

Speech Intelligibility Classifiers from 550k Disordered Speech Samples

Subhashini Venugopalan¹, Jimmy Tobin¹, Samuel J. Yang¹, Katie Seaver^{1,2}, Richard J.N. Cave¹, Pan-Pan Jiang¹, Neil Zeghidour¹, Rus Heywood¹, Jordan Green^{1,2}, Michael P. Brenner^{1,3}; ¹Google Research, ²MGH Institute of Health Professions, ³Harvard University
vsubhashini,jtobin@google.com

Introduction

Intelligibility classifier uses

- Atypical speech can manifest from a variety of conditions, including neurological diseases such as ALS, Parkinson's Disease, and Cerebral Palsy.
- They can also be used to detect such speech in YouTube, to allow better transcriptions from specialized Automatic Speech Recognition (ASR) systems, or used by researchers as an objective measure to monitor decline in speech, e.g., in ALS.
- Automatic assessments of speech intelligibility can help predict how well voice-based assistive technologies might aid a person with speech disorders.
- Such classifiers can also help identify variable manifestations of impaired speech, to enable automatic collection of such data at scale to teach and improve ASR systems.

Will ASR on device work for you?
Or do you need a custom model?



Can users monitor deterioration?
Across different speaking disorders.



Improve video transcriptions.
Collect disordered speech at scale.



Dataset and Method

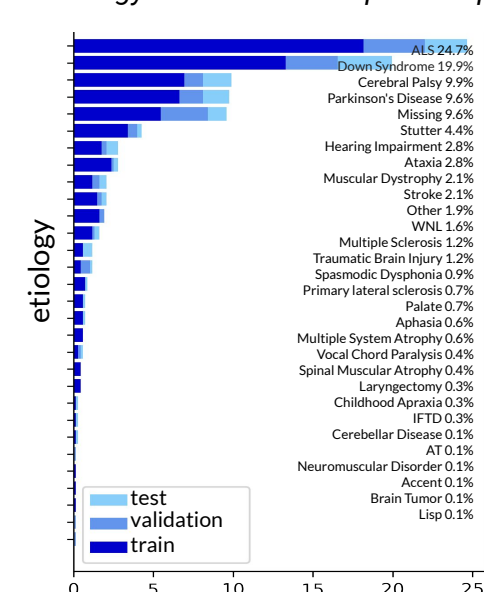
The Euphonia-SpICE Dataset

The Euphonia-SpICE dataset is a subset of the Euphonia dataset. It contains data from 677 speakers (756,147 utterances) who were rated by speech-language pathologists (SLPs) on a five-point Likert scale of intelligibility. The scale was mapped to five classes: typical, mild, moderate, severe, and profound. All utterances from a speaker are labeled with the same rating.

Table 1: Count of speakers and utterances in Euphonia-SpICE.

Intelligibility	# speakers			# utterances		
	Train	Val.	Test	Train	Val.	Test
TYPICAL	161	41	25	149,941	24,142	10,664
MILD	161	29	37	208,843	22,532	39,007
MODERATE	83	23	19	124,984	48,814	21,214
SEVERE	54	12	15	60,692	13,868	22,397
PROFOUND	9	4	4	6,716	1,691	642
OVERALL	468	109	100	551,176	111,047	93,924

Etiology breakdown of Euphonia-SpICE



Datasets for Generalization

- UASpeech: Speech produced by speakers with CP
- TORG0: Speech produced by speakers with either CP or ALS
- ALS-TDI PMP dataset: Speech produced by speakers with ALS.
- SpICE-V: A dataset of unprompted speech from speakers with different disorders, curated from a collection of web videos.

Different representation backbones: CNN, CNN+Transformers, RNN-T

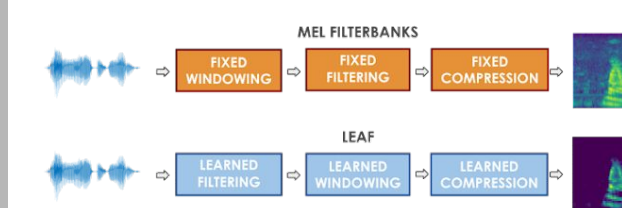
LEAF + CNN: This model trains a fully learnable convolutional classifier with a LEAF frontend which jointly learns filtering, pooling, compression and normalization from data.

wav2vec 2.0: This model uses self-supervised representations from the final layer of the wav2vec 2.0 model, which is publicly available on HuggingFace.

ASR-enc: This model uses an LSTM encoder that models acoustic inputs in an ASR system based on an RNN transducer (RNN-T) model.

