

How You Say It Matters: Measuring the Impact of Verbal Disfluency Tags on Automated Dementia Detection

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Abstract

Automatic speech recognition (ASR) systems usually incorporate postprocessing mechanisms to remove disfluencies, facilitating the generation of clear, fluent transcripts that are conducive to many downstream NLP tasks. However, verbal disfluencies have proved to be predictive of dementia status, although little is known about how various types of verbal disfluencies, nor automatically detected disfluencies, affect predictive performance. We experiment with an off-the-shelf disfluency annotator to tag disfluencies in speech transcripts for a well-known cognitive health assessment task. We evaluate the performance of this model on detecting repetitions and corrections or retracing, and measure the influence of gold-annotated versus automatically detected verbal disfluencies on dementia detection through a series of experiments. We find that removing both gold and automatically-detected disfluencies negatively impacts dementia detection performance, degrading classification accuracy by 5.6% and 3% respectively.

1 Introduction

As populations grow older worldwide, the number of people with Alzheimer’s disease (AD) and related dementia is also on the rise (Alzheimer’s Association, 2018). Significant changes to speech and language use caused by dementia occur early in disease progression (Bucks et al., 2000). Interesting case studies have demonstrated how diachronic analysis of patients’ language use may reveal signs of dementia, using writing samples from British novelists Iris Murdoch, who ultimately perished with Alzheimer’s, and Agatha Christie, who was suspected of it (Le et al., 2011). Numerous studies have also sought to automatically detect early signs of the disease and model its progression using speech and writing samples (Becker et al., 1994; Herd et al., 2014; Yancheva et al., 2015; Masrani, 2018; Di Palo and Parde, 2019; Zhu et al., 2019;

Fraser et al., 2019; Eyre et al., 2020; Farzana and Parde, 2020; Sarawgi et al., 2020).

Although some studies have pointed to disfluency patterns as an important predictor of AD status (Lopez-de Ipina et al., 2017; Mueller et al., 2018), research in this area has been limited by several factors. Disfluency detection is a challenging and resource-intensive task in itself (Wang et al., 2017; Jamshid Lou and Johnson, 2017; Zayats and Ostendorf, 2019), and may lie out of scope for many interdisciplinary researchers already straddling boundaries between NLP and clinical practice. Rich manual disfluency annotations are present in some datasets common in automated dementia detection (Becker et al., 1994), but off-the-shelf ASR systems do not typically transcribe disfluencies. Moreover, inconsistencies between automatically generated and gold standard transcripts may pose significant challenges for modeling dementia in real-world applications (Balagopalan et al., 2020), for which ASR will be a necessary component of any speech-based pipeline.

We address these limitations, by investigating the impacts of automatically derived disfluencies on modeling cognitive decline. Our key contributions are as follows:

1. We experiment with an off-the-shelf disfluency detection model to automatically assign word- and phrase-level disfluency tags to samples from the most popular dementia detection dataset, focusing on repetitions and retraces.
2. We measure the influence of these disfluency types on the downstream task of dementia detection by systematically ablating gold-labelled and automatically tagged disfluencies from manual transcripts.
3. We compare AD classification performance on manually and automatically generated transcripts, and compare the removal of gold and

automatically detected disfluencies from manual transcripts, to investigate the influence verbal disfluencies have on dementia detection.

This analysis not only paves the way for the discovery of approaches to automated dementia detection that are more suitable for realistic scenarios, but also enhances our understanding of the individual contributions of different disfluency types to this task. We report on related studies and provide relevant background for automatic disfluency detection in §2. We describe our datasets and task setup in §3, and detail our methods in §4. We report the results of our experiments in §5, and further analyze our findings in §6 before concluding in §7.

