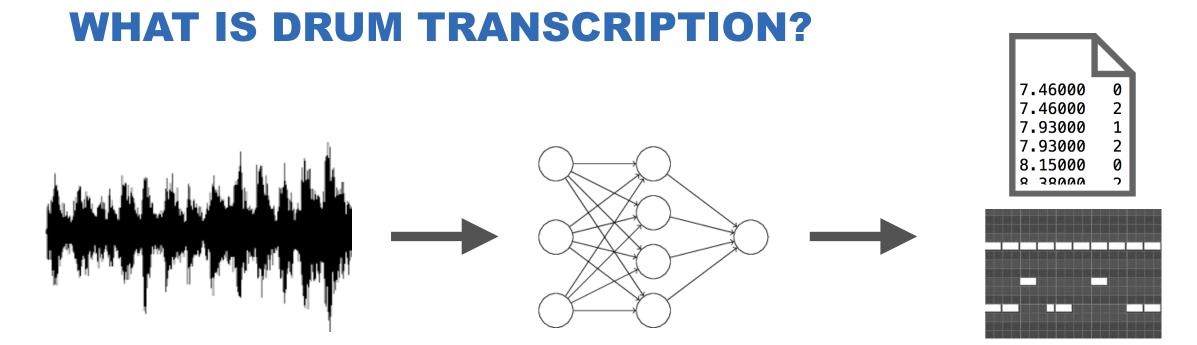
DRUM TRANSCRIPTION VIA JOINT BEAT AND DRUM MODELING USING CONVOLUTIONAL RNNs

Richard Vogl^{1,2}, Matthias Dorfer², Gerhard Widmer², Peter Knees¹

richard.vogl@tuwien.ac.at, matthias.dorfer@jku.at, gerhard.widmer@jku.at, peter.knees@tuwien.ac.at









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





WHAT IS DRUM TRANSCRIPTION?

Focus on the three major drum instruments:

- bass or kick drum (KD)
- snare drum (SD)
- hi-hat (HH)

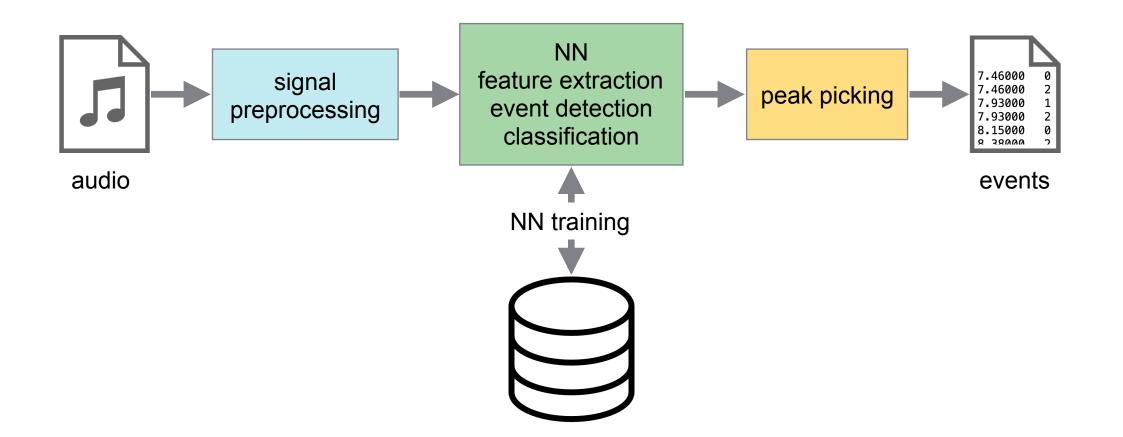
Reasons:

