CROSS-DOMAIN VOICE ACTIVITY DETECTION WITH SELF-SUPERVISED REPRESENTATIONS

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ABSTRACT

Voice Activity Detection (VAD) aims at detecting speech segments on an audio signal, which is a necessary first step for many today’s speech based applications. Current state-of-the-art methods focus on training a neural network exploiting features directly contained in the acoustics, such as Mel Filter Banks (MFBs). Such methods therefore require an extra normalisation step to adapt to a new domain where the acoustics is impacted, which can be simply due to a change of speaker, microphone, or environment. In addition, this normalisation step is usually a rather rudimentary method that has certain limitations, such as being highly susceptible to the amount of data available for the new domain. Here, we exploited the crowd-sourced Common Voice (CV) corpus to show that representations based on Self-Supervised Learning (SSL) can adapt well to different domains, because they are computed with contextualised representations of speech across multiple domains. SSL representations also achieve better results than systems based on hand-crafted representations (MFBs), and off-the-shelf VADs, with significant improvement in cross-domain settings.

Keywords voice activity detection · cross-domain · self-supervised representations · wav2vec2

1 Introduction

The very first step to most of speech based applications such as Automatic Speech Recognition (ASR) or Speaker Emotion Recognition (SER), is Voice Activity Detection (VAD) [Eyben 2015, Cen et al. 2016, Harár et al. 2017, Tong et al. 2019]. Indeed, in any speech based system, we must first identify and isolate speech segments coming from the continuous input audio stream, which may include environmental noises.

Current VAD systems rely on supervised deep learning models trained on acoustic features such as Mel Filter Banks (MFBs), to detect speech segments. Subsequently, in real life usage, such models are usually confronted with a domain mismatch issue, because the data, as represented by the MFBs, may differ significantly from those used for model training. This problem is usually tackled by a normalisation of the acoustic features with statistics computed on the novel data [Eyben et al. 2013a], but this approach is rather rudimentary and further requires to have a sufficient amount of samples of the new domain to be effective.

On the other hand, Self-Supervised Learning (SSL) methods, such as Wav2Vec2 [Baevski et al. 2020], have shown improvements in different speech related tasks when used as speech representations compared to traditional acoustic features [Evain et al. 2021a, Keeseing et al. 2021]. Indeed, speech is not directly represented by its spectral information, but rather by generic descriptors that aim to predict whether the acoustic is likely to be coming from distractors or
genuine speech samples. This makes SSL representations more robust against domain mismatch issues Latif et al. [2020], Alisamir and Ringeval [2021]. Training of the model can also be further realised on several different domains to improve robustness against unseen data Hsu et al. [2021].

Given that SSL representations have improved many speech downstream tasks, here, we investigate their relevance for the task of VAD on a large variety of speech data collected with close-talk microphones at home, with the ultimate goal of driving a virtual assistant at home in the context of digital therapies Tarpin-Bernard et al. [2021]. We compare the results of Wav2Vec2 (W2V2) representations to traditional MFB features and off-the-shelf VADs. We also study the impact of real-time processing where less a priori knowledge about the target domain is available to perform VAD.

2 Related Work

Many current state-of-the-art VAD system mainly focus on different deep learning architectures that take acoustic features as input and then are tested on the same data distribution as the training partition Jung et al. [2018], Lee et al. [2020], Zheng et al. [2020]. Whereas this approach can perform well on controlled experimental data, it fails to achieve similar performance on unseen data, which is problematic for real life use cases.

Furthermore, having mostly ASR in mind, most use cases of VADs today are to first simply detect non silent segments and then use a noise robust Speech-To-Text (STT) model to predict transcriptions. In the end, speech segments that do not contain any verbal information that can be detected by the model are discarded Yoshimura et al. [2020], which is problematic for speech technologies relying on the non-verbal analysis of speech Tarpin-Bernard et al. [2021].

Recurrent Neural Networks, as equipped with Long Short-Term Memory cells (LSTM-RNN), have shown better generalisation capabilities and overall performance compared to state-of-the-art methods based on statistical algorithms Eyben [2015]. Gated Recurrent Units (GRU), which are a simplified version of the LSTM cells, have also been investigated in combination with CNNs, and showed improvement over state-of-the-art models Wang and Zhang [2019]. However, all studies reported degraded performance when testing on domains different from those used for model learning, showing that VAD systems based on deep learning architectures fail to generalise to new domains when represented by acoustic features of the speech signal.

