

Pseudo-Level Transfer from Frame-Level to Note-Level in a Teacher-Student Framework for Singing Transcription from Polyphonic Music



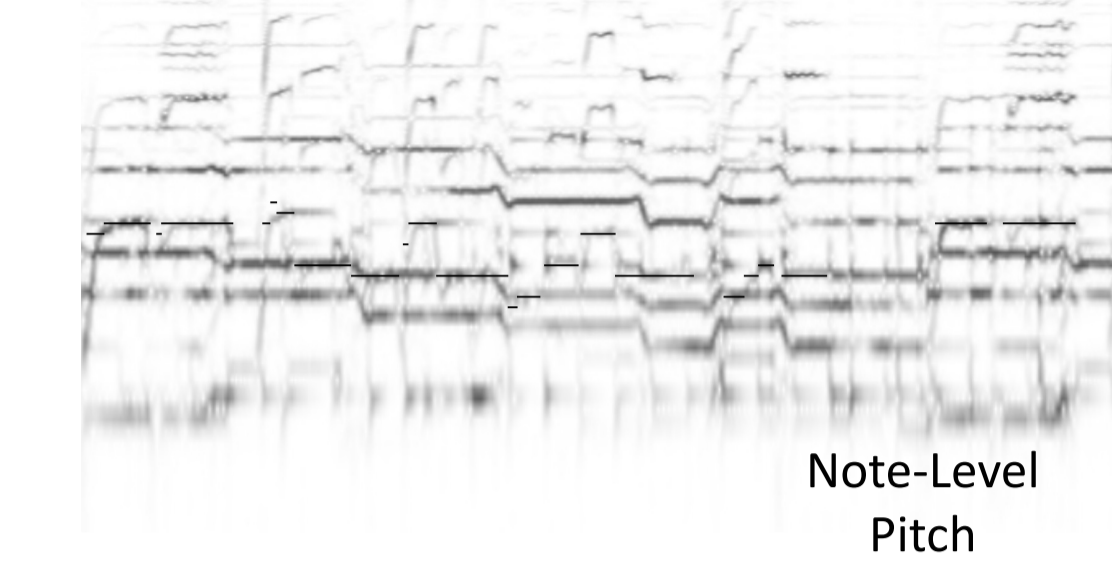
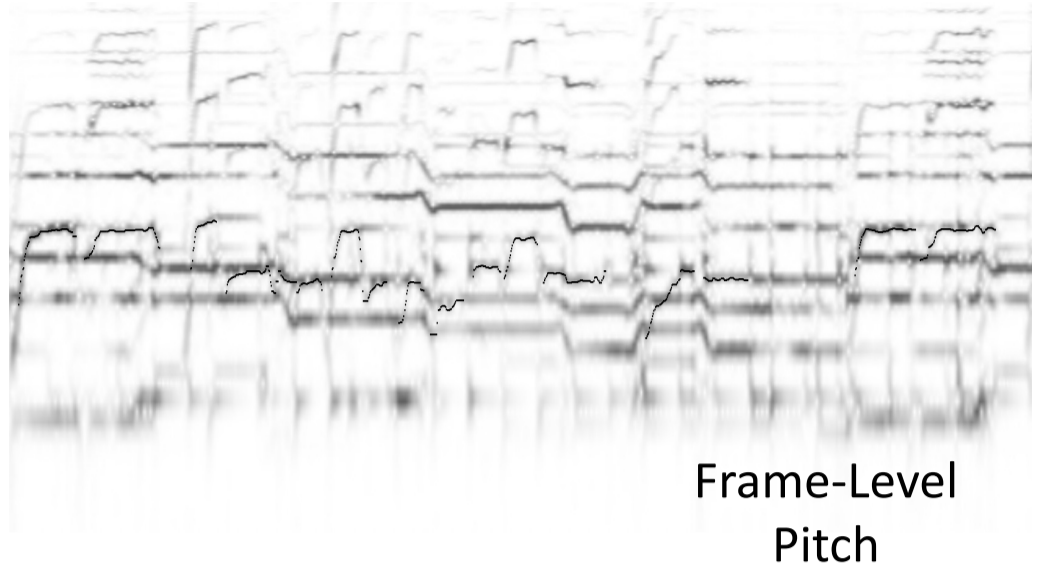
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Introduction