2 Related Work

2.1 Studies of Disfluency in the Context of Cognitive Decline

Disfluency, defined as any interruption in the normal flow of speech, is prevalent in spoken language. Verbal disfluency comprises several major subcategories: *false starts*, *repetitions*, *filled pauses* (e.g., “uh,” “um,” etc.), and *sentence corrections* (Shriberg, 1994). Although verbal and nonverbal (*unfilled pauses*) disfluencies are common in spontaneous speech, there is a fine line between normal and abnormal disfluencies. This boundary can be exploited to facilitate modeling cognitive decline.

Studies have found that verbal fluency is an effective indicator of cognitive decline, as fluency declines rapidly for subjects suffering from early stage Mild Cognitive Impairment (MCI) relative to healthy controls (Mueller et al., 2018). Anomic aphasic subjects tend to produce more disfluent speech than non-aphasic subjects during word retrieval tasks, with disfluencies or “stutterings” including part-word repetitions, vocal segregate repetitions, and prolongations (Brown and Cullinan, 1981). Researchers have previously leveraged both acoustic and transcript-based fluency features to automatically detect MCI (Lopez-de Ipina et al., 2017; Mueller et al., 2018).

Transcript-based normalized verbal disfluency features (e.g, *filled pause count*, *retracing count*, and *repetition count*) have proved to be discriminative in predicting outcomes from cognitive screening tests such as the Mini Mental State Examination (MMSE) and AD classification, as have concatenations of automatically detected verbal disfluency segments (e.g., *repair onset*, *edit term*, and

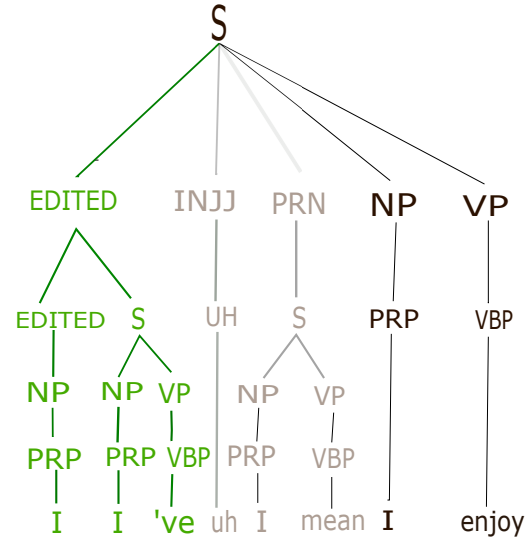


Figure 1: An example of gold labelled parse tree (Jamshid Lou et al., 2019).

fluent words) with word vectors (Farzana and Parde, 2020; Rohanian et al., 2020, 2021). Automatically extracted non-verbal disfluency features from both transcripts and speech (e.g., *silent pauses*, *speed of articulation*, and *pronunciation*) have also shown performance boosts in AD classification (Yuan et al., 2020; Qiao et al., 2021).

2.2 Automatic Disfluency Detection

Disfluency detection is a key challenge in parsing transcribed speech. Disfluencies are defined structurally with three main components (Shriberg, 1994): the *reparandum*, the *interregnum* and the *repair*. The *reparandum* is replaced by the *repair* segment and the *interregnum* is an optional part of the structure consisting of filled pauses (e.g., “uh”) and discourse connectives (e.g., “I mean”). We present an example disfluency with all three components present below:

$$\overbrace{II've}^{\text{reparandum}} \overbrace{uhI\text{mean}}^{\text{interregnum}} \overbrace{I\text{enjoy}}^{\text{repair}} \quad (1)$$

Disfluencies are further categorized into repetition, correction/retracing, and false start (Jamshid Lou and Johnson, 2020a), following established typology of speech repairs (Shriberg, 1994). Repetition contains identical *reparandum* and *repair* segments, whereas the *reparandum* and *repair* differ in correction/retracing. The latter is much harder to detect automatically.

