural network and the clinician) lay on the main diagonal (going from top left to bottom right) and the incorrect or confused data points lie on the anti-diagonal. The sum across all cells corresponds to the total number of data points and the model accuracy is the main diagonal sum divided by the sum over the entire grid.

§ 5.1.3 Difference in Perplexity Plot

The perplexity difference plot helps visualize the difference in perplexity across an entire set of transcripts in a given comparison scenario. Transcripts are laid out on the X-axis and the Y-axis notes the perplexities. The yellow line was made to represent an individual's own group model's perplexity [1] while the blue line was made to represent the other group model's perplexity. So in a Broca vs Control scenario, for a transcript of a person with Broca's aphasia, the own group model would be a Broca's model while the other group model would be Control model, and it would be the other way around if the transcript was

[1]Note that since a leave one participant out cross validation scheme is being followed, the own group model denotes the language model trained on all the transcripts belonging to the individual's group but his or her own transcripts. the other group model in contrast is trained on every transcript for that group

from a person from the control group - the own group model in that case would be a Control model and the other model would be Broca's model. This line plot helps visualize how the two perplexities vary across a set of transcripts. Own group perplexity line staying below the other group perplexity line indicates correct classifications - for the model trained on one's own group's speech transcripts is showing lower perplexity - and any jumps above the blue line signal a misclassification. The area between the two lines serves as a measure of the difference in perplexity. The transcripts were simply sorted on other group perplexity (blue line) just so that one of the lines would behave and then one would be able to see what other line was doing relative to it.

§ 5.2 Broca vs Control

The classification accuracy across discourse tasks is very high for all classification scenarios involving Broca's aphasia, as reflected in confusion matrices in Table 5.1. The numbers stand at close to double the baseline indicating that the neural architecture and the proposed classification method are competent at separating people with Broca's aphasia from controls using any of the discourse tasks considered in this study. Furthermore, the amount of data available per task was also highly variable as can be gleaned from the data distribution table of the previous chapter (see Table 4.4) - ranging from 73/73 (Broca/Control) for the Event task to 231/247 for the Window task. This indicates that the method employed is robust to the amount of training data available as well for this type of aphasia (and other types too as demonstrated in the subsequent sections). The difference in perplexity plots laid out in Figure 5.1 show a wide gap in perplexities across tasks demonstrating that the models are discriminating with ease.

§ 5.3 Wernicke vs Control

In comparison to people with Broca's aphasia, the accuracies were not as high for scenarios involving people with Wernicke's aphasia, as shown in Table 5.2. The overall accuracy remains high since there's almost no confusion regarding control cases and there are a lot of control cases but that class imbalance also means that the baseline accuracies were high to begin with. At least 2 factors could be contributing to this comparatively poor observed performance level - (1) lack of training data - the least amount

Table 5.1: Broca vs Control: Confusion Matrices

cinderella	neural network		
		broca	control
clinician	broca	204	20
	control	1	244
		accuracy	95.5224
		baseline	52.2388

window	neural network		
		broca	control
clinician	broca	206	25
	control	0	247
		accuracy	94.7698
		baseline	51.6736

sandwich	neural network		
		broca	control
clinician	broca	192	11
	control	0	241
		accuracy	97.5225
		baseline	54.2793

event	neural network		
		broca	control
clinician	broca	62	11
	control	0	73
		accuracy	92.4658
		baseline	50.

of training data was available for people with Wernicke's aphasia and the most amount of data was on controls generally, so this data imbalance could have played a role, and/or (2) the fact that Wernicke's aphasia is a fluent type of aphasia and speech, although semantically bizarre, can possess good grammar and this may be presenting a harder learning problem than before (Broca's). In any case, performance on Sandwich task was better than other tasks - controls were classified nearly perfectly and people with Wernicke's aphasia were classified with an accuracy of about 75%. Figure 5.2 shows shows difference in perplexity plots for comparison scenarios pertaining to Wernicke's. There were fewer points (transcripts) compared to the Broca's vs Healthy Controls task (previous section) and a higher proportion of errors.

§ 5.4 Anomic vs Control

Classification results for comparison scenarios pertaining to people with Anomic aphasia are presented in Table 5.3. The classification accuracy is fairly high for this scenario ranging roughly from 86-91 percent, with the method being more performant on Sandwich and Event tasks. The perplexity difference plots are presented in Figure 5.3 and they are notably different than those presented for Broca vs Control. The difference between the lines is quite thin and although there is separation and the classification decisions - although still correct to a high degree - are being made at a much shorter margin than Broca's. The two

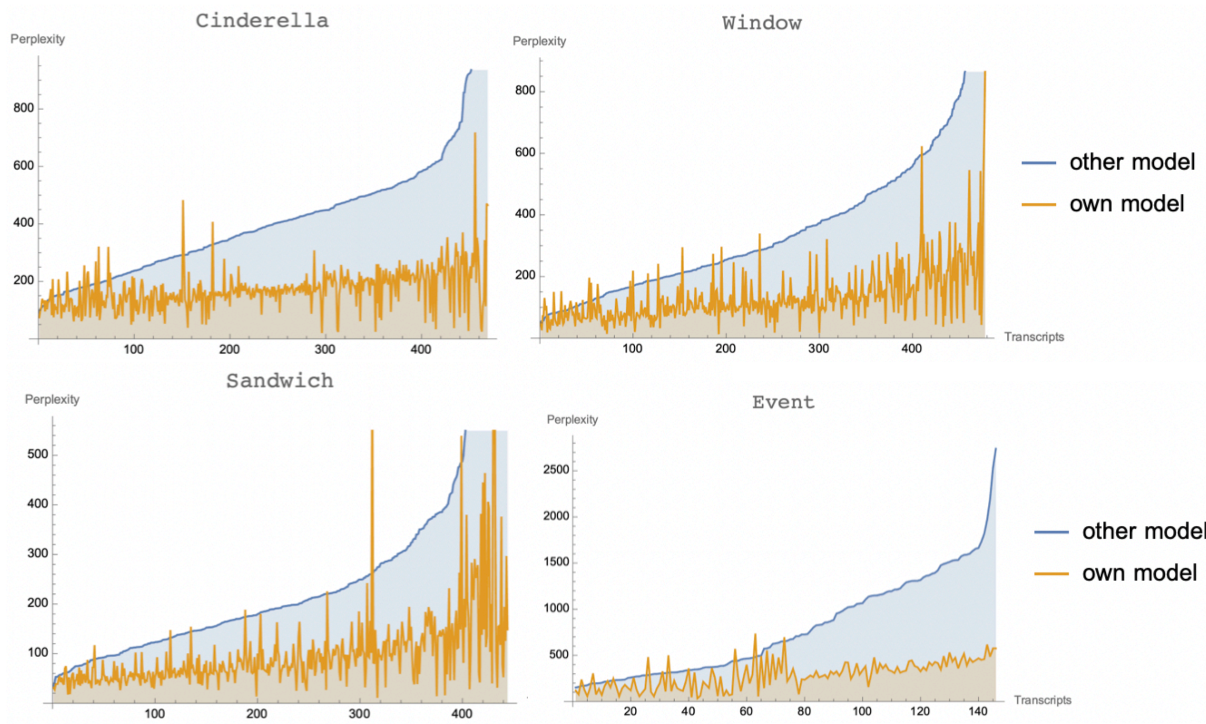

Figure 5.1: Broca Vs. Control - Perplexity Difference Plots

language models are finding speech from each other's group rather familiar; so language alteration in case of Anomic aphasia does not seem to be as distinct as Broca's.

§ 5.5 Conduction vs Control

Classification results for this comparison scenario are presented in Table 5.4. The language models are, once again, a significant improvement over the baselines from the majority class classifier signaling that the neural architecture and the classification scheme are still performant. The classification accuracy is especially high for the Sandwich task, surpassing the 95% mark, while at the same time, there is a fair bit of confusion when it comes to the Event and Window tasks. The confusion remains mainly with Conduction group however, the classification of controls is almost perfect regardless of the task. The difference in perplexity plots are shown in Figure 5.4; the perplexity difference remains thin like last time with the own model perplexity line closely following the other model perplexity line.

Table 5.2: Wernicke vs Control: Confusion Matrices

cinderella	neural network		
clinician		control	wncke.
	control	245	0
	wncke.	17	22
		accuracy	94.0141
		baseline	86.2676

window	neural network		
clinician		control	wncke.
	control	247	0
	wncke.	18	24
		accuracy	93.7716
		baseline	85.4671

sandwich	neural network		
clinician		control	wncke.
	control	240	1
	wncke.	8	23
		accuracy	96.6912
		baseline	88.6029

event	neural network		
clinician		control	wncke.
	control	73	0
	wncke.	11	13
		accuracy	88.6598
		baseline	75.2577

Table 5.3: Anomic vs Control: Confusion Matrices

cinderella	neural network		
clinician		anomic	control
	anomic	106	49
	control	4	241
		accuracy	86.75
		baseline	61.25

window	neural network		
clinician		anomic	control
	anomic	106	52
	control	4	243
		accuracy	86.1728
		baseline	60.9877

sandwich	neural network		
clinician		anomic	control
	anomic	119	27
	control	8	233
		accuracy	90.9561
		baseline	62.2739

event	neural network		
clinician		anomic	control
	anomic	81	17
	control	1	72
		accuracy	89.4737
		baseline	57.3099

Table 5.4: Conduction vs Control: Confusion Matrices

cinderella	neural net		
clinician		cond.	control
	cond.	91	28
	control	1	244
		accuracy	92.033
		baseline	67.3077

window	neural network		
clinician		cond.	control
	cond.	83	40
	control	0	247
		accuracy	89.1892
		baseline	66.7568

sandwich	neural network		
clinician		cond.	control
	cond.	95	15
	control	1	240
		accuracy	95.4416
		baseline	68.661

event	neural network		
clinician		cond.	control
	cond.	30	23
	control	0	73
		accuracy	81.746
		baseline	57.9365

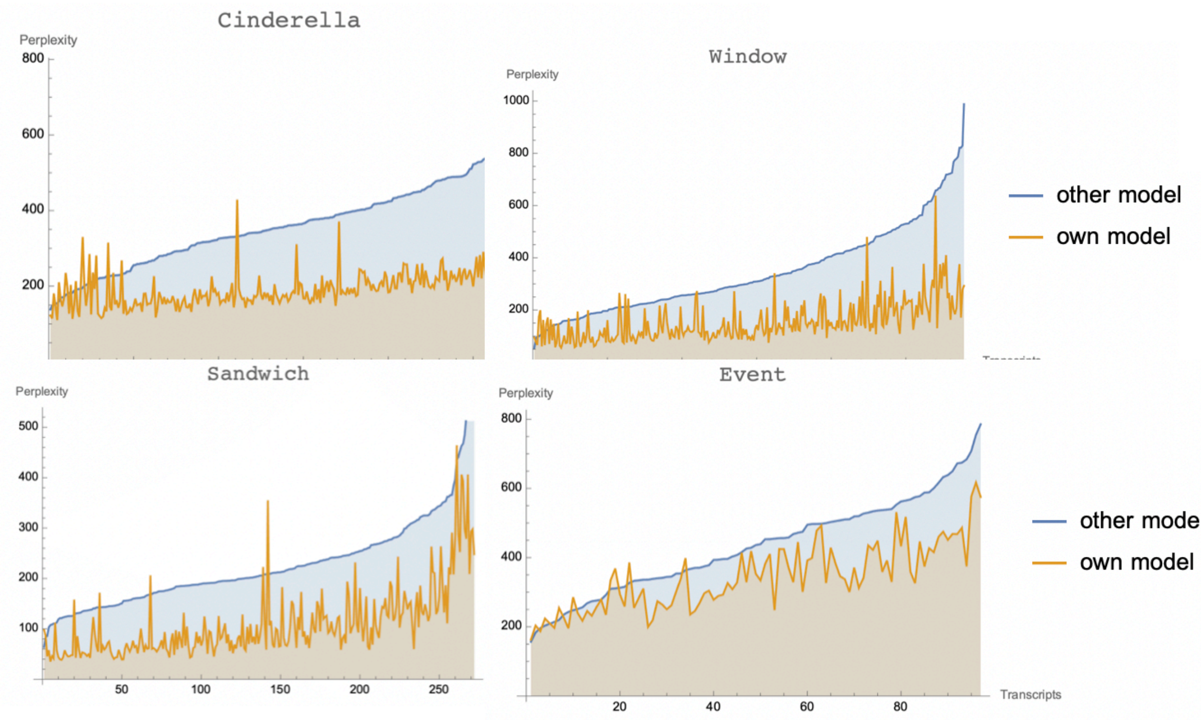

Figure 5.2: Wernicke Vs. Control - Perplexity Difference Plots

§ 5.6 Discussion

Overall, the lower perplexity method and the accompanying neural architecture seem to be very effective at discerning between speech of an aphasic population and healthy controls. In terms of discourse tasks, Sandwich task comes out at top - it consistently provided the highest accuracies across all aphasia types. While getting speech data from multiple varied elicitation tasks is desirable for clinicians so as to paint a complete picture of a participant's language abilities (Stark and Fukuyama, 2020), clinician's and transcriber's times are quite expensive and if a task recommendation were to be made, especially with the view of making a diagnostic tool, Sandwich task would be the one. The classification accuracy for any aphasia type comparison was the highest for the Sandwich discourse task. In terms of Aphasia types, accuracies were particularly high for scenarios created for people with Broca's aphasia. It would be worth noting here that Broca's aphasia was the only non-fluent aphasia type among the types considered in our study,

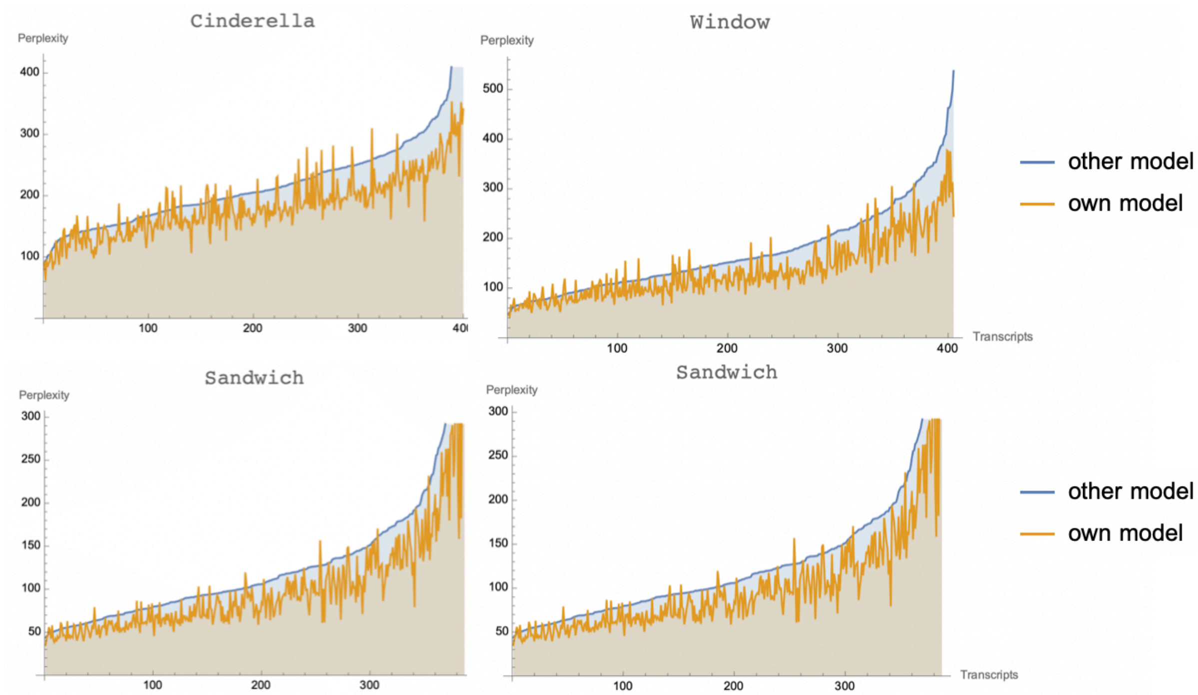

Figure 5.3: Anomic Vs. Control - Perplexity Difference Plots

and we have only considered input from language production tasks here. A clinician's diagnosis is based on evaluations along two additional testing dimensions - repetition and comprehension, so perhaps given the distinct and severe language alteration in Broca's aphasia, production task carries enough information for an accurate diagnosis of this type to be made. The other types in this study - all fluent aphasia types - perhaps pose a harder problem in absence of data form those additional tasks. Nonetheless, language production is never spared in aphasia, so language signal is a strong one and the method was generally performant. Moreover, the accuracy never dipped blow 90% if we only consider the Sandwich task.

