

# Acoustic Model Pretraining Enables End-to-End Automatic Speech Recognition and Disfluency Removal

Saksham Bassi  
sb7787

Giulio Duregon  
gjd9961

Siddhartha Jalagam  
scj9994

David Roth  
dsr331

## Abstract

Prior work combining Automatic Speech Recognition (ASR) and Disfluency Detection into a single end-to-end model (Lou and Johnson, 2020) was found to yield inferior results compared to a two-stage formulation, despite the information-rich prosody cues available only to audio based models. We believe that previous attempts at end-to-end disfluency removal have fallen short because of the representational advantage that large-scale language model pretraining has given to lexical models. Until recently, the high dimensionality and limited availability of large audio datasets inhibited the development of large-scale self-supervised pretraining objectives for learning effective audio representations, giving a relative advantage to the two-stage approach, which utilises pretrained representations for lexical tokens. In light of recent successes in large scale audio pretraining, we revisit this comparison and find that audio based language models pretrained using self-supervised objectives match or exceed the performance of similarly trained two-stage models, and further, that the choice of pretraining objective substantially effects a model’s ability to be adapted to the disfluency removal task.<sup>1</sup>

## 1 Introduction

Conversations, dialogue, and spontaneous speech differ from text sources in that they often contain errors that are self-corrected throughout a given utterance. Phrases are amended, repeated and taken back, hesitations are common, and interjections frequently occur. Further, spoken language contains cues from tempo and intonation which change the meaning of the words we communicate- while the subtleties of the spoken word are interpreted easily by human listeners, the same cannot be said for most speech to text NLU models.

Many modern applications, including Amazon’s Alexa, Apple’s Siri and Google’s Voice Search use speech recognition software to convert speech signals into a text format that is interpretable by an

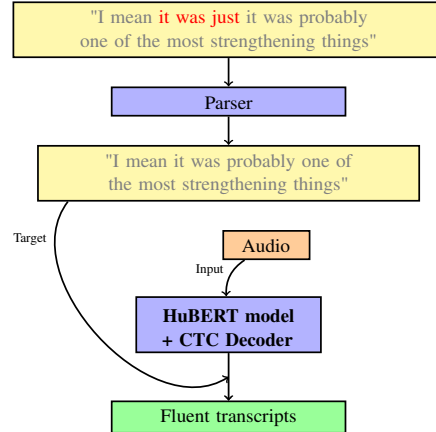


Figure 1: Model Flow of the end-to-end system

inference model to determine user intent. Spoken word audio is recorded as input, transformed into text representations via a transcription model, and mapped to outputs based on the interpreted meaning. These models often use text pretraining to improve their performance, but the divergence between written and spoken sources creates difficulties for interpreting disfluent speech, making proper handling of speech disfluencies critical for downstream applications.

To bridge the gap between the written texts that inference models are trained on and the spontaneous speech captured from downstream users, modern ASR systems can include a text-based disfluency detection step, in which tokenized lexical representations produced by a transcription model are fed to a disfluency classification step to remove disfluencies before ingested by an inference model (Jamshid Lou et al., 2019). We believe that end-to-end approaches can utilize prosody cues for disfluency detection that are not captured by tokenized lexical representations and hope to improve their performance and/or identify scenarios where prosody information leads to better performance.

We investigate an end-to-end approach, using a pretrained acoustic model to directly predict fluent transcripts of disfluent speech. We train our model on Switchboard (Godfrey et al., 1992) and evaluate using Word Error Rate (WER) and Character Error Rate (CER) on disfluency filtered text.

<sup>1</sup>Code: <https://github.com/davidsroth/hubert-disfl/>

We also investigate the effect that the choice of pretraining objective plays in our model’s performance by comparing the fine-tuning performance of two Conformer (Gulati et al., 2020) based models, one utilizing a contrastive Masked Language Modeling pretraining objective and one utilizing a lower dimensional clustering based objective.

## 2 Background

### 2.1 Automatic Speech Recognition (ASR)

Computational approaches to Automatic Speech Recognition go back as far as the 1950’s. The earliest systems used template matching against known speech patterns to map sections of spoken audio to transcriptions, but were highly limited in their scope, only transcribing digits from a single speaker (Li and Mills, 2019). Later, more advanced techniques utilizing Hidden Markov Models (HMM) were used to map audio data into sequences of phonemes, which were translated into likely sequences of words using dynamic programming via beam search (Meng et al., 2012). Following the successes of Deep Learning approaches to image recognition and natural language processing in the 21st century, HMM systems evolved into Recurrent Neural Network (RNN) and Convolutional Neural Network approaches, which achieved impressive gains over their predecessors.