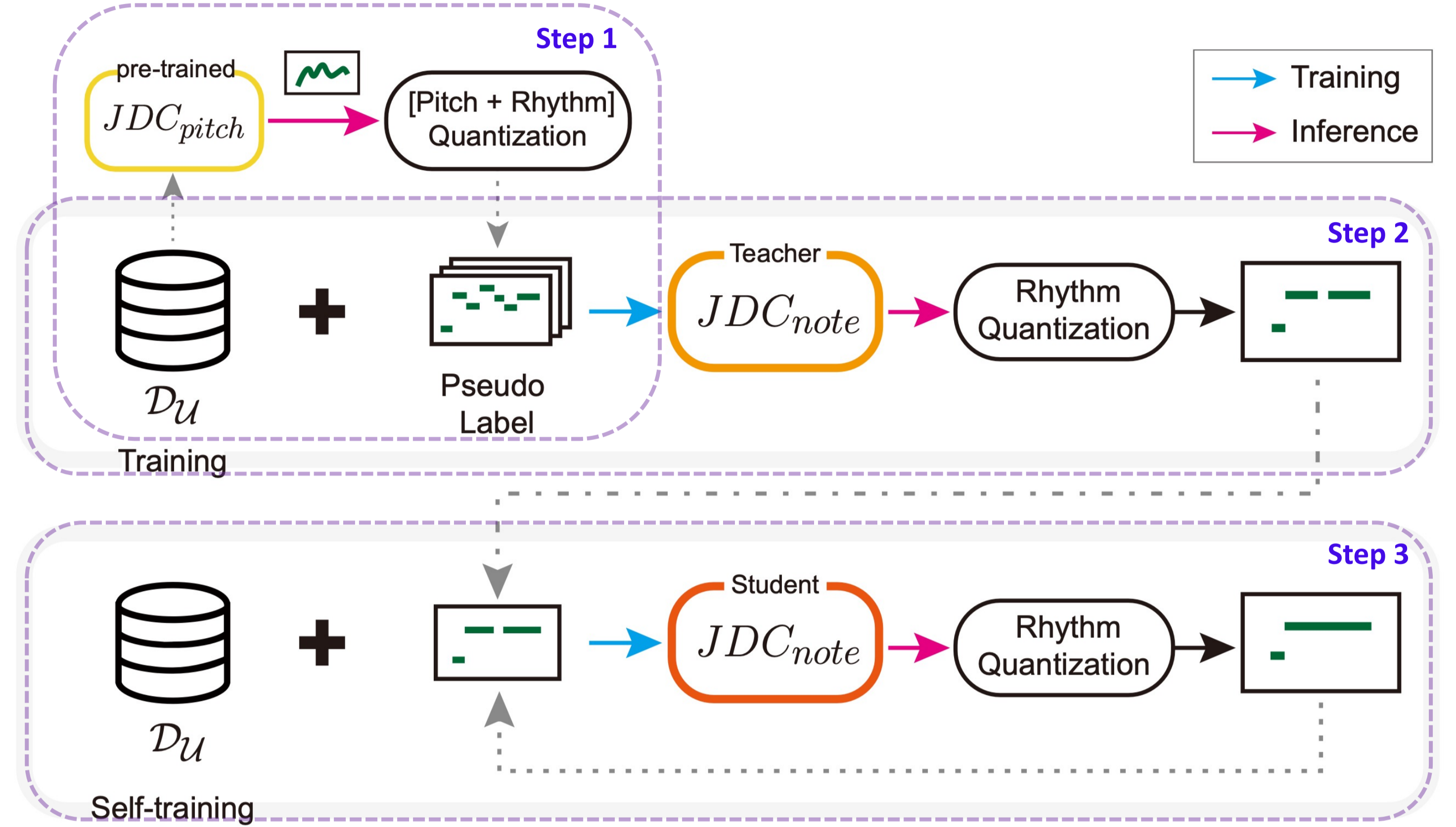
- STP includes several **sub-tasks**:
 - Singing voice detection
 - Singing pitch estimation
 - Note-level segmentation
 - Onset/offset detection



