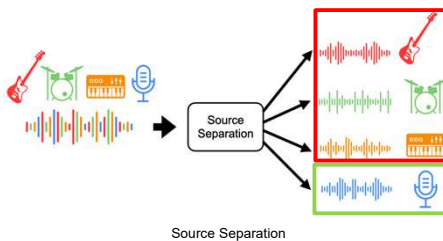


Karaoke Maker Using Deep Learning

Izar Hasson, Supervised by Hadas Ofir

Introduction

- Audio source separation involves isolating individual components (e.g., vocals, drums, bass) from a mixed audio signal.
- This technology has applications in music production, audio restoration, and more.
- Deep learning-based approaches, have proven effective, but challenges remain in improving accuracy and handling diverse audio conditions.



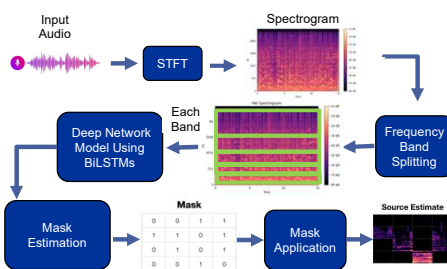
Goals

- Develop a deep learning model for audio source separation.
- Leverage spectral information and advanced neural network architectures.
- Achieve high separation accuracy across varied audio tracks.

Challenges

- Overlapping Frequencies: Sources share similar spectral components.
- Background Noise: Environmental noise complicates separation.
- Variability: Diverse genres, recording conditions, instruments, and sound quality.
- Model Complexity: Balancing accuracy and computational efficiency.

Vocal Separation

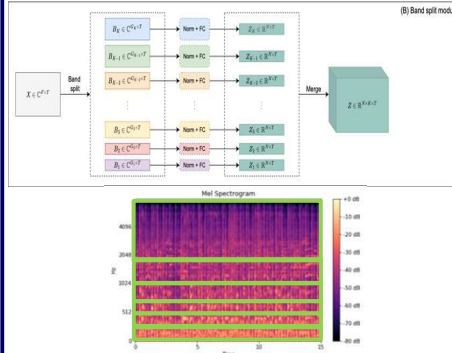


- The input is an audio mix
- After band splitting, each band is processed through our deep network
- The Mask get multiplied with the input spectrogram to get the estimated spectrogram
- The estimated spectrogram goes through ISTFT to get the audio back

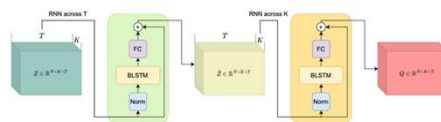
Frequency Band Splitting

- Allows specialized processing for different frequency ranges
- The chosen frequency bands are designed to align with the distribution of musical components
- Band splitting improves separation accuracy

F, T - the frequency and time dimensions
K- number of bands
N- the chosen size of the dimension of the latent space

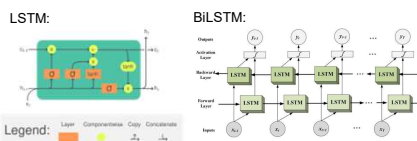


Band and Sequence Modeling Module



F, T - the frequency and time dimensions
K- number of bands
N- the chosen size of the dimension of the latent space

- Band and Sequence Modeling Module is an efficient feature extraction Module
 - Suggested in [Yi Luo et al., 2022]
- Processes the frequency bands sequentially to capture temporal dependencies and relationships across sub-bands.
- The model applies bidirectional LSTM layers (BiLSTMs) in two dimensions: across time and across frequency sub-bands.
- This dual-path processing enhances the model's ability to track temporal structures while maintaining spectral consistency, leading to improved audio source separation.

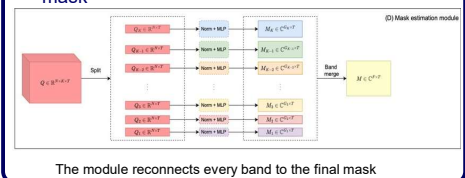


BiLSTMs (Bidirectional Long Short-Term Memory networks) are a type of recurrent neural network (RNN) that process data in both forward and backward directions.

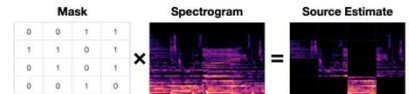
- This allows the model to capture both past and future context, making them highly effective for sequential tasks like audio processing.

Mask Estimation

- Generating a spectral mask that highlights the target source while suppressing unwanted components.
- The refined feature maps provide a better representation of the audio for our task.
- The mask estimation module then applies a learned transformation to predict the optimal mask



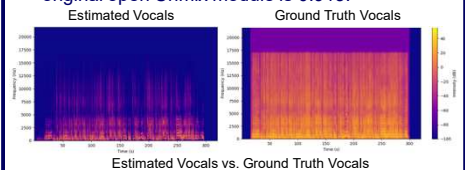
Application of the Mask



- Element-wise multiplication of the predicted spectral masks with the original spectrogram.
- The masked spectrogram is then used to produce a clean extraction of individual instruments or vocals from the mixture.

Results

- Songs were processed through our module
- For comparison to ground truth, we used 50 songs from the test set in our dataset. Meaning we know the ground truth vocals, drums etc.
- Results show a Mean Squared Error of 0.875. For comparison, the mean squared error of the original open Unmix module is 0.913.



- main differences are in the high frequencies, which the human ear can't notice
- The results are mostly pleasing to the human ear

Conclusions

- Successfully separated audio sources with pleasing accuracy using deep learning techniques
- Effective band-splitting and sequential modeling frequency representation
- BiLSTM-based sequence modeling
- Feasible for practical applications in music processing and source separation tasks