Recent successes in image and language tasks with the Transformer architecture prompted exploration into self-attentive approaches to ASR, but the comparatively large sequence lengths of audio signals and the quadratic complexity inherent to Transformer models presented significant computational challenges for self-attentive audio models. In the last few years, models that use Convolutional Neural Networks (CNN) to downsample audio sequences before processing with transformers, combined with systems with larger computational capacity, enabled self-attentive approaches to audio, which have since overtaken RNNs and LSTMs as the strongest performers in many audio-based tasks (Gulati et al. (2020) ; Han et al. (2020)). This approach has proved quite effective, with *Conformer* achieving a state of the art performance on the LibriSpeech benchmark, achieving a WER of 1.9%/3.9% on the test\_clean / test\_other portions of the LibriSpeech test sets.

### 2.2 Acoustic Model Pretraining

Performance gains from self-supervised pretraining using Transformers have led to strong performance gains on many natural language tasks, prompting exploration into extensions to the pretraining framework for acoustic modeling. Here, as before, the high dimensionality of audio data presented difficulties in training these systems using a masked objective (Chung et al., 2021). HuBERT (Hsu et al., 2021) is a pretraining framework that uses a Conformer (Gulati et al., 2020) architecture to process sequences of audio frames and a kNN clustering step to provide a lower-dimensional, stable training signal for masked token prediction over high-dimensional audio features. The model is trained to predict a sequence of hidden states  $[Z_1, Z_2, \dots, Z_t]$  over masked portions of the final Conformer output layer, where  $Z_t$  is a C-class categorical variable corresponding to cluster assignments produced by an ensemble of clustering models that are iteratively refined during the training process. This pretraining formulation was found to produce speech token representations that significantly improve ASR performance, particularly in contexts with limited training data.

### 2.3 Disfluency Detection

Early attempts at using statistical modeling to identify disfluencies in spoken language used a combination of prosodic and lexical cues to detect errata and reparanda, but found greater gains from lexical representations (Baron et al. (2002), Snover et al. (2004), Shriberg et al. (1997)). The increasing availability of large, open text corpora fueled subsequent improvements to representations from deep architectures, making lexical representations increasingly the focal point for disfluency detection approaches (Qian and Liu (2013), Wang et al. (2016), Jamshid Lou and Johnson (2020)). Subsequent approaches to improve disfluency detection performance used data augmentation and semi-supervised objectives to expand the volume of "disfluent" lexical data available for training (Wang et al. (2020), Jamshid Lou and Johnson (2020)) and introduced secondary syntactic objectives for multi-task training (Lee et al. (2021), Honnibal and Johnson (2014)). Zayats and Ostendorf re-introduced prosody cues by providing prosody features learned through text-based distributional prediction alongside lexical features during training and inference.

## 2.4 End-to-End ASR and Disfluency Detection Models

Recent work (Lou and Johnson, 2020) attempting to use an end-to-end system in place of a two-stage ASR and disfluency detection model found that the end-to-end formulation produced marginally worse results compared to a two-stage approach. The architectures that were used were based on 3 models: A CNN model, a Bahdanau attention LSTM and a Transformer model. Out of the three, the end-to-end Transformer model performed best but failed to match the performance of the two-stage system. At the time of that evaluation, however, large-scale pretraining objectives for audio data were not common, forcing the audio model to learn meaningful feature representations entirely from scratch during training. We explore results on disfluency removal using pretrained models for effective audio representations, which were not evaluated in Lou and Johnson (2020).

## 3 Data & Methodology

### 3.1 Dataset

The dataset used for fine-tuning and evaluation is Switchboard: a collection of 2,400 two-sided telephone conversations between 543 (302 Male, 241 Female) paid volunteers in the United States prompted by a set of 70 discussion topics. The data was collected by Texas Instruments with funding from DARPA (Godfrey et al., 1992). A subset of these conversations was then annotated for syntactic structure and disfluencies by SRI International as part of the Penn Treebank project (Shriberg, 1996) according to the methods laid out in Shriberg (1994). We will be using these annotations to define our targets for fine-tuning and evaluation. We also make use of transcription and word alignment corrections from Godfrey, John J. and Holliman, Edward (1993).