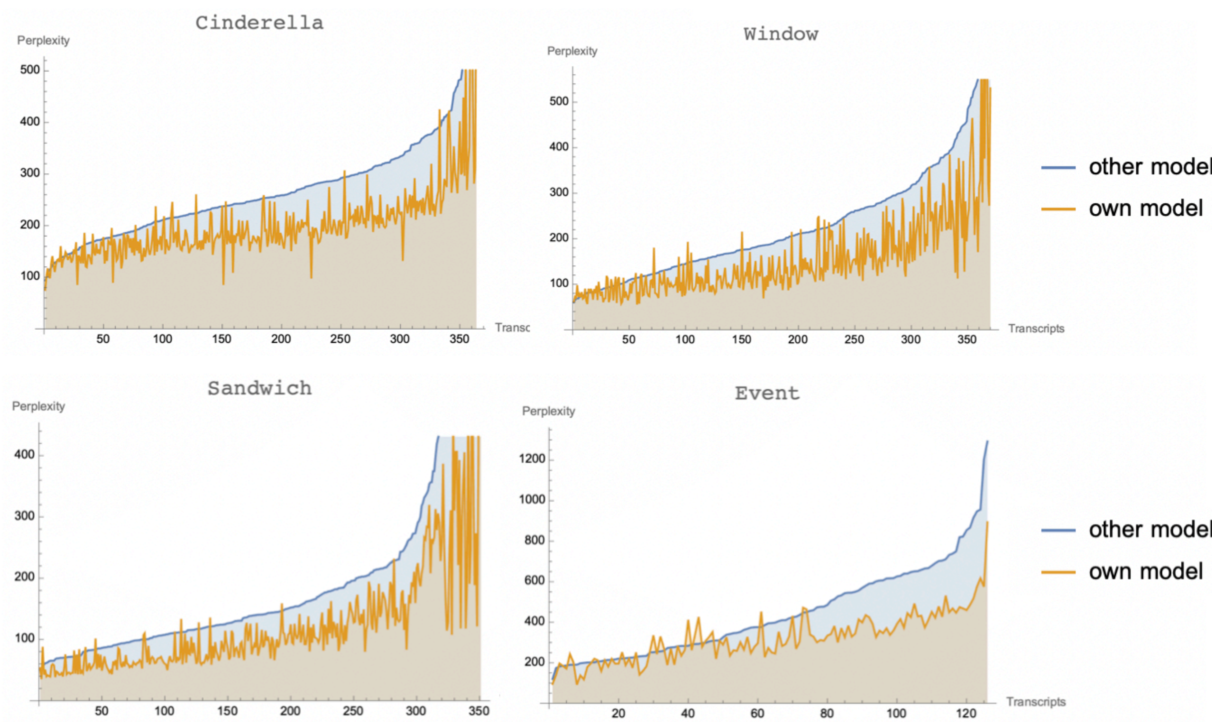

Figure 5.4: Conduction Vs. Control - Perplexity Difference Plots

CHAPTER 6

PROBING

The previous chapter showed that the language models based classification method - termed lower perplexity method - was able to significantly improve over the majority class baseline classifier for a range of classification scenarios and discourse elicitation tasks. This chapter probes into the language models to find out what they've learnt by looking at what words (or lexical categories of words) are driving the difference in perplexity observed in Chapter 5. It interprets these differences in terms of linguistics properties of the various aphasia syndromes.

§ 6.1 Method

Language models are sequence models that 'read' a transcript word by word, generating probability distribution for a next word in the sequence before actually 'seeing' it. The actual surprisal at 'seeing' that next word underlies the calculation of overall perplexity for perplexity is nothing but a monotonically increasing function of mean surprisal across all words, as presented in Section 3.4. So, as our two models are 'seeing' a transcript together, the word level difference in surprisal underlies the outcome. The model that is at an average less surprised wins the 'race' and gets to assign the new transcript its label.

Let s_{own} and s_{other} be the surprisals of the two models on seeing the i^{th} word or token w_i of the transcript and define a quantity called influence to be the difference between the two taken as $s_{other} - s_{own}$. A positive influence serves to widen the gap in perplexities while a negative difference serves to bridge that gap. A positive sum total leads to a correct classification outcome.

Table 6.1: Special Part of Speech Tags Used

Special PoS Tag	**Description**
unintelligible (xxx)	The symbol xxx is used when the transcriber can not hear or understand what the speaker is saying
paraphasia (x)	This special token stands for paraphasias which are a type of language output errors commonly associated with aphasia, and characterized by the production of unintended syllables, words, or phrases during the effort to speak.
terminal	This is a special token '<end>' used to mark the end of a discourse
filler	Denotes a filled pause like 'um' or 'uh'

§ 6.2 Example

This section walks through a surprisal difference plot showing the probing method presented above in action. Figure 6.1 shows the influence values for words in a transcript of a person with Broca's aphasia who is retelling the Cinderella story. Some things worth observing are: (1) unrevealing start of the discourse - the words 'i am' didn't make the decision lean in any direction by any significant amount, it was the subsequent words that made big influences on difference in perplexity, (2) paraphasias had big positive influence on the decision. These were the made up words 'trella', 'trellawilson', 'trellawella', 'frellarella', 'frellya' and 'frillowella'. The control (other) model found them to be significantly more surprising than Broca's (own). (3) The unintelligible speech token 'xxx' (refer 6.1) was very revealing of aphasic speech as well imparting the highest positive influence for any token in the example. (4) On the other hand, the occurrences of word 'means' and 'being' are serving to confuse the model by imparting a significant negative influence. The sum total remains positive nonetheless and the final classification decision is in agreement with the clinician. (5) The end of discourse token '<end>' also left a positive influence which makes sense in light of the fact that people with Broca's aphasia have lower productivity than healthy controls, and that translated into Broca's model being more eager to terminate the discourse at that point than the control.

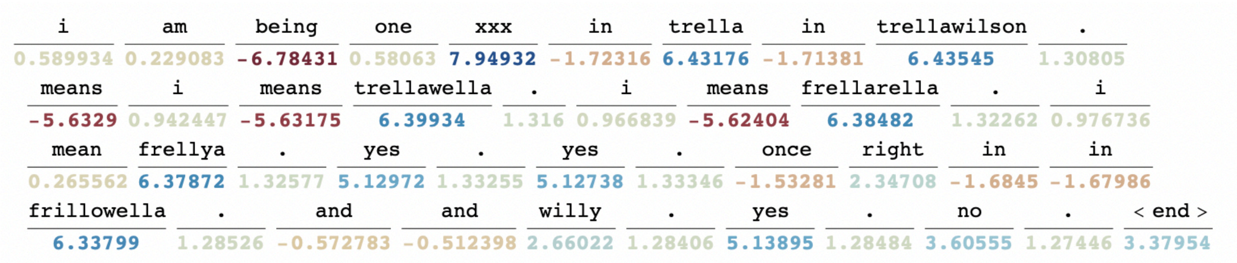

Figure 6.1: Token-wise influence computed for a transcript of a person with Broca's aphasia who is retelling the Cinderella story. The influence values are written under the words and color coded using a heat-map coloring scheme. Strong positive values are colored deep blue and the negative ones are coded red. Net influence here is positive so the final classification decision here is correct.

§ 6.3 Analysis

Individual words were analyzed across all the comparison scenarios and tasks presented in the last chapter for their mean influence and percent total influence to figure out the drivers for the perplexity difference (the separation between blue and yellow lines). The total influence for a word was computed as the sum total of individual influence values over all the instances of the word. Percent total influence for a word was computed as its total influence divided by the (absolute) sum of total influence for all words.

As an example, consider the occurrences of some select tokens on the Control side and Broca's side in a Broca vs Control comparison scenario employing the transcripts from the Cinderella task (Tables 6.2 and 6.3). On the Broca's side (Table 6.2), the closed class elements ('of','to','her','was','she','the') can be seen exerting a negative influence meaning that the Broca's model is more surprised to see these than the Control model which is a reasonable thing for the models to be doing for the production of closed class elements is a marked impairment in Broca's aphasia.The paraphasia token ('x') and the unintelligible speech token ('xxx') were, on the other hand exerting a high positive influence, helping push the classification decision in the correct direction. Note that because of the very low occurrence counts of the closed class elements, the negative influence doesn't serve to confuse the models much (i.e. low percent total values). The paraphasia and unintelligible speech tokens had high percent total contributions on the other hand.

Table 6.2: Broca's side: Summary Statistics for some select words in transcripts of people with Broca's aphasia on the Cinderella story re-tell task. Elements with positive influence are ones that were found to be more surprising by the control model than the Broca's model.

Token	PoS Tag	Mean	Occurrences	Percent Total
x	paraphasia	5.95507	2007	13.2771
xxx	unintelligible	7.68604	1489	12.7136
um	filler	2.68489	2448	7.30142
stepsisters	noun	-5.92394	9	0.0592274
of	preposition	-2.65172	146	0.430081
was	verb	-1.59074	282	0.498332
her	pronoun	-3.20512	182	0.648016
to	preposition	-1.74467	500	0.969066
she	pronoun	-2.12216	608	1.43335
the	determiner	-0.952404	2458	2.60059

The inverse of these claims are true for the Control side (Table 6.3). Closed class elements are exerting a positive influence here and are present in far greater numbers (hence greater percent total influence). The paraphasia ('x') [1] and unintelligible speech token ('xxx') were however having a negative influence on the control side, which is again a reasonable things for these models to be doing. The occurrences of these two tokens on the control side is however low which leads to a low percent total contribution.

The combined summary statistics from the two tables - i.e., the entirety of transcripts in the comparison scenario; both Broca's and Control - are shown in Table 6.5. The subsequent tables in this chapter are all listing combined statistics, picking only the top $10s$ by percent total influence in each comparison scenario.

§ 6.4 Broca vs Control

The probing results for comparison scenarios pertaining to people with Broca's aphasia are presented in Tables 6.2 through 6.5. Looking at the tokens, one can glean that the paraphasia token 'x' and the unin-

[1] The paraphasias on control side are appearing for there were some out of standard English dictionary elements (the default dictionary in Wolfram Mathematica was used for this work) in control transcripts. Perhaps these should've been manually corrected for but the occurrences on control side are very low with very little contribution to percent total influence so they don't have much influence on the decision making

Table 6.3: Control side: Summary Statistics for some select words in transcripts of healthy controls on the Cinderella story re-tell task. Elements with positive influence are ones that were found to be more surprising by the Broca's model than the Control model.

Token	PoS Tag	Mean	Occurrences	Percent Total
x	paraphasia	-6.06549	133	0.343946
xxx	unintelligible	-7.8466	28	0.0936725
um	filler	-2.63483	1369	1.5379
stepsisters	noun	4.6796	511	1.01953
of	preposition	2.84434	1640	1.98883
was	verb	1.68531	1760	1.26464
her	pronoun	3.09623	3426	4.52265
to	preposition	1.73871	4242	3.14464
she	pronoun	1.86461	4134	3.28648
the	determiner	0.776381	8708	2.88248

telligible speech token 'xxx' were generally highly influential - as measured by both percent influence and mean influence - and by the fact that they made it to the top-10 on 3/4 tasks. Paraphasias are a hallmark of aphasic speech and the unintelligible speech token is also related to paraphasias (see Table 6.1), and the neural models seem to have picked up on it. A salient feature of speech in Broca's aphasia is that it is telegraphic and lacks the use of closed class lexical elements. The tables presented are absolutely dominated by closed class lexical elements - these would be all the pronouns, prepositions, particles, determiners and conjunctions in terms of part of speech tags. Rarely any verbs show up and of those that do, only one of them is a lexical verb. The other three are auxiliary verbs or linking verbs which are again closed class elements. These tables show that the neural language models have picked up on a well known aspect, if not the most salient feature, of speech of people with Broca's aphasia. Figure 6.2 shows a diagnosis of a control transcript in this scenario. Being control, the speech is fluent and full of function words that are overwhelmingly exerting a positive influence on the classification decision

§ 6.5 Wernicke vs Control

The probing results for comparison scenarios pertaining to people with Wernicke's aphasia are presented in Tables 6.6 through 6.9. The speech in Wernicke's aphasia is known to be semantically bizarre or off

Table 6.4: Broca vs Control: Top 10 tokens for Broken Window picture description task

Token	PoS Tag	Mean	Occurrences	Percent Total
his	pronoun	6.01802	497	5.57758
xxx	unintelligible	7.12317	289	3.8389
x	paraphasia	4.03512	468	3.52158
neighbor	noun	11.3878	149	3.16417
through	preposition	3.15162	302	1.77491
um	filler	1.2198	695	1.58091
playing	noun	4.98069	166	1.54182
soccer	noun	1.79027	436	1.4556
young	adjective	11.4801	65	1.39153
window	noun	0.892993	787	1.31056

Table 6.5: Broca vs Control: Top 10 tokens for Cinderella story retelling task

Token	PoS Tag	Mean	Occurrences	Percent Total
xxx	unintelligible	7.39935	1517	4.83773
x	paraphasia	5.208	2140	4.80338
her	pronoun	2.77836	3608	4.32034
to	preposition	1.37142	4742	2.80282
she	pronoun	1.35344	4742	2.76607
the	determiner	0.39582	11166	1.90483
of	preposition	2.39505	1786	1.84357
um	filler	0.776928	3817	1.2781
was	verb	1.23289	2042	1.08503
stepsisters	noun	4.49607	520	1.00763

Table 6.6: Broca vs Control: Top 10 tokens for Important Event narrative task

Token	PoS Tag	Mean	Occurrences	Percent Total
the	determiner	2.18688	1164	3.54325
was	verb	2.07796	804	2.3255
of	preposition	3.28821	445	2.03677
in	preposition	2.88507	466	1.8714
and	conjunction	0.778954	1719	1.86385
had	verb	3.24706	332	1.50056
yeah	adverb	5.04849	205	1.44058
we	pronoun	2.80109	352	1.37244
him	pronoun	11.0126	89	1.36428
out	particle	11.2449	84	1.3148

Figure 6.2: Broca vs Control: Neural Networks diagnosing a control sample (richardson192). The transcript is full of function words, which are exerting an overwhelmingly positive influence.

topic in a conversation. One thing that immediately springs out in the tables is that they're filled with main elements expected in a response (which is unlike Broca's tables which were filled with function words). For the Window task, these would be the soccer ball, window, kicking, neighbor and window; for the Cinderella task, it would be cinderella, stepsisters, ball, stepmother and prince; for the peanut butter and jelly task, these would be take, bread, slices and spread. It would seem that an appropriate response to this task must make a mention of these elements and yet, as can be seen in the detailed distribution in Table 6.12, these are rarely being mentioned by Wernicke's group. Granted, there was an asymmetric data

Table 6.7: Broca vs Control: Top 10 tokens for PB & J Sandwich procedural description task

Token	PoS Tag	Mean	Occurrences	Percent Total
x	paraphasia	5.79512	513	5.26289
of	preposition	2.51942	1054	4.70095
the	determiner	1.0232	2503	4.53382
you	pronoun	1.82818	1178	3.81248
xxx	unintelligible	7.54517	257	3.43278
take	verb	4.29118	350	2.65882
on	preposition	1.84489	795	2.59646
out	particle	4.65299	270	2.22402
peanutbutter	noun	12.4401	98	2.15821
your	determiner	6.24783	167	1.8471

distribution with very few Wernicke's transcripts (refer Table 4.4) - but the occurrences are still extremely low. For instance, in the 42 Wernicke's transcripts on the Window task, the word 'window' appears 26 times - not even one mention per transcript. As another examples, the word 'spread' appears nowhere in any of the Wernicke's group members' response to the task asking for the recipe for a peanut butter and jelly sandwich. Semantically bizarre indeed and the neural models seem to have picked up on this known feature of speech of people with Wernicke's aphasia. Note that unlike for people with Broca's aphasia, the paraphasia token ('x') and the unintelligible speech token ('xxx') have not made it to top-10s this time. Figure 6.3 shows an example diagnosis of a control transcript in this scenario. The Wernicke's model appeared to be more surprised at the mentions of main elements of the Cinderella storyline, many of which are highlighted to make it convenient to see them