Disfluency detection on pre-segmented utterances from the Switchboard treebank corpus (Godfrey and Holliman, 1993; Marcus et al., 1999) has

been the focus of many prior works (Johnson and Charniak, 2004; Charniak and Johnson, 2001; Qian and Liu, 2013; Honnibal and Johnson, 2014). In the Switchboard corpus, reparanda, filled pauses, and discourse connectives are marked by EDITED, INTJ, and PRN labels respectively (illustrated in Figure 1). Conventional syntactic parsers often fail to capture the unconventional relation between reparandum and repair, where repair uses similar words to the reparandum in the same order, functioning as a “rough copy” rather than providing additional information (Johnson and Charniak, 2004; Charniak and Johnson, 2001). Because of the difficulty of addressing disfluency within the task of syntactic parsing, systems have instead been developed to detect and remove disfluency prior to parsing (Charniak and Johnson, 2001; Kahn et al., 2005; Lease and Johnson, 2006). Nonetheless, transition-based dependency parsers designed with special mechanisms to handle disfluencies have proven useful for detecting and removing disfluent words and their dependencies from sentences (Honnibal and Johnson, 2014; Rasooli and Tetreault, 2013; Yoshikawa et al., 2016; Tran et al., 2018). Moreover, encoder-decoder constituency parsing models using lexical and prosodic cues (Tran et al., 2018) have resulted in small performance gains both in parsing and disfluency detection. Augmenting parsing models with location-aware attention mechanisms has also been especially effective for disfluency detection (Tran et al., 2018).

Specialized disfluency detection models frame the problem as a sequence labelling task where each word in the input is labelled as disfluent or not. Neural models (CNNs and LSTMs) have been employed for this task (Zayats et al., 2016; Jamshid Lou et al., 2018; Wang et al., 2016) but until recently have not performed very well. A recent state-of-the-art approach introduced a semi-supervised approach using a self-attentive model (Wang et al., 2018) that jointly performs syntactic parsing and disfluency detection.

The incremental approach for disfluency detection has been explored on both unsegmented and pre-segmented utterances from manual and automated transcripts using LSTM with different decoding schemes (Hough and Schlangen, 2015, 2017) leveraging joint and multitask settings. Another recent approach introduced the incremental processing of words to a Transformer model (BERT (Devlin et al., 2019)) to detect speech disfluency

(Rohanian and Hough, 2021). However, these incremental approaches perform poorly on detecting *reparanda* of longer lengths.

3 Data and Task Setup

We used the ADReSS Challenge corpus for our experiments (Luz et al., 2020). The ADReSS Challenge corpus, developed as part of a shared task for INTERSPEECH 2020, is a benchmark dataset of spontaneous speech in the domain of AD classification and MMSE score prediction. It has been acoustically preprocessed, and is balanced in terms of age and gender. The data consists of audio recordings and manual transcriptions of spoken picture descriptions elicited from participants through the Cookie Theft task from the Boston Diagnostic Aphasia Exam (Roth, 2011). The corpus is a subset of the Pitt corpus,¹ which is itself a subset of the DementiaBank dataset (Becker et al., 1994).

In the Cookie Theft task, an investigator and a participant (in this case, an older adult) carry on a conversation in which the investigator asks the participant to describe what is depicted in an eventful image containing, among other subjects, a boy stealing a cookie from a cookie jar.² There is no specific time limit for the conversation, allowing participants to talk as long as they want. In the Pitt corpus and by extension the ADReSS Challenge corpus, these conversations were recorded and manually transcribed using the CHAT transcription protocol (MacWhinney, 2000). Participants were labelled as HC (healthy control with no cognitive decline) or AD (declined cognitively) based on their prior diagnostic test results.

We report the transcript-level mean utterance count and standard deviation (SD) for data collected from AD and HC participants in Table 1, showing that the lengths of conversations across groups were fairly balanced (HC = 13.79 ± 5.21 utterances; AD = 13.93 ± 9.54 utterances). We also report the mean MMSE score and SD for each speaker category, showing a significant difference in cognitive health between groups (HC = 29.11 ± 0.98 MMSE; AD = 17.06 ± 5.46 MMSE). To assess significance, we applied the Mann–Whitney U test (as the normality assumption was violated) across the two speaker groups,

¹<https://dementia.talkbank.org/access/English/Pitt.html>

²We refer interested readers to Karlekar et al. (2018), Mueller et al. (2018), or some others cited in this paper for a copy of the original image.