### 3.2 Dataset Preprocessing

Annotations for Switchboard, (Shriberg, 1996) are provided in Penn-Treebank format by Zayats and Ostendorf (2019) in an XML format containing text tokens, word-aligned time stamps for each conversation in the set and additional metadata for edit, interruption and repair points.

We make use of code from Singh (2019) and Cai (2016) to parse the XML files containing the Penn Treebank annotations, which we modify to suit our needs. We produce fluent transcripts by removing

sections of text between edit and interruption points and, when applicable, keeping corresponding sections marked as repair. We also remove 'Uh's, 'Um's and tokens ending in "-" which designate words that were cut off before completion. Lastly, we use timestamp annotations to extract audio segments corresponding to each utterance, which are fed to our transcription model and trained using filtered fluent text as target labels.

### 3.3 Modeling

To embed our raw audio file inputs with meaningful representations, we use Hsu et al.'s Hidden-Unit BERT (HuBERT), in particular the version distributed by the HuggingFace API. The HuBERT model is well suited for the task we are trying to accomplish: it is a self-supervised model that has been demonstrated to produce meaningful audio representations for downstream tasks.

To that end, we use a Conformer architecture (Gulati et al., 2020) pretrained using the offline clustering task defined by HuBERT (Hsu et al., 2021) to selectively ignore disfluencies using a fine-tuning approach. We leverage the pretrained weights of Facebook's Hubert-large-ls960-ft model, which consists of a HuBERT base with a CTC decoding head fine-tuned on LibriSpeech (Panayotov et al., 2015). Per the original HuBERT paper, we also freeze the weights of the convolution feature encoder during fine-tuning. We filter our audio samples to keep only audio samples 3-15 seconds long and remove special characters from our target text labels, retaining only the text and apostrophes. Additionally, we upsample the 8khz voice recordings from Switchboard to the 16kHz HuBERT expects.

We also evaluate a two-stage model following the work of Rocholl et al. (2021) by fine tuning a HuBERT ASR model on unfiltered Switchboard transcripts, training a per-token classifier using the Switchboard disfluency annotations and evaluating word and character error rates using disfluency filtered transcripts.

## 4 Results

In our experiments using the Switchboard test set, our end-to-end disfluency model slightly outperforms a two-stage model, achieving a WER of 12.2% and a CER of 7.3%, against the two stage model's WER of 13.1% and CER of 7.6%.

Additionally, we found that the choice of pre-training objective substantially affects the fine-

tuning performance for the disfluency removal task. A pretrained Wav2Vec2 achieves test set performance on WER of 23.9% and 13.3%, respectively. This is a significant difference in performance between the two Conformer models. The Wav2Vec2 pretraining objective utilizes a contrastive MLM loss over the full, high dimensional output layer weights; In contrast, HuBERT’s auxiliary cluster-prediction pretraining task appears to learn more stable and flexible representations. The HuBERT model significantly outperformed the Wav2Vec2 model on our fine-tuning task, despite the two being competitive on the standard, unmodified ASR task.

## 5 Ethical Considerations

### 5.1 Dataset Composition

The Switchboard dataset contains conversations from a limited selection of speakers, all living in the United States, which, according to the original publication, covers "every major dialect of American English". Utterances are annotated with their associated dialects as one of "SOUTHERN", "WESTERN", "NORTHERN", "NEW", "NYC", "MIXED" or "UNK". The limited variety of speech signatures present in the data presents a risk of poor performance on those not appearing in Switchboard.

In addition to the risk of faulty transcriptions for dialects and varieties of speech not present in the pretraining and fine-tuning sets, this model is optimized to reject segments of speech it has determined are "disfluent". In comparison to models that produce full transcripts, incorrect or misinterpreted as they may be, there is the risk that this model not only misinterprets incoming speech but rejects it altogether, distorted or not. For systems that utilize voice as their primary interaction method, this behavior could render them completely inaccessible to speech varieties not covered by the data, and restrict inputs available to downstream systems that utilize its transcriptions of "fluent" speech, as it’s determined by our model.

On the other hand, this model also has the potential to make voice systems accessible to users with speech irregularities whose spoken inputs were previously uninterpretable by current systems. The relative risks and benefits of deploying such a system need to be weighed and evaluated before relying on a model that imposes strong priors on the speech they consume.