- Dominant instruments: most onsets
- Common subset for public datasets

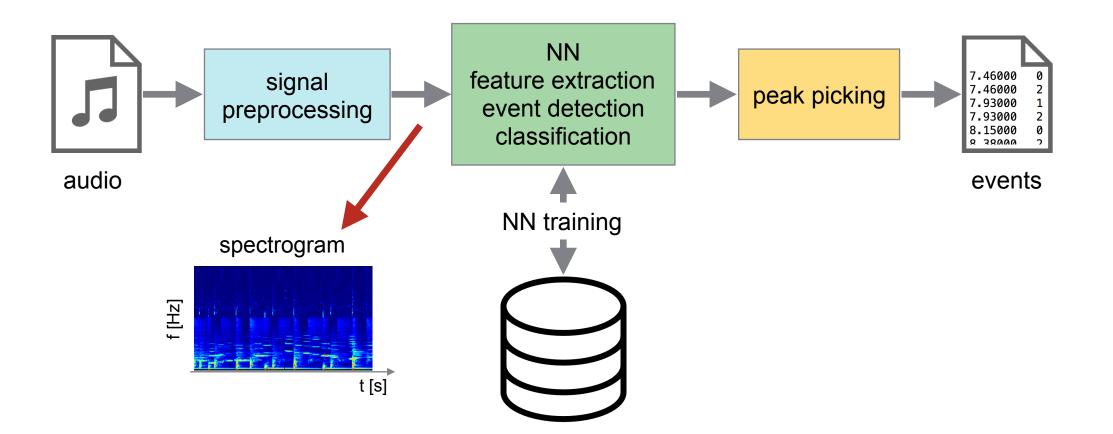




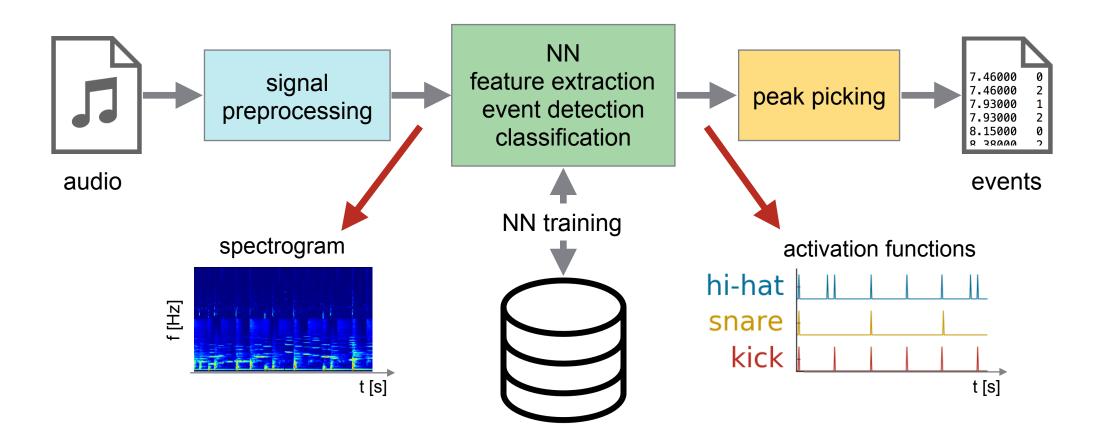




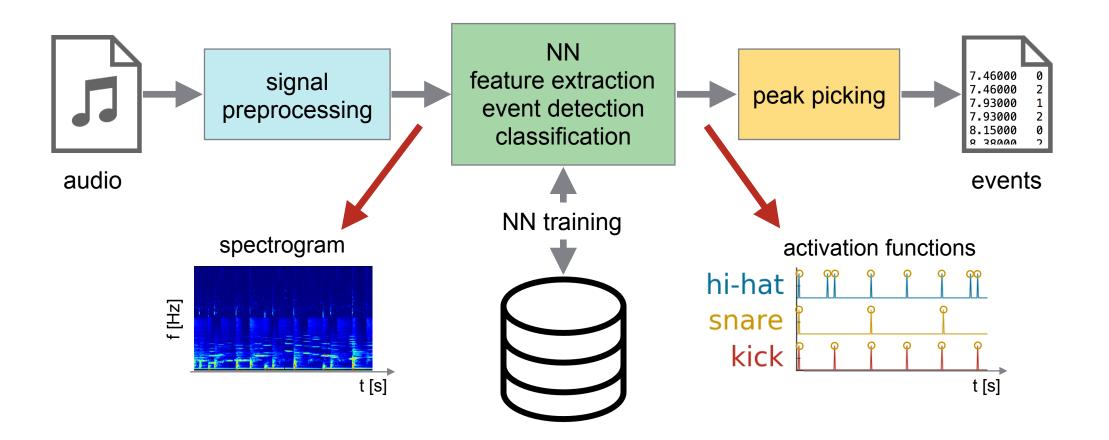


















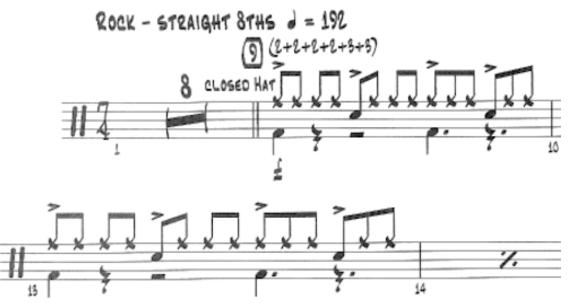
Performance not satisfying on real music





Performance not satisfying on real music

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

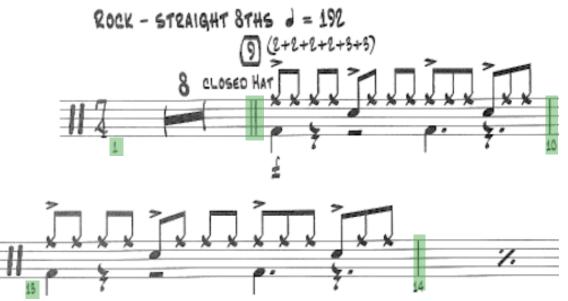




Performance not satisfying on real music

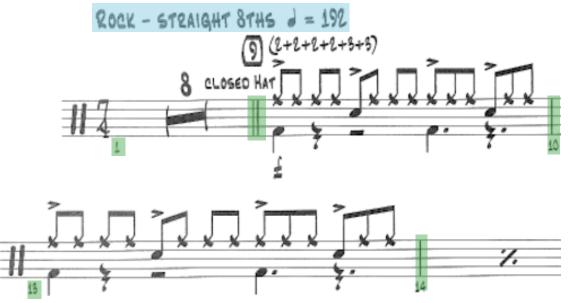
Do not produce additional information for transcripts drum onset detection vs drum transcription

bars lines



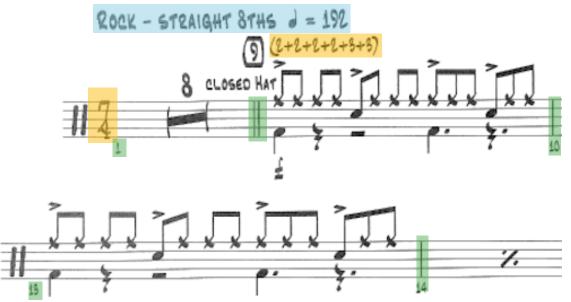


- Performance not satisfying on real music
- Do not produce additional information for transcripts drum onset detection vs drum transcription
 - bars lines
 - tempo



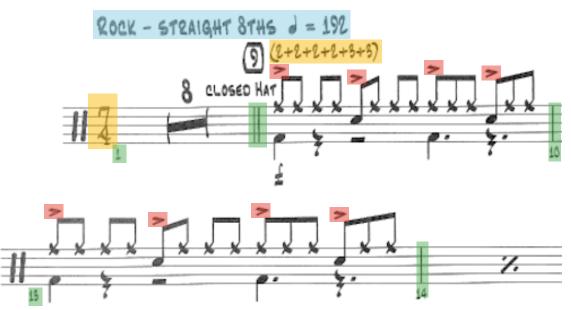


- Performance not satisfying on real music
- Do not produce additional information for transcripts drum onset detection vs drum transcription
 - bars lines
 - tempo
 - meter



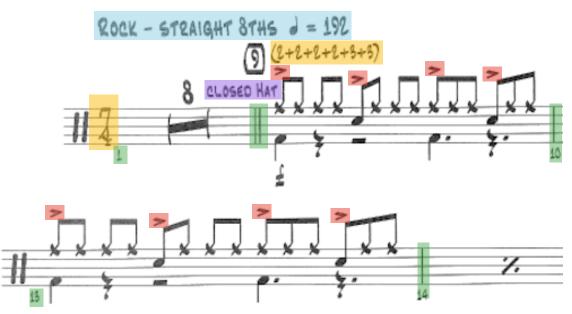


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 - bars lines
 - tempo
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 - dynamics / accents





