Artificial Disfluency Detection, Uh No, Disfluency Generation for the Masses

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Abstract—Existing approaches for disfluency detection typically require the existence of large annotated datasets. However, current datasets for this task are limited, suffer from class imbalance, and lack some types of disfluencies that can be encountered in real-world scenarios. This work proposes LARD, a method for automatically generating artificial disfluencies from fluent text. LARD can simulate all the different types of disfluencies (repetitions, replacements and restarts) based on the reparandum/interregnum annotation scheme. In addition, it incorporates contextual embeddings into the disfluency generation to produce realistic context-aware artificial disfluencies. Since the proposed method requires only fluent text, it can be used directly for training, bypassing the requirement of annotated disfluent data. Our empirical evaluation demonstrates that LARD can indeed be effectively used when no or only a few data are available. Furthermore, our detailed analysis suggests that the proposed method generates realistic disfluencies and increases the accuracy of existing disfluency detectors.

Index Terms—Disfluency Detection, Data Augmentation

I. INTRODUCTION

AUTOMATIC Speech Recognition (ASR) technology has recently achieved remarkable progress and is now an integral part of a wide range of intelligent systems, such as general-domain virtual assistants and specialized spoken dialogue systems for healthcare (Latif et al., 2020), migration (Wanner et al., 2021), finance (Wang et al., 2020a) and education (Maxwell-Smith and Foley, 2021). An important challenge when deploying such technology in a real-world application is speech disfluencies, such as filled pauses, self-repairs, repetitions, hesitations, and false starts. These linguistic phenomena are a common feature of spontaneous human speech (Shriberg, 1996).

The presence of speech disfluencies can have a negative impact not only on the readability of generated transcripts, but also on the performance in downstream tasks, such as machine translation, question answering, and summarization. For example, Gupta et al. (2021) have shown that the presence of disfluencies in questions can significantly drop the performance of a question-answering model. Existing conversational systems have a varying degree of robustness against speech disfluencies, either handling such phenomena implicitly as part of a downstream task model (Jamshid Lou and Johnson, 2020a), or explicitly as a post-processing step after the ASR component and before a downstream task model (Zayats et al., 2016) and Jamshid Lou et al. (2018). Recent literature has shown that the latter approach can significantly improve the performance of ASR systems, bringing them closer to human-level performance (Jamshid Lou and Johnson, 2020a).

Several methods for explicitly handling disfluencies with a separate component have been proposed in the literature. The most common is sequence tagging (Ostendorf and Hahn, 2013; Liu et al., 2006; Ferguson et al., 2013), where each token of the input sequence is classified as fluent or disfluent. The advent of deep learning (DL) led to even more powerful models for disfluency detection, varying from recurrent neural networks (RNNs) (Hough and Schlangen, 2015) and convolutional neural networks (CNNs) (Jamshid Lou et al., 2018) to more recent Transformer-based methods (Dong et al., 2019; Wang et al., 2020b; Rocholl et al., 2021).

Despite the great progress of these models, they still suffer from a significant limitation: they heavily rely on the existence of annotated datasets for training and evaluation. However, existing datasets for disfluency detection are limited and do not cover sufficiently all the different types of disfluency that can be encountered in real-world scenarios. For example, Switchboard (Godfrey et al., 1992), the largest and most commonly used dataset for disfluency detection, has a highly imbalanced distribution among the different disfluency classes, with more than 50% of the examples belonging to repetitions (Shriberg, 1996), which is the easiest class of disfluencies according to the literature (Zayats et al., 2016; 2019). Training models on Switchboard can lead to a significant bias towards the repetition class, while evaluating models on it will lead to misleading results with respect to their real-world performance (Passali et al., 2022). An option to remedy this drawback would be to manually annotate datasets with more complex disfluencies like replacements and restarts. However, this would require enormous human labeling effort and appropriately trained personnel.

Motivated by this observation, we propose an approach for automatically generating highly realistic context-aware
artificial disfluencies from existing fluent dialogue corpora, without any human supervision. These artificial disfluencies can be used directly for training any disfluency detection model, contrary to existing augmentation techniques which are used only for self-supervised pre-training (Dong et al. 2019; Yang et al. 2020; Wang et al. 2020b) via a denoising objective. In particular, we propose three distinct algorithms, one for each of the three most common categories of disfluencies: repetitions, replacements, and restarts. To the best of our knowledge, this is the first work that takes into account context-based representations for artificially labeling data in disfluency detection.