### 5.2 Data Collection and Use

The data used in Switchboard was collected as part of an effort by DARPA to develop speech recognition, translation and knowledge distillation technologies for their Global Autonomous Language Exploitation (GALE) program. Some of the technologies developed by this program were eventually leveraged in systems to assist American soldiers stationed abroad in communicating with local populations ([SRI International \(a\)](#); [Maeda](#)). Outcomes of this program include the *IraqComm* system, which was developed and deployed during the Iraq War and used to facilitate two-way conversations between the US military and the local Iraqi population ([SRI International, b](#)). The production of speech datasets and transcription models are directly tied to the strategic interests of the funding organizations that enable their creation and are inseparable from the downstream systems they ultimately serve. This is true for systems that cover languages with strong representation in current methods, as well as systems for learning representations for underrepresented languages, which can be utilized against the interests of the underrepresented communities they are ostensibly meant to serve.

## 6 Conclusion and Next Steps

In this work, we evaluated the feasibility of training end-to-end ASR and disfluency removal models in light of recent developments in large scale acoustic model pretraining. We showed that Conformer models fine tuned from weights learned during masked audio pretraining can achieve performance on par or better than a two stage approach fine tuned on similar data. We also showed the effect that the choice of pretraining objective can have on the ability of an acoustic model to adapt to a new task.

We note several limitations of this work and potential directions for subsequent work. Firstly, in conducting evaluations on the same data distribution that is used for fine tuning we risk of overstating "in-the-wild" performance of our trained model. This work does not evaluate out-of-distribution performance of our model, and we expect that applications of our model to data distributions not seen during training could result in degenerate performance.

On a more optimistic note, we note that the data used to learn HuBERT’s pretrained weights came from a large dataset of non-spontaneous speech;



LibriSpeech consists of recordings of audiobooks, which often contain dialogue taking the form of spontaneous speech, but are nonetheless distinct from organic speech. Follow up work could explore the effect that pretraining on a dataset consisting of spontaneous speech, like Mozilla’s Common Voice (Ardila et al., 2019), could have on a disfluency model.

Finally, a more thorough investigation of the performance of our model between fluent and disfluent sections of speech could bring more nuance to the analysis of the disfluency removal capacities of all of the models evaluated here, which risk being obscured by general ASR metrics like WER and CER. The inclusion of Lou and Johnson (2020)’s Fluent Error Rate and Disfluent Error rate was planned for this work, but was ultimately omitted due to time constraints. We leave this analysis for later work.

## 7 Collaboration Statement

All team members were active participants in the group’s responsibilities to brainstorm project ideas and accumulate related literature. For our project, there were two main coding tasks: modeling and data preprocessing. David was responsible for the contributions to model development, training and evaluation, while Saksham developed the parsing preprocessing library used to transform Penn Treebank formatted data into a representation that could be ingested by our model. He was also responsible for model diagrams. Giulio was responsible for communications with Angelica Chen to establish our baseline two-stage approach, conducting background research, and contributing to the write-up. Siddhartha primarily worked on our two-stage ASR to disfluency detection baseline. He also worked on additional model research.

## References

Rosana Ardila, Megan Branson, Kelly Davis, Michael Henretty, Michael Kohler, Josh Meyer, Reuben Morais, Lindsay Saunders, Francis M. Tyers, and Gregor Weber. 2019. *Common voice: A massively-multilingual speech corpus*. *CoRR*, abs/1912.06670.

Don Baron, Elizabeth Shriberg, and Andreas Stolcke. 2002. Automatic punctuation and disfluency detection in multi-party meetings using prosodic and lexical cues. pages 949–952.

Jon Cai. 2016. *switchboard\_parse*. [https://github.com/Jonbean/switchboard\\_parse](https://github.com/Jonbean/switchboard_parse).

Yu-An Chung, Yu Zhang, Wei Han, Chung-Cheng Chiu, James Qin, Ruoming Pang, and Yonghui Wu. 2021. w2v-bert: Combining contrastive learning and masked language modeling for self-supervised speech pre-training. *2021 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU)*, pages 244–250.

J.J. Godfrey, E.C. Holliman, and J. McDaniel. 1992. *Switchboard: telephone speech corpus for research and development*. In *[Proceedings] ICASSP-92: 1992 IEEE International Conference on Acoustics, Speech, and Signal Processing*, volume 1, pages 517–520 vol.1.