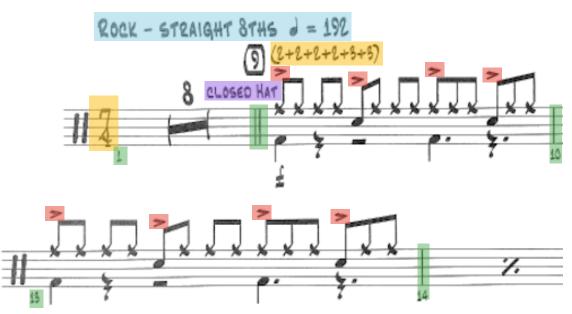
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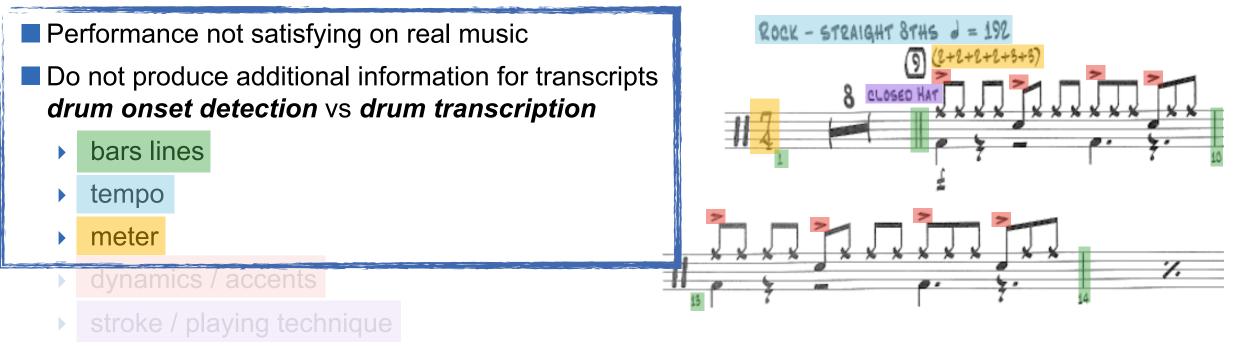
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- Only three instrument classes

etc.









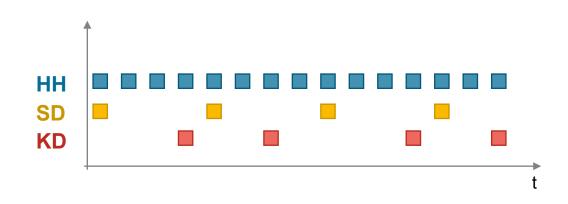
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Only three instrument classes

etc.

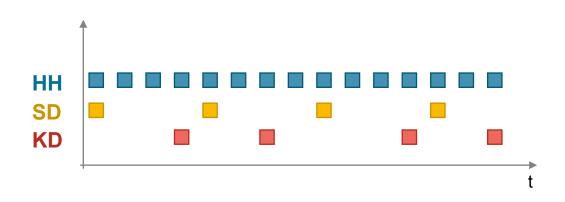








Use **beat and downbeat tracking** to get:

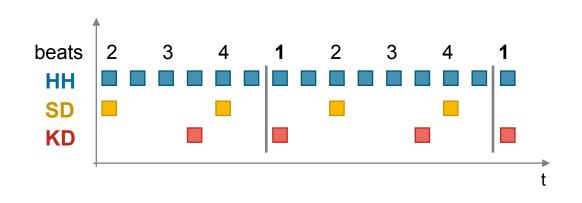






Use **beat and downbeat tracking** to get:

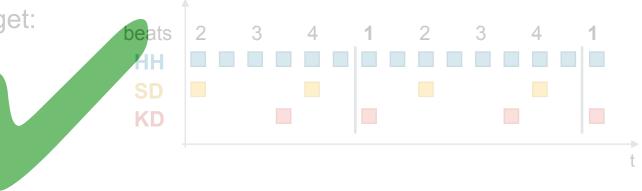
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- tempo
- meter





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

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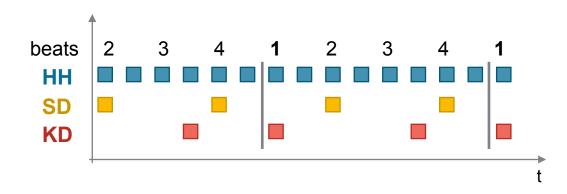
IMPROVE PERFORMANCE

Three components to reach this goal:

- 1. Leverage beat information
- 2. Better model for drum detection
- 3. Dataset with real music for training

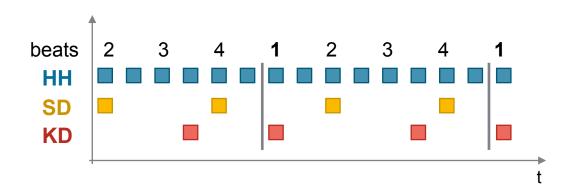








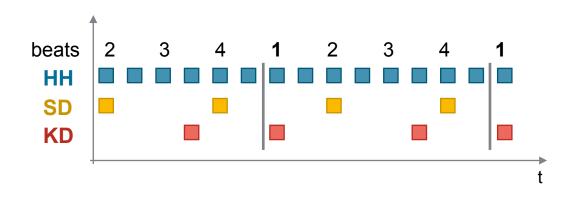




Beats are **highly correlated** with drum patterns





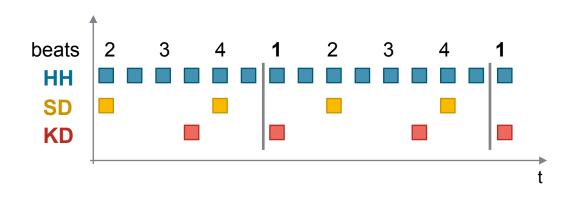


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Assume that prior knowledge of beats is helpful for drum transcription (drum hit locations / repetitive patterns)







Beats are highly correlated with drum patterns

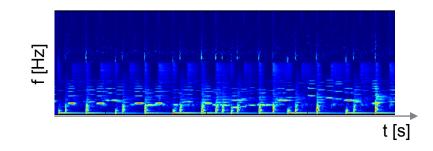
- Assume that prior knowledge of beats is helpful for drum transcription (drum hit locations / repetitive patterns)
- Use **multi-task learning** for beats and drums





input

output

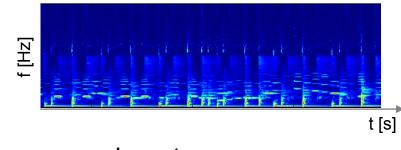






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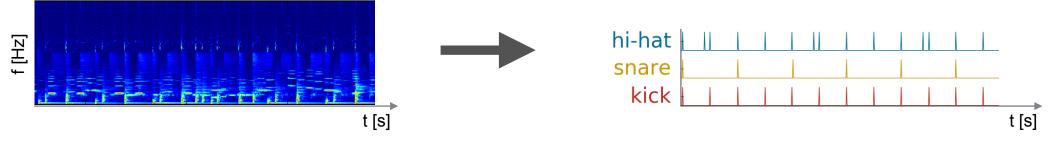
Three experiments:





