DRUM TRANSCRIPTION VIA JOINT BEAT AND DRUM MODELING USING CONVOLUTIONAL RNNs

Richard Vogl

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TECHNISCHE UNIVERSITÄT WIEN

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Institute of Computational Perception

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Richard Vogl[1,2], Matthias Dorfer[2], Gerhard Widmer[2], Peter Knees[1]

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ISMIR

2017, SUZHOU, CHINA

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PART 1
AUTOMATIC DRUM TRANSCRIPTION

Task Definition, Problem Modeling, Architectures

PART 2
MULTI-TASK LEARNING

Metadata for Transcripts

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Task Definition, Problem Modeling, Architectures

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MULTI-TASK LEARNING

Metadata for Transcripts

WHAT IS DRUM TRANSCRIPTION?

audio

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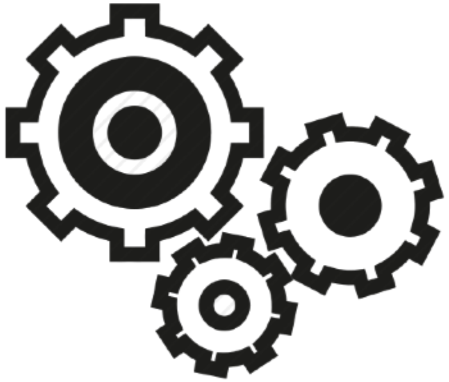
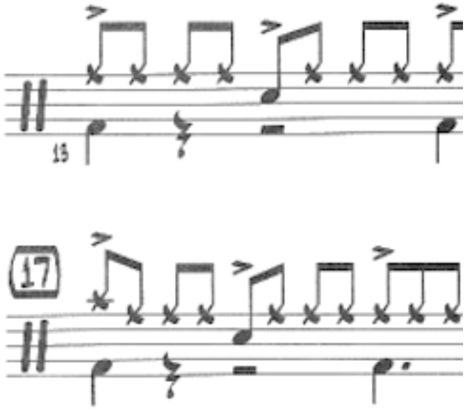
ADT system



symbolic representation
of drum notes



sheet music

- **Input:** western popular music containing drums
- **Output:** symbolic representation of notes played by drum instruments

WHAT IS DRUM TRANSCRIPTION?

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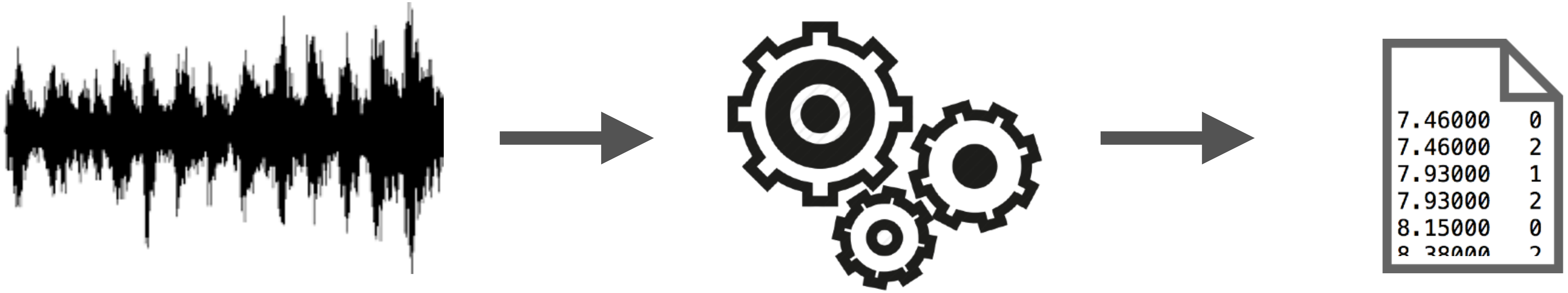

list of events

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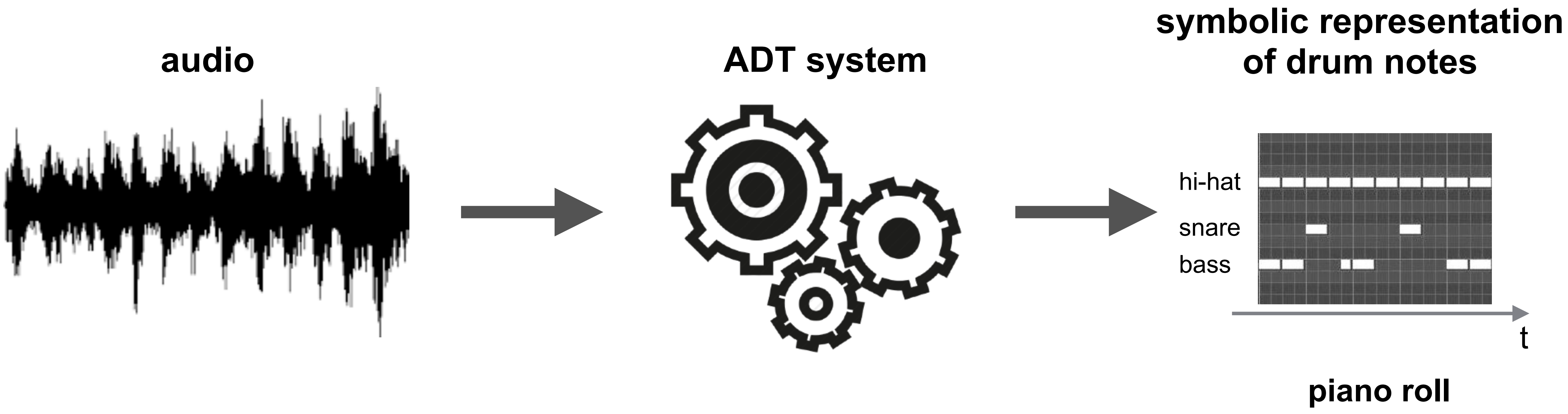

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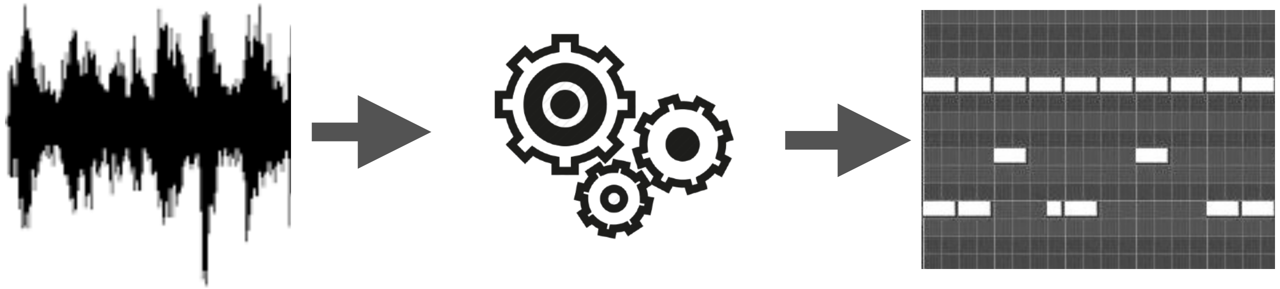
audio **ADT system** **notes**



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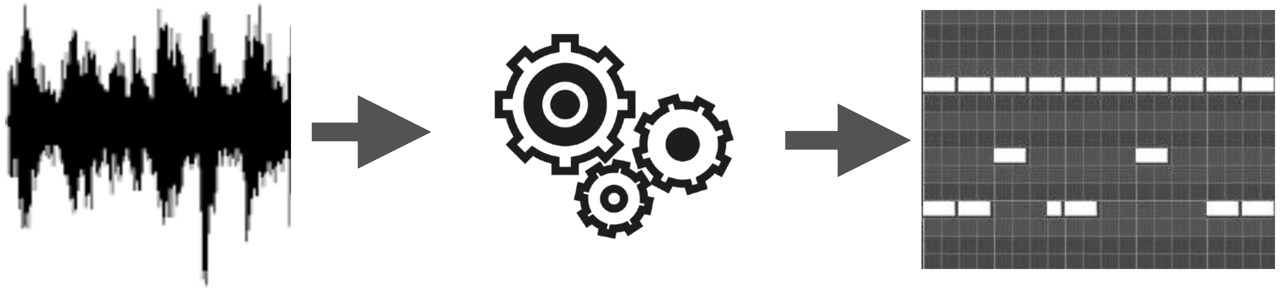
audio ADT system notes



♫

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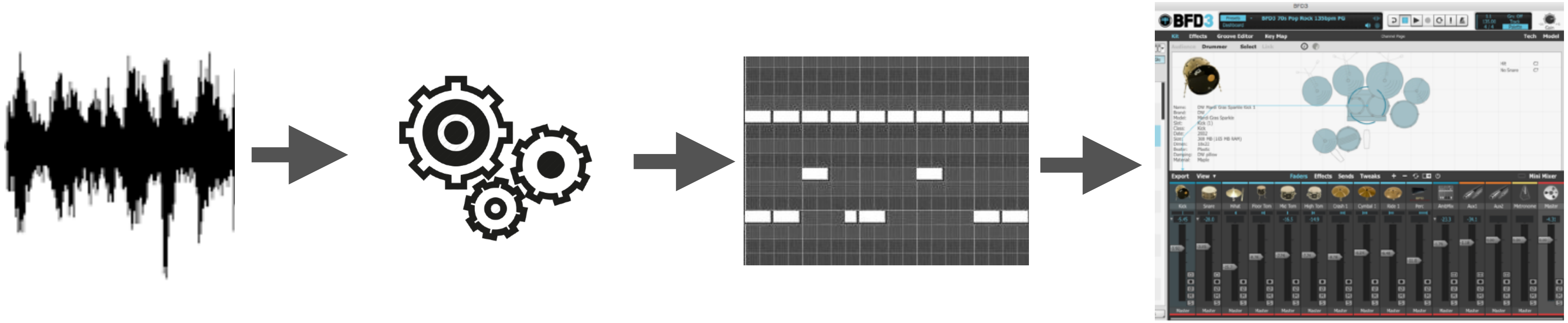
audio ADT system notes drum sampler



WHAT IS DRUM TRANSCRIPTION?

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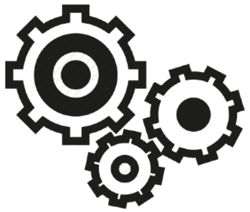
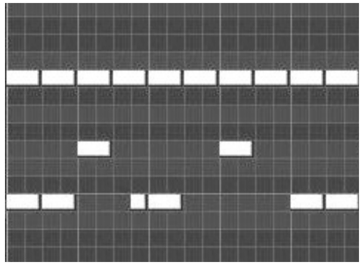


notes



drum sampler

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♫

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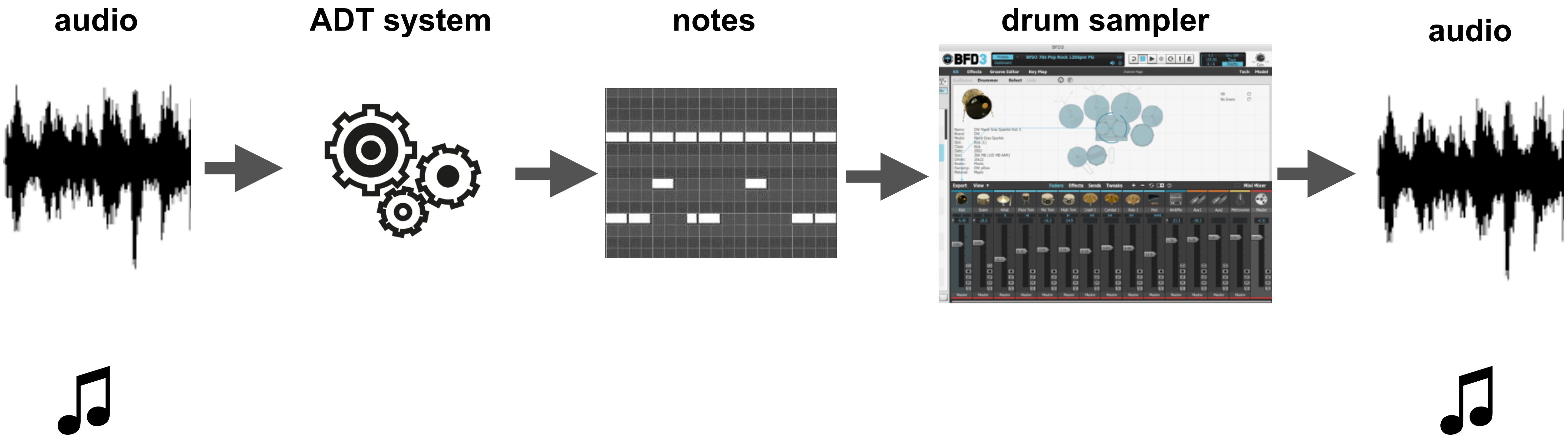

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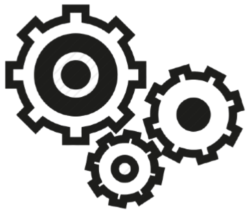

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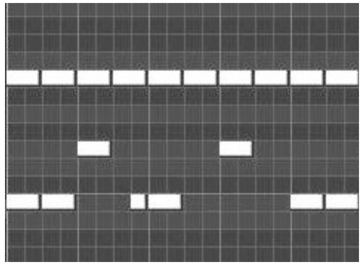

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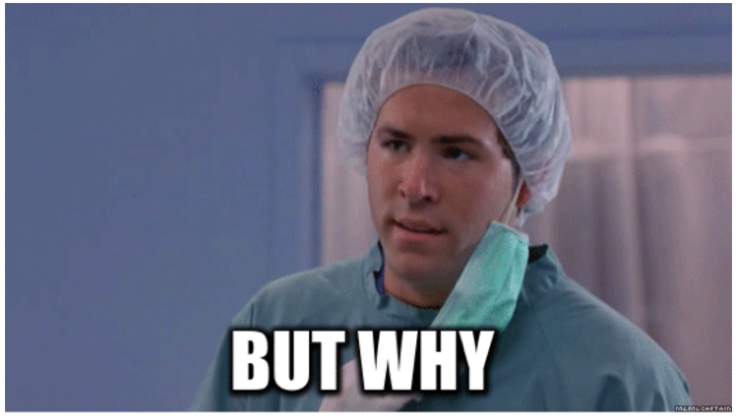

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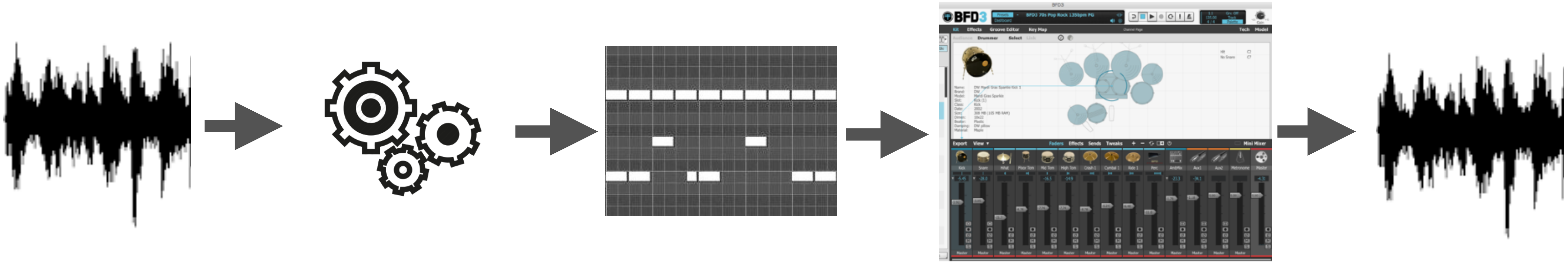
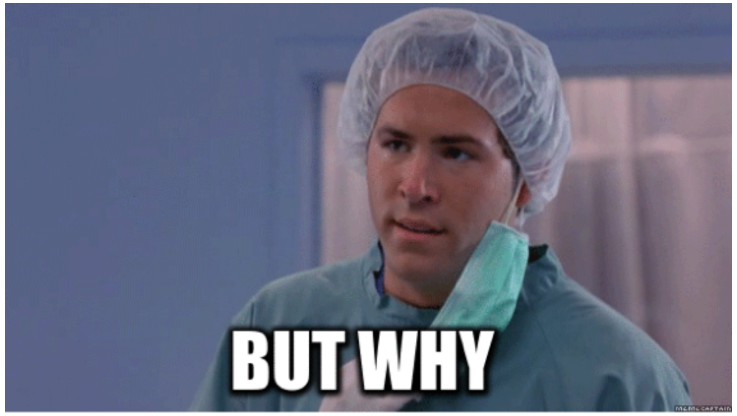
audio | ADT system | notes | drum sampler | audio





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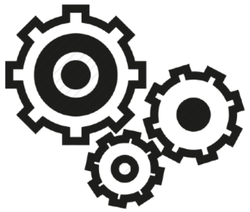

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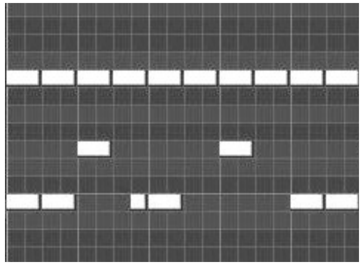

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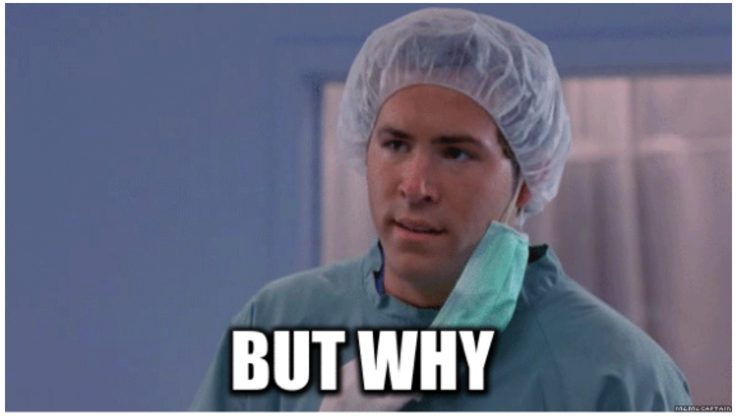

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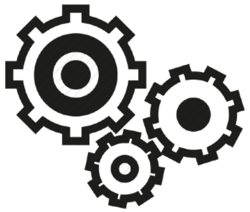

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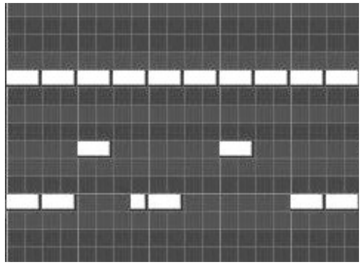

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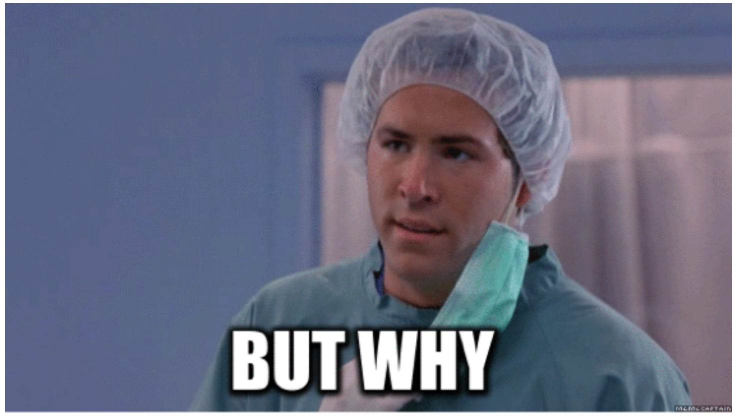

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- Wide range of application
  - Generate **sheet music**
  - **Music production**
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  - Higher level **MIR tasks**
    use drum patterns for other tasks
    genre classification
    song segmentation

FOCUSED INSTRUMENTS

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- ADT methods focus bass drum (BD) snare (SD) and hi-hat (HH)

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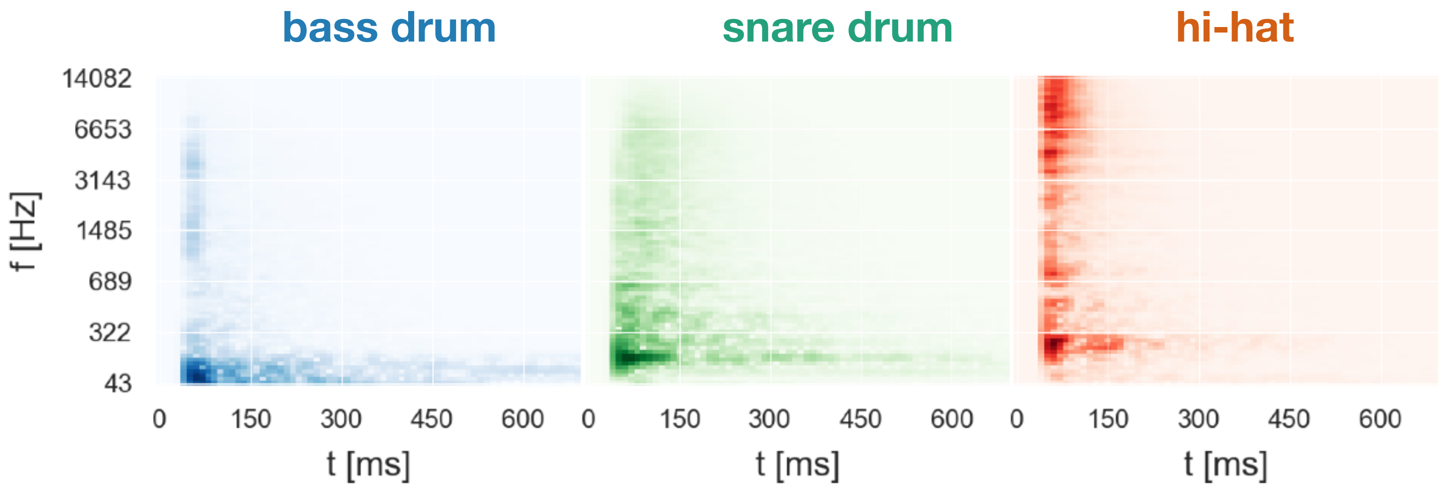

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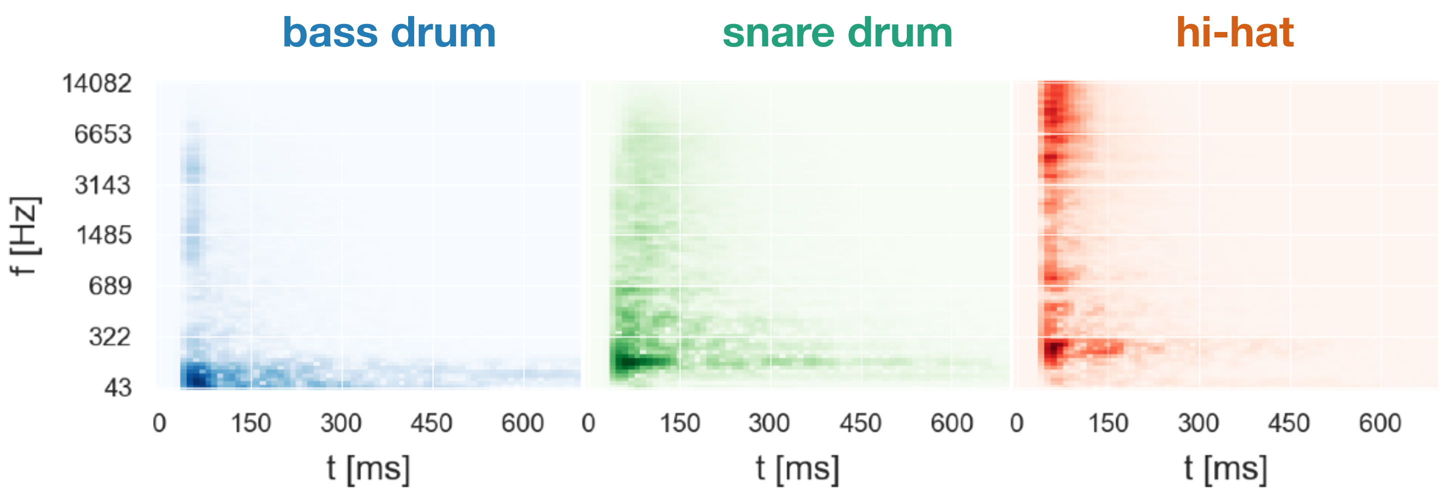

