Automatic Transcription: An Enabling Technology for Music Analysis

Simon Dixon

simon.dixon@eecs.qmul.ac.uk

Centre for Digital Music
School of Electronic Engineering and Computer Science
Queen Mary University of London

Queen Mary University of London

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Research Councils UK Digital Economy Transforming Business and Society

JISC

Semantic Audio

- Extraction of symbolic “meaning” from audio signals: How would a person describe the audio?
  - Solo violin, D minor, slow tempo, Baroque period
  - Bar 12 starts at 0:21.961
  - 2nd verse starts at 1:43.388
  - Quarter comma meantone temperament
- Annotation of audio
  - Onset detection
  - Beat tracking
  - Segmentation (structural, ...)
  - Instrument identification
  - Temperament and inharmonicity analysis
  - Automatic transcription
- Automatically generated annotations are stored as metadata
  - Matched against content-based queries
  - Also useful for navigation within a document

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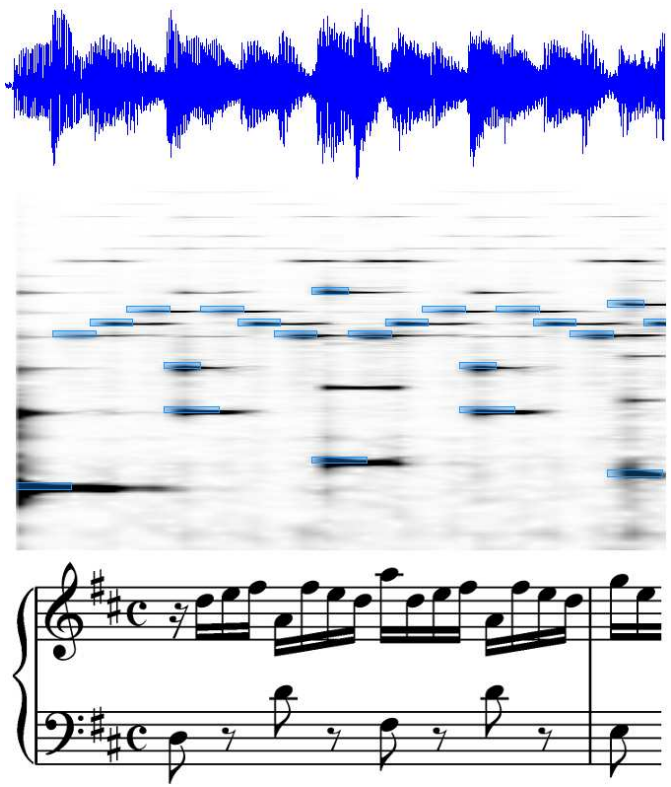
Automatic music transcription (AMT)

- Audio recording → Score
- Applications:
  - Music information retrieval
  - Interactive music systems
  - Musicological analysis
- Subtasks:
  - Pitch estimation
  - Onset/offset detection
  - Instrument identification
  - Rhythmic parsing
  - Pitch spelling
  - Typesetting
- Still remains an open problem



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Background (1)

- Core problem: Multiple-F0 estimation
- Common time-frequency representations:
  - Short-Time Fourier Transform
  - Constant-Q Transform
  - ERB Gammatone Filterbank
- Common estimation techniques:
  - Signal processing methods
  - Statistical modelling methods
  - NMF/PLCA
  - Sparse coding
  - Machine learning algorithms
- HMMs commonly used for note tracking