Unsupervised learning techniques alleviate the need for labels. They allow to learn how data are generated by exposing a model to huge amounts of samples where predictions related to it are learnt. SSL representations of speech have recently been shown to be significantly more robust against domain mismatch, compared to using acoustic features Gimeno et al. [2021], on conversational audio from Apollo space missions Aditya et al. [2021].

3 Method

3.1 Dataset

As our ultimate objective is to drive a virtual assistant supporting digital therapies at the home of patients, we focused on detecting French speech in close-talking microphones collected in home scenarios, and used the French partition (cv-corpus-7.0-2021-07-21) of the Common Voice (CV) corpus, which is a gigantic collection of transcribed read speech collected by the Mozilla foundation with crowd-sourcing techniques Ardila et al. [2019]. Each speaker reads a series of text from Wikipedia at home using their own recording devices. Overall, there are more than 410k utterances collected from 600 speakers, and for a total duration of 16.42 hours. The CV corpus is therefore highly relevant to investigate the robustness of VAD systems over multiple domains at once.

3.2 Data pre-processing

The CV corpus is provided with segmented speech utterances. Since models based on LSTM or GRU are able to exploit long-term dependencies between input and output data, they may preferably be provided with long sequences of audio signals. Speech utterances of the Common Voice dataset were thus concatenated and interspersed with a pause of randomly chosen duration. The distribution of pause duration as observed in real conversations Ringeval et al. [2013] was approximated with a Gaussian distribution; $\mu = 2.22$ seconds, $\sigma = 1.83$ seconds. Because speech utterances are further combined with four different types of noises, and three different levels of noise, we did not use all the data of the CV corpus, and exploited a portion of it summing up to an overall duration of at least 2 hours per speaker-independent partitions; the length of each partition is summarised in Table 1.
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Table 1: Duration of the partitions of the CV corpus used for training, developing, and testing our VAD systems.

| Speech type                                      | Training (hh:mm:ss) | Development (hh:mm:ss) | Test (hh:mm:ss) |
|------------------------------------------------|---------------------|------------------------|-----------------|
| Close-talking microphone, crowd-sourced         | 2:08:07             | 2:08:04                | 2:09:03         |

Table 2: Total duration collected for the different types of investigated additive noises.

| Partition | Ads       | Music      | News       | Talk shows |
|-----------|-----------|------------|------------|------------|
| Length (hh:mm:ss) | 1:38:43   | 1:52:09    | 1:21:04    | 1:21:27    |

3.3 Synthetic noise degradation

Since most of the recorded utterances present in the CV corpus have little to no noise, and that our objective is to detect voice specially in the presence of home noise, we first need to gather noise data before adding them to speech utterances.

3.3.1 Gathering noise data

There exists several data sets of acoustic noises, such as DCASE or NIGENS [Trowitzsch et al. 2019], but as their focus is on general sound event detection, we gathered our own noise data set, focusing on noises that are more likely to be present in the acoustic background of an average home user. We generated/collected five different types of noise: (i) White, (ii) Ads, (iii) Music, (iv) News, and (v) Talk shows. White noise was generated through a random distribution with zeros mean and unique variance. Ads published on the French television between 2018 and 2020 were crawled from the culturepub.fr website. Musics were taken from our personal libraries and chosen specifically to be popular songs in France within the same period as used for ads according to billboard.

All noise data were concatenated for each type of noise and then split into three partitions, i.e., training, development, and test, so that noises are unique per partition. The length of each noise type per partition is given in Table 2.

3.3.2 Adding noises to speech utterances

We randomly selected a portion of the audio noises with the same duration as the target speech and then added them together, with the noise being multiplied by a gain ($g_n$) following [Eyben 2015]:

$$g_n = 10^{\left(\log(g_s) - \frac{SNR}{20}\right)} \quad (1)$$

where $g_s$ is the gain of the clean speech file and $SNR$ is Signal-to-Noise Ratio.

