Towards A Neural Machine Translation Proposal to Help Everyday Communication for People with Broca's Aphasia

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Abstract. Stroke is among the most common causes of death and disability worldwide. More than 12 million people suffer from a stroke every year, 4 million of whom develop an aphasia. Aphasia is a language disorder that affects up to 0.6% of the global population. Broca's aphasia is a form of aphasia that affects the ability to articulate speech, but not the ability to understand it. It has a negative impact on the mental health and quality of life of people who suffer from it. Patients may suffer from communication difficulties in daily life. A tool to help patients with aphasia in their daily communication could be useful. In this scope, our contribution in this paper is twofold. First, we propose a method to convert correct French sentences into sentences containing errors that could have been produced by aphasic people. For that, we use lexical errors produced by ChatGPT. We use this method to create a synthetic parallel corpus of French sentences and their Broca's aphasia equivalents. Second, we propose a transformer-based translation model to map aphasic sentences back to their correct form. Our model is trained on the synthetic parallel corpus and achieves a BLEU score of 79.61.

Keywords: aphasia · inclusion · neural machine translation.

1 Introduction

Stroke is the second leading cause of death worldwide. According to the World Stroke Organization[3], 12.2 million people suffer from strokes each year, which amounts to 1 in 4 adults over the age of 25 experiencing a stroke in their lifetime. The same source reports that over 101 million people worldwide are living with the physical, cognitive, and emotional consequences of stroke, aphasia being one of them [6].

Aphasia is an acquired neurogenic communication disorder that affects language reception, expression, or both [2]. Common causes of aphasia include

[3] https://www.world-stroke.org/

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stroke, traumatic brain injury, brain infection, brain tumors, metabolic disorders, and neurodegenerative diseases [9]. Broca's aphasia is an expressive aphasia[4], caused by a lesion in an area of the inferior frontal lobe of the brain known as Broca's area [2].

People who suffer from Broca's aphasia have difficulties performing daily tasks, including communicating with close ones, participating in social activities, and working [20]. Combined with their awareness of the inadequacy of their speech, this can lead to frustration, low self-esteem, social isolation [23], clinical depression [19], and even suicidal thoughts [4]. This last point is particularly problematic given that people with Broca's aphasia are less likely to communicate their suicidal thoughts due to a combination of their condition and their social isolation [19,4].

All the above-mentioned problems are compounded by the relatively high prevalence of Broca's aphasia. While difficult to measure exactly, some studies [3,5,7] estimate that the prevalence of aphasia in the global north is between 0.1% and 0.6%. According to the National Aphasia Association[5], in the United States alone, the number of people with aphasia is estimated to be well over 2 million. Of these, around 28% are estimated to be Broca's aphasia cases [28,12]. The incidence of aphasia is estimated to be $0.02 - 0.06\%$ per year [3].

The most common treatment for Broca's aphasia is speech therapy [8], which requires the patient's physical presence [10,14]. In this paper, we propose complementing speech therapy with an automated natural language processing system for French. Such a system could be used to provide a patient who has already received speech therapy with additional practice available 24 hours a day, 7 days a week. It could also be deployed as a communication aid for people with Broca's aphasia, helping others understand them and reducing their social isolation. Such a communication aid could be a life-saver in emergency situations, where the patient is unable to communicate their needs to responders.

2 Related Work

The use of natural language processing based systems to better understand and treat aphasia is a research area that has been expanding in recent years. Works in this area have explored multiple aspects of the problem, including data collection [17], data synthesis, and corrective modeling [18], [25].

2.1 Data Collection

Many efforts have been made to compile aphasic speech data sets. Chief among them is the AphasiaBank project [17], part of the TalkBank project [15]. AphasiaBank is a collection of audio and video recordings of people with aphasia performing various standardized tests in multiple languages. These recordings are

[4] Meaning that it affects the ability to produce language, leaving language understanding intact.
[5] `https://www.aphasia.org/`

accompanied by transcripts, in `CHAT` format [16], annotations, metadata, and test scores. However, corrections to the transcripts are not included in the AphasiaBank dataset, nor in any other dataset we are aware of. This absence of corrections is problematic because machine translation requires the presence of a parallel corpus [27]. Moreover, AphasiaBank contains only a few recordings in French, of which only one is of a person with Broca's aphasia.