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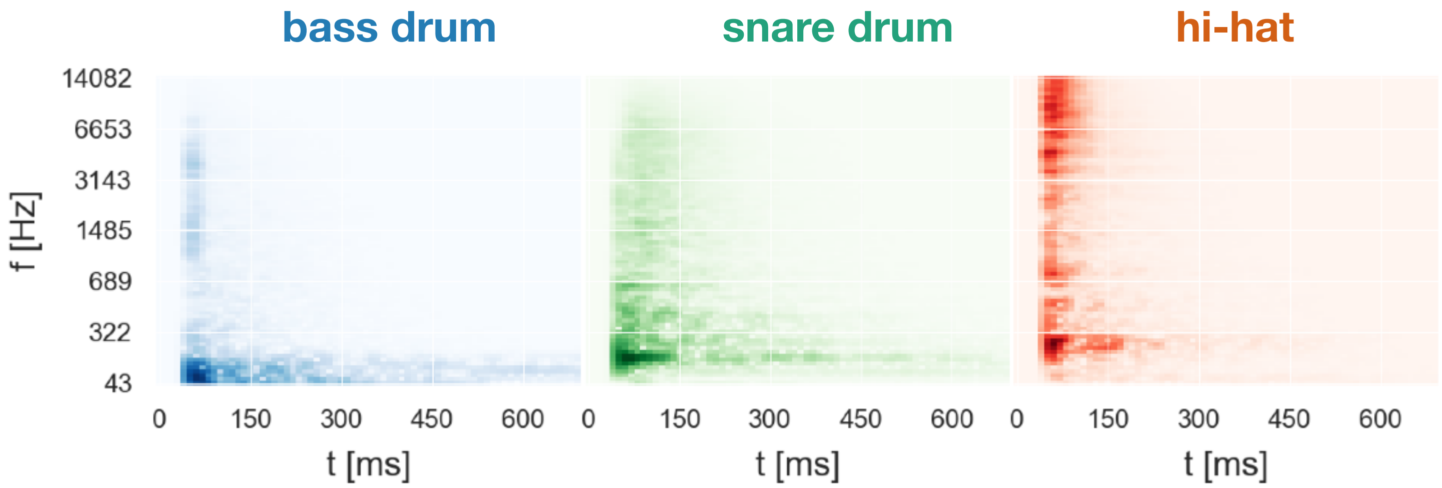

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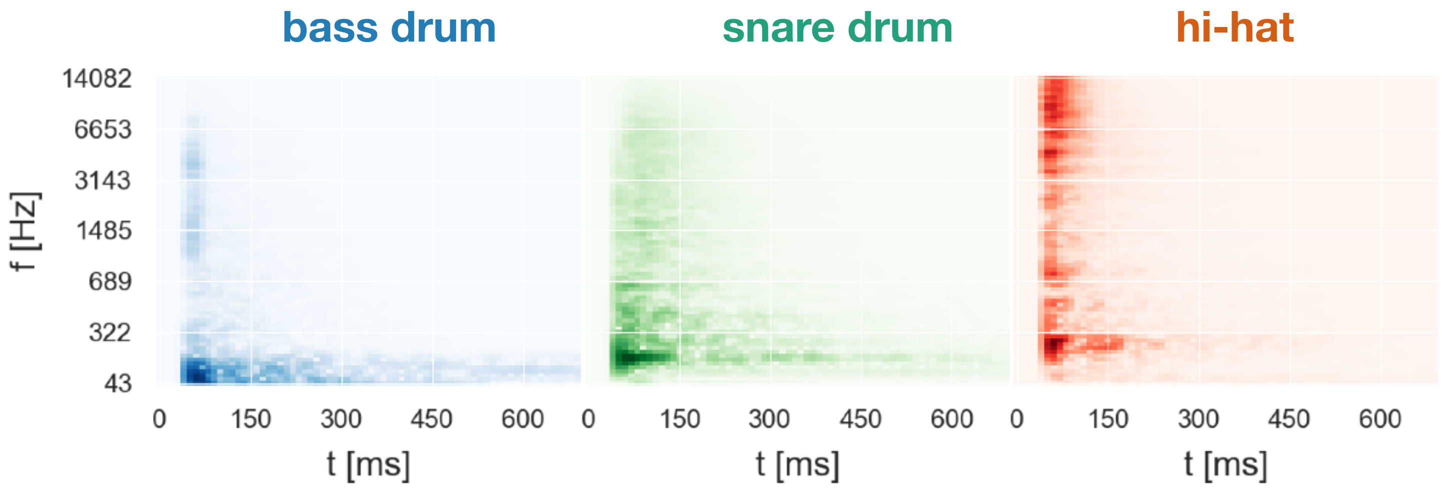
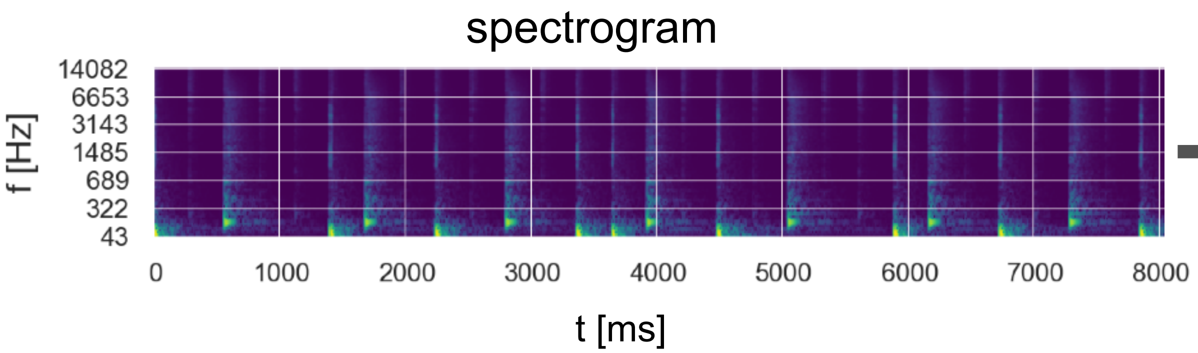
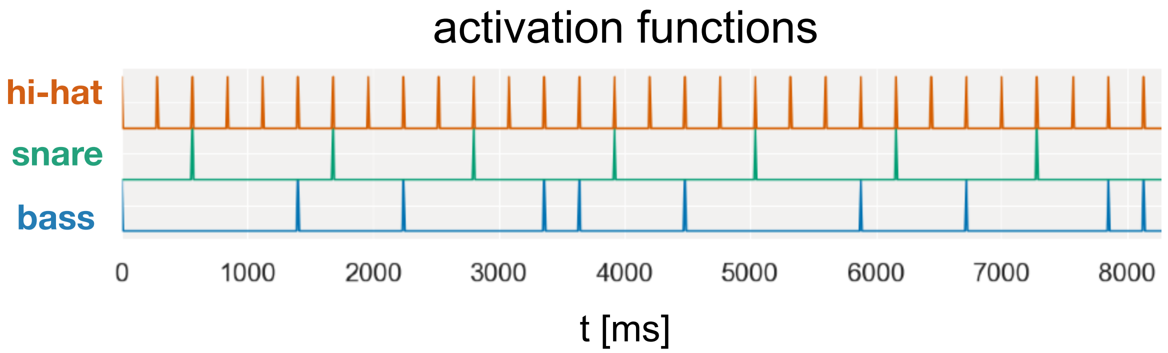


STATE OF THE ART





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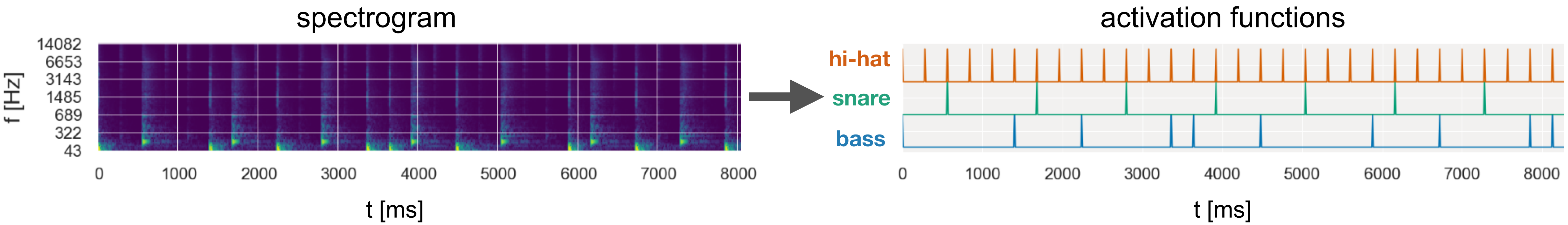
- End-to-end / **activation-function-based**
- **Neural Networks** and **NMF-based** approaches



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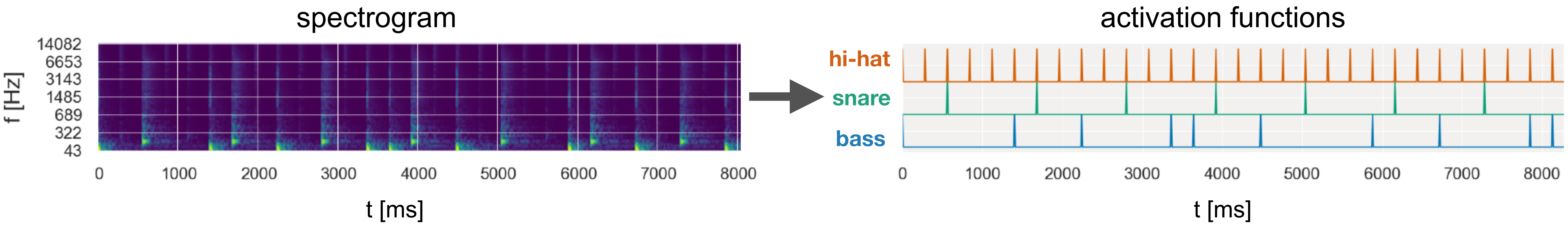
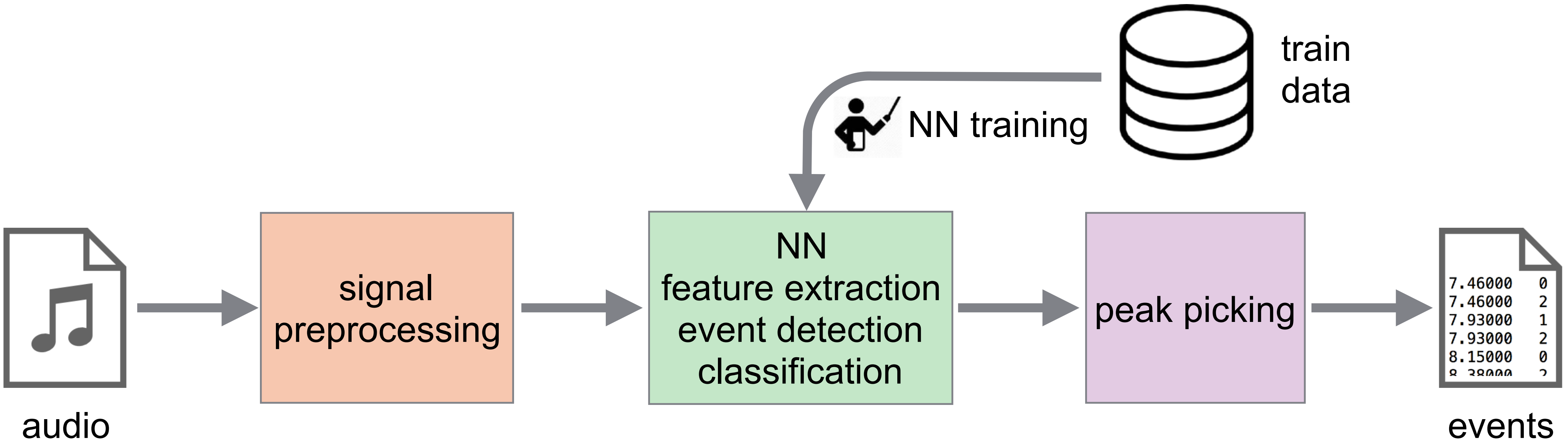


- Overview Article

  Wu, C.-W., Dittmar, C., Southall, C.,Vogl, R., Widmer, G., Hockman, J., Müller, M., Lerch, A.: "**An Overview of Automatic Drum Transcription**," IEEE TASLP, vol. 26, no. 9, Sept. 2018.

SYSTEM OVERVIEW



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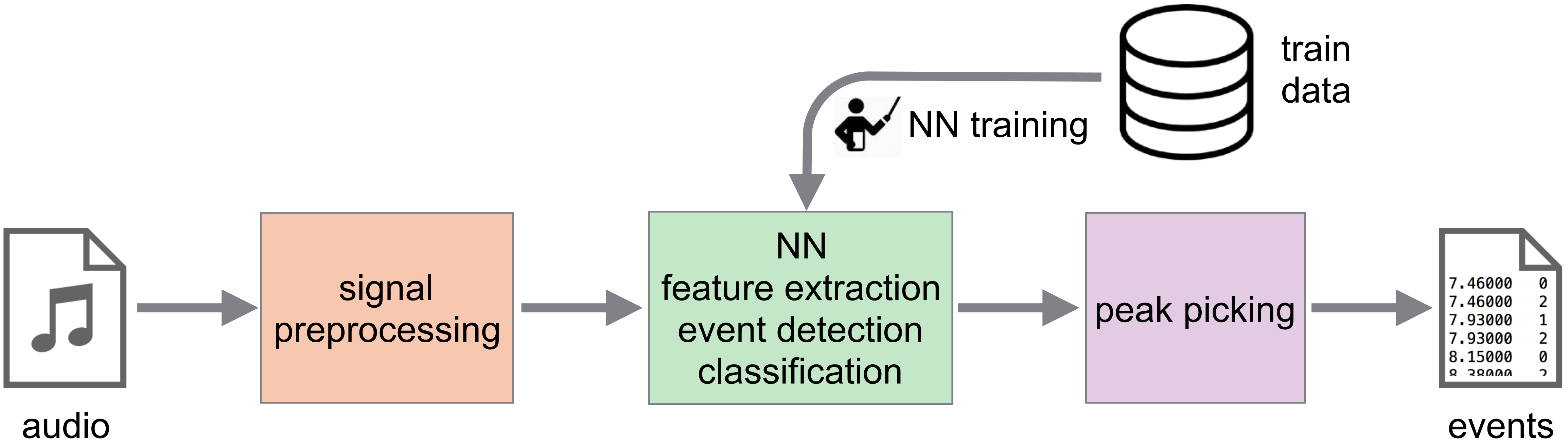

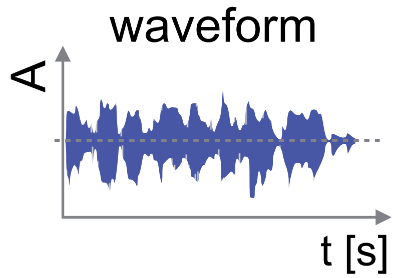

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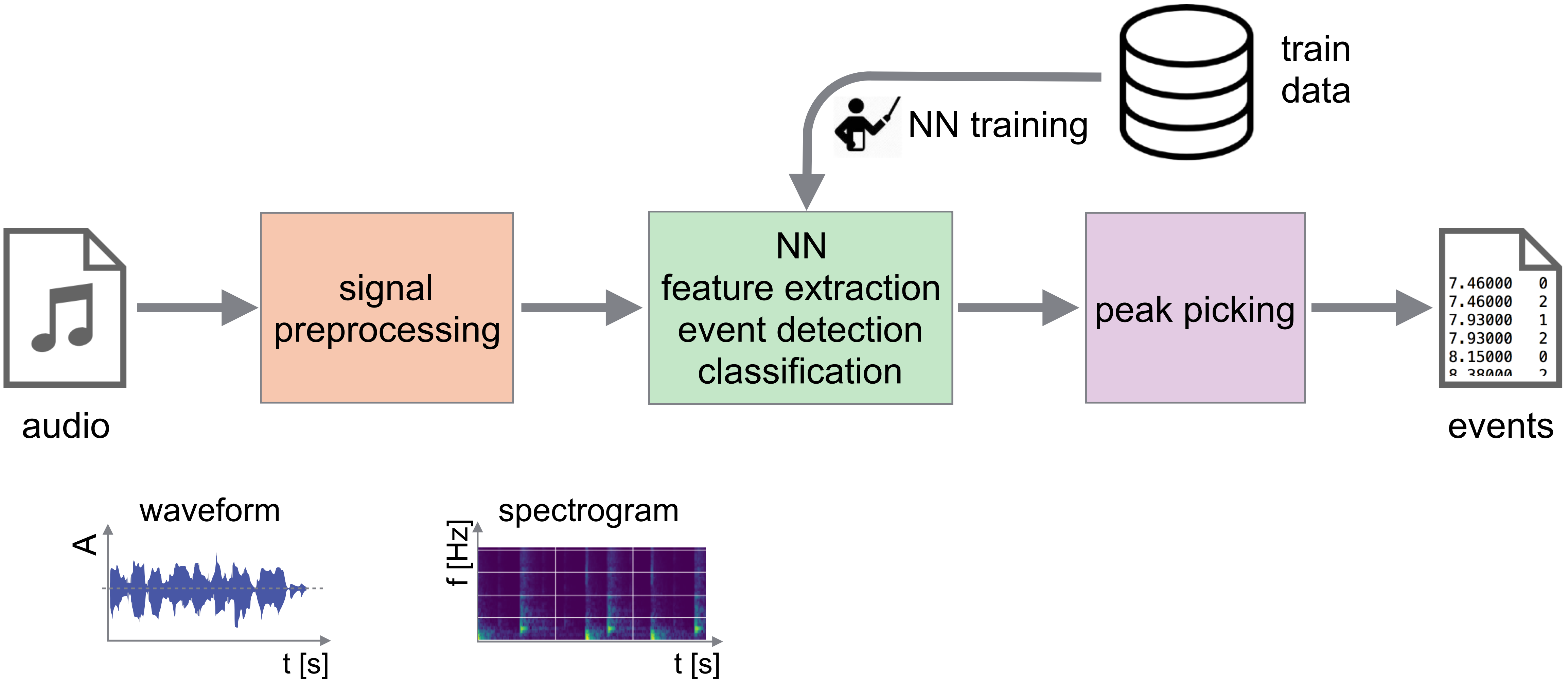

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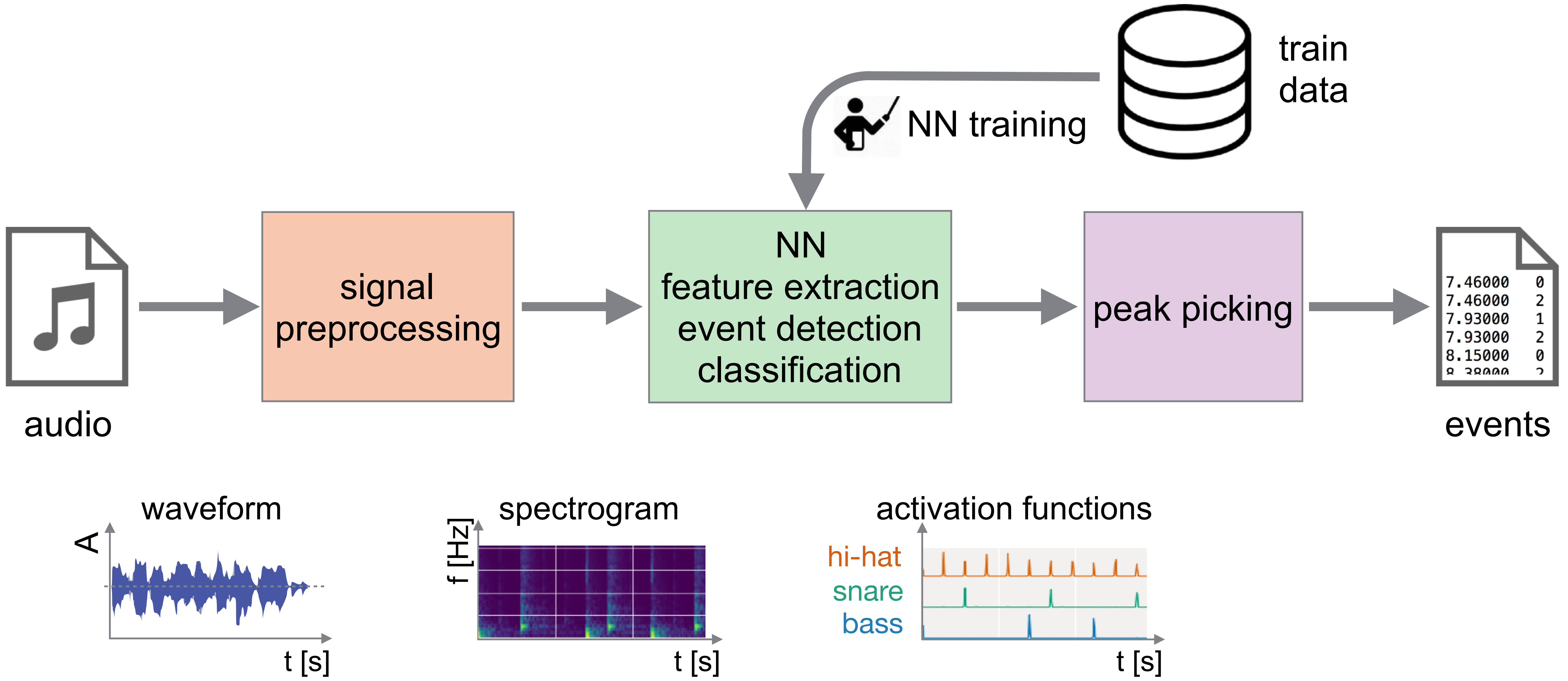

