Annotated Resources

# References – IEEE Volume 36 January 2019 Automatic Music Transcription

**[E. Benetos, S. Dixon, Z. Duan, S. Ewert, “Automatic Music Transcription”, in IEEE SPS Journal Vol. 36 January]**

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* General overview of field
* Errors present in current models
* Characteristics of musical notes
* Description of unpitched sound problem Ch. 5

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* General overview of field
* Future challenges
* Polyphonic instruments challenge
* Problems with current models

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* Relation to source separation

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* Relation to Information Retrieval tasks like music similarity

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* Relation to Information Retrieval tasks like music similarity
* Neural Network (NN) and Music Language Model (MLM)
* NN MNE does not consider note interactions
* NN MNE considers note interactions
* Polyphonic music detection via RBM machine with RNN to postprocess the acoustic output of an AMT system
* Modelling high dimensional sequences with deep learning methods

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* AMT and sound event detection (SED)
* Similarity of methodologies used in SED with AMT methods

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* Way to circumvent lack of ground truth transcriptions using music performers
* Lack of annotated datasets

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* Probabilistic MPE modelling

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* Spectral likelihood model for MNE considers note interactions

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* MPS instrument tracking

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* MPE using traditional Signal Processing techniques
* Largest dataset of several hours of piano music
* Challenges to NN

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* Bayesian MPE

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* NMF MPE

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* NMF MPE
* Supervised NMF narrow-band sub templates to enforce harmonic structure for all NMF templates
* Remove interference from templates by extracting templates from recordings with only one note

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* NMF MPE
* MPS instrument tracking
* Shift invariant dictionaries can represent multiple F0s
* Sharing parameters between pitches
* Markov process to model note evolutionary phases

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* NMF MPE
* Shift invariant dictionaries can represent multiple F0s
* Sharing parameters between pitches

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* NN MPE
* MLM considers note interactions
* Long range dependencies between notes using an acoustic front end with a symbolic level module resembling an MLM
* Use of MIDI data a recurrent NN was trained to predict active notes in the next frame given those in the past
* NADE architecture and WaveNet
* RNN-RBM MM combined with acoustic predictions using a probabilistic graph model

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* NN MPE
* Large scale hyperparameter search describing individual system components
* Performed well against other models

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* MNE interonset interval approach considers note interactions
* Marolts Sonic System based on NNs
* Analyzing the output of adaptive oscillators to track and group partials in the output of a gammatone filterbank

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* MNE considers note interactions through unifed framework that estimates pitch,onset and offset together
* Context specific transcription : single instruments have become much more accurate

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* MNE considers note interactions through unifed framework that estimates pitch,onset and offset together
* Markov process to model note evolutionary phases
* Comparison to Marolt’s Sonic System
* Limitations of NNs: cold start problem
* Context specific transcription : single instruments have become much more accurate

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* MNE considers note interactions through unifed framework that estimates pitch,onset and offset together
* Google Brain general purpose piano transcription
* Two networks: one focuses on note onsets and informs the network focused on perceiving note lengths
* Limitations of NNs: cold start problem

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* Notation level pitch Spelling

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* Notation level timing quantization

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* Notation level voice separation

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* Notation level method to convert MIDI to music notation with comparison to commercial packages and performance transcription

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* Explanation and advantages of NMF algorithms

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* Sparse coding approach to obtain solutions that are dominated by activations that are few but substantial
* Unsupervised NMF

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* NNs learning nonlinear functions and optimization methods
* Stochastic gradient descent
* Convolutional networks in the time direction
* Long Short-Term Memory Layers
* Interpolation of templates and valid spectra manifolds in NN

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* NNs revival
* Two spectrograms for high time and frequency resolution
* Benefits of LTSMs to model long range dependencies
* Probability of measuring a particular chord sequence

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* Score informed transcription

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* Non-Western music problem

# References – Tutorial ISMIR 2015 AMT

**[Z. Duan, E. Benetos, “Automatic Music Transcription”, Tutorial at ISMIR 2015, available:** [**http://c4dm.eecs.qmul.ac.uk/ismir15-amt-tutorial/**](http://c4dm.eecs.qmul.ac.uk/ismir15-amt-tutorial/) **[Accessed 3/8/2019] ]**

Tutorial Slides: <file:///C:/Users/olli/Desktop/ENGN4200/resources/AMT_tutorial_ISMIR_2015.pdf>

Tutorial website: <http://c4dm.eecs.qmul.ac.uk/ismir15-amt-tutorial/>

slide 60 - list of AMT academic open source software

slide 61 - list of AMT commercial software

slide 61 – Demo of Silvet Vamp plugin