CAPP 30255
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Final Report

How Do Children Learn a Language? A Machine Learning Analysis of Childes Data

Abstract

How children gradually acquire a language has been a popular research topic in the field of linguistics and developmental studies for decades. However, researchers are still unsure that how and why children tend to comprehend and produce certain sentence structures ahead of others. In order to explore more thoroughly on the pattern of language acquisition, this project applies machine learning techniques on the open-sourced Childes data, analyzing 5- to 11-year-old children's language production. The objective of this project is to find the pattern of sentence structures produced by children at different ages by examining their transcripts on a word level, as well as based on the part-of-speech tags of produced words. Simultaneously, the project also aims to distinguish the difference in such pattern produced by children with and without language impairment. Results suggest that children tend to produce more clauses containing interrogative and relative pronouns and fewer nouns and verbs as they grow up, and this pattern differed significantly between children with and without language impairment. Future research utilizing similar methodologies could use a larger corpus for analysis.

How Do Children Learn a Language? A Machine Learning Analysis of Childes Data

Children's language development has been a popular topic for psychologists and linguists to research over the past decades. However, most studies focused on a relatively young infant population of the age 0 to 3 years old. According to the past literature, children with English as the first language seemed to acquire certain elements before others (Gentner, 1975). Nonetheless, it is still unclear what sentence structures can be more easily acquired by children and why. Therefore, to further explore the pattern of sentence structure acquisition, I analyzed young children's language production over the age of 5 to 11, and I utilized some neural network and machine learning techniques for analysis. Moreover, because little research has been done to compare the sentence structures produced by children with and without language impairment, this study also aims to fill in this gap of the literature.

Before getting to the description of this current study, I would like to first review the past literature on the pattern of language acquisition. Overall, the research direction has changed from recognizing that there is a noun-verb distinction in infants' language acquisition, to expanidng that distinction to other sentence structures.

Literature Review

The noun-verb distinction in language acquisition

According to the previous research on developmental psychology and linguistics, children's ability to acquire verbs seemed to lag behind their ability to acquire nouns. Young children's abilities to lean (Nelson, 1974), to understand (Gentner, 1975), and to produce nouns (Goldin-Meadow, Seligman, & Gelman, 1976) seemed to be better than verbs at an early stage of language learning. For example, as shown by a series of studies conducted by Waxman and his colleagues (2001, 1995, 2009), infants as young as 12-24 months could successfully map novel nouns to objects, while the same ability for mapping verbs to actions and events did not come up until 24 months of age. In another experimental study (Goldin-Meadow, Seligman, & Gelman, 1976), two-year-olds showed a better ability to both comprehend and produce nouns than verbs. This noun-verb distinction does not only persist across different ages at the early stage of development, but it also seems to appear in languages other than English. For instance, in a cross-cultural study by Imai et al. (2008), 3-and 5-year-old children whose mother tongues are either Japanese, English, or Chinese all exhibited better abilities to generalize novel nouns than novel verbs despite nuanced differences in the process of learning novel words.

In order to explain this pattern in noun and verb acquisition, many hypotheses have been proposed by linguists and psychologists. In the book *Language Development: Language, Thought, and Culture* by Gentner (1982), two theories - the Natural Partitions hypothesis and the Linguistic Relativity theory - were compared to aim to explain this pattern. The first hypothesis claims that there is a linguistic distinction between nouns and predicate terms such as verbs and prepositions. In our perceptual world, concrete concepts, represented using nouns in general, are easier to grasp than abstract concepts of actions, change-of-state, or causal relations conveyed using verbs. On the other hand, Linguistic Relativity theory is a counterview of the previous, and it argues that there is no perceptual difference in viewing concrete versus abstract concepts. According to this theory, nouns are learned before verbs in English because English is a noun-centered language, and this pattern may be different on children in other languages that are verb-centered such as Chinese and Japanese, a belief that was later refuted by cross-cultural studies such as Imai et al. (2008).

The idea of Natural Partitions was extended in McDonough et al. (2011) to suggest that, because nouns represent more concrete concepts, they are generally more imageable than verbs that represent abstract terms. Therefore, the term word imageability was defined to measure the ease for a concept to evoke a mental image. Findings suggested that imageability of a word was negatively correlated to the age of acquisition: the easier for a word to evoke a concrete mental image, the earlier it could be acquired by children (McDonough et al., 2011). A relevant view was proposed by Leddon et al. (2011), who argued that it would take longer for children to verbs because verbs convey more information than nouns. In other words, in order to comprehend a verb, a child does not only need to understand the action itself but also the arguments that the verb acts on and the relationship between them. Both claims by McDonough et al. (2011) and Leddon et al. (2011) have supported the idea that the noun-verb distinction pattern in language acquisition relates to how children perceive the world. Therefore, by exploring this learning pattern more closely, psychologists would better understand how children gradually learn language structures as well as learn to perceive and to describe the world.

