Deep learning architectures for music audio classification: a personal (re)view

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Acronyms

MLP: multi layer perceptron ≡ feed-forward neural network
RNN: recurrent neural network
LSTM: long-short term memory
CNN: convolutional neural network
BN: batch normalization

..the following slides assume you know these concepts!

Outline

Chronology: the big picture

Audio classification: state-of-the-art review

Music audio tagging as a study case

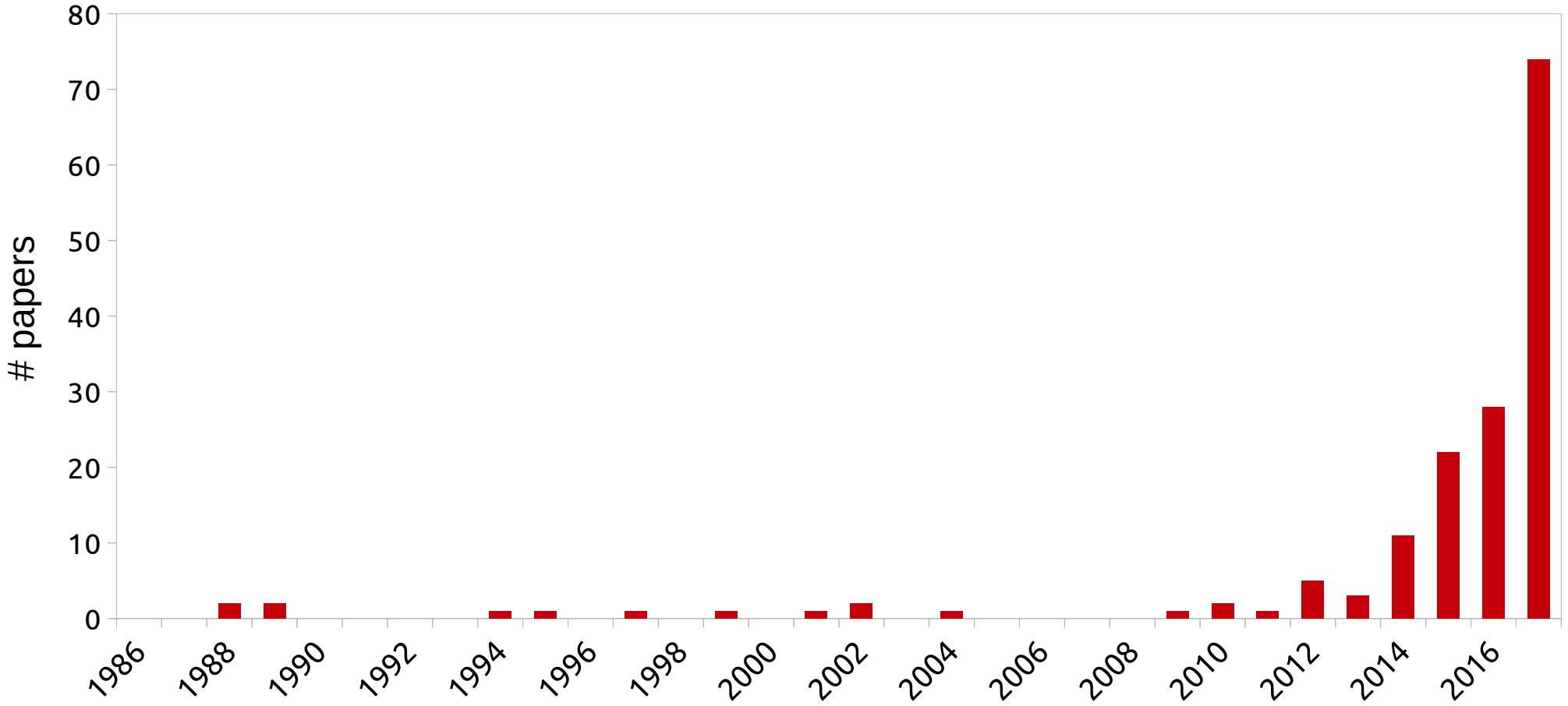
Outline

Chronology: the big picture

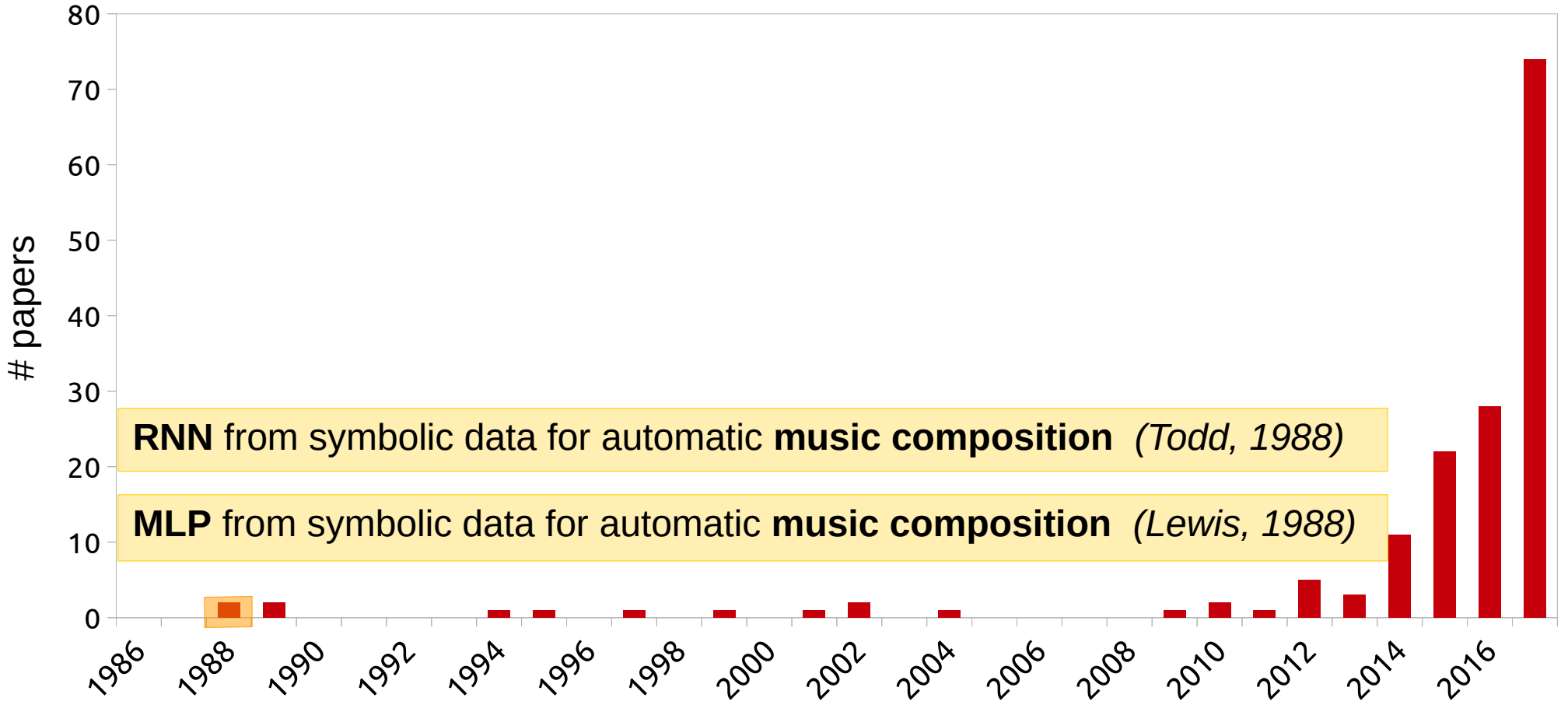
Audio classification: state-of-the-art review

