GCT634/AI613: Musical Applications of Machine Learning

Automatic Music Transcription: Monophonic

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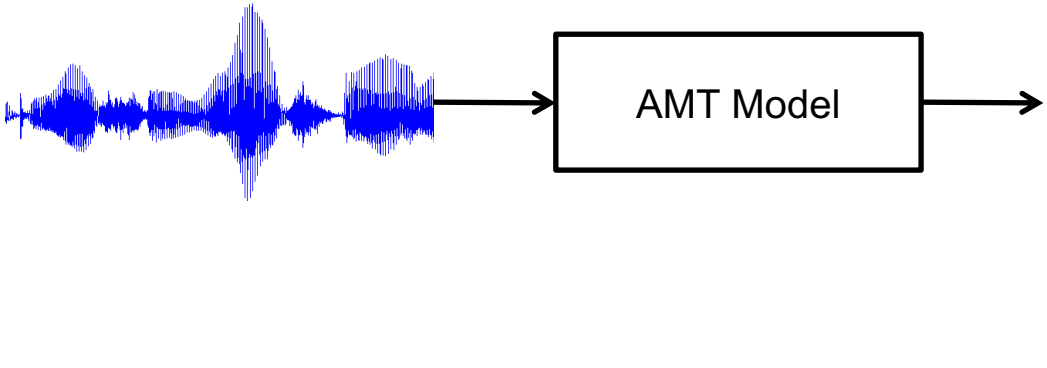
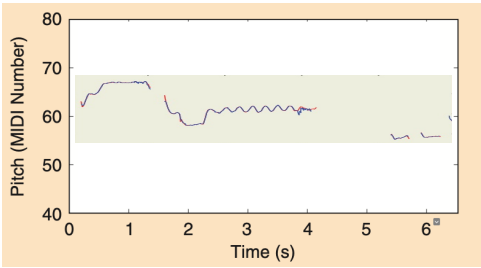
Overview of Automatic Music Transcription (AMT)

- Predict score information from acoustic music signals
  - Pitch contour: frame-level continuous pitch curves
  - MIDI: note-level events or piano rolls
  - Sheet music: symbolic music notation

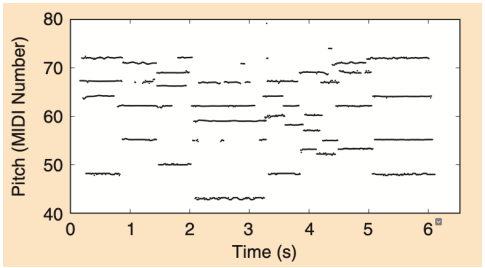


AMT Tasks

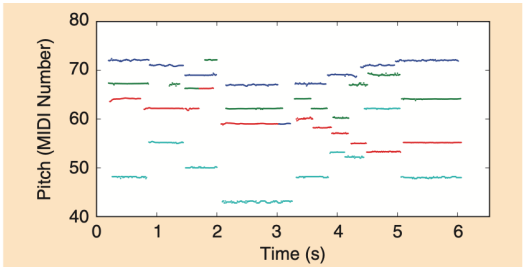
- Pitch estimation (frame-level)
  - Monophonic pitch estimation from a single sound source
  - Polyphonic pitch estimation from multiple sound sources
    - Polyphonic single instrument: piano, guitar
    - Polyphonic multiple instrument: violin + cello + piano (stream-level)
  - Melody estimation: single melodic pitch estimation from multiple sound sources



Monophonic



Polyphonic



Polyphonic + instrument

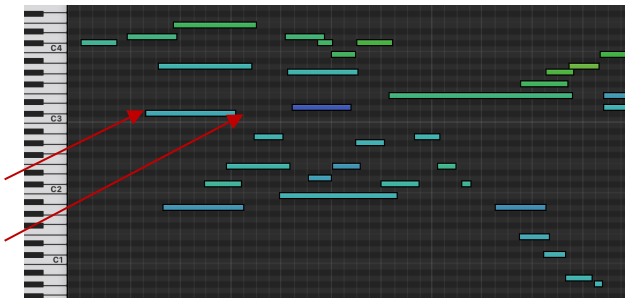
Automatic Music Transcription: An Overview, Emmanouil Benetos, Simon Dixon, Zhiyao Duan, and Sebastian Ewert, IEEE SPM, 2018

AMT Tasks

- Note Transcription (note-level)
  - Based on the frame-level pitch estimation
  - Identify a note by detecting the onset and offset → MIDI note on/off events
  - The task is challenging when the pitch is expressive (e.g. singing, violin)

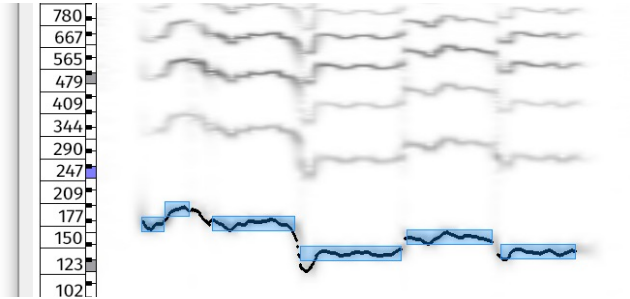
MIDI Messages

"Note on: note=61, vel=80"
"Note off: note=61, vel=80"