2.2 Data Synthesis

Errors made by patients with aphasia may appear on the syntax level [18] or on the word level. In the latter case, words may be omitted [13] or modified (insertion, deletion, and substitution of letters and syllables) [25]. In this work, we are continuing our research on the automatic creation of modified versions of words to approximate aphasic-like errors [25].

To address the lack of parallel corpora, some researchers [13,18,25] have proposed methods to alter regular sentences to simulate aphasic patterns of speech. The hope is that models trained on such simulated corpora will be able to generalize to real aphasic speech.

The proposed error generation methods are diverse. In [25], a rule-based approach is used to create lexical errors. Starting with a non-parallel corpus $\mathcal{C}$ of French sentences, every word w of every sentence $s \in \mathcal{C}$ is replaced by a word w' with probability p. The replacement word w' is generated by randomly inserting, deleting, or replacing characters in w. This gives a set of n candidate words, from which w' is chosen as the word with the maximal character 4-gram score.

Other works used a neural approach. In order to detect speech errors associated with dementia and Alzheimer's disease, the authors of [13] combined GPT-2 with GPT-D, a deliberately degraded version of the same model, obtained by corrupting its weights. This is done by masking half of the parameters of the embedding layer and the value matrices of self-attention layers. Although this method was designed for speech impairments associated with dementia and Alzheimer's disease, aphasia is one such impairment [9]. The approach we propose in this paper is related to [13] because we propose to automatically correct aphasic sentences by using a machine translation system.

In [18], the authors used a linguistic approach. Sentences are first filtered by length and then parsed into syntactic trees. This is followed by a second non-deterministic filtering step to remove sentences that have a high noun-to-verb ratio. The remaining sentences are processed by a part-of-speech tagger. Every word in the sentence is deleted with a probability that depends on its part-of-speech tag. The sentences produced by this method are similar to aphasic speech as measured by noun-to-verb ratio, mean sentence length, and complex-to-simple sentence ratio [18].

2.3 Corrective Modeling

The main interest of our work is in the correction of aphasic speech. To the best of our knowledge, only two previous works have attempted to address this problem [18,25]. These works adopted two different approaches. While [18] opted to fine-tune text-to-text transfer transformer (T5) using their synthetic corpus, [25] chose to train a long short-term memory (LSTM) model from scratch on theirs. These works achieved BLEU (BiLingual Evaluation Understudy) [21] scores of 82.7 and 38.6 respectively on their respective test corpora.

3 Constructing a Synthetic Parallel Corpus

To create our parallel corpus, we followed a similar approach to [25]. Starting with the French part of the English-French file produced by Tatoeba project[6] we created a parallel corpus by introducing lexical errors. Contrary to [25], we did not use a rule-based system to alter words. Instead, we selected a subset of the vocabulary of the corpus and used ChatGPT[7] to generate multiple erroneous versions of each word.

The choice of the vocabulary subset was based on the difficulty of pronunciation (for which we used the number of syllables as a proxy) and frequency. More concretely, we selected all words with 3 or more syllables and sorted them by frequency. The first 1,000 words were then selected.

3.1 Generating Lexical Errors

To generate erroneous variants of these words, we used the OpenAI API to prompt ChatGPT with the following text:

```
Modify the word "<word>" in the way a person with
Broca's aphasia would. Respond with one word.
```

where `<word>` is replaced by the word to be modified. By passing `n=10` to the application programming interface call, 10 variants were generated for each word. We checked the quality of the variants for the most frequent 217 words from the 1,000 words list. In this list, we point out that ChatGPT did not systematically produce 10 variants despite our prompt. In fact, the minimum number of variants for a word is 4, the maximum is 15 and the average is 9.08. Finally, there were 1,970 variants. Among them, very few were common to several words: 22 variants were common to two words; when this was the case, the common words were from the same root. For example, ChatGPT produced the same variant *rivé* for the words *arriver* (arrive) and *arrivée* (arrived or arrival). From the whole set of variants, we manually filtered the ones that were not realistic in terms of morphological constraints. For example, *maitéeent* (produced from *maintenant*) can not exist in French, *téviyon* (produced from *télévision*) should have been written *tévillon*, etc. For the 217 words, an average of 5.04 variants per word were kept. This led to 1,093 variants.

