BER: BALANCED ERROR RATE FOR SPEAKER DIARIZATION

Tao Liu, Kai Yu *

MoE Key Lab of Artificial Intelligence, AI Institute, X-LANCE Lab, Shanghai Jiao Tong University

ABSTRACT

DER is the primary metric to evaluate diarization performance while facing a dilemma: the errors in short utterances or segments tend to be overwhelmed by longer ones. Short segments, e.g., ‘yes’ or ‘no,’ still have semantic information. Besides, DER overlooks errors in less-talked speakers. Although JER balances speaker errors, it still suffers from the same dilemma. Considering all those aspects, duration error, segment error, and speaker-weighted error constitute a complete diarization evaluation, we propose a Balanced Error Rate (BER) to evaluate speaker diarization. First, we propose a segment-level error rate (SER) via connected subgraphs and adaptive IoU threshold to get accurate segment matching. Second, to evaluate diarization in a unified way, we adopt a speaker-specific harmonic mean between duration and segment, followed by a speaker-weighted average. Third, we analyze our metric via the modularized system, EEND, and the multi-modal method on real datasets. SER and BER are publicly available at https://github.com/X-LANCE/BER.

Index Terms— Speaker Diarization, Diarization Error Rate, Segment-level, Balanced Error Rate

1. INTRODUCTION

Speaker diarization identifies the talkers and their talking duration, solving the problem of ‘who spoke when.’ Speaker diarization is often used as a pre-processing step in audio tasks, and it has several application scenarios: meeting, telephone recording, etc. With the development of speaker diarization, datasets and methods in speaker diarization have shown new trends. For diarization datasets, datasets become more in line with real scenarios, which consist of spontaneous speeches, diverse sources, and so on. Those features make a large variance in speaker number and speech duration, especially shorter utterances, which is shown in Table 2. For diarization methods, joint optimized methods, like VBX-based methods or End-to-end neural diarization (EEND), and multi-modal methods emerge. Those approaches can handle overlapped speech and short utterances well.

However, conventional evaluation metrics can not evaluate those features well. Diarization error rate (DER), and Jaccard error rate (JER) have a common issue: they evaluate from the duration view, which will cause a phenomenon that errors by short utterances, e.g., less than one second, are often overlooked because the longer ones occupy most to the duration error. Compared with DER, JER can evaluate speaker-weighted duration error. Conversational diarization error rate (CDER) proposes a metric to alleviate the issue by evaluating from the segment view. The segment means the segmentation from the reference or the hypothesis and may be different from the utterance. In some circumstances, they are the same. CDER counts all unmatched segment numbers via intersection over union (IoU) matching. But, to allow arbitrary segmentation of the hypothesis, CDER merges the adjacent segments with the same speakers. This merging operation will lead to an unexpected bias if the speech interval is large. Besides, a fixed IoU threshold strategy in CDER will lead to a higher tolerance on longer segment lengths. Segment-level metric remains to be improved.

From the above analysis, we can find that DER, JER, and CDER evaluate speaker diarization from limited views, and CDER has improvement rooms. So in this paper, we first proposed an improved segment-level metric: SER. Based on the metric, we offer BER a balanced error rate to cover all aspects considered by DER, JER, and SER. The comparison is shown in Table 1. We hope BER forms a comprehensive metric for the speaker diarization community.

Our contributions are summarized as follows.

1. SER. Segment-level error rate to evaluate the segment error. To accurately evaluate the segment error, we introduce connected sub-graphs for arbitrary segmentation and IoU adaptation strategy to control offset tolerance.
2. BER. Balanced error rate to evaluate speaker-weighted error, duration error, and segment error in a unified way.
3. Extensive analysis and experiments. We evaluate our metric on several dataset including audio-only and audio-visual datasets. Besides, we conduct the experiment on several methods: modularized system, VBX-based system, and EEND. The results reflect that BER can provide a complete analysis.