Polyphonic piano transcription

https://piano-scribe.glitch.me/

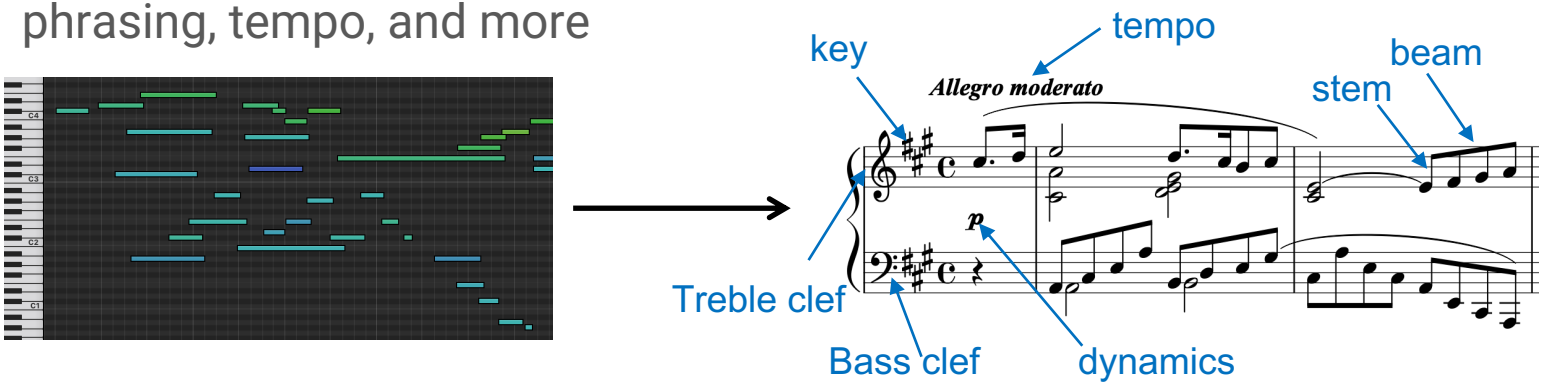


Singing Note Transcription (Tony)

https://www.sonicvisualiser.org/tony/

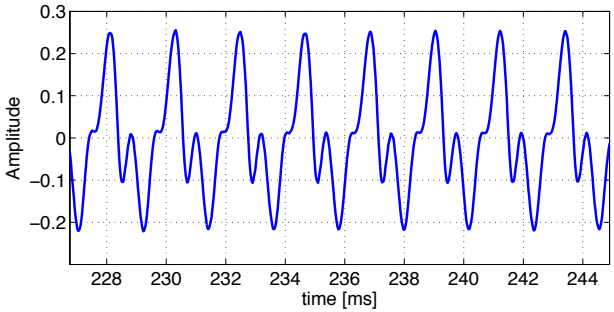
AMT Tasks

- The sheet music needs a lot more information (complete AMT)
  - Based on the note transcription
  - Metric analysis: tempo estimation, beat/downbeat detection
    → quantize onset and offsets to beat-based time units
  - Key detection: 12 pitch classes and major/minor (e.g. C major)
  - Notes: clef, stem, beam
  - Expressions: dynamics (e.g. piano/forte), articulation (e.g. staccato), phrasing, tempo, and more

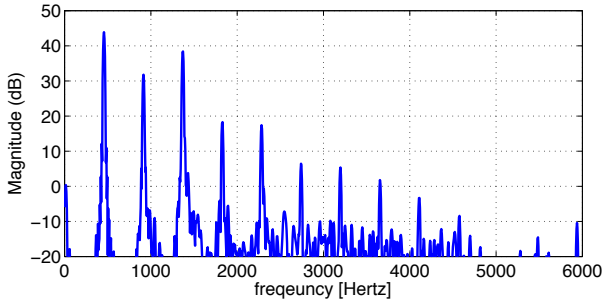


Monophonic Pitch Estimation

- When a tone is generated with a pitch, the waveform is periodic (or nearly periodic) and the spectrum is harmonic (or nearly harmonic)
- Pitch is often called fundamental frequency or “F0” (F0 =1/period)
- Traditional approaches (digital signal processing)
  - Time-domain approach: estimate the period of the waveform
  - Frequency-domain approach: exploit the harmonic pattern



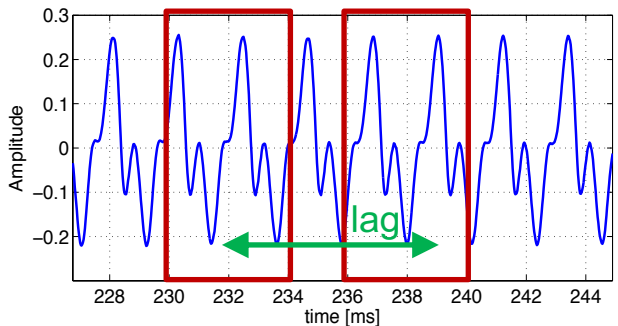
Waveforms of Flute A4 note



Spectrum of Flute A4 note

Time-Domain Approach

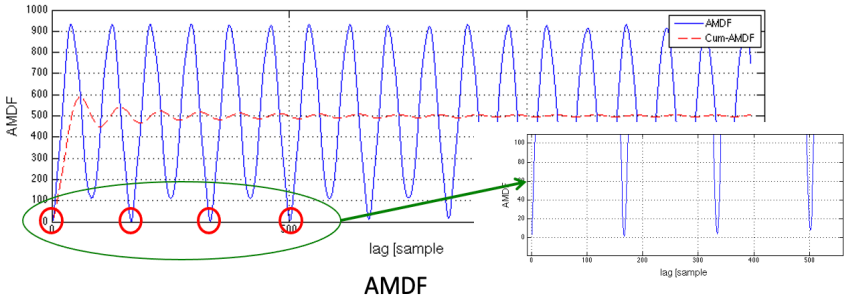
- Measure the period: $x(t) = x(t + T)$
- Calculate the distance between a segment in a fixed window and another segment in a sliding window
  - Auto-correlation function (ACF): distance by the inner product
  - Average magnitude difference function (AMDF) : Euclidean distance
  - AMDF is more robust to the amplitude changes compared to ACF
- Find the time difference (lag) that makes the best match