Language Learning and Language Impairment

Although plenty of studies have been conducted to investigate the noun-verb distinction in language acquisition, many of them share two major limitations. First, many early studies consider this learning pattern to be distinctively a difference between nouns and verbs. Some recent evidence posited that the underlying mental representation of words might be a more influential driving factor of the age of their acquisition than whether it is a verb or a noun (McDonough et al., 2011). In addition, Gentner (1982) summarized words to four types - nominal, interminate, predicate, and expressive, instead of simply nouns versus verbs, when studying early language learning in order to find the underlying mechanism that makes verbs easier to acquire by young children. Specifically, nominal terms have concrete object references; predicate terms refer to actions, change of state, or other predicate notions and are mainly verbs and prepositions; expressive terms directly portray feelings and thoughts; and, finally, intermediate terms have ambiguous usage. According to Gentner (1982), nominal words were learned earliest and followed by intermediate words, while other verb-like predicate and expressive terms entered considerably later. However, Gentner's findings (1982) were primarily based on case studies, and linguists and psychologists still lack the knowledge about what characteristic of a word, in general, predicts the average age of its acquisition.

Second, due to the lack of data available, most linguists studied this pattern of language acquisition on children with normal language abilities. Though some neuroscientists studied noun-verb processing on patients with mental disorders such as aphasia and amnesia (Alyahya, 2018), most are conducted on adults. The literature on how language impaired children learn and use language is largely missing in the field of developmental psychology. However, knowing the differences between the language learning process of normal versus language impaired children can give crucial insights to the understanding and the treatment for language impairment. It could help clinicians to better explain what hinders language impaired children to acquire a complete language system and, thus, come up with efficient treatments to facilitate their language learning. Therefore, this current project would utilize the open-sourced data from the database Childes (https://childes.talkbank.org/) and the corpus used by Gillam (2004) to compare the language acquisition pattern between children with and without impaired language abilities.

In conclusion, I reviewed the literature on the pattern in children's early language acquisition. In general, consistent results were reported to suggest that infants across culture tend to learn nouns before verbs. Among the two early hypotheses, Natural Partitions and Linguistic Relativity, the latter was refuted by cross-cultural empirical studies. But there is also not sufficient evidence to support the first. The underlying reason for certain types of words to be acquired earlier than others remains controversial in the field of developmental psychology. But some researchers suggested that words with higher imageability could be learned more easily by young children. Moreover, whether language impaired children showed a similar trend is unknown. The literature seems to overlook the population of children with impaired language abilities. Therefore, the proposed study will utilize the Gillam corpus on Childes (2004) to examine the characteristics of the first-learned words in order to give implications to future developmental and clinical research on language development.

Methods

In this section, I would describe the data I used in this experiment and the machine learning tools I used as well as the neural network models I built for data analysis. This current study aims to extract features of words produced by children of different ages and with different language abilities. Transcripts would be analyzed in word level, and models in this study took words and part-of-speech (POS) tags as input and predicted either Language Impairment (Impaired vs. Normal) or Age (ranges from 5 years 0 months to 11 years 11 months).

Dataset

For this project, I used the Gillam corpus (Gillam & Pearson, 2004) from the open-sourced database, Childes (MacWhinney, 2000). Childes stands for the Child Language

Data Exchange System, coming from a project started by MacWhinney and his colleagues in 1984 in order to establish a language acquisition database for researchers studying in various languages and all around the world.

Specifically, Gillam corpus contained linguistic data produced by 250 children with language impairment and 520 with normal language abilities. The original purpose of this corpus was to build the Test of Narrative Language (TNL; Gillam & Pearson, 2004), a test that aims to evaluate the quality of narratives produced by children and, therefore, to assist the diagnosis of language disorders. Linguistic data were obtained in a naturalistic study, in which children participants were asked to tell a story in a given scene (in McDonald's in this experiment). Children were also audiotaped during storytelling, and the audio files were transcribed later to CHAT format and uploaded to Childes under Gillam corpus.

Data preprocessing. In order to apply neural network models and other data analytical tools to the dataset, I preprocessed the data so that separate transcripts were combined into one file. First, I utilized childes-db (Sanchez et al., 2018), an API that helps to transform CHAT files from Childes database to more accessible and reproducible tabular format. I further processed the obtained tabular format to CSV format and kept only columns that are relevant to the current study: id (the identification number for each sentence), transcript_id (the identification number for each transcript/child), gloss (one gloss is a sentence produced by a child), part_of_speech (POS tags as defined by Childes), Impaired (whether a child has impaired = 1 or normal = 0 language abilities), Age, and Gender (female = 0 and male = 1).

After renaming and organizing columns of the dataset, each row represents one sentence produced by a child. Rows with empty gloss were dropped. As Gillam corpus dropped some children's data, only 668 children's data were analyzed. There are 497 children who had normal language abilities, and 171 had impaired abilities; 323 were female and 345 were male. Children were ranged from age 5 to 11 years old, and specific statistics of age are included in Figure 1.

Preliminary Analysis

Before applying any deep learning models to the data, I first conducted some preliminary analysis using the frequencies of verbs and nouns children produced during storytelling as the input variable and their language abilities and Age as dependent variables. Logistic regression was used for the preliminary analysis. Besides verbs and nouns, frequencies of other POS tags were also reported in order to examine if there are patterns of other POS tags, besides verbs and nouns, that might be predicting features of the two output variables.

Word-Based Analysis

The word-based analysis was conducted using different neural networks with the column "gloss" as input and either Language Impairment or Age as output.