3.4 Representations

3.4.1 Mel-scale Filter Bank (MFB)

As acoustic low-level-descriptors (LLDs), we extracted the first 80 Mel-scale Filter Bank (MFB) coefficients from the audio signal. The feature extraction is realised on a 25 ms window that is shifted forward in time each 10 ms. All features were normalised to have zero mean and unit variance according to statistics computed on the training partition, excepted for our investigations on real-time robustness, cf. Section 4.2, where normalisation is performed for each instance.

3.4.2 Wav2vec2

W2V2 is a recent popular SSL model that exploits a contrastive predicting model to extract acoustic representations of speech [Baevski et al. 2020]. Taking benefits from our previous investigations on SSL representations for downstream speech tasks on French [Evain et al. 2021b], we exploited different W2V2 models specifically trained on different types of French speech, as well as a model trained on multilingual data [Conneau et al. 2020]. The list of the different W2V2 models used here is brought in Table 3. These models, once trained, are supposed to provide speech representations that are more contextualised and less impacted by noises compared to acoustic features obtained with LLDs.
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Table 3: Summary of the different W2V2 representations of speech used for VAD.

| Name | # Training epochs | Hours of speech | Speech Language | Speech type               |
|------|-------------------|-----------------|-----------------|---------------------------|
| wav2vec2-FR-2.6K-base Evain et al. [2021b] | 500k | 2.6k | French | Read                     |
| wav2vec2-FR-3K-base Evain et al. [2021b] | 500k | 3k   | French | Read, Spontaneous, Emotional |
| wav2vec2-FR-3K-large Evain et al. [2021b] | 500k | 3k   | French | Read, Spontaneous, Emotional |
| wav2vec2-large-xlsr-53 Conneau et al. [2020] | 250k | 56k  | 53 languages | Read                     |
| wav2vec2-large-xlsr-53-french Conneau et al. [2020] | 250k+20k | 56k+353 | 53 languages + fine-tuning on French | Read |

3.5 VAD model

RNN based models, using mainly LSTM and lately GRU, have long been used in speech related tasks in order to reach state-of-the-art results, because of their ability to model the context of data Eyben et al. [2013b], Wang and Zhang [2019], Heitkaemper et al. [2020]. Thus, we also experiment with a GRU model, followed by a linear layer, to map the hidden size of the GRU to the number of outputs (here one), and a tangent hyperbolic function, to map the output to the range of \([-1, +1]\), with \(-1\) and \(+1\) representing non-speech frames and speech frames, respectively.

Also, as fine-tuning has been reported to improve the results of W2V2 models in several different studies in related domains Evain et al. [2021a], Conneau et al. [2020], here we also tried fine-tuning our W2V2 models for the task of VAD, i.e. we did not freeze any W2V2 parameter while training the VAD. However, we faced convergence issues that require further investigations.

4 Experiments

All experiments were performed using the open-source SpeechBrain toolkit Ravanelli et al. [2021]. We explain in the followings the set of hyper-parameters used for our VAD model, followed by the experiments that were conducted to evaluate its real-time performance.

4.1 Hyper-parameters

In order to save computation time, hyper-parameters were defined only for the normalised MFB features, because they are still the most widely used audio descriptors for speech processing in the literature Latif et al. [2020]. For selecting the number of layers and nodes for our GRU model, we used the following range of complexity: 1 layer with 64 nodes (1L64N), 2 layers with 128 nodes (2L128N), and 4 layers with 256 nodes (4L256N). Adam optimiser with 0.01, 0.001, and 0.0001 learning rates was used for training the model. We chose the GRU-1L64N trained with a 0.001 learning rate because it reached very close performance to our best setup, which was GRU-4L256N with 0.0001 learning rate, while requiring much less training time.

4.2 Robustness for real-time systems on limited data

Current real-time – or close to real-time – systems receive packets of data from users over very short spans of time (e.g. 10 ms) Loreto and Romano [2014]. Thus, a VAD system based on deep learning would exhaust resources of a modern system today if it would need to consume every new packet of data received from the user. Therefore, a buffer is defined to continuously store the data, and then, at certain intervals of time (e.g. 1 s), the VAD model is run only on the data contained in the buffer to detect speech segments.
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Figure 1: Comparison of performance, as measured by the Area Under the Curve (AUC), obtained by our GRU based VAD model using either MFB features or W2V2 representations, for different types of noises (Ads, Music, News, TalkShows and White), and SNRs (5-10-15), on the test set. We also report the performance obtained with two commonly used off-the-shelf VAD systems (SpeechBrain-CRDNN [Ravanelli et al. 2021], and openSMILE-LSTM [Eyben et al. 2013b]).