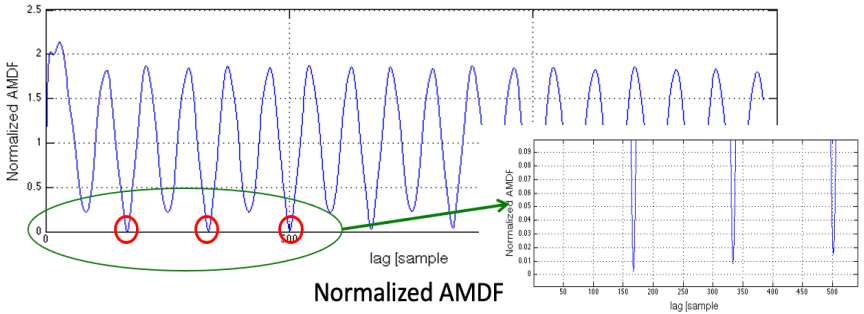


Time-Domain Approach: YIN

- Based on the normalized AMDF
  - Choose the minimum notch below a threshold

$$\hat{d}(l) = \begin{cases} d(l)/[\frac{1}{l}\sum_{u=1}^{l} d(u)] & \text{otherwise} \\ 1 & l = 0 \end{cases} \qquad d(l): \text{AMDF}$$

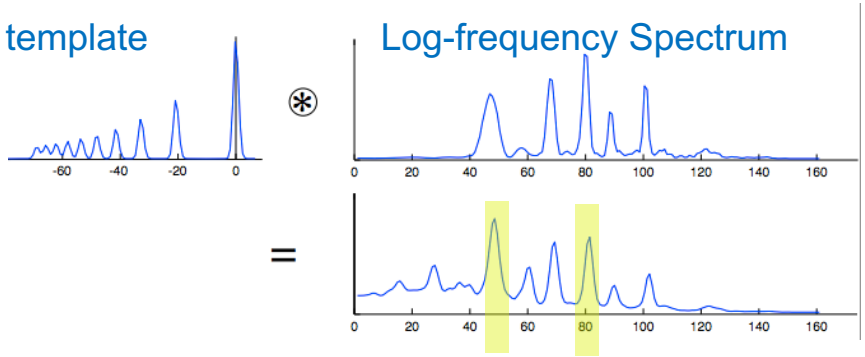


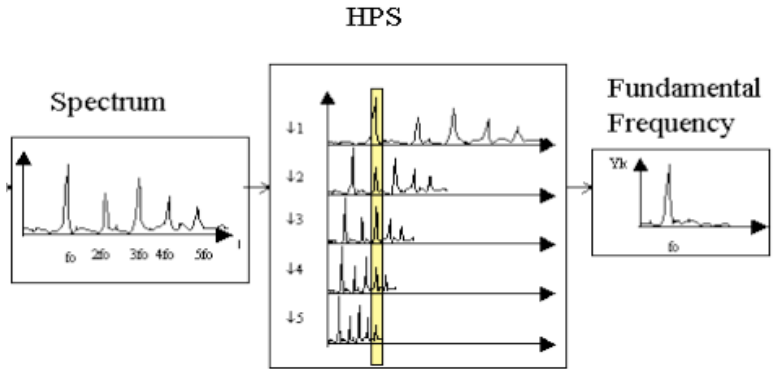


YIN, a fundamental frequency estimator for speech and music, Alain de Cheveigne, Hideki Kawahara, JASA, 2002

Frequency-domain Approach

- Pattern matching: cross-correlation between log-frequency spectrum with a pre-defined harmonic template
  - SWIPE: use the spectrum of sawtooth waveform
- Harmonic product sum (HPS): successive product with harmonically down-sampled spectra
  - Use as a pitch salience function

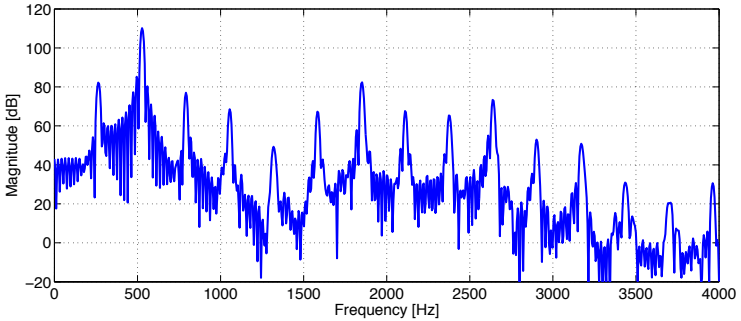




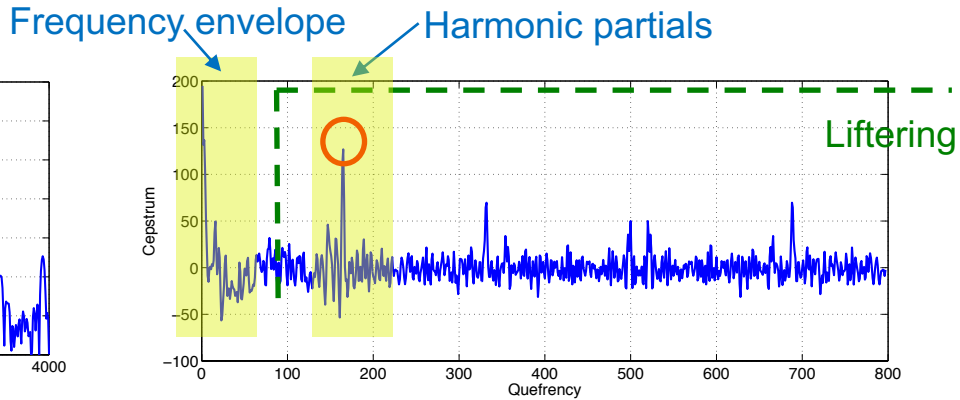
A Sawtooth Waveform Inspired Pitch Estimator for Speech and Music, Arturo Camacho and John G Harris, JASA, 2008.