Word embeddings. After processing the Gillam data, each word in gloss was vectorized to be able to use as inputs to complex machine learning models. Three embedding methods were used: GloVe, Word2Vec using a continuous Bag-of-Words (CBOW) architecture, and Word2Vec using a Skip-Gram (SG) architecture.

The Global Vectors for Word Representation (GloVe) is an unsupervised algorithm that represents words using pre-trained vectors (Pennington, Socher, & Manning, 2014). In this study, I used the word vector file "Glove.6B.zip", which was trained on Wikipedia 2014 and Gigaword to obtain the embedding matrix.

Word2Vec is another word vectorizing approach developed by Mikolov and colleagues (2013). Different from other word vectorizers, it produces vectors for a target word based on its context, specifically, words surrounding the target word. CBOW- and Skip-Gram-based Word2Vec are slightly different in how they define and predict the context of a given word. Two different embedding matrices were computed in this study for further word-based analysis.

Vocabulary. Each row in gloss was a sentence produced by a child, and it was regarded as one sample. In total, there are totally 24609 examples in the preprocessed data. The data was divided into a training set (68% of the data), a validation set (12% of the data), and a test set (20% of data). A vocabulary of 3958 words was obtained from the dataset and was used to create three different embedding matrices.

Model Construction. Several deep learning models were built and manually tuned using word embeddings as input and either Language Impairment or Age as output.

Naive Simple RNN model as a baseline. During analysis, I used a simple recurrent neural network model without pre-trained embedding matrices as a baseline model. Because I was interested in two output variables - Age and Language Impairment, two baseline models were trained and evaluated for both word- and POS tag-based analyses.

Two models are of the same architecture. Each model has one embedding layer, which transforms vocabulary index to word embeddings, as no pre-trained matrix was used. The model has three hidden layers, each with 64 neurons and an activation function of ReLU (Rectified Linear Unit). For Age, the output layer used Softmax function to perform a multinomial classification, while for Language Impairment, the output layer used a sigmoid function to perform binary classification.

LSTM-based RNN. Three Recurrent Neural Network (RNN) models were then trained using three embedding matrices obtained respectively using GloVe, CBOW-based Word2Vec, and Skip-Gram-based Word2Vec for word-based analysis. For POS-tags, the same initial models were used despite that the input was vectorized tags and tag-bigrams.

By comparing the initial models, I selected one based on the reported validation loss and accuracy and built an RNN model stacked with a Long Short-Term Memory (LSTM) layer with modified numbers of hidden layers and neurons per layer. Because no overfitting was observed for word-based analysis, I did not use any dropout or regularizers.

Finally, the best model for each output variable was selected and evaluated on the held-out test set.

POS-Tag-Based Analysis

Since the purpose of the study is to examine whether children of different ages learn certain words better and faster than other words, POS tags were more important than original words in the analysis.

POS bigrams and trigrams. POS tags were not only analyzed in a single-tag manner, but they were also grouped into bigrams and trigrams. Each bigram/trigram was indexed and vectorized separately using the TfidVectorizer provided by the Sklearn package in Python. This tool vectorizes each input, character, word, or bigram, according to its TF-IDF (Term Frequency-Inverse Document Frequency) score. This vectorizer enables researchers to take account into the frequency of words appeared in documents while also offset the natural imbalance in using certain words more frequently than others.

Model construction. Several models were tested and manually tuned using POS vectors as input and either Language Impairment or Age as output. After excluding those models that did not converge, I further tuned five models - Logistic Regression, Naive Bayes, Linear Support Vector Machine Classifier (LinearSVC), Ridge, and Random Forest Classifier. See Figure 2 for their best validation mean squared errors (MSE). The ridge model was selected as the best model for both outputs.

Feature selection. The model was tested on the test set. Feature importance plots were generated for both Impairment and Age to evaluate what factors tended to be most influential. Individual Conditional Expectation (ICE) plots were created for the five most influential factors in order to interpret the direction of effects.

Results

Preliminary Results

Noun-Verb Patterns. In order to test whether the early hypothesis of the noun-verb distinction continues to children aged 5 to 10, I analyzed whether the ratio of noun versus verb was correlated to Age. The result was neither significant on the whole sample nor on the subsamples separated by language impairment. However, when analyzing the correlation between the proportion of nouns and verbs together across all words produced, both groups, Impaired and Typical, showed a decrease ($p < .05$) in the percentage of nouns and verbs among all produced words (Figure 3). Moreover, this decreasing trend differed significantly between two groups ($F = 5.13$, $p < .05$), where the Impaired group had a sharper decrease in noun and verb use than the controlled group.

Other Part-of-Speech Use. Besides of nouns and verbs, I also calculated the proportions of the use of all the other 42 different types of part-of-speech (POS) in children's language production. Only proportions of use of the interrogative (e.g., "what") and relative (e.g., "when") pronouns were significantly correlated to Age (See Figure 4). I also separately analyzed by language impairment conditions. Although children with language impairment used fewer interrogative and relative pronouns than children with typical language abilities throughout the development, the differences tended to converge as they grow up (refer to Table 1 for specific test statistics).

Word-Based Results

The baseline sequential model returned low maximum validation accuracy (*val_acc* = 0.24) and high minimum validation cost (*val_cost* = 2.23) in predicting Age, but it returned relatively better results for Language Impairment (*val_acc* = 0.78, *val_loss* = 0.50).