§ 6.6 Anomic vs Control

The probing results for people with Anomic aphasia are presented in Tables 6.10-6.13. People with this type of aphasia have fluent speech but are faced with chronic word retrieval difficulties. In a speech transcript, these word finding difficulties often show up in the form of pauses. The tokens 'um' and 'uh' correspond to filled (meaning not silent) pauses and these fillers show up in the top-10 tokens for 3 out of 4 discourse tasks. This is again a demonstration that these neural models are picking up on known linguis-

Table 6.8: Wernicke vs Control: Top 10 tokens for Broken Window picture description task

Token	PoS Tag	Mean	Occurrences	Percent Total
window	noun	2.61248	698	4.29725
neighbor	noun	11.001	149	3.86277
soccer	noun	3.41603	390	3.13957
his	pronoun	2.42073	504	2.87515
the	determiner	0.401033	2153	2.03473
kicking	noun	6.42496	123	1.86234
ball	noun	1.15249	664	1.80338
to	preposition	1.44032	455	1.54438
through	preposition	2.19086	294	1.5179
a	determiner	0.723147	780	1.32924

Table 6.9: Wernicke vs Control: Top 10 tokens for Cinderella story retelling task

Token	PoS Tag	Mean	Occurrences	Percent Total
her	pronoun	1.46847	3574	2.67387
to	preposition	0.999631	4489	2.28618
prince	noun	4.08389	1087	2.26165
xxx	unintelligible	5.0283	679	1.73945
stepmother	noun	6.5178	511	1.69685
a	determiner	1.15732	2715	1.60083
of	preposition	1.82542	1701	1.58194
ball	noun	2.80154	1010	1.44158
cinderella	noun	1.82066	1546	1.43403
stepsisters	noun	5.12859	516	1.34824

Table 6.10: Wernicke vs Control: Top 10 tokens for Important Event narrative task

Token	PoS Tag	Mean	Occurrences	Percent Total
the	determiner	2.22952	1176	7.12104
he	pronoun	2.23977	355	2.15952
in	preposition	1.57801	478	2.04862
of	preposition	1.54531	463	1.94322
"	punctuation	1.61936	396	1.74166
on	preposition	2.588	207	1.45499
a	determiner	0.717008	726	1.41379
was	verb	0.529736	851	1.22437
his	pronoun	5.55365	81	1.22177
my	pronoun	1.37783	319	1.19375

Table 6.11: Wernicke vs Control: Top 10 tokens for PB & J Sandwich procedural description task

Token	PoS Tag	Mean	Occurrences	Percent Total
you	pronoun	2.72644	1094	5.75971
spread	verb	9.27897	279	4.99909
of	preposition	2.26413	1017	4.44641
would	verb	5.62044	313	3.39705
the	determiner	0.692926	2214	2.96245
take	verb	4.38978	349	2.95839
and	conjunction	0.756216	1901	2.77597
on	preposition	1.87759	754	2.73375
bread	noun	1.43836	871	2.4192
slices	noun	8.07319	153	2.38519

Table 6.12: Wernicke vs Control: Frequency Distribution of selected Main Elements

Token	PoS Tag	Control Total	Wernicke Total	Grand Total
window	noun	672	26	698
neighbor	noun	149	0	149
soccer	noun	377	13	390
kicking	noun	121	2	123
ball	noun	620	44	664
prince	noun	1072	15	1087
stepmother	noun	506	5	511
ball	noun	995	15	1010
cinderella	noun	1508	38	1546
stepsisters	noun	511	5	516
spread	noun	279	0	279
take	noun	345	4	349
bread	noun	841	30	871
slices	noun	153	0	153

Figure 6.3: Wernicke vs Control: Neural Networks diagnosing a control sample (wright12) on Cinderella task. The mention of main elements - characters and key points in storyline are highlighted. Wernicke's model was usually much more surprised than control at these points in the discourse.

tic features of aphasia. Furthermore, consider the accurate diagnosis of a patient with anomic aphasia in Figure 6.4. At every instance of word finding difficulties (and unintelligible speech), the influence goes up. Difficulty in finding words is the hallmark symptom of this type of aphasia.

§ 6.7 Conduction vs Control

Results for people with Conduction aphasia are presented in Table 6.17 - Table 6.16. People with this type of aphasia have difficulty producing the correct phonetic structure of a word and this leads to frequent phonemic paraphasias in their speech. This difficulty is more likely to occur when a patient is trying to utter a word that is semantically important or phonologically complex. The tables are filled with words that are semantically important - window, neighbor, yard, playing, cinderella, stepsister, ball, slipper, bread, peanut butter etc. These were top drivers of difference in perplexity. This is similar to the case for

Table 6.13: Anomic vs Control: Top 10 tokens for Broken Window picture description task

Token	PoS Tag	Mean	Occurrences	Percent Total
um	filler	1.09746	608	3.36076
his	pronoun	1.06625	585	3.14166
uh	filler	0.66479	857	2.86953
practicing	verb	10.1601	50	2.55867
soccer	noun	0.716571	486	1.75405
a	determiner	0.321666	1004	1.62661
knocks	verb	4.13505	71	1.47872
,	punctuation	0.700904	416	1.46858
playing	noun	1.39058	198	1.38678
xxx	unintelligible	3.31579	63	1.05214

Table 6.14: Anomic vs Control: Top 10 tokens for the Cinderella story retelling task

Token	PoS Tag	Mean	Occurrences	Percent Total
um	filler	0.786482	4237	4.80169
xxx	unintelligible	4.35607	495	3.10704
to	preposition	0.223726	5884	1.89686
her	pronoun	0.258402	4428	1.64874
uh	filler	0.230432	4950	1.6436
of	preposition	0.547731	2009	1.5856
x	paraphasia	1.68263	624	1.51294
and	conjunction	0.0758542	12147	1.32769
,	punctuation	0.405082	2223	1.29757
stepsisters	noun	1.45106	579	1.21063

Table 6.15: Anomic vs Control: Top 10 tokens for the Important Event narrative task

Token	PoS Tag	Mean	Occurrences	Percent Total
um	filler	1.77419	893	5.75541
yeah	adverb	4.38202	187	2.97674
i	pronoun	0.182472	2799	1.85534
oh	interjection	2.268	169	1.39237
uh	filler	0.169599	1997	1.23034
the	determiner	0.159221	1691	0.978064
in	preposition	0.40505	661	0.9726
we	pronoun	0.448537	506	0.824466
had	verb	0.386977	453	0.636807
a	determiner	0.159687	1001	0.58067

Table 6.16: Anomic vs Control: Top 10 tokens for the PB& J Sandwich task

Token	PoS Tag	Mean	Occurrences	Percent Total
peanutbutter	noun	11.8685	101	5.60083
of	preposition	0.803098	1240	4.65291
you	pronoun	0.692628	1406	4.55009
the	determiner	0.262338	2986	3.66004
jar	noun	3.42706	184	2.94628
your	determiner	2.01361	179	1.68408
a	determiner	0.421302	841	1.65548
xxx	unintelligible	4.59408	77	1.65281
knife	noun	0.858253	359	1.43961
spread	verb	0.830413	346	1.34247

Table 6.17: Conduction vs Control: Top 10 tokens for Broken Window picture description task

Token	PoS Tag	Mean	Occurrences	Percent Total
his	pronoun	1.09961	596	2.45857
neighbor	noun	4.24261	152	2.41921
xxx	unintelligible	4.78445	124	2.22561
window	noun	0.685929	820	2.11003
yard	noun	9.49047	57	2.02936
playing	noun	2.84287	175	1.86634
practicing	verb	9.85159	50	1.84787
picks	verb	9.37997	47	1.65385
out	particle	1.65819	261	1.62357
through	preposition	1.04068	331	1.29223

Wernicke's in that tables are abundant with main elements of respective task but the elements here just happen to be different. The detailed distribution of these elements is shown in Table 6.21. Paraphasia token also shows up in top-10 for two out of the four tasks which again makes sense for frequent paraphasias is typical of speech production in Conduction aphasia. The unintelligible speech token 'xxx' shows up for three out of the four tasks. As an example, consider the correct diagnosis of a person with Conduction aphasia in Figure 6.5, The transcript is filled with phonemic paraphasias and the difference in surprisal is higher than normal at these place, meaning that the models are looking at phonemic paraphasias to discern that this is a patient with conduction aphasia, not a healthy control

Table 6.18: Conduction vs Control: Top 10 tokens for the Cinderella story retelling task

Token	PoS Tag	Mean	Occurrences	Percent Total
xxx	unintelligible	5.35681	858	4.12244
x	paraphasia	3.07335	1029	2.83654
to	preposition	0.514741	5258	2.42756
,	punctuation	1.01516	1987	1.80923
her	pronoun	0.4723	4240	1.79616
slipper	noun	2.72511	678	1.6572
cinderella	noun	1.06619	1685	1.61137
stepsisters	noun	3.05558	535	1.46625
ball	noun	1.43813	1092	1.40858
of	preposition	0.785432	1950	1.37374

Table 6.19: Conduction vs Control: Top 10 tokens for the Important Event narrative task

Token	PoS Tag	Mean	Occurrences	Percent Total
in	preposition	0.85865	598	1.66655
to	preposition	0.501057	997	1.62137
.	punctuation	0.117714	4087	1.56147
yeah	adverb	3.67386	118	1.40703
was	verb	0.391196	1032	1.31031
we	pronoun	0.692114	454	1.01984
day	noun	4.17708	69	0.935453
and	conjunction	0.13023	2041	0.862691
he	pronoun	0.614879	428	0.854149
of	preposition	0.364389	572	0.67649

Table 6.20: Conduction vs Control: Top 10 tokens for the PB & J Sandwich procedural description task

Token	PoS Tag	Mean	Occurrences	Percent Total
of	preposition	1.28975	1119	4.6811
the	determiner	0.530564	2561	4.40716
butter	noun	1.39674	907	4.10897
peanutbutter	noun	12.0894	83	3.25457
peanut	noun	0.962479	876	2.73469
you	pronoun	0.60591	1284	2.5234
bread	noun	0.737134	984	2.35263
xxx	unintelligible	6.21223	109	2.19627
x	paraphasia	3.21235	201	2.09426
out	particle	1.57697	285	1.45774

Table 6.21: Conduction vs Control: Frequency Distribution of selected Main Elements

Token	PoS Tag	Control Total	Conduction Total	Grand Total
neighbor	noun	149	3	152
window	noun	672	148	820
playing	noun	154	21	175
slipper	noun	642	36	678
cinderella	noun	1508	177	1685
stepsisters	noun	511	24	535
ball	noun	995	97	1092
butter	noun	837	70	907
peanutbutter	noun	83	38	83
peanut	noun	785	91	876
bread	noun	841	43	884

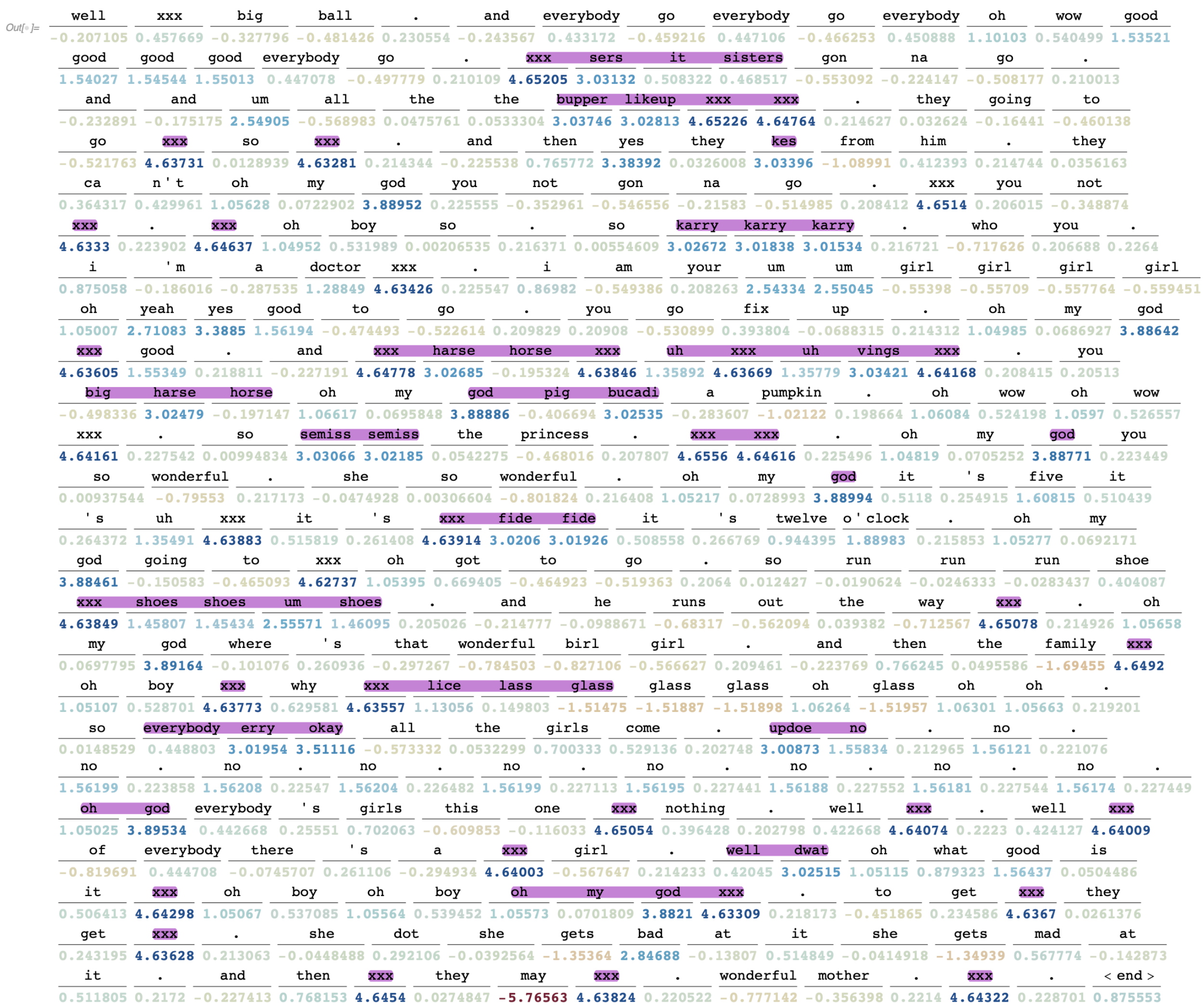

Figure 6.4: Anomic vs Control: Neural Networks diagnosing a patient with anomic aphasia (polar-1066). Word finding difficulties and unintelligible speech areas in the discourse are highlighted. These are notably showing high difference in surprisal meaning that the neural networks are driving difference in perplexity from these areas to make a correct classification.