input

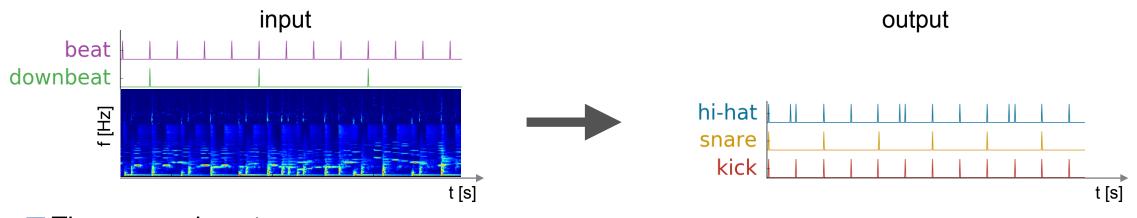
output



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



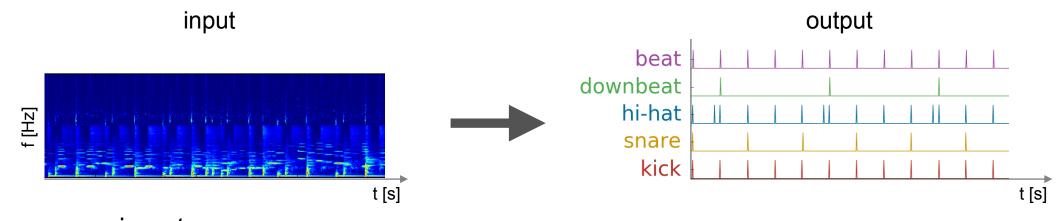




- Three experiments:
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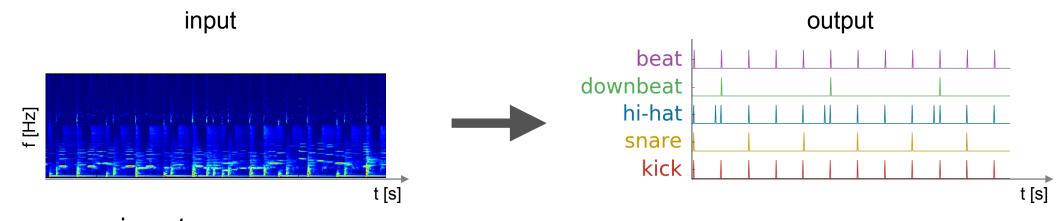




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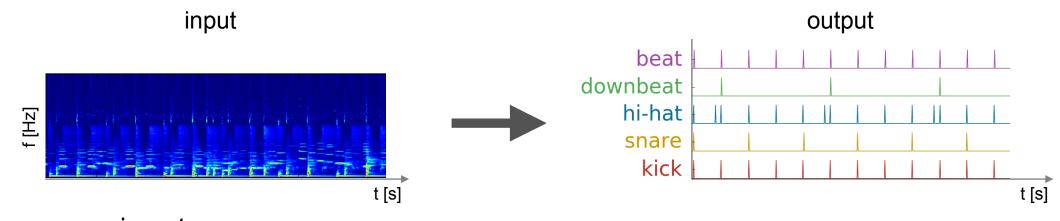


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Expected increase in performance for *BF* compared to *DT*





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Expected increase in performance for *MT* compared to *DT*



2. NETWORK MODELS — BASELINE MODELS





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Recurrent neural networks

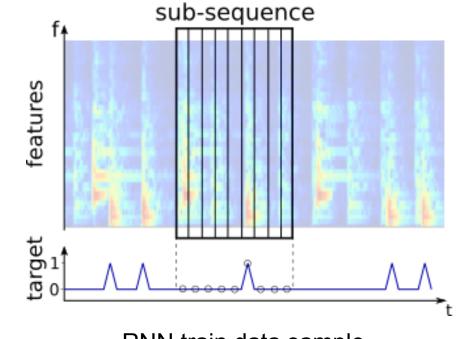




2. NETWORK MODELS — BASELINE MODELS

Recurrent neural networks

- Recurrent connections act as memory
- Processing of sequential data



RNN train data sample

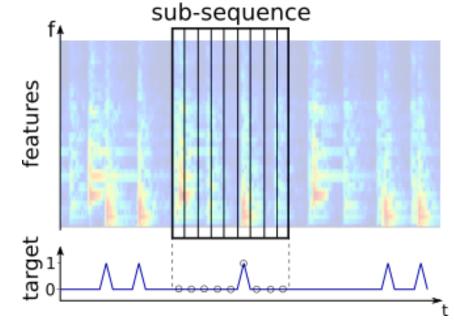
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- Work well for drum detection and beat tracking [Böck et al. ISMIR'16]



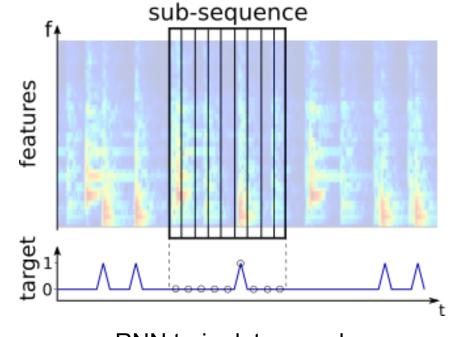
RNN train data sample



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Recurrent neural networks

- Recurrent connections act as memory
- Processing of sequential data
- Work well for drum detection and beat tracking [Böck et al. ISMIR'16]
- RNN with label time shift (*tsRNN*) state-of-the-art baseline [Vogl et al. ICASSP'17]
- Bidirectional recurrent NN (BDRNN) [Vogl et al. ISMIR'16] [Southall et al. ISMIR'16]
 - Similar performance tsRNN



RNN train data sample



2. NETWORK MODELS — NEW FOR DT

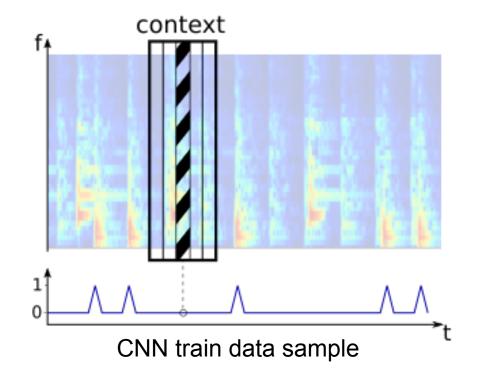




2. NETWORK MODELS — NEW FOR DT

Convolutional NN (CNN)

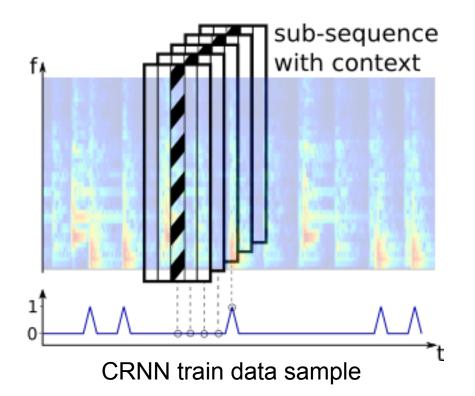
- Convolutions capture local correlations
- Acoustic modeling of drum sounds





2. NETWORK MODELS — NEW FOR DT

- Convolutional NN (CNN)
 - Convolutions capture local correlations
 - Acoustic modeling of drum sounds
- Convolutional BDRNN (**CRNN**)
 - "best of both worlds"
 - Low-level CNN for acoustic modeling
 - Higher-level RNN for repetitive pattern modeling