Modified models returned similar results predicting Age, suggesting that either using single words produced by children participants might not give significant insights to what age group they belong or the training data size was too small.

Modified RNN models using LSTM architecture predicting Language Impairment returned better results. Among all the three embeddings (Table 2 for statistics of all three embeddings), the model using GloVe embedding was selected to be the best according to its performance (see Figure 5 for performance over epochs. When testing on the test set, the test loss was similar to the validation loss, indicating that there was no overfitting. However, all machine learning models that used word embeddings as inputs stopped learning at *val_loss* = 0.7731. It implies that my training data was too small in size so that it does not provide enough information for my models to train.

POS-Based Results

As mentioned earlier, the ridge model was selected as the best model for both Impairment and Age as outputs (see Figure 6 for the feature importance plot for language impairment and Age). For Impairment, the following five bigrams appeared to be most important among all bigrams and trigrams: subjective pronoun + infinitive, conjunction + article (determiner), coordinator + article (determiner), conjunction + subjective pronoun, coordinator + subjective pronoun, interjection + subjective pronoun. The coordinator + article (determiner) bigram was used less frequently by children with typical language abilities but more frequently by those with impaired abilities. Other four bigrams were all more frequently used by language impaired children.

For Age, interjection + subjective pronoun, conjunction + subjective pronoun, preposition + article (determiner), coordinator + subjective pronoun, and coordinator + proper noun were found as the most important features. Except for preposition + article (determiner), all the other bigrams appeared to be used less frequently after children grew up.

Discussion

According to the results of this analysis, I could draw some important conclusions about children's produced sentence structures at the age of 5 to 11. First, older children seemed to produce more clauses led by interrogative and relative pronouns. Although children with language impairment and typical language abilities seemed to differ, at all age levels, in their proportional use of these two pronouns, the differences tended to converge as they grow up. This finding implies that language impaired children may be slow to acquire certain sentence structures when they were young, but they could still catch up with children with typical abilities later in their childhood.

In addition, language impaired children seemed to prefer certain sentence structures over others. For example, they tended to use sentences like “and I”, “and she”, “so she”, and other pairs of conjunction/coordinator and subjective pronoun during conversations. One possibility is that conjunctions, compared with clauses, can be more easily learned. Therefore, when language impaired children are attempting to express complex meanings, they would use conjunctions followed by another full sentence instead of clauses.

Interestingly, the difference between children with and without language impairment seemed to match the difference between old and young children. It suggests that children with language impairment may be lagged in the typical language development trajectory, but, in my analysis, the difference in both group’s learning abilities tended to disappear gradually as children grew up.

Despite the findings of this analysis, this study suffers from many limitations. First, when using neural networks in the word-based analysis, I used each sentence as one input example for predicting Impairment and Age. However, there were in total 24,609 sentences produced by children participants but 3809 words in the vocabulary as input features. The data size was indeed too small to train such a large amount of features. Therefore, future studies might consider using a larger corpus for deep learning analyses. Second, children’s produced sentences were drastically different in length. This could partially affect the training process. I have not figured out an effective approach in preprocessing the data to avoid the noise created by imbalanced sentence lengths. Therefore, future research may search for other ways of controlling for sentence lengths. Third, I recognized that categorizing children to language-impaired versus typical might be greatly imprudent. The severity of language impairment was not measured so that correlations between language impairment severity and certain sentence structures could not be drawn. Therefore, more detailed clinical reports would be needed if researchers want to explore more closely to language impairment.

Overall, this study aimed to examine the pattern of sentence structure produced by children of different ages and with different language abilities. Three types of analyses were conducted: the Preliminary Analysis (using proportional use of POS tags), the Word-based Analysis (using word embeddings as inputs and neural network models for analysis), and the POS-tag-based Analysis (using vectorized POS tags as inputs and machine learning models for analysis). Although the results gave some insightful findings regarding the pattern of sentence structures produced by children across Age, many neural network models built in the study were largely limited in accuracy and learning abilities due to the small data size. However, the study pointed out a potential future direction for linguists and psychologists by adopting machine learning techniques to analyze language production.

My Effort

As I did this project on my own, I pre-processed all the data files and conducted all the analyses. I divided my analyses into four parts:

Combine files: this was the part that took me the longest to figure things out. Because different types of analysis required me to pre-process my data files into different formats, I would have to create many files to try on different analyses to see which ones would work.

- I am familiar with Pandas, so this part was not too time-consuming for me.
- I did not know much about R, but only R has an API that specializes in pre-processing Childes transcripts. So I had to learn how to use that API myself.

Preliminary Analysis: I calculated the proportional use of POS tags myself.

- I am pretty much familiar with how to add new columns to Pandas Dataframes.

Word-based Analysis: I first used the three word embedding techniques to process the document. Then I built and manually tuned different architectures to implement neural network models.

- This part took me the longest to finish. I tunned around 30 models, which all stopped learning at *val_loss* = 0.7731.
- Packages I learned: GloVe, Word2Vec, Keras.

  Other techniques I learned: Early stopping, class_weights and multi_class for multinomial classification.

POS-based Analysis: this part is easy for me. However, how to reverse the vectorization process was not intuitive. The ICE plots also took hours to complete.