Music audio tagging as a study case

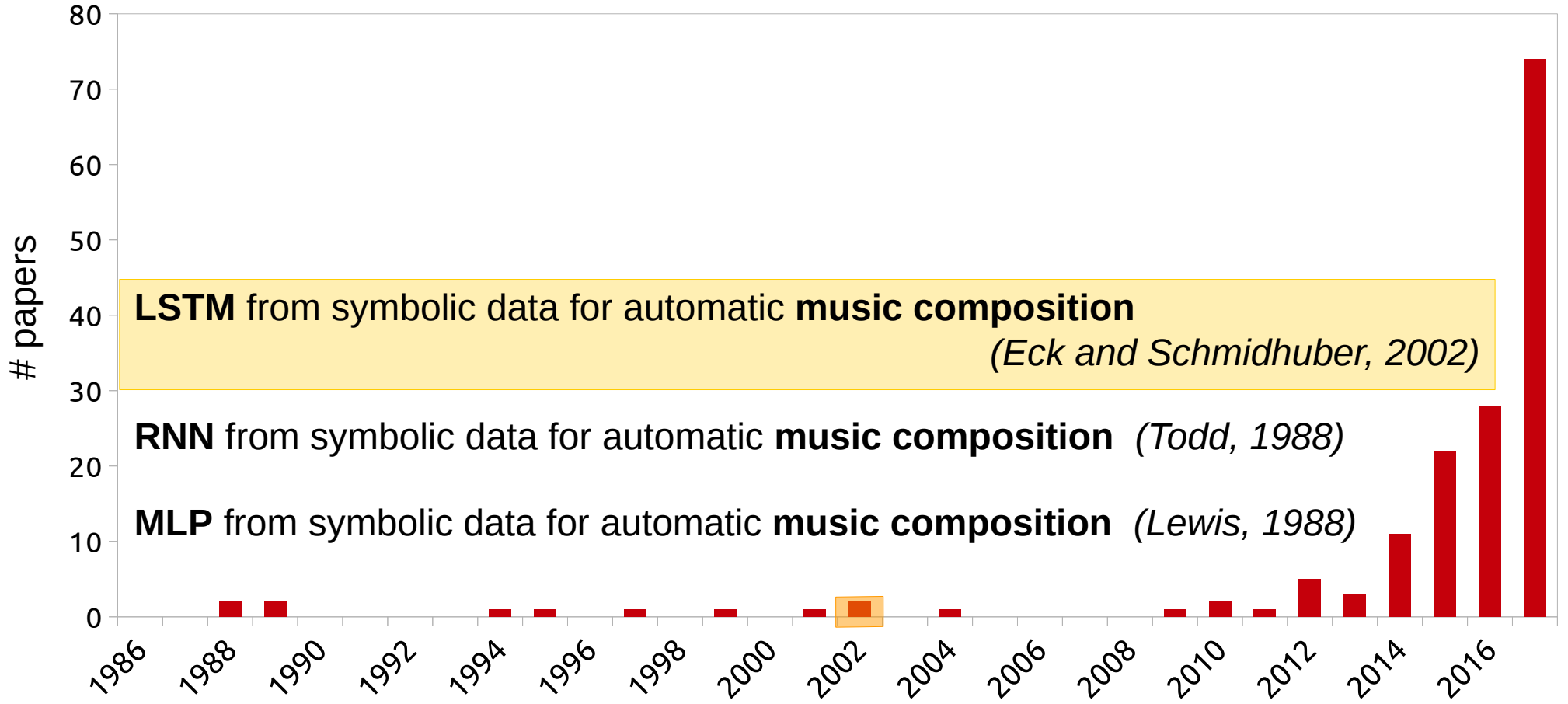
“Deep learning & music” papers: milestones



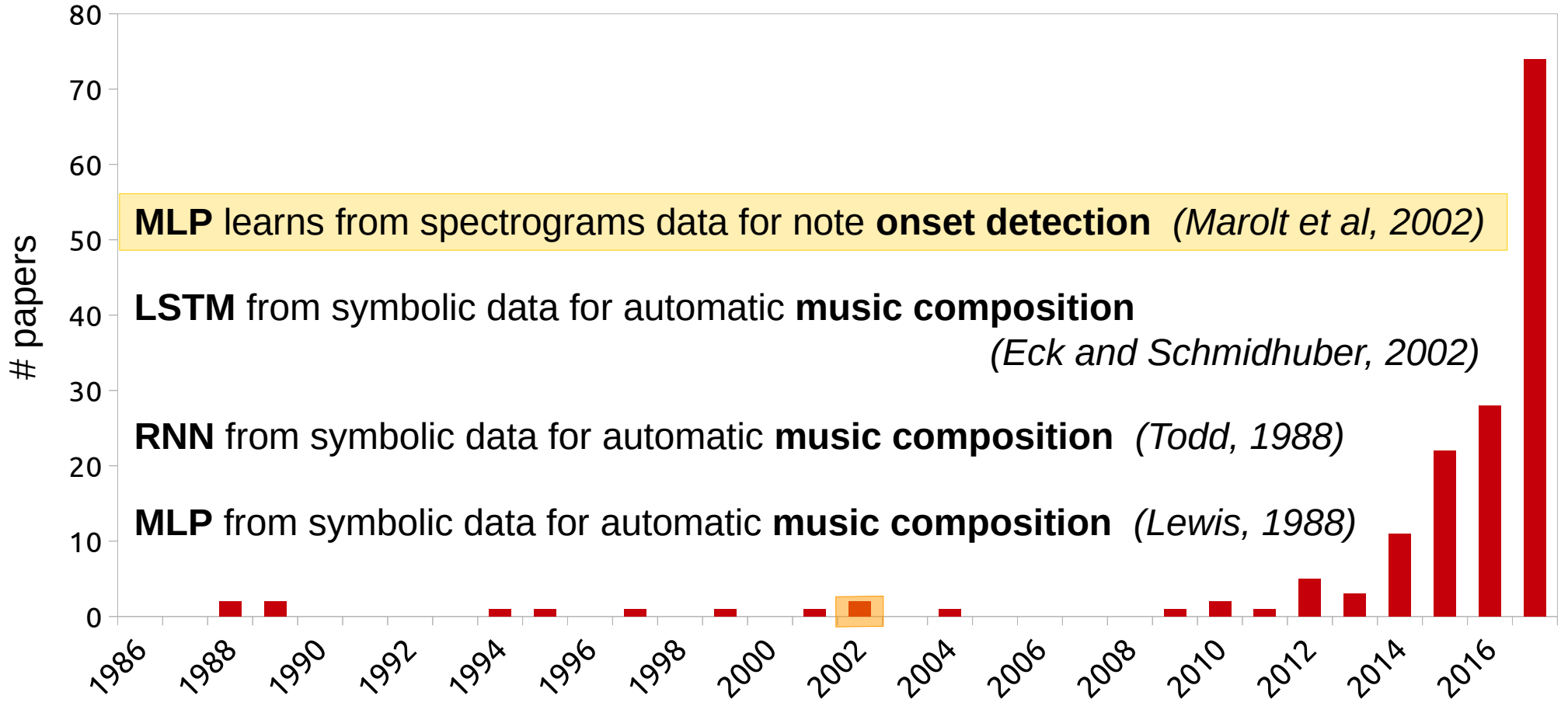
“Deep learning & music” papers: milestones