NETWORK MODELS

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







IDMT-SMT-Drums [Dittmar and Gärtner 2014]

- Solo drum tracks, recorded, synthesized, and sampled
- > 95 tracks, total: **24m**, onsets: **8004** + training samples





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ENST-Drums [Gillet and Richard 2006]

- Recordings, three drummers on different drum kits, **optional accompaniment**
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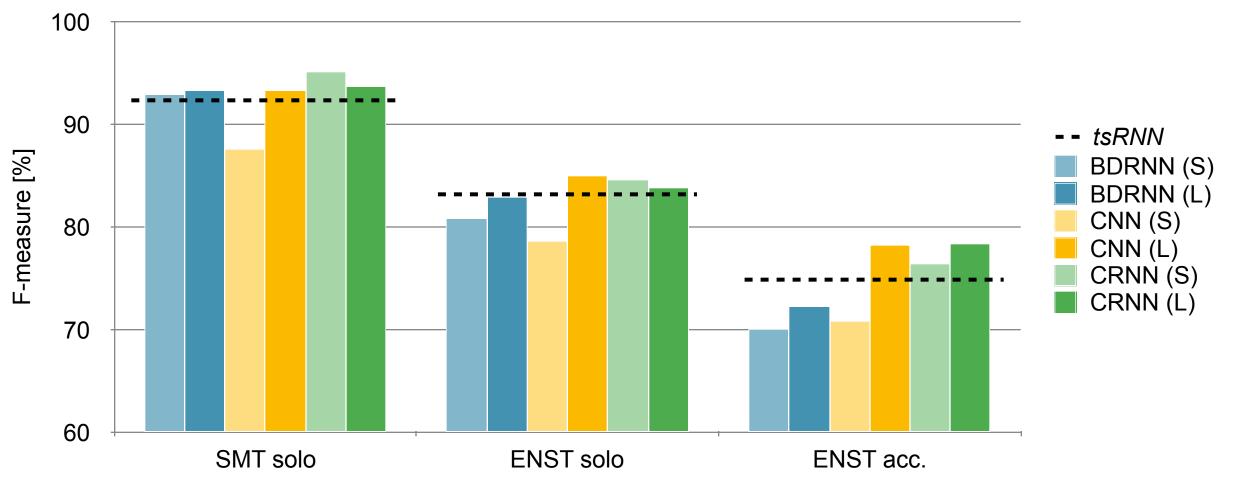
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DT 3-FOLD CV RESULTS ON CLASSIC DATASETS





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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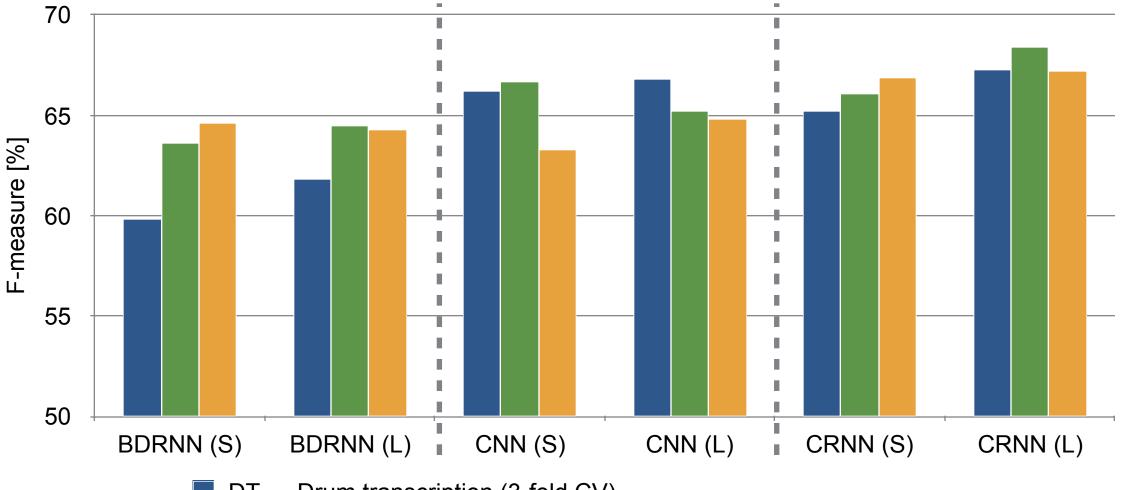
Multi-task evaluation

- DT: Drum transcription / three fold cross-validation (same as on SMT and ENST)
- *BF*: Drum transcription using annotated beats as additional input features
- MT: Drum transcription and beat detection via multi-task learning





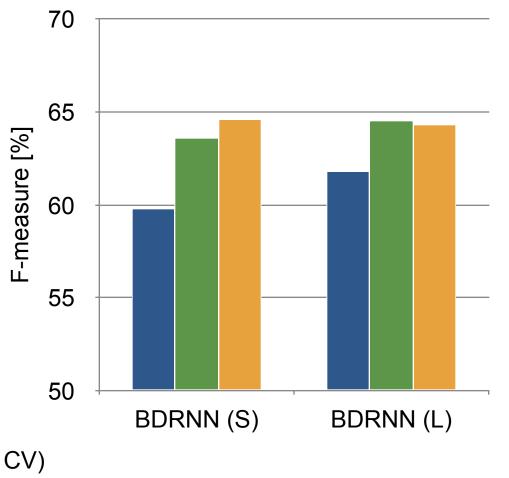
RESULTS ON RBMA13



DT ... Drum transcription (3-fold CV)

BF ... Drum transcription using annotated beats as additional input features

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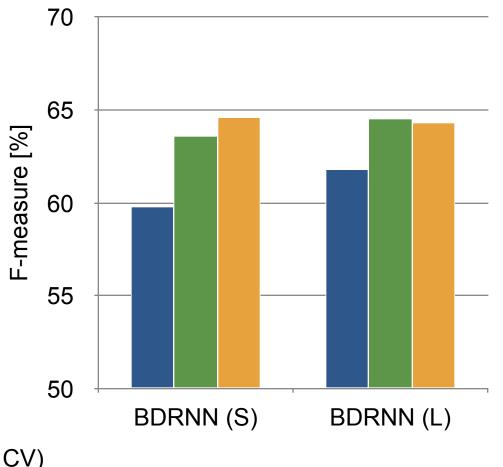


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Impact on bi-directional RNNs:



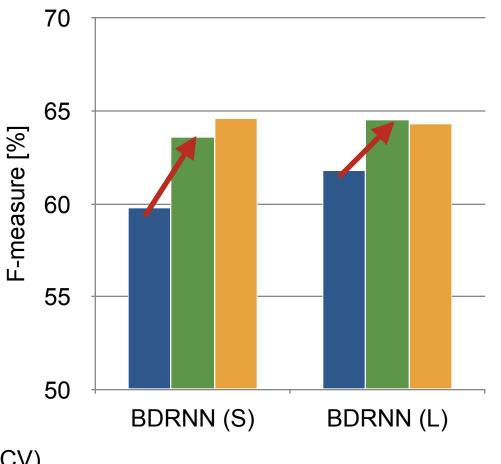
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BF ... Drum transcription using annotated beats as additional input features

