SPEECH INTELLIGIBILITY DATA IMPROVES MUSIC INTELLIGIBILITY

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ABSTRACT

Music is better enjoyed when listeners can understand the lyrics. This is often difficult and is especially hard for listeners using hearing aids. In this work, we present an approach to learn a metric to automatically quantify how intelligible the lyrics of a given piece of music is. The ability to automatically do this correctly will enable the development of algorithms to improve music understanding, especially for hearing aid users. In this work, we develop a transformer-based system to directly predict lyric intelligibility using the provided processed audio signal (with hearing loss already simulated). Our system achieved a RMSE value of 26.82% on the provided validation set and 26.67% on the evaluation set, coming fourth on the final evaluation leaderboard. Our system will appear in the challenge overview [1].

***Index Terms*—** Whisper, Music Intelligibility, Speech Processing, Deep Learning, Transformers

1. INTRODUCTION

Lyric intelligibility prediction is the problem of creating a metric to automatically assess how much of a given piece of music would be understandable to the average human. As in speech technology, having an automatic way to predict intelligibility can enable creating algorithms, which could make listening to music much more enjoyable to humans, especially those using hearing aids [2].

The ICASSP 2026 Cadenza challenge [2] aims to enable the creation of such a metric by providing English music data, some with hearing loss simulated and some without, and the corresponding intelligibility score obtained from native English-speaking PhD students from the Universities of Salford and Sheffield [3]. The aim of the challenge is to predict the correct intelligibility score, given the provided music data.

Similar to the Cadenza challenge is the Clarity Prediciton Challenge (CPC) [4]. The aim in that challenge is to predict intelligibility but for speech data. In addition to the speech data provided in that challenge having a hearing loss simulated, the data also has noise added to it. Deep learning approaches are the leading solutions in that challenge [5].

Following a similar deep learning-based approach, we show in this work that an approach that first extracts audio features from a frozen pretrained speech foundation model using only the processed signal and then uses those features to train another transformer from the ground up leads to competitive results on this (Cadenza) challenge. Furthermore, we show that taking samples from the CPC3 data, we can fine-tune our model to obtain improvements in the final RMSE scores.