- Packages I learned: ICE.
- What I know already: Sklearn, Feature importance techniques.

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Figure 1. Descriptive statistics of Age in Gillam corpus data.

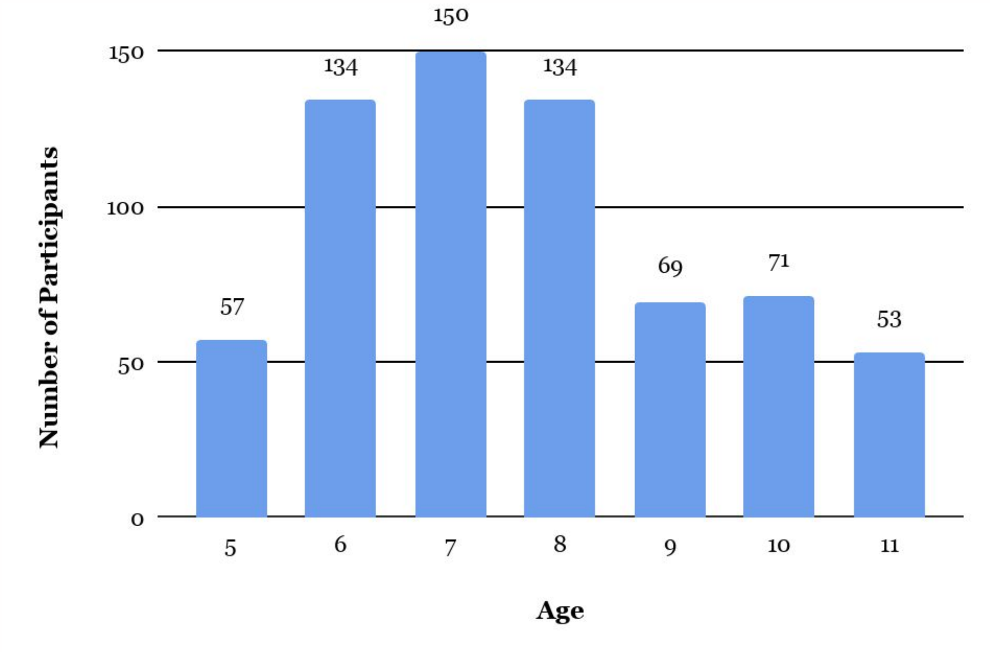


Figure 2. Mean Squared Errors (MSEs) for all machine learning models. *The left* is the error rates for Language Impairment, and *the right* is the error rates for Age.

Figure 3. The proportional use of nouns and verbs across Age, separately analyzed by Language Impairment conditions.

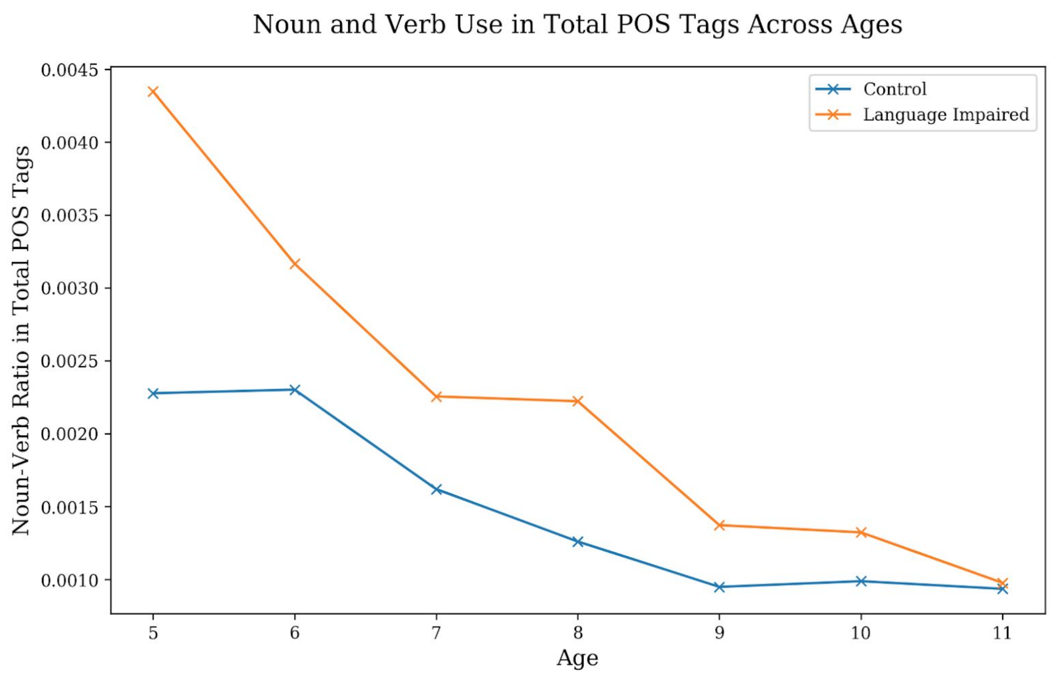


Figure 4. The proportional use of interrogative and relative pronouns across Age, separately analyzed by Language Impairment conditions.