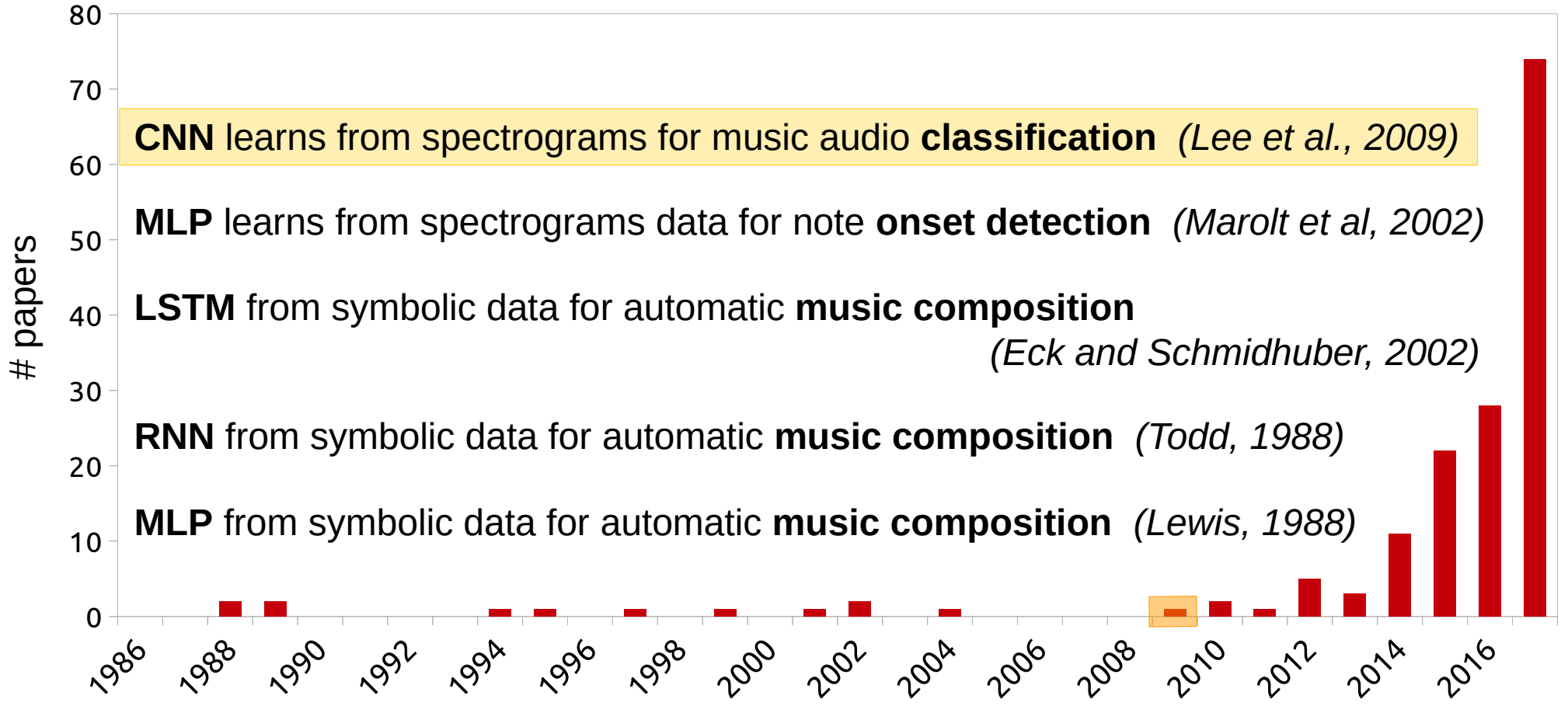
“Deep learning & music” papers: milestones



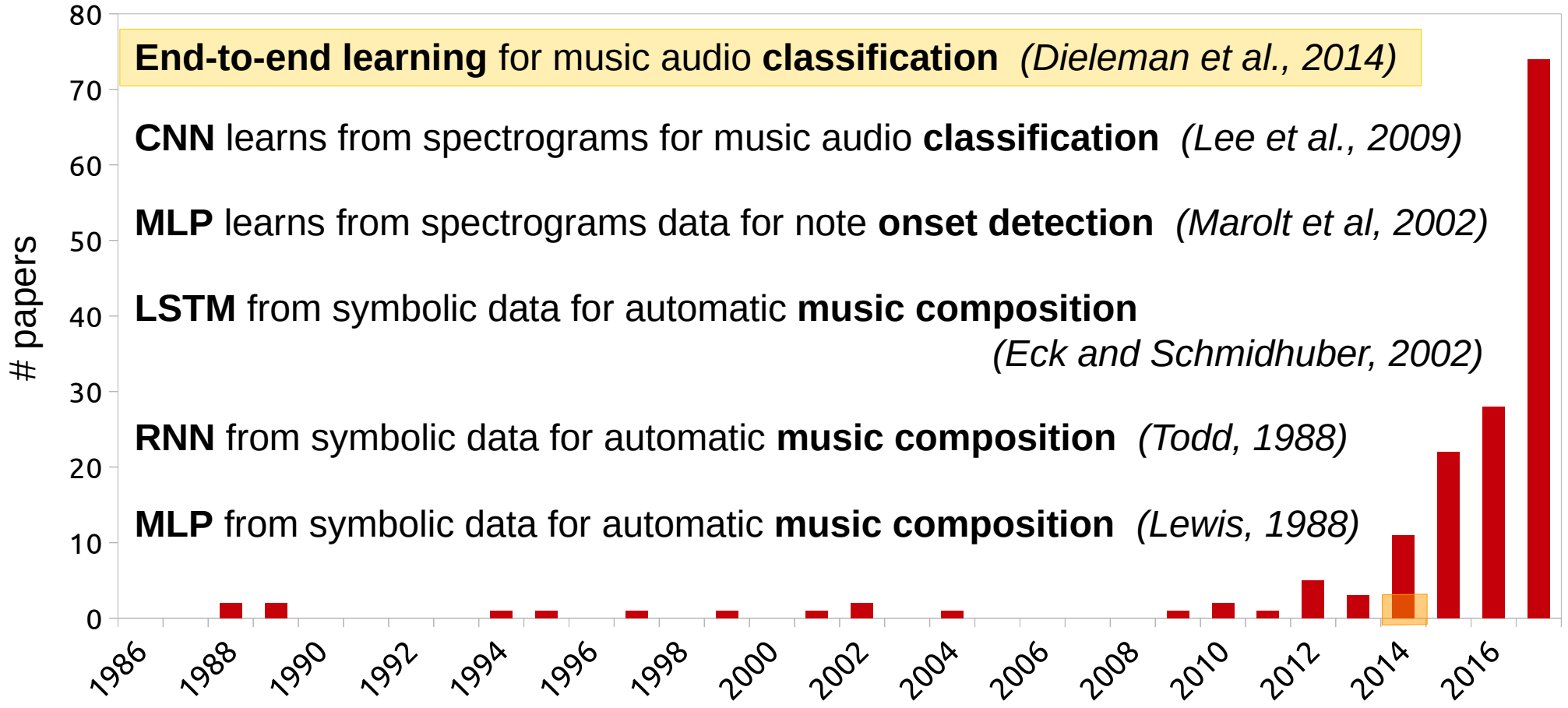
“Deep learning & music” papers: milestones



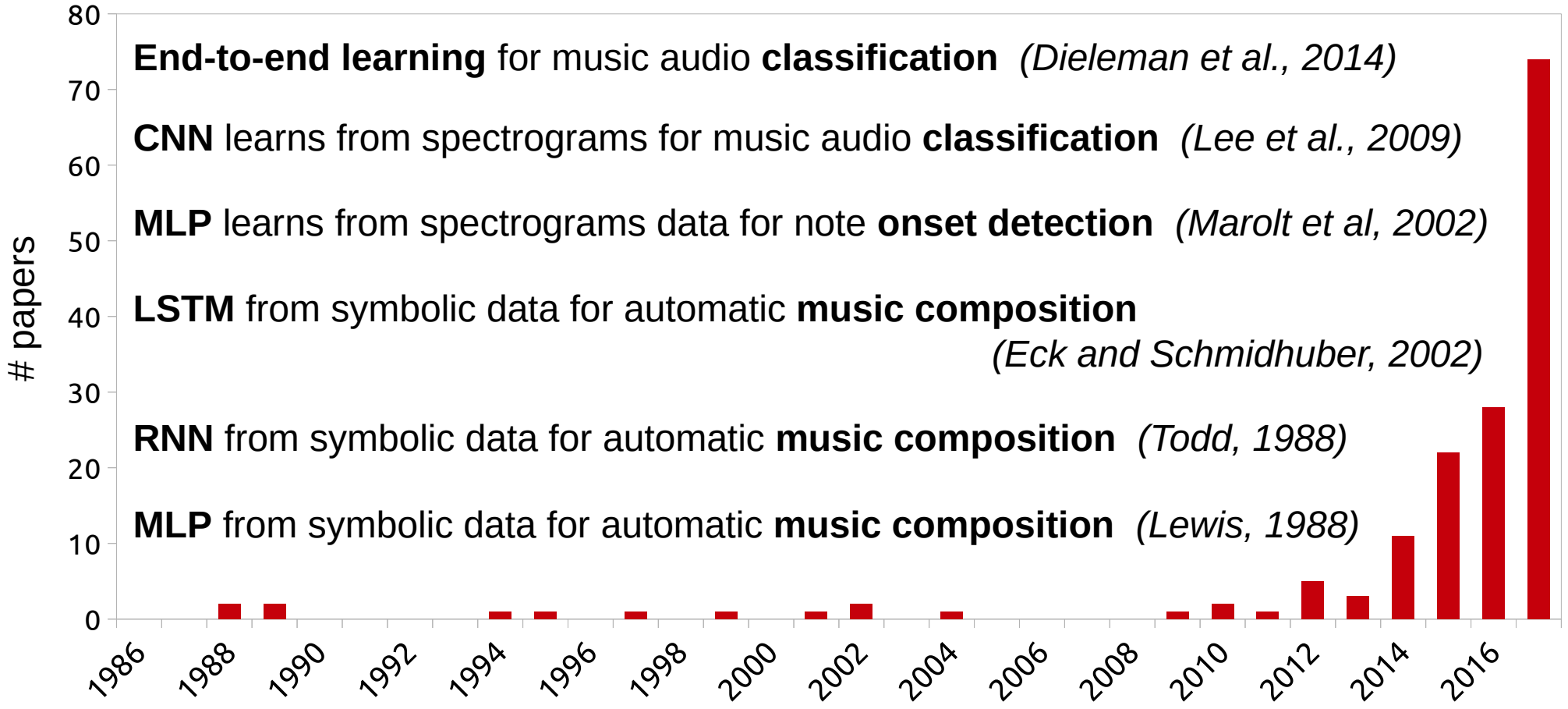
“Deep learning & music” papers: milestones