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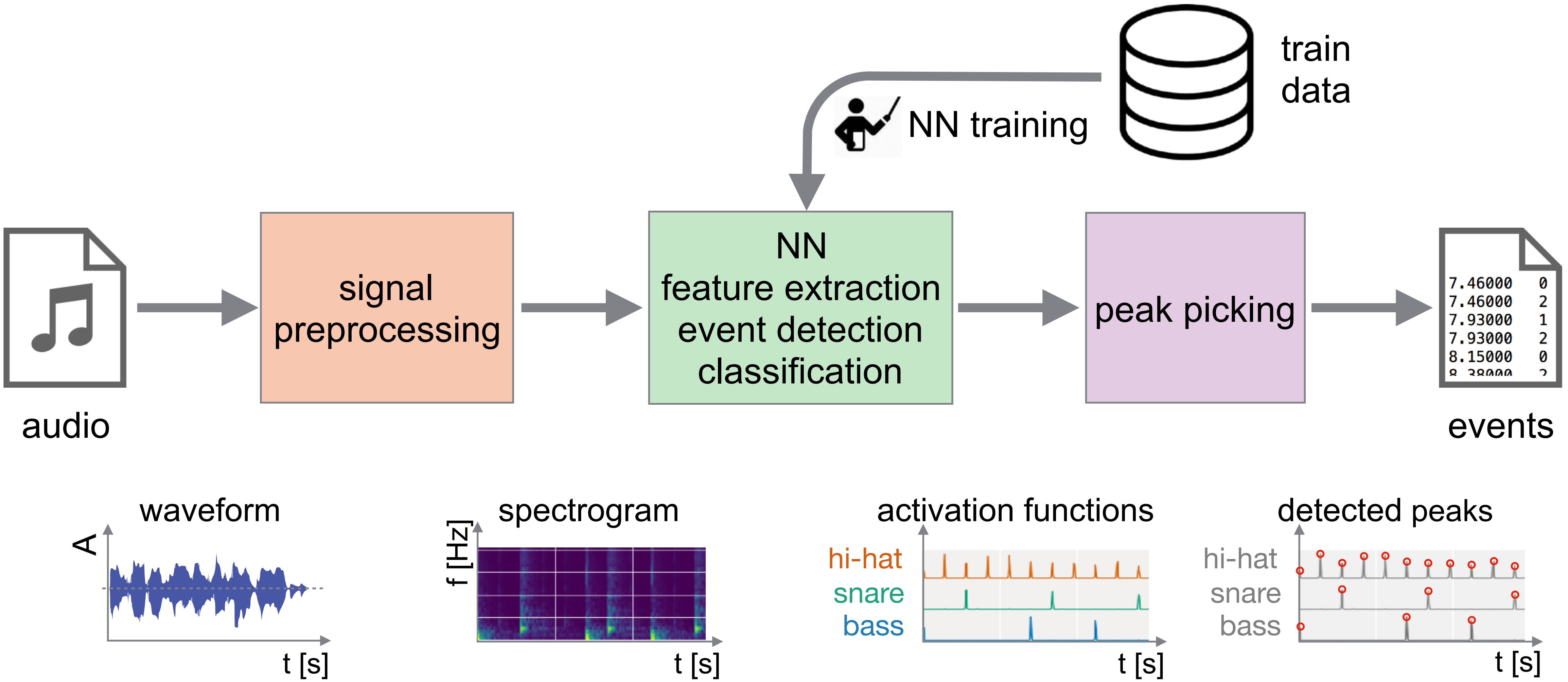

NETWORK MODELS — RNN

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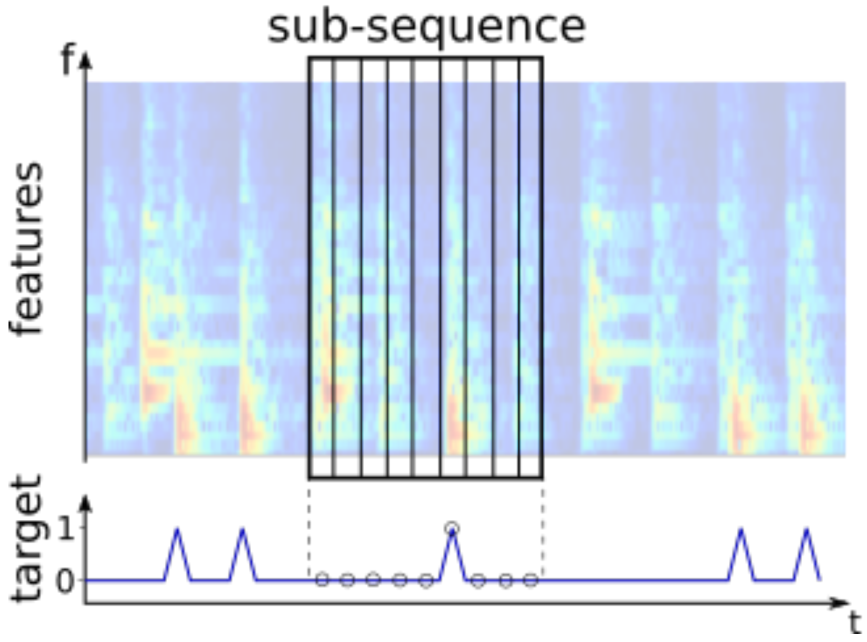

RNN train data sample

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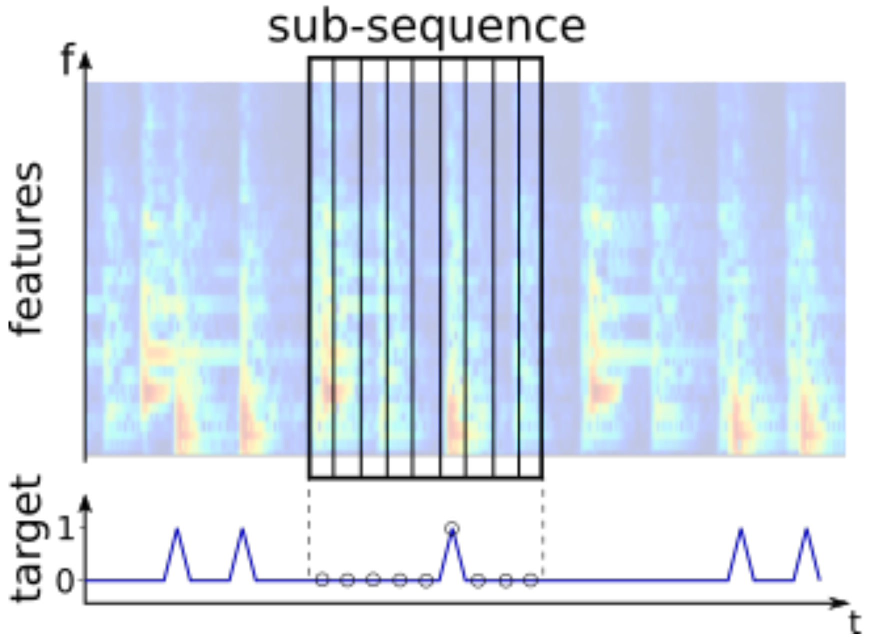
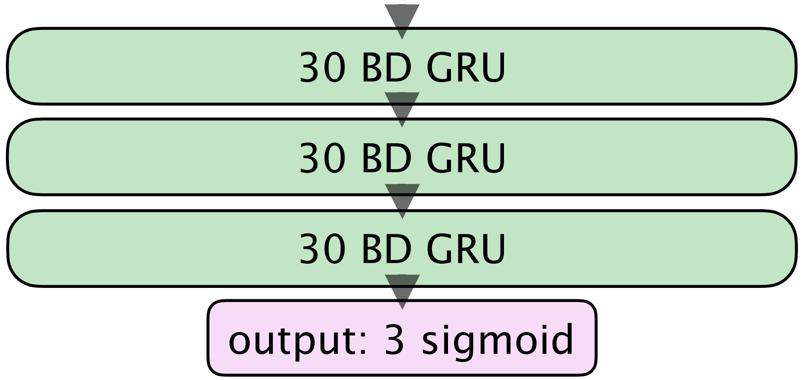


RNN train data sample

bidirectional RNN architecture with GRUs:



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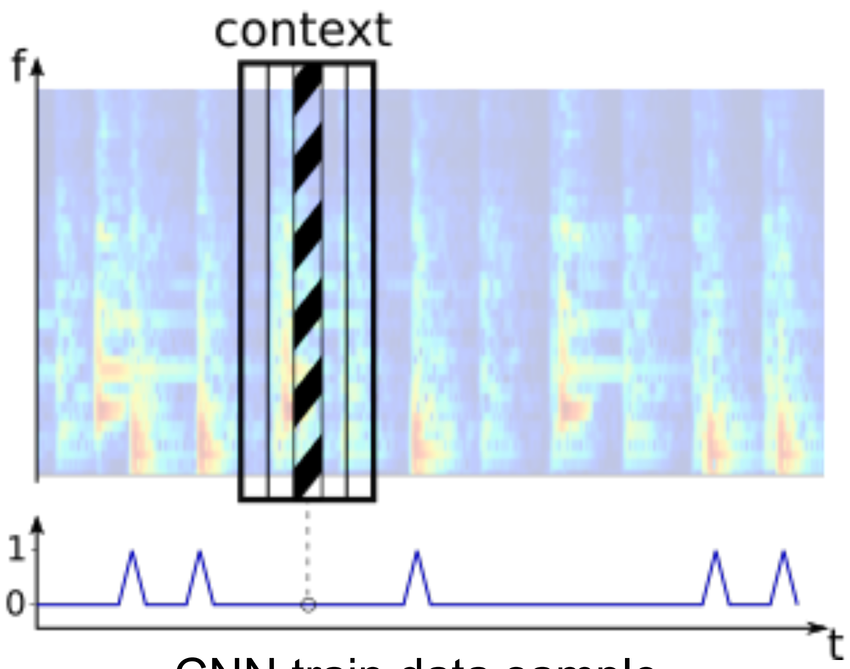

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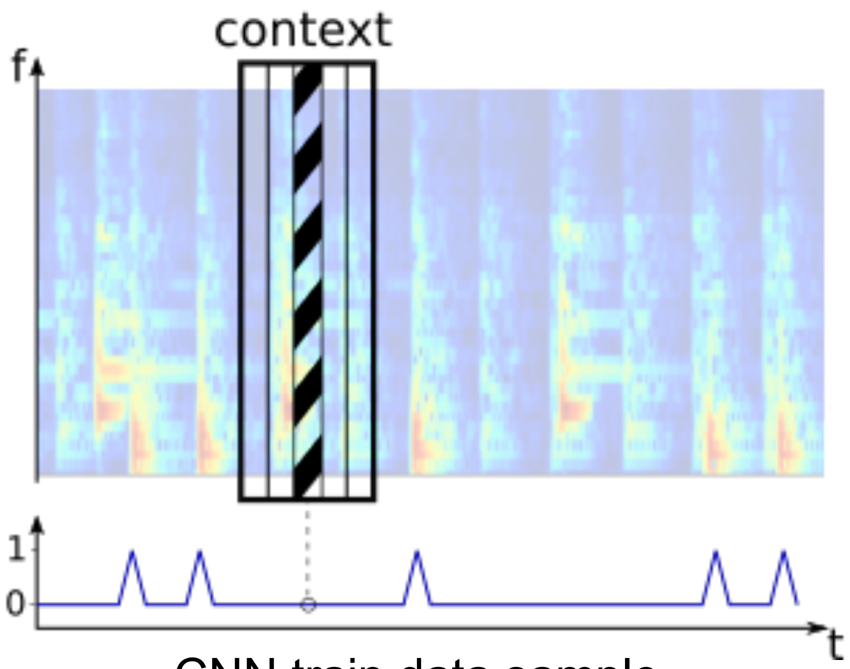

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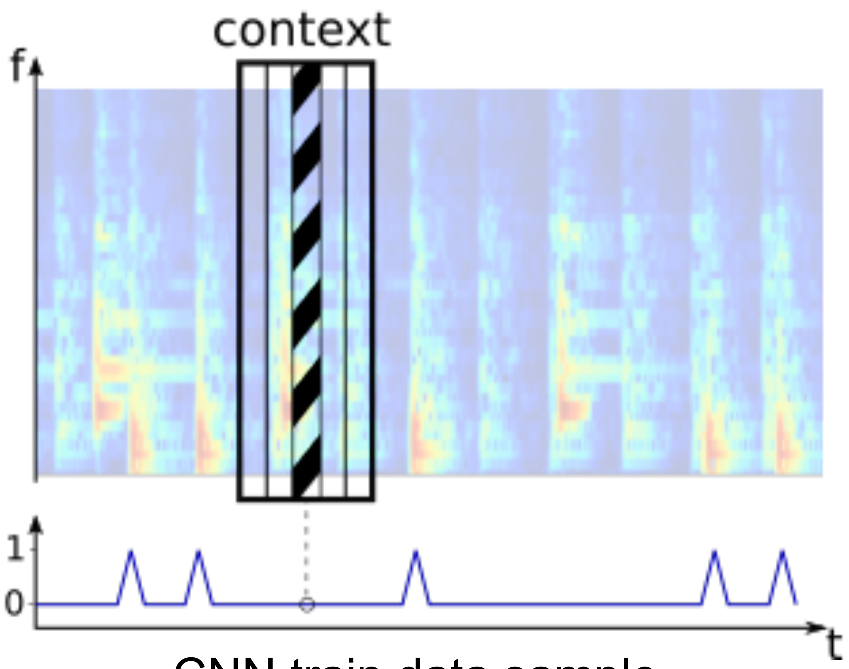

CNN train data sample

VGG - style architecture:

- 2 x conv: 32 x 3x3 (batch norm)
- max pool: 3x3
- 2 x conv: 64 x 3x3 (batch norm)
- max pool: 3x3
- 2 x dense: 256 ReLU
- output: 3 sigmoid

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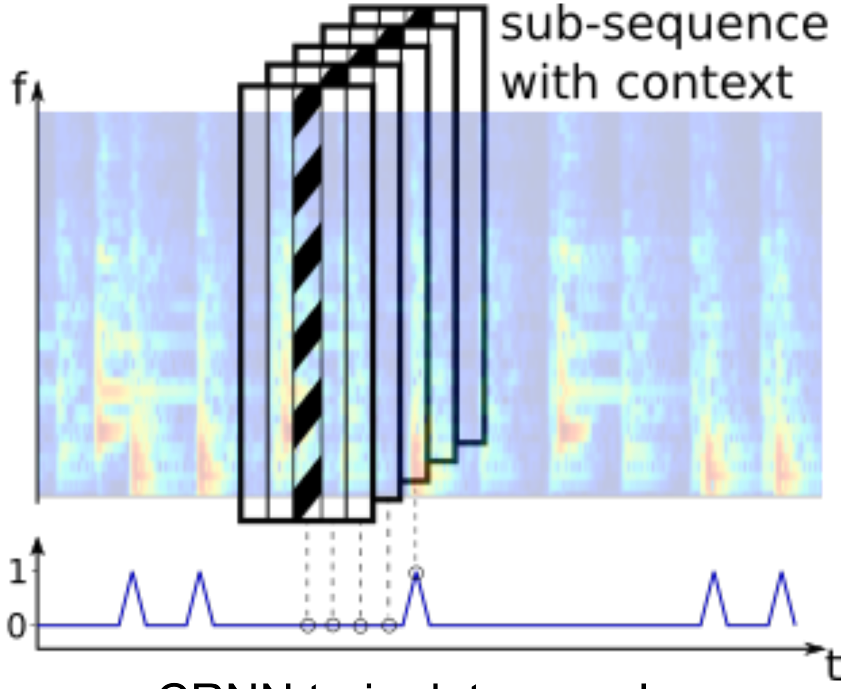

CRNN train data sample

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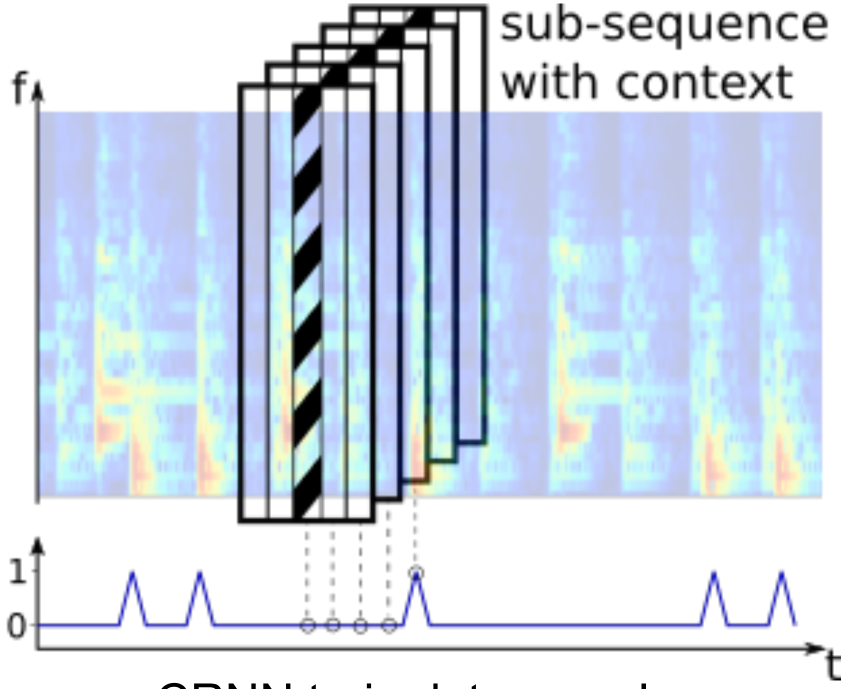

CRNN train data sample

stacked CNN + RNN architecture:

2 x conv: 32 x 3x3 (batch norm)

max pool: 3x3

2 x conv: 64 x 3x3 (batch norm)

max pool: 3x3

3 x RNN: 50 BD GRU

output: 3 sigmoid

WHY IS CONTEXT RELEVANT?

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- Instruments from the same class often **sound quite different**
  Similar sound for different instruments

snare drums: ♫

crash v.s. splash: ♫

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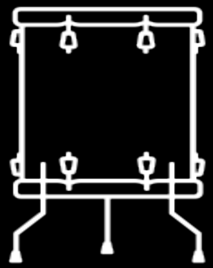
- ***Music Language Model***

BASS DRUM OR LOW TOM?

♫ ♫

1: bass drum



2: floor tom

3: ? ? ?

BASS DRUM OR LOW TOM?

♫ ♫

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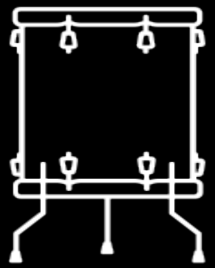

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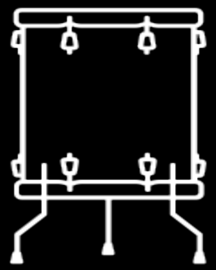

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BASS DRUM OR LOW TOM?

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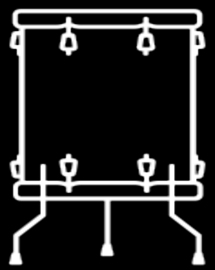

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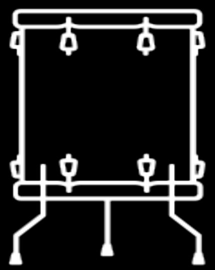

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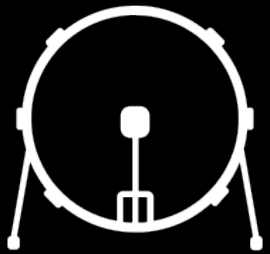

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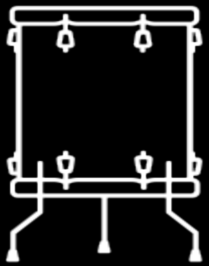

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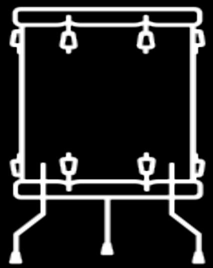
context

1: bass drum



2: floor tom

DATASETS

DATASETS

- **IDMT-SMT-Drums** [Dittmar and Gärtner 2014]
  - **Solo** drum tracks, recorded, synthesized, and sampled
  - 95 tracks, total: **24m**, onsets: 8004

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♫

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  - Recordings, three drummers on different drum kits, **optional accompaniment**
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♫

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ENST solo ♫ ♫

(harder!)

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ENST solo (harder!)

ENST acc. (difficult!)

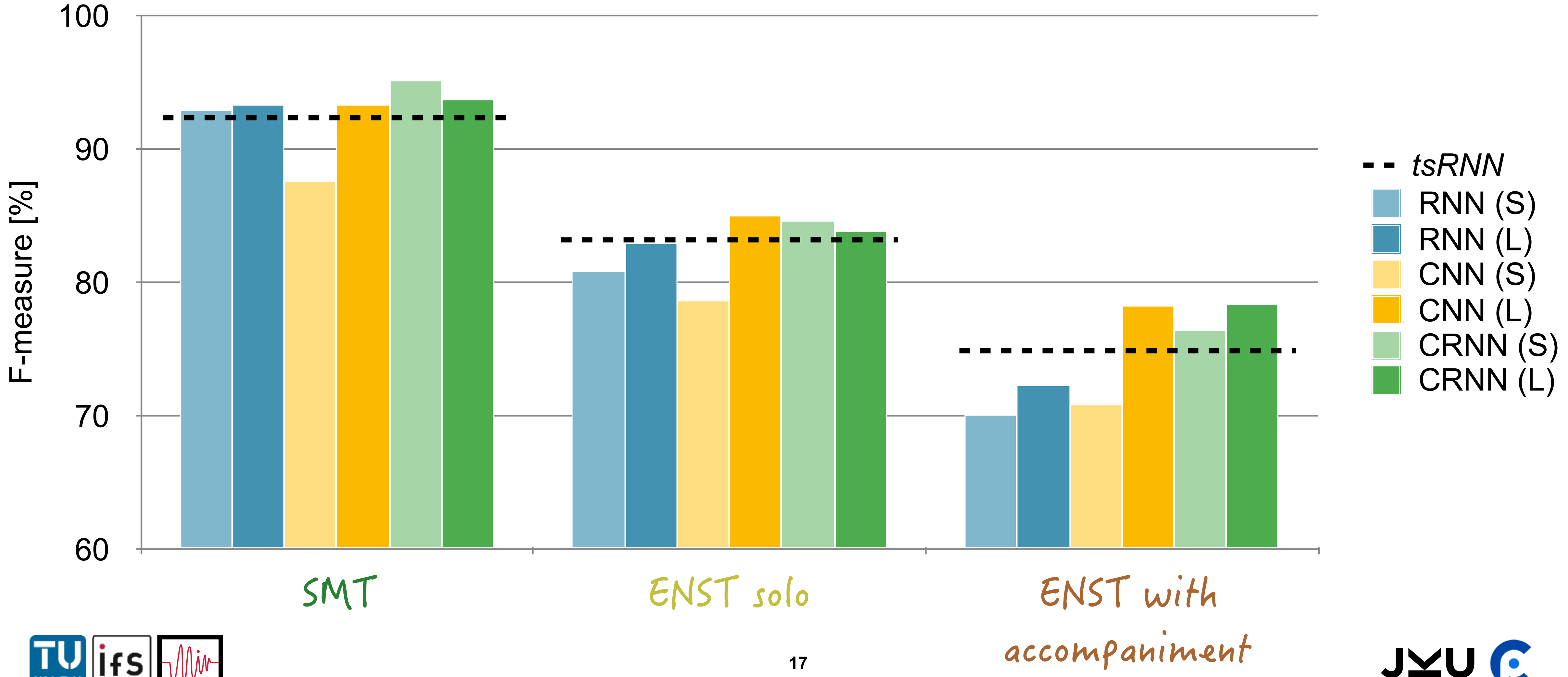
NETWORK MODELS

Architecture

	Frames	Context	Conv. Layers	Rec. Layers	Dense Layers
RNN (S)	100	—	—	2x50 GRU	—
RNN (L)	400	—	—	3x30 GRU	—
CNN (S)	—	9	2 x 32 3x3 filt. 3x3 max pooling 2 x 64 3x3 filt. 3x3 max pooling all w/ batch norm.	—	2x256
CNN (L)	—	25		—	2x256
CRNN (S)	100	9		2x50 GRU	—
CRNN (L)	400	13		3x60 GRU	—
tsRNN	*baseline* [Vogl et al. ICASSP'17]				

- Early stopping
- Batch normalization
- L2 norm
- Dropout
- ADAM optimizer

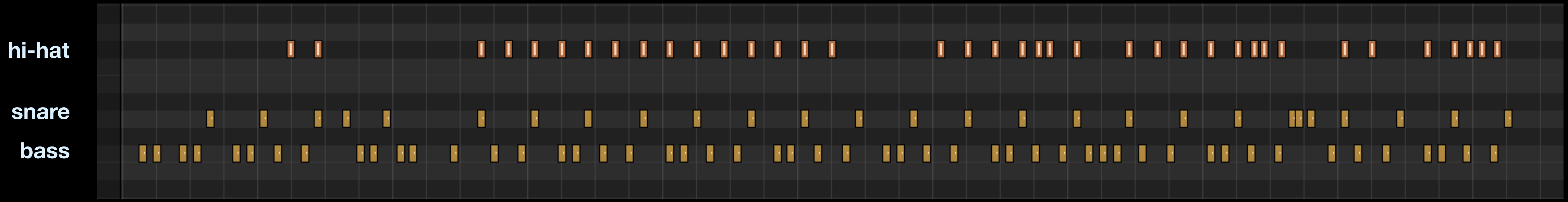
RESULTS



100
90
80
70
60
F-measure [%]
tsRNN
RNN (S)
RNN (L)
CNN (S)
CNN (L)
CRNN (S)
CRNN (L)
SMT
ENST solo
ENST with accompaniment

HOW DOES IT SOUND?