A preliminary version of this work was presented in Passali et al. (2022). Here, we extend our previous approach by: a) incorporating context-aware representations for generating more complicated disfluencies such as replacements, b) refining the previously proposed algorithms to improve the quality of the generated disfluencies, and c) providing an in-depth experimental evaluation using an additional dataset, both in a regular and in a low-resource setup. In particular, the replacement algorithm works by first extracting possible repair candidates for the replacement using semantic relations such as hypernyms and hyponyms and then selecting the best repair candidate using a BERT-based language model. This way, we ensure that the inserted replacement does not affect the semantic relation between the fluent and the generated disfluent sequence. In addition, we appropriately modify the repetition and restart algorithms to filter non-realistic results.

Our contributions can be summarized as follows:

- We propose a method for automatically generating realistic artificial repetitions, replacements, and restarts.
- We provide an empirical evaluation of the proposed method on Switchboard and Disfl-QA. Results show that our method can boost the performance of existing models for disfluency detection.
- We conducted a proof-of-concept experiment in a low-resource setup, demonstrating that our method can be successfully used with few or no data at all. This is especially important for low-resource languages where disfluent data is scarce.

The rest of this paper is organized as follows. Section II discusses the structure of disfluencies in human dialogue. Section III reviews related literature. Section IV introduces the proposed method. Section V presents and discusses the results of our empirical evaluation. Finally, Section VI concludes our work and points to interesting future research directions.

II. DISFLUENCIES IN HUMAN DIALOGUE

This section introduces the structure, as well as the different categories of disfluencies.

A. Structure of Disfluencies

Shriberg (1994) introduced a standard annotation scheme, called reparandum/interregnum, for identifying disfluencies. This annotation scheme involves the following fragments: a) the reparandum, b) the interruption point, c) the repair, and optionally, d) the interregnum, which is located right before the repair.

The reparandum indicates the disfluent part of the utterance: the part that is not correct and must be replaced or ignored. Typically, the speaker attempts to rephrase, edit or restate the reparandum. The reparandum is usually short, involving 2 to 3 words. Even though the reparandum is usually considered as a “rough” copy of the repair, it can also be completely irrelevant to the repair.

The interruption point indicates the start of the repair, if no interregnum exists. If an interregnum exists, then the interruption point indicates the start of the interregnum, after which the repair follows. The interruption point does not indicate an actual word, it rather marks the moment of speech when a speaker realizes the error and initiates the correction process. In other words, the interruption point typically occurs right after the last word that is being told before the interruption of speech.

The interregnum consists of repair cues, such as those shown in Table I that are typically used to fill the gap between the disfluent speech and the associated repair. These types of fillers are generally ignored from dialogue systems as they do not contain any useful information. Most of the time, the presence of a repair cue indicates the presence of a disfluency in the utterance. Interregnums are relatively easy to detect as they are usually fixed phrases, in contrast to reparandums that require a deeper understanding of the complex dialogue flow. For this reason, many methods ignore the interregnum and focus only on the detection of the reparandum and the repair (Zayats et al. 2016, 2019; Jamshid Lou et al. 2018; Bach and Huang 2019).

| Repair cues | Examples |
|-------------|----------|
| filled pauses | um, uh |
| editing phrases | oops, no, sorry, wait, I meant to say |
| discourse phrases | well, actually, okay, you know, I mean |

We typically meet a repair in a speaker’s utterance either after the presence of an interregnum or directly after the interruption point. The repair is the corrected fragment of speech and is usually different from the reparandum. However, in some cases the repair can be exactly the same as the reparandum or even completely empty.

An example of the aforementioned annotation scheme is described in Fig. 1, where the speaker mistakenly says Tuesday instead of Friday. The disfluent part of this example consists of the words “on Tuesday” (reparandum), which is followed by an interregnum (“I mean”), and eventually by the correct repair.

Fig. 1. An example of a disfluency, where the reparandum, interregnum and repair are illustrated. The vertical bar indicates the interruption point.
choice of day ("on Friday") that makes the particular repair. To simplify the presentation of disfluencies under this scheme, the following notation is typically used to indicate the different parts of disfluencies:

\[
\text{[reparandum + \{interregnum\} repair]}
\]

In this notation, the brackets ("[") and "") are used to indicate the disfluency along with the repair. The interruption point is indicated by the plus symbol ("+"), while the interregnum, if present, is indicated by curly brackets ("{", "}").