Of the 1,093 variants that were retained, 189 were processed (corresponding to 32 different correct words) to extract statistics about error types. Four error

[6] https://www.manythings.org/anki/

[7] `https://openai.com`

types in sequences of letters were identified: deletion (a sequence of letters is removed), addition (a sequence of letters is inserted), substitution (a sequence of letters is replaced by another one), and transposition (two sequences of letters are interchanged). An average of 1.7 errors per variant was observed. Among all errors, 51% were deletions, 25% were substitutions, 13% were transpositions and 11% were insertions. The distribution of error types is shown in Figure 1. This shows that sequences of letters tend to be deleted. We compared by hand the number of syllables of the correct words and their variants: on average, the number of syllables is reduced by 17.5%.

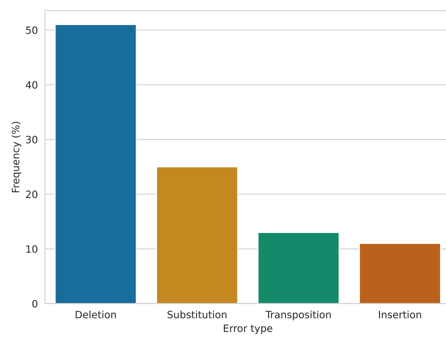

Fig. 1. Distribution of error types.

3.2 Generating the Corpus

The retained 1,093 variants were then used to transform the words in the original corpus. For each French sentence s in the Tatoeba corpus[8] (in fact, we selected from Tatoeba the sentences that contain words that can be altered according to the set described in Section 3.1), we generated a set Z of modified sentences. These sentences were then added to the parallel corpus along with s (see Algorithm 1). The process of altering a sentence (`list_alters` in Algorithm 1) involves systematically considering from s all the words that can be altered (the words that are in the list described in Section 3.1). To modify the sentence s, we identified the subset s' of words within s that possess aphasic variants. For each word w in this subset, we then selected one variant among all possible variants of w, replacing the original word w with its chosen counterpart, resulting in a modified sentence. The process enumerates over all possibilities, this can potentially modify from 0 to all words within the sentence that have aphasic variants. Table 1 presents the output of `list_alters` for an illustrative example.

[8] `https://www.manythings.org/anki/fra-eng.zip`

Table 1. An illustrative example of the output of `list_alters` in Algorithm 1.

Correct French sentence s		
a b c d		
Available aphasic variants		
`a : a1 a2`	`c : c1 c2 c3`	
`b : none`	`d : none`	
Aphasic variants of s (output of `list_alters` in Algorithm 1)		
`a b c d` (see note below)	`a1 b c d`	`a2 b c d`
`a b c1 d`	`a1 b c1 d`	`a2 b c1 d`
`a b c2 d`	`a1 b c2 d`	`a2 b c2 d`
`a b c3 d`	`a1 b c3 d`	`a2 b c3 d`
note: it is possible that the aphasic patient pronounces correctly the sentence. In this case, the corrective tool should not change the sentence.		

Algorithm 1: Generating a synthetic parallel corpus.

Input: $\mathcal{C}$, a corpus of French sentences
E, a set of pairs (w, V); w is a word and V is a set of variants of w
Output: $\mathcal{P}$, a parallel corpus of French sentences with errors
begin
  $\mathcal{P} \leftarrow \emptyset$
  foreach $s \in \mathcal{C}$ **do**
    $Z \leftarrow$ `list_alters(`s, E`)`
    `//` Z `is a set of totally or partially modified sentences`
    $\mathcal{P} \leftarrow \mathcal{P} \cup Z \times \{s\}$
  end
  return $\mathcal{P}$
end

3.3 Evaluating the Resulting Corpus

The resulting corpus contains 282,689 sentence pairs. A sample of these pairs is shown in Table 2. Measuring the BLEU score of aphasic sentences against their original counterparts yielded 62.72. This relatively high value can be explained by the fact that, in this work, we focus only on word alterations, keeping word order unchanged.