	AD	HC	Test Statistics
Utterance Count	13.93 (SD=9.54)	13.79 (SD=5.21)	$U=135.0$ $p=0.25$
MMSE Score	17.06 (SD=5.46)	29.11 (SD=0.98)	$U=47.5$ $p=0.00$

Table 1: Mean utterance count and MMSE score for the AD and HC groups, with standard deviations in parentheses. Statistical significance (p) for differences between groups is reported along with the Mann-Whitney U test statistic.

Ref.: and **UM THAT 'S UH** that 's about all i can see
 Aligned: *** ** ***** ** not ***** ** ***** all i can see

Figure 2: The reference (*Ref.*) and aligned ASR output for a sample utterance from the ADReSS Challenge corpus. The reference transcript is human-transcribed speech with gold disfluent words (red, capitalized) and fluent words (black). *Aligned* refers to the desired alignment of ASR output with the reference text for making meaningful FER and DER evaluations (Jamshid Lou and Johnson, 2020a).

and we also report the test statistic (U) and significance value (p) for each group in Table 1.

3.1 ASR Setup

We used the phone call enhanced model (16kHz) of the Google Cloud-based Speech Recognizer to automatically transcribe the audio files in the ADReSS Challenge corpus to facilitate our comparisons of manually and automatically-generated transcriptions. Manually segmented utterances were fed to the speech recognizer for transcription. To evaluate the performance of the speech recognizer, we estimated the fluent and disfluent error rates (FER and DER). We provide the equations for computing both below, where d_f , s_f , i_f , and n_f refer to the number of deleted, substituted, inserted, and total fluent words, respectively, and d_d , s_d , i_d , and n_d refer to the number of deleted, substituted, inserted, and total disfluent words, respectively (Jamshid Lou and Johnson, 2020a):

$$\text{FER} = \frac{d_f + s_f + i_f}{n_f} \quad (2)$$

$$\text{DER} = \frac{d_d + s_d + i_d}{n_d} \quad (3)$$

Group	FER	DER
AD	53.30%	77.60%
HC	47.30%	80.70%
Overall	50.20%	78.80%

Table 2: Rates of ASR error on the ADReSS Challenge dataset, both at the class level (AD and HC) and overall. For DER calculation, we consider all the disfluencies in Table 6 as well as the Filled pauses (e.g. *uh*, *um*)

	Repetition	Retracing
DER	76.50%	61.10%

Table 3: DER of broad disfluency categories (repetition and retracing, as defined in Table 6).

To calculate DER,³ we considered *word repetition*, *multiple repetition*, *phrase repetition*, *word retracing*, and *phrase retracing*, with additional details regarding each disfluency type provided in Table 4. We show an alignment between gold and automatically generated transcriptions for an example utterance from the ADReSS Challenge corpus in Figure 2. Computing FER for this example would set $d_f = 4$, $s_f = 0$, $i_f = 0$, and $n_f = 8$, resulting in FER=0.5. Computing DER for the same sample would set $d_d = 3$, $s_d = 1$, $i_f = 0$, and $n_f = 4$, resulting in DER=1.0. We report FER and DER across the entire ADReSS Challenge corpus for AD, HC, and all participants in Table 2 and the breakdown of DER for broad disfluency types (repetition, encompassing *word repetition*, *multiple repetition*, and *phrase repetition*, and retracing, encompassing *word retracing* and *phrase retracing*) is shown in Table 3.