### B. Categories of Disfluencies

According to the speech repair typology of Shriberg (1994), disfluencies can be categorized into three distinct classes, as described below:

- **Repetitions**: The speaker repeats a word, a phrase or a sequence of words. In repetitions, the reparandum and the corresponding repair are actually the same. This type of disfluency is the most common and is particularly easy to be detected (Zayats et al., 2014/2019).
- **Replacements**: The speaker replaces the disfluent word(s) or phrase with the fluent one. In replacements, the reparandum is replaced by the repair.
- **Restarts**: The speaker abandons completely the initial utterance and restarts it. This type of disfluency does not actually involve a repair as the speaker begins a completely new utterance.

Table II presents an example for each of these three categories of disfluencies.

| Type       | Example                                               |
|------------|-------------------------------------------------------|
| repetition | Let’s meet [today + today].                            |
| replacement| I want [the blue + [no] the red ] one.                |
| restart    | [Why don’t you + ] I will do it later.                |

### III. RELATED WORK

This section reviews related work on disfluency detection. First, we provide an overview of existing models and methods for detecting disfluencies. Then, we present datasets that are used to train the aforementioned models. Finally, we discuss existing augmentation techniques that have been proposed to address the issue of limited data for disfluency detection.

#### A. Disfluency Detection Models

Several approaches have been proposed for handling speech disfluencies in a dialogue. These approaches are divided into four significant categories: a) **sequence tagging**, b) **translation-based**, c) **parsing-based** and d) **noisy-channel** methods. Sequence tagging, which is the most common approach for disfluency detection, classifies each token of the input sequence as fluent or disfluent. This approach includes a wide range of different models varying from Hidden Markov Models (Liu et al., 2006), Conditional Random Fields (CRFs) (Georgila, 2009; Ostendorf and Hahn, 2013), Semi-Markov CRFs (Ferguson et al., 2015), CNNs (Jamshid Lou et al., 2018), RNNs (Zayats et al., 2016), to more recent Transformer-based architectures (Dong et al., 2019; Wang et al., 2020b; Chen et al., 2022), and even using an on-device lightweight setup (Rocholl et al., 2021). On the other hand, translation-based methods approach disfluency detection as a sequence-to-sequence problem using encoder-decoder models to generate the corrected sequence without the disfluent fragments by "translating" the disfluent input into a fluent sequence (Saini et al., 2021). Parsing-based approaches detect concurrently both the syntactic structure and the disfluencies of the input sequence (Wang et al., 2017; Tran et al., 2019). These approaches require corresponding annotated training datasets that include both syntactic and disfluency annotations. Noisy-channel models (Charniak and Johnson, 2001; Johnson and Charniak, 2004) detect disfluencies by computing the similarity between the reparandum and the repair.

#### B. Disfluency Detection Datasets

**Switchboard** (Godfrey et al., 1992) is the most popular disfluency detection dataset. It is the largest human-annotated dataset with real disfluencies at token-level, based on the reparandum/interregnum scheme. Even though Switchboard contains approximately 190,000 multi-speaker transcriptions of English dialogues on different topics, it has a highly imbalanced class distribution, with only 5.9% of tokens being disfluent. In addition, more than 50% of these disfluent tokens belong to simple repetitions (Charniak and Johnson, 2001), which has been shown to be the most trivial to tackle disfluency type (Charniak and Johnson, 2001).

**Disfl-QA** (Gupta et al., 2021) is a recent dataset for disfluency detection containing 12,000 human-annotated disfluent questions in English. In contrast to Switchboard, Disfl-QA has a higher number of more complicated disfluencies, such as replacements and restarts. However, it is significantly smaller. Furthermore, because it lacks token-level annotations, it can only be used directly by translation-based models.

**Fisher English Training Transcripts** (Cieri et al., 2004) contains approximately 1.3 million transcriptions of real dialogues between speakers. Despite being larger than Switchboard, it lacks annotations for the disfluencies it contains and thus cannot be readily used for the task of disfluency detection.

#### C. Data Augmentation Techniques

Despite the significant progress of DL models, they still rely heavily on the quality and quantity of training data. To address the issue of limited datasets, some early steps towards data augmentation have been made, varying from semi-supervised techniques (Wang et al., 2018) to self-training approaches (Jamshid Lou and Johnson, 2020b), either by annotating unlabeled datasets, such as Fisher, using existing disfluency detectors trained on Switchboard, or by unsupervised pre-training techniques using artificial data (Dong et al., 2015), CNNs (Jamshid Lou et al., 2018), RNNs (Zayats et al., 2016), to more recent Transformer-based architectures (Dong et al., 2019; Wang et al., 2020b; Chen et al., 2022), and even using an on-device lightweight setup (Rocholl et al., 2021). On the other hand, translation-based methods approach disfluency detection as a sequence-to-sequence problem using encoder-decoder models to generate the corrected sequence without the disfluent fragments by "translating" the disfluent input into a fluent sequence (Saini et al., 2021). Parsing-based approaches detect concurrently both the syntactic structure and the disfluencies of the input sequence (Wang et al., 2017; Tran et al., 2019). These approaches require corresponding annotated training datasets that include both syntactic and disfluency annotations. Noisy-channel models (Charniak and Johnson, 2001; Johnson and Charniak, 2004) detect disfluencies by computing the similarity between the reparandum and the repair.