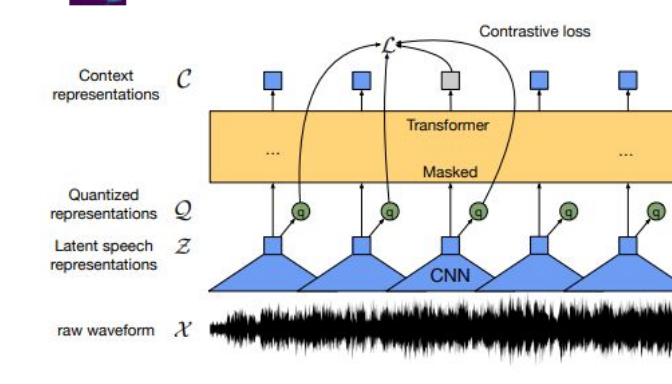
LEAF + CNN

Learnable frontend [4]



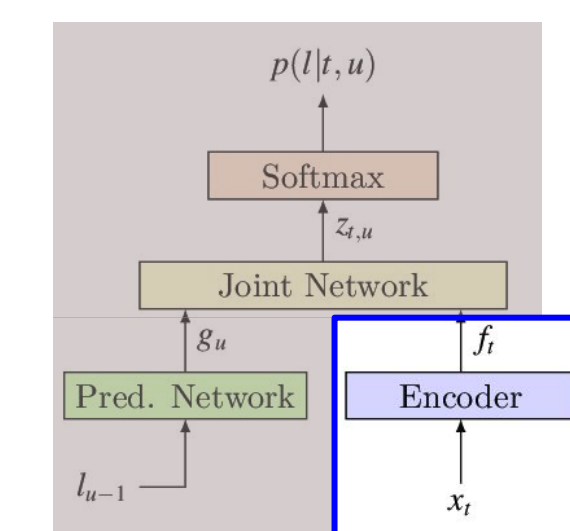
wav2vec2

Transformer+CNN [5] and is open-source and includes model weights.



ASR encoder representations

RNN-T model trained on typical speech [3]



[4] LEAF: A Learnable Frontend for Audio Classification (ICLR '21)

[5] wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations (NeurIPS '20)

[3] Narayanan et al. Recognizing longform speech in end-to-end models (ASRU '19)

Results

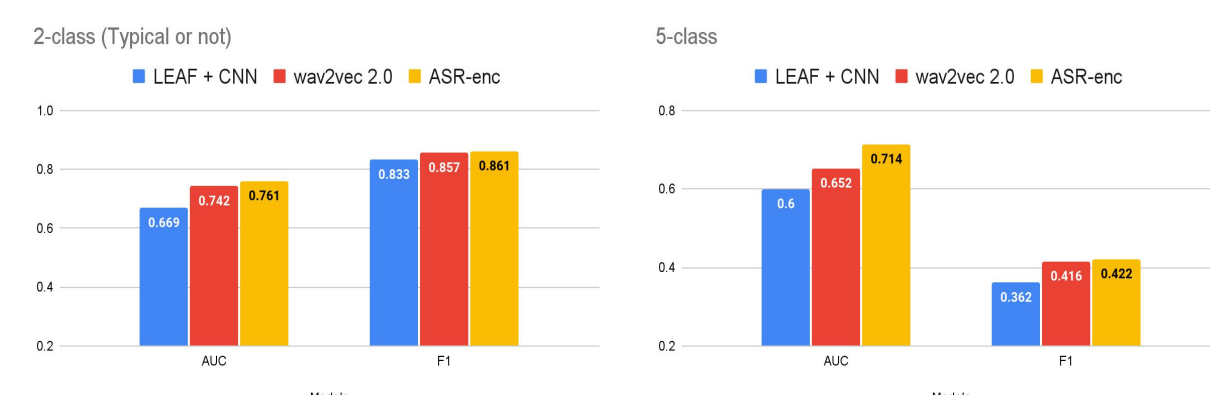
Euphonia SpICE performance

Performance on two classification tasks:

Task 1: 2-class
0: {TYPICAL} or 1: {MILD, MODERATE, SEVERE, PROFOUND}
Task 2: 5-class
0: {TYPICAL} or 1: {MILD} or 2: {MODERATE} or ...

Evaluation metrics: AUC, F1 and Accuracy

The ASR-enc model had the best performance on both tasks, followed by the wav2vec 2.0 model. LEAF + CNN model performed comparably worse.