Cepstrum

- Decompose spectrum into harmonic partials (periodic) and frequency envelope (slowly-varying)
  - Real Cepstrum: $c_x(l) = \text{real}\{\text{FFT}^{-1}(\log|FFT(x)|)\}$
  - “Liftering” to remove the frequency envelope



$\log|FFT(x)|$

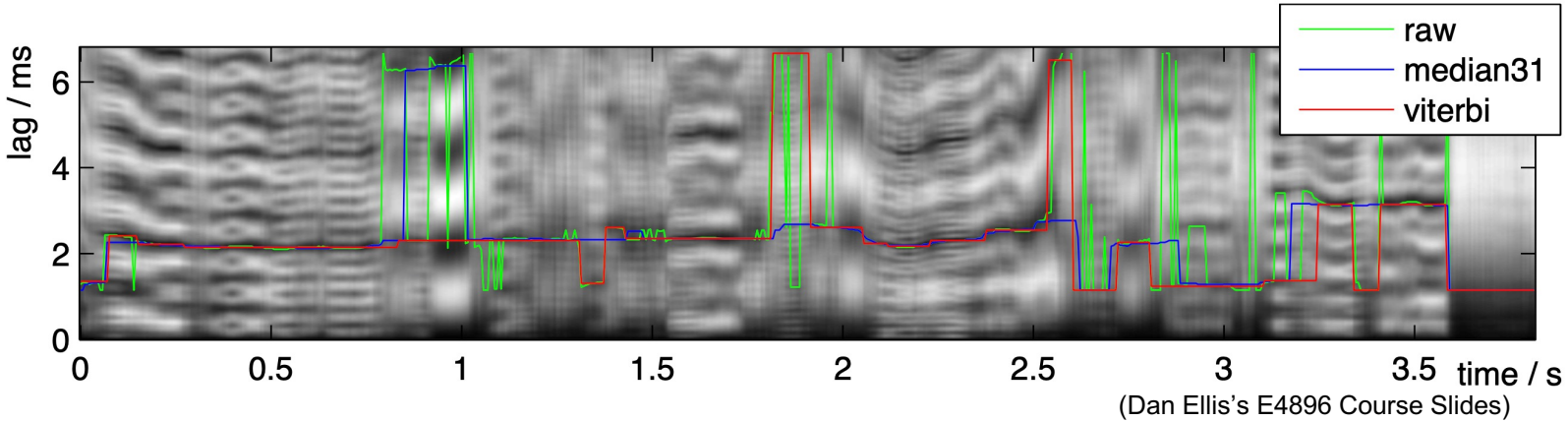


$c_x(l)$

Cepstrum Pitch Determination, A. Michael Noll, JASA, 1967.

Post processing: Smoothing

- Median filtering
  - Handy and useful to remove outliers (e.g. octave jump)
- Viterbi decoding (based on hidden Markov model)
  - Find the best path with the maximum likelihood considering pitch transition
  - PYIN: use a probabilistic threshold and find the best sequence (Tony)



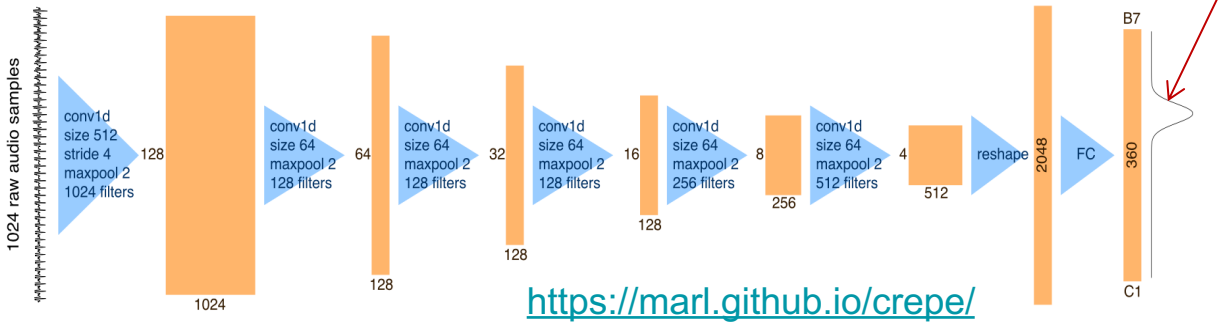
(Dan Ellis's E4896 Course Slides)

PYIN: A fundamental frequency estimator using probabilistic threshold distributions, Matthias Mauch, Simon Dixon, ICASSP, 2014

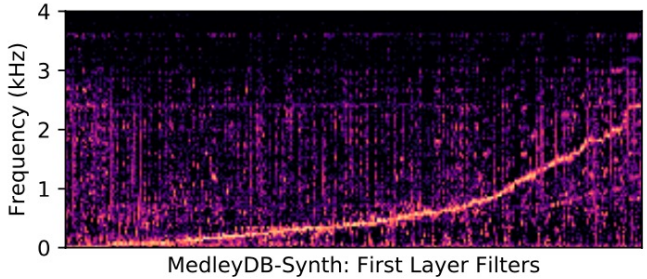
CREPE: Monophonic Pitch Estimation Using Supervised CNN