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Our work is closer to the latter approach. Dong et al. (2019) corrupt the input sequence for pre-training by adding noise based on randomly selected input words, while a similar approach is adopted by Yang et al. (2020), where a simple planner-generator model is used to generate and place disfluent text in a fluent sentence. Wang et al. (2020b) generate artificial disfluencies by randomly repeating, inserting, and removing words. As the inserted tokens are randomly selected, the semantic consistency between the created disfluent sentence and the fluent one cannot be guaranteed. The aforementioned approaches rely on simple rules and techniques that are incapable of generating all the different kinds of complex disfluencies that occur in real-world scenarios. Our work differs from these approaches in several aspects. First, it is carefully designed to generate and handle all types of disfluencies. In addition, the proposed method incorporates contextual representations for the generation of synthetic disfluencies, leading to disfluencies that are closer to the ones occurring in natural dialogue flows. Finally, the proposed method can be used to generate annotated disfluencies for directly training supervised disfluency detectors, instead of defining a denoising pre-training objective, which can be computationally costly.

IV. PROPOSED METHOD

In this section, we introduce our improved Large-scale Artificial Disfluency (LARD) generation method for synthesizing artificial disfluencies from fluent text. The proposed method consists of three algorithms for supporting the corresponding types of disfluencies, namely repetitions, replacements, and restarts.

Given any set of fluent sentences, we can use these algorithms to generate a new set of annotated disfluent sentences containing artificial repetitions, replacements, and restarts at any ratio. Even though all the algorithms can consume the same fluent sentence to generate disfluencies, we use different sub-sets of the fluent set for each algorithm to increase the variation of the generated examples.

A. Repetition Algorithm

The procedure used for generating artificial repetitions is summarized in Alg. [1] This algorithm works by randomly repeating words or sequences of words based on a given degree ranging from 1 to 3.

For example, given the fluent sequence “Thank you for your help”, we can simulate an artificial disfluent sequence that includes a degree 1 repetition by repeating the word “for” in the third position, or a degree 2 repetition by repeating the sequence of words “thank you”, starting from the first position as follows:

Degree 1: Thank you [for + for] your help
Degree 2: [Thank you + thank you] for your help

During this procedure, we ensure that we select only valid candidates for repetition by excluding tokens that belong to punctuation marks. The repetition algorithm can be used for generating up to degree 3 repetitions, but it can also be easily modified to generate repetitions of higher degrees according to the length of the input sequence.

B. Replacement Algorithm

To preserve the semantic consistency between the initial fluent sentence and the generated disfluent one, we introduce a two-step replacement candidate selection process exploiting the semantic relation of the selected candidate with hypernyms and hyponyms. Then, a BERT-based language model is used to select the best candidate from a set of possible candidates. The replacement algorithm is described in Alg. 2. The steps for generating artificial replacements can be summarized as follows:

1) First, we extract a random word of the initial fluent sentence, whose part-of-speech (POS) is either noun, verb, or adjective, to serve as our repair candidate. The POS tagger of NLTK (Bird et al., 2009) is used in this step.

2) We detect the hypernym class of the repair candidate, namely its broader semantic category, using NLTK (Bird et al., 2009). In case more than one hypernym exist, we extract all the possible hypernyms.

3) For each hypernym, apart from the original candidate, we extract N hyponyms, namely words that belong to the same broader semantic category. Since hyponyms share common semantic relations, we assume they will be semantically close to the initial repair candidate.

4) For each hyponym, we generate a new sentence based on the initial sentence by substituting the selected repair candidate with the corresponding hyponym. Then, we compute the similarity between all the generated sentences and the original sentence.

5) Instead of randomly selecting a hyponym from the extracted set of hyponyms, we select the best candidate, the one in the sentence with the highest similarity. The best candidate serves as our reparandum candidate.