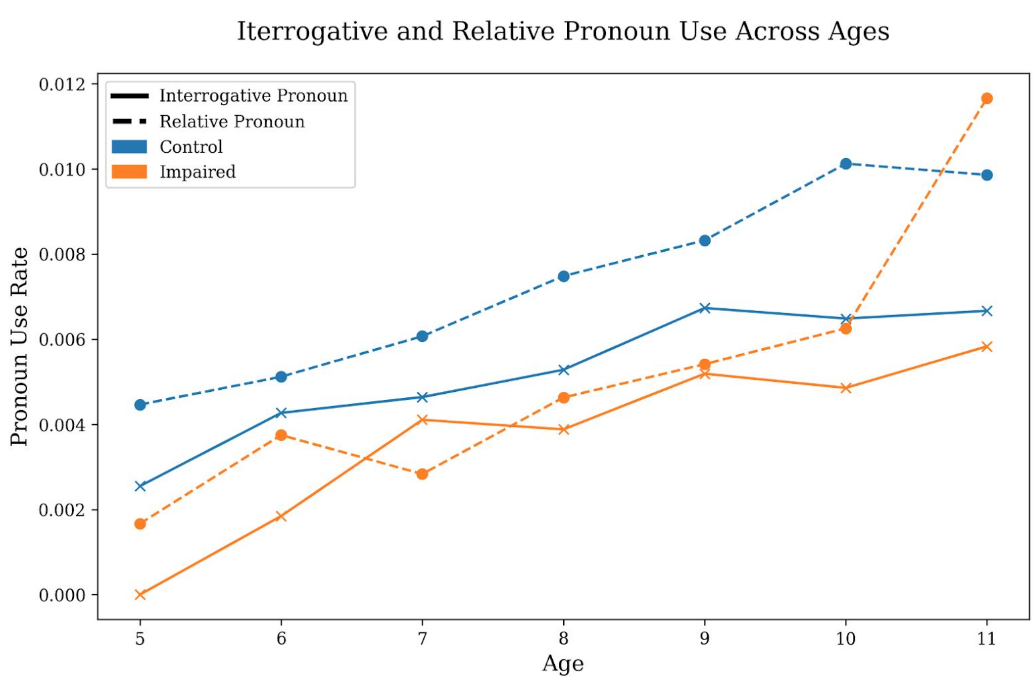


Figure 5. Validation accuracy and loss of the simple RNN model stacked with a LSTM layer over epochs, early stopped at epoch = 11.