“Punk” MEDLEY DB



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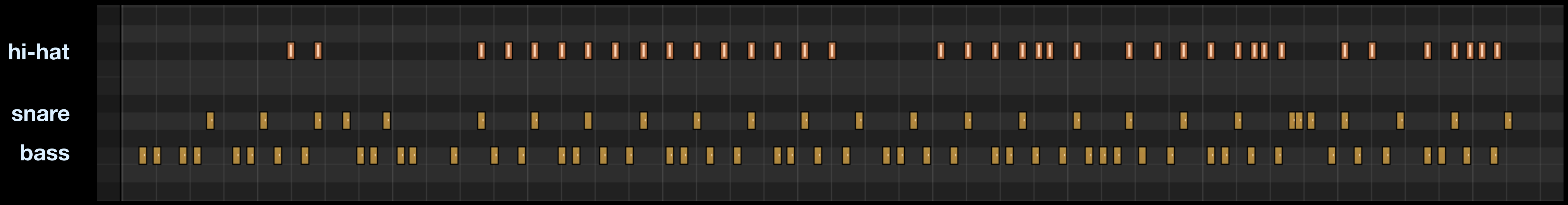
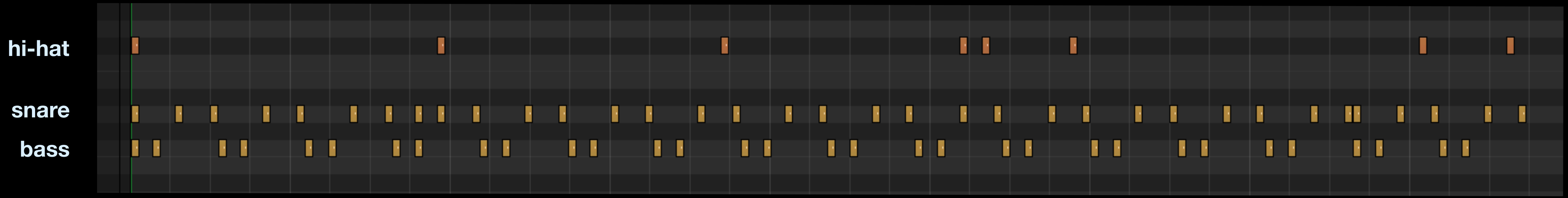


HOW DOES IT SOUND?

“Hendrix” MEDLEY DB



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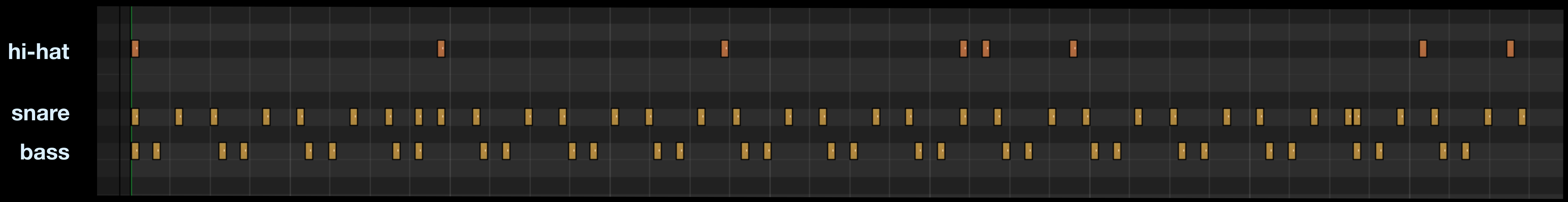
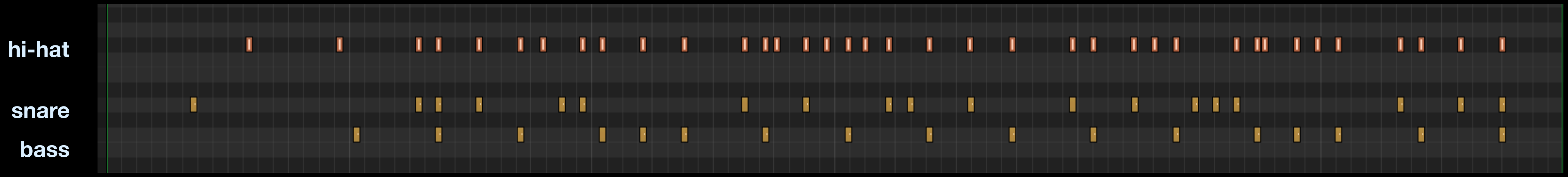
“Hendrix” MEDLEY DB



HOW DOES IT SOUND?

Alexa, play some music…



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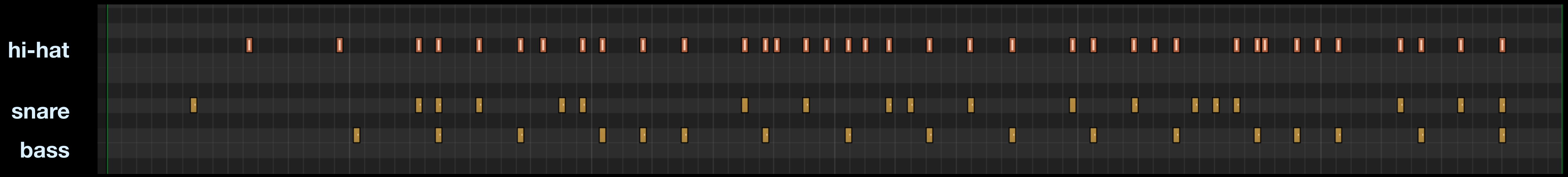

PART 1
AUTOMATIC DRUM TRANSCRIPTION

Task Definition, Problem Modeling, Architectures

PART 2
MULTI-TASK LEARNING

Metadata for Transcripts

LIMITATIONS OF CURRENT SYSTEMS

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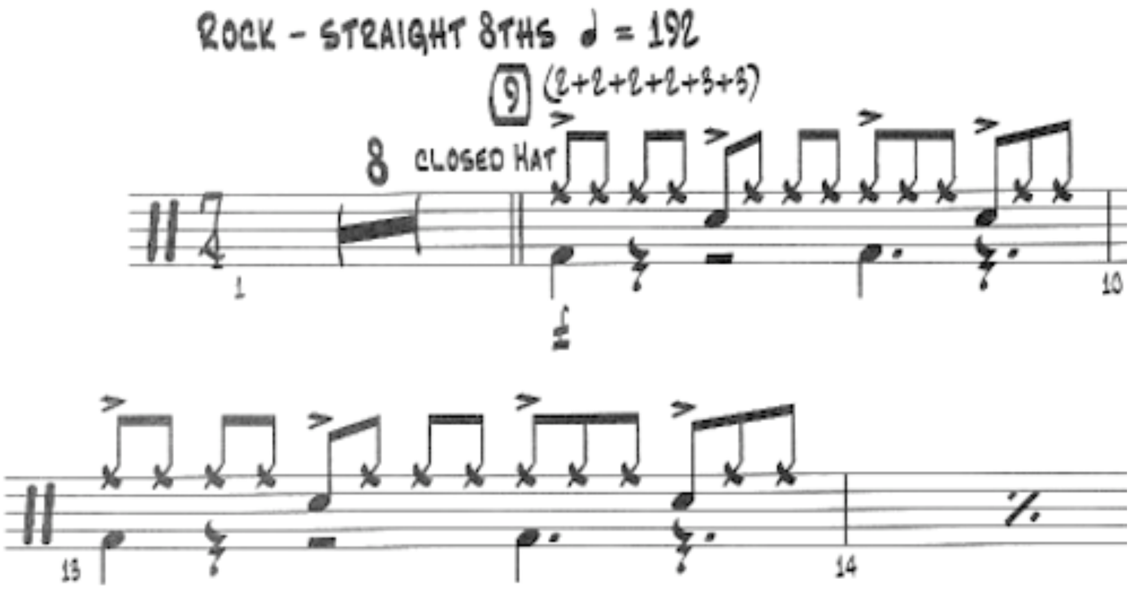
- Do not produce additional information for transcripts
  drum onset detection vs ***drum transcription***



LIMITATIONS OF CURRENT SYSTEMS

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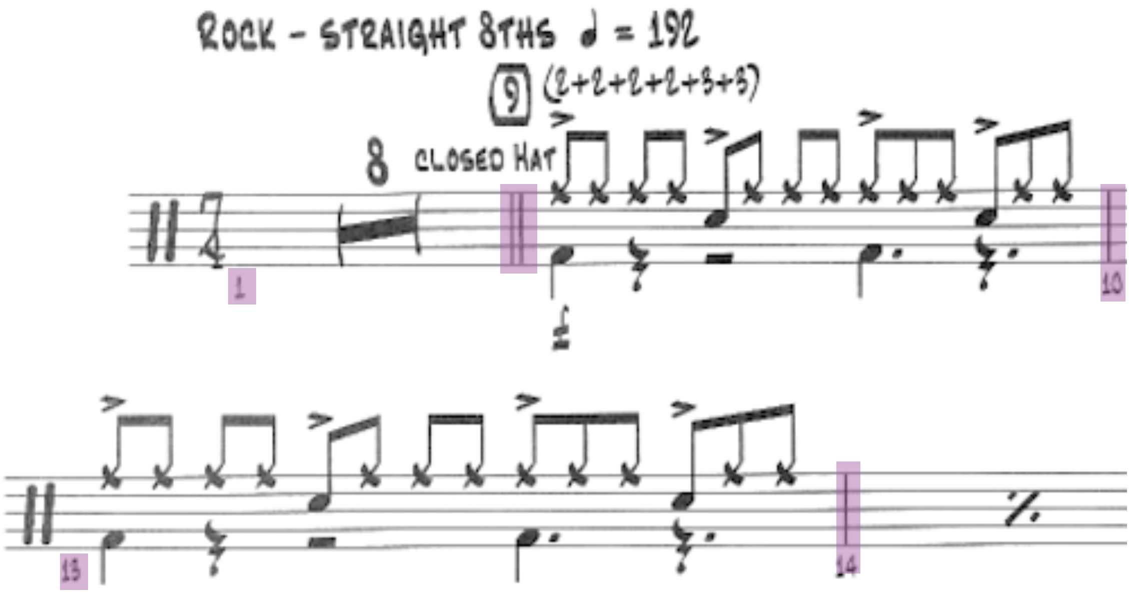

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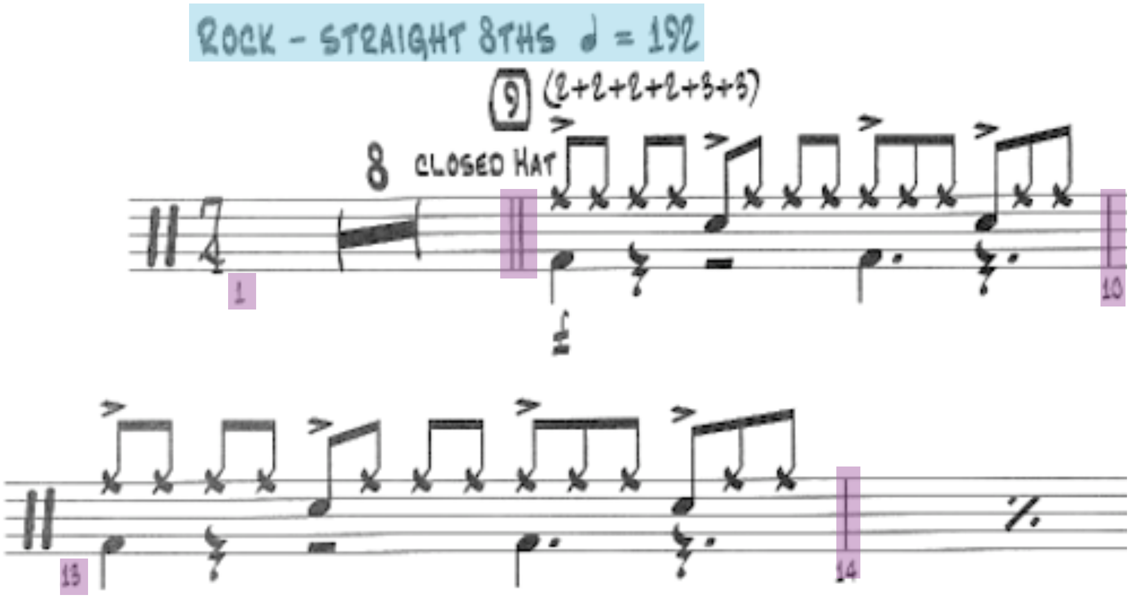

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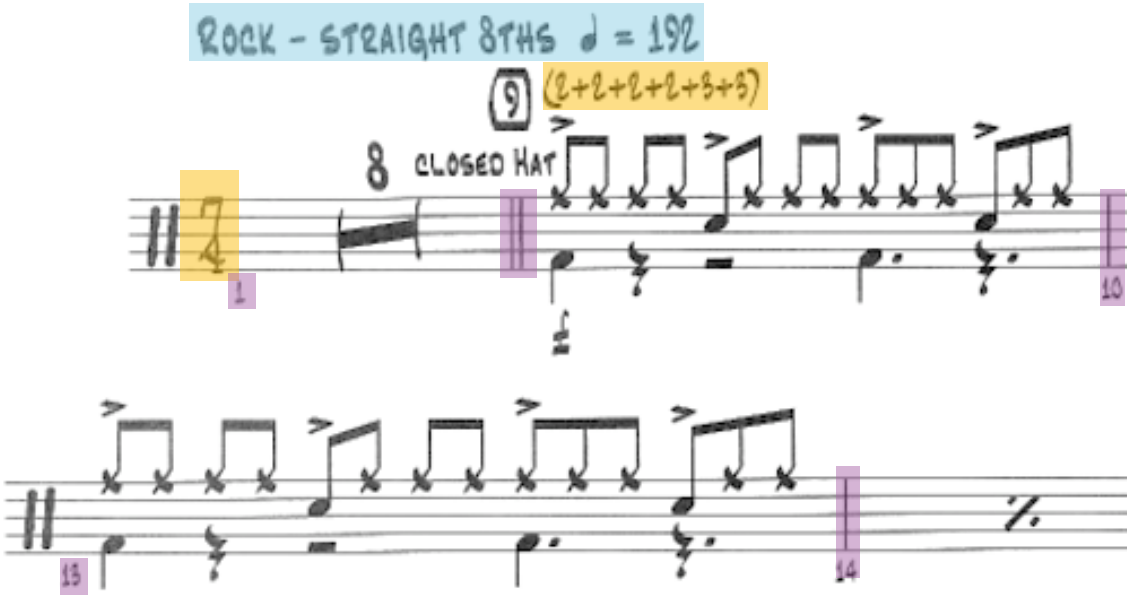

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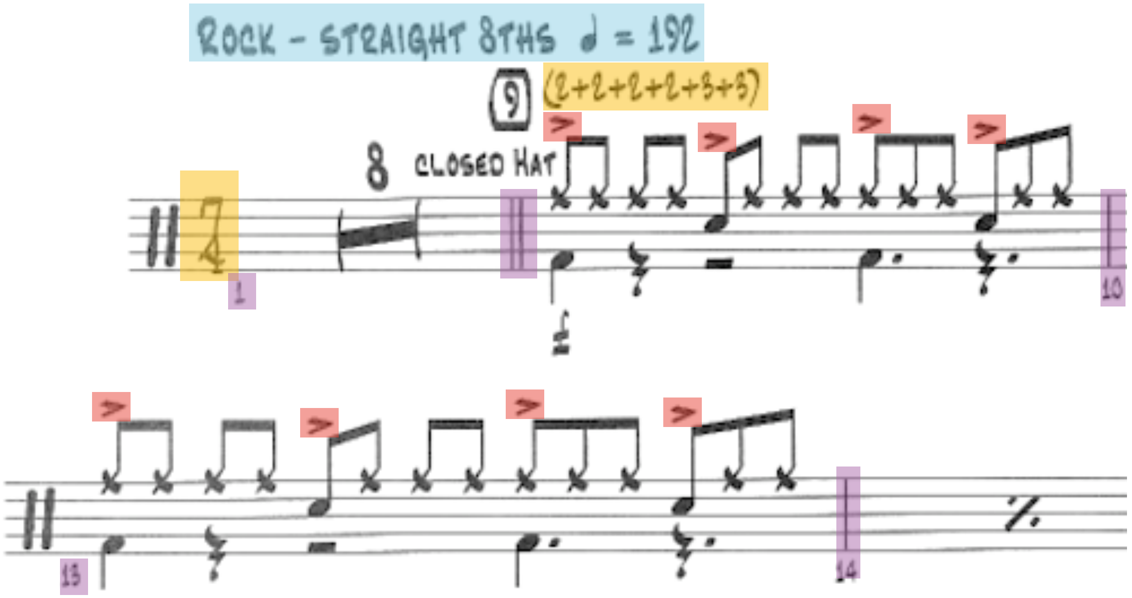

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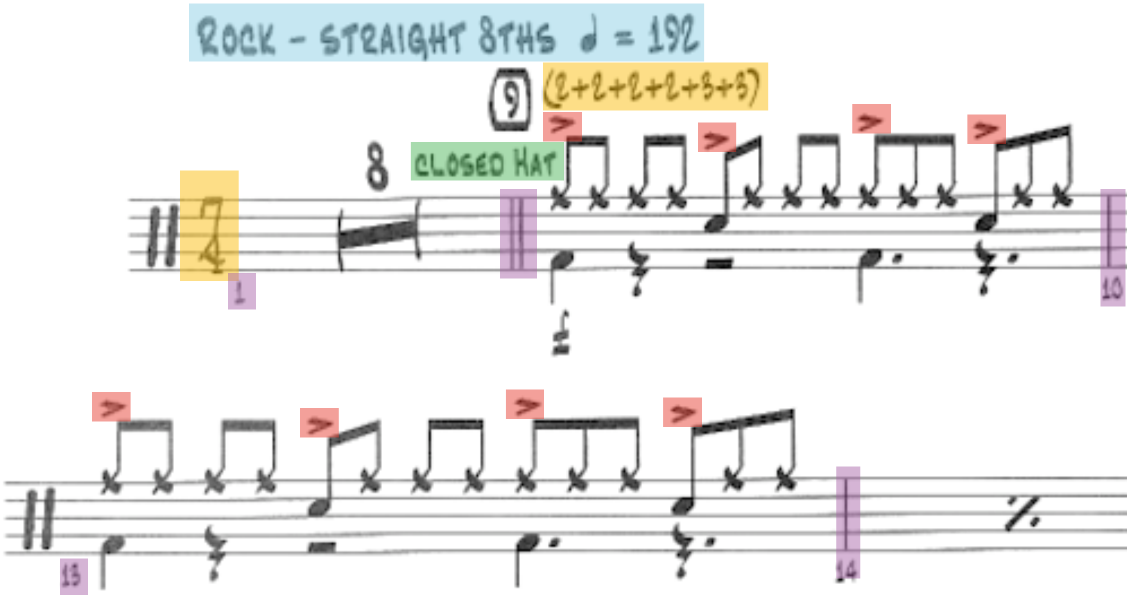

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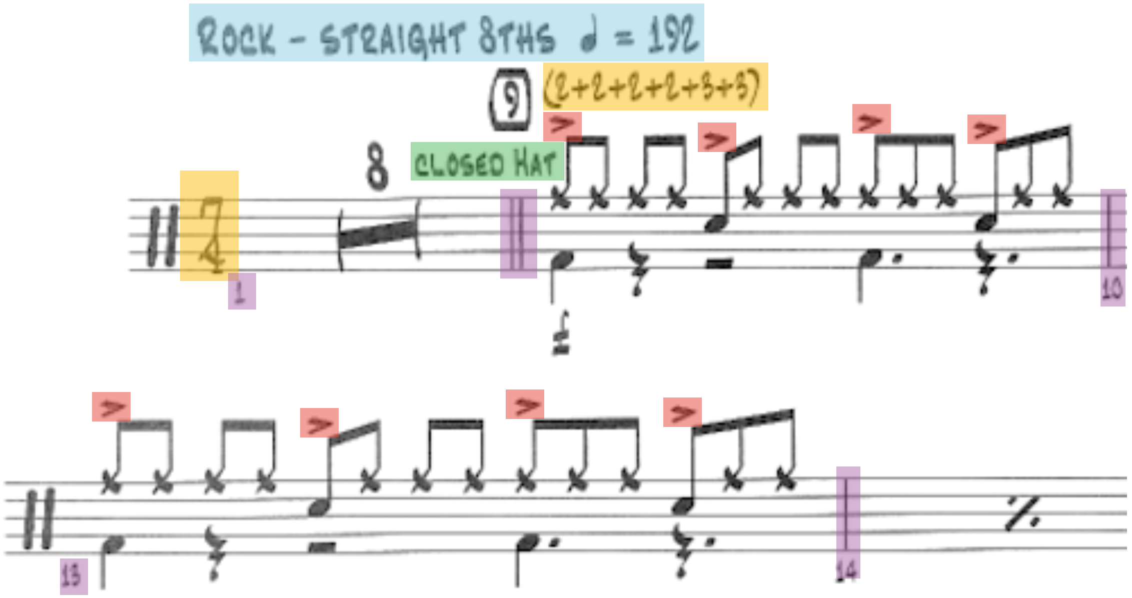
- Only three instrument classes