In order to measure the gap between the synthetic aphasic corpus and the initial correct corpus, we measured the perplexity of both corpora using 4 different language models trained on clean data:

– `gpt2`[9] [22]: 124M parameters, 52k vocabulary.
– `gpt2-large`[10] [22]: 774M parameters, 52k vocabulary.

[9] `https://huggingface.co/gpt2`
[10] `https://huggingface.co/gpt2-large`

– `gpt-fr-cased-small`[11] [24]: 124M parameters, French language model, 52k vocabulary.
– `gpt-fr-cased-base`[12] [24]: 1.017B parameters, French language model, 52k vocabulary.

The results are shown in Figure 2. All models have higher perplexity on the aphasic corpus than on the original (correct) corpus. This difference is more pronounced for the French language models.

Table 2. A sample of generated aphasic sentences and their original counterparts.

Generated aphasic sentence	Original sentence (English translation)
Je veux arvailer.	Je veux travailler. (I want to work.)
Voizo un incompréhent à ce que je me serve ?	Voyez-vous un inconvénient à ce que je me serve ? (Do you see any inconvenience in me using it?)
Tom n'est problament pas cup mantant.	Tom n'est probablement pas occupé maintenant. (Tom is probably not busy now.)
Je sais exacment où je veux aller.	Je sais exactement où je veux aller. (I know exactly where I want to go.)
Ce fut la meilleure chose qui m'est jamais aribé.	Ce fut la meilleure chose qui m'est jamais arrivée. (It was the best thing that ever happened to me.)
Tellement la question était difici que nul ne sut répondre.	Tellement la question était difficile que nul ne sut répondre. (The question was so difficult that no one knew how to answer.)

4 Training a Translation Model on the Corpus

In order to perform error correction, we trained a machine translation model on the corpus we created in Section 3. We used a transformer-based model architecture [26] and opted for from-scratch training rather than fine-tuning a pre-trained model.

4.1 Model Architecture

Our model is based on the vanilla transformer [26]. We used 3 layers of encoder and decoder blocks, with 4 attention heads each. The model dimension and the feed-forward dimension were set to 64. Hugging Face tokenizers' implementation of the WordPiece tokenizer[13] was used to tokenize the inputs with a vocabulary size of 5,000 tokens. We used PyTorch's embedding modules for both token and positional embeddings. The detailed architecture is shown in Figure 3.

[11] `https://huggingface.co/asi/gpt-fr-cased-small`
[12] `https://huggingface.co/asi/gpt-fr-cased-base`
[13] `https://github.com/huggingface/tokenizers`

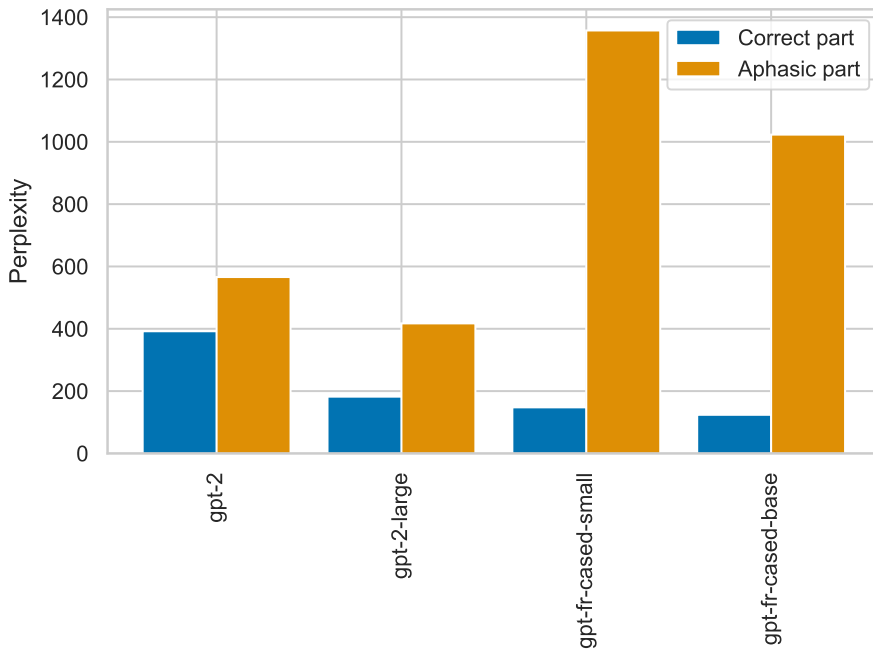

Fig. 2. Perplexity of the corpus.