2. RELATED WORKS

Diarization error rate (DER) proposed by NIST is the standard scoring metric in speaker diarization datasets and challenges. DER is the summary of false alarm, missed speech, and speaker confusion time to the reference time. DER is widely used in speaker diarization because this metric is straightforward and intuitive. However, DER is less sensitive to short duration. There are two reasons accounting for this. First, the short-duration occupation is naturally less than the longer ones, resulting in more punishment in errors of longer ones. Second, collar is a time option in DER. If collar is
Table 2. Dataset statistics. #spk.: The min/average/max speaker number per video. spk. speech std. (s): Speaker speech standard deviation in seconds. segment duration (s): 25%, 50% and 75% percentiles of the segment length in seconds. Datasets vary in those aspects, and conventional metrics can not reflect those aspects well.

| Dataset   | #spk. | spk. speech std. (s) | segment duration (s) |
|-----------|-------|----------------------|----------------------|
| AMI       | 3/3.99/5 | 340                       | 0.47/1.52/4.51       |
| CALLHOME  | 2/2.57/7 | 49                        | 0.73/1.53/2.94       |
| DIHARD2   | 2/6.78/14 | 111                      | 0.64/1.29/2.34       |
| VoxConverse | 1/5.55/21 | 135                      | 1.12/3.16/8.73       |
| MSDWild   | 2/2.73/10 | 80                       | 0.75/1.47/3.13       |

set to more than zero, the period within collar size before and after the segment boundary will be abandoned in evaluation. This option was originally designated to avoid manual labeling noise near the boundaries, but a segment duration with less than two enlargements will also be excluded from evaluation. The DER formulation is shown in Equation 1 where FAlt, MSAlt, SCAlt represents total false alarm, missed and speaker confusion duration, respectively. REFAll is the total reference duration. The DER result is the percentage of all error duration divided by the reference duration.

\[
\text{DER} = \frac{\text{FAlt} + \text{MSAlt} + \text{SCAlt}}{\text{REFAll}}
\]  

Stage 1. Optimal matching. Optimal matching is to assign speaker identities of reference to the prediction segments due to permutation problems in speaker label assignment. This forms a bipartite graph matching problem which is often saved by Hungarian algorithm[19]. Optimal matching is a standard stage for diarization metrics like DER[13], JER[3], and CDER[14], and we also use the Hungarian algorithm to assign speaker labels. If the speaker number of the hypothesis is larger than the reference, the spare part is not matched. JER ignores this part and does not calculate its error. For SER, we follow JER and do not calculate this part, but in BER, this part is denoted as \(E_{\text{Speaker}}^{b/a}\), representing errors caused by false alarm speakers. Errors caused by false alarm speakers can not be ignored if a system predict too much candidates, especially in EEND that can not handle arbitrary speaker number well. \(E_{\text{Speaker}}^{b/a}\) is the harmonic mean of duration and segment error rate of false alarm speakers.

To ensure one-to-one speaker mapping for the following steps, we add an empty hypothesis (\(\emptyset\)) to fill the gap if the speaker number of the reference is larger than the hypothesis. This step is represented by Algorithm 1 (line 2 to 13) and the \(E_{\text{Speaker}}^{b/a}\) part is formulated in line 33.

Stage 2. Speaker-specific duration and segment errors. We calculate duration and segment errors for each one-to-one speaker mapping.

Duration errors. Duration rate of speaker \(E_{s}^{\text{DUR}}\) is the sum of false alarm (FA_{s}^{\text{DUR}}) and missed duration (MS_{s}^{\text{DUR}}) to the reference duration (REF_{s}^{\text{DUR}}), shown in Equation 4. Different from JER, our denominator part is the reference duration not the union duration (UNION) which is also denoted in Algorithm 1 (line 16).

\[
E_{s}^{\text{DUR}} = \frac{\text{FA}_{s}^{\text{DUR}} + \text{MS}_{s}^{\text{DUR}}}{\text{REF}_{s}^{\text{DUR}}}
\]

Segment errors. Unlike direct merging adjacent speakers in CDER[14], we adopt a graph-based segment-matching strategy. Specifically, we build a graph to formulate the relations between reference and hypothesis segments. In the graph, the node is the segment or the utterance. If there exists an overlap between the reference and hypothesis, we assign an edge between them. After the graph is constructed, we calculate the connected sub-graphs. We adopt an IoU matching strategy in the reference and hypothesis nodes in each connected sub-graph. It is noted that gaps between nodes are not merged. If IoU is larger than a threshold, we consider that nodes in this sub-graph are connected, which means the reference and hypothesis segments or utterances are matched. Otherwise, the reference segment number in this sub-graph will be considered the error. Through connected sub-graph strategy and only considering reference segment number, segment-level errors can be calculated in arbitrary hypothesis segmentation. This part is consisted with Algorithm 1 (line 17 - 25) and an illustrated example is shown in Figure 4. Isolated nodes (without overlapping) in the reference are also considered errors.