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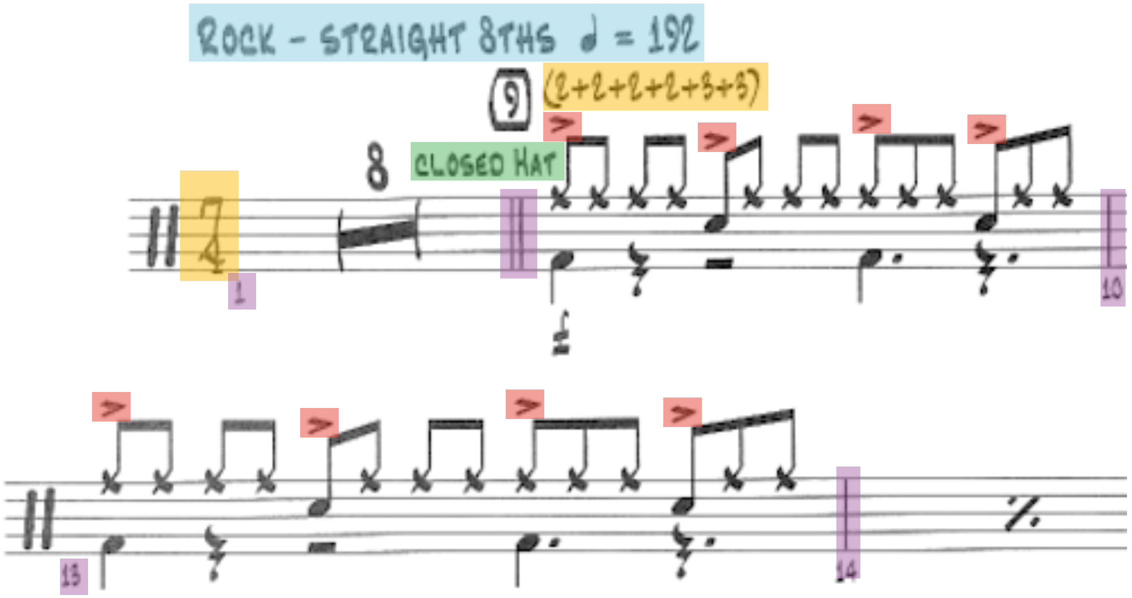

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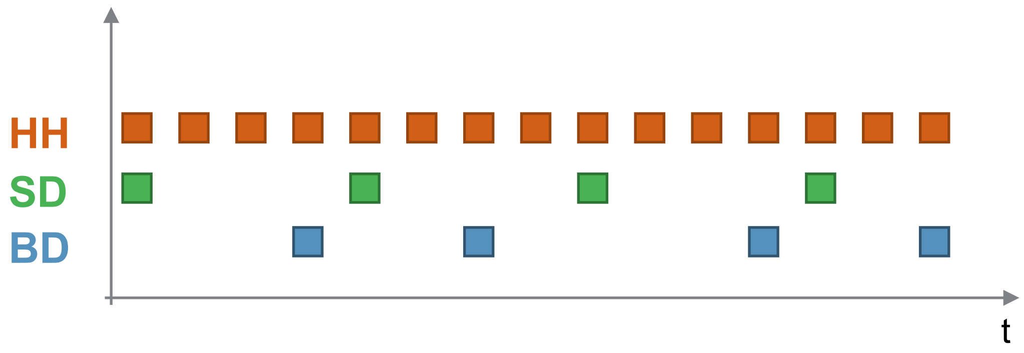

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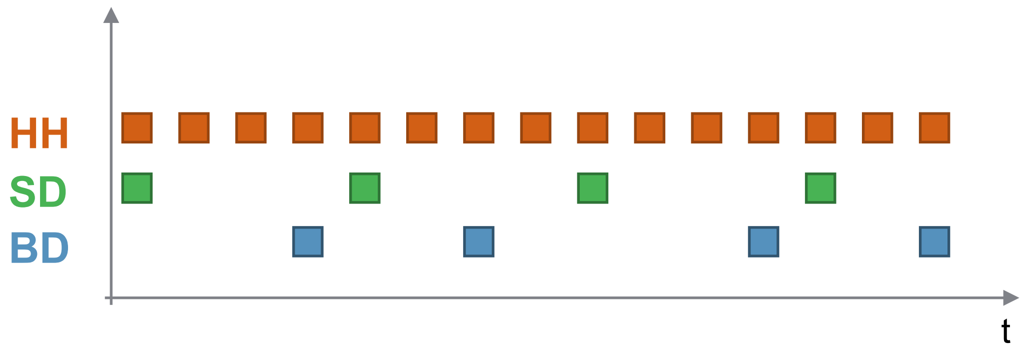

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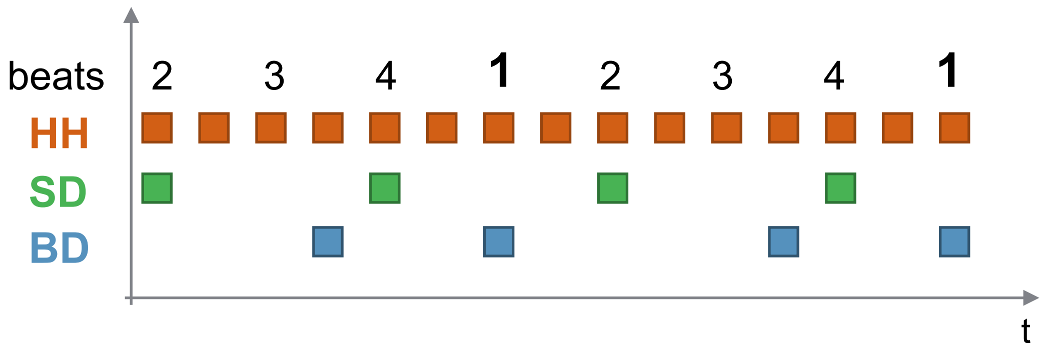
- Use **beat and downbeat tracking** to get:



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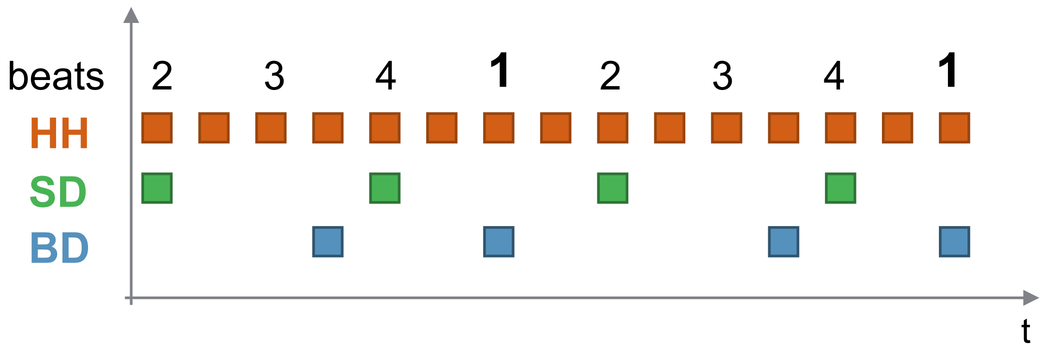

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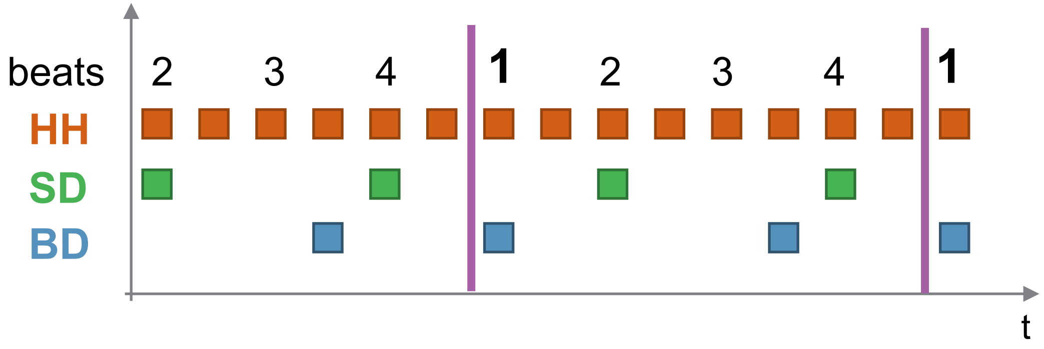

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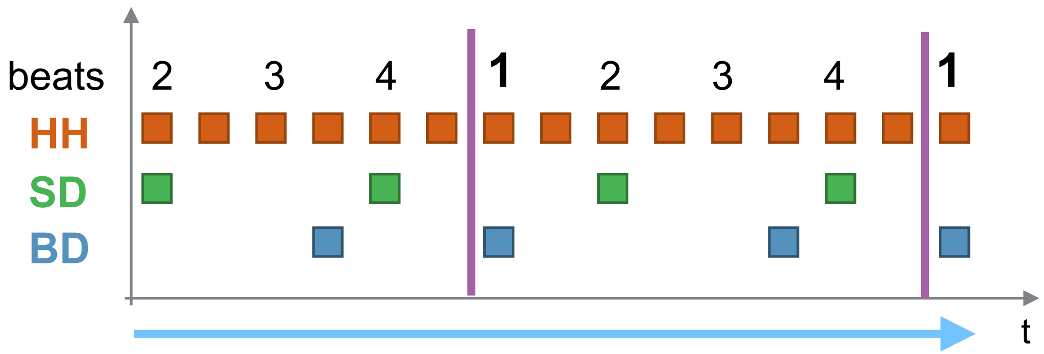

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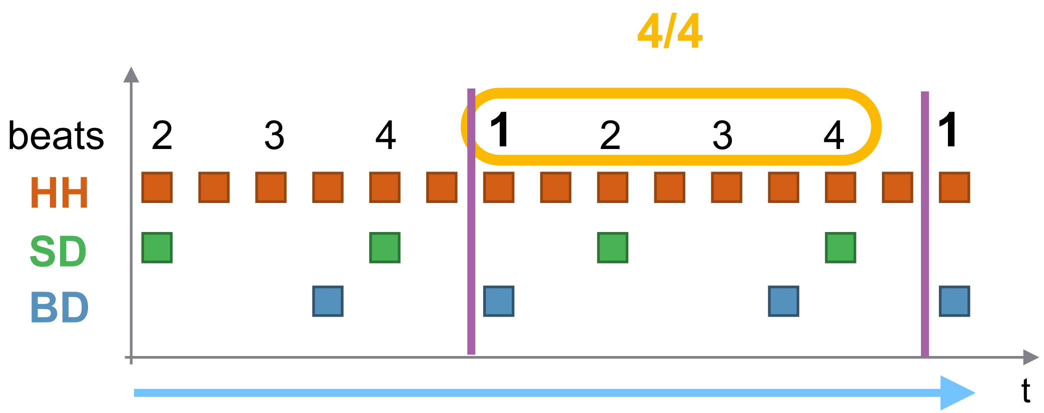

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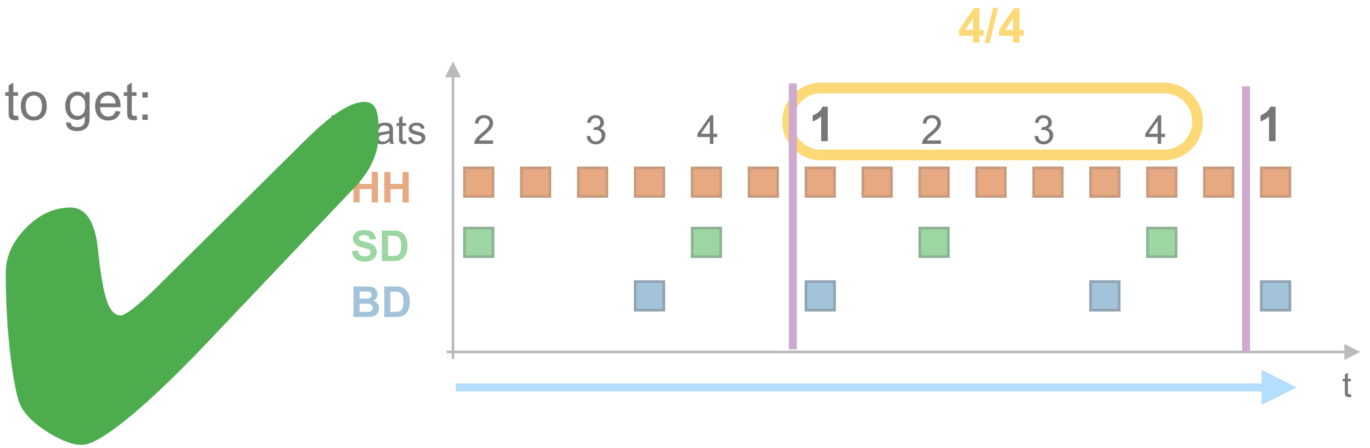
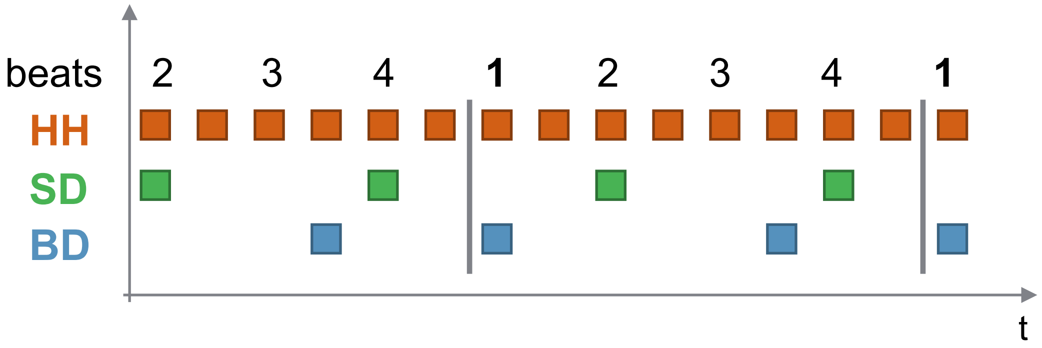


LEVERAGE BEAT INFORMATION



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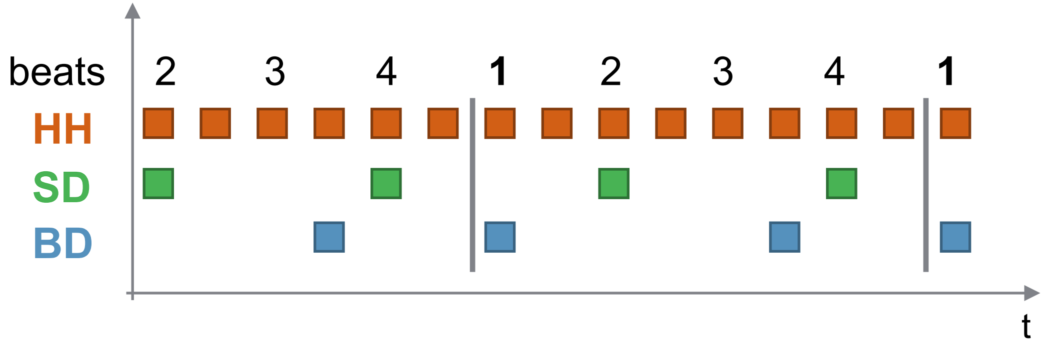

- Beats are **highly correlated** with drum patterns (drum onset locations / repetitive patterns)

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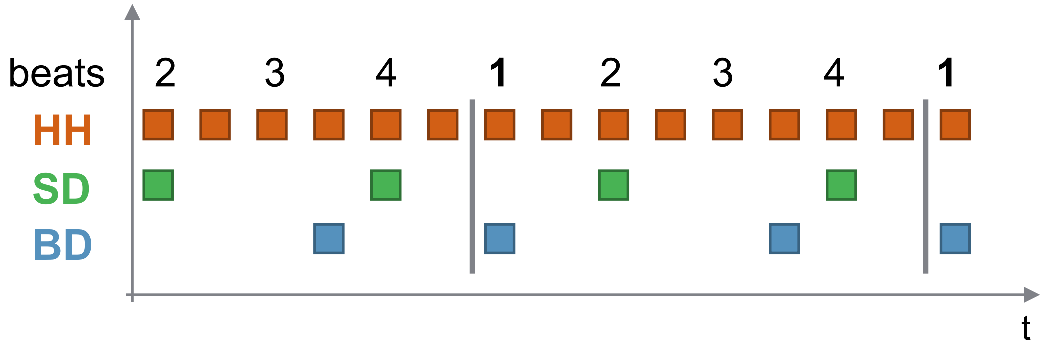

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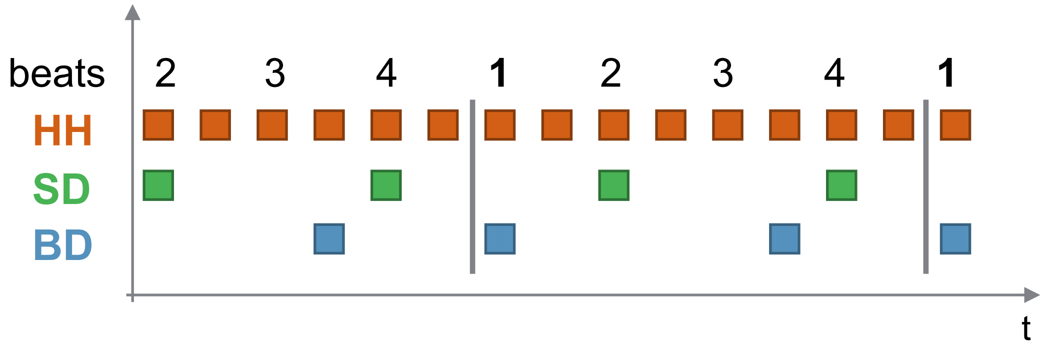

- Beats are **highly correlated** with drum patterns (drum onset locations / repetitive patterns)
- Assume that **prior knowledge** of beats is helpful for drum transcription
- Use **multi-task learning** for beats and drums

MULTI-TASK LEARNING

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  - **Improve performance** for each subtask ➡ context!

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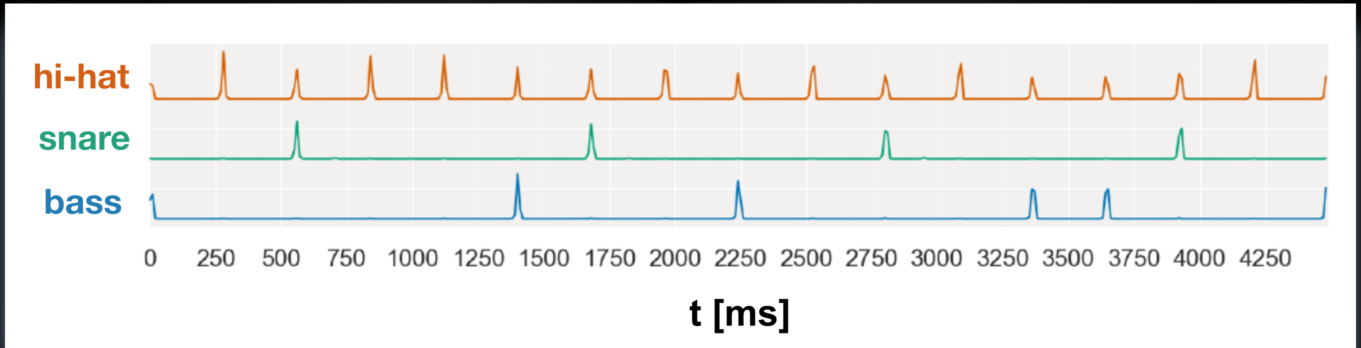

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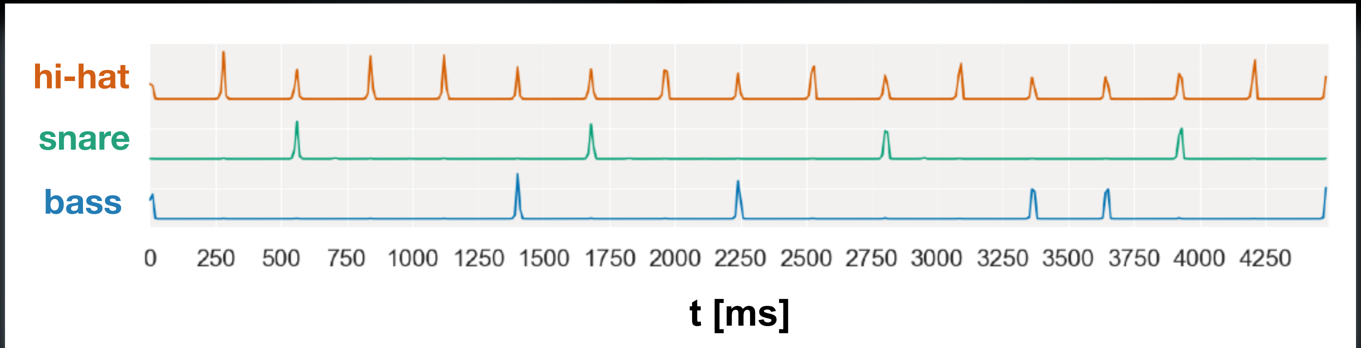

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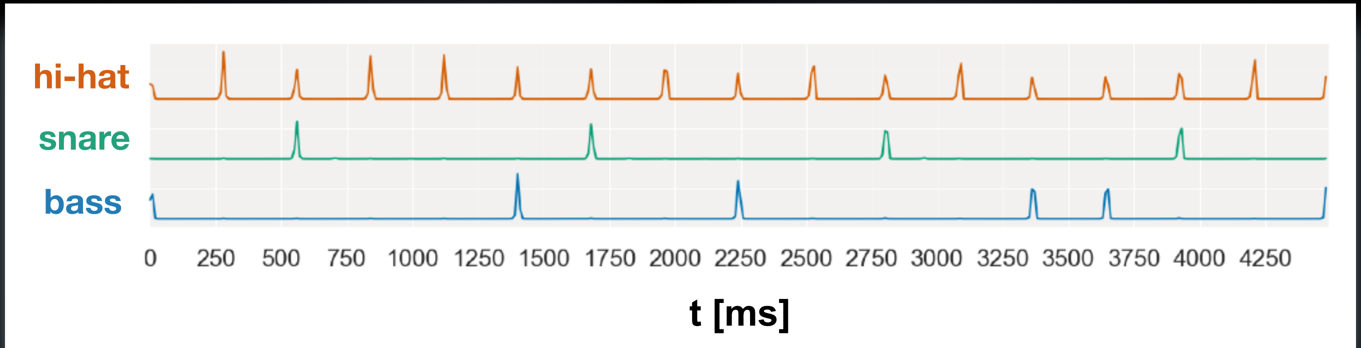