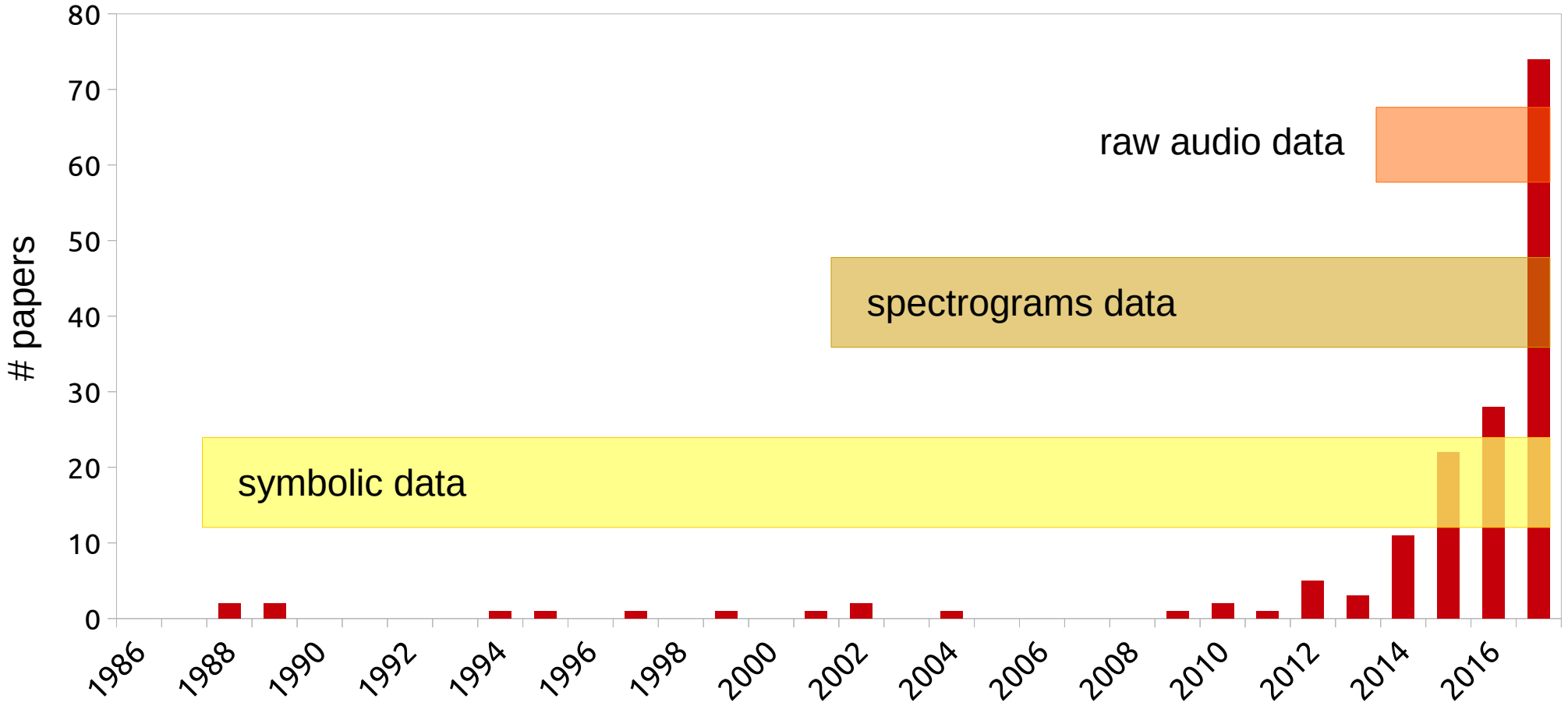
“Deep learning & music” papers: milestones



“Deep learning & music” papers: milestones



“Deep learning & music” papers: data trends



“Deep learning & music” papers: some references

Dieleman et al., 2014 – **End-to-end learning for music audio**
in International Conference on Acoustics, Speech and Signal Processing (ICASSP)

Lee et al., 2009 – **Unsupervised feature learning for audio classification using convolutional deep belief networks**
in Advances in Neural Information Processing Systems (NIPS)

Marolt et al., 2002 – **Neural networks for note onset detection in piano music**
in Proceedings of the International Computer Music Conference (ICMC)

Eck and Schmidhuber, 2002 – **Finding temporal structure in music: Blues improvisation with LSTM recurrent networks**
in Proceedings of the Workshop on Neural Networks for Signal Processing

Todd, 1988 – **A sequential network design for musical applications**
in Proceedings of the Connectionist Models Summer School

Lewis, 1988 – **Creation by Refinement: A creativity paradigm for gradient descent learning networks**
in International Conference on Neural Networks

Outline

Chronology: the big picture

Audio classification: state-of-the-art review

Music audio tagging as a study case

Which is our goal / task?

waveform

or any audio representation!

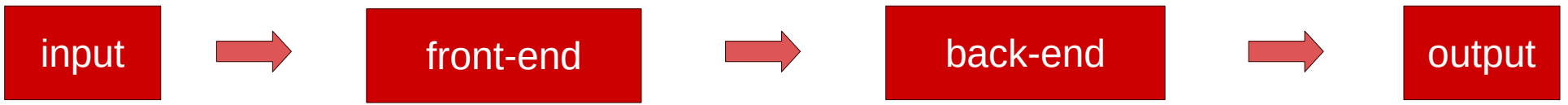
deep learning model

phonetic transcription

describe music with tags

event detection

The deep learning pipeline



waveform

or any audio representation!

phonetic transcription

describe music with tags

event detection

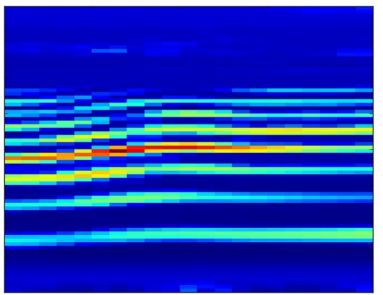
The deep learning pipeline: input?

?

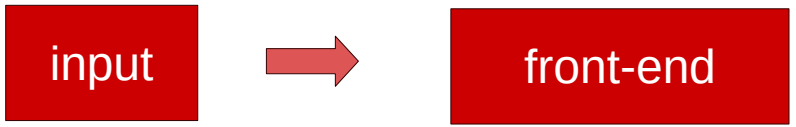
How to format the input (audio) data?