\[
E_{s}^{\text{SEG}} = \frac{\#\text{error segs}}{\#\text{REF segs}}
\]

For IoU matching strategy, we utilize an adaptive IoU threshold which depends on reference segment duration (DUR) and number (#NUM). Specifically, we add prior information, collar, in this IoU adaption: the offset of the prediction segments must be lower than the size: 2 * collar * #NUM. The lower bound of this in Equation is to prevent too much offset for short segments. The formulation is shown in Equation 6.
**Fig. 1.** Graph-based segment matching examples. Instead of IoU matching between segments, we run IoU matching under the connected sub-graph. In the graph, nodes are the segments, and edges are the relation between the reference and hypothesis node. The edge exists if there exists an overlap. Nodes and edges in the dashed line mean a connected sub-graph. Via this strategy, our segment-level metric can handle arbitrary segmentation.

\[
\text{IoU}_\text{Adaption}(\text{DUR}, \#\text{NUM}) = \max\left(\frac{\text{DUR} - 2\times\text{eps} + \#\text{NUM} + \text{lb}}{\text{DUR} + \#\text{NUM} + \text{lb}}\right)
\]

**Stage 3. Speaker-specific harmonic errors.**

After speaker-specific duration error \(E_{\text{DUR}}^s\) and segment error \(E_{\text{SEG}}^s\) are calculated, we calculate the harmonic mean \(E_s\) between them, which is shown in Equation (7). Compared with arithmetic mean, harmonic mean prefers to the better result between duration and segment error. In addition, eps is used here to avoid errors being zero.

\[
E_s = \frac{2}{\frac{1}{E_{\text{DUR}}^s} + \frac{1}{E_{\text{SEG}}^s}} - \text{eps}
\]

**Stage 4. Speaker-weighted errors.**

Then speaker-weighted errors can be calculated by the average of all speaker-specific errors, which is same to JER. This part is shown in Equation (8) and Algorithm 1 (line 35).

\[
E_{\text{Speaker spectrum}}^s = \frac{1}{M} \sum_{s=1}^{M} E_s
\]

**Stage 5. SER and BER.**

Finally, we can get the final SER and BER. SER is the total number of error segments to the reference segments. We do not use hypothesis because its segmentation will affect the result. BER is the summary of speaker-weighted and false alarm speaker errors. SER and BER is shown in Equation (9) and (10) respectively.

\[
\text{SER} = \frac{\#\text{error segs}}{\#\text{REF segs}}
\]

\[
\text{BER} = E_{\text{Speaker spectrum}}^s + E_{\text{Speaker FA}}^s
\]

**4. EXPERIMENTS**

**4.1. Setups**

All metrics are evaluated with overlapped speech and no forgiveness collar for all duration errors. We use IoU 0.5 for CDER and adaption IoU with a lower bound \(lb\) IoU 0.5 for SER and BER. It is noted that collar used in segment-level metrics, SER and BER, is intended for segment-level IoU threshold, not for boundary collar. For the

---

**Algorithm 1: Pseudo code for SER and BER**

**Input:** \(S_i^{\text{REF}} = \{U_n\}_{n=1}^{M}, i \in \mathbb{N}^+\); \(S_j^{\text{HYP}} = \{U_n\}_{n=1}^{M}, j \in \mathbb{N}\); // \(S_i^{\text{REF}}\) and \(S_j^{\text{HYP}}\) represents reference speaker \(i\)’s and hypothesis speaker \(j\)’s utterances set respectively. \(U\) represents utterance or segment.