4.2 Training

We randomly segmented our corpus into three parts: training (80%), development (10%) and testing (10%). Finally, in this model, an aphasic error is considered as an unknown word, and the system has to retrieve the correct word while not disturbing the not altered words.

To train our model, we used the Adam optimizer [11] with a batch size of 256. The learning rate η and model dropout rate p were chosen via Bayes search [1]. They were sampled from log-uniform distributions with bounds $\left[10^{-5}, 10^{-1}\right]$ and $[0.1, 0.5]$ respectively. Validation BLEU score after 2 epochs was used as the objective function and 20 iterations were performed. At the end of the search, the best values were $\eta \approx 0.001849$ and $p \approx 0.101$.

We trained the model with the obtained hyperparameters with a maximum of 20 epochs. The training stopped after 8 epochs, as the validation BLEU score did not improve anymore. The training and validation curves for the loss and BLEU scores are shown in Figures 4 and 5. For both the loss and the BLEU scores, the training and validation curves are very close. This indicates that the model is not overfitting the training data. The BLEU score on the test set is 79.61 whereas the initial BLEU without correction by our system was 62.72. The relative improvement is 26.9%.

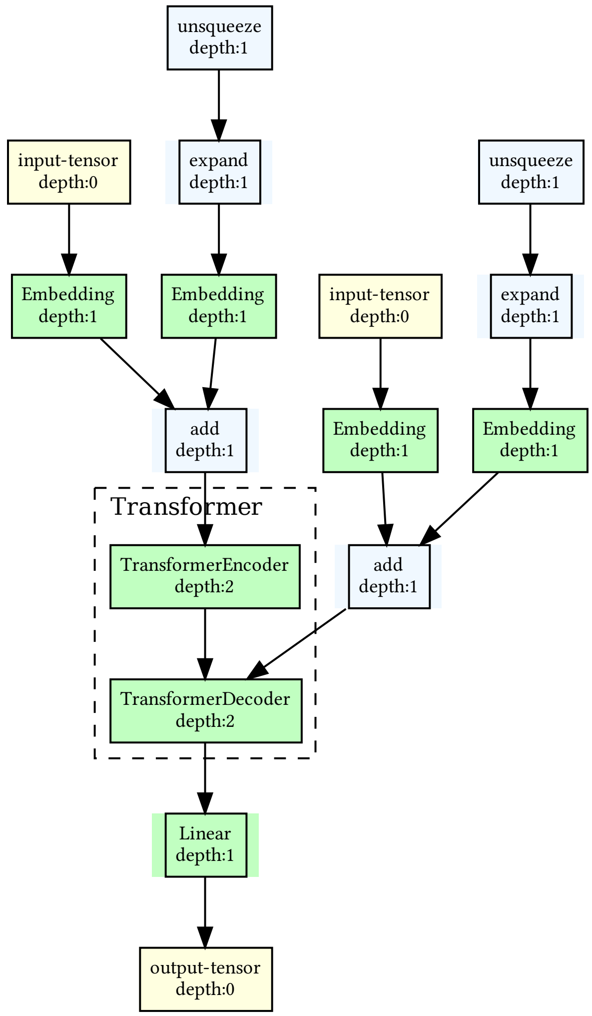

Fig. 3. Machine translation model architecture.