3.2 Disfluency Annotator Setup

We leverage the self-attentive neural parsing model (Jamshid Lou and Johnson, 2020b) to automatically detect disfluencies in the ASR-generated transcripts. The model is trained to jointly parse and detect disfluency using contextualized word embeddings (BERT (Devinney et al., 2020) or ELMO (Peters et al., 2018)) and currently produces state-of-the-art performance with a parsing accuracy of 93.9% and a disfluency detection F₁-score of 0.924 on the Switchboard development set (Jamshid Lou

³Although the original DER formulation counts the number of copies, we replace this with the number of deletions since we expect the ASR to transcribe disfluent as well as fluent words.

Disfluency Type	Example
Word Repetition	the [/] the cabinet door has just swung open
Multiple Repetition	there's nothing going on outside there's just bushes [x 3].
Phrase Repetition	<what are> [/] what are the instructions ?
Word Retracing	and there are dishes [/ /] &uh &uh two cups and a saucer on the sink
Phrase Retracing	and outside the window there's a <walk with a> [/ /] &c curved walk with a garden .

Table 4: Example of different types of disfluencies from transcripts annotated using the CHAT protocol (MacWhinney, 2000). Disfluencies are bold-faced followed by disfluency markers. Angle brackets indicate phrase-level disfluencies, whereas [x n] indicates that the word before the marker is repeated *n* times.

and Johnson, 2020b) in the joint task. We use the pretrained version of the disfluency detector and parser.⁴ This version is self-trained on the Switchboard gold parse trees (Marcus et al., 1999) and Fisher Corpus Part 1 (Cieri et al., 2004) and Part 2 (Cieri et al., 2005) silver parse trees, using *BERT-base-uncased* word representations.

4 Methods

4.1 Verbal Disfluency Types

We consider several distinct disfluency types in this investigation: *word repetition*, *phrase repetition*, *word retracing*, and *phrase retracing*. We provide examples of each of these in Table 4.⁵ Word and phrase repetition indicate repeated utterance of the same word or phrase in such a way that is disfluent with the natural flow of speech, whereas word and phrase retracing indicate verbal “backtracking” to correct a previously uttered word or phrase. In Table 5, we report the frequencies of these disfluency types across speaker groups.

⁴<https://github.com/pariajm/english-fisher-annotations>

⁵Although *multiple repetition* is coded distinctly from single *word repetition* under the CHAT transcription protocol, we consider both as members of the *word repetition* category.

Disfluency	AD	HC
<i>Word Repetition</i>	96	29
<i>Phrase Repetition</i>	27	17
<i>Word Retracing</i>	48	35
<i>Phrase Retracing</i>	67	46
<i>Disfluency-Tagged</i>	317	176

Table 5: Frequencies of disfluency types across AD HC participants, where *Disfluency-Tagged* refers to the sum of all disfluencies reported for the specified group (including those not in the focus of this investigation).

4.2 Automatic Disfluency Annotation

We leveraged the self-attentive neural disfluency annotator described in §3.2, trained on the Penn Treebank-3 SWBD corpus (Marcus et al., 1999) and the Fisher I and II corpora (Cieri et al., 2004, 2005) using a semi-supervised approach (Jamshid Lou and Johnson, 2020b). This multi-task learning setup enables the model to predict both parse trees and disfluency tags for utterances. The disfluency annotator adds word-level annotations to disfluent words, or those acting as *EDITED*, *INTJ*, or *PRN* nodes (illustrated in Figure 1).

We preprocessed both the reference and ASR-generated transcripts by removing punctuation and (for the reference transcripts) existing disfluency tags. We then fed the disfluency annotator one utterance per line, in turn producing both a parse tree and a disfluency-tagged version of the utterance as output. Figure 3 shows an example utterance with: (1) the actual text and disfluency tags from the ADRess Challenge corpus, considering the disfluency types referred in Table 4; (2) the gold disfluency tags formatted as the expected output from the automatic disfluency annotator; and (3) the predicted word-level disfluency tags from the automatic disfluency annotator. Phrase repetition accuracy for the utterance in Figure 3 would be 100% as both the words in the repeated phrase (highlighted in red) are predicted correctly, whereas phrase retracing accuracy would be 0%, as no words in the retraced phrase (highlighted in blue) are predicted as disfluent.