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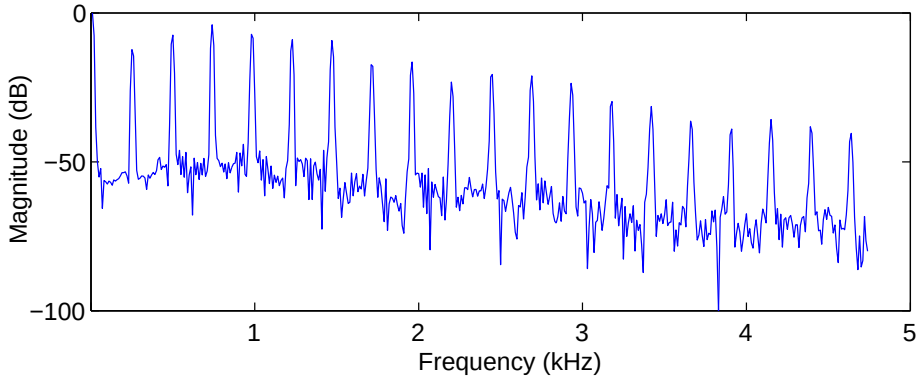
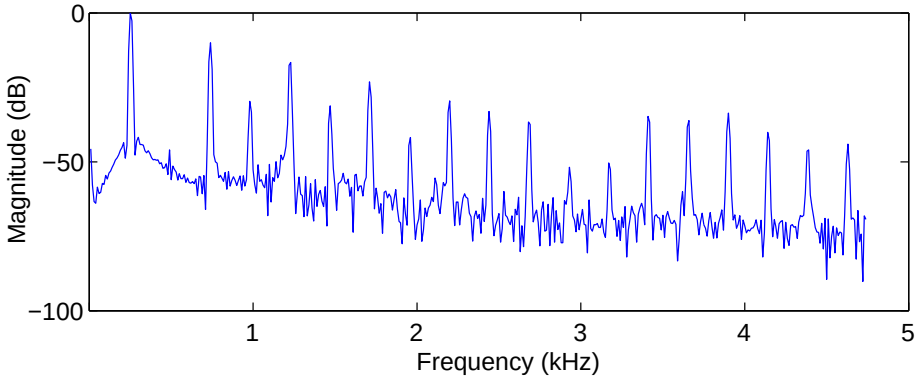
Background (2)

- **mirex** evaluation:
  - Best results achieved by signal processing methods
- Multiple-F0 estimation approaches rely on assumptions:
  - Harmonicity
  - Power summation
  - Spectral smoothness
  - Constant spectral template





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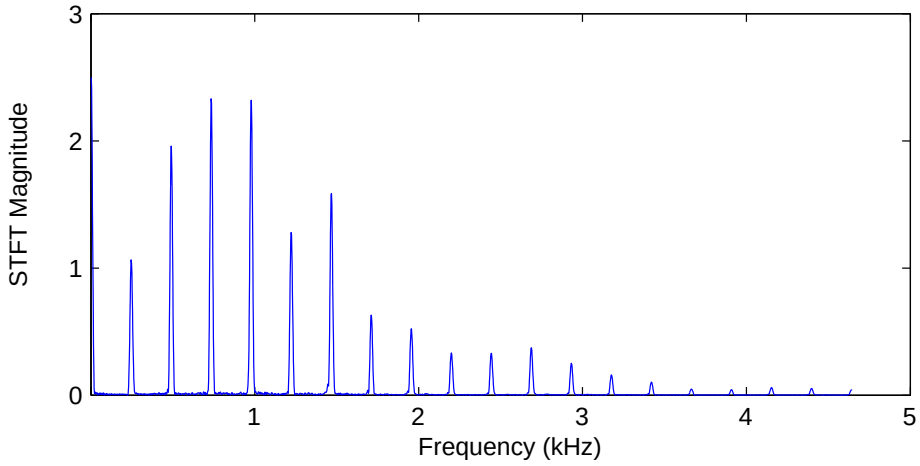
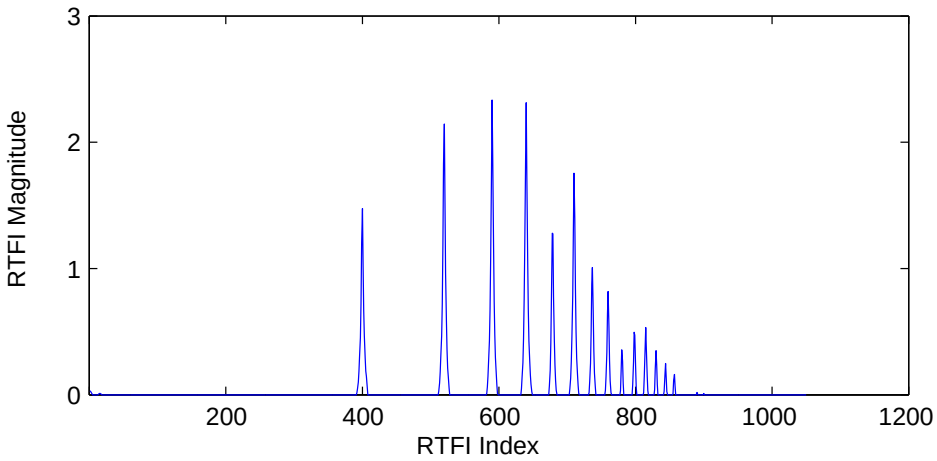
Background (3)