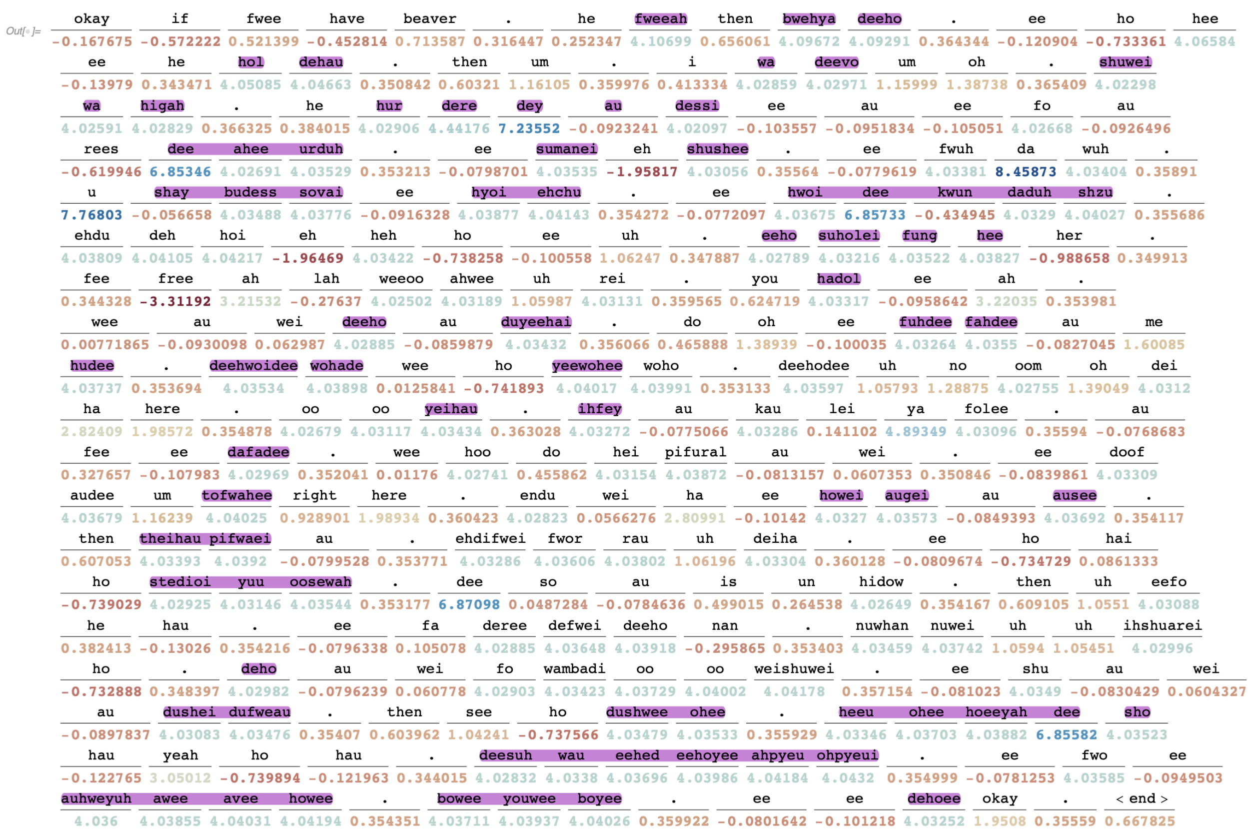

Figure 6.5: Neural Networks diagnosing a patient with severe conduction aphasia (polar-1056). The transcript is filled with paraphasias, many of them are highlighted. Once again, there is a high difference is surprisal associated with these paraphasias demonstrating that the paired models are aware of this salient feature of conduction aphasia.

CHAPTER 7

CONCLUSION

In this study, recent techniques proposed for automated diagnosis of Alzheimer's Disease (AD) were extended to people with aphasia. The language models developed for the purpose using a single neural architecture were found to be leading to significant improvements in classification accuracy over the baseline set by a majority class classifier. A varied set of discourse elicitation tasks were considered in our work to study the effect of task on performance. Here, it was found that the classification accuracies for the Sandwich task were maximum regardless of the aphasia type in question. From this observation, a task recommendation for eliciting language samples was made towards the goal of making an automated diagnostic tool for people with aphasia.

The language models had the highest performance for Broca vs Control comparison scenario regardless of the task, which is something that was speculated in the beginning. The reason for the speculation was the distinct language alteration in people with Broca's aphasia. The models quantify the agrammatic character of Broca's aphasia in terms of perplexity differences as shown in Figure 5.1 of Chapter 5.

In the second part of this study, the language models were probed to find out what was driving the difference in perplexities. Evidence was presented in support of the claim that the neural models were picking up on known linguistic deficits in aphasia. For Broca's models, the evidence came in the form of dominance of function words in the influence ranking tables. For people with Wernicke's aphasia, the influence ranking tables showed a significant number of instances of words capturing main story elements. These elements, however, were unevenly distributed between the two groups (healthy controls and people with Wernicke's aphasia) and were mostly presenting themselves in healthy control transcripts, as was detailed in the frequency distribution table (Table 6.12). So it could be inferred that (1) it was Wernicke's model that was finding these words more surprising and (2) this corresponded to the bizarre semantics of people with Wernicke's aphasia. For people with Conduction aphasia, a set of main elements – albeit different from Wernicke's – again showed up at in the influence rankings and these were once again unevenly distributed with heavy presence on the healthy control side. Like in instance of Wernicke's, it could be inferred that (1) it was the Conduction model that was finding these words more surprising and (2) this corresponded to the inability of people with conduction aphasia to get the semantically important elements of the discourse right. An example was also presented where the language models were found to be very sensitive to phonemic paraphasias of a person with severe conduction aphasia. A similar example was shown for people with Anomic aphasia where the difference in surprisal went up during the segments impacted by word finding difficulties.

APPENDIX A

The following is a list of all the paraphaisas in the dataset, in alphabetical order:

aaaakay, aahing, aahleen, aba, abah, abanick, abau, abc, abcd, abcde, abcdef, abcdefg, abcdefghih, abcdefghijkl, abcdesghij, abebber, aberdina, abew, accidently, adda, addsapt, adiosspa, adsid, advisor, af, afah, afer, affer, affily, afind, afster, aftily, afty, agro, ahah, ahahuwehhu, ahcross, ahee, ahek, ahh, ahhah, ahhs, ahiy, ahjes, ahjoot, ahjus, ahl, ahn, ahnta, aho, ahpyeu, ahris, ahs, ahsa, ahsess, ahso, ahsu, ahu, ahwee, ai, aight, aigun, ajoot, akidentally, alangerella, alanta, albost, aleak, aleh, aleksandr, alirght, allisuh, alls, allsa, allsuun, aloo, alow, alrightie, altanta, alway, amalaroo, amasin, amazingness, amd, amehlevyese, amercian, amose, ampa, ampah, ampamuh, amperor, ampuh, ampus, ams, analretentive, ance, anefing, aneses, angiously, anight, anmal, anmals, annt, anobai, anone, anoth, anpo, anses, ansy, anter, antithic, anuh, anwich, anytation, anyum, apgar, aplaying, apout, apper, appry, appy, apross, ard, arge, argh, arhar, aristocratette, arl, arman, armpin, armpra, armprin, arnold, arns, aroh, arou, ars, arviously, asa, asagna, asate, ase, aserjed, ases, asher, ashland, asidema, assa, assah, asss, assuh, ast, astre, atcher, atchu, ather, athol, atsidentally, attle, audee, audo, augei, auhweyuh, auntas, auntena, auntis, auntra, auntus, ausee, auta, autie, autis, auwizah, avee, avited, awa, awar, awchoo, awday, awdayus, awdis, awdiss, awdisses, awdisseses, awdoe, awduh, awee, awhy, awich, awjus, awound, awses, awshhh, awtis, aww, awwess, awzis, ayayay, ayed, ayone, aysi, ayway, azit, bɑ, bəɚ, babeli, babril, babwi, bacheloet, bachelorettes, backet, backly, backy, badakapan, badess, badih, bads, baduh, badus, bae, baed, baeg, bahal, bahb, bahd, bahoo, bahoyee, baid, baier, bains, bairy, bakt, balati, balla, ballie, bameh, bamich, bammo, bampa, bana, banabaums, bananutbutter, banbee, bandoet, banky, bann, bannel, banny, bansed, bants, banuhnuh, bappy, barbart, bardy, barket, bashaball, basih, bassing, bassy, bæt, batended, bater, batsing, batt, battuh, bau, baudi, baught, bauki, baus, baut, bavee, baw, bayeedee, bayih, bayk, bayses, baz, bɚbændɚ, bɛd, bea, beada, beadut, beakand, beanut, beanutbutter, beas, beathers, beauf, beauiful, beautif, beautifor, beautifur, bebah, bebutter, bedd, bedda, beddetbutter, beddy, bedney, bedters, beed, beek, beel, beesh, beezah, beeze, bef, beggy, begi, begiber, beging, beh, behd, beik, bein, beis, bek, beker, bemuhi, bencuts, benets, benning, benutbutter, benza, beppy, ber, berada, bere, berls, berly, berryman, berson, bertend, bery, bes, bestard, beter, bethers, beuiul, bew, bibityp, bibloh, bice, bich, bick, bickit, bicks, bicole, bidih, bie, bif, biggy, bigs, bih, binabella, binbella, binnow, bipityi, bippety, bippity, bir, birlts, birs, birst, biss, bisses, bistap, bith, bither, biv, bizi, bɛkol, bɪkɚtəgətɚ, blant, blead, bleautiful, bleesatow, bles, blike, blings, blipper, blippers, blok, bloof, bloor, blop, blother, blowk, bɑlte, blu, bluejean, blus, bɛn, bɪnso, bɪntɚ, bo, boato, bobityp, bobli, boday, bodmother, bodum, boh, bohelei, boid, boing, boken, bollow, bome, bons, boodiful, booh, booi, bool, booluh, boop, bootball, bootfall, bootiful, bopityi, boppety, boppity, bor, bosed, boshem, bost, botburger, bouce, bouing, bouy, bove, bowee, bown, boyee, boyn, boys, boyt, baɪr, bræʃ, braht, braks, bral, bralods, brancer, brandnew, brate, brayley, brea, bready, breakin, breas, breat, breffast, breffess, breh, brekɪd, brella, brelly, brendo, brenny, bres, bresh, bresha, bress, bretet, bretty, bricce, briddy, brince, brincess, brinch, brinchess, brincture, brind, bris, britahow, brite, broterson, brou, browf, bʌrəownde, brox, bruh, bruk, brunhilda, brunken, brunster, brunter, brutter, bɚs, bɪsowɛso, bɪt, bʌt, bɛɚɛtɚsɛsə, bubba, bucadi, bucing, budder, buddon, budduh, buder, budess, budest, budu, budumbum, buggie, buh, buhben, buhbend, buhbens, buhduh, buhlala, buhlass, buhm, bui, buiful, buil, bukamas, bullou, bumbpin, bumkin, bumpin, bumtin, bunella, buotsh, bupper, buppet, buppin, burbu, burella, burnie, burse, burtle, buse, butchel, butchmen, butde, buther, butiful, butow, butso, buttare, buttles, buttum, buwuh, buyo, bwa, bwe, bwead, bwee, bwehya, bwiched, bwoar, bwoken, bwum, byald, bye-bye, byem, byolls, byoom, byu, bɛΘɚ, cabery, cact, cah, cahs, caht, cak, caki, cakis, cald, calg, calleed, calli, callo, callsiz, camet, can, cana, cand, caneane, cannos, canswad, caperher, carbir, caref, carge, carin, caro, carous, carrah, carri, carriad, carriage, carriase, carriate, carriuh, cas, casis, casses, cassidy, catceted, catched, cath, catus, cau, cclonel, cedewella, cella, celle, cellerell, cellerella, cemetary, cen, cer, cerella, ces, chabas, chall, chame, chamwich, chank, chapas, characterer, charchar, charl, charlevoix, charot, charwich, chastized, chayi, ched, cheddy, cheebaldin, cheenie, cheh, chel, cheld, chell, chellen, chelly, chepbuh, cheppa, chetek, chik, chil, children, childrens, chinderella, chmurcial, choclih, choes, choo, chooch, choochoo, chood, choot, chor, chorge, choutch, choy, chrass, chu, chuh, chur, churks, chush, cias, cidda, cided, cidereda, cideredduw, cidla, cidrella, ciers, cigeler, cigna, cihera, ciherella, cihrella, cil, cila, cilee, cill, cillas, cillatin, ciller, cillerella, cilleretty, cilless, cimiderella, cin, cina, cinamonerella, cinana, cincinatti, cind, cinda, cindabrella, cindaela, cindaella, cindaletter, cindamela, cindarella, cindas, cindeall, cindealle, cindela, cindelaa, cindelal, cindelea, cindelela, cindella, cinderall, cinderalla, cinderdella, cindereda, cinderedda, cinderedder, cinderel, cinderell, cinderelleda, cindereller, cinderellet, cinderellie, cinderelly, cinderena, cinderetta, cinderlater, cindermella, cindervella, cinderwella, cindewella, cindrelal, cindrella, cindrum, cinduwella, cindwella, cindweller, cineela, cineer, cinela, cinelal, cineller, ciner, cinera, cinerel, cinerela, cinereler, cinerella, cinerellas, cinereller, cinerelly, cinerels, cinerledda, cinerlla, ciners, cineulella, cinewedu, cinewella, cinicinnati, cinineralla, cininerel, cinkella, cinna, cinnahrella, cinnas, cinnerall, cinneredda, cinnerela, cinnerella, cinnereller, cinneretta, cinnuhrella, cinnuhwella, cinnus, cinrella, cinserella, cinsher, cintella, cinter, cinterella, cinuelela, cinuella, cinuellea, cinueller, cinuhrella, cinuhwella, cinulella, cinulera, cinurell, cinwawedda, cippa, cipplas, ciren, cirinella, clawles, cleeks, cless, cleten, clo, cloathe, clyd, cmon, cɑn, coc, coe, cok, collegebut, colz, commercialed, commercinal, compeled, competive, cona, conce, conchu, condin, coolis, corben, corchman, cors, corses, cotis, cou, coulda, couldn, cout, coutside, cown, crahb, craintz, cras, crasht, cratis, crɛd, creammate, crechur, creem, cremmet, crie, cright, crim, crimmer, crince, crise, critch, criter, crocle, crunchies, cuh, cuk, cunry, cutchion, cwashed, d, dɚ, dabassew, dæd, dadada, dadadada, dadders, daduh, dae, daee, daf, dafadee, dagent, daha, dahau, dahdah, dahuh, daif, daird, dairs, daity, dal, dalking, danah, dancey, dancih, dancuh, danforth, danj, danshing, dant, danvers, daol, dappy, das, dase, dats, datto, dau, daud, daugh, daughters, dauh, daut, dauts, daw, dawai, dawani, dawd, dawder, dawk, dawp, dazz, deah, debil, ded, dedder, dedei, deedeeduhu, deeg, deehau, deehei, deeher, deehers, deeho, deehodee, deehon, deehwa, deehwoidee, deekoof, deemee, deenuh, deeo, deeou, deeping, deerfield, deesaw, deesuh, deeuh, deevo, deewei, defsiper, defwei, degined, deh, dehau, dehdeh, dehel, deho, dehoee, dei, deiha, dekrinin, dellas, delly, demeetee, denada, dence, denk, denn, dep, depen, deppermodder, deree, derekon, derella, derinderella, derrr, derthers, dery, des, desa, desoto, dess, dessa, dessay, desser, desses, dessi, dessmower, detekin, detfather, dethers, dethi, dets, devasated, dey, deya, dezza, dezzit, dgap, dger, dhank, dider, diderstated, didscor, difdas, difeego, dih, dihreh, dii, dinderella, dinderes, dinduhwinduh, dinerella, diningroom, dinjow, diny, dirl, disney, disneylike, dispear, dissasah, dissos, dissus, dit, dits, dittew, diw, diz, dʌlɑɪdəl, doag, doccer, docdid, dod, dodavo, dodaway, doday, dodee, dodei, dodem, doedi, doez, dogis, dogso, dohn, doi, doin, doit, dok, doke, doken, dokey, dol, domake, doni, donly, dono, don/t, doo, doobly, doobood, dooda, dooded, doodee, doodoodoo, doof, dooleey, doon, doooter, doot, dops, dor, dordous, dorry, dosemen, dotter, dou, doubledecker, doudey, doudi, douh, dov, dovuh, dowah, dowei, downstors, dowuti, doy, doya, doylabella, dra, draf, dragg, drah, drance, drapies, drass, draun, drazell, drɛd, dred, dredding, dree, dreff, dregni, drel, drelly, dresh, dressingroom, drexel, dri, dright, drik, drinderella, dring, drit, drizella, dɛɚʌrɛlə, drobs, droe, drok, drry, drucella, druh, druster, druzella, dsi, dudnt, dududugu, dufweau, duggor, duhd, duhduhduh, duhh, duhlala, duhwatagatu, dujat, dum, dumi, dunt, dup, durd, dus, dushei, dushwee, duss, dut, duyeehai, duz, duzay, dwarer, dwat, dwead, dwess, dwether, dwo, dya, dzam, eadit, eah, eahhh, eanutbutter, eary, eaya, eber, ebsolved, ecause, edie, eeah, eeba, eef, eefo, eehai, eehed, eehee, eeho, eehou, eehoyee, eehu, eemee, eeno, eenu, eeru, ees, eeso, eet, eewa, eewatai, eeway, eeyah, eeyee, eeything, eez, effer, efor, efter, eftert, ehchu, ehdifwei, ehdu, eheh, eheheh, eher, eheway, ehgo, ehh, ehhhjjjj, eho, ehowe, ehwei, ei, ej, eksen, elbuz, ellerenda, elly, els, else, elvee, elysees, enana, enda, endjoy, endoy, endu, ene, enlandote, enning, enuh, erbow, erella, errantly, erry, erv, ervy, erway, eryone, eryti, erywhere, escatoo, escorage, ese, esebae, eseh, eselay, eshuut, esjote, eso, ess, esses, esso, esyes, ets, euh, ev, evee, eveone, everly, everthing, everybud, everytay, everythings, everytime, everyvody, everywawhere, everyy, evey, eviditly, evih, evter, evvy, ew, exwife, ey, eywan, ez, ezeebuh, ezekiel, fabrelly, fæd, fadder, fadderd, faderd, fadi, fafer, fah, fahdee, fahluhf, fahp, fahty, fairfax, fairygodmother, faitee, fala, faled, fallah, fallory, fally, fantasialand, fard, farow, farriage, fater, fatha, fatheh, fatnum, fauger, faut, faver, faw, fawer, fawl, fazih, feas, feathe, feaver, feddy, fedlin, feeduh, feefee, felagret, feld, felder, fellee, fello, fellwell, felve, fenn, fera, fermuver, ferro, ferson, fery, fessional, fethygodmother, fi, fiancé, fickie, fiddla, fide, fiefer, fien, fif, fifty-one, fiks, filas, filla, fina, finbing, finderella, finderfellow, fineries, fini, finit, firdidmast, firk, firls, firsook, firstname, firt, fis, fishmarket, fith, fithbo, fitin, fize, flae, flaup, fle, flead, flehsh, fles, flubber, flupra, fʌɪf, fo, foar, foccer, fodo, foght, folee, folli, fom, fon, foofah, fooh, foom, foop, foopri, foor, foors, footpall, footsman, foregot, forrestal, forweay, fosin, foughto, fourt, fow, fra, frad, frah, frairy, frall, fransisco, fras, frases, frassa, fraug, fraugs, fre, fread, freds, freeuh, freh, frein, frellarella, frellya, fren, fres, frest, fretel, frethsh, frett, fric, frillowella, frin, frince, frind, fris, frise, fɝs, fsansuh, fsirt, fsu, fəɚtɛ, fu, fud, fue, fuf, fuh, fuhdee, fuhred, fuld, fult, fuluh, fung, funly, fuond, fuquay, fwa, fwai, fwee, fweeah, fwo, fwor, fwroyee, fwuh, fyde, fyep, gabas, gae, gaeg, gafter, gah, gahd, gaim, gallig, gan, gændo, gare, gart, gass, gat, gats, gaulsez, gaurds, gavy, geg, geh, gei, geim, genna, gert, gesmofer, getete, getha, geting, getta, gettogether, gewupa, gi, gick, gicking, gih, gillek, ginder, ginette, ging, gir, girls, girlt, girr, gɛl, glah, glas, glay, gless, glived, glock, glocksta, gloop, gloranne, glu, glutenfree, gɪn, goach, goccer, godfairy, godmether, godmotho, godperson, godsister, godsisters, godwom, goed, goeen, gof, gogetter, goi, goih, goins, gokay, goldig, gomen, gomma, gonstom, goodess, goodis, goodmother, gooness, gopy, gor, gord, gother, gotit, gots, gotstha, gouse, gow, goz, gozing, graass, gradmamma, grae, grandkid, grandkids, grandmom, grandparents, gras, grat, gratma, graun, gread, gream, greco, gredients, gree, greem, gress, grest, grewing, grirl, griting, groated, groupy, growed, gthey, gəɪto, gu, guardman, gudesdis, gues, guh, guhn, guhoo, guhry, guhs, guid, gumbonet, gunna, gusgus, guther, gutshu, gutwrenching, gwee, gymp, hɝ, haae, hab, habbing, hackensack, hada, hadily, hading, hadn, hadol, hadta, haffer, hafta, hahee, hahodaei, hald, halfsisters, halfways, hallin, hamen, handie, hanimals, hannukah, hapfily, happerer, happry, happygolucky, happying, happyly, har, hars, harse, harses, harv, hase, hases, hass, hasther, hathin, hatten, hatway, hauhus, haum, hauts, haverhill, hawd, haye, hayv, haz, heach, headandfoot, heary, hecked, hecks, hed, hedes, hedherdhers, hee, heeda, heee, heepus, heeu, heff, hefwadder, heh, hei, heiberei, helpulled, helt, henn, henny, heppy, heps, herbie, hercher, herda, herdasep, herdumders, hern, hersel, het, hever, heyr, hidow, hiered, higah, highschools, hih, hihuh, hilbil, hinerella, hiz, hkum, hmhm, hmi, hoap, hoas, hobbledy, hobing, hoce, hockten, hocus, hodau, hoday, hodee, hodei, hodey, hodwho, hoee, hoeeyah, hoh, hohenfels, hoi, hoiee, hoiyah, hojuhjuhjuh, hol, holded, hom, homin, hona, hoo, hoolihoo, hopsital, hor, horbo, hore, horses, horseys, horsh, horshes, hort, hosa, hoss, hots, hou, houch, houdey, howdee, howee, howei, hown, howto, hɛste, hətɛes, hu, hudee, huhaunt, huiha, hunhunh, hupening, hur, husb, huwa, huwee, huwuh, huyyah, huzzle, hʌvs, hwau, hwoi, hyoi, ich, ick, icking, idaseder, idono, idus, iffen, ifi, igpeared, ih, ihdi, ihfey, ihhu, ihn, ihoi, ihshuarei, ik, ilambo, iliinois, i/m, ima, imee, imm, imma, imment, impak, impren, inaducing, inan, inatation, inda, inderella, induh, inerbella, iniation, injur, inlaw, inlaws, inna, innih, innrva, innutasen, instedat, intraguh, invired, invitement, inwito, iow, iowno, irs, iruguay, ish, isohau, iss, issodei, issowai, ist, isthistuh, itand, ith, its, itz, itzuhah, iwuh, iwuz, iz, izuh, ja, jabbo, jache, jah, jaiden, jane, jap, jecking, jeddy, jedy, jeh, jel, jeldy, jella, jellen, jelliwa, jelo, jelssiy, jely, jem, jen, jerchch, jersh, jerst, jery, jes, jestice, jesush, jete, jett, jewelhe, jewwy, jif, jiles, jinnunredda, jisisi, jjoot, jklm, joas, johnem, johnjohn, johnstown, joly, joo, jooo, jootjus, jope, jor, jorn, jossin, jote, jred, ju, juh, juhjuh, juive, jur, jurn, jus, juss, jutter, juweh, ka, kada, kadiho, kadmay, kah, kake, kako, kakus, kall, kam, kænso, kænt, kappy, kardsman, kardsmen, karee, karry, kartis, kas, kaski, kass, kassus, kassuz, kats, kau, kaylin, kazam, kazzus, kdis, kee, keeple, kelo, ker, kerson, kes, kessler, keta, kets, kɝɪg, ki, kic, kickeded, kickis, kidin, kik, kiking, killas, killgtee, kimercials, kindgom, kindin, kingbom, kingdɚ, kingdin, kinit, kint, kinuberella, kirl, kis, kitt, kiz, klaki, klass, kleɑns, kley, klotɛl, knice, knifefuls, knockeded, knowitall, ko, koe, kootenay, kop, kot, kream, kreams, kreddij, kreem, kreen, kress, krin, kring, krɑstæm, ɪksætɚ, ktɚ, ku, kuchap, kugether, kuh, kuhmary, kumpun, kunitsen, kunt, kupat, kus, kutər, kwakle, kwana, kwih, kyeah, kyewin, kyold, lɪɚ, ladies, ladry, laey, lais, lal, lall, lamber, lambo, lameh, lampnes, lampo, lampoo, lape, lar, laster, lastname, latta, lau, laut, lazers, leab, leake, lebo, lecksus, leee, lef, leh, lehlehl, lehluh, lehoo, leka, lekwick, lel, lenda, lep, lepper, leti, lettis, leuh, leved, lewis, lewisburg, lexipro, leyuhs, lʌfɚ, libah, libbing, lickin, licon, liffe, lighd, lih, liho, lihu, likeup, lil, lill, lilluh, limberg, lindow, liquidy, lise, lisuh, litta, littleones, littlesisters, littus, livingroom, liwwle, lizle, lockerz, locted, lod, loh, lok, lololo, loog, looh, lookin, lookuh, loow, lopardee, lor, lorvay, losee, lovee, loy, ʌlɪtɚ, ʌlɛtəl, lɪtr, lubdublublala, lud, ludghe, luffy, luh, luhbair, luhl, luhlalal, luhng, lum, luray, lutta, lutuz, luwooheh, lyfe, maam, maby, machet, maddie, madrick, maduh, magit, mah, mahket, mahl, mahp, maiding, makebelieve, maked, mal, mala, malbrit, mamich, man, mance, mand, manda, mandals, mandus, mang, manich, manservants, mantch, mape, marde, margaree, marky, marror, mase, masectomy, masss, masst, massy, matah, matel, mathet, mattick, matty, mauth, mavma, maydis, maykul, maysville, mayuls, mazarell, mazarella, mazera, mazic, mazied, mccord, mcgilicuddy, mcmansion, mɛdəmɚ, mea, meak, meanial, meanutbutter, mease, meast, mee, meece, meedle, meel, meels, mees, meese, meh, mehiheh, meht, mella, mellee, melluh, mem, memarries, memmihwelluh, men, menella, menite, ment, mer, mercial, merlandubool, merr, merra, meshaw, messs, mestepen, metter, mewda, mewuh, mguh, mhmm, mɝi, mices, michael, midder, middleaged, middler, midute, miggin, mighta, mighter, mih, mik, mikaela, miltow, mindight, minenuh, minerello, minight, minite, minner, minought, miskicks, mit, mitzvahed, miy, mkay, mmah, mmgm, mmhmm, mmm, ʌməntɚnɑɪsɚ, mocksville, moda, modder, mof, mofer, mogare, moher, moken, mol, monitee, monny, monosodium, montauk, moolbil, mor, morning, mosu, mothathu, motherlaw, mou, moufs, mout, mouv, mouver, mouz, moy, muast, muh, muhder, muhluhlil, muhmella, muhmuttuh, muhnuh, mumb, mundelein, murdle, mut, mutcha, muts, muver, muverer, myeh, myuh, naden, nahunh, nake, namp, nar, nare, nas, nass, nastaday, navvuh, naw, ɪndɚɛlə, neckle, necklex, neeahs, needta, neeuh, neeya, neez, nef, neh, nehnuht, nehr, nekl, nelled, nemo, nennuh, ner, nere, nerson, nes, nesklasce, neverland, newburyport, nex, next, nidnighht, nim, nisser, nister, niy, nol, nomuch, nomuh, nooki, noone, noor, noot, nort, northbrook, norvell, notgins, nother, nover, nowheres, nown, nowns, ɪntɚju, ɪntrətədus, ɛntu, nught, nuh, nuheir, nuhluhluh, nuhmee, nuhnuh, nuhting, nuhuh, nuhuhhih, nunny, nunu, nur, nuwah, nuwei, nuwhan, nye, nyu, oach, oal, oare, oarrr, oay, obe, obu, obydie, ock, ocksin, o'clcok, o'cock, oday, odewa, odie, odosh, oduh, odur, oe, offafuluf, ofthe, oftt, ogay, ohduh, ohee, ohh, ohjay, ohjuhjuh, ohlemar, ohn, ohpyeui, ojurt, ol, oll, olly, oluh, ome, ona, oney, o'nock, onta, oo, ool, oom, oooddjuh, oooo, oop, oosewah, oout, oovode, opɚ, opay, ork, orse, orses, orye, orzuhz, ose, oses, otay, ote, otheda, other, othwuh, otside, ou, ouf, oughta, ouh, ous, ouse, ouside, ousside, out, outa, outf, outfoot, outtide, ov, overcommitting, oversi, ovrefurday, owah, owdee, oweti, owf, oy, oyee, oyt, paat, pabuh, paceserate, packt, packy, padl, paducah, pag, pahs, pake, pana, panch, pancing, pancy, pandidose, panfy, pank, pann, panses, panta, pantchs, panthy, pantitigah, panutbutter, papabu, papen, parents, parets, parkinst, pase, pashure, paspo, pature, pau, pausdee, pazuws, pbj, pɛdʒɪ, pe, peabea, peabu, peabut, peabutter, pead, peadubutte, peadut, peadutbuddee, peaduts, peael, peaid, peain, peainbutter, peamutbutter, peanbutbutter, peantbutter, peanu, peanuck, peanumer, peanutbol, peanutbuer, peanutbuh, peanutbunny, peanutbut, peanutbutchu, peanutbutrer, peanutbutta, peanutbuttee, peanutbutter, peanutbutteruh, peanutbuttle, peanutbutture, peanutpeair, peanutter, peanututter, peanutwater, peanutwutter, peany, peaterbutter, peatobutter, peautiful, peaututter, pebutter, peby, ped, peea, peebutter, peeitbutter, peeleebagget, peespe, peet, peetle, peetlebutter, peetpunter, peey, peezuh, pefwaity, peh, pehns, peir, pel, peld, pelly, peloponnesus, penabutter, pences, penibut, pennybut, penpal, pentunei, penuh, penutbutter, peop, pepperdine, perd, pere, perper, perser, pershon, persining, pessahbutter, petebutter, peterbutt, peterbutter, petuhbutter, pey, pez, pezzy, pft, philip, pices, picher, pickdiv, pickidu, picle, picsure, pictogruh, pid, piecee, pieded, piepulz, pifural, pifwaei, piggrow, piggybank, pih, piin, pil, pilla, pillbean, pilly, pillygo, pince, pind, pinerella, pinka, pinn, pinsuw, pintow, pippon, pises, pishure, pista, pisuh, pitsuw, pizeda, pizzy, pjbutter, pking, pɪkɚs, plam, plankin, plannt, plass, playee, pleesed, pler, plince, plut, pockin, pocus, poid, pokyo, polihtashes, pollace, ponc, ponto, pook, poosh, pootball, popy, por, pornt, portentia, portugese, possibry, pper, pɛpubɛtɚ, prʌ, praca, praice, prakins, pran, prary, pras, prateint, pratteenus, pread, preads, preanutbutter, pred, preentry, preexamination, prelly, presliced, prestroke, pricen, pridas, priece, prih, prin, prince, princell, prinsa, pris, priss, privin, prɪɛlə, probab, prok, prond, prɪsɛ, pruddy, pəsɛs, pʌte, pɛtər, pucking, puda, pudd, pudli, pudu, pudy, puh, puhle, puk, pumercial, pumkin, pumkum, pummercial, pumpin, pumpins, pumpk, pumplikin, pumtin, punkmen, punnot, purda, purds, puskin, puth, pwince, pyo, pʊΘ, qrueen, queeng, quingin, rab, raduh, ragons, raht, raight, rait, rako, raks, ramone, ramones, rampments, rance, rango, rary, raseva, raspberrybutter, rass, rau, ʃʌrdərər, reanut, rebroke, reck, redd, redeh, ree, reeses, reeth, refridgerate, refrigeraoo, refrigerater, refrigerer, refrigerut, reh, rei, reindeers, rella, ren, renarella, renay, renchure, renduhrella, repee, reporer, rescrew, reseen, ress, ret, retty, retur, ri, righ, rinden, rinderella, rine, ris, ritu, riverdale, rlot, roa, rodney, romantical, roohdall, ros, rouh, rouw, rown, roxboro, ʌrət, ruckin, ruh, ruhluhluh, rul, runding, runned, rup, ryann, saed, sagres, saguenay, saht, saig, saiy, sajote, salih, sallih, samich, samish, samm, sammich, sammiches, sammitz, sammlich, samthing, samwich, samwitch, samwithes, sandwhich, sanwich, sapril, sarp, sart, sarts, sas, satter, sault, saun, saunder, saur, sause, savannal, sawberry, sawled, sawn, sawr, saydda, sayes, saysenance, sayso, sayuh, saze, sʌbɪn, sʌbɚt, scals, scance, scgoing, schlap, schmoozy, scisors, scissorz, scols, scont, scoon, scr, scramlich, scrange, scras, screamhen, screwbolt, scrimper, scruk, scween, sɪɚdsə, seaford, seb, seca, sed, seddid, seebyurler, seegir, seell, seengs, seezers, seflus, sefsisssiser, seher, sei, selfrighteousness, semiss, senout, sep, sepbundun, sepmen, sepmom, sepmother, sepmover, seppers, sepra, sepras, sepsisers, sepsisters, ser, serava, sern, serpa, sers, serted, ses, seseion, sesemmuh, seshin, sesmufer, sest, sethmer, sethsituhs, settavich, settitay, sevy, sey, seyes, sez, sgillek, shamm, shamri, shandwich, shanked, shanwich, sharberry, sharon, sharwberry, shati, shattled, shaubrum, she, shebedit, shede, sheeps, shek, shelv, shend, shere, sherp, shers, she/s, shfell, shi, shickjall, shid, shind, shinderella, shindewella, shinerwella, shing, shisher, shishu, shlippa, shnee, sho, shoccer, shon, shoop, shootiful, shorp, shou, shoulda, shoup, shouper, showe, showeek, shree, shreid, shrem, shresh, shried, shrim, shrip, shrong, shrugen, shu, shudih, shuk, shulder, shushee, shutty, shuver, shuwedi, shuwei, shweam, shweeping, shzu, sibebadi, sibi, siblons, sichers, sicilly, sidder, sidderon, siddla, siddy, sidla, sidler, siduh, siffus, siker, sikid, siler, sillas, siller, sillida, sillie, silter, siluh, silup, silvr, sim, simber, simbra, sinder, siner, sinerbella, sinerledda, sininuh, sinished, sinisters, sipas, siper, sippa, sippla, sippler, sipra, sipras, sipsusissus, sipter, sipters, sirra, siser, sising, sisl, sisla, sislas, sisner, sisser, sisserch, sissers, sisserz, sissibus, sissla, sissle, sissor, sissors, sissuh, sist, sisters, sistuh, siter, sither, sitia, sitis, sitla, sitlas, sitlus, sitper, sitras, sitta, sittas, sittus, siu, sivy, siwu, siz, sizers, sizzer, sizzers, sked, skgees, skissed, skoundrin, skruh, sɪl, sla, sleeeper, slent, sler, slet, sli, slulla, sluppa, slyther, smacken, smah, smean, smoosh, smucker, smuh, smuhay, smush, snapchat, snea, snepmother, sɪnsɚɛlə, sɪntɚs, snuckers, sobol, socalled, soccerball, soccuh, soe, soih, solih, solpas, som, somebum, somemen, sondee, sonuh, soo, sooh, sopper, sorras, sory, sos, sote, sotter, sovai, sowei, spad, spand, spaned, spart, spast, spe, spead, speds, spelly, sper, spich, spig, spil, spitten, splen, spli, splin, spo, spooh, spreh, sprell, spresa, sprez, sɛptɚ, spuhs, sput, squal, squeach, squirtable, srawberry, sɪs, ss, ʌstɚ, stɚ, staht, stal, standyar, stanrus, stap, stardu, starmy, stas, staz, stedioi, stee, steen, stef, stefmofer, stefmother, stefmower, stefmuder, stefmuver, stepa, stepaunt, stepchildren, stepdad, stepdaugher, stepfamily, stepgirl, stepgirls, stepgrandchildren, steplady, stepmama, stepmodder, stepmom, steppy, stepsiblings, stepsishers, stepsisters, stepstissuz, stepstisters, steptsisters, sterry, stesmofer, stickin, stiduweduw, stigital, stindewella, stippers, stis, stisters, sto, stoccer, stoof, stoores, storn, stra, streh, strench, streps, strordenaire, strucken, strucks, sttep, studur, stufanly, stuma, stwo, su, sudn, suh, suhied, suhlee, suholei, suhwent, suhwuh, suk, suky, suluh, suly, sumanei, sumaze, sumi, summin, sunderella, sunduweduh, sunly, superberlous, supod, sus, susing, suthu, suv, suwuh, suz, svin, swead, sweetß, sweird, swice, swihsh, swince, swirch, swoo, swu, syndey, ɛt, ɛtɚ, tɚ, taat, taber, tadi, taepe, tah, taid, tair, taks, tal, tamich, tamikel, tance, tand, tænk, tanm, tappy, tarht, tas, tase, tassahara, tata, tatatatatatai, tato, taun, tayk, tayp, tayt, tbread, tch, tchap, teanut, teanutbutter, teb, tecket, tedy, teeka, teel, teep, teepi, tegever, teh, teke, tekter, telp, telv, telve, tem, tene, tenih, ten-tuw, teo, ter, teramdeh, tero, tertdeterduh, tery, tes, teven, tfevvygodmother, tha, thah, thair, thal, thanf, thang, thangs, thas, thashed, thass, thassah, that, thata, thayko, thayt, the, thed, theeng, thef, theh, thei, theihau, their, thelly, them, themsel, thench, thendo, thep, thepster, ther, thes, thesegoh, thesso, thesus, theyp, theyw, thez, thi, thid, thinderella, thinderelly, thinderetta, thinerella, thinerruruh, thinerwetta, thingin, thinretter, thinurella, thirdybird, thisa, thissa, thissay, thissit, thissuh, thister, thit, thlade, thlip-per, thoing, thowing, thows, threenutbutter, threer, threeuhbutter, threeutbutter, thres, threst, throup, thruh, thubuh, thudderbut, thuhoh, thup, thuwai, tibut, tickereh, ticksuh, tid, tieing, tif, tihn, tik, tilla, timey, tims, tinderella, tinerella, tingliner, tirty, tis, tisoni, tiss, tithu, tittis, tizuh, tʃɛker, tɪl, tlaud, tʌm, ɛtɪndɪntəl, toap, toas, tock, tocks, tode, tofedi, tofwahee, togedduw, togethf, togewuh, tok, toka, tol, tolo, toltol, tooch, tood, tooked, tookin, toos, toote, torry, toth, tou, touchyfeely, towne, tox, tps, trʃæɪŋ, trabol, tradewinds, trady, trair, trake, tramane, transamerica, trassh, trather, tratih, traysee, treanutbut-ter, treehouse, trella, trellawella, trellawilson, tremane, trempts, tren, trents, tric, trince, tripa, tripla, triv, triver, trone, troo, tərpi, truandford, truets, trurn, truzta, tryin, tryna, tryng, tsi, tɑt, tɚtə, tɛtɚɛs, tɛtwənz, tudu, tuh, tuhud, tumersh, tummercial, tummercials, tunina, tuot, tupaping, turbden, ture, turee, tu-rits, tuv, tuwa, tuwn, tuz, tɛvɚ, twarp, tway, twel, twell, twenabella, twent, twike, twince, twinerwello, twive, twoh, tworoo, twuv, tyalie, tye, tɛΘhərdɛ, udda, udi, udu, ududu, uff, ug, ugether, uggle, uglies, uh, uhbethe, uhboohduh, uhdeedor, uhder, uhdo, uhf, uhh, uhlal, uhlil, uhlooh, uhm, uhmm, uhnuh, uhrw, uhs, uhsback, uhsu, uhuh, uhuhahey, uhuhuh, uku, ulay, uly, um, umass, umato, umbrace, um-fee, unbi, undat, unfa, ungerl, ungry, unhunh, unlikaly, unpat, uns, upbi, updairs, updoe, uppy, up-sidedown, urduh, ursula, uset, useta, ushla, ut, uther, uts, uty, uver, uwaid, uzzle, vake, vall, vantos, varina, varry, vass, vasses, ved, ver, versace, versh, videe, vig, viko, vindow, vings, vini, vioala, vipe, vis, vit, viti, vlippers, voke, vood, voto, vowld, vra, vrae, vrass, vread, vress, vresses, vrice, vrindow, vu, vut, vwahen, vxcrack, wɛ, wa, waduh, waduhdoot, wafway, wagg, wah, waha, wahd, wahe, wahedoi, wahee, wahodei, wai, waiyu, wajoot, wal, walkin, waltham, wambadi, wambich, wana, wandedoh, wandu, wanta, wardrome, warried, wasedded, washiday, washtt, washu, wass, wat, waterhouse, wats, watsh, wau, waus, wauzee, wauzu, wawa, waz, wazinski, wɪdoz, weads, weady, wedesuh, weels, weem, weeoo, weepin, weet, weg, weh, weheeheewa, wehoday, weiher, weihowei, weishuwei, welbar, welch, welmar, wence, wendo, wenewella, wep, wer, werchch, weres, weret, werry, wers, werth, wery, werz, wes, wess, westville, wetch, wetier, weu, wewuhw, wh, wha, whammo, whatcha, whatchacallit, whatev, whatyacallit, wheda, whedo, where, whih, whoever, whon, whoo, whosever, whuch, whut, wi, wich, wid, wies, wih, wihnd, wilind, willams, wime, windoros, windyes, winnay, winneh, winnih, winno, winnowello, winow, winows, winrows, winterpark, winties, wintow, wiou, wip, wishga, wishwa, witcz, withouther, withow, witi, wittuls, wiun, wiy, wɑl, wʌn, woah, woar, wobeya, woh, wohade, woheir, woho, wokin, wom, womans, women, wond, wooddice, wooh, woot, wopen, wor, workaba, wos, wosh, wotes, woul, woulda, wouse, woya, wrate, wreckness, wərtɛ, wɛs, wʌt, wucoilim, wud, wudawei, wudding, wuduh, wuh, wuhdei, wuhs, wuhsuhsuh, wui, wuiya, wujuhjuh, wun, wundus, wunned, wunnin, wunning, wunowei, wunt, wunth, wurs, wurt, wush, wuts, xxxbutter, y, yad, yadeyada, yadi, yah, yahlih, yahohee, yake, yall, yan, yancey, yar, yas, yasm, yay, yayah, yayuh, yeaheah, yeaheheah, yeaherr, yeahoh, yeahum, yearold, yeck, yeewohee, yeh, yehr, yeihau, yeir, yel, yerh, yers, yev, yewe, yick, yicking, yig, yiwuh, yiyuh, yoe, yogleh, yongbur, yonker, yoo, yope, yor, youm, youwee, yudu, yuee, yuh, yuhahh, yuhihuh, yura, yurchild, yuu, yuyuh, yyado, za, ze, zee, zellas, zelly, zeppole, zeroy, zeuh, zey, zher, zhil, zhu, zide, zis, zlipper, zooch, zoot, zorthy, zummercials, zur