Table 6 illustrates the performance of the automatic disfluency annotator at predicting different disfluency types for the ADRess Challenge training set, providing evidence that retracing/correction (especially at the phrase level) is harder to predict

Actual text: *his sister <has her> [//] has her <hand up> [//] finger up to her mouth like she's saying.*

Gold tag: *his _ sister _ has E her E has _ her _ hand E up E finger _ up _ to _ her _ mouth _ like _ she _ 's _ saying _*

Predicted tag: *his _ sister _ has E her E has _ her _ hand _ up _ finger _ up _ to _ her _ mouth _ like _ she _ 's _ saying _*

Figure 3: Example utterance annotated by automatic disfluency annotator. **Actual text** represents the gold label annotated utterance from the ADReSS Challenge training set. **Gold tag** represents the expected word level annotation given the gold labels, whereas **Predicted tag** shows the predicted disfluency annotations (fluent words are followed by _ tags and disfluent words are followed by E tags) by the disfluency tagger. Repetition is highlighted in red and retracing in blue.

Disfluency Type	Accuracy
Word Repetition	72.65%
Phrase Repetition	73.61%
Word Retracing	50.00%
Phrase Retracing	42.64%

Table 6: Percentage of disfluent words in the ADReSS Challenge training set tagged with different disfluency labels (*multiple repetition* is considered a subset of word repetition) by the Fisher annotator.

than repetition. The annotator often fails to detect cases of *multiple repetition* (accuracy=11.11%, making it lowest among all disfluency types in Table 6), likely because it was intermixed with word-level repetition in the training data.

4.3 Disfluency Removal

We implement two methods for removing disfluencies from transcribed speech, described further in §4.3.1 and §4.3.2.

4.3.1 Gold Disfluency Removal

We removed gold labelled disfluencies from the manually created reference transcripts. We did this by removing different CHAT transcription tags corresponding to repetition and retracing behaviors. Thus, the text in Figure 3 was converted to:

• **Repetition Removal:** *his sister has her hand up finger up to her mouth like she's saying.*

• **Retracing Removal:** *his sister has her has her finger up to her mouth like she's saying.*

4.3.2 Fisher Disfluency Removal

We removed disfluencies predicted by the Fisher tagger (described in §4.2) from the automatically transcribed speech. To remove words of a particular disfluency type, we matched the relevant segment of text with the predicted tag (see Figure 3) and removed the words tagged as *E* (representing *errors*, or disfluencies). For instance, to remove retracing, the blue segments of actual text and predicted tags in Figure 3 are matched, and since none of the words are predicted as *E*, none are removed. Thus, after the removal of disfluencies according to the Fisher tagger, the text in Figure 3 was converted to:

• **Repetition Removal:** *his sister has her hand up finger up to her mouth like she's saying.*

• **Retracing Removal:** *his sister has her has her hand up finger up to her mouth like she's saying.*

4.4 Classification Setup

4.4.1 Input and Output

The ADReSS Challenge training corpus included data from $N=108$ participants. The input for a given data point was a sequence of words from the processed transcript, and the output was the class of the speaker: 0 for HC, or 1 for AD.