- Major obstacle to **Singing Transcription from Polyphonic music (STP)** = Lack of large-scale **note-level** labeled data for **VOCALS**

>> Contribution

- To obtain effective pseudo-labels, we **use vocal pitch estimation model** to predict frame-level label and **convert it to note-level label**.
- The proposed method (pseudo labeling, teacher-student framework, and JDC network) can achieve comparable results to the previous work using **only unlabeled data**, even if there is **no source separation algorithm**.
- With additional labeled data, it achieves better performance than the model trained with only labeled data.

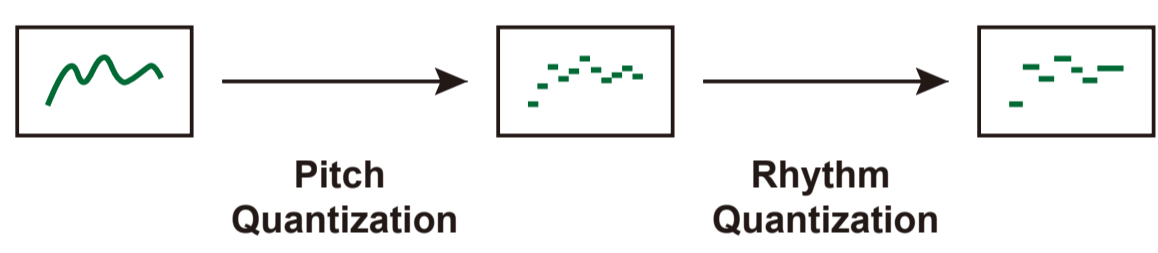


Method

Dataset

Labeled Dataset	Unlabeled dataset
<ul style="list-style-type: none"> Cmedia (100): test MIR-ST500 (500) [1]: training 	<ul style="list-style-type: none"> In-house (2000): training FMA (168,000): training

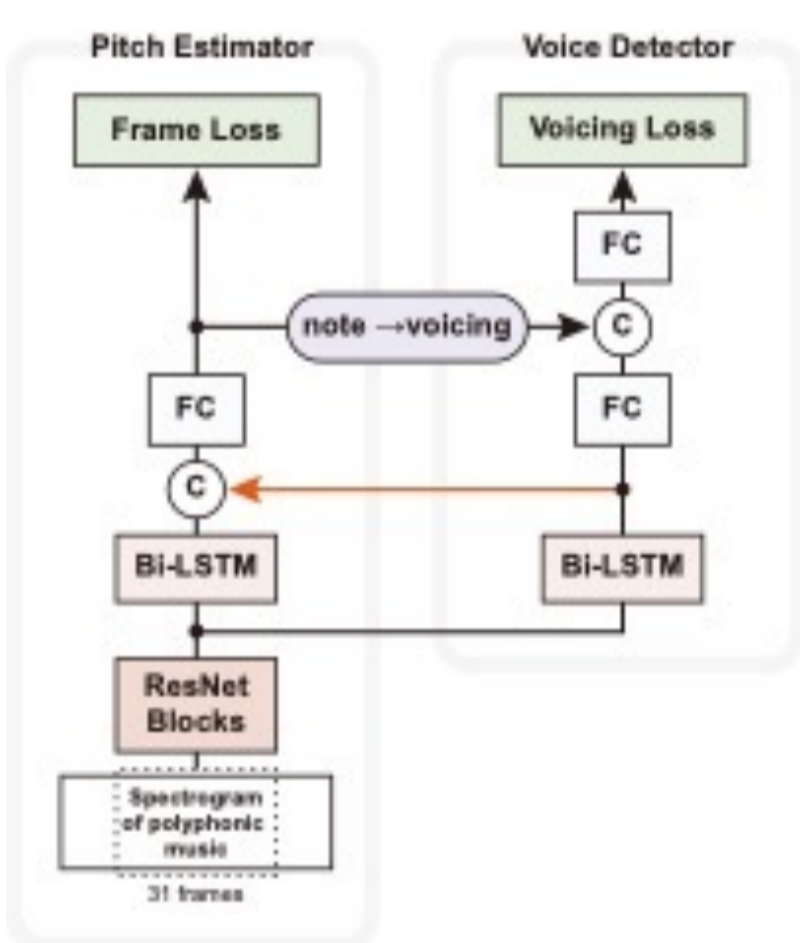
[Step 1] Making pseudo labels using vocal pitch estimation model from Unlabeled dataset