**Output:** SER and BER.

1. Init: \(E_{\text{TOTAL}} = \text{list}()\), \(\text{FA.error.duration} = 0\), \(\text{global.REF.duration} = 0\), \(\#\text{FA.error.segs} = 0\), \(\#\text{global.error.segs} = 0\), \(\#\text{global.REF.segs} = 0\).
2. operate optimal matching and gets matched sets:
   - \(\text{Set}^\text{M} = \{S_i, S_j\}, \ldots\) and unmatched sets:
     - \(\text{Set}^\text{PA,REF} = \{S_i, \ldots\}\), \(\text{Set}^\text{PA,HYP} = \{S_j, \ldots\}\);
     // \((S_i, S_j)\) means a optimal mapping result between speaker, and speaker,
3. if \(\text{Set}^\text{PA,HYP} \notin \emptyset\) then
   // FA means false alarm speaker caused by optimal mapping
4. foreach \(S_i^{\text{PA,HYP}} \in \text{Set}^\text{PA,HYP}\) do
   // calculate speaker-specific errors
5.  \(E_{\text{DUR}}^{\text{FA,REF}} = \frac{\#\text{FA.error.duration}}{\#\text{REF.segs}}\);
6.  \(\#\text{FA.error.duration} += \text{total duration of } S_i^{\text{PA}}\);
7. end
8. end
9. if \(\text{Set}^\text{PA,REF} \notin \emptyset\) then
10. foreach \(S_i^{\text{PA,REF}} \in \text{Set}^\text{PA,REF}\) do
11.  \(\text{add } (S_i^{\text{PA}}, \emptyset ) \text{ to Set}^M\); // ensure one-to-one mapping for reference speaker
12. end
13. end
14. \(s = 0\); // reference speaker index
15. foreach \((S_i, S_j) \in \text{Set}^m\) do
16.  // calculate speaker-specific errors
17. \(E_s = \frac{\#\text{FA.error.duration}}{\#\text{REF.segs}}\);
18. // duration errors
19. \(#\text{error.segs} = 0\), \(#\text{REF.segs} = 0\);
20. calculate connected subgraphs \(G\);
21. foreach \(\text{REF nodes and HYP nodes in } G\) do
22.  \(#\text{REF.segs} += \#\text{REF nodes}\)
23.  \(\text{IoU} = \text{REF nodes} \cap \text{HYP nodes} \cdot \text{IoU} \cdot \#\text{DUR}\);
24.  if \(\text{IoU} < \text{IoU}_\text{Adaption}\) then
25.    \(#\text{error.segs} += \#\text{REF nodes}\)
26.  end
27. \(E_{\text{SEG}} = \frac{\#\text{error.segs}}{\#\text{REF.segs}}\);
28. // segment errors
29. \(E_s = \text{harmonic.mean}(E_{\text{DUR}}, E_{\text{SEG}})\);
30. // speaker’s error
31. \(#\text{global.error.segs} += \#\text{error.segs}\);
32. \(#\text{global.REF.segs} += \#\text{REF.segs}\);
33. \(\text{global.REF.duration} += \text{total duration of } S_i\);
34. \(s += 1\);
35. end
36. \(E_{\text{Speaker spectrum}}^{\text{PA}} = \frac{1}{M} \sum_{m=1}^{M} E_s\);
37. \(\text{BER} = E_{\text{Speaker spectrum}}^{\text{PA}} + E_{\text{Speaker FA}}^{\text{PA}}\);
38. return SER, BER
evaluating dataset, we test our metric on AMI\cite{15} (Mix-Headset) test set, CALLHOME\cite{15} (LDC2001S97, Disk-8) part II, DIHARD II\cite{3} test set, VoxConverse\cite{4} test set and MSDWild\cite{5} few-talker set. For CALLHOME\cite{16}, part I and part II splitting follows Kaldi Calihome diarization recipe.

4.2. Experiments

4.2.1. Metric comparison across different datasets

First, we compare our proposed metrics, SER and BER, with other metrics on several publicly available datasets. The comparison result is shown in Figure\cite{4} All results except for MSDWild (AV) are generated by Pyannote\cite{20}. For Pyannote, we adopt a modularized pipeline: segmentation, ECAPA-TDNN-based\cite{21} embedding extractor, and agglomerative hierarchical clustering (AHC). MSDWild (AV), taking videos and audio as the input, utilizes a multi-modal diarization system, and we follow experiment settings from\cite{5}.

Compared with other metrics, BER considers all aspects: speaker-weighted, duration, and segment error. For example, in AMI, JER is low while BER is high. We find that there are plenty of false alarm segments. That segment duration is short while the total number is large, leading to a high SER and BER. In the MSDWild, benefiting from the visual, the method can predict speech duration more accurately, which reduces DER by 27% but BER by 46%. Those examples indicate that our proposed BER can provide an overall evaluation for system comparison.