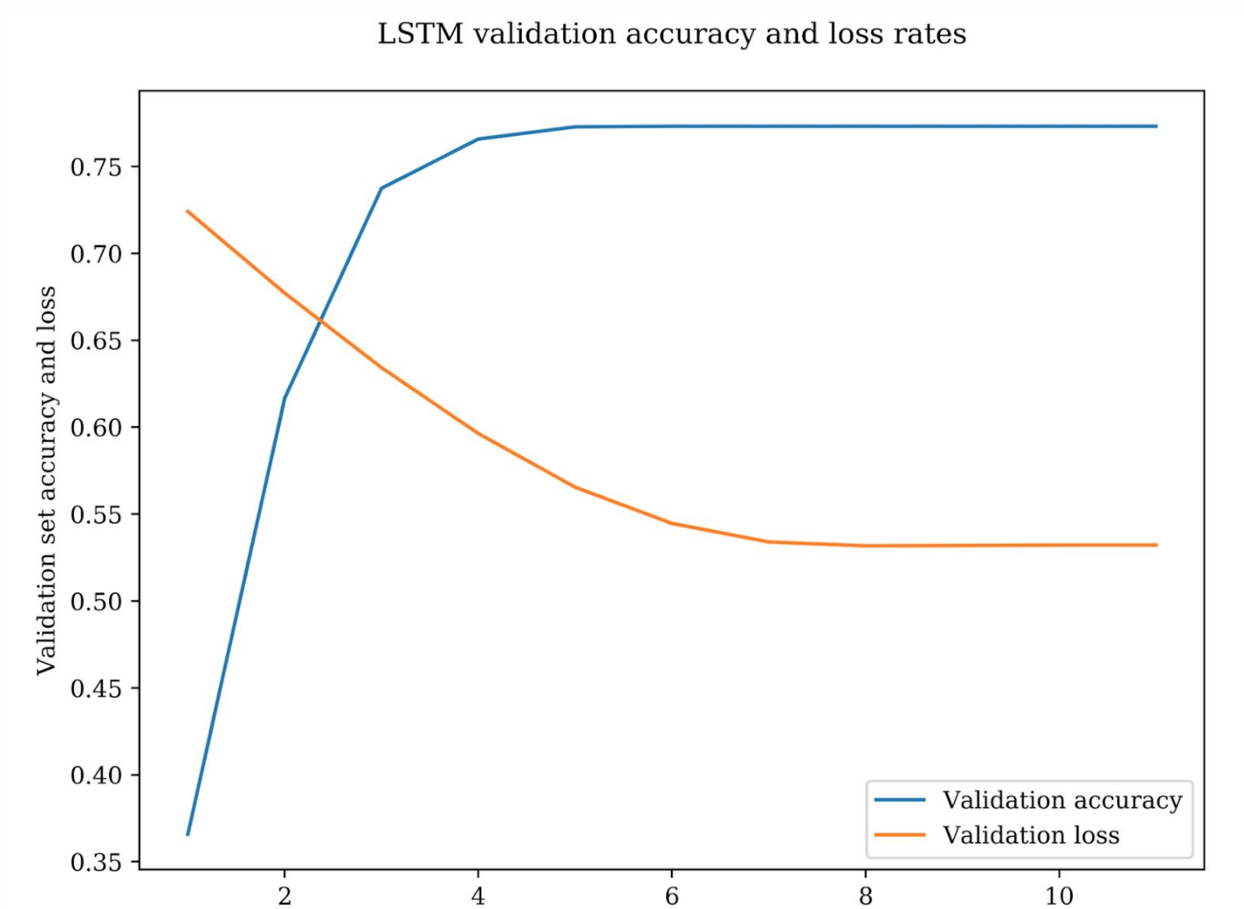
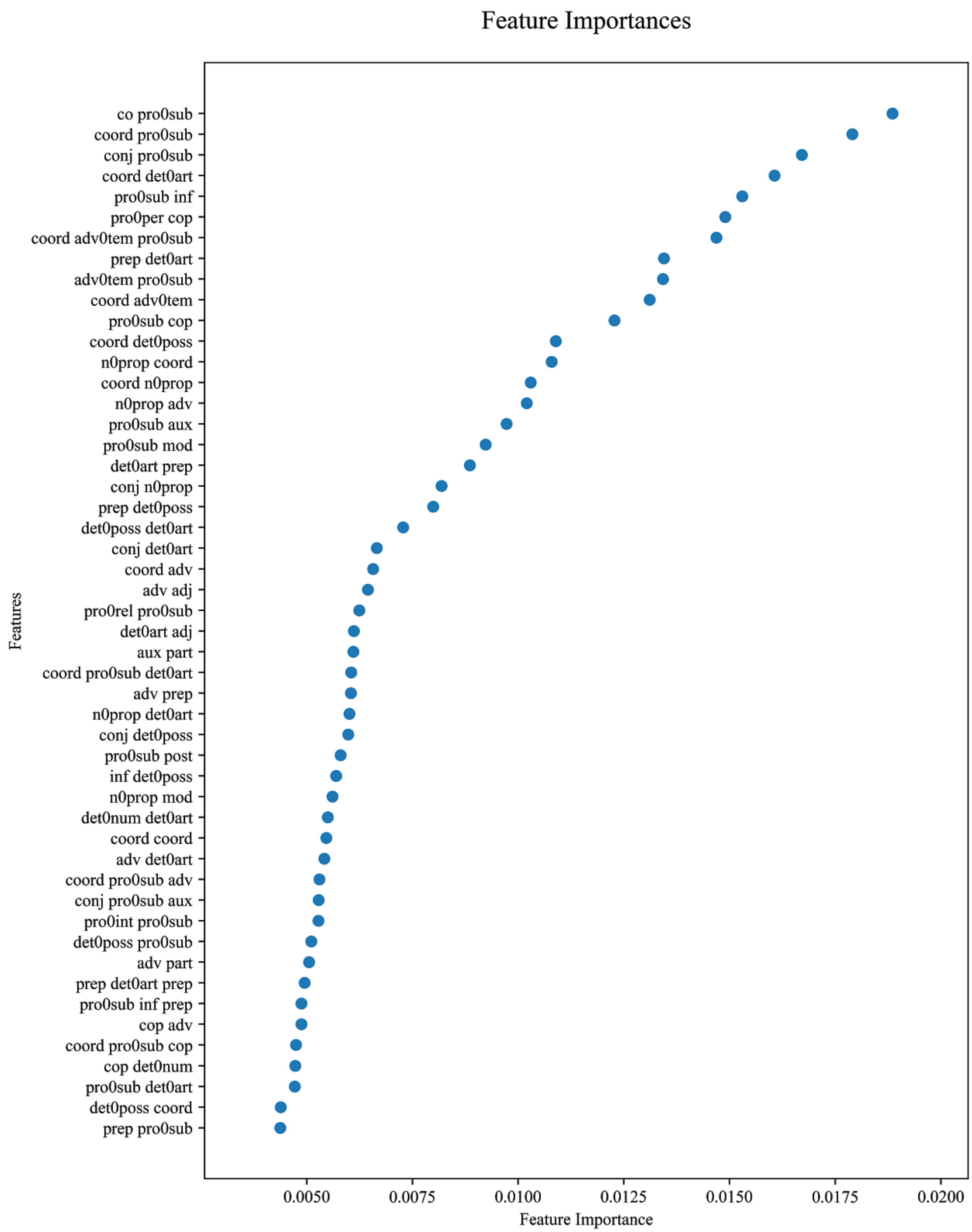


Figure 6. Feature importance plot of the 50 most important POS bigrams, *the first plot* is for predicting Language Impairment, and *the second* is for predicting Age.