As previously explained, a VAD system using normalised MFB features is highly susceptible to the amount of data available for normalisation, which are very limited when using an audio buffer. Hence, we limited in this experiment the size of the audio data when testing our models, to evaluate the impact of a VAD system functioning in (close-to) real-time constraints. This was achieved by cutting each input signal into smaller parts equivalent to an audio buffer, which would later be used as the model’s inputs. Thus, in this experiment, we divide the input sequence with different window lengths with respect to the whole available audio input. Using a range of different lengths for the buffer size allows us to evaluate how different speech representations perform when having access to different amounts of input data. We believe this test to be based on a realistic scenario for comparing normalised MFB features with W2V2 representations, when having less access to \textit{a priori} data of a new domain.

5 Results

Figure 1 contains different types of comparisons between different representations, noise types, and off-the-shelf models. The metric used for the reported results is Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve.

5.1 Comparing Representations

Even though our wav2vec2-FR-2.6K-base model significantly outperforms classical MFB features in all settings, reaching almost perfect results on clean speech, MFB features can still achieve comparable results to state-of-the-art.

One may further note that, the performance of W2V2 representations highly depends on the data used for training them. For example, the multilingually trained W2V2 is worse on average than the same model fine-tuned for French data, which shows that VAD models based on W2V2 representations are language dependent. Thus, using contextualised representations, trained for the same language being detected, helps improve the performance.

Furthermore, the W2V2 large models used here, which use a normalisation layer, do not perform better than the smaller W2V2 base models, which do not use any normalisation. Since the best results is achieved by a W2V2 architecture, we can conclude that once trained with enough data from different domains, W2V2 representations can perform much better than classical acoustic features, without the need to be normalised to the new domain using data at hand.
5.2 Comparison with off-the-shelf VADs

Here, to compare our models to off-the-shelf VADs, we chose the commonly used open-source OpenSMILE toolkit\textsuperscript{1} Eyben et al. [2010] as well as the already available recipe for VAD in the open-source SpeechBrain toolkit\textsuperscript{2} Ravanelli et al. [2021].

As can be seen from Figure 1, all of our models consistently and significantly outperform off-the-shelf VADs. The difference in performance is more highlighted in the presence of noise, suggesting that our scheme of training a VAD model under different noisy scenarios is especially effective for detecting French speech from close-talking microphones. We also used the RECOLA dataset, which consists of close-talking French speech, and observed the consistent better performance of our GRU model with wav2vec2-FR-2.6K-base representation compared to off-the-shelf VADs still holds true; on average, 0.921 AUC for our system vs 0.877 AUC for SpeechBrain-CRDNN and 0.804 for openSMILE-LSTM.

5.3 Limiting the buffer size for real-time analysis

For this experiment, we picked wav2vec2-FR-2.6K-base representation, since it achieved the most performant VAD, and compared it to normalised MFB features. We considered a range of different lengths for our buffer to compare the two representations (c.f. Section 4.2). Figure 2 shows the performance of the model considering different buffer lengths, and thus different amounts of data as input. Since our samples have at least one minute length, and can be some seconds longer depending on the speech utterance, the 100% represents at least one minute in length. Thus, we can see that while the performance of MFB features are very poor when faced with 4% of data (around 2.5 s), the W2V2 representations can perform well. Using only 16% of the buffer size (around 10 s), we can see that the W2V2 representation can already pass the best performance of the normalised MFB features, with all the data available to it. This clearly shows that W2V2 representations with no normalisation can outperform traditionally used normalised MFB features, with less need for data from the target domain.

6 Conclusions

In this paper, we focused on how SSL methods, especially W2V2 representations, can help VAD systems to achieve robust predictions on French speech recorded by close-talking microphones at home. We showed that such representations trained for the target language can help the VAD to perform better than traditional methods across different noise

\textsuperscript{1}https://www.audeering.com/research/opensmile/
\textsuperscript{2}https://huggingface.co/speechbrain/vad-crdnn-libriparty
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types. We also showed that W2V2 representations need less a priori information, in order to obtain better results than normalised MFB features commonly used today.