Table 3. Metric comparison across different systems on CALLHOME part II.

| Method                | DER | JER | CDER | SER | Speaker\textsuperscript{AV} | Speaker\textsuperscript{AV} | Total |
|-----------------------|-----|-----|------|-----|----------------------------|----------------------------|-------|
| Modularized system    | 27.68 | 48.81 | 81.2 | 44.95 | 49.19 | 0.47 | 49.66 |
| VBx\cite{8}           | 21.06 | 33.44 | 27.7 | 36.53 | 36.61 | 0.42 | 37.72 |
| EEND-VC\cite{10}      | 23.48 | 29.03 | 23.3 | 23.3 | 28.2 | 1.15 | 29.35 |

4.2.2. Metric comparison across different systems

We also run our metrics on three diarization systems: Modularized system, VBx\cite{8} and EEND-VC\cite{10}, which is shown in Table\cite{4} Our modularized system contains oracle VAD, ECAPA-TDNN-based\cite{21} embedding extractor, and spectral clustering. For a fair comparison, both the modularized system and VBx use oracle VAD, VoxCeleb-based\cite{22} training corpus for speaker embedding, and do not handle overlap speeches. Compared with the modularized system, VBx, a VB-HMM-based diarization algorithm, utilizes HMM to model speaker transitions and adopt variational Bayes (VB) inference to estimate the model parameters. From the first row and the second row in Table\cite{4} we can see VBx method is superior to the modularized system in reducing duration errors (DER) and segment-level errors (SER), which also reduces BER.

EEND takes speaker diarization as a multi-label classification problem and optimizes the speaker diarization label. To alleviate the long-recording issue and arbitrary speaker numbers in EEND, EEND-VC\cite{10} first splits the recording into several chunks (30 seconds here). Then, for each chunk, EEND methods, based on permutation invariant training (PIT)\cite{23} training, are used to generate overlap-aware segmentation. Finally, vector clustering (VC) methods are adopted to cluster all utterances. For the experiment of EEND-VC reported here, we do not add any prior information, including the oracle speaker number and oracle segmentation. So the DER score is worse than VBx. Although it is unfair to directly compare the results of those two methods, this comparison can indicate a conflict: for EEND-VC, the DER score is worse, but the SER score is better, shown in the second row and the third row in Table\cite{4} This conflict illustrates that: although EEND-VC does not use oracle segmentation, it is more capable of discriminating segments via PIT and ‘can-not link’ constraints, which reduces SER and BER. Besides, in BER’s second part (Speaker\textsuperscript{AV}), which means balanced errors caused by false alarm speakers, EEND-VC’s is much worse than the modularized system and VBx. This phenomenon is also inconsistent with the fact: the insufficient ability of EEND methods under arbitrary speaker numbers. From the above analysis, our proposed metric, SER and BER, can evaluate systems from more perspectives.

5. CONCLUSION

This paper proposes two metrics SER and BER. SER is the segment-level error rate, and BER is the balanced error rate. Using the connected sub-graph and IoU adaptation strategy, SER is proposed to accurately solve the segment-matching problem under arbitrary segmentation. Based on SER and motivated by several conventional metrics, BER evaluate speaker-weighted, duration, and segment errors in a unified way. With the experiment, BER shows the potential for emerging algorithms like multi-modal or EEND methods. We hope this metric becomes a valuable tool for the speaker diarization community.

6. ACKNOWLEDGEMENTS

This work was supported by State Key Laboratory of Media Convergence Production Technology and Systems Project (No. SKLMPCTS2020003), Shanghai Municipal Science and Technology Major Project (2021SHZDZX0102), and National Natural Science Foundation of China (Grant No. 92048205).
7. REFERENCES

[1] Tae Jin Park, Naoyuki Kanda, Dimitrios Dimitriadis, Kyu J Han, Shinji Watanabe, and Shrikanth Narayanan, “A review of speaker diarization: Recent advances with deep learning,” Computer Speech and Language, vol. 72, pp. 101317, 2022.

[2] Hagai Aronowitz, Weizhong Zhu, Masayuki Suzuki, Gakuto Kurata, and Ron Hoory, “New advances in speaker diarization,” in International Speech Communication Association (Interspeech), 2020.

[3] Neville Ryant, Kenneth Church, Christopher Cieri, Alejandrina Cristia, Jun Du, Sriram Ganapathy, and Mark Liberman, “The second dihard diarization challenge: Dataset, task, and baselines,” arXiv preprint arXiv:1906.07839, 2019.

[4] Joon Son Chung, Jaesung Huh, Arsha Nagrani, Triantafyllos Afouras, and Andrew Zisserman, “Spot the conversation: speaker diarisation in the wild,” in International Speech Communication Association (Interspeech), 2020.

[5] Tao Liu, Shuai Fan, Xu Xiang, Hongbo Song, Shaoxiong Lin, Jiaqi Sun, Tianyuan Han, Siyuan Chen, Binwei Yao, Sen Liu, Yifei Wu, Yanmin Qian, and Kai Yu, “MSDWild: Multi-modal Speaker Diarization Dataset in the Wild,” in Proc. Interspeech 2022, 2022, pp. 1476–1480.