- Design considerations:
  - Time-frequency representation
  - Iterative/joint estimation method
  - Sequential/joint pitch tracking





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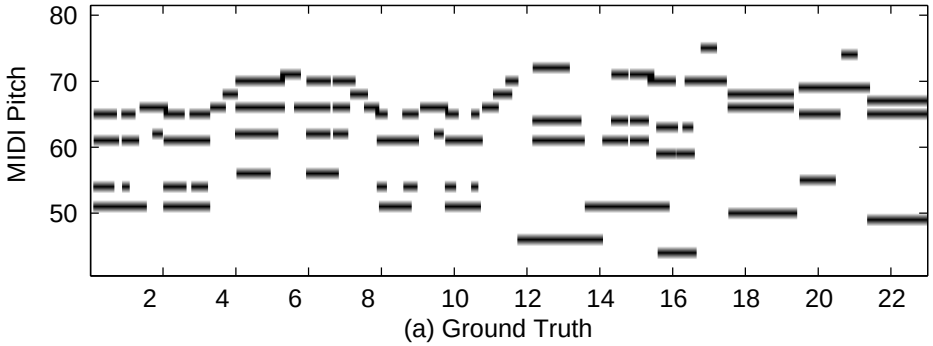
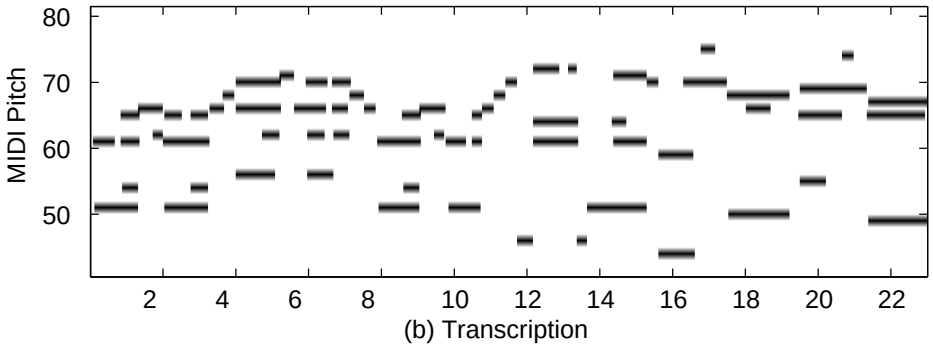
Signal Processing Approach (ICASSP 2011)

- RTFI time-frequency representation
- Preprocessing: noise suppression, spectral whitening
- Onset detection: late fusion of spectral flux & pitch salience
- Pitch candidate combinations are evaluated, modelling tuning, inharmonicity, overlapping partials and temporal evolution
- HMM-based offset detection

(a) Ground-truth guitar excerpt 'RWC MDB-J-2001 No. 9' ♩♩



(b) Transcription output of the same recording ♩♩



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Background: Non-negative Matrix Factorisation (NMF)

- $X = WH$
  - X is the power (or magnitude) spectrogram
  - W is the spectral basis matrix (dictionary of atoms)
  - H is the atom activity matrix
- Solved by successive approximation
  - Minimise $|| X - WH ||$
  - Subject to constraints (e.g. non-negativity, sparsity, harmonicity)
- Elegant model, but ...
  - Not guaranteed to converge to a meaningful result
  - Difficult to extend / generalise

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PLCA-based Transcription

(Ref: Benetos and Dixon, SMC 2011)

- Probabilistic Latent Component Analysis (PLCA): probabilistic framework that is easy to generalize and interpret
- PLCA algorithms have been used in the past for music transcription
- Shift-invariant PLCA-based AMT system with multiple templates:

$$P(\omega, t) = P(t) \sum_{p,s} P(\omega|s,p) *_{\omega} P(f|p,t) P(s|p,t) P(p|t)$$

$P(\omega, t)$ is the input log-frequency spectrogram,
$P(t)$ the signal energy,
$P(\omega|s,p)$ spectral templates for instrument s and pitch p,
$P(f|p,t)$ the pitch impulse distribution,
$P(s|p,t)$ the instrument contribution for each pitch, and
$P(p|t)$ the piano-roll transcription.