6) To simulate an artificial replacement, the reparandum candidate is placed right before the repair candidate in

Algorithm 1 Repetition algorithm

Input: A fluent sequence $S_f$, the degree of repetition $d_r \in \{1, 2, 3\}$

Output: A disfluent sequence $S_d$ which contains a repetition based on given degree $d_r$

1: procedure GENERATE REPETITIONS($S_f, d_r$)
2: \[ l_s \leftarrow \text{length}(S_f) \]
3: Choose \[ \text{random}_{idx} \leftarrow \text{uniform}(0, l_s - d_r) \]
4: satisfying the condition that the word of the selected index, as well as words up to degree $d_r$ of the subsequent indexes, do not belong to punctuation marks.
5: \[ S_d \leftarrow \text{Repeat the subsequence of tokens in } S_f \text{ starting from index } \text{random}_{idx} \text{ to degree } d_r. \]
6: return $S_d$
7: end procedure

### Footnotes

[2019] [Yang et al. 2020] [Wang et al. 2020b].
Algorithm 2 Replacement algorithm

Input: A fluent sequence $S_f$, part-of-speech $s_{pos} \in \{\text{noun, verb, adjective}\}$, the range of hyponyms $N$, a boolean variable $\text{cue}$.

Output: A disfluent sequence $S_d$ which contains a replacement based on the part-of-speech $s_{pos}$

1: procedure CREATE REPLACEMENT($S_f$, $s_{pos}$, $N$, $\text{cue}$)
2: while there is $s_{pos}$ in $S_f$ do
3: $W_{pos}$ ← a list with all of the available words of the sequence $S_f$ that belong to the selected input part-of-speech $s_{pos}$
4: Select randomly one of the available words from $W_{pos}$ to serve as repair candidate
5: Detect the hypernym of the repair candidate. If there are more than one hypernym extract all the possible hypernyms.
6: Extract $N$ hyponyms for each hypernym, excluding the repair candidate.
7: $\{S\} \leftarrow N$ new sequences based on $S_f$ with the substitution of the repair candidate with the corresponding hyponym in $S_f$
8: Compute the similarity between all the sentences and the $S_f$ and select as reparandum candidate the hyponym whose sentence has the highest similarity.
9: $d_r \leftarrow \text{uniform}(0, 3)$
10: Repeat $d_r$ tokens before the replacement candidate
11: Place the reparandum candidate
12: if $\text{cue} == \text{True}$ then randomly select a repair cue from list and place it after the reparandum candidate.
13: end if
14: Continue the rest of $S_f$
15: return $S_d$
16: end while

end procedure

The initial sentence, to ensure that the fluent sentence will be realistic. The repair candidate is always one word, but the reparandum candidate can vary from 1 to 4 words according to the extracted hyponym.

Optionally, we can add a repair cue between the replacement and the repair candidate. We create a fixed list of repair cues with some variations of words and phrases from Table I. Note that filled pauses, such as um and uh, are not included in this list as these types of disfluencies are typically removed automatically from recent ASR systems.

To compute the similarity between each generated sentence with the initial sentence, we first employ a BERT-based model to extract sentence embeddings $SE$, by mean-pooling all the token embeddings of the given sentence as follows:

$$SE = \frac{1}{n} \sum_{i=0}^{n-1} TE(i),$$  \hspace{1cm} (1)

where $TE(i)$ represents the token embedding of the $i^{th}$ token, while $n$ denotes the number of tokens in the given sentence.

The final reparandum candidate $r$ is selected as follows:

$$r = \max_{i \in T} \{\text{sim}(SE_r, SE_i)\},$$  \hspace{1cm} (2)

where $T$ represents the set of the hyponym-generated sentences, $SE_r$ and $SE_i$ denote the sentence embeddings of the initial sentence $s$ and the generated sentence with the hyponym $i$ of the set $T$ respectively, while $\text{sim}$ denotes the cosine similarity between two vectors $x_y$ and $x_z$, computed as follows:

$$\text{sim}(x_y, x_z) = \frac{x_y \cdot x_z}{\|x_y\| \|x_z\|}.$$

(3)

The replacement algorithm can generate simple replacements involving only one word, but can also be used to simulate more complicated $n$-word replacements ($n > 1$) involving multiple words in both reparandum and repair. For the latter, we repeat a sequence of words before the reparandum candidate. We limit this sequence length to 3 words in order to ensure that the generated sentences will be coherent and realistic.