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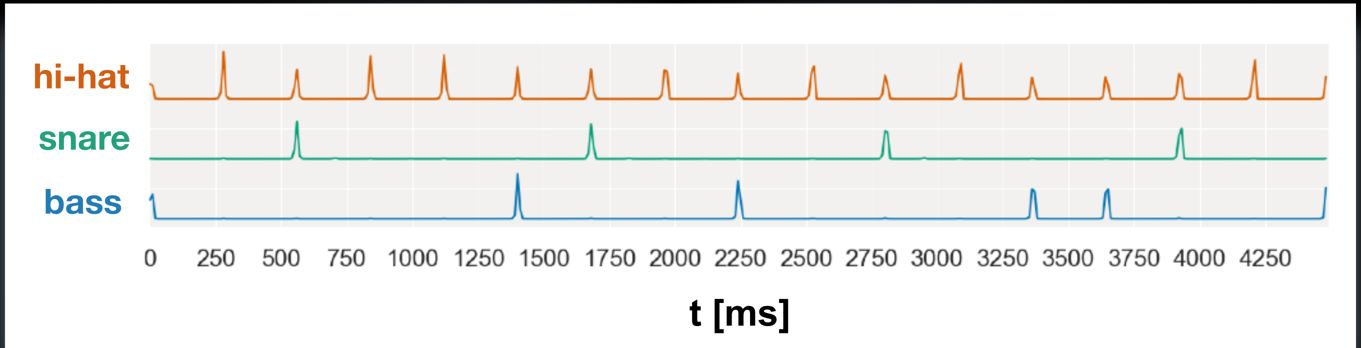
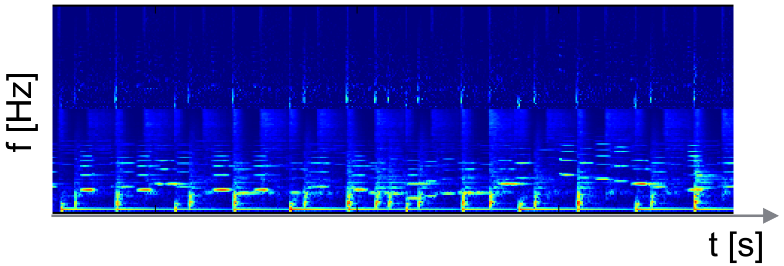
  - MIREX results show that **it works better**



MULTI-TASK EXPERIMENTS

input

output



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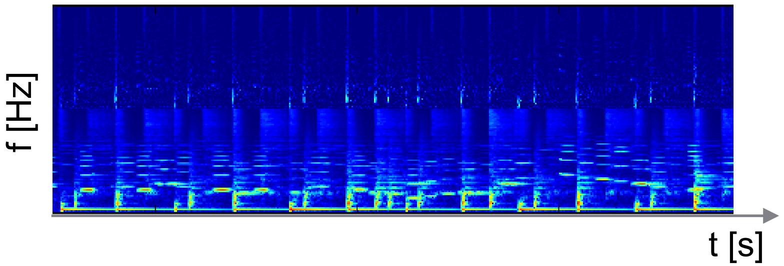
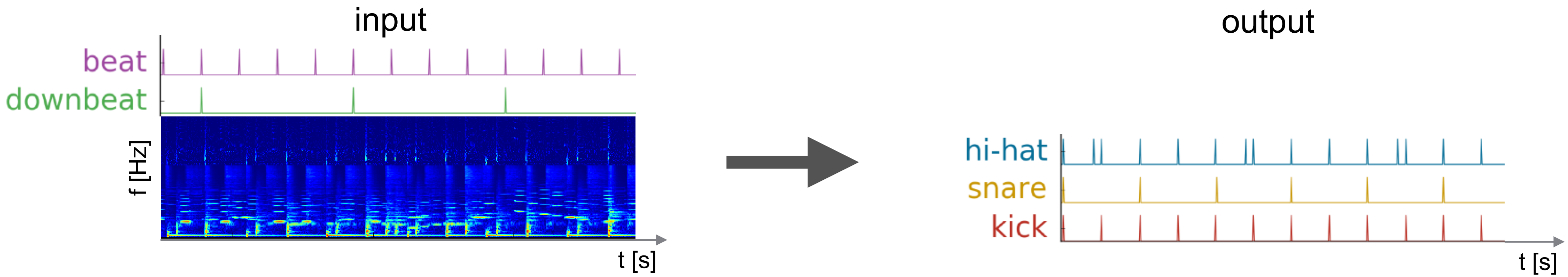


- Three experiments:

MULTI-TASK EXPERIMENTS

- Three experiments:
  - Training on drum targets (***DT***)

MULTI-TASK EXPERIMENTS



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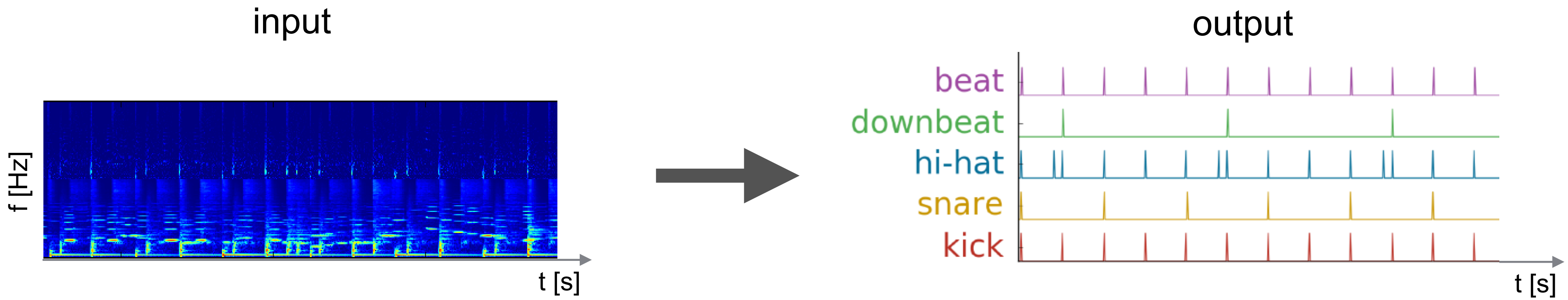
MULTI-TASK EXPERIMENTS



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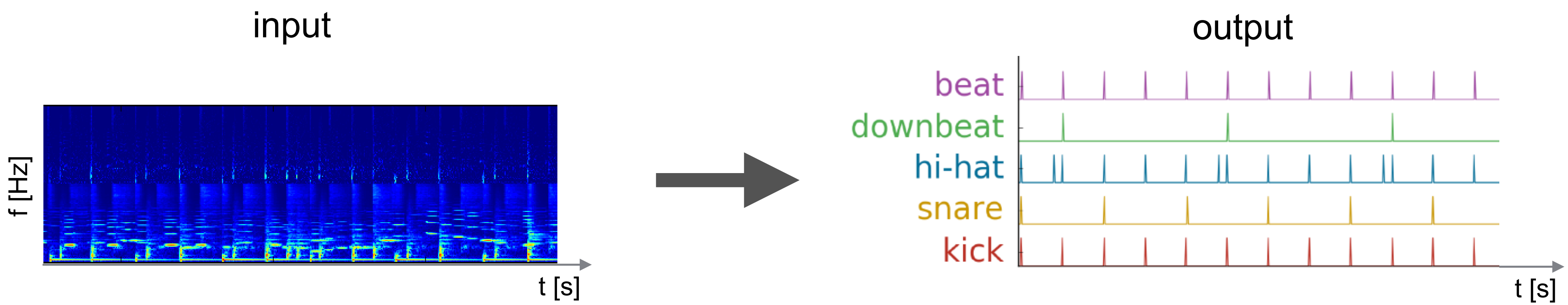
MULTI-TASK EXPERIMENTS



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- Expected increase in performance for *BF* compared to *DT*

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- Three experiments:
  - Training on drum targets (***DT***)
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- Expected increase in performance for ***BF*** compared to ***DT***
- Desirable increase in performance for ***MT*** compared to ***DT***

NEW DATASETS

NEW!

RBMA13-Drums [http://ifs.tuwien.ac.at/~vogl/datasets/]

- Free music from the 2013 Red Bull Music Academy, different styles
- 27 tracks, total: **1h 43m**, onsets: 24365
- **drum, beat, and downbeat** annotations

♫ ♫

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RBMA
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♫ ♫

RBMA
(super difficult!)

RESULTS

Model	DT	BF	MT
RNN (S)	59.8	63.6	64.6
RNN (L)	61.8	64.5	64.3
CNN (S)	66.2	66.7	63.3
CNN (L)	66.8	65.2	64.8
CRNN (S)	65.2	66.1	66.9
CRNN (L)	**67.3**	**68.4**	**67.2**

(Columns: Experiment)

% F-measure for drum onsets, tolerance: ±20ms, 3-fold cross-validation

DT … drum transcription
BF … DT plus beats as input features
MT … DT and beat detection multi-tasking

RESULTS

RBMA
(super difficult!)

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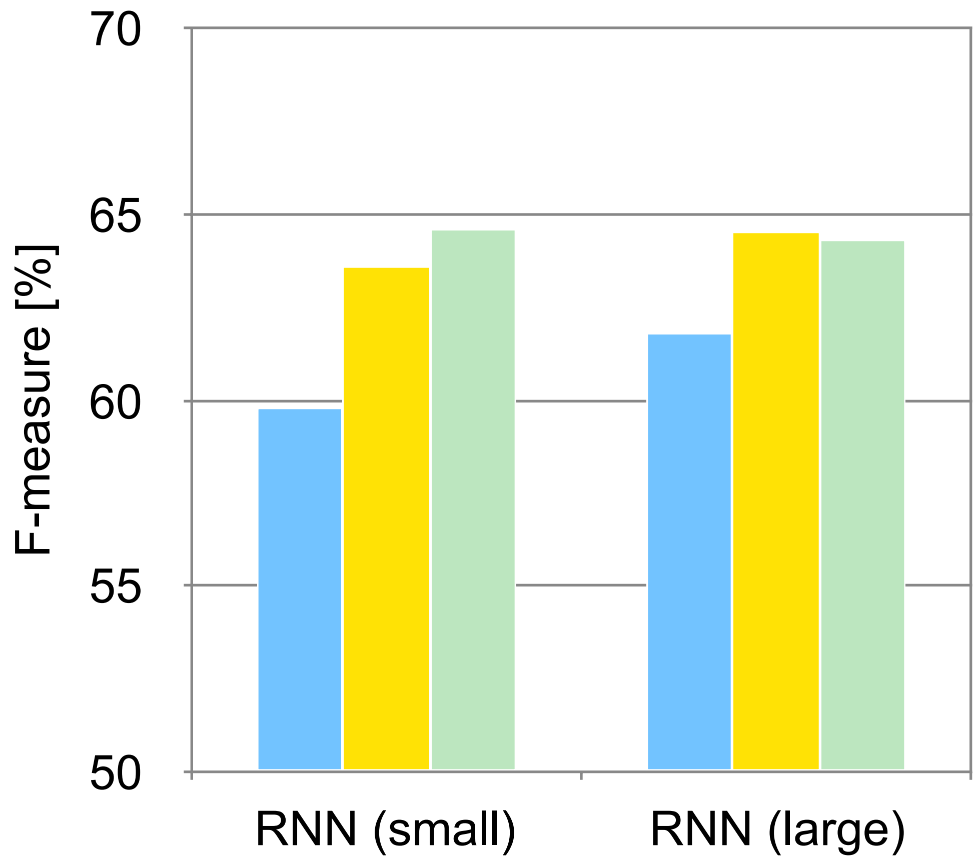

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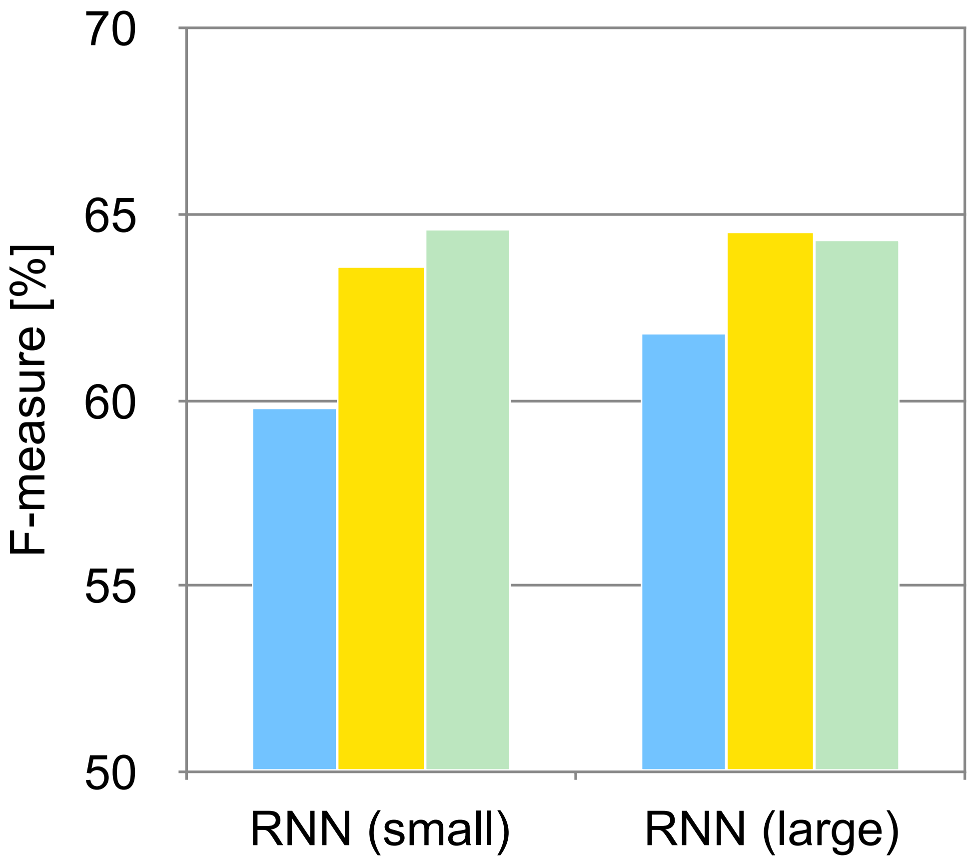
Impact of **beats for RNN**s:



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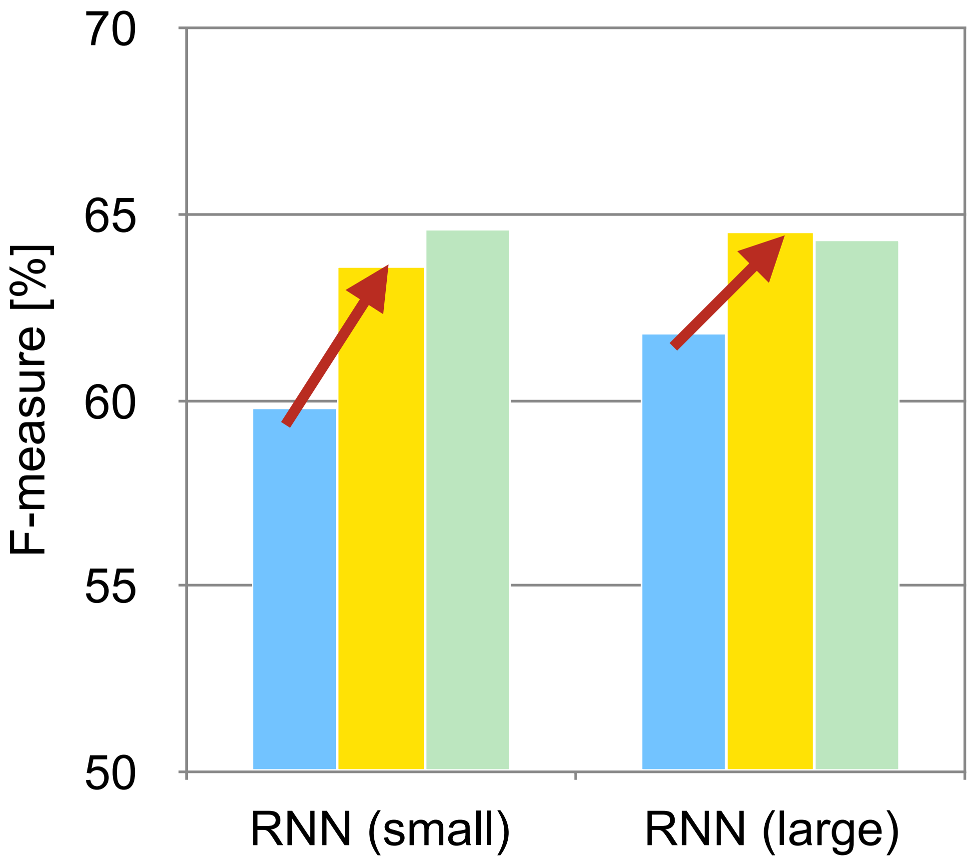
Impact of **beats for RNN**s:

- BF improves for both models ✔



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BF … DT plus beats as input features
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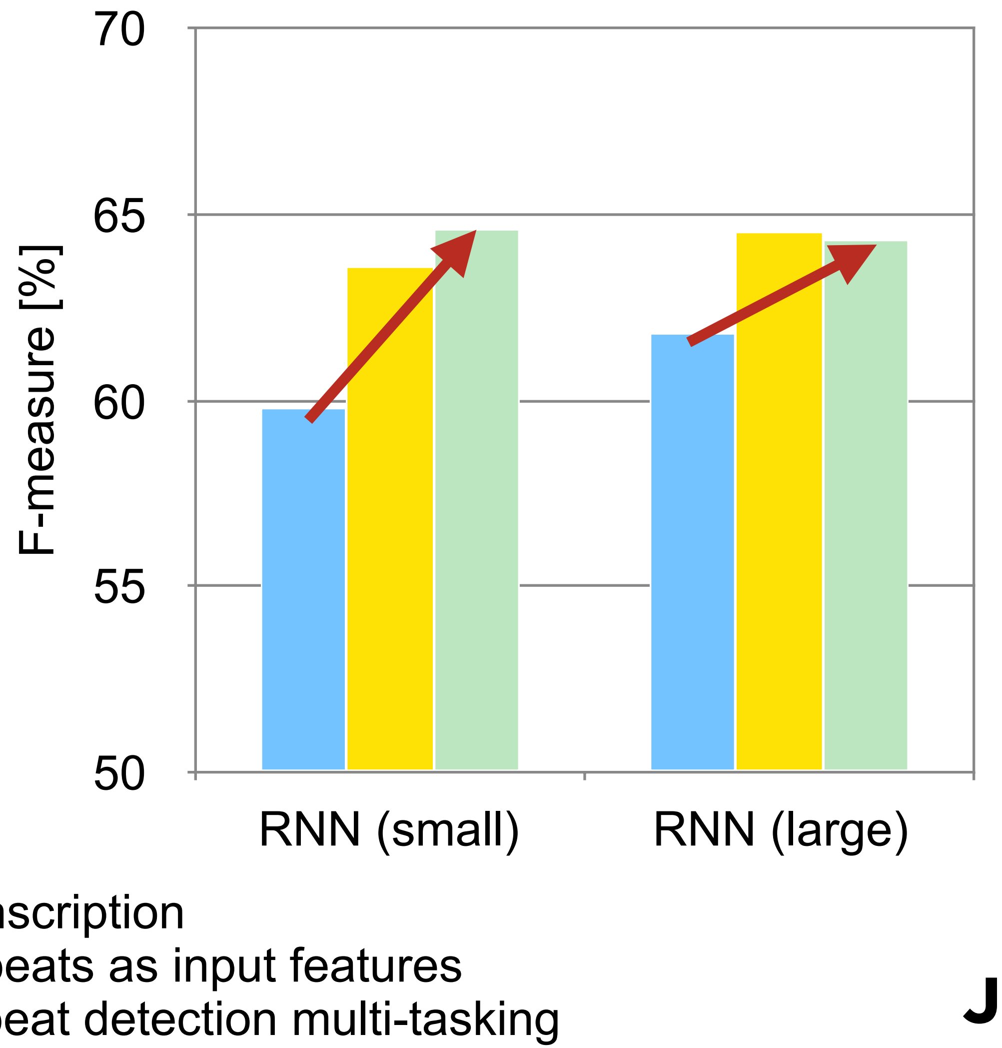
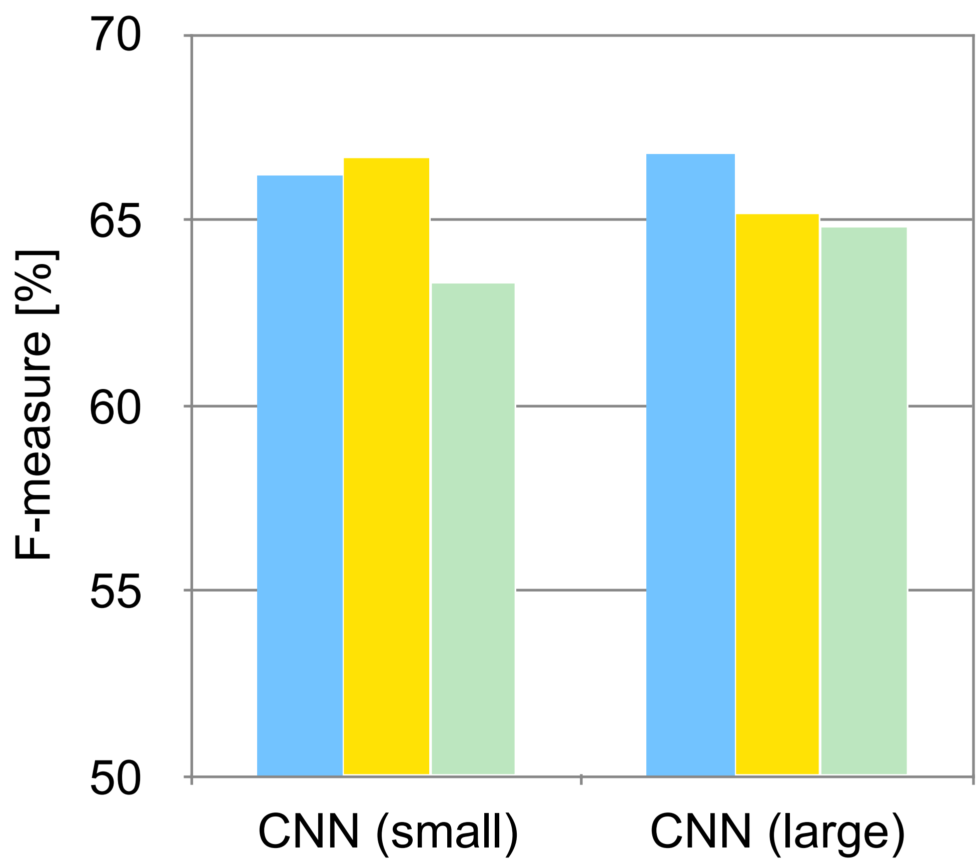
RESULTS: RNNs

Impact of **beats for RNN**s:

- **BF** improves for both models ✔
- **MT** improves for both models ✔



RESULTS: CNNs



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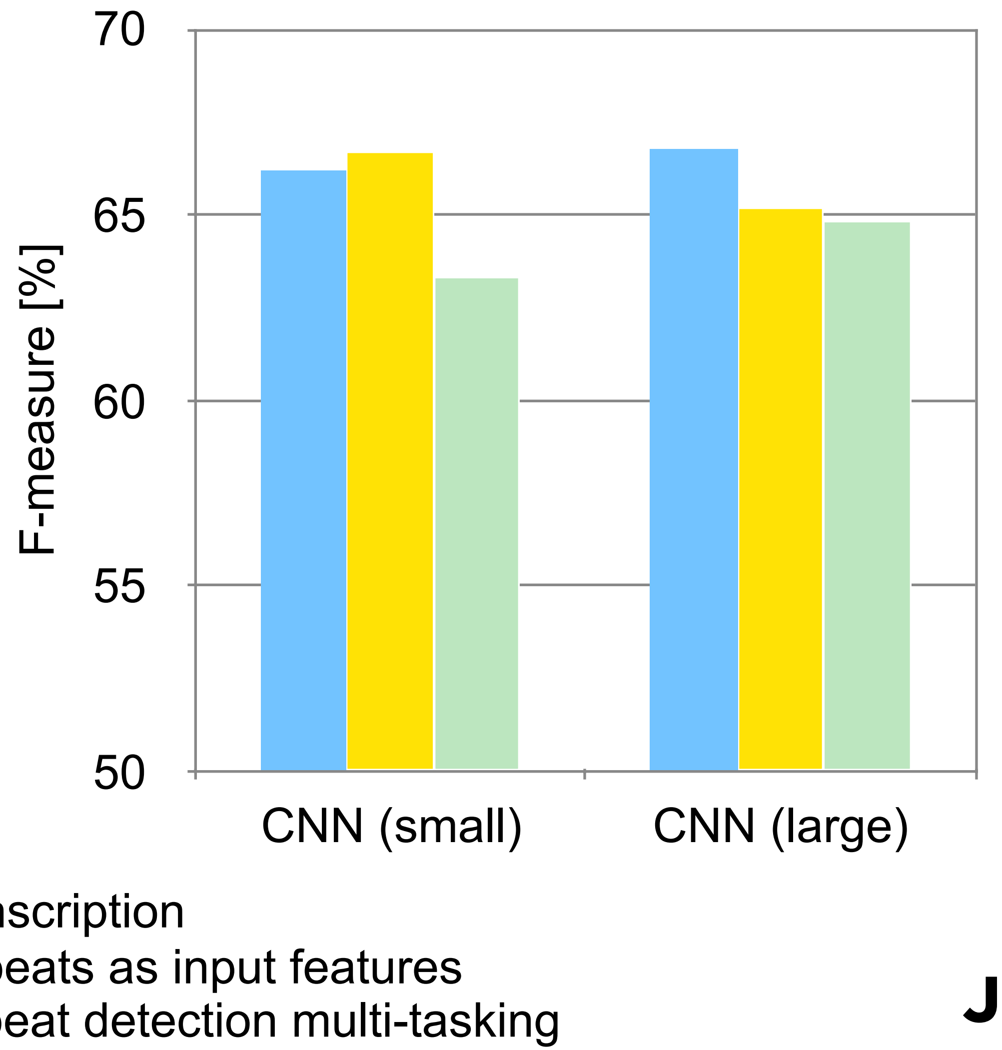
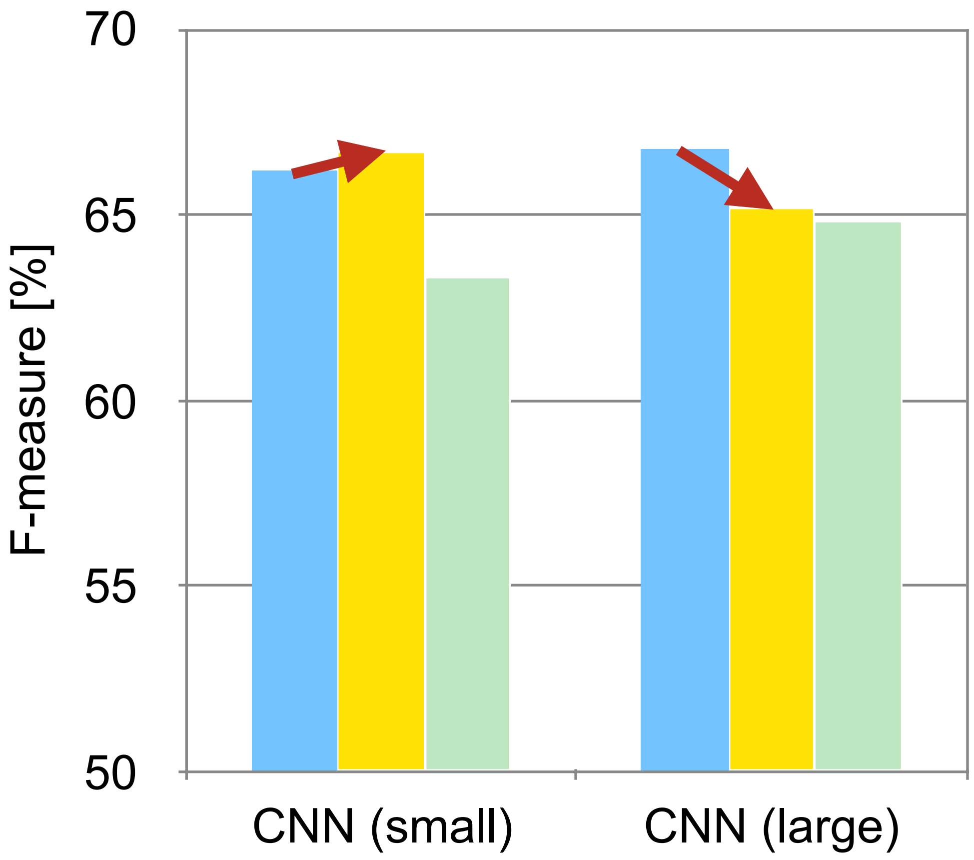
Impact of **beats for CNNs**:



RESULTS: CNNs

Impact of **beats for CNN**s:

- BF inconsistent



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RESULTS: CNNs

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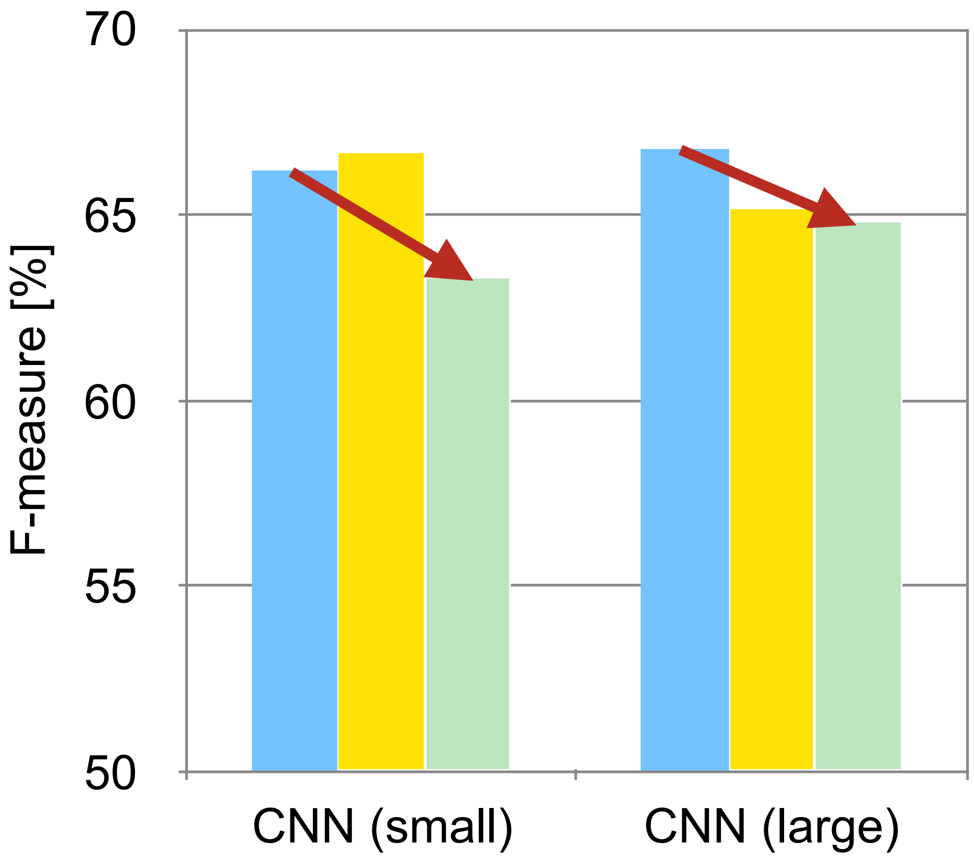

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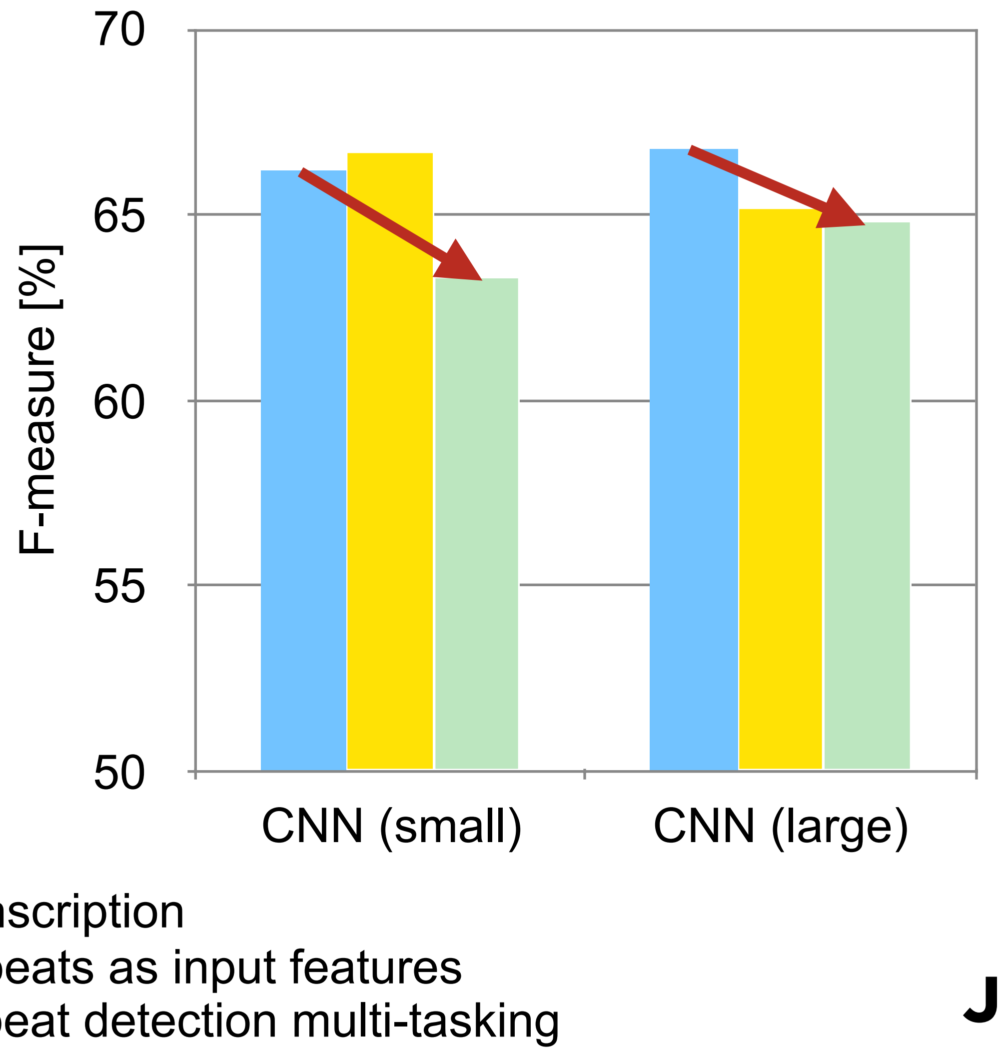
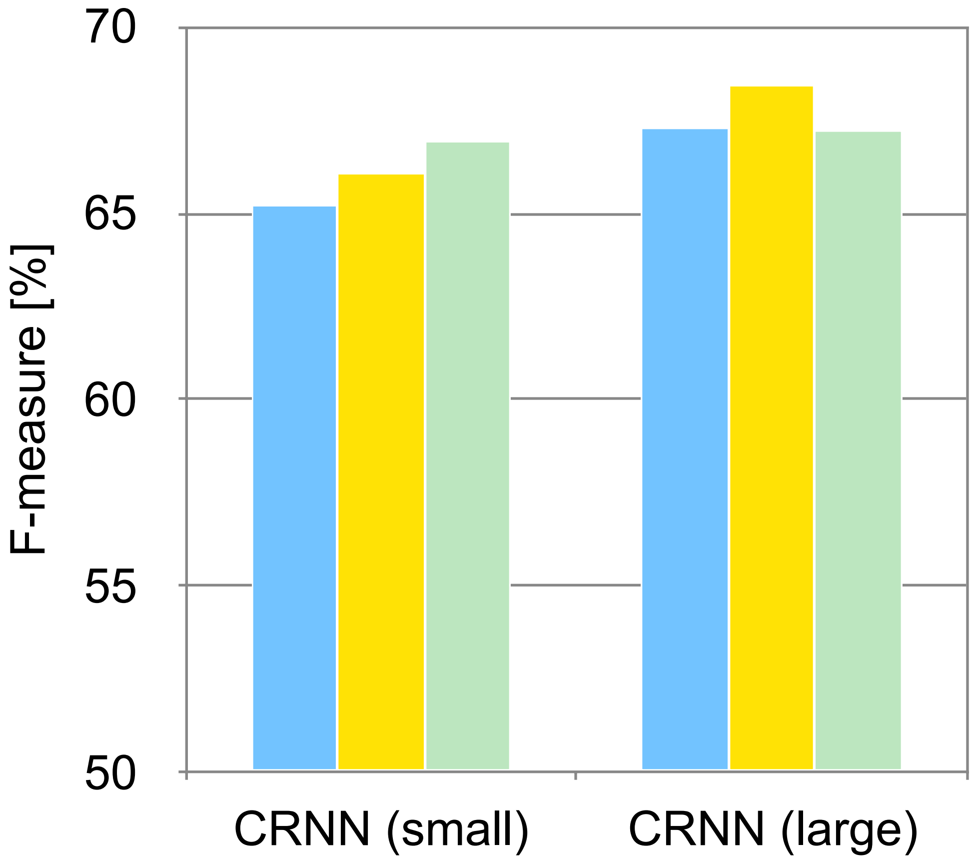
- Expected: CNNs have too little context for beats



RESULTS: CRNNs



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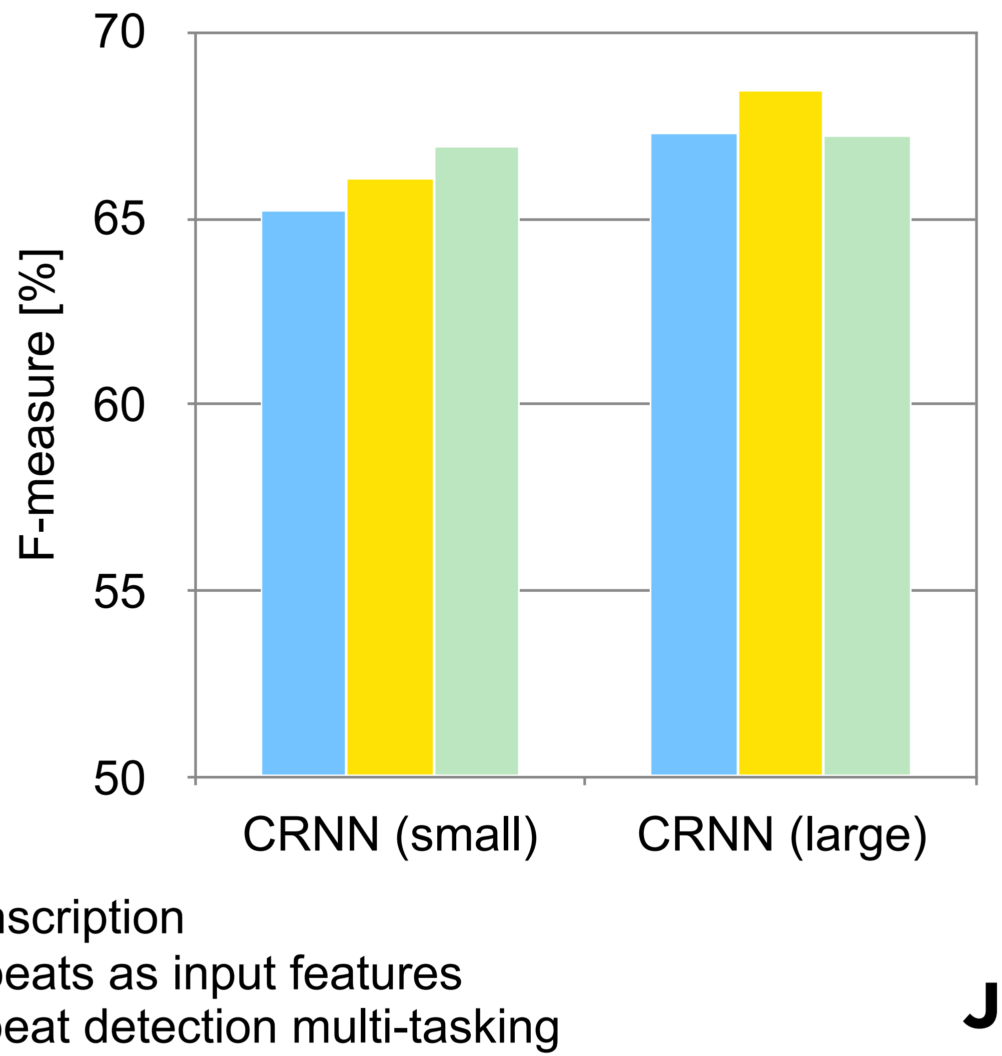

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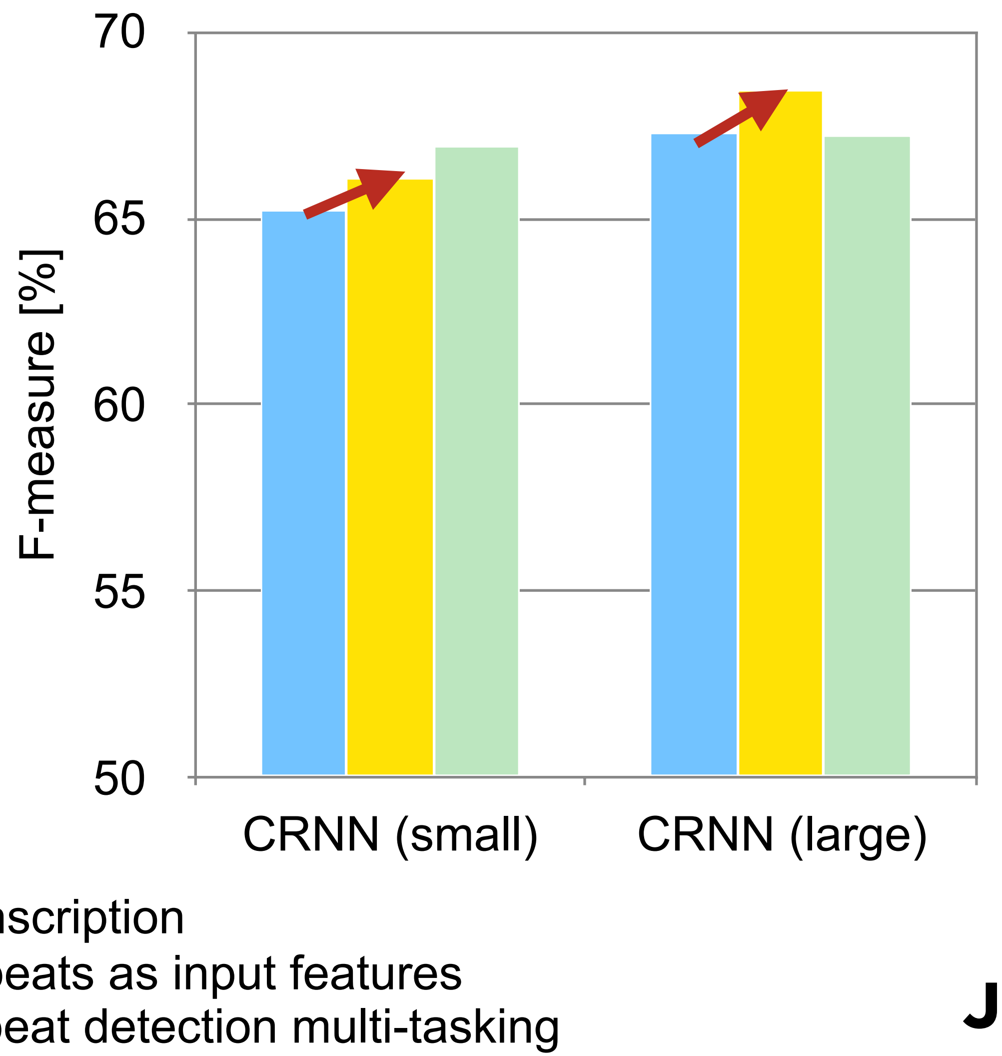
Impact of **beats for CRNNs**:

- BF improves for both models ✔



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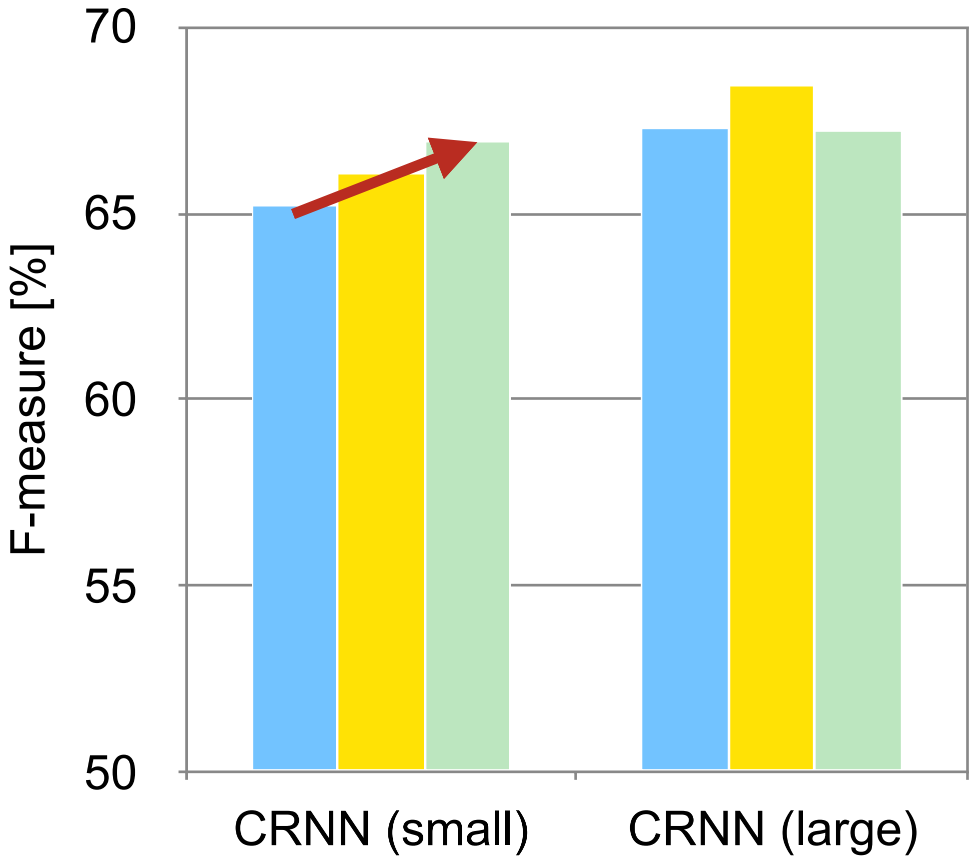

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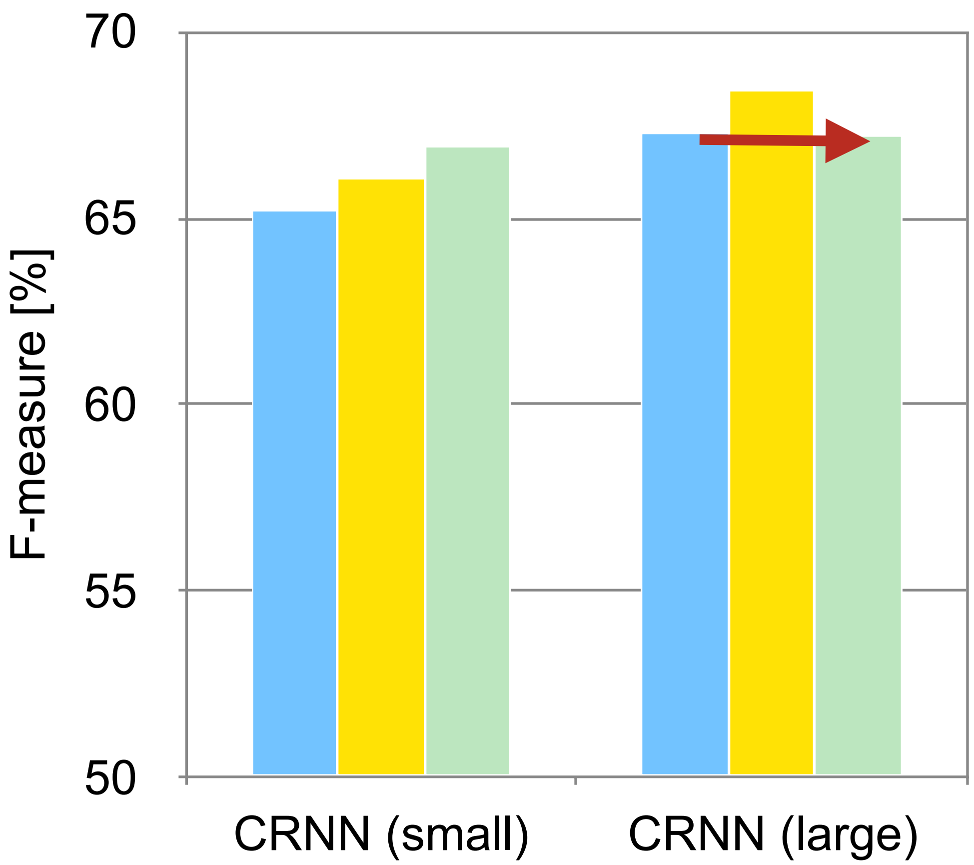
- MT equal for large model ?