Transcripts were preprocessed to remove disfluency markers, punctuation, and digits. When *multiple repetition* markers followed a word in any utterance, the word was added the specified number of times, and the marker was then removed. An excerpt from a processed transcript is below:

(AD) *alright I see the little boy stealing cookies from the cookie jar and the little girl's uh he gave some to the little girl and she's eating some of the cookies and I guess this is mama and she's washing the dishes and she dropped a dish no no she didn't drop a dish uh the the water that she's washing the dishes with she let run and it's overflown o overflown o o overflown that doesn't that doesn't sound right did it uh we forgot to turn off the spigot and so the water is running off*

into the onto the floor here and mom apparently is washing the dishes and here's this little boy stealing the cookie j cookies he's gonna gonna fall

4.4.2 Model

We used Bert-for-Sequence-Classification⁶ to implement our model, experimenting with *bert-base-uncased* as our base model and using the following hyperparameters: learning rate = $2e-5$, batch size = 4, epochs = 8, max input length of 256 (a length sufficient to cover most cases). The standard default tokenizer was used. Two special tokens, [CLS] and [SEP], were added to the beginning and the end of each transcript utterance. We chose these model and parameter settings since they attained promising performance in previously published work (Yuan et al., 2020) with leave-one-out cross-validation on the ADReSS Challenge dataset.

5 Experiments

5.1 Experimental Setup

To evaluate the impact of disfluency presence and type on classifying AD status, we performed experiments considering the following conditions:

- **ALLTEXT:** The baseline condition using the original manually-created transcripts, complete with gold disfluencies, preprocessed as defined in §4.4.
- **ASR:** Transcripts are generated using ASR (explained in §3.1), and the ASR-generated transcripts are fed to the model.
- **-REP.:** Repetitions (both word- and phrase-level) are removed from ALLTEXT transcripts using either the gold or Fisher disfluency removal method.
- **-RET.:** Incidents of retracing (both word- and phrase-level) are removed from ALLTEXT using either the gold or Fisher disfluency removal method.
- **-DISF.:** Transcripts are processed so that all cases of word- or phrase-level repetition or retracing are removed. When using the Fisher disfluency removal method, this includes all disfluency-tagged words.

⁶<https://github.com/huggingface/transformers>

We report accuracy, precision, recall, and F_1 for each condition. When performing development experiments, we observed large performance differences across folds. Such brittleness has also been reported previously (Yuan et al., 2020), and may be attributed to the use of a large model (BERT) for classification on a small dataset. To address this, we perform three runs, each using different random seeds, of five-fold cross-validation and report averages and standard deviations across runs.

5.2 Results

We report our evaluation results in Table 7. As expected, we observe the highest performance in the baseline condition. The ASR condition exhibits the worst performance, with accuracy, F_1 for AD, and F_1 for HC decreasing 17.7%, 14%, and 33% respectively relative to the baseline. This underscores one of our primary motivations in conducting this work—namely, that ASR has a high error rate in real-world settings and particularly in this task environment, and moreover that its mistagging (or in some cases, purposeful removal) of disfluency has a deleterious impact on dementia detection performance. We observe from Tables 2 and 3 that DER is much higher than FER for ASR output. ASR tends to delete or replace repetitive words, increasing overall word error rate and leading to poor performance in the AD detection task. Prior work has clearly suggested that disfluencies are important indicators of cognitive health status (Lopez-de Ipina et al., 2017; Mueller et al., 2018).

Furthermore, performance clearly degrades relative to the baseline when gold disfluencies are removed (-REP._G, -RET._G, and -DISF._G). Although retracing removal caused a slightly higher decrease in accuracy than repetition removal, there is no significant difference in performance between the -REP._G and -RET._G conditions across metrics. Accuracy and F_1 decrease 5.6% and 6% (for both AD and HC) compared to the baseline when all gold disfluencies are removed from the transcripts.

Removal of Fisher disfluencies also leads to performance degradation across all metrics. Since the Fisher disfluency annotations are more limited than the gold disfluency labels, performance in this condition (-REP._F, -RET._F, and -DISF._F) degrades less than is observed with gold disfluency removal. Accuracy, F_1 for AD, and F_1 for HC decrease 3%, 4%, and 2% respectively compared to the baseline when all Fisher-predicted disfluencies are removed.