For example, given fluent sequence “I would like to eat pancakes for breakfast”, we can simulate an artificial noun-replacement by selecting the word “pancakes”, whose POS is a noun, as our repair candidate. We extract its hypernym class, namely “cake”. Some possible hypernyms for the word “cake” are “gingerbread”, “cheesecake”, “doughnut”, “honey cake”, “brownie” etc. Then, we generate all the possible sentence candidates, like “I would like to eat gingerbread for breakfast” and “I would like to eat cheesecake for breakfast”, and compute their similarity with the initial fluent sentence. The best candidate e.g., “cheesecake”, is the one belonging to the sentence with the highest similarity. Note that we can also use a repair cue from the fixed list of repair cues e.g., “no wait”. Finally, we can generate a simple artificial disfluent sequence by replacing the reparandum candidate “cheesecake” with the repair candidate “pancakes” or a three-word replacement by also repeating the sub-sequence of words “to eat”, starting from the fourth position as follows:

One-word: I would like to eat [cheesecake + {no} pancakes] for breakfast

Three-word: I would like [to eat cheesecake + {no} to eat pancakes] for breakfast

Following this procedure, we can simulate six different subclasses of replacements: noun replacement with and without repair cue, verb replacement with and without repair cue and adjective replacement with and without repair cue.

C. Restart Algorithm

Contrary to the repetition and replacement algorithm, this algorithm assumes the existence of a set of two or more fluent sentences. The steps for generating artificial restarts are summarized in Alg. 3. First, we extract two different sentences from a given fluent set. Then, we split the first sentence at a random position and we concatenate this broken sentence with the second fluent one.

3: end while
Algorithm 3 Restart algorithm

Input: Two fluent sequences \(S_{f1}\) and \(S_{f2}\), with \(S_{f1} \neq S_{f2}\)
Output: A disfluent sequence \(S_d\)

1: \textbf{procedure} CREATE RESTARTS(\(S_{f1}, S_{f2}\))
2: \(S'_{f1} \leftarrow S_{f1}\) broken in a random position.
3: \textbf{while} \(S'_{f1} \neq \) beginning of \(S_{f2}\) \textbf{do}
4: \quad Check for connective words at the end of \(S'_{f1}\) or at the beginning of \(S_{f2}\)
5: \quad \textbf{if} no connective words detected \textbf{then}
6: \quad \quad \(S_d \leftarrow \text{join}(S'_{f1}, S_{f2})\)
7: \quad \textbf{return} \(S_d\)
8: \quad \textbf{else}
9: \quad \quad Select another sequence \(S_{f2}\)
10: \quad \textbf{end if}
11: \textbf{end while}
12: \textbf{end procedure}

For example, given two fluent sequences “I would like to buy a new dress” and “Can we meet on Tuesday?”, we can simulate a disfluent sentence with an artificial restart by splitting the first sentence in the second position and concatenating it with the second sentence as follows:

[I would +] can we meet on Tuesday?

As discussed in Section II, this type of disfluency does not involve a repair as the speaker abandons the previous sentence and restarts with a new one.

During this procedure, it is possible to accidentally generate a fluent sentence instead of a disfluent one. This might happen when the connection point for the given sentences happens to belong to a connective word or phrase. As connective words are typically used to link one sentence with another, their presence might result in a fluent and coherent sentence. To alleviate this issue, we create a list of possible connectives according to the different types that can occur in a real dialogue flow, e.g., additive (and, also etc.), causal (because, if, since etc.), adversative (but, however, etc.), and temporal (after, before, etc.). Then, while concatenating the two sentences, we check for the presence of connective words and filter such sentences to avoid the generation of fluent examples. Also, we ensure that the end of the first broken sentence is not the same as the beginning of the second sentence to avoid unintentionally generating a repetition instead of a restart.

V. Empirical Evaluation

In this section, we introduce the training and evaluation details of our experimental setup, as well as present and discuss the results of our empirical evaluation.

A. Experimental Setup

We conduct experiments with sequence tagging and translation-based approaches. For sequence tagging, we use the pre-trained BERT-base uncased model, which consists of 12 encoder layers with 12 attention heads as well. In addition, for extracting vector representations when generating artificial replacements, we use the multi-qa-distilbert-cos-v1 model (Reimers and Gurevych 2019), which is a lightweight distilBERT-based model fine-tuned appropriately for the task of semantic search.

We fine-tune all the models for 10 epochs with learning rate 2e-5 and batch size 16. We do not perform extensive hyper-parameter search as this lies beyond the scope of this paper. Further fine-tuning or more extensive hyper-parameter tuning could lead to improved models. All the conducted experiments were performed using the Hugging Face library [6].