Impact on bi-directional RNNs:BF improves for both models



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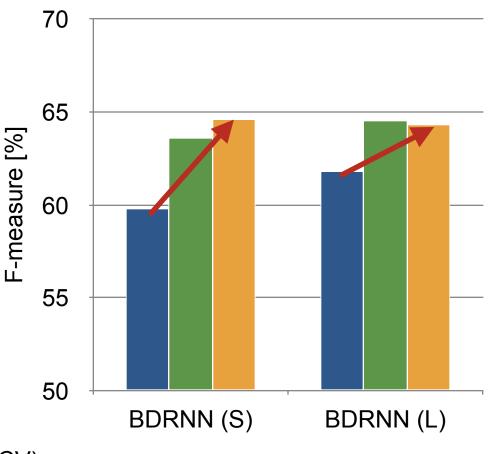
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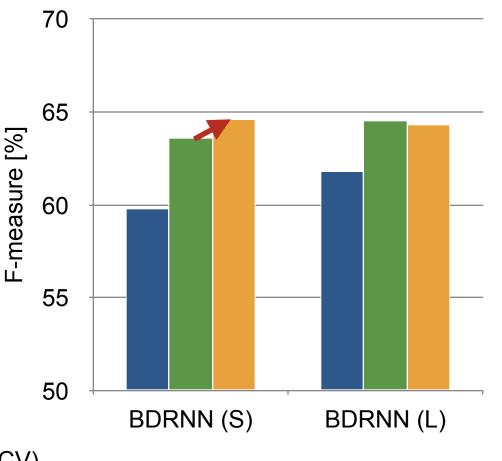


Impact on bi-directional RNNs:

BF improves for both models

MT improves for both models

MT even better than BF for small model !

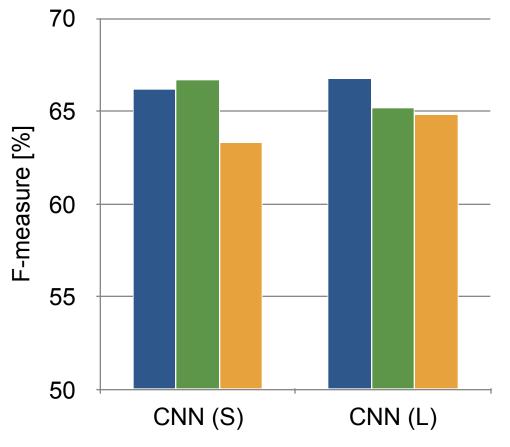




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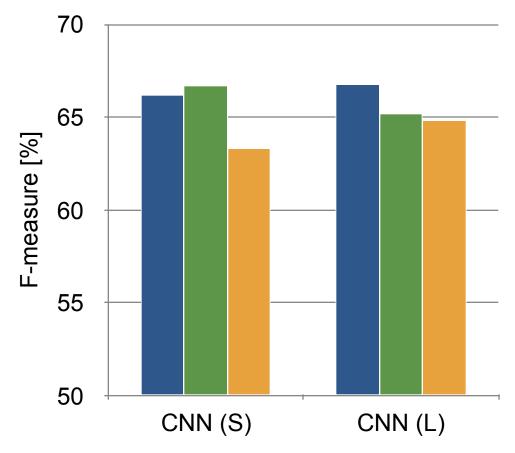




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Impact on CNNs:





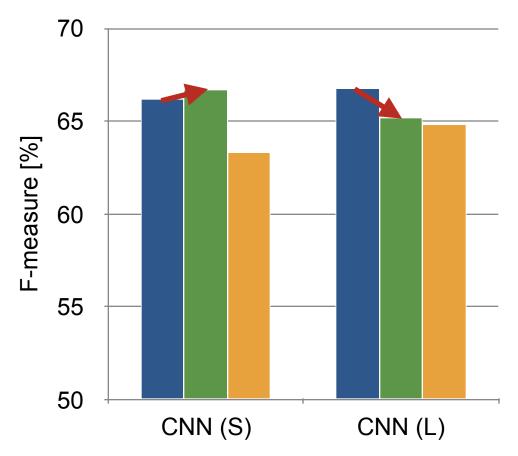
DT ... Drum transcription (3-fold CV)

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Impact on CNNs:

BF inconsistent





DT ... Drum transcription (3-fold CV)

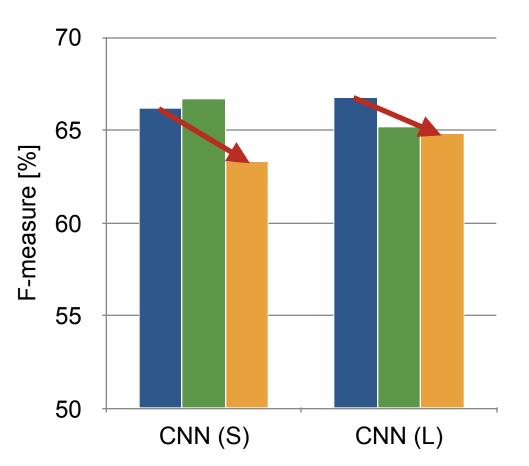
BF ... Drum transcription using annotated beats as additional input features MT ... Drum transcription and beat detection via multi-task learning

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Impact on CNNs:

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MT declines for both models

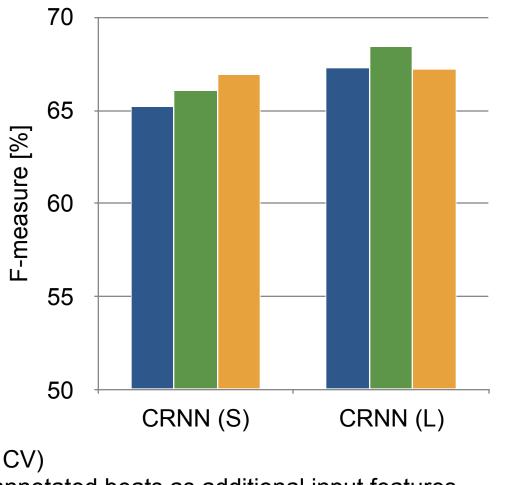




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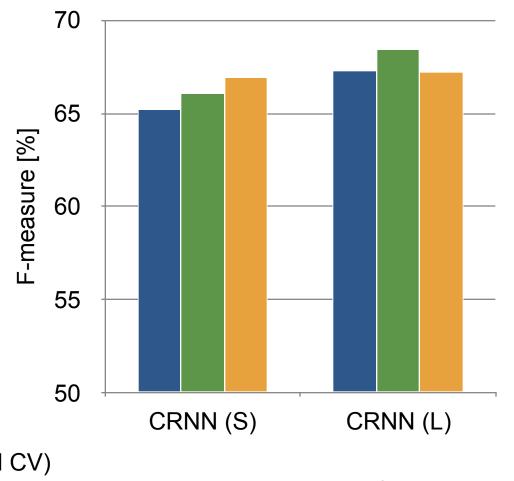
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DT ... Drum transcription (3-fold CV)