APPENDIX B

This appendix presents more probing tables. In Chapter 6, a word level probing analysis was presented where multiple instances of the same word were grouped together and various summary statistics on influences were computed. The tables presented in this appendix are results of similar analysis but the words were grouped on the basis of lexical category here. Mean Influences and Percent Total Influence across discourse tasks and comparison scenarios are presented below,

Table 7.1: Broca vs Control: Mean influence by lexical category and discourse task

Lexical Category	Cinderella	Window	Sandwich	Event
Noun	1.63184	1.67456	1.43829	2.49984
Verb	1.53929	1.87817	1.81859	2.13276
Preposition	1.54541	1.53484	1.70004	2.36552
Pronoun	1.07263	1.07661	0.939173	0.877544
Adjective	1.91976	2.38567	1.27922	2.54399
Adverb	1.02773	1.69414	1.43217	1.5528
Filler	0.45759	0.923141	0.425816	0.0335332
Determiner	0.525091	0.322148	1.31574	1.88554
Punctuation	0.121663	0.203791	0.0594878	-0.266386
Particle	1.6103	1.23701	3.34	4.70165
Conjunction	0.223718	0.251832	0.221019	0.876258
Interjection	1.61459	1.56081	1.46939	1.62772
Wh-Adverb	1.27442	2.65938	0.0325048	2.9726
Propernoun	1.00584	1.34815	1.60613	2.79195
Wh-Determiner	1.07178	1.4315	2.70114	3.73543
Possessive Modifier	-0.333079	0.484186	-0.32781	-0.941571
Terminal	-0.15481	0.153417	-0.0113118	0.0470119
Numeral	-0.0535222	0.121822	0.115386	-0.0986109
Wh-Pronoun	-0.226223	-0.0631807	-0.0528901	-0.494573
Unintelligible	7.39935	7.12317	7.54517	1.01292
Paraphasia	5.208	4.03512	5.79512	-0.699546

Table 7.2: Broca vs Control: Percent Influence by lexical category and discourse task

Lexical Category	Cinderella	Window	Sandwich	Event
Noun	21.3659	23.5643	22.1513	21.8251
Verb	20.5979	22.6259	20.4359	20.8054
Preposition	11.2202	8.66557	11.6305	12.8865
Pronoun	10.0039	8.01623	6.85904	6.95042
Adjective	8.00489	7.79695	3.24899	9.74877
Adverb	5.49934	7.16225	6.59269	6.84732
Filler	1.86133	2.83414	1.19953	0.0911136
Determiner	4.55785	2.81994	11.0329	8.90486
Punctuation	1.22699	2.18768	0.590551	2.13082
Particle	1.59094	1.62797	3.39457	2.78639
Conjunction	1.51411	1.28683	1.28879	3.19212
Interjection	0.923846	1.16866	0.570208	0.760278
Wh-Adverb	0.324561	0.793162	0.00273631	0.910703
Propernoun	0.20721	0.261497	0.154993	0.406645
Wh-Determiner	0.235984	0.226909	0.443681	0.981815
Possessive Modifier	0.0616919	0.159557	0.0161535	0.0977314
Terminal	0.0343056	0.152949	0.0103121	0.0114908
Numeral	0.0436989	0.0302355	0.168207	0.087223
Wh-Pronoun	0.0335629	0.0212156	0.00369222	0.0985296
Unintelligible	5.30362	4.29354	3.9814	0.128877
Paraphasia	5.26596	3.93865	6.10399	0.159274

Table 7.3: Wernicke vs Control: Mean influence by lexical category and discourse task

Lexical Category	Cinderella	Window	Sandwich	Event
Noun	2.65973	2.56043	1.96701	0.0292134
Verb	1.14154	1.57199	1.96272	0.396137
Preposition	1.03587	1.05108	1.65767	0.781645
Pronoun	0.202656	1.85852	0.725644	0.389476
Adjective	1.99994	2.00695	0.56472	0.312044
Adverb	0.787359	1.15609	0.478494	0.300293
Filler	-0.434206	-0.236617	-0.903617	-0.786657
Determiner	0.461327	0.50449	0.65286	1.23243
Punctuation	-0.151542	-0.221632	-0.209318	0.0725134
Particle	0.978736	1.63272	2.73886	2.49373
Conjunction	-0.221596	-0.00360838	0.661162	-0.026112
Interjection	0.49341	0.469092	0.83456	-0.51829
Wh-Adverb	0.0885429	3.60439	1.82752	0.644769
Propernoun	1.83986	1.85852	1.00025	0.222838
Wh-Determiner	2.0079	1.62796	0.65286	0.455872
Possessive Modifier	-0.0732376	0.0565029	-0.246416	-0.378685
Terminal	-1.21677	-0.258496	-0.892026	-0.502179
Numeral	-0.464248	0.328661	-0.34704	-0.397269
Wh-Pronoun	-1.35184	-0.105024	−0.641122	-0.805953
Unintelligible	5.0283	4.95003	4.60509	0.576045
Paraphasia	0.242024	-0.191328	0.939883	-0.553727

Table 7.4: Wernicke vs Control: Percent influence by lexical category and discourse task