We train and evaluate our disfluency models on Switchboard and Disfl-QA. Switchboard provides token-level annotations and can be easily used for both sequence-tagging and translation-based approaches. For sequence tagging, we classify each token as fluent or disfluent. More specifically, we classify as disfluent all the tokens that are located before the repair inside the disfluent fragment. Similarly, we classify as fluent all the tokens after the interruption point inside the disfluent fragment as well as all the tokens located outside the disfluent fragment. We use the established train/validation/test split for training and evaluation [Charniak and Johnson 2001]. Following [Rocholl et al., 2021], we also discard partial words and words that belong to interregnum such as “uh”, “um”, etc. because they are trivially detected by recent ASR systems.

Disfl-QA provides only raw disfluent sentences accompanied with their respective target fluent versions. Therefore, it can only be used with translation-based models. We adapt this dataset for sequence tagging by mapping one-to-one annotations between the fluent and disfluent sentences. Examples where fluent sentences are not sub-sentences of the disfluent ones are discarded. Some statistics for both datasets are shown in Table III.

| Dataset            | Train  | Validation | Test  |
|--------------------|--------|------------|-------|
| Switchboard        | 165,463| 14,026     | 7,406 |
| Disfl-QA (original)| 7,182  | 1,000      | 3,643 |
| Disfl-QA (sequence tagging) | 5,537 | 780        | 2,460 |

For all the sequence tagging models, we report token-based recall, precision and F-measure. For translation-based models, we report BLEU score [Papineni et al., 2002].

B. Results

To demonstrate the effectiveness of the proposed method, we conduct two different types of experiments, examining: a) the effect of the proposed method in a low resource setup when no or few data are available, and b) the compatibility of the generated artificial disfluencies with real data.

1) Low-resource setting: In this experiment, we simulate a low-resource setting by keeping only a few samples from each dataset according to their initial size. We use a sequence-tagging model for all these experiments. Our evaluation includes the following setups:

https://huggingface.co/
• Only artificial samples (Switchboard). We use LARD to generate different types of artificial disfluencies on the fluent set of Switchboard (82,315 fluent sentences). To get closer to the original distribution of the Switchboard test set (~22% disfluent sentences), we generate 31,034 examples of artificial disfluencies, consisting of 17,047 repetitions and 13,987 replacements. We do not include any artificial restarts because, as demonstrated later in this section, the nature of Switchboard dialogues can negatively affect the model’s performance when the restart algorithm is used. We fine-tune the model on 82,315 fluent examples of Switchboard combined with the 31,034 generated artificial disfluencies, leading to an artificial training set of 113,349 examples. We do not include any real disfluency from the original dataset.

• Only artificial samples (Disfl-QA). We use the 5,537 target fluent sentences of Disfl-QA to generate different types of artificial disfluencies. Similar to Switchboard, we maintain the original distribution of disfluencies in the Disfl-QA dataset (more than 65% replacements and 30% restarts). After applying LARD, we obtain 3,600 artificial replacements and 1,937 artificial restarts. We do not include artificial repetitions since repetitions are not included in the original training set of Disfl-QA. We do not include any real disfluency from the original datasets.

• 1K/2K/5K real samples (Switchboard). We sample 1,000 (841 fluent and 169 disfluent), 2,000 (1,682 fluent and 318 disfluent) and 5,000 (4,217 fluent and 783 disfluent) examples from the original Switchboard training dataset and we fine-tune the model on the corresponding subset. We keep the original distribution of the training data regarding the number of repetitions, replacements, and restarts.

• Artificial + 1K/2K/5K real samples (Switchboard). We combine the samples of real examples of Switchboard with the corresponding generated artificial disfluencies.

• 100/200/500 real samples (Disfl-QA). We sample 100, 200 and 500 disfluent examples from the original Disfl-QA training and we fine-tune the model on the corresponding subset. Since Disfl-QA is a significantly smaller dataset than Switchboard, we reduce the samples of real examples by an order of magnitude. Note that Disfl-QA contains only the original disfluent examples.

• Artificial + 100/200/500 real samples (Disfl-QA): We combine the samples of real examples of Disfl-QA with the corresponding generated artificial disfluencies.

All the models were evaluated on the original test sets of Switchboard and Disfl-QA. Results in Table IV demonstrate that even when no real disfluent data are used, we can achieve an adequate performance of more than 84% in terms of F1 for both datasets, only with artificial disfluencies. This finding is promising, as it suggests that the proposed method can be successfully used for low-resource languages, where annotated datasets for disfluency detection do not typically exist. In addition, we can achieve better performance on the Switchboard dataset when only artificial disfluencies are used compared to the model fine-tuned with 1000 samples of real data, which achieves 82.41% in terms of F1. The same conclusions can be drawn for the Disfl-QA dataset, where better performance is achieved with only artificial disfluencies compared to the model fine-tuned with 100 disfluent samples with only 78.09% F1.