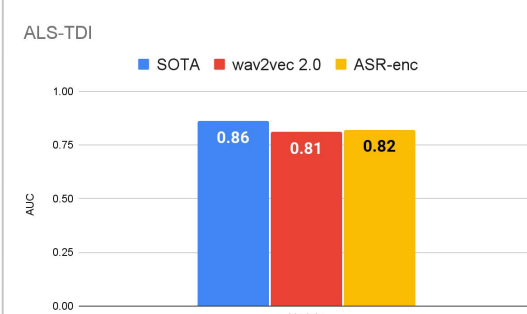
TORG0

14 speakers
7 controls, 7 - CP/ ALS

Speaker	wav2vec 2.0	ASR-enc
FC01	typ. (96.2)	typ. (96.2)
FC02	typ. (95.9)	typ. (100)
FC03	typ. (83.2)	typ. (78.4)
MC01	typ. (96.6)	typ. (92.4)
MC02	typ. (94.3)	typ. (92.6)
MC03	typ. (98.3)	typ. (98.3)
MC04	typ. (98.3)	typ. (99.2)
F03	mild (87.0)	mild (88.0)
F04	typ. (91.8)	typ. (74.2)
M03	typ. (98.9)	typ. (100)
F01	mod. (100)	mod. (100)
M02	mild (100)	mild (100)
M04	sev. (100)	mod. (100)
M05	sev. (100)	mod. (100)

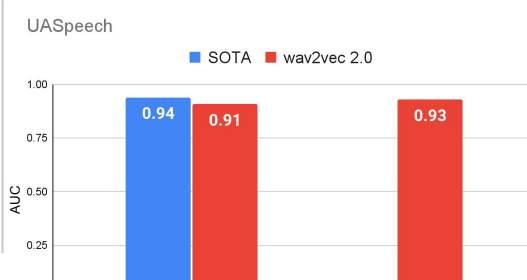
ALS-TDI

Test set: 90 speakers,
~1330 recordings
"I owe you a yoyo" x 5



UASpeech

28 speakers
13 - controls, 15 - CP
765 words per speaker



Generalization

SpICE-V

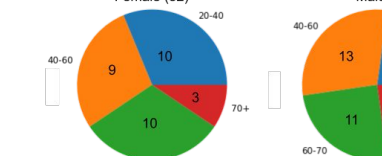
106 Dysarthric speakers + 76 Controls sourced from AudioSet

Sourcing dysarthric speech from the web

2 Run a different binary classifier to tag "regions of interest" (ROIs)
ASR-enc trained additionally on Audio Set (0.94 non-speech and 0.6M typical speech utterances)
1 Search to filter videos based on relevant topics.
3 Further manual filtering. And SLPs tag/edit "regions of interest" (ROIs)

SLPs label
• ROI - time segments when dysarthric speaker is speaking
• severity and intelligibility - 5-point Likert
• inferred gender (to help balance)

Distribution of SpICE-V control videos/speakers



Results

Comparing accuracy of identifying atypical speech

Group	w. Typ. non-ctrl	# Utts.	Total (Atyp.) # Spkr	wav2vec 2.0 spkr	Acc. (%)	ASR-enc Acc. (%)
Controls	×	76	76 (0)	76.32	76.32	96.42
Dysarthric (-Typ.)	×	1489	76 (76)	93.42	94.83	66.92
Dysarthric (all)	✓	2221	106 (76)	77.36	75.64	68.65
All (-Typ.& Dys.)	×	1565	152 (76)	84.87	93.93	78.29
All	✓	2297	182 (76)	76.92	75.66	78.57

Sliced by Etiology

Etiology	# Utts.	# Spkr	wav2vec 2.0 spkr	Acc. (%)	ASR-enc Acc. (%)
ALS	443	21 (4)	90.5	87.6	76.2
PD	498	21 (5)	85.7	84.9	61.9
CP	620	25 (8)	72.0	69.8	72.0
MS	352	20 (8)	55.0	57.5	60.0
Ataxia	308	19 (5)	84.2	75.6	68.4

Takeaways

- We developed & compared different approaches to classifying intelligibility of speech
- Our models were trained on utterances from over 650 speakers.
- The models generalized well to different datasets - TORG0, ALS-TDI and UASpeech.
- Collected SpICE-V dataset of realistic speech from videos.
- Dysarthric speakers with typical speech are harder to classify.
- Models do well on ALS, PD, CP and Ataxia.

Conclusion

Links

- Link to paper: <https://arxiv.org/abs/2303.07533>
- Github: https://github.com/google-research/google-research/tree/master/euphonia_spice