- Classification-based approach using CNN
  - Input: a single frame of waveforms (1024 samples, resampled to 16kHz)
  - Output: quantized pitch with a resolution of 20 cents --> 360 classes
  - The output labels are smoothed using a Gaussian function: softening the penalty for near-correct predictions

$$y_i = \exp\left(-\frac{(\text{¢}_i - \text{¢}_{\text{true}})^2}{2 \cdot 25^2}\right)$$



https://marl.github.io/crepe/

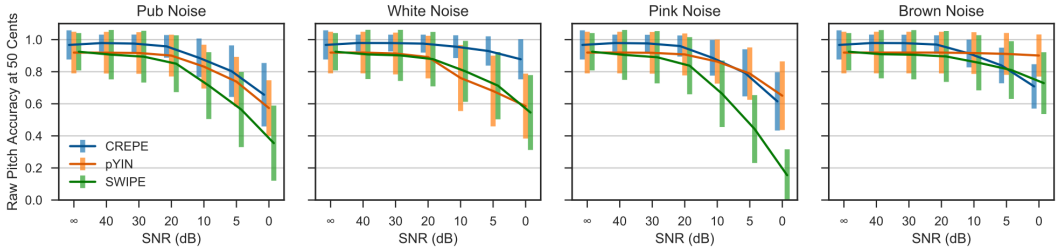


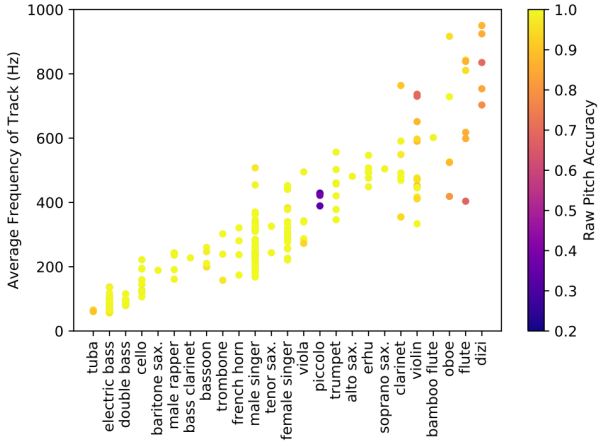
CREPE: A Convolutional Representation for Pitch Estimation, Jong Wook Kim, Justin Salamon, Peter Li, Juan P. Bello, ICASSP, 2018

CREPE: Monophonic Pitch Estimation Using Supervised CNN

- Higher performance than traditional DSP methods
  - Higher raw pitch accuracy (RPA) and raw chroma accuracy (RCA)
  - Robust when a certain noise is added
  - But, low accuracy when the training set does not cover a wider pitch range or the pitch annotation is not consistent

Dataset	Metric	CREPE	pYIN	SWIPE
RWC-synth	RPA	**0.999±0.002**	0.990±0.006	0.963±0.023
	RCA	**0.999±0.002**	0.990±0.006	0.966±0.020
MDB-stem-synth	RPA	**0.967±0.091**	0.919±0.129	0.925±0.116
	RCA	**0.970±0.084**	0.936±0.092	0.936±0.100

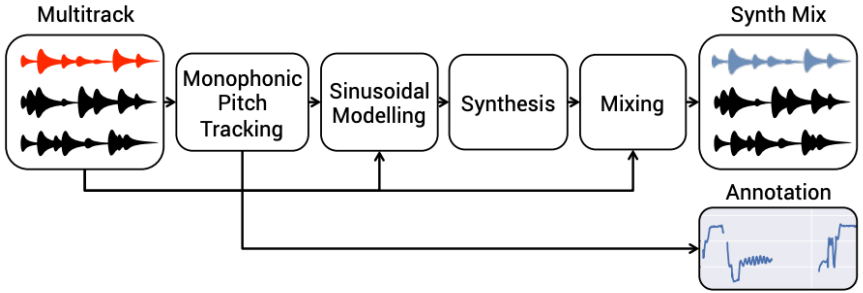




CREPE: A Convolutional Representation for Pitch Estimation, Jong Wook Kim, Justin Salamon, Peter Li, Juan P. Bello, ICASSP, 2018

CREPE: Monophonic Pitch Estimation Using Supervised CNN

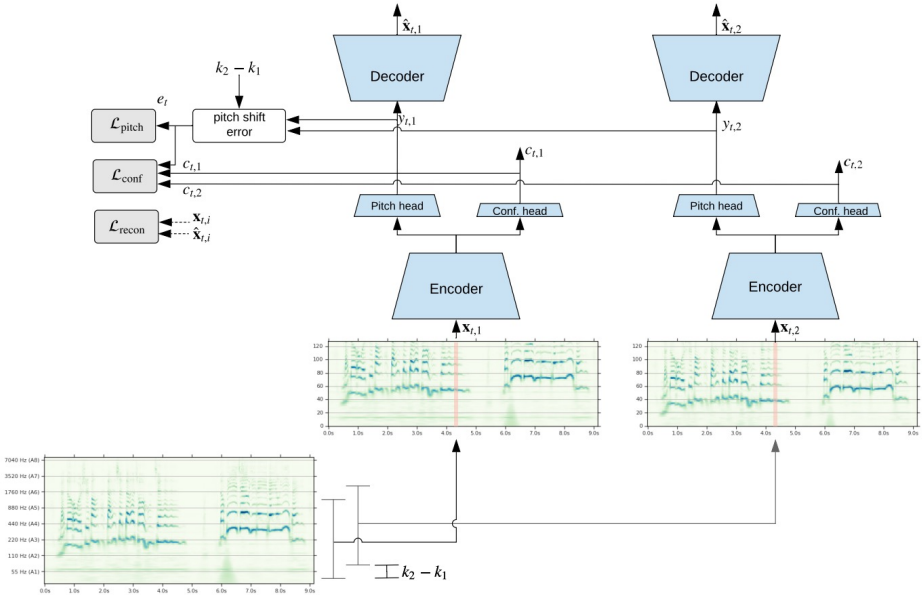
- Dataset issue in the supervised-learning approach
  - It is very tedious to annotate frame-level pitch labels on audio files. How can we obtain large-scale pitch annotations?
- Solution: **Analysis-Resynthesis approach**
  - Use a monophonic pitch estimator and obtain **pseudo pitch labels** (F0)
  - Re-synthesize the input source using the F0 values
  - Originally used for melody extraction in mixed audio