Waveform
end-to-end learning

Pre-processed waveform
e.g.: spectrogram



The deep learning pipeline: front-end?



waveform

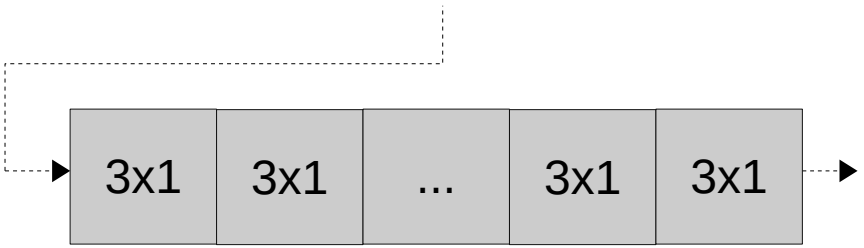
spectrogram

?

based on domain knowledge?	filters config?	input signal?	
		waveform	*pre-processed waveform*

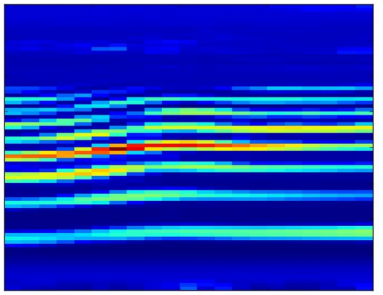
CNN front-ends for audio classification

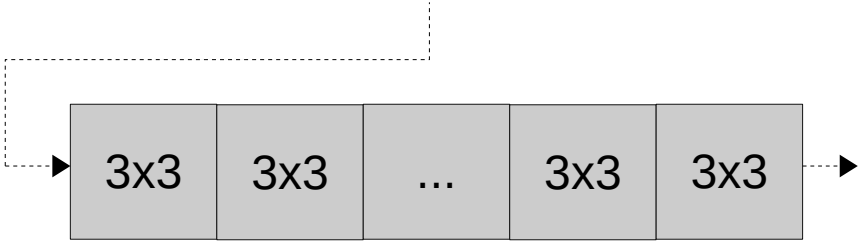
Waveform
end-to-end learning



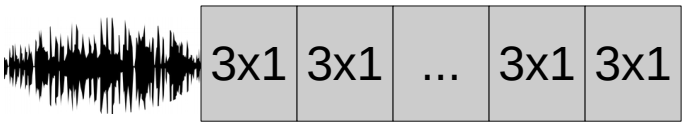
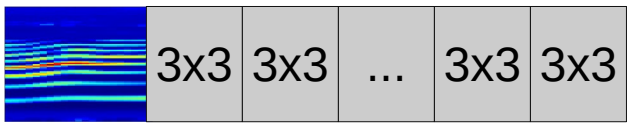
Sample-level

Pre-processed waveform
e.g.: spectrogram





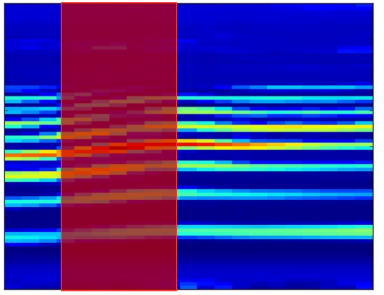
Small-rectangular filters

based on domain knowledge?	filters config?	input signal?	
		waveform	*pre-processed waveform*
no	*minimal filter expression*	sample-level 	small-rectangular filters 

Domain knowledge to design CNN front-ends

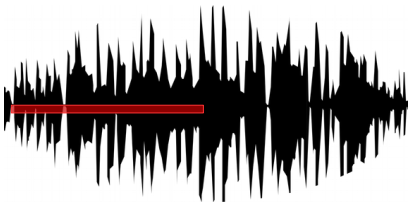
Waveform
end-to-end learning

Pre-processed waveform
e.g.: spectrogram



Domain knowledge to design CNN front-ends

Waveform
end-to-end learning

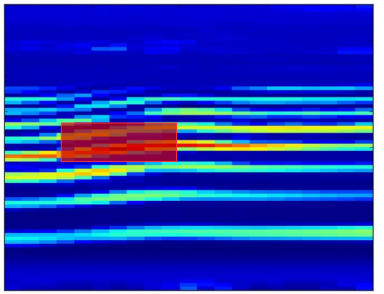


filter length: 512
stride: 256

window length?
hop size?

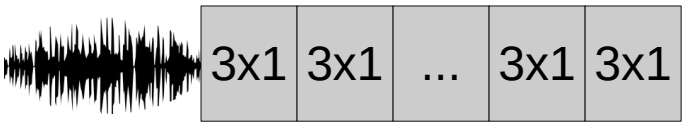
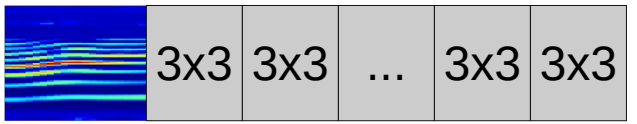
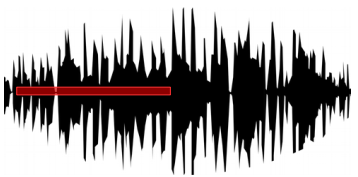
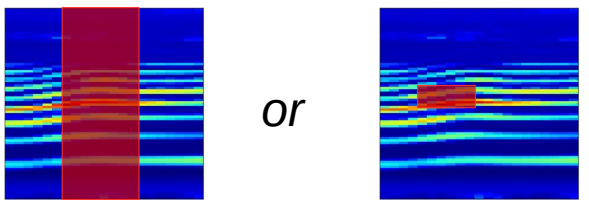
frame-level

Pre-processed waveform
e.g.: spectrogram



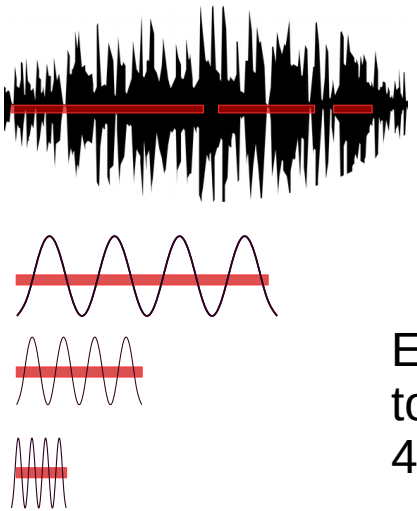
Explicitly tailoring the CNN towards learning temporal ***or*** timbral cues

vertical or horizontal filters

based on domain knowledge?	filters config?	input signal? *waveform*	input signal? *pre-processed waveform*
no	*<u>minimal</u> filter expression*	sample-level 	small-rectangular filters 
yes	*<u>single</u> filter shape in 1st CNN layer*	frame-level 	vertical *OR* horizontal 

DSP wisdom to design CNN front ends

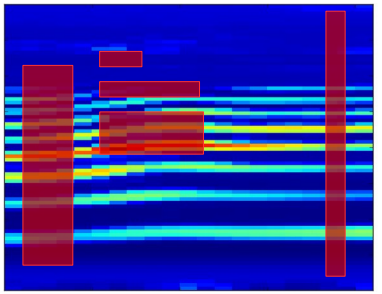
Waveform
end-to-end learning



Efficient way
to represent
4 periods!

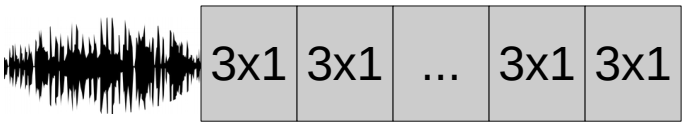
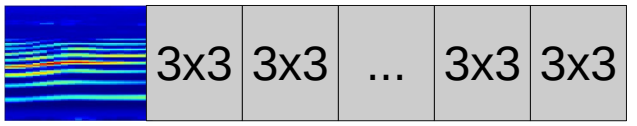
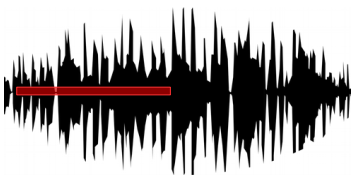
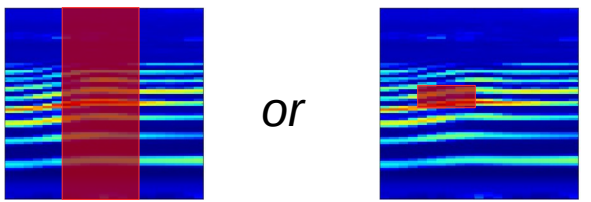
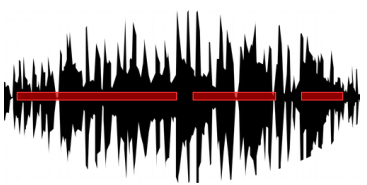
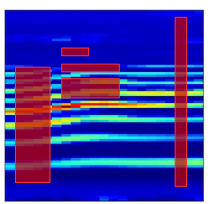
Frame-level (many shapes!)