BF ... Drum transcription using annotated beats as additional input features

Impact on CRNNs:



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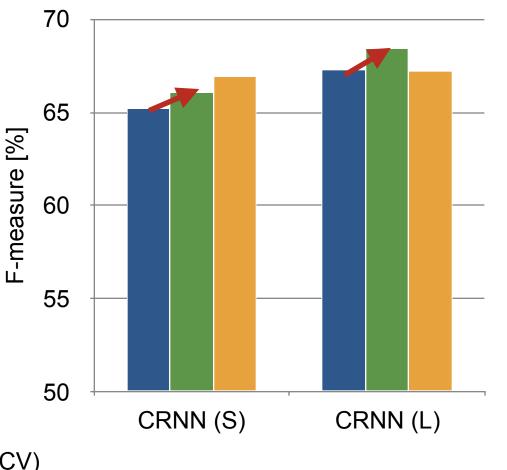


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Impact on CRNNs:

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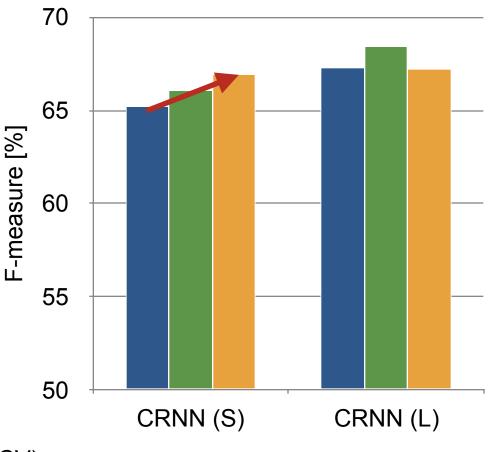
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Impact on CRNNs:

BF improves for both models

MT improves for small models



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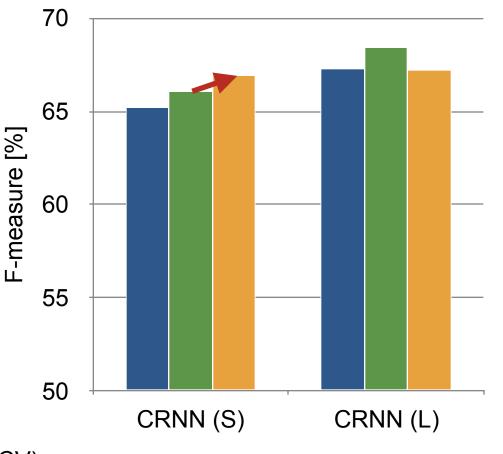


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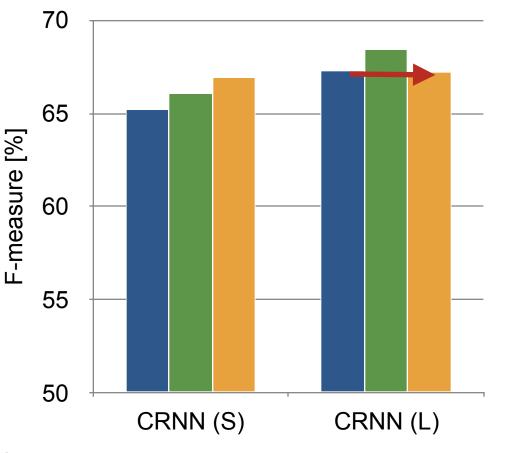


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- MT equal for large model ?