5 Discussion

In this work, we use GPT to produce lexical errors that could resemble those produced by patients with aphasia. A first question is if GPT can produce such aphasic errors. It was our first conclusion based on preliminary experiments. This

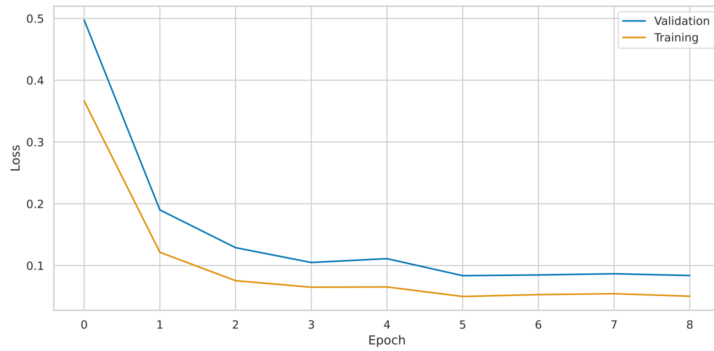

Fig. 4. Time evolution of the loss scores during training.

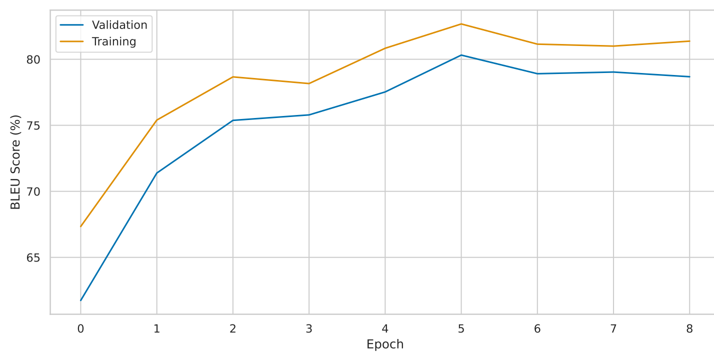

Fig. 5. Time evolution of the BLEU scores during training.

work allows us to confirm that GPT can produce variants of words that could have been pronounced by people with aphasia. This is surprising because there is no large mass of aphasic data on the web that can be used to train GPT. In fact, GPT also produces dubious variants, and even variants that do not respect the morphological constraints of French. Finally, because of such errors, after manual checking, we kept only half of the proposed variants by GPT (see Section 3.1). This selection rate seems to show that GPT lacks performance in generating aphasic variants. To take this evaluation further, GPT's ability to deal with aphasic data could be automatically measured by testing it on the task of distinguishing real aphasic variants in a list containing both real and synthetic ones. However, the best way to decide whether the variants are close to aphasic speech is to ask a speech therapist to analyse the corpus.

Moreover, the method we propose in this paper is based on the textual modality: the variants are generated from the orthographic form of the words. Our final objective is to deal with the speech modality. Therefore, the method should be based on the pronunciation of the words; our research will develop in this direction. This will pose additional difficulties because speech is continuous, meaning changes could span two or more words. In addition, a textual training corpus for speech recognition will pose the problem of generating orthographic forms matching with pronunciation and morphological constraints.

Another point is that we opted for from-scratch training rather than fine-tuning a pre-trained model. Our first idea was that, in fact, few words in sentences are altered (it is why the baseline BLEU, without correction is high, see Section 4.2). Therefore, our hypothesis is that the training corpus does not need to be huge. The fact that the LSTM model allows to improve the BLEU score by 26.9% could confirm this hypothesis. But, in the future, with available large language models, we believe that these results can be improved.

6 Conclusion

Our results seem to suggest that the use of natural language processing based methods for the correction of aphasic speech is feasible. An improvement of the BLEU score of the initial test set was achieved (from 62.72 to 79.61).

More research is required to validate this conclusion and improve the results. The most obvious way to do so is to apply the model to real aphasic data, the collection of which is the next logical step in this research project. Moreover, we will organize a qualitative assessment and user studies with individuals who have Broca's aphasia and with speech therapists.

Another research direction is to combine the model with an automatic speech recognition system and a text-to-speech system to create a complete speech-to-speech system aiming at helping a person with aphasia to communicate in daily life. For that, the system should take into account the speech modality. This is not the case in this work because aphasic variants are generated from the written form of words. A more realistic system should start from speech, or at least phonemes, introduce errors at this level, and propose a sequence of words correcting the errors.

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