Pre-processed waveform
e.g.: spectrogram



Explicitly tailoring the CNN towards
learning temporal ***and*** timbral cues

Vertical and/or horizontal

based on domain knowledge?	filters config?	input signal? *waveform*	input signal? *pre-processed waveform*
no	*minimal filter expression*	sample-level 	small-rectangular filters 
yes	*single filter shape in 1st CNN layer*	frame-level 	vertical *OR* horizontal 
yes	*many filter shapes in 1st CNN layer*	frame-level 	vertical *AND/OR* horizontal 

CNN front-ends for audio classification

Sample-level: Lee et al., 2017 – **Sample-level Deep Convolutional Neural Networks for Music Auto-tagging Using Raw Waveforms** *in Sound and Music Computing Conference (SMC)*

Small-rectangular filters: Choi et al., 2016 – **Automatic tagging using deep convolutional neural networks** *in Proceedings of the ISMIR (International Society of Music Information Retrieval) Conference*

Frame-level (single shape): Dieleman et al., 2014 – **End-to-end learning for music audio** *in International Conference on Acoustics, Speech and Signal Processing (ICASSP)*

Vertical: Lee et al., 2009 – **Unsupervised feature learning for audio classification using convolutional deep belief networks** *in Advances in Neural Information Processing Systems (NIPS)*

Horizontal: Schluter & Bock, 2014 – **Improved musical onset detection with convolutional neural networks** *in International Conference on Acoustics, Speech and Signal Processing (ICASSP)*

Frame-level (many shapes): Zhu et al., 2016 – **Learning multiscale features directly from waveforms** *in arXiv:1603.09509*

Vertical and horizontal (many shapes): Pons, et al., 2016 – **Experimenting with musically motivated convolutional neural networks** *in 14th International Workshop on Content-Based Multimedia Indexing*

The deep learning pipeline: back-end?

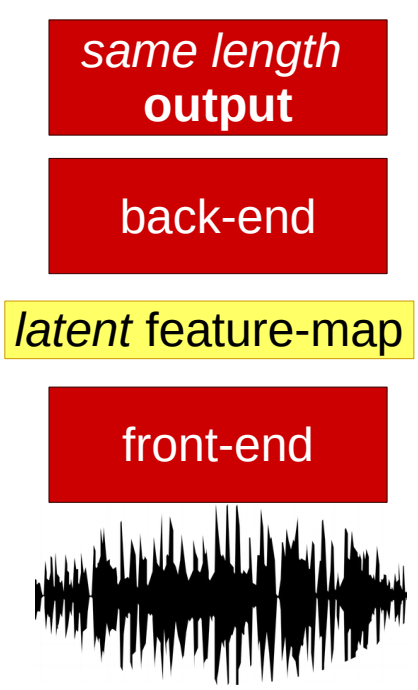
waveform

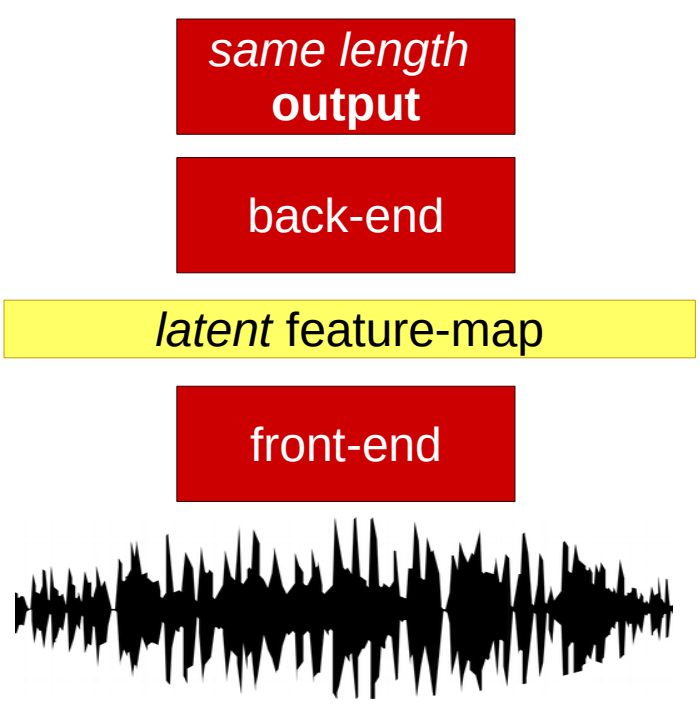
spectrogram

several CNN architectures

?

What is the back-end doing?





*Back-end **adapts** a variable-length feature map to a fixed output-size*

Back-ends for variable-length inputs

- **Temporal pooling:** max-pool or average-pool the temporal axis

  Pons et al., 2017 – **End-to-end learning for music audio tagging at scale**, in proceedings of the ML4Audio Workshop at NIPS.

- **Attention:** weighting latent representations to what is important

  C. Raffel, 2016 – **Learning-Based Methods for Comparing Sequences, with Applications to Audio-to-MIDI Alignment and Matching.** PhD thesis.

- **RNN:** summarization through a deep temporal model

  Vogl et al., 2018 – **Drum transcription via joint beat and drum modeling using convolutional recurrent neural networks,** In proceedings of the ISMIR conference.

..music is generally of variable length!

Back-ends for fixed-length inputs

Common trick: let's assume a fixed-length input

- **Fully convolutional stacks:** adapting the input to the output with a stack of CNNs & pooling layers.

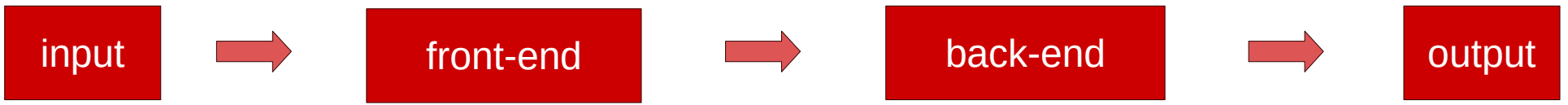
  Choi et al., 2016 – **Automatic tagging using deep convolutional neural networks** in proceedings of the ISMIR conference.

- **MLP:** map a *fixed-length* feature map to a *fixed-length* output

  Schluter & Bock, 2014 – **Improved musical onset detection with convolutional neural networks** in proceedings of the ICASSP.

..such trick works very well!

The deep learning pipeline: output



waveform

spectrogram

several CNN architectures

MLP

RNN

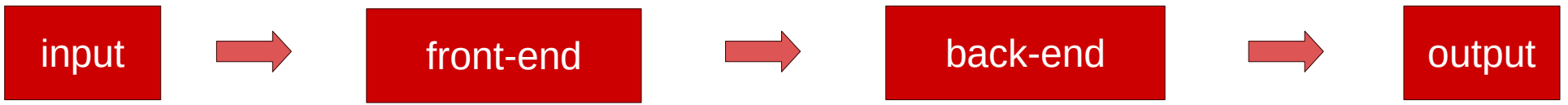
attention

phonetic transcription

describe music with tags

event detection

The deep learning pipeline: output



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Outline

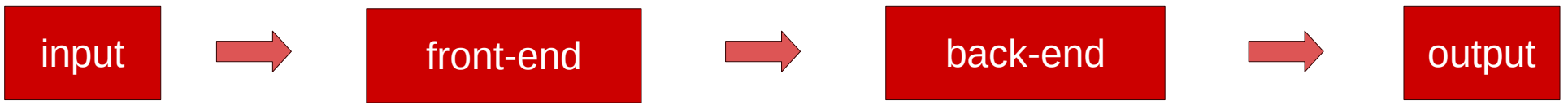
Chronology: the big picture

Audio classification: state-of-the-art review

Music audio tagging as a study case

Pons et al., 2017. **End-to-end learning for music audio tagging at scale**,
in ML4Audio Workshop at NIPS *Summer internship @ Pandora*

The deep learning pipeline: input?