[6] Fabio Valente and Christian Wellekens, “Variational bayesian methods for audio indexing,” in International Workshop on Machine Learning for Multimodal Interaction. Springer, 2005, pp. 307–319.

[7] Patrick Kenny, “Bayesian analysis of speaker diarization with eigenvoice priors,” CRIM, Montreal, Technical Report, p. 25, 2008.

[8] Federico Landini, Ján Profant, Mireia Diez, and Lukáš Burget, “Bayesian hmm clustering of x-vector sequences (vbx) in speaker diarization: theory, implementation and analysis on standard tasks,” Computer Speech & Language, vol. 71, pp. 101254, 2022.

[9] Yusuke Fujita, Naoyuki Kanda, Shota Horiguchi, Kenji Nagamatsu, and Shinji Watanabe, “End-to-end neural speaker diarization with permutation-free objectives,” arXiv preprint arXiv:1909.05932, 2019.

[10] Keisuke Kinoshita, Marc Delcroix, and Naohiro Tawara, “Advances in integration of end-to-end neural and clustering-based diarization for real conversational speech,” arXiv preprint arXiv:2105.09040, 2021.

[11] Chenyu Yang and Yu Wang, “Robust End-to-end Speaker Diarization with Generic Neural Clustering,” in Proc. Interspeech 2022, 2022, pp. 1471–1475.

[12] Mao-Kui He, Jun Du, and Chin-Hui Lee, “End-to-End Audio-Visual Neural Speaker Diarization,” in Proc. Interspeech 2022, 2022, pp. 1461–1465.

[13] NIST, “The 2009 (rt-09) rich transcription meeting recognition evaluation plan,” 2009.

[14] Gaofeng Cheng, Yifan Chen, Runyang Yang, Qingxuan Li, Zehui Yang, Lingxuan Ye, Pengyuan Zhang, Qingqing Zhang, Lei Xie, Yanmin Qian, et al., “The conversational short-phrase speaker diarization (cssd) task: Dataset, evaluation metric and baselines,” arXiv preprint arXiv:2208.08042, 2022.

[15] Iain McCowan, Jean Carletta, Wessel Kraaij, Simone Ashby, S Bourban, M Flynn, M Guillelmet, Thomas Hain, J Kadlec, Vasílis Karaíkos, et al., “The ami meeting corpus,” in Proceedings of the 5th international conference on methods and techniques in behavioral research. Citeseer, 2005, vol. 88, p. 100.

[16] “Nist sre 2000 evaluation plan,” https://catalog.ldc.upenn.edu/LDC2001S97, 2000.

[17] Przybocki Mark and Alvin Martin, “2000 nist speaker recognition evaluation ldc2001s97,” Philadelphia: Linguistic Data Consortium, 2001.

[18] Neville Ryant, Prachi Singh, Venkat Krishnamohan, Rajat Varma, Kenneth Church, Christopher Cieri, Jun Du, Sriram Ganapathy, and Mark Liberman, “The third dihard diarization challenge,” arXiv preprint arXiv:2012.01477, 2020.

[19] Harold W Kuhn, “The hungarian method for the assignment problem,” Naval research logistics quarterly, vol. 2, no. 1-2, pp. 83–97, 1955.

[20] Hervé Bredin, Ruiqing Yin, Juan Manuel Coria, Gregory Gelly, Pavel Korshunov, Marvin Lavechin, Diego Fustes, Hadrien Titoux, Wassim Bouaziz, and Marie-Philippe Gill, “pyannote.audio: neural building blocks for speaker diarization,” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, May 2020.

[21] Brecht Desplanques, Jenthe Thienpondt, and Kris Demuynck, “Ecapa-tdnn: Emphasized channel attention, propagation and aggregation in tdm based speaker verification,” arXiv preprint arXiv:2005.07143, 2020.

[22] Joon Son Chung, Arsha Nagrani, and Andrew Zisserman, “Voxceleb2: Deep speaker recognition,” Proc. Interspeech 2018, pp. 1086–1090, 2018.

[23] Dong Yu, Morten Kolbæk, Zheng-Hua Tan, and Jesper Jensen, “Permutation invariant training of deep models for speaker-independent multi-talker speech separation,” in 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2017, pp. 241–245.