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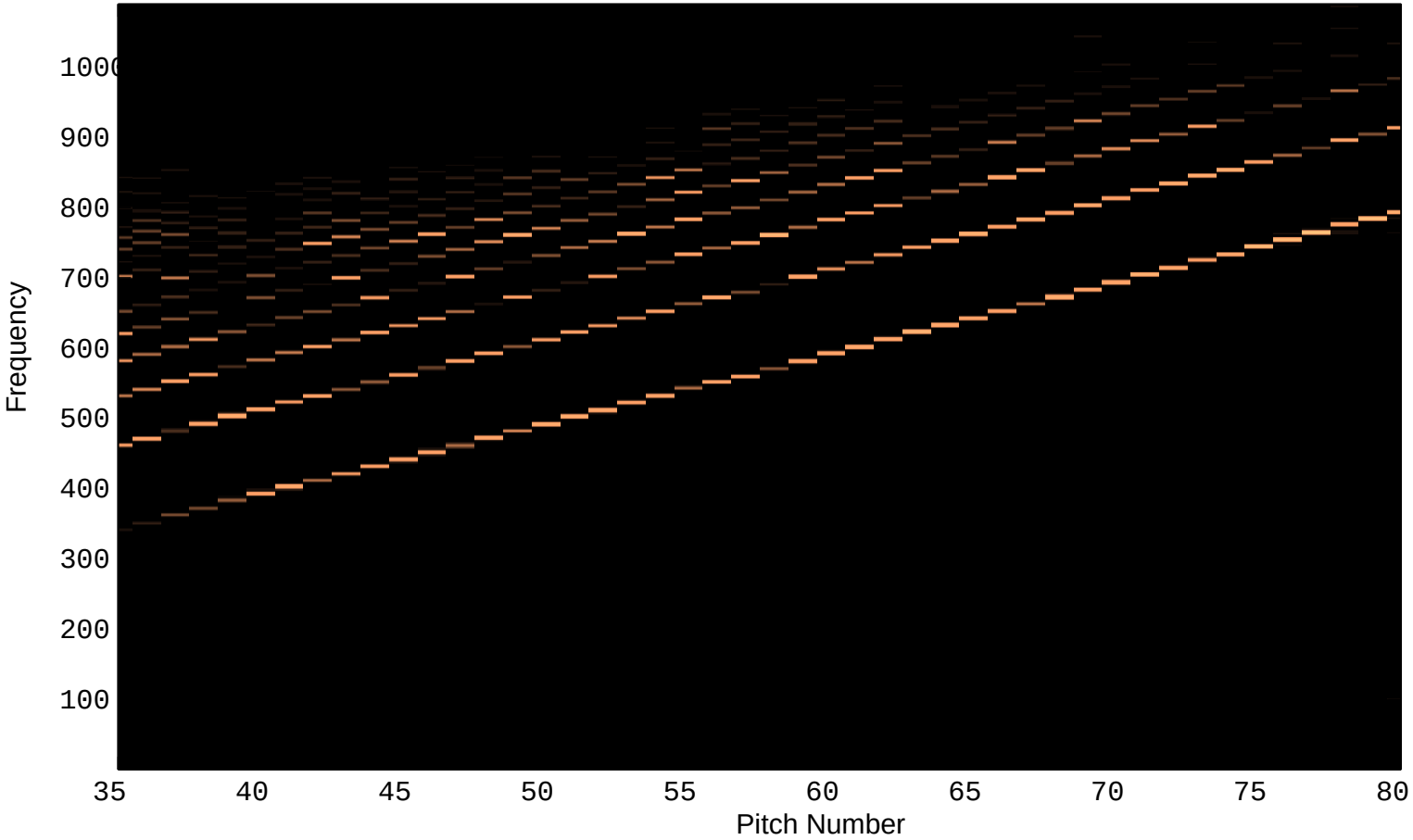
PLCA-based Transcription (2)