?

describe music
with tags

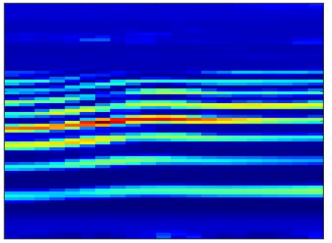
How to format the input (audio) data?

waveform

already: zero-mean
& one-variance

NO pre-procesing!

log-mel spectrogram

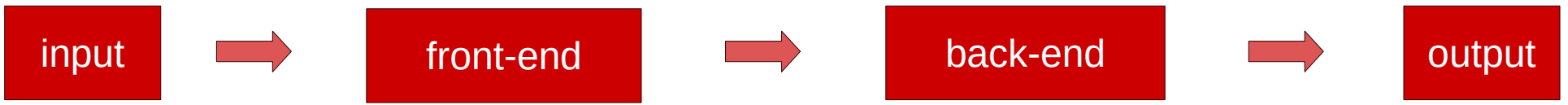


– **STFT & mel mapping**
reduces size of the input by removing perceptually irrelevant information

– **logarithmic compression**
reduces dynamic range of the input

– **zero-mean & one-variance**

The deep learning pipeline: input?

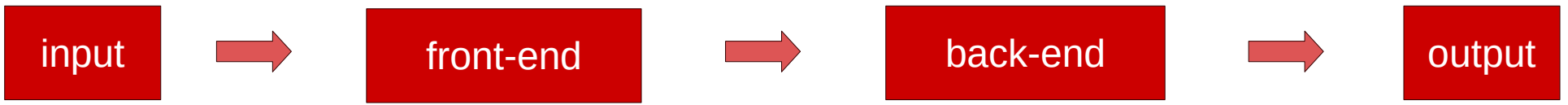


waveform

log-mel spectrogram

describe music with tags

The deep learning pipeline: front-end?

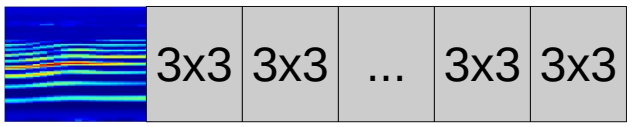
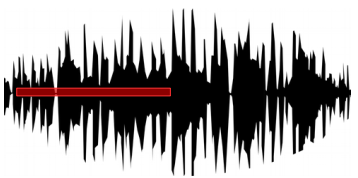
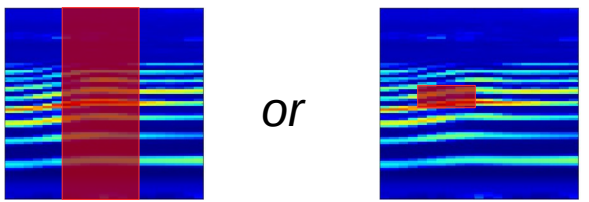
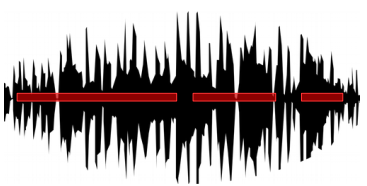
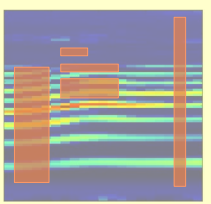


waveform

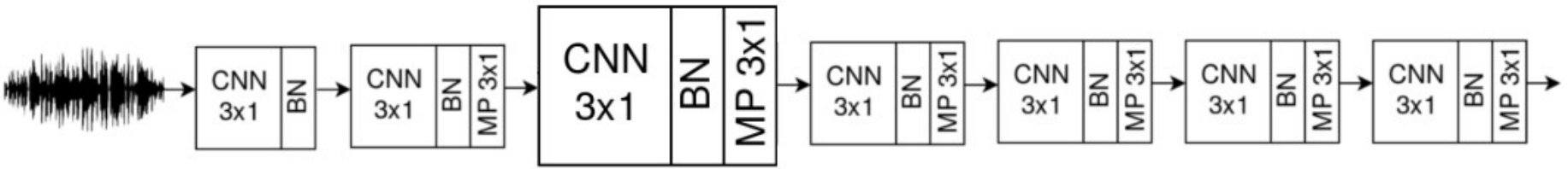
log-mel spectrogram

?

describe music with tags

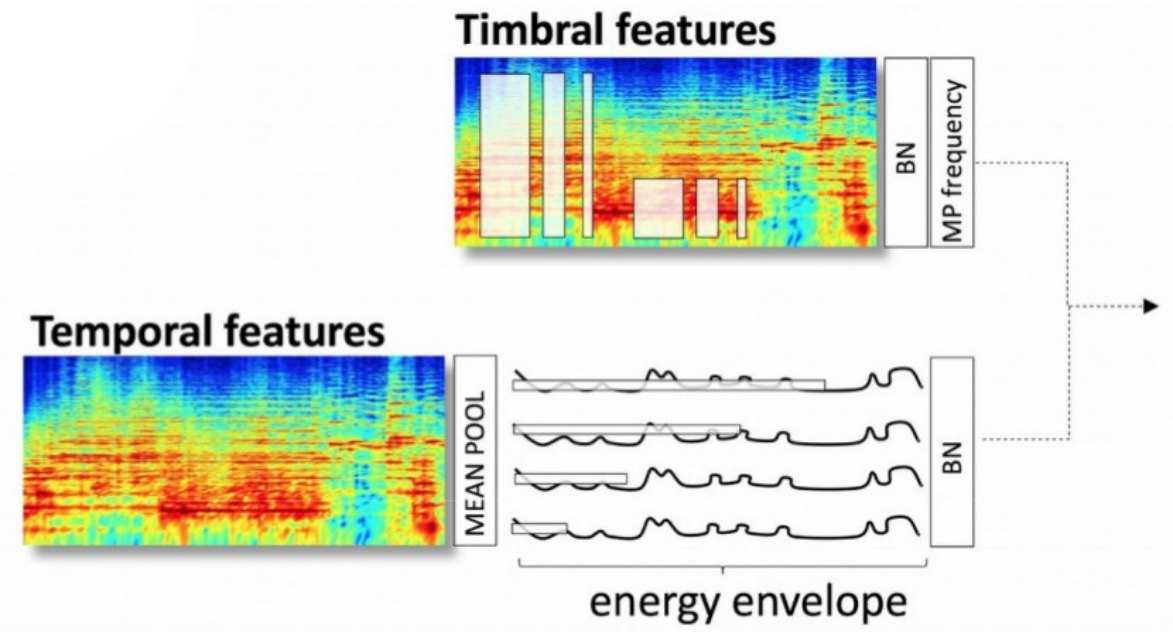
based on domain knowledge?	filters config?	input signal? *waveform*	input signal? *pre-processed waveform*
no	*minimal filter expression*	sample-level 	small-rectangular filters 
yes	*single filter shape in 1st CNN layer*	frame-level 	vertical *OR* horizontal 
yes	*many filter shapes in 1st CNN layer*	frame-level 	vertical *AND/OR* horizontal 

Studied front-ends: waveform model



sample-level *(Lee et al., 2017)*

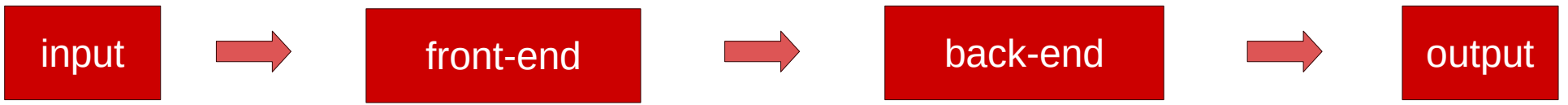
Studied front-ends: spectrogram model



vertical and horizontal
musically motivated CNNs

(Pons et al., 2016 – 2017)

The deep learning pipeline: front-end?



waveform

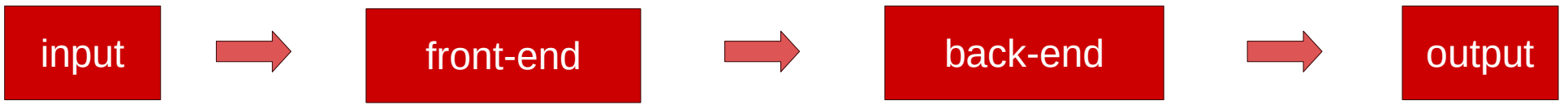
log-mel spectrogram

sample-level

vertical and horizontal

describe music with tags

The deep learning pipeline: back-end?