Lexical Category	Cinderella	Window	Sandwich	Event
Noun	39.9844	39.3839	32.233	0.961609
Verb	18.4916	22.5083	24.551	15.4321
Preposition	9.83138	7.61172	13.3167	17.7685
Pronoun	2.33434	2.92037	5.91788	12.5585
Adjective	9.86691	7.84491	1.5586	4.6445
Adverb	4.76503	5.44192	2.28738	5.06127
Filler	1.20468	0.4614	1.45595	6.01143
Determiner	4.6441	4.87029	6.06927	23.6843
Punctuation	1.58088	2.22744	1.96932	1.99206
Particle	1.27578	2.82563	3.35497	5.72689
Conjunction	1.69032	0.0196088	3.8159	0.368317
Interjection	0.146776	0.2608	0.24603	0.524406
Wh-Adverb	0.0309325	1.42844	0.162556	0.836931
Propernoun	0.397493	0.386816	0.0457565	0.114217
Wh-Determiner	0.534007	0.292415	0.15148	0.515872
Possessive Modifier	0.0179869	0.0264198	0.013151	0.148724
Terminal	0.226922	0.212993	0.616622	0.324251
Numeral	0.38077	0.0871457	0.566223	1.53907
Wh-Pronoun	0.191747	0.034435	0.0439923	0.627691
Unintelligible	2.24203	0.804447	1.22885	0.306759
Paraphasia	0.0462488	0.0474584	0.267525	0.442311

Table 7.5: Anomic vs Control: Mean influence by lexical category and discourse task

Lexical Category	Cinderella	Window	Sandwich	Event
Noun	0.50538	0.447236	0.618008	0.536172
Verb	0.27691	0.42936	0.306647	0.270086
Preposition	0.272415	0.243137	0.278509	0.221956
Pronoun	0.206441	0.0977992	0.288238	0.172401
Adjective	0.49331	0.627916	0.388347	0.363601
Adverb	0.127813	0.552057	0.234755	0.352877
Filler	0.48688	0.844355	0.314476	0.665412
Determiner	0.0861608	0.141034	0.388347	0.164486
Punctuation	0.0116108	0.077832	-0.0135382	0.0268926
Particle	0.265039	0.320343	0.331031	0.35619
Conjunction	0.0872415	0.144598	0.0223205	0.030537
Interjection	0.403654	0.708878	0.290513	1.53604
Wh-Adverb	0.0541942	0.0281724	0.205337	0.0292909
Propernoun	0.0206441	0.470775	1.54398	-0.142874
Wh-Determiner	0.423341	0.174239	0.732602	0.3914145
Possessive Modifier	-0.0668993	0.0637945	-0.577563	-0.110483
Terminal	-0.165384	-0.380984	0.305437	0.208537
Numeral	-0.106723	0.261623	0.142563	0.0802679
Wh-Pronoun	-0.0416381	0.0730885	0.476492	-0.0865
Unintelligible	4.35607	3.31579	4.59408	0.866827
Paraphasia	1.68263	1.20863	1.74803	-0.107424

Table 7.6: Anomic vs Control: Percent influence by lexical category and discourse task

Lexical Category	Cinderella	Window	Sandwich	Event
Noun	30.9189	24.3041	36.1206	25.1349
Verb	18.3197	21.3997	14.1288	15.7195
Preposition	10.3658	6.08719	7.98192	7.07602
Pronoun	0.976874	3.06883	8.94413	8.71546
Adjective	9.93853	8.62546	3.93687	7.78087
Adverb	3.15788	8.46396	4.26716	8.77562
Filler	9.2931	9.21973	3.14959	12.7564
Determiner	3.63818	5.17499	11.2516	4.42008
Punctuation	0.497003	2.74684	0.466104	1.16596
Particle	1.34689	1.87669	1.42224	1.15776
Conjunction	2.66117	2.77736	0.47949	0.646589
Interjection	0.777418	1.29976	0.369439	3.90247
Wh-Adverb	0.0743125	0.0413662	0.0619614	0.0559583
Propernoun	0.14172	0.301764	0.399345	0.124155
Wh-Determiner	0.481108	0.123374	0.505293	0.579004
Possessive Modifier	0.0639358	0.0974748	-0.0788419	0.0608294
Terminal	0.137442	1.15005	0.849251	0.236547
Numeral	0.37162	0.245698	0.788679	0.443001
Wh-Pronoun	-0.0334786	0.0920643	0.181441	0.0929544
Unintelligible	4.47987	1.55698	2.54152	0.511754
Paraphasia	2.18142	1.29721	1.93407	0.115439

Table 7.7: Conduction vs Control: Mean influence by lexical category and discourse task

Lexical Category	Cinderella	Window	Sandwich	Event
Noun	1.11965	1.0306	1.35526	1.01307
Verb	0.49959	0.716106	0.625648	0.42931
Preposition	0.571705	0.568344	0.724757	0.451573
Pronoun	0.00207374	0.212217	0.257749	0.0365743
Adjective	0.773197	0.681559	0.933908	0.831706
Adverb	0.409437	0.682813	0.296191	0.539636
Filler	-0.205578	0.304886	-0.274777	-0.118984
Determiner	0.139546	0.104279	0.472684	0.191262
Punctuation	0.0430306	0.106862	0.042421	0.0197111
Particle	0.265039	1.12656	1.07471	1.18598
Conjunction	0.124046	0.173583	0.0752506	0.11919
Interjection	0.33719	0.855617	0.40692	0.667461
Wh-Adverb	0.249570	0.77218	-0.0673323	0.0252814
Propernoun	1.19766	0.536662	1.70363	0.413349
Wh-Determiner	0.307507	0.0417765	0.147458	0.248475
Possessive Modifier	-0.416007	0.144531	-0.338723	-0.336451
Terminal	-0.351214	-0.310658	0.27057	-0.230138
Numeral	-0.189793	0.256271	0.164891	-0.042967
Wh-Pronoun	-0.147858	-0.0621178	0.637743	0.005129
Unintelligible	5.35681	4.78445	6.21223	0.276671
Paraphasia	3.07335	1.41491	3.21235	0.0369344

Table 7.8: Conduction vs Control: Percent influence by lexical category and discourse task

Lexical Category	Cinderella	Window	Sandwich	Event
Noun	36.312	34.1326	41.2348	34.9411
Verb	17.85	22.1277	15.1568	18.1555
Preposition	11.4831	8.49313	10.5778	10.8187
Pronoun	0.05462	4.22489	4.18692	1.32207
Adjective	8.34827	5.52222	5.18039	12.5892
Adverb	5.33378	6.81377	2.85867	9.65145
Filler	1.45085	1.38802	1.09487	1.14153
Determiner	3.12813	2.25981	8.3407	3.94313
Punctuation	0.992895	2.33169	0.782025	0.612712
Particle	1.5139	3.7697	2.36323	2.69038
Conjunction	1.99842	2.01398	0.820834	1.77008
Interjection	0.269694	0.853819	0.235474	0.938228
Wh-Adverb	0.1733	0.632547	0.0114107	0.0352483
Propernoun	0.569074	0.162525	0.295754	0.236192
Wh-Determiner	0.189475	0.0180443	0.0505884	0.289642
Possessive Modifier	-0.209499	0.127006	0.039202	0.119196
Terminal	0.151484	0.570656	0.392547	0.165694
Numeral	0.34948	0.139953	0.469593	0.180701
Wh-Pronoun	0.0532613	0.0434836	0.134438	0.004572
Unintelligible	5.44611	2.9454	2.79885	0.10276
Paraphasia	3.74732	1.12393	2.66885	0.0320791

APPENDIX C - APHASIABANK TRANSCRIPT IDS

This appendix lists all the AphasiaBank participant IDs for discourses used in this study.

§ 7.1 Transcript IDs: Broken Window Task

§ 7.1.1 Aphasic

acwt01a, acwt05a, acwt08a, acwt09a, acwt10a, acwt11a, acwt12a, adler01a, adler02a, adler05a, adler06a, adler08a, adler09a, adler10a, adler11a, adler12a, adler13a, adler14a, adler15a, adler16a, adler17a, adler19a, adler20a, adler21a, adler23a, adler24a, adler25a, bu01a, bu03a, bu04a, bu05a, bu06a, bu07a, bu08a, bu09a, bu10a, bu11a, bu12a, cmu03a, elman01a, elman02a, elman03a, elman05a, elman06a, elman07a, elman08a, elman09a, elman10a, elman11a, elman12a, elman13a, elman14a, elman15a, fridriksson01a, fridriksson02a, fridriksson03a, fridriksson04a, fridriksson05a, fridriksson06a, fridriksson09a, fridriksson10a, fridriksson12a, fridriksson13a, garrett01a, garrett02a, kansas01a, kansas02a, kansas05a, kansas06a, kansas08a, kansas09a, kansas10a, kansas11a, kansas12a, kansas13a, kansas14a, kansas15a, kansas16a, kansas18a, kansas19a, kansas20a, kansas21a, kansas22a, kansas23a, kempler02a, kempler03a, kempler04a, kurland02a, kurland03a, kurland07a, kurland08a, kurland09a, kurland10a, kurland12a, kurland13a, kurland14a, kurland15a, kurland16a, kurland17a, kurland18a, kurland19a, kurland20a, kurland21a, kurland22a, kurland23a, kurland24a, kurland25a, kurland26a, kurland27a, kurland28a, kurland29a, msu01a, msu03a, msu04a, msu05a, msu06a, msu07a, msu08a, scale01a, scale02a, scale03a, scale04a, scale06a, scale07a, scale08a, scale10a, scale11a, scale13a, scale14a, scale15a, scale17a, scale18a, scale22a, scale23a, scale24a, scale25a, scale26a, scale27a, scale28a, scale30a, scale31a, scale32a, scale33a, scale34a, scale35a, scale36a, scale38a, star03a, tap01a, tap02a, tap04a, tap05a, tap06a, tap07a, tap08a, tap10a, tap11a, tap12a, tap13a, tap14a, tap15a, tap16a, tap17a, tap18a, tap19a, tcu01a, tcu03a, tcu05a, tcu07a, tcu08a, thompson01a, thompson02a, thompson03a, thompson04a, thompson05a, thompson06a, thompson07a, thompson08a, thompson10a, thompson11a, thompson12a, thompson13a, thompson14a, tucson02a, tucson03a, tucson06a, tucson07a, tucson08a, tucson09a, tucson10a, tucson11a, tucson12a, tucson13a, tucson14a, tucson15a, tucson16a, tucson19a, tucson20a, unh02a, unh03a, unh04a, unh05a, unh06a, unh07a, unh08a, unh10a, whiteside01a, whiteside02a, whiteside03a, whiteside04a, whiteside05a, whiteside06a, whiteside07a, whiteside08a, whiteside09a, whiteside10a, whiteside11a, whiteside12a, whiteside13a, whiteside14a, whiteside15a, whiteside16a, whiteside19a, whiteside20a, williamson01a, williamson02a, williamson03a, williamson04a, williamson06a, williamson07a, williamson08a, williamson09a, williamson11a, williamson12a, williamson14a, williamson15a, williamson17a, williamson18a, williamson19a, williamson23a, williamson24a, wozniak01a, wozniak02a, wozniak03a, wozniak04a, wozniak05a, wozniak07a, wright201a, wright202a, wright203a, wright204a, wright205a, wright206a, wright207a.

§ 7.1.2 Control

capilouto01a, capilouto02a, capilouto03a, capilouto04a, capilouto05a, capilouto06a, capilouto07a, capilouto08a, capilouto09a, capilouto10a, capilouto11a, capilouto12a, capilouto13a, capilouto14a, capilouto15a, capilouto16a, capilouto17a, capilouto18a, capilouto19a, capilouto20a, capilouto21a, capilouto22a, capilouto23a, capilouto24a, capilouto25a, capilouto26a, capilouto27a, capilouto28a, capilouto29a, capilouto30a, capilouto31a, capilouto32a, capilouto33a, capilouto34a, capilouto35a, capilouto36a, capilouto37a, capilouto38a, capilouto39a, capilouto40a, capilouto41a, capilouto42a, capilouto43a, capilouto44a, capilouto45a, capilouto46a, capilouto47a, capilouto48a, capilouto49a, capilouto50a, capilouto51a, capilouto52a, capilouto53a, capilouto54a, capilouto55a, capilouto56a, capilouto57a, capilouto58a, capilouto59a, capilouto60a, capilouto61a, capilouto62a, capilouto63a, capilouto64a, capilouto65a, capilouto66a, capilouto67a, capilouto68a, capilouto76a, capilouto77a, capilouto78a, capilouto79a, capilouto80a, capilouto81a, kempler01a, MSUC01a, MSUC01b, MSUC02a, MSUC02b, MSUC03a, MSUC03b, MSUC04a, MSUC04b, MSUC05a, MSUC05b, MSUC06a, MSUC06b, MSUC07a, MSUC07b, MSUC08a, MSUC08b, MSUC09a, MSUC09b, richardson165a, richardson166a, richardson167a, richardson168a, richardson169a, richardson17a, richardson170a, richardson171a, richardson172a, richardson173a, richardson174a, richardson175a, richardson176a, richardson177a, richardson178a, richardson179a, richardson18a, richardson184a, richardson185a, richardson186a, richardson188a, richardson189a, richardson19a, richardson191a, richardson192a, richardson194a, richardson195a, richardson196a, richardson197a, richardson198a, richardson199a, richardson20a, richardson200a, richardson201a, richardson202a, richardson203a, richardson204a, richardson205a, richardson206a, richardson21a, richardson22a, richardson23a, richardson24a, richardson25a, richardson34a, richardson35a, richardson36a, richardson37a, richardson38a, richardson39a, richardson41a, richardson42a, richardson54a, richardson58a, richardson59a, richardson60a, richardson92a, wright01a, wright02a, wright03a, wright04a, wright05a, wright06a, wright07a, wright08a, wright09a, wright10a, wright100a, wright101a, wright102a, wright11a, wright12a, wright13a, wright14a, wright15a, wright16a, wright17a, wright18a, wright19a, wright20a, wright21a, wright22a, wright23a, wright24a, wright25a, wright26a, wright27a, wright28a, wright29a, wright30a, wright31a, wright32a, wright33a, wright34a, wright35a, wright36a, wright37a, wright38a, wright39a, wright40a, wright42a, wright43a, wright45a, wright46a, wright47a, wright48a, wright49a, wright50a, wright51a, wright52a, wright53a, wright55a, wright57a, wright58a, wright59a, wright60a, wright61a, wright62a, wright63a, wright64a, wright65a, wright66a, wright67a, wright68a, wright69a, wright70a, wright71a, wright72a, wright73a, wright74a, wright75a, wright77a, wright78a, wright79a, wright80a, wright81a, wright82a, wright83a, wright84a, wright85a, wright86a, wright87a, wright88a, wright89a, wright90a, wright91a, wright92a, wright93a, wright94a, wright95a, wright96a, wright97a, wright98a, wright99a

§ 7.2 Cinderella Task Transcripts

§ 7.2.1 Aphasic

acwt01a, acwt08a, acwt09a, acwt10a, acwt11a, acwt12a, adler01a, adler02a, adler05a, adler06a, adler08a, adler09a, adler10a, adler11a, adler12a, adler13a, adler14a, adler15a, adler16a, adler17a, adler19a, adler20a, adler21a, adler23a, adler24a, adler25a, bu01a, bu03a, bu04a, bu05a, bu06a, bu07a, bu08a, bu09a, bu10a, bu11a, bu12a, cmu03a, elman01a, elman02a, elman03a, elman05a, elman06a, elman07a, elman09a, elman10a, elman11a, elman12a, elman13a, elman14a, elman15a, fridriksson01a, fridriksson02a, fridriksson03a, fridriksson04a, fridriksson05a, fridriksson06a, fridriksson09a, fridriksson10a, fridriksson12a, fridriksson13a, kansas01a, kansas09a, kansas10a, kansas11a, kansas12a, kansas13a, kansas14a, kansas15a, kansas16a, kansas18a, kansas19a, kansas20a, kansas21a, kansas22a, kansas23a, kempler02a, kempler03a, kempler04a, kurland02a, kurland03a, kurland07a, kurland08a, kurland09a, kurland10a, kurland12a, kurland13a, kurland14a, kurland15a, kurland16a, kurland17a, kurland18a, kurland19a, kurland20a, kurland21a, kurland22a, kurland23a, kurland24a, kurland25a, kurland26a, kurland27a, kurland28a, kurland29a, msu01a, msu04a, msu05a, msu06a, msu07a, msu08a, scale01a, scale02a, scale03a, scale04a, scale06a, scale08a, scale10a, scale11a, scale13a, scale15a, scale17a, scale18a, scale22a, scale23a, scale25a, scale26a, scale27a, scale28a, scale30a, scale31a, scale32a, scale33a, scale34a, scale35a, scale36a, scale38a, star03a, tap01a, tap02a, tap04a, tap05a, tap07a, tap08a, tap10a, tap11a, tap13a, tap16a, tap17a, tap18a, tap19a, tcu01a, tcu03a, tcu05a, tcu07a, tcu08a, thompson01a, thompson02a, thompson03a, thompson04a, thompson05a, thompson06a, thompson07a, thompson08a, thompson10a, thompson11a, thompson12a, thompson13a, tucson02a, tucson03a, tucson06a, tucson07a, tucson08a, tucson09a, tucson10a, tucson12a, tucson13a, tucson14a, tucson15a, tucson16a, tucson19a, tucson20a, unh02a, unh03a, unh04a, unh05a, unh06a, unh07a, unh08a, unh10a, whiteside01a, whiteside02a, whiteside03a, whiteside04a, whiteside05a, whiteside06a, whiteside07a, whiteside08a, whiteside09a, whiteside10a, whiteside11a, whiteside12a, whiteside13a, whiteside14a, whiteside15a, whiteside16a, whiteside19a, whiteside20a, williamson01a, williamson02a, williamson03a, williamson04a, williamson06a, williamson07a, williamson08a, williamson09a, williamson11a, williamson12a, williamson14a, williamson15a, williamson17a, williamson18a, williamson19a, williamson23a, williamson24a, wozniak01a, wozniak02a, wozniak03a, wozniak04a, wozniak05a, wozniak07a, wright201a, wright202a, wright203a, wright204a, wright205a, wright206a, wright207a.

