Deep Learning Approach for Singer Voice Classification of Vietnamese Popular Music

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Motivation

The collections of digital music is growing rapidly.

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- Specifically, we are tackling the singer problem.

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    - Short-Time Fourier Transform (STFT)
    - Mel Frequency Cepstrum Coefficients (MFCC)

Sun*

Our model

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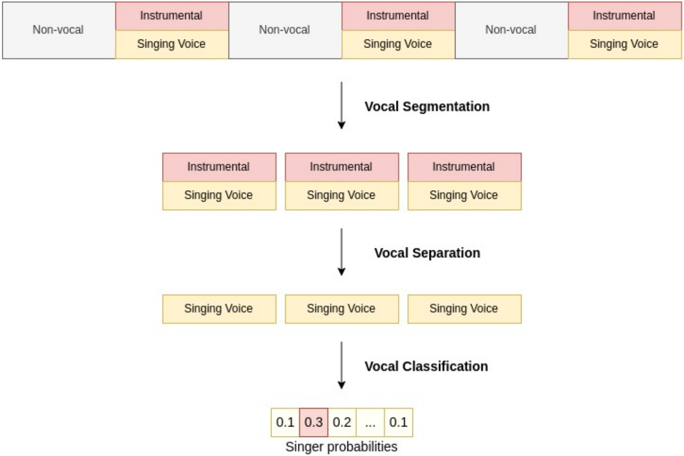
- Vocal Classification

Model visualization



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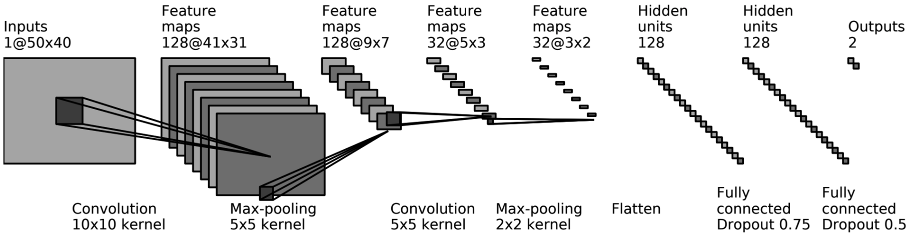
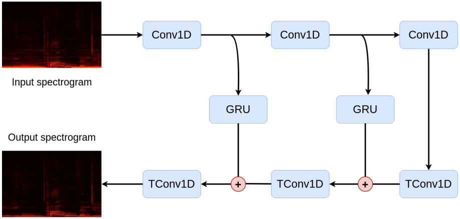
Vocal Segmentation

We use Convolutional Neural Network on the audio spectrogram.



Vocal Separation

- The model is a derivative of U-Net



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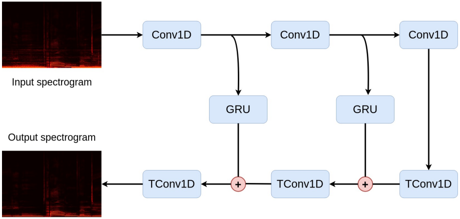

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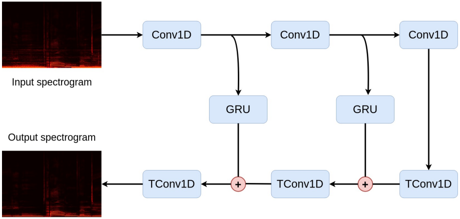
- Input and output are spectrograms.



Vocal Classification

Very standard audio classification settings:

- 13 MFCCs with 26 filter bands
- 3 stacked bidirectional LSTMs
- Softmax loss

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Vocal Segmentation

Table: Vocal and non-vocal segmentation result

Song genre	CNN Precision			CNN + Viterbi Precision		
	Vocal	Non vocal	Mean	Vocal	Non vocal	Mean
Country	91.30	97.20	94.25	97.82	99.64	98.73
Balad	92.85	94.24	93.55	98.65	99.86	99.26
Bolero	94.32	90.24	92.28	96.30	98.12	97.21
Rock	88.23	97.15	90.69	90.64	90.67	97.10

Vocal Separation

Table: The result of vocal separation

	DSD100	MUSDB18
GRU Skip connection	5.92	5.84
LSTM Skip connection	5.82	5.78

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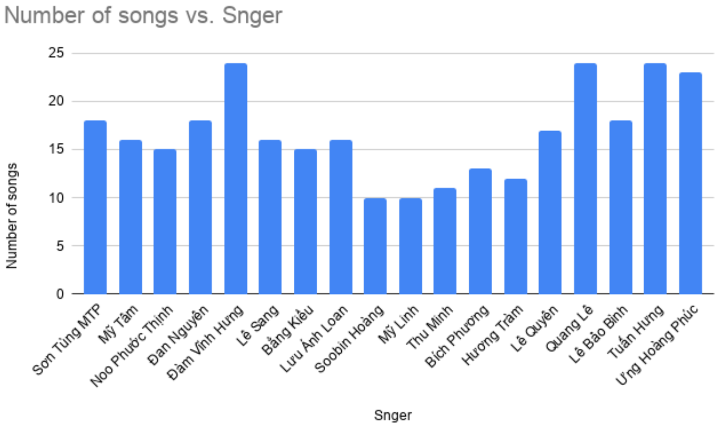
Vocal Classification Dataset

Distribution of the dataset:



Vocal Classification Result

Table: The result of vocal classification with two audio signal

	Mean precision	Mean recall	Mean F1 score
Raw signal	85.4	82.6	83.96
Separated signal	93.94	91.78	92.84

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Future works

- Comparisons to be done

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- Improvements to be made

Thank you for listening!