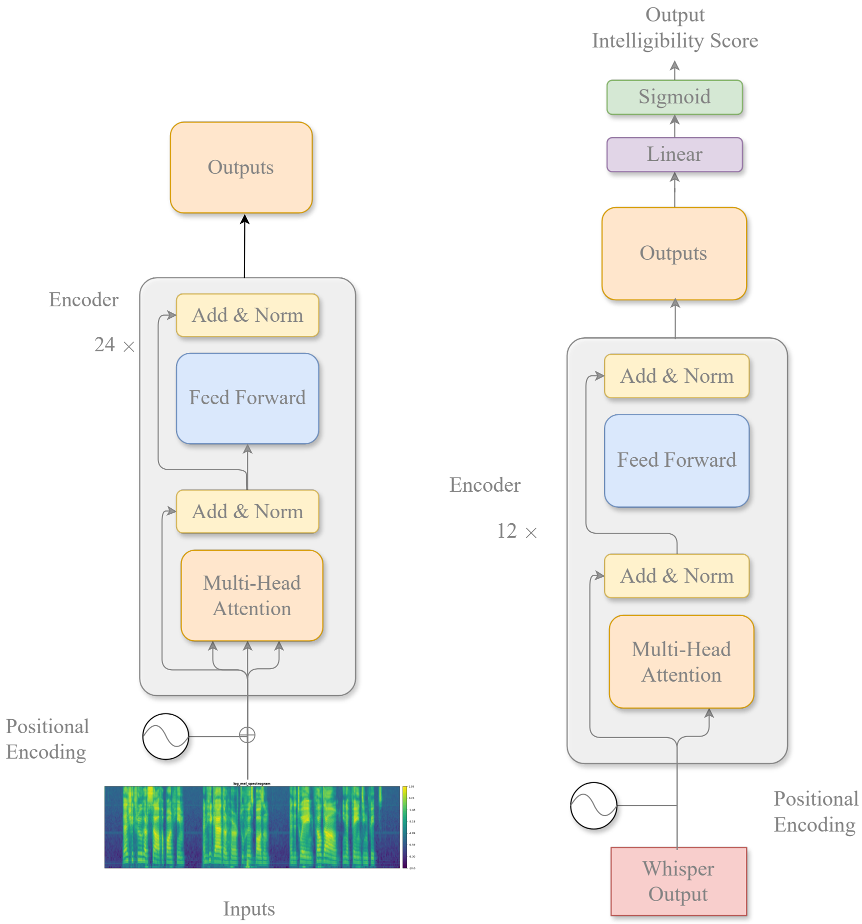
2. MODEL

Our model consists of two stages. We first extract features by passing the processed audio signal to a speech foundation model. After the feature extraction, we then use the extracted features as inputs into a randomly initialized transformer encoder.

For the speech foundation model, we use the encoder of the medium English version of the Whisper model from OpenAI [6]. This model requires the input sample to be resampled to 16kHz and converted to a Log-Mel spectrogram. We choose our features to be the output of the final layer of the Whisper encoder. Our subsequent encoder is simply a transformer encoder with 12 heads and 12 layers. From our encoder, we obtain the output as the final layer of the encoder output, ignoring the middle layers. At each time step, we project the model output using a linear layer followed by a non linearity. We average the results across time and then use a linear layer to obtain our intelligibility score. A sigmoid layer is then used to map this output to the $[0, 1]$ range. The system is shown in Figure 1.

3. EXPERIMENTAL SETUP

For our baseline model, we extracted the features from the Whisper model, as already discussed. We trained using the default training parameters using the HuggingFace Transformers library [7]. We used a learning rate of $1e-3$ for training and train for 10 epochs with a batch size of 16. We additionally used SpecAugment for data augmentation during training as a regularization method [8]. For this baseline, we performed 5 fold cross-validation. Training was done using A100 GPUs available on Google Colab. In this case, training took 50 minutes for the 10 epochs.



(a) Whisper Model (b) Transformer Encoder Architecture

Fig. 1: System illustration. With (a) showing the pretrained Whisper encoder and (b) showing the subsequent transformer encoder architecture described in this work.

After obtaining the baseline system, we obtained data from the CPC3 challenge. The distribution of intelligibility scores differed from that of our problem as there was a high fraction of 100% correctness scores in the CPC3 data. To make the distribution similar to that of our problem, we selected only the data samples where the score is not 100%. We used these data to augment the original per fold training set and then finetuned the baseline models using the new augmented data. For both the baseline and finetuned models, our final predictions for each input were the average of the outputs for all five models. Results on the validation and evaluation sets for the baseline and the models trained using the augmented data are shown in Table 1.

4. RESULTS AND ANALYSIS

As can be seen in the table, our baseline system achieved a RMSE value of 26.92% on the validation set and 26.81% on the evaluation set, outperforming the best baseline provided by the organizers 29.32% and 29.08% on the validation and evaluation sets respectively. Additionally, using the CPC3 data improved the performance of the baseline model on both the validation and final evaluation sets.

Table 1: RMSE comparison across methods for validation and evaluation datasets (↓ indicates lower is better).

Method	**Valid ↓**	**Eval ↓**
Provided Baseline (STOI-based)	36.11	34.89
Provided Baseline (Whisper-based)	29.32	29.08
Our Baseline	26.92	26.81
Our Baseline + CPC3 data	**26.82**	**26.67**

5. CONCLUSION

We have been able to show that transformer-based models can be used to directly estimate intelligibility scores without the need to first obtain a transcript. Additionally, we have been able to show that speech intelligibility data can be used to improve the music intelligibility model. This implies that available data can be easily used to improve systems without the need to collect extra expensive data. In future work, we would like to explore longer training and how the downstream transformer is initialized. Also, it would be interesting to explore incorporating the reference text into the model and exploring how much improvement can be gained in doing so.

6. REFERENCES

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