waveform

log-mel spectrogram

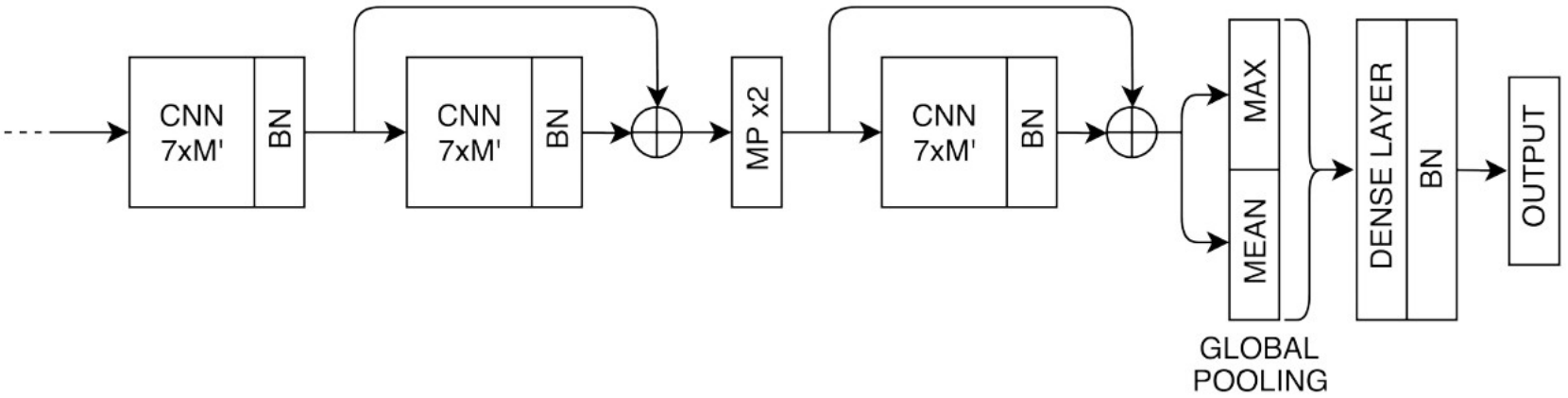
sample-level

vertical and horizontal

?

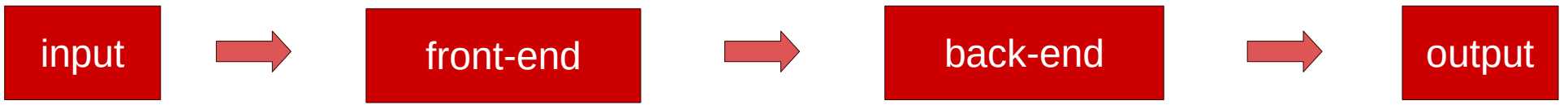
describe music with tags

Studied back-end: music is of variable length!



Temporal pooling *(Dieleman et al., 2014)*

The deep learning pipeline: back-end?



waveform

log-mel spectrogram

sample-level

vertical and horizontal

temporal pooling

describe music with tags

MagnaTT
25k
songs

Million song dataset
250k
songs

1M
songs

spectrograms > waveforms

MagnaTT
25k
songs

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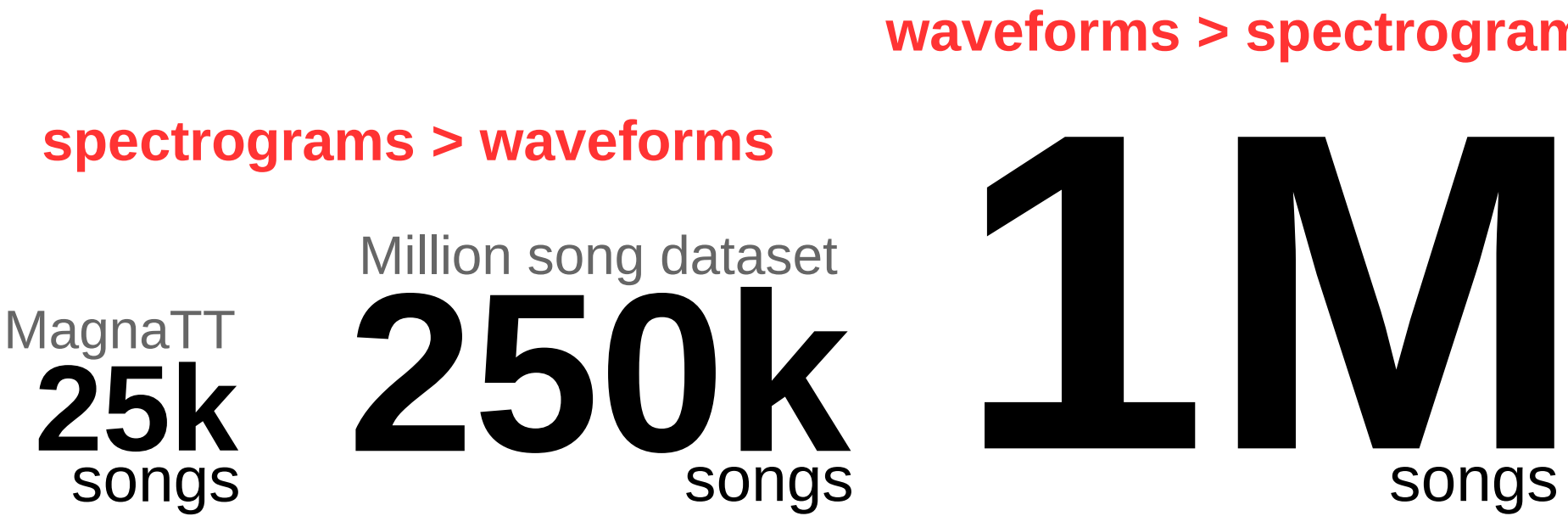
spectrograms > waveforms
MagnaTT
25k
songs
Million song dataset
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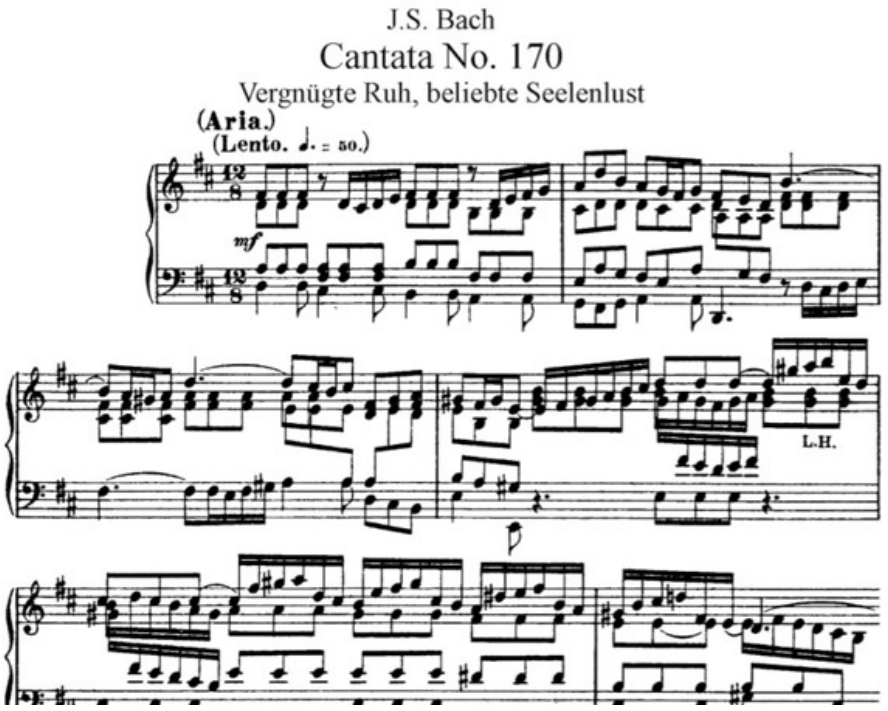
songs

Let’s listen to some music: **our model** in action



acoustic

string ensemble

classical music

period baroque

compositional dominance of lead vocals

major

Deep learning architectures for music audio classification: a personal (re)view

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