However, one issue with W2V2 representations compared to MFB features is that they are slower and require more computational resources. Thus, we realised a system that first uses classical MFB based VAD to first detect possible segments, and then activate a more accurate W2V2 based VAD to verify and more accurately detect the speech segments. We were able to run this system on a normal CPU (1.4 GHz Quad-Core Intel Core i5) in real-time (under 1 s) for a buffer size of 15 s.

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References

Florian Eyben. Real-time speech and music classification by large audio feature space extraction. Springer, 2015.

Ling Cen, Fei Wu, Zhu Liang Yu, and Fengye Hu. A real-time speech emotion recognition system and its application in online learning. In Emotions, technology, design, and learning, pages 27–46. Elsevier, 2016.

Pavol Harár, Radim Burget, and Malay Kishore Dutta. Speech emotion recognition with deep learning. In 4th International Conference on Signal Processing and Integrated Networks (SPIN), pages 137–140. IEEE, 2017.

Sibo Tong, Nanxin Chen, Yanmin Qian, and Kai Yu. Evaluating vad for automatic speech recognition. In 12th International Conference on Signal Processing (ICSP), pages 2308–2314. IEEE, 2014.

Florian Eyben, Felix Weninger, Stefano Squartini, and Björn Schuller. Real-life Voice Activity Detection with LSTM Recurrent Neural Networks and an Application to Hollywood Movies. In Proceedings of ICASSP 2013, pages 483–487, Vancouver, Canada, May 2013a. IEEE.

Alexei Baevski, Henry Zhou, Abdelrahman Mohamed, and Michael Auli. wav2vec 2.0: A framework for self-supervised learning of speech representations. arXiv preprint arXiv:2006.11477, 2020.

Solène Evain, Ha Nguyen, Hang Le, Marcely Zanon Boito, Salima Mdahfar, Sina Alisamir, Ziyi Tong, Natalia Tomashenko, Marco Dinarelli, Titouan Parcollet, et al. Task agnostic and task specific self-supervised learning from speech with lebenchmark. In 35th Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2), 2021a.

Aaron Keesing, Yun Sing Koh, and Michael Witbrock. Acoustic features and neural representations for categorical emotion recognition from speech. In Proceedings of the 22nd Annual Conference of the International Speech Communication Association, Brno, Czech Republic; pages 3415–3419, 2021.

Siddique Latif, Rajib Rana, Sara Khalifa, Raja Jurdak, Junaid Qadir, and Björn W Schuller. Deep representation learning in speech processing: Challenges, recent advances, and future trends. arXiv preprint arXiv:2001.00378, 2020.

Sina Alisamir and Fabien Ringeval. On the evolution of speech representations for affective computing: A brief history and critical overview. IEEE Signal Processing Magazine, 38(6):12–21, 2021.

Wei-Ning Hsu, Anuroop Sriram, Alexei Baevski, Tatiana Likhomanenko, Qiantong Xu, Vineel Pratap, Jacob Kahn, Ann Lee, Ronan Collobert, Gabriel Synnaeve, et al. Robust wav2vec 2.0: Analyzing domain shift in self-supervised pre-training. arXiv preprint arXiv:2104.01027, 2021.

Franck Tarpin-Bernard, Joan Fruitet, Jean-Philippe Vigne, Patrick Constant, Hanna Chainay, Olivier Koenig, Fabien Ringeval, Béatrice Bouchot, Gérard Balilty, François Portet, Sina Alisamir, Yongxin Zhou, Jean Serre, Vincent Delerue, Hippolyte Fournier, Kévin Berenger, Isabella Zsoldos, Olivier Perrotin, Frédéric Elisei, Martin Lenglet, Charles Puaux, Léo Pacheco, Mélodie Fouillen, and Didier Ghennassia. THERADIA: Digital Therapies Augmented by Artificial Intelligence. In Proceedings of the International Conference on Applied Human Factors and Ergonomics: Advances in Neuroergonomics and Cognitive Engineering), pages 478–485, New York, USA, August 2021. Springer.