Additional gains are observed when artificial data are combined with samples of real data. We can notice that all the models fine-tuned with combined data outperform all the models that are fine-tuned only with the corresponding samples of real data in terms of F1 for both datasets. Furthermore, the best performance for the Switchboard dataset is achieved, when 5,000 samples are combined with artificial disfluent data, with an increase of more than 6 points in terms of precision (98.08% compared to 91.23%) and more than two points in terms of F1 (89.71% compared to 87.60%). Similarly, we obtain the best performance for the Disfl-QA dataset, when 500 samples are inserted into artificial disfluent data, with an increase of more than 5 points in terms of precision (92.34% compared to 86.64%) and more than 3 points in terms of F1 (91.63% compared to 78.09%). In all cases, a performance increase is noticed, which further demonstrates the capability of the proposed method to achieve strong performance with no or only a few annotated data.

2) Artificial data with real data: In many cases, the insertion of artificial disfluencies directly into real data for training can lead to a performance decrease due to distribution shifts between the real and artificial data (Dong et al., 2019; Yang et al., 2020). However, in this experiment, we demonstrate that the proposed method does not alter the distribution of real data, by generating realistic disfluencies, which increases the accuracy of existing models. In particular, we investigate the effect of artificial disfluencies when inserted directly into the full Switchboard and Disfl-QA training sets. We extract all the fluent sentences of both datasets and we generate all the different types of artificial disfluencies, namely repetitions, replacements, and restarts. We insert 3,000 and 10,000 artificial repetitions, replacements and restarts for Disfl-QA and Switchboard, respectively. Then, we fine-tune both sequence tagging and translation-based models on the original training datasets with different types of inserted disfluencies. Results of inserted repetitions, replacements, and restarts on the Disfl-QA and Switchboard dataset are shown in Table VI and VII respectively. All the models were evaluated on the original test set of Disfl-QA and Switchboard, respectively.

Results in Table VI indicate that when synthetic data of any type are inserted, the performance of all the sequence tagging models is increased, contrary to when no synthetic data is used. Similar results are observed for the majority of the translation-based models, where inserted replacements and restarts lead to an increased performance as well. The highest accuracy is achieved when artificial restarts are inserted for the sequence tagging model with 96.69% compared to 96.04% in terms of F1 and when both artificial replacements and restarts are inserted for the translation-based model with 95.10% compared to 94.95% in terms of BLEU score. This finding suggests that the generated artificial disfluencies can be effectively combined with existing datasets that contain real disfluencies without altering their distributions.
Similar results are obtained on the Switchboard dataset as shown in Table VI, where the majority of fine-tuned models with inserted disfluencies achieve an increased accuracy. However, contrary to Disfl-QA, we noticed a slight drop in performance when artificial restarts are inserted into the original dataset. This can be attributed to the nature of Switchboard examples, which are typically incomplete sentences. In some cases, this can be tricky for the restart algorithm, leading to misclassified fluent sentences. Therefore, even though the drop in performance is not significant, artificial restarts should be used with caution. Additionally, the best performance is obtained when both repetitions and replacements are inserted with 94.18% in terms of F1 and 92.05% in terms of recall, compared to the 93.89% and 91.63% of the model fine-tuned on the original dataset. For the translation-based model, we achieve the best accuracy when only artificial repetitions are inserted with 91.24% compared to 91.18% in terms of BLEU score. Since translation-based is a more challenging task, we expect a slighter increase in contrary to the sequence tagging task. In addition, the combination of both repetitions and replacement still increases the accuracy of the original model with 91.21% compared to 91.18% BLEU score.

VI. Conclusions and Future Work

We proposed LARD, a method for automatically generating artificial disfluencies. The proposed method consists of three different algorithms for handling the three most common types of disfluencies: repetitions, replacements, and restarts. LARD can be directly used without any labeled data to successfully train disfluency detection models. Our empirical evaluation showed the effectiveness of the proposed method in a low resource setup, when none or few annotated data are available. In addition, our analysis confirmed that LARD can generate realistic disfluencies which do not alter the distribution of data that contain real disfluencies.

Future work could examine the effect of the proposed method for generating more than one disfluency per sentence. Furthermore, it would be very interesting to extend the proposed method to other languages, where disfluent data are not readily available.

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VII. BIOGRAPHY SECTION

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