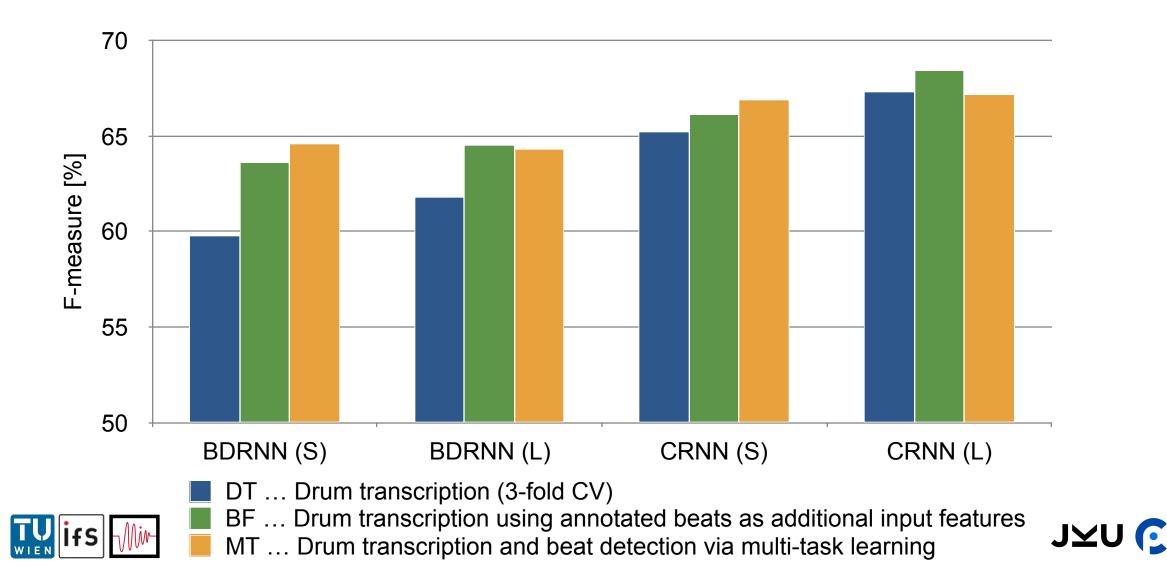


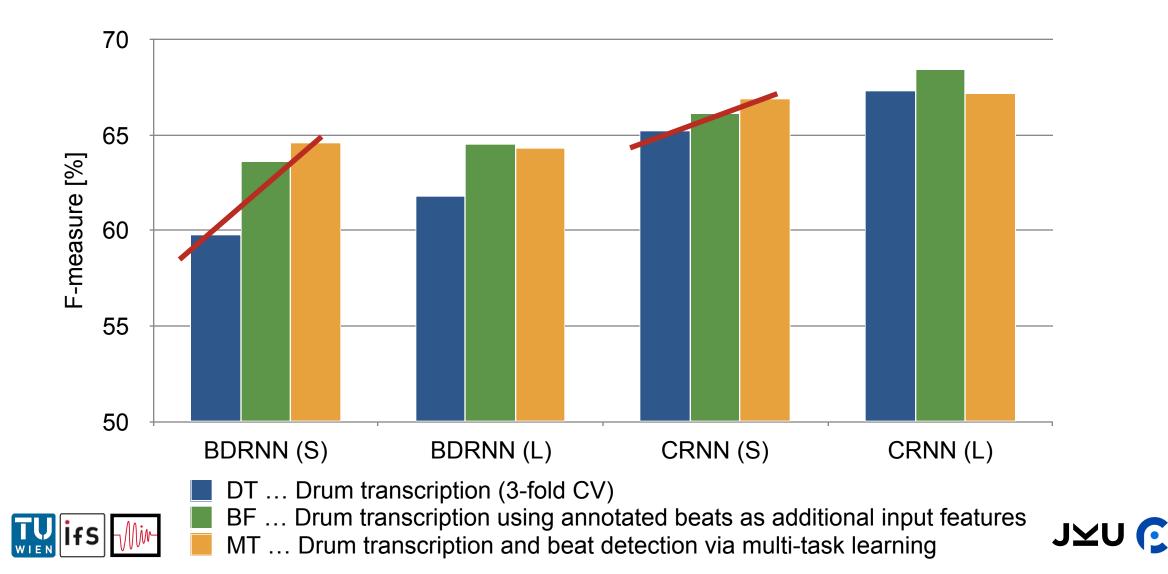


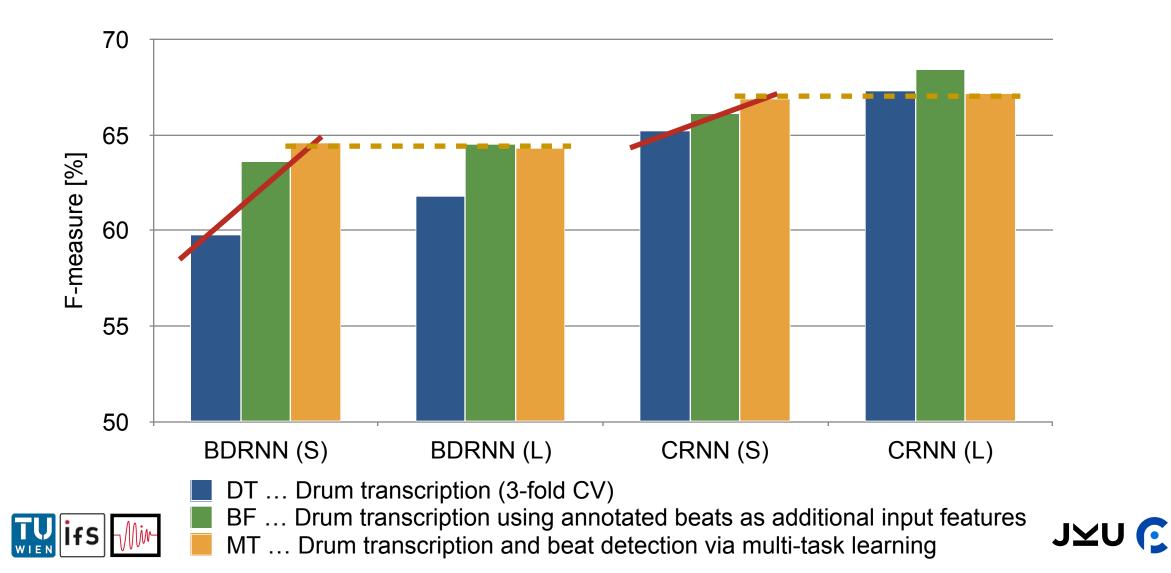
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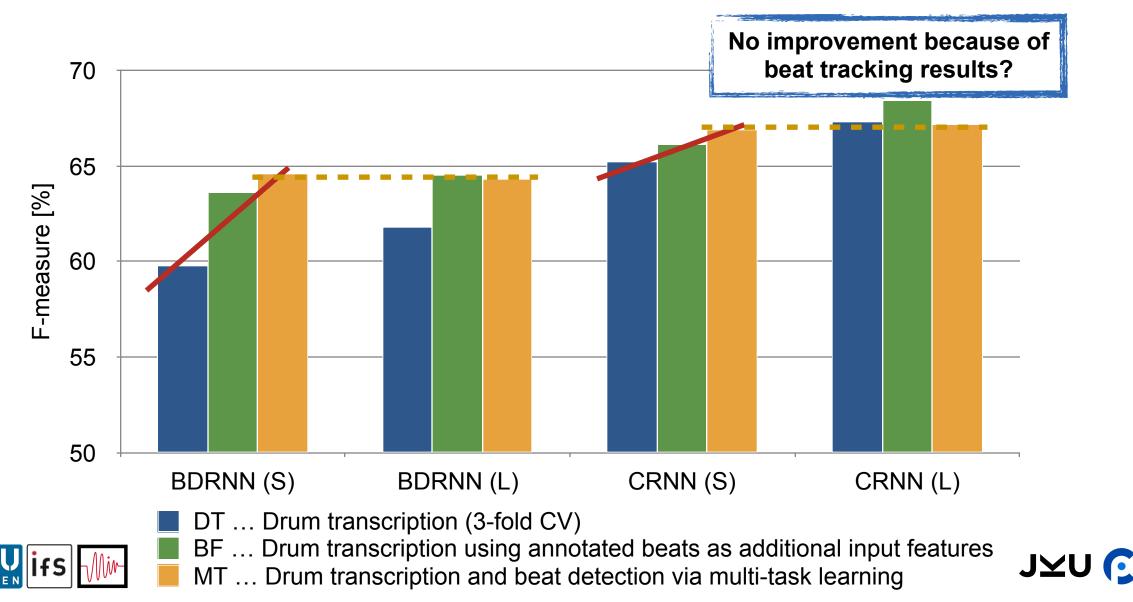
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Use beats and downbeats to get **meta information** for transcripts





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Multi-task learning for drums and beats can be beneficial for recurrent architectures





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Multi-task learning for drums and beats can be beneficial for recurrent architectures

CRNNs can outperform RNNs





Use beats and downbeats to get **meta information** for transcripts

- **Multi-task learning** for drums and beats can be beneficial for recurrent architectures
- **CRNNs** can outperform RNNs
- CRNN best overall results @ MIREX'17 drum transcription

MIREX system: <u>http://ifs.tuwien.ac.at/~vogl/models/mirex-17.zip</u> madmom: <u>https://github.com/CPJKU/madmom</u>





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New dataset with free music featuring beat, and drum annotations http://ifs.tuwien.ac.at/~vogl/datasets/





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