An Analysis/Synthesis Framework for Automatic f0 Annotation of Multitrack Datasets, Justin Salamon, et al., ISMIR, 2017

SPICE: Monophonic Pitch Estimation Using SSL

- Train a pitch estimation network without pitch labels
  - Siamese network to estimate a pitch difference when a pair of constant-Q transform has the same relative pitch difference



$0 \le y_t \le 1$

Relative pitch difference estimation error

$$e_t = |(y_{t,1} - y_{t,2}) - \sigma(k_{t,1} - k_{t,2})|$$

$$\mathcal{L}_{\text{pitch}} = \frac{1}{T}\sum_t h(e_t) \qquad h(x) = \begin{cases} \frac{\mathbf{x}^2}{2}, & |x| \le \tau \\ \frac{\tau^2}{2} + \tau(|x| - \tau) \end{cases}$$

Huber norm

Reconstruction error

$$\mathcal{L}_{\text{recon}} = \frac{1}{T}\sum_t \|\mathbf{x}_{t,1} - \hat{\mathbf{x}}_{t,1}\|_2^2 + \|\mathbf{x}_{t,2} - \hat{\mathbf{x}}_{t,2}\|_2^2,$$

Confidence level estimation

$$\mathcal{L}_{\text{conf}} = \frac{1}{T}\sum_t |(1 - c_{t,1}) - e_t/\sigma|^2 + |(1 - c_{t,2}) - e_t/\sigma|^2$$

Final pitch estimation: the scale and offset are learned using a small labeled dataset

$$\hat{p}_{0,t} = b + s \cdot y_t = b + s \cdot Enc(\mathbf{x}_t)$$

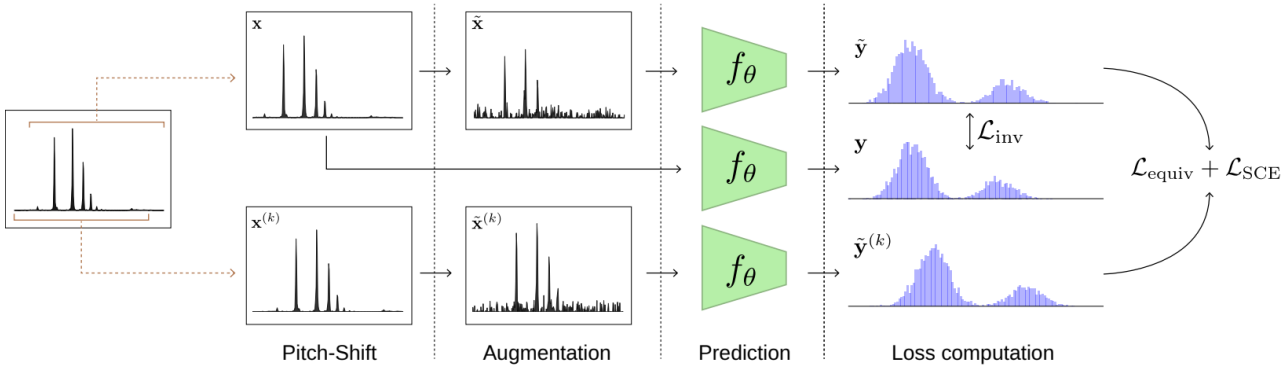
SPICE: Self-Supervised Pitch Estimation, B. Gfeller, C. Frank, D. Roblek, M. Sharifi, M. Tagliasacchi, and M. Velimirovic, IEEE TASLP, 2020

PESTO: Monophonic Pitch Estimation Using Equivariant SSL

- Minimize the equivariance and invariance
  - The output of the network y is a multinomial distribution (pitch classification)
  - Equivariance: shifting + cross-entropy for k transposition

$$\begin{array}{rccc}\phi & : & \mathbb{R}^d & \to & \mathbb{R} \\ & & \mathbf{y} & \mapsto & (\alpha, \alpha^2, \ldots, \alpha^d)\mathbf{y}\end{array} \qquad \mathcal{L}_{\text{equiv}}(\mathbf{y}, \mathbf{y}^{(k)}, k) = h_\tau\left(\frac{\phi(\mathbf{y}^{(k)})}{\phi(\mathbf{y})} - \alpha^k\right) \qquad \mathcal{L}_{\text{SCE}}(\mathbf{y}, \mathbf{y}^{(k)}, k) = \sum_{i=0}^{d-1} y_i \log\left(y_{i+k}^{(k)}\right)$$

  - Invariance: add pitch-invariant transform (e.g. add noise) and cross-entropy



$$\begin{aligned}\mathcal{L}(\mathbf{y}, \tilde{\mathbf{y}}, \tilde{\mathbf{y}}^{(k)}, k) = \lambda_{\text{inv}} \ \mathcal{L}_{\text{inv}}(\mathbf{y}, \tilde{\mathbf{y}}) \\ + \lambda_{\text{equiv}} \ \mathcal{L}_{\text{equiv}}(\tilde{\mathbf{y}}, \tilde{\mathbf{y}}^{(k)}, k) \\ + \lambda_{\text{SCE}} \ \mathcal{L}_{\text{SCE}}(\tilde{\mathbf{y}}, \tilde{\mathbf{y}}^{(k)}, k)\end{aligned}$$

PESTO: Pitch Estimation with Self-supervised Transposition-equivariant Objective, Alain Riou, Stefan Lattner, Gaëtan Hadjeres, Geoffroy Peeters, ISMIR, 2023