§ 7.2.2 Control

capilout001a, capilout002a, capilout003a, capilout004a, capilout005a, capilout006a, capilout007a, capilout008a, capilout009a, capilout010a, capilout011a, capilout012a, capilout013a, capilout014a, capilout015a, capilout016a, capilout017a, capilout018a, capilout019a, capilout020a, capilout021a, capilout022a, capilout023a, capilout024a, capilout025a, capilout026a, capilout027a, capilout028a, capilout029a, capilout030a, capilout031a, capilout032a, capilout033a, capilout034a, capilout035a, capilout036a, capilout037a, capilout038a, capilout039a, capilout040a, capilout041a, capilout042a, capilout043a, capilout044a, capilout045a, capilout046a, capilout047a, capilout048a, capilout049a, capilout050a, capilout051a, capilout052a, capilout053a, capilout054a, capilout055a, capilout056a, capilout057a, capilout058a, capilout059a, capilout060a, capilout061a, capilout062a, capilout063a, capilout064a, capilout065a, capilout066a, capilout067a, capilout068a, capilout076a, capilout077a, capilout078a, capilout079a, capilout080a, capilout081a, kempler01a, MSUC01a, MSUC01b, MSUC02a, MSUC02b, MSUC03a, MSUC03b, MSUC04a, MSUC04b, MSUC05a, MSUC05b, MSUC06a, MSUC06b, MSUC07a, MSUC07b, MSUC08a, MSUC08b, MSUC09a, MSUC09b, richardson165a, richardson166a, richardson167a, richardson168a, richardson169a, richardson17a, richardson170a, richardson171a, richardson172a, richardson173a, richardson174a, richardson175a, richardson176a, richardson177a, richardson178a, richardson179a, richardson18a, richardson184a, richardson185a, richardson186a, richardson188a, richardson189a, richardson19a, richardson191a, richardson192a, richardson194a, richardson195a, richardson196a, richardson197a, richardson198a, richardson199a, richardson20a, richardson200a, richardson201a, richardson202a, richardson203a, richardson204a, richardson205a, richardson206a, richardson21a, richardson22a, richardson23a, richardson24a, richardson25a, richardson34a, richardson36a, richardson37a, richardson38a, richardson39a, richardson41a, richardson42a, richardson54a, richardson58a, richardson59a, richardson60a, richardson92a, wright01a, wright02a, wright03a, wright04a, wright05a, wright06a, wright07a, wright08a, wright09a, wright10a, wright100a, wright101a, wright102a, wright11a, wright12a, wright13a, wright14a, wright15a, wright16a, wright17a, wright18a, wright19a, wright20a, wright21a, wright22a, wright23a, wright24a, wright25a, wright26a, wright27a, wright28a, wright29a, wright30a, wright31a, wright32a, wright33a, wright34a, wright35a, wright36a, wright37a, wright38a, wright39a, wright40a, wright42a, wright43a, wright45a, wright46a, wright47a, wright48a, wright49a, wright50a, wright51a, wright52a, wright53a, wright55a, wright57a, wright58a, wright59a, wright61a, wright62a, wright63a, wright64a, wright65a, wright66a, wright67a, wright68a, wright69a, wright70a, wright71a, wright72a, wright73a, wright74a, wright75a, wright77a, wright78a, wright79a, wright80a, wright81a, wright82a, wright83a, wright84a, wright85a, wright86a, wright87a, wright88a, wright89a, wright90a, wright91a, wright92a, wright93a, wright94a, wright95a, wright96a, wright97a, wright98a, wright99a

§ 7.3 Important Event Task Transcripts

§ 7.3.1 Aphasic

acwt01a, acwt05a, acwt08a, acwt09a, acwt10a, acwt11a, acwt12a, adler01a, adler02a, adler05a, adler06a, adler08a, adler09a, adler10a, adler11a, adler12a, adler13a, adler14a, adler15a, adler16a, adler17a, adler19a, adler20a, adler21a, adler23a, adler24a, adler25a, bu01a, bu03a, bu05a, bu06a, bu07a, bu08a, bu09a, bu10a, bu11a, bu12a, cmu03a, elman01a, elman02a, elman03a, elman05a, elman06a, elman07a, elman09a, elman10a, elman11a, elman12a, elman13a, elman14a, elman15a, fridriksson01a, fridriksson02a, fridriksson03a, fridriksson04a, fridriksson05a, fridriksson06a, fridriksson09a, fridriksson10a, fridriksson12a, fridriksson13a, garrett01a, garrett02a, kansas01a, kansas02a, kansas05a, kansas06a, kansas08a, kansas09a, kansas10a, kansas11a, kansas12a, kansas13a, kansas14a, kansas15a, kansas16a, kansas18a, kansas19a, kansas20a, kansas21a, kansas22a, kansas23a, kempler02a, kempler03a, kempler04a, kurland02a, kurland03a, kurland07a, kurland08a, kurland09a, kurland10a, kurland12a, kurland13a, kurland14a, kurland15a, kurland16a, kurland17a, kurland18a, kurland19a, kurland20a, kurland21a, kurland22a, kurland23a, kurland24a, kurland25a, kurland26a, kurland27a, kurland28a, kurland29a, msu01a, msu03a, msu04a, msu05a, msu07a, scale01a, scale02a, scale03a, scale04a, scale06a, scale08a, scale10a, scale11a, scale13a, scale14a, scale15a, scale17a, scale18a, scale22a, scale23a, scale24a, scale25a, scale26a, scale27a, scale28a, scale30a, scale31a, scale32a, scale33a, scale34a, scale35a, scale36a, scale38a, star03a, tap01a, tap02a, tap04a, tap05a, tap06a, tap07a, tap08a, tap10a, tap11a, tap12a, tap13a, tap14a, tap15a, tap16a, tap17a, tap18a, tap19a, tcu01a, tcu03a, tcu05a, tcu07a, tcu08a, thompson01a, thompson02a, thompson03a, thompson04a, thompson05a, thompson06a, thompson07a, thompson08a, thompson10a, thompson11a, thompson12a, thompson13a, thompson14a, tucson02a, tucson03a, tucson06a, tucson07a, tucson08a, tucson09a, tucson10a, tucson11a, tucson12a, tucson13a, tucson15a, tucson16a, tucson19a, tucson20a, unh02a, unh03a, unh04a, unh05a, unh06a, unh07a, unh08a, unh10a, whiteside01a, whiteside02a, whiteside03a, whiteside04a, whiteside05a, whiteside06a, whiteside07a, whiteside08a, whiteside09a, whiteside10a, whiteside11a, whiteside12a, whiteside13a, whiteside14a, whiteside15a, whiteside16a, whiteside19a, whiteside20a, williamson01a, williamson02a, williamson03a, williamson04a, williamson06a, williamson07a, williamson08a, williamson09a, williamson11a, williamson12a, williamson14a, williamson15a, williamson17a, williamson18a, williamson19a, williamson23a, williamson24a, wozniak01a, wozniak02a, wozniak03a, wozniak04a, wozniak05a, wozniak07a, wright201a, wright202a, wright203a, wright204a, wright205a, wright206a, wright207a.

§ 7.3.2 Control

capilouto01a, capilouto02a, capilouto03a, capilouto04a, capilouto05a, capilouto06a, capilouto07a, capilouto08a, capilouto09a, capilouto10a, capilouto11a, capilouto12a, capilouto13a, capilouto14a, capilouto15a, capilouto16a, capilouto17a, capilouto18a, capilouto19a, capilouto20a, capilouto21a, capilouto22a, capilouto23a, capilouto24a, capilouto25a, capilouto26a, capilouto27a, capilouto28a, capilouto29a, capilouto30a, capilouto31a, capilouto32a, capilouto33a, capilouto34a, capilouto35a, capilouto36a, capilouto37a, capilouto38a, capilouto39a, capilouto40a, capilouto41a, capilouto42a, capilouto43a, capilouto44a, capilouto45a, capilouto46a, capilouto47a, capilouto48a, capilouto49a, capilouto50a, capilouto51a, capilouto52a, capilouto53a, capilouto54a, capilouto55a, capilouto56a, capilouto59a, capilouto60a, capilouto61a, capilouto62a, capilout063a, capilout064a, capilout065a, capilout066a, capilout067a, capilout068a, capilout077a, capilout078a, capilout079a, capilout080a, kempler01a, MSUC08a, MSUC09a

§ 7.4 PB & J Sandwich Task Transcripts

§ 7.4.1 Aphasic

acwt01a, acwt09a, acwt10a, acwt12a, adler01a, adler02a, adler05a, adler06a, adler08a, adler09a, adler11a, adler12a, adler13a, adler14a, adler15a, adler16a, adler17a, adler20a, adler21a, adler24a, adler25a, bu01a, bu03a, bu04a, bu05a, bu09a, cmu03a, elman01a, elman02a, elman03a, elman05a, elman07a, elman09a, elman10a, elman11a, elman14a, elman15a, fridriksson01a, fridriksson02a, fridriksson03a, fridriksson04a, fridriksson05a, fridriksson09a, fridriksson10a, fridriksson12a, fridriksson13a, kansas06a, kansas09a, kansas10a, kansas11a, kansas15a, kansas18a, kansas19a, kansas20a, kansas21a, kansas22a, kempler02a, kempler03a, kempler04a, kurland03a, kurland07a, kurland08a, kurland09a, kurland10a, kurland12a, kurland13a, kurland14a, kurland15a, kurland16a, kurland17a, kurland18a, kurland19a, kurland20a, kurland21a, kurland22a, kurland23a, kurland24a, kurland25a, kurland26a, kurland27a, kurland28a, kurland29a, msu01a, scale01a, scale02a, scale06a, scale08a, scale10a, scale11a, scale13a, scale14a, scale15a, scale17a, scale18a, scale22a, scale23a, scale26a, scale30a, scale32a, scale33a, scale34a, scale35a, scale36a, scale38a, tap01a, tap02a, tap04a, tap07a, tap08a, tap12a, tap15a, tap18a, tcu01a, tcu03a, tcu08a, thompson01a, thompson02a, thompson03a, thompson04a, thompson05a, thompson06a, thompson07a, thompson08a, thompson10a, thompson11a, thompson13a, thompson14a, tucson02a, tucson03a, tucson06a, tucson07a, tucson08a, tucson09a, tucson10a, tucson11a, tucson12a, tucson13a, tucson14a, tucson15a, tucson16a, tucson20a, unh02a, unh03a, unh04a, unh05a, unh06a, unh07a, unh08a, unh10a, whiteside01a, whiteside02a, whiteside04a, whiteside05a, whiteside06a, whiteside07a, whiteside08a, whiteside09a, whiteside10a, whiteside11a, whiteside12a, whiteside13a, whiteside14a, whiteside15a, whiteside19a, whiteside20a, williamson01a, williamson02a, williamson04a, williamson07a, williamson08a, williamson09a, williamson11a, williamson12a, williamson14a, williamson15a, williamson17a, williamson18a, williamson19a, williamson23a, williamson24a, wozniak01a, wozniak02a, wozniak04a, wozniak05a, wright201a, wright202a, wright203a, wright204a, wright205a, wright207a.

§ 7.4.2 Control

capilout001a, capilout002a, capilout003a, capilout004a, capilout005a, capilout006a, capilout007a, capilout008a, capilout009a, capilout010a, capilout011a, capilout012a, capilout013a, capilout014a, capilout015a, capilout016a, capilout017a, capilout018a, capilout019a, capilout020a, capilout021a, capilout022a, capilout023a, capilout024a, capilout025a, capilout026a, capilout027a, capilout028a, capilout029a, capilout030a, capilout031a, capilout032a, capilout033a, capilout034a, capilout035a, capilout036a, capilout037a, capilout038a, capilout039a, capilout040a, capilout041a, capilout042a, capilout043a, capilout044a, capilout045a, capilout046a, capilout047a, capilout048a, capilout049a, capilout050a, capilout051a, capilout052a, capilout053a, capilout054a, capilout055a, capilout056a, capilout057a, capilout058a, capilout059a, capilout060a, capilout061a, capilout062a, capilout063a, capilout064a, capilout065a, capilout066a, capilout067a, capilout068a, capilout076a, capilout077a, capilout078a, capilout079a, capilout080a, capilout081a, kempler01a, MSUC01a, MSUC01b, MSUC02a, MSUC02b, MSUC03a, MSUC03b, MSUC04a, MSUC04b, MSUC05a, MSUC05b, MSUC06a, MSUC06b, MSUC07a, MSUC07b, MSUC08a, MSUC08b, MSUC09a, MSUC09b, richardson165a, richardson166a, richardson167a, richardson168a, richardson169a, richardson17a, richardson170a, richardson171a, richardson172a, richardson173a, richardson174a, richardson175a, richardson176a, richardson177a, richardson178a, richardson179a, richardson18a, richardson184a, richardson185a, richardson186a, richardson188a, richardson189a, richardson19a, richardson191a, richardson192a, richardson194a, richardson195a, richardson196a, richardson197a, richardson198a, richardson199a, richardson20a, richardson200a, richardson201a, richardson202a, richardson203a, richardson204a, richardson205a, richardson206a, richardson21a, richardson22a, richardson23a, richardson24a, richardson25a, richardson34a, richardson36a, richardson37a, richardson38a, richardson39a, richardson41a, richardson42a, richardson58a, richardson59a, richardson60a, richardson92a, wright01a, wright02a, wright03a, wright04a, wright06a, wright07a, wright09a, wright10a, wright100a, wright101a, wright102a, wright11a, wright12a, wright14a, wright15a, wright16a, wright17a, wright18a, wright19a, wright20a, wright21a, wright22a, wright23a, wright24a, wright25a, wright26a, wright27a, wright28a, wright29a, wright30a, wright31a, wright32a, wright33a, wright34a, wright35a, wright36a, wright37a, wright38a, wright39a, wright40a, wright42a, wright43a, wright46a, wright47a, wright48a, wright49a, wright50a, wright51a, wright52a, wright53a, wright55a, wright57a, wright58a, wright59a, wright60a, wright61a, wright62a, wright63a, wright64a, wright65a, wright66a, wright67a, wright68a, wright69a, wright70a, wright71a, wright72a, wright73a, wright74a, wright75a, wright77a, wright78a, wright79a, wright80a, wright81a, wright82a, wright83a, wright84a, wright85a, wright86a, wright87a, wright88a, wright89a, wright90a, wright91a, wright92a, wright93a, wright94a, wright95a, wright96a, wright97a, wright98a, wright99a

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