Godfrey, John J. and Holliman, Edward. 1993. *Switchboard-1 release 2*.

Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, and Ruoming Pang. 2020. *Conformer: Convolution-augmented transformer for speech recognition*.

Wei Han, Zhengdong Zhang, Yu Zhang, Jiahui Yu, Chung-Cheng Chiu, James Qin, Anmol Gulati, Ruoming Pang, and Yonghui Wu. 2020. Contextnet: Improving convolutional neural networks for automatic speech recognition with global context. *Proceedings of Interspeech*.

Matthew Honnibal and Mark Johnson. 2014. *Joint incremental disfluency detection and dependency parsing*. *Transactions of the Association for Computational Linguistics*, 2:131–142.

Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhotia, Ruslan Salakhutdinov, and Abdelrahman Mohamed. 2021. Hubert: Self-supervised speech representation learning by masked prediction of hidden units. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:3451–3460.

Paria Jamshid Lou and Mark Johnson. 2020. *Improving disfluency detection by self-training a self-attentive model*. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3754–3763, Online. Association for Computational Linguistics.

Paria Jamshid Lou, Yufei Wang, and Mark Johnson. 2019. *Neural constituency parsing of speech transcripts*. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2756–2765, Minneapolis, Minnesota. Association for Computational Linguistics.

Dongyub Lee, Byeongil Ko, Myeong Cheol Shin, Taesun Whang, Daniel Lee, EungGyun Kim, EungGyun Kim, and Jaechoon Jo. 2021. Auxiliary sequence labeling tasks for disfluency detection. In *Interspeech*.

- Xiaochang Li and Mara Mills. 2019. Vocal features: from voice identification to speech recognition by machine. *Technology and culture*, 60(2):S129–S160.
- Paria Jamshid Lou and Mark Johnson. 2020. [End-to-end speech recognition and disfluency removal](#). *Findings of the Association for Computational Linguistics*.
- Mari Maeda. [Spoken language communication and translation system for tactical use \(transtac\)](#).
- Jianliang Meng, Junwei Zhang, and Haoquan Zhao. 2012. [Overview of the speech recognition technology](#). In *2012 Fourth International Conference on Computational and Information Sciences*, pages 199–202.
- Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur. 2015. Librispeech: an asr corpus based on public domain audio books. In *Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on*, pages 5206–5210. IEEE.
- Xian Qian and Yang Liu. 2013. [Disfluency detection using multi-step stacked learning](#). In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 820–825, Atlanta, Georgia. Association for Computational Linguistics.
- Johann C. Rocholl, Vicky Zayats, Daniel D. Walker, Noah B. Murad, Aaron Schneider, and Daniel J. Liebling. 2021. [Disfluency detection with unlabeled data and small bert models](#).
- Elizabeth Shriberg. 1996. Disfluencies in switchboard.
- Elizabeth Shriberg, Rebecca Bates, and Andreas Stolcke. 1997. A prosody only decision-tree model for disfluency detection. In *Fifth European Conference on Speech Communication and Technology*.
- Elizabeth Ellen Shriberg. 1994. Preliminaries to a theory of speech disfluencies. Technical report.
- Nihal Singh. 2019. Nxt-switchboard-disfluency-parser. <https://github.com/nihal111/NXT-Switchboard-Disfluency-Parser>.
- Matthew G. Snover, Bonnie J. Dorr, and Richard M. Schwartz. 2004. [A lexically-driven algorithm for disfluency detection](#). In *HLT-NAACL (Short Papers)*.
- SRI International. a. [Gale - global autonomous language exploitation](#).
- SRI International. b. [Speech translation research at sri international](#).
- Shaolei Wang, Wanxiang Che, Qi Liu, Pengda Qin, Ting Liu, and William Yang Wang. 2020. Multi-task self-supervised learning for disfluency detection. *ArXiv*, abs/1908.05378.
- Shaolei Wang, Wanxiang Che, and Ting Liu. 2016. [A neural attention model for disfluency detection](#). In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pages 278–287, Osaka, Japan. The COLING 2016 Organizing Committee.
- Vicky Zayats and Mari Ostendorf. 2019. [Giving attention to the unexpected: Using prosody innovations in disfluency detection](#). In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 86–95, Minneapolis, Minnesota. Association for Computational Linguistics.