	Accuracy	Precision		Recall		F1	
		AD	HC	AD	HC	AD	HC
ALLTEXT	0.843±.015	0.88±.017	0.82±.020	0.80±.028	0.89±.019	0.84±.016	0.85±.013
A	0.670±.037	0.69±.062	0.54±.032	0.72±.060	0.52±.121	0.70±.023	0.52±.065
-REP_G	0.797±.034	0.81±.044	0.79±.034	0.78±.049	0.80±.053	0.80±.021	0.79±.036
-RET_G	0.787±.024	0.77±.043	0.80±.012	0.81±.015	0.76±.060	0.80±.017	0.78±.035
-DISF_G	0.787±.020	0.78±.025	0.77±.028	0.76±.040	0.81±.030	0.78±.026	0.79±.020
-REP_F	0.827±.015	0.86±.021	0.80±.010	0.78±.011	0.88±.021	0.82±.014	0.84±.014
-RET_F	0.820±.010	0.86±.013	0.79±.021	0.78±.032	0.87±.019	0.82±.013	0.83±.006
-DISF_F	0.813±.006	0.85±.018	0.78±.004	0.76±.000	0.87±.018	0.80±.008	0.83±.010

Table 7: Five-fold cross-validation results, averaged across three runs with different random seeds on the ADReSS Challenge training set. The subscript *G* refers to gold disfluency removal and *F* refers to Fisher disfluency removal.

5.3 Distinctive Effects of Disfluency Removal

To further investigate why disfluency removal influences classification performance, we experiment with measures of syntactic complexity, context-free grammar rules, and measures of vocabulary richness⁷ to identify linguistic features having moderate to high correlation with disfluency (as measured by normalised disfluency count, repetition count, and retracing count). We find that disfluency count (considering all disfluencies in Table 4) has significant, high negative Spearman correlation ($r = -0.55$, $p < 0.001$) with type token ratio (TTR). This indicates that verbal disfluencies are highly negatively correlated with vocabulary richness, which is in turn an important feature of AD detection (Masrani, 2018). Some context-free grammar rules (INTJ, INTJ_to_UH, VP_to_VBG, VP_to_AUX) and syntactic complexity features (constituency parse tree height), also key features for AD detection (Masrani, 2018), exhibit moderate correlation with disfluency frequency. Such results show that vocabulary richness and the syntactic structure of language are vulnerable to the deletion of disfluencies, which may in turn lead to classification performance degradation.

6 Discussion

From our corpus analyses, we find that members of the AD group exhibit more verbal disfluency (Table 2), with increased rates of repetition and correction relative to the HC group. This is in line with our expectations, since disfluencies and speech errors are correlated with cognitive functions such as cog-

nitive load, arousal, and working memory (Arciuli et al., 2010; Daneman, 1991); with increased impairment of these functions, hesitations and disfluencies increase. Previous studies have also reported that verbal disfluency frequency can be an important predictor of fine-grained cognitive status of older adults (Farzana et al., 2020). Our evaluation provides evidence that removing both gold-labelled and Fisher-annotated verbal disfluencies leads to changes in AD detection performance, opening intriguing questions for follow-up work that may further tease apart the nature of these contributions.

We speculate that some of these findings may transfer to other conditions as well. For example, studies have also reported that filled pauses are less frequently uttered by children with autism spectrum disorder than typically developed children (Gorman et al., 2016; Irvine et al., 2016). It is possible that incorporating richer disfluency information in speech-based systems for autism detection and monitoring may improve performance similarly to that seen with AD detection.

7 Conclusion

Verbal disfluencies are an important indicator of AD, and current ASR systems fail to capture and label word- and phrase-level disfluencies adequately. Doing so is necessary to generate useful transcripts with minimal human intervention, such that they can be leveraged for successful AD detection. Our future work will focus on training an end-to-end ASR system on disfluent speech so that it can generate richer disfluency annotated transcripts, which will pave the way for building end-to-end speech-based dementia detection systems.

⁷https://github.com/vmasrani/dementia_classifier

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