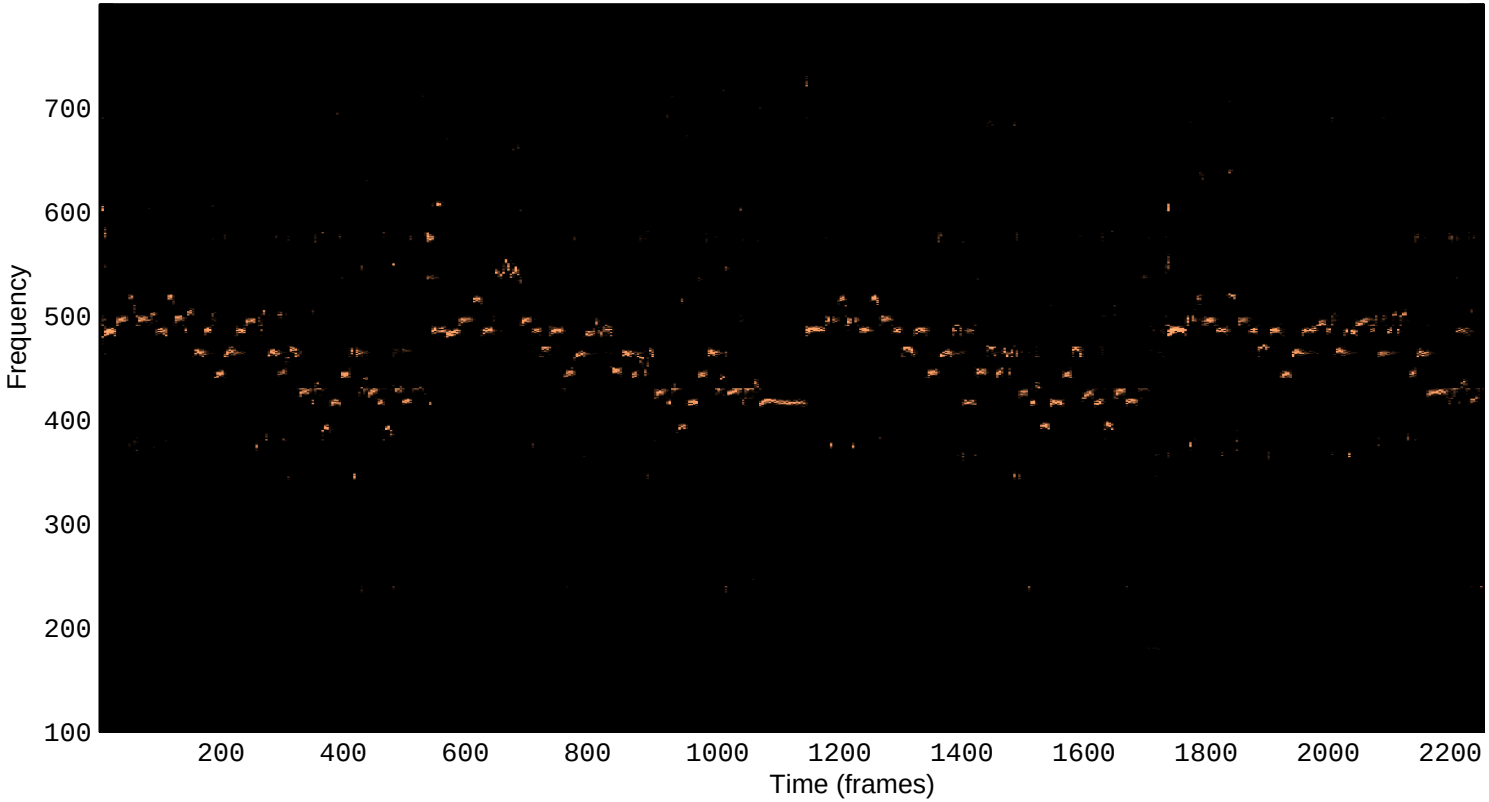
System is able to utilize sets of extracted pitch templates from various instruments (Figure: violin templates)



PLCA-based Transcription (3)

Figure: transcription of a Cretan lyra excerpt

Original:  Transcription: 



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Application 1: Characterisation of Musical Style

(Ref: Mearns, Benetos and Dixon, SMC 2011)

- Bach Chorales: audio and MIDI versions
- Audio transcribed and segmented by beats
- Each vertical slice is matched to chord templates based on Schoenberg's definition of diatonic triads and 7ths for the major and minor modes
- HMM detects key and modulations
  - Observations are chord symbols, hidden states are keys
  - Observation matrix models relationships between chords and keys
  - State transition matrix models modulation behaviour
  - Various models based on Schoenberg and Krumhansl — comparison of models from music theory and music psychology

	Transcription	Chords	Key
Audio	33%	56%	64%
MIDI	(100%)	85%	65%

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Application 2: Analysis of Harpsichord Temperament

(