Pitch + Rhythm Quantization

- Rounds the continuous pitch to semi-tone
- Smoothing the quantized pitch with a series of three median filters
- Remove small fragments

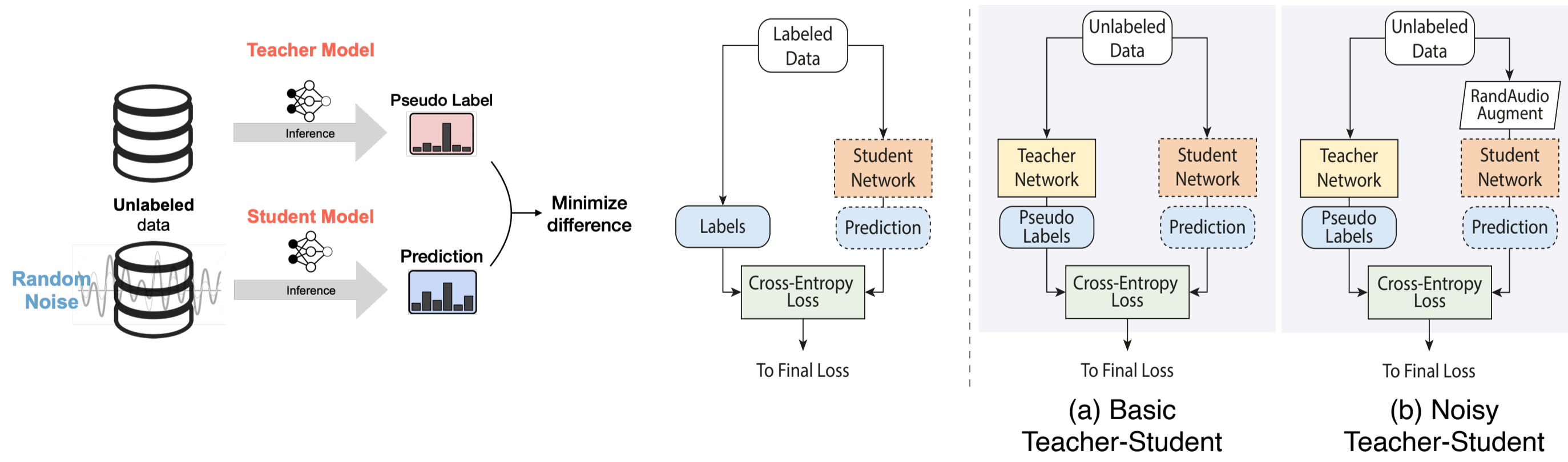
[Step 2] Training Model



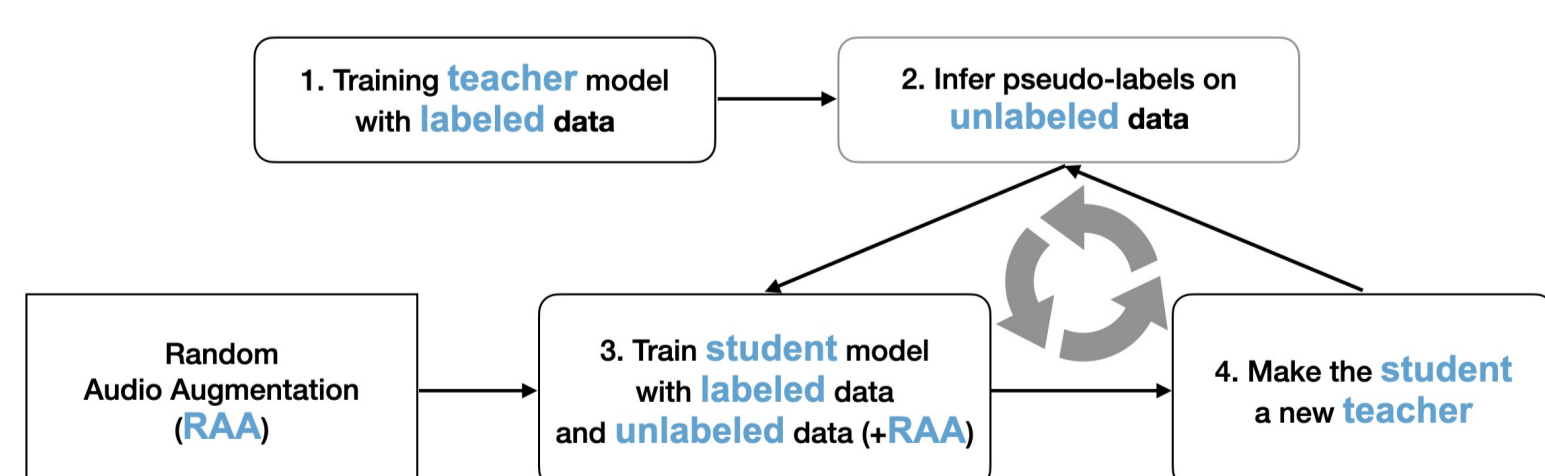
- The model architecture for STP is based on the joint detection and classification (**JDC**) model [2]
- Training teacher model for singing transcription (JDC_{pitch}) using pseudo label from JDC_{note}

[Step 3] Teacher-Student Framework [3] for singing transcription

- Noisy Student



- Iterative Training



Conclusion

- We presented a method for STP that uses **pre-trained vocal pitch estimation models** and **unlabeled datasets**.
- The method **converts the frame-level pseudo labels to note-level** and augments the label quality through **self-training** in the teacher-student framework.
- The **unsupervised model** trained through the proposed method can **achieve comparable results** to the previous works
- With **additional labeled data**, it **achieves better performance** than the model trained with only labeled data.

Experiments

1. Comparison of Pitch Estimation Models

Repurposed Models	Initial Pseudo Labels		JDC_note (Teacher)	
	Demucs + CREPE	JDC_pitch	Demucs + CREPE	JDC_pitch
COOnPOff	22.43	25.44	24.71	28.97
COOnP	45.01	48.48	48.64	53.32
COOn	57.65	61.94	62.32	64.74

- JDC**: Vocal melody extraction from **polyphonic** music
- Demucs**: music source separation
- CREPE** [4]: pitch estimation from **monophonic** music

JDC > Demucs + CREPE

: Separation algorithms **cannot separate only the main vocal melody** and polyphonic vocals are still remained
 → Low performance