PESTO: Monophonic Pitch Estimation Using Equivariant SSL

- Transpostion-preserving architecture
  - 1D-Conv: the frequency resolution remains unchanged
  - A softmax layer for the output
  - Toeplitz fully-connected layer: preserve the transposition ($m + n - 1$ elements instead of mn): equivalent to convolution

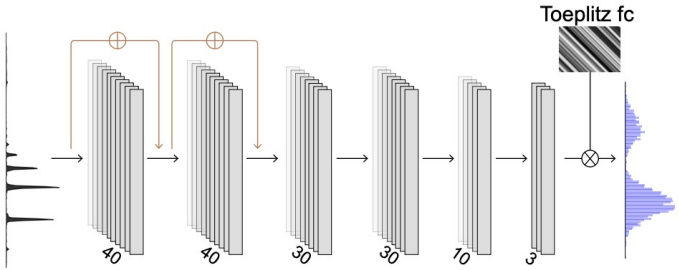


Figure 3. Architecture of our network f_θ. The number of channels varies between the intermediate layers, however the frequency resolution remains unchanged until the final Toeplitz fully-connected layer.

$$A = \begin{pmatrix} a_0 & a_{-1} & a_{-2} & \cdots & a_{-n+2} & a_{-n+1} \\ a_1 & a_0 & a_{-1} & \ddots & \ddots & a_{-n+2} \\ a_2 & a_1 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ a_{m-1} & \cdots & \cdots & \cdots & \cdots & a_{m-n} \end{pmatrix}$$

Toeplitz Matrix

PESTO: Pitch Estimation with Self-supervised Transposition-equivariant Objective, Alain Riou, Stefan Lattner, Gaëtan Hadjeres, Geoffroy Peeters, ISMIR, 2023

PESTO: Monophonic Pitch Estimation Using Equivariant SSL

- A lightweight model

Model	# params	Trained on	Raw Pitch Accuracy *MIR-1K*	Raw Pitch Accuracy *MDB-stem-synth*
SPICE [19]	2.38M	private data	90.6%	89.1%
DDSP-inv [45]	-	*MIR-1K* / *MDB-stem-synth*	91.8%	88.5%
PESTO (ours)	28.9k	*MIR-1K*	**96.1%**	94.6%
PESTO (ours)	28.9k	*MDB-stem-synth*	93.5%	**95.5%**
CREPE [16]	22.2M	many (supervised)	**97.8%**	**96.7%**

- Robustness test

Model	Raw Pitch Accuracy (*MIR-1K*) clean	20 dB	10 dB	0 dB
SPICE [19]	91.4%	91.2%	90.0%	81.6%
PESTO				
$\beta = 0$	**94.8%**	90.7%	79.2%	50.0%
$\beta = 1$	94.5%	94.2%	92.9%	**83.1%**
$\beta \sim \mathcal{U}(0, 1)$	94.7%	94.4%	92.9%	81.7%
$\beta \sim \mathcal{N}(0, 1)$	**94.8%**	**94.5%**	**93.0%**	82.6%
$\beta \sim \mathcal{N}(0, \frac{1}{2})$	**94.8%**	**94.5%**	92.9%	81.0%
CREPE [16]	**97.8%**	**97.3%**	**95.3%**	**84.8%**

Table 2. Robustness of PESTO and other baselines to background music with various Signal-to-Noise ratios. Adding background music to training samples significantly improves the robustness of PESTO (see section 4.4.2).

- Ablation Study

	MIR-1K RPA	MIR-1K RCA	MDB RPA	MDB RCA
PESTO baseline	96.1%	96.4%	94.6%	95.0%
Loss ablations				
w/o $\mathcal{L}_{\text{equiv}}$	5.8%	8.6%	1.3%	6.1%
w/o $\mathcal{L}_{\text{inv}}$	96.1%	96.4%	92.5%	94.5%
w/o $\mathcal{L}_{\text{SCE}}$	96.1%	96.5%	86.9%	93.8%
Miscellaneous				
no augmentations	94.8%	95.4%	94.8%	95.2%
non-Toeplitz fc	5.7%	8.7%	1.2%	6.1%

Table 3. Respective contribution of various design choices of PESTO for a model trained on *MIR-1K*.

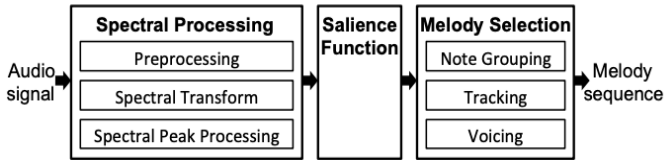
Source Code / Inference Models

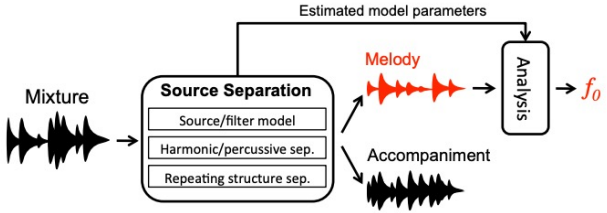
- PYIN: https://librosa.org/doc/main/generated/librosa.pyin.html
- CREPE: https://github.com/marl/crepe
- SPICE: https://www.tensorflow.org/hub/tutorials/spice
- PESTO: https://github.com/SonyCSLParis/pesto

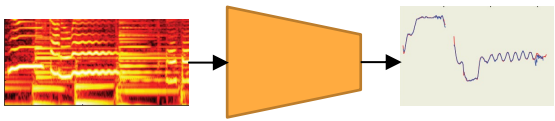
- The neural pitch estimators use food names…