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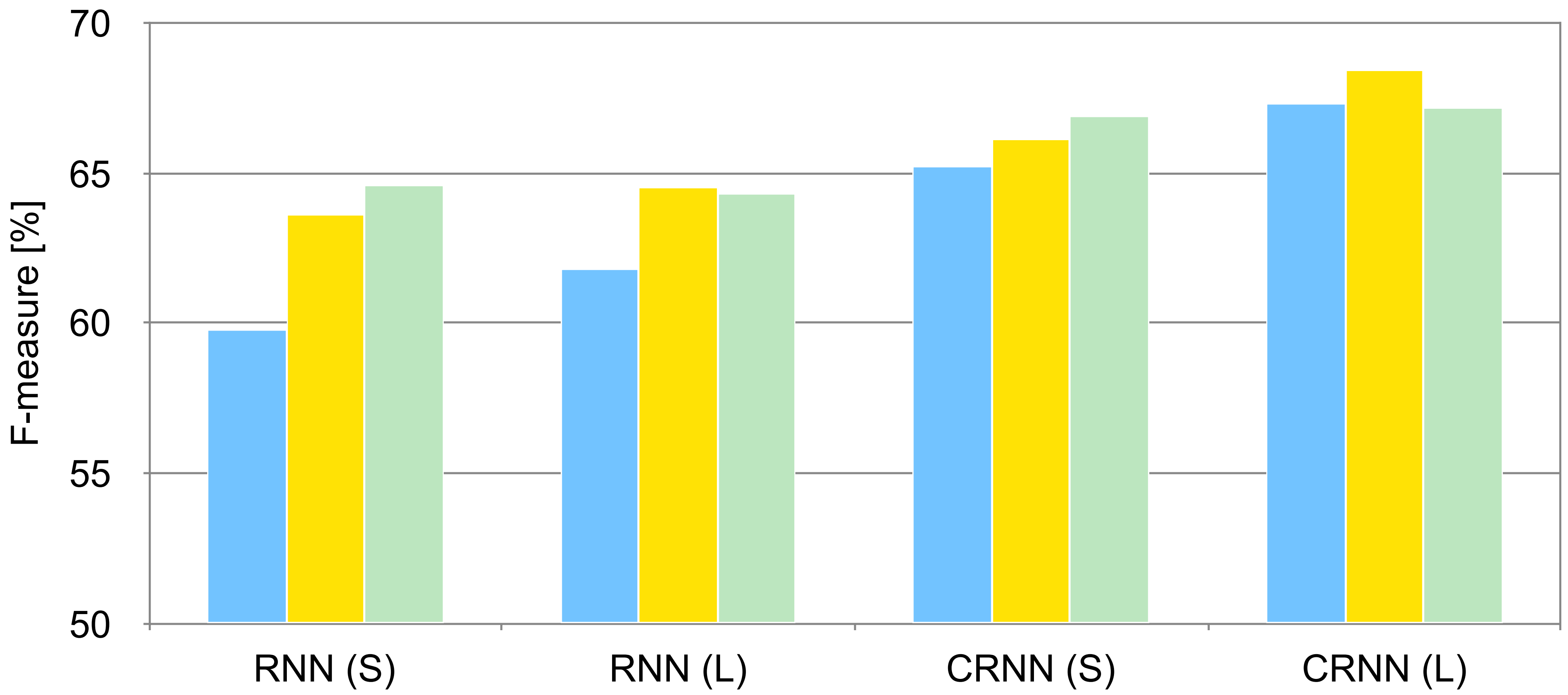
RESULTS FOR RECURRENT ARCHITECTURES



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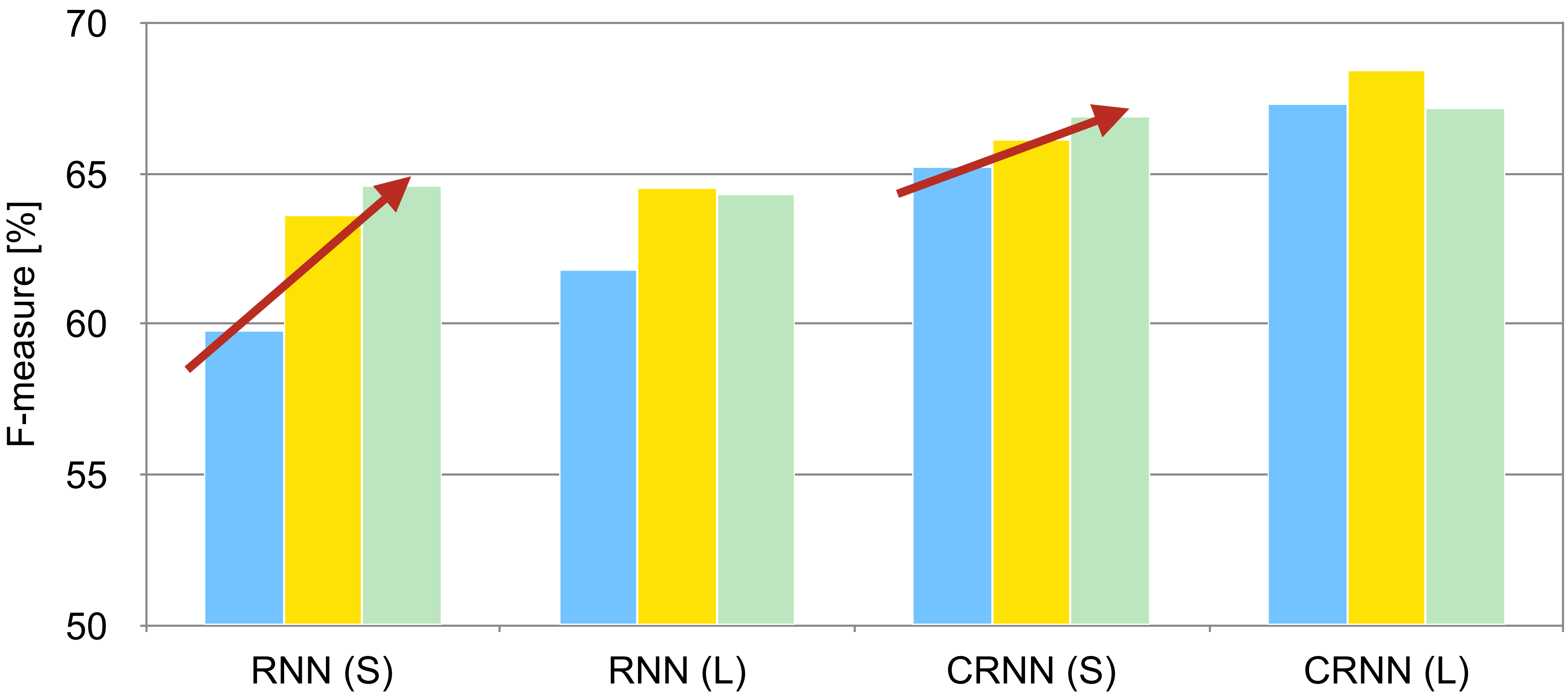

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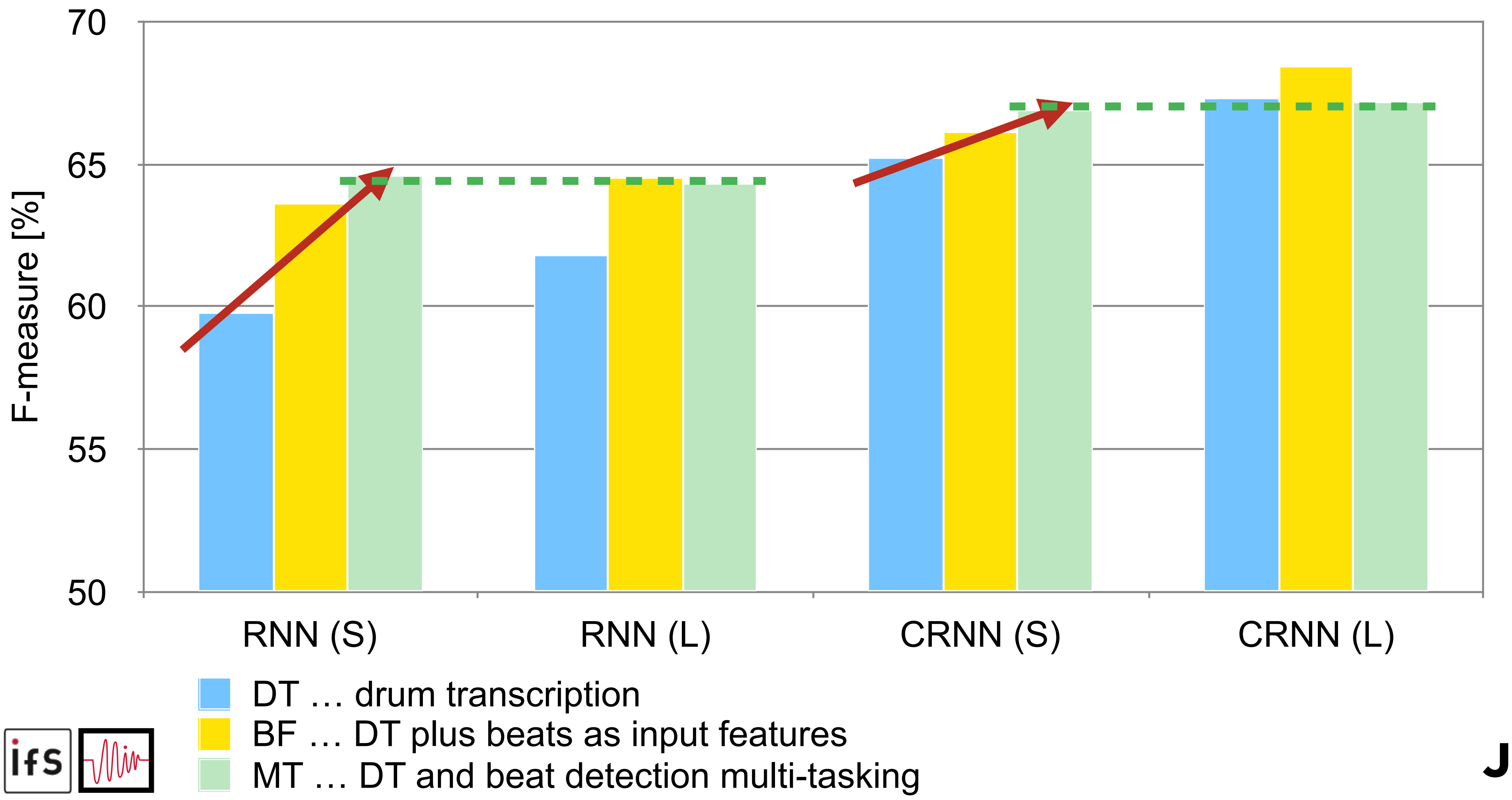

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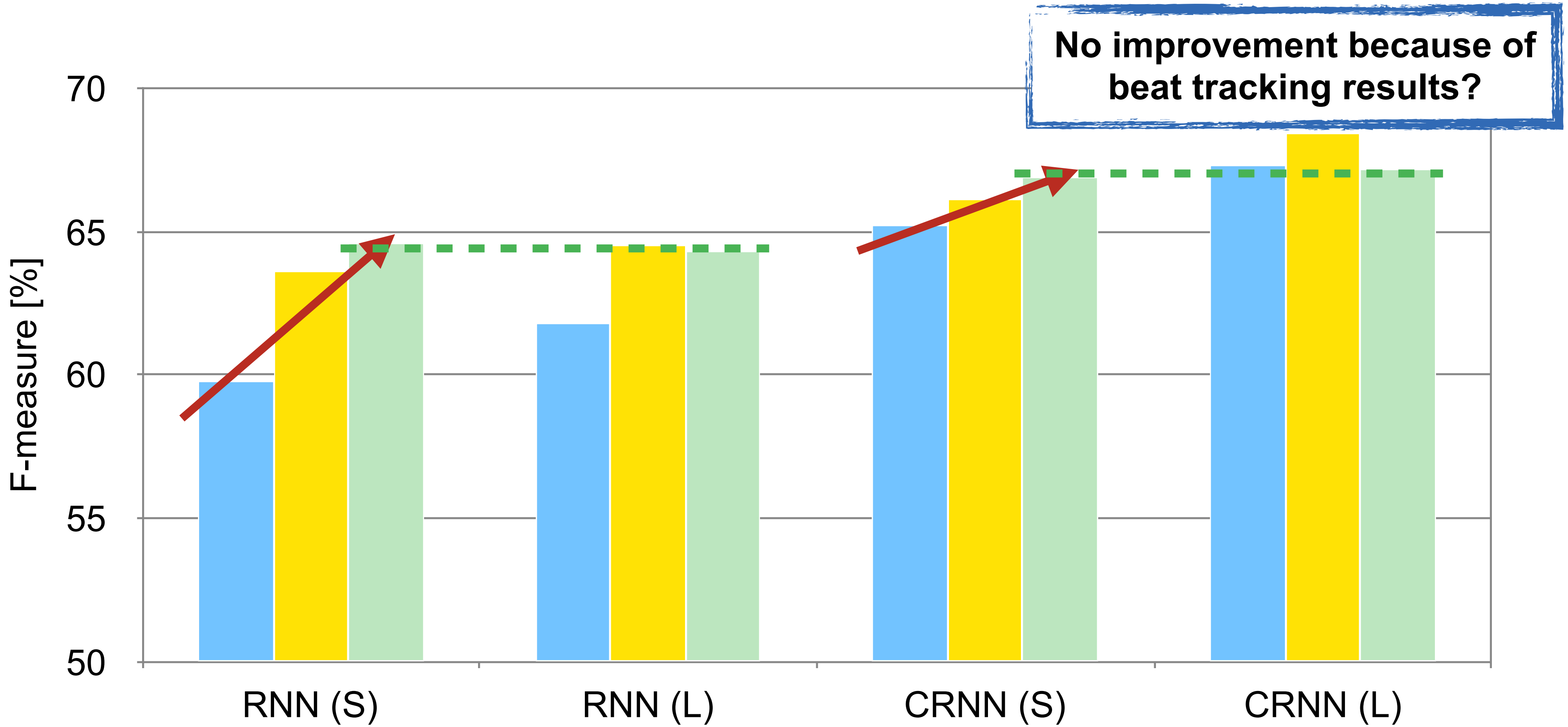

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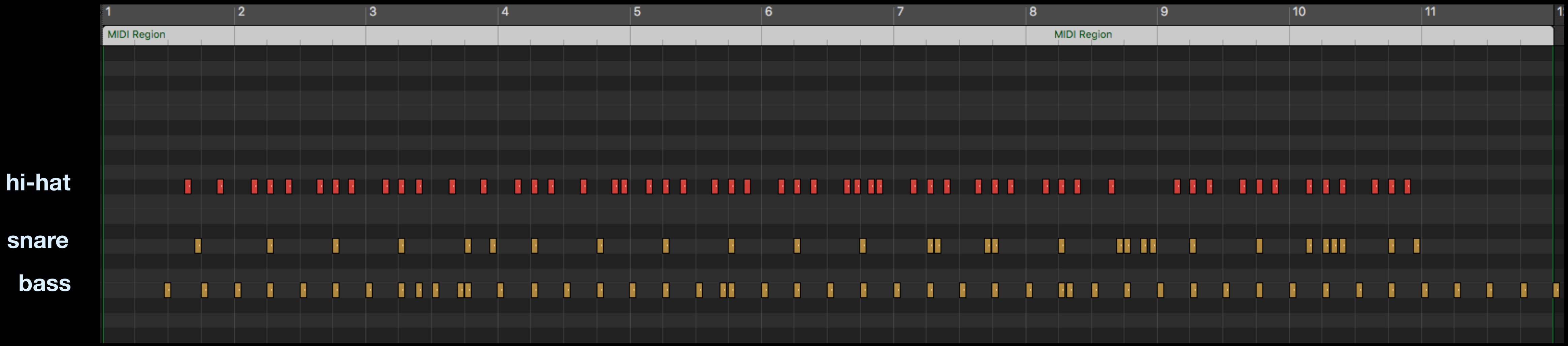
HOW DOES IT SOUND?

three instruments + beats



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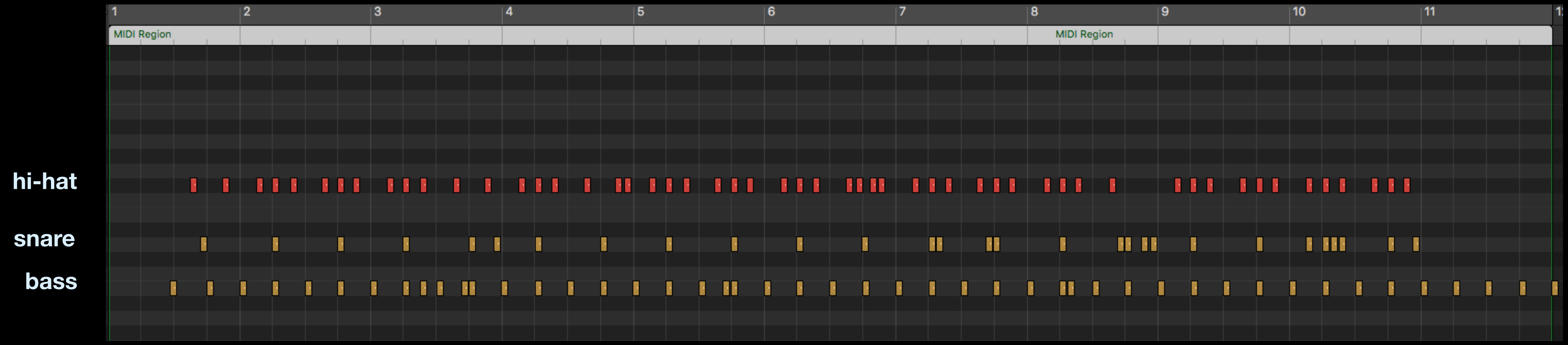
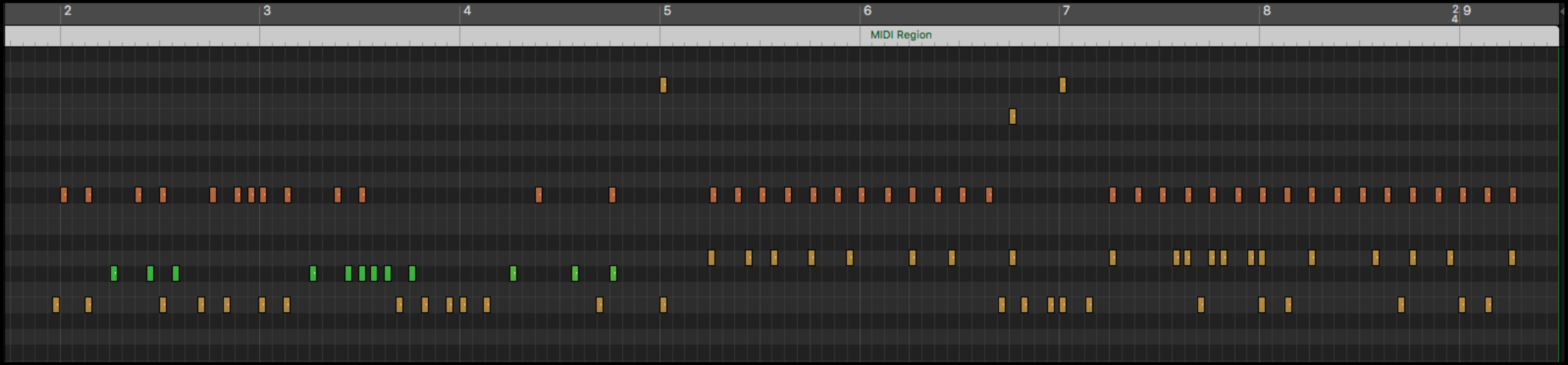


HOW DOES IT SOUND?

eight instruments + beats



crash
tom
hi-hat
snare
side stick
bass

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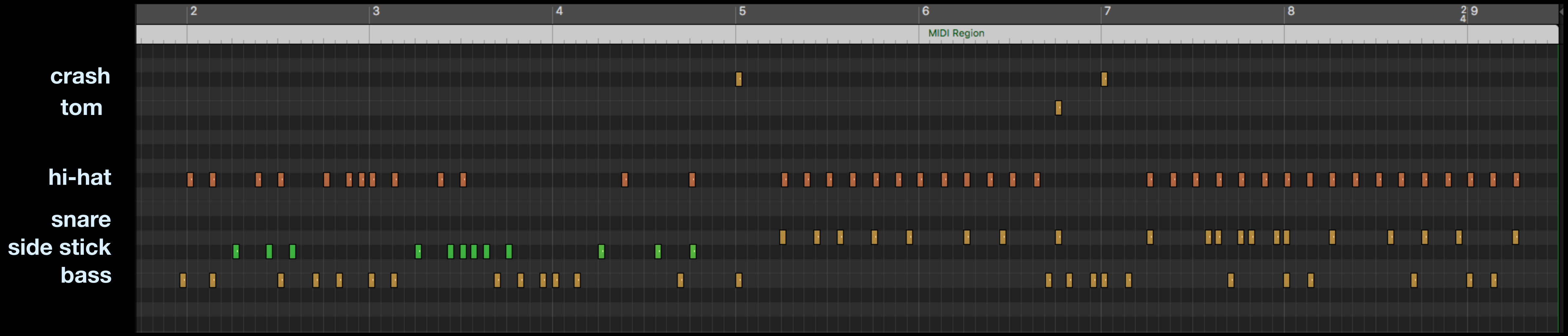

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