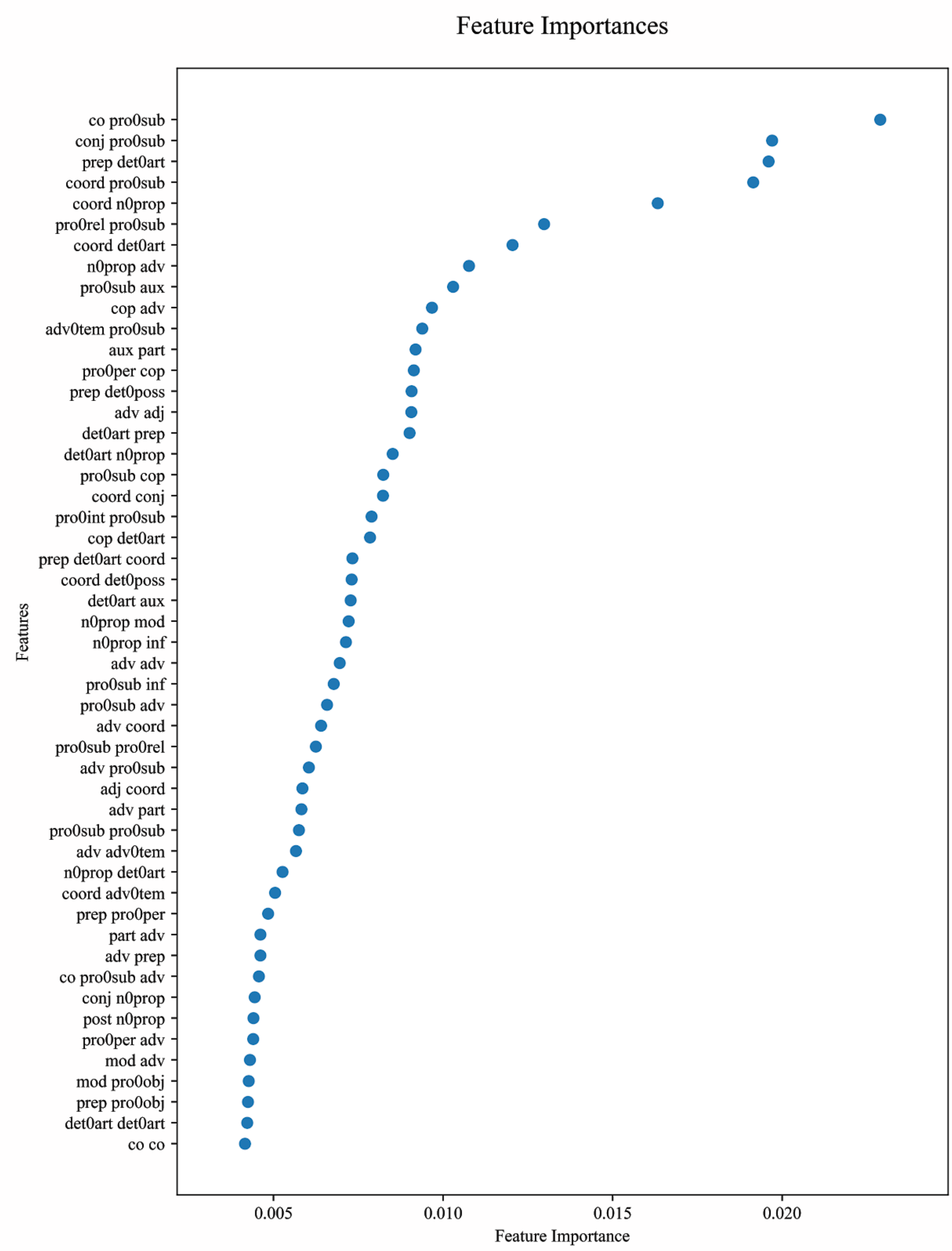

Feature Importances
co pro0sub
conj pro0sub
prep det0art
coord pro0sub
coord n0prop
pro0rel pro0sub
coord det0art
n0prop adv
pro0sub aux
cop adv
adv0tem pro0sub
aux part
pro0per cop
prep det0poss
adv adj
det0art prep
det0art n0prop
pro0sub cop
coord conj
pro0int pro0sub
cop det0art
prep det0art coord
coord det0poss
det0art aux
n0prop mod
n0prop inf
adv adv
pro0sub inf
pro0sub adv
adv coord
pro0sub pro0rel
adv pro0sub
adj coord
adv part
pro0sub pro0sub
adv adv0tem
n0prop det0art
coord adv0tem
prep pro0per
part adv
adv prep
co pro0sub adv
conj n0prop
post n0prop
pro0per adv
mod adv
mod pro0obj
prep pro0obj
det0art det0art
co co
Features
0.005
0.010
0.015
0.020
Feature Importance

Table 1. Test statistics for the correlation between the proportional use of interrogative and relative pronouns and Age, separatedly analyzed by Language Impairment conditions.

	Coefficient	Standard error	t statistics	p-value
	Impaired Language Abilities			
Interrogative pronouns	67.71	21.93	3.09	.002**
Relative pronouns	59.46	20.29	2.93	.004**
	Typical Language Abilities			
Interrogative pronouns	80.88	15.88	5.09	.000***
Relative pronouns	83.41	12.41	6.72	.000***

Table 2. Validation loss and accuracy using three models with LSTM architecture for predicting Language Impairment.

	Model 1 - GloVe	Model 2 - CBOW	Model 3 - SG
Parameters	LSTM architecture with 1 hidden layer Number of nodes per layer = 64 Number of epochs = 20 Batch size = 512		
Maximum validation accuracy	0.78	0.78	0.78
Minimum validation loss	0.61	0.66	0.63