Melody Extraction

- Extract melodic pitch contours from polyphonic music
  - Pre-dominant pitch estimation in the presence of multiple sound sources
- Methods
  - Salience-based approach: use a saliency function (e.g. HPS)
  - Source separation approach: separate the melodic source and use the monophonic pitch estimation
  - Classification-based approach: use CNN or CRNN



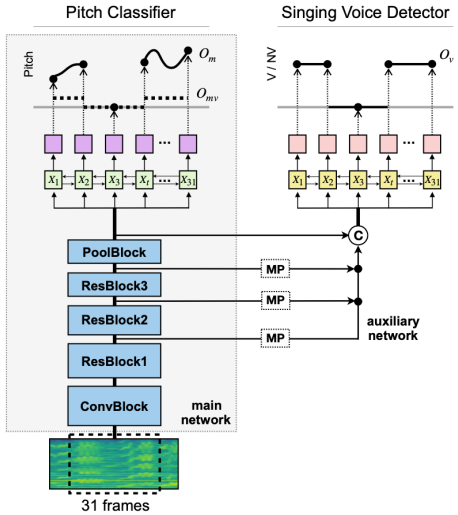




Melody Extraction from Polyphonic Music Signals: Approaches, Applications and Challenges, J. Salamon, E. Gómez, D. P. W. Ellis and G. Richard, IEEE SPM, 2014

Singing Melody Extraction

- Joint learning of singing voice detection and vocal pitch estimation
  - Combining the loss functions from the two tasks
  - Vocal pitch classification (CRNN)
    - ResNet stacks: “no pooling over time”
    - Bi-directional LSTM-RNN to learn temporal dependency
    - Use the Gaussian blurring in the output layer
  - Singing voice detector (CRNN)
    - Use the shared features from the three layers of the pitch classifier: “hierarchical” audio features (e.g., vocal formant, vibrato, portamento)
    - Bi-directional LSTM-RNN
  - https://github.com/keums/melodyExtraction_JDC



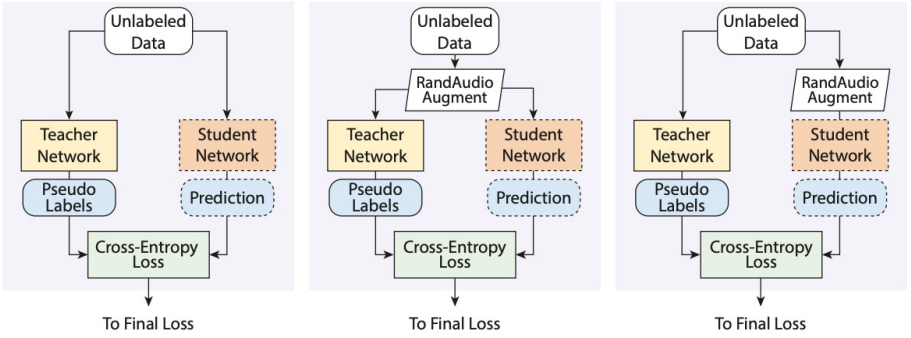
	Components		Output Size	
	Main	*Main + AUX*	*Main*	*Main + AUX*
Input	-		31 × 513	
Conv block	[3 × 3, 64] × 2		31 × 513, 64	
ResNet Block 1	[3 × 3, 128] × 2		31 × 128, 128	
ResNet Block 2	[3 × 3, 192] × 2		31 × 32, 192	
ResNet Block 3	[3 × 3, 256] × 2		31 × 8, 256	
Pool block	-		31 × 2, 256	
Bi-LSTM	256	256 + 32	31 × 512	31 × (512 + 64)
FC	722	722 + 2	31 × 722	31 × (722 + 2)

Joint Detection and Classification of Singing Voice Melody Using Convolutional Recurrent Neural Networks, Sangeun Kum and Juhan Nam, 2019

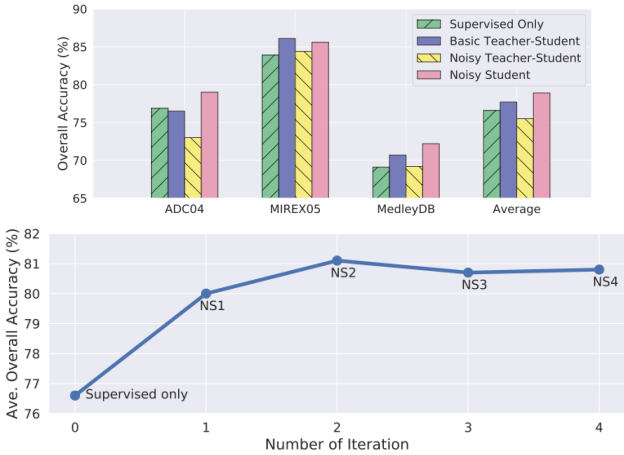
Singing Melody Extraction Using Teacher-Student Models

- Semi-supervised learning
  - Labeled data: used to train a teacher network
  - Unlabeled data: used to train a student network to predict the output of the teacher network
- Random data augmentation makes the student network perform betters

	Dataset	Number of Tracks	Total Length
Training (Labeled)	RWC	100	6h 47m
	MedleyDB	61	2h 39m
	iKala	262	2h 6m
Training (Unlabeled)	In-house	535	6h 21m
	FMA_small	3,521 / 8,000	25h / 60h
	FMA_medium	10,639 / 25,000	89h / 208h
	FMA_large	40,505 / 106,574	337h / 888h
Test	ADC04	12	4m
	MIREX05	9	4m
	MedleyDB	12	43m
	AST218	218	14h 53m



https://github.com/keums/melodyExtraction_SSL



Semi-Supervised Learning Using Teacher-Student Models for Vocal Melody Extraction, Sangeun Kum and Juhan Nam, 2020