Youngmoon Jung, Younggwon Kim, YeuNju Choi, and Hoirin Kim. Joint learning using denoising variational autoencoders for voice activity detection. In INTERSPEECH, pages 1210–1214, 2018.

Joohyung Lee, Youngmoo Jung, and Hoirin Kim. Dual attention in time and frequency domain for voice activity detection. arXiv preprint arXiv:2003.12266, 2020.
Zhenpeng Zheng, Jianzong Wang, Ning Cheng, Jian Luo, and Jing Xiao. Mlnet: An adaptive multiple receptive-field attention neural network for voice activity detection. *arXiv preprint arXiv:2008.05650*, 2020.

Takenori Yoshimura, Tomoki Hayashi, Kazuya Takeda, and Shinji Watanabe. End-to-end automatic speech recognition integrated with ctc-based voice activity detection. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6999–7003. IEEE, 2020.

Guan-Bo Wang and Wei-Qiang Zhang. An rnn and crnn based approach to robust voice activity detection. In *Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, pages 1347–1350. IEEE, 2019.

Pablo Gimeno, Alfonso Ortega, Antonio Miguel, and Eduardo Lleida. Unsupervised representation learning for speech activity detection in the fearless steps challenge. In *INTERSPEECH*, pages 4359–4363. ISCA, 2021.

Joglekar Aditya, Seyed Omid Sadjadi, Meena Chandra-Shekara, Christopher Cieri, and John HL Hansen. Fearless Steps Challenge Phase-3 (FSC P3): Advancing SLT for Unseen Channel and Mission Data across NASA Apollo Audio. In *INTERSPEECH*, pages 986–990, 2021.

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

Fabien Ringeval, Andreas Sonderegger, Juergen Sauer, and Denis Lalanne. Introducing the recola multimodal corpus of remote collaborative and affective interactions. In *10th IEEE international conference and workshops on automatic face and gesture recognition (FG)*, pages 1–8. IEEE, 2013.

Ivo Trowitzsch, Jalil Taglia, Youssef Kashef, and Klaus Obermayer. The nigens general sound events database. *arXiv preprint arXiv:1902.08314*, 2019.

Solene Evain, Ha Nguyen, Hang Le, Marcely Zanon Boito, Salima Mdhaffar, Sina Alisamir, Ziyi Tong, Natalia Tomashenko, Marco Dinarelli, Titouan Parcollet, et al. Lebenchmark: A reproducible framework for assessing self-supervised representation learning from speech. *arXiv preprint arXiv:2104.11462*, 2021b.

Alexis Conneau, Alexei Baevski, Ronan Collobert, Abdelrahman Mohamed, and Michael Auli. Unsupervised cross-lingual representation learning for speech recognition. *arXiv preprint arXiv:2006.13979*, 2020.

Florian Eyben, Felix Weninger, Stefano Squartini, and Björn Schuller. Real-life voice activity detection with lstm recurrent neural networks and an application to hollywood movies. In *IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 483–487. IEEE, 2013b.

Jens Heitkaemper, Joerg Schmalenstroer, and Reinhold Haeb-Umbach. Statistical and neural network based speech activity detection in non-stationary acoustic environments. *arXiv preprint arXiv:2005.09913*, 2020.

Mirco Ravanelli, Titouan Parcollet, Peter Plantinga, Aku Rouhe, Samuele Cornell, Loren Lugosch, Cem Subakan, Nauman Dawalatabad, Abdelwahab Heba, Jianyuan Zhong, Ju-Chieh Chou, Sung-Lin Yeh, Szu-Wei Fu, Chien-Feng Liao, Elena Rastorgueva, François Grondin, William Aris, Hwidong Na, Yan Gao, Renato De Mori, and Yoshua Bengio. SpeechBrain: A general-purpose speech toolkit, 2021. arXiv:2106.04624.

Salvatore Loreto and Simon Pietro Romano. *Real-time communication with WebRTC: peer-to-peer in the browser*. O’Reilly Media, Inc., 2014.

Florian Eyben, Martin Wöllmer, and Björn Schuller. Opensmile: the munich versatile and fast open-source audio feature extractor. In *Proceedings of the 18th ACM international conference on Multimedia*, pages 1459–1462, 2010.