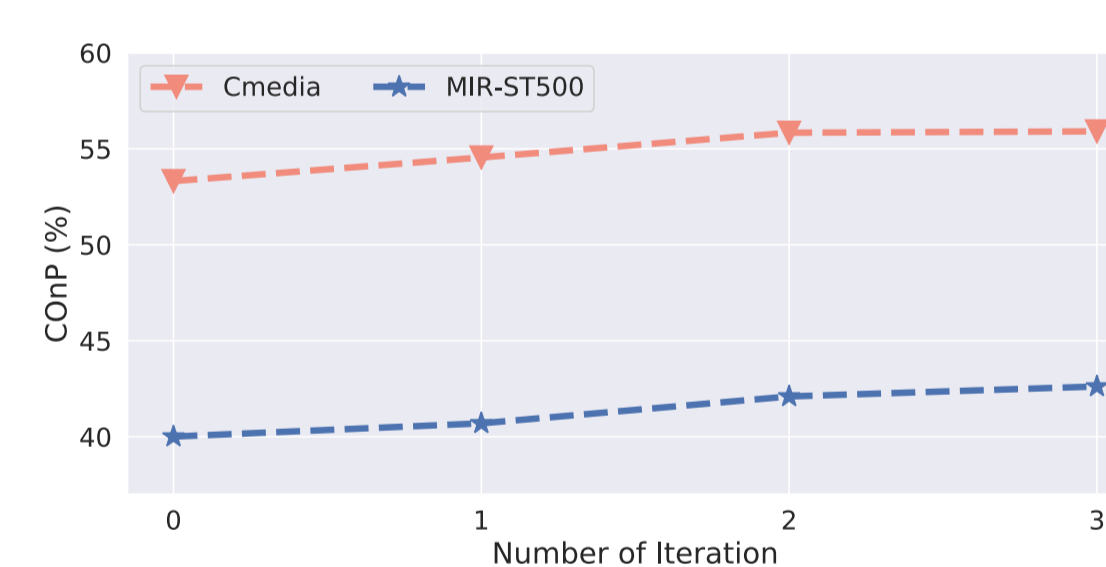
2. Basic Teacher-Student VS. Noisy Student

Models	Cmedia		MIR-ST500	
	TS	NS	TS	NS
COOnPOff	28.97	29.62	22.12	22.62
COOnP	53.32	54.55	40.01	40.70
COOn	64.74	65.61	56.90	57.87

Noisy Student > Basic TS

: The student produce consistent outputs that minimize the difference from the teacher even though the input is perturbed

3. Iteration of Self-Training



Iterative Training

: The performance continuously increases up to 2 iterations

4. Comparison with Supervised and Semi-Supervised Models

	Description		
JDC_note(U)	Unsupervised model with unlabeled data D_u		
JDC_note(L)	Supervised model with labeled data D_L		
JDC_note(L+U)	Semi-supervised model with D_L and D_u		

HZ [5]: Rule-based model
 VOCANO [6]: Semi-supervised model
 EFN [1]: Supervised model

EFN > JDC(U) > VOCANO > HZ

: This validates that the proposed method is superior to the semi-supervised method in VOCANO or the rule-based approach in HZ

Model	Cmedia				
	HZ	VOCANO	EFN	JDC_note	
COOnPOff	17.18	28.28	35.13	30.13	35.95
COOnP	41.43	48.33	60.77	55.84	62.50
COOn	63.63	64.56	76.40	65.72	73.88

Model	MIR-ST500				
	HZ	VOCANO	EFN	JDC_note	
COOnPOff	-	-	45.78	23.48	40.57
COOnP	-	-	66.63	42.10	67.55
COOn	-	-	75.44	58.61	74.94

JDC(L+U) > EFN > JDC(L) > VOCANO > HZ

1. Given that JDC(L) was also trained with the same training set that was used in EFN, the two models seem to be comparable to each other.

2. JDC(U+L) pushes the accuracy levels higher, achieving best performances.

5. Demo video

- <https://tinyurl.com/yyxsbly>
- <https://tinyurl.com/y4nngs2k>

Reference

[1] Wang, J., & Jang, J., "On the preparation and validation of a large-scale dataset of singing transcription," in Proc. ICASSP, 2021
 [2] Kum, S., & Nam, J., Joint detection and classification of singing voice melody using convolutional recurrent neural networks. Applied Sciences, 2019
 [3] Kum, S., Lin, J. H., Su, L., & Nam, J., Semi-supervised learning using teacher-student models for vocal melody extraction. ISMIR, 2020
 [4] Kim, J. W., Salamon, J., Li, P., & Bello, J. P. Crepe: A convolutional representation for pitch estimation, ICASSP, 2018
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 [6] Hsu, J. & Su, L., "VOCANO: A note transcription framework for singing voice in polyphonic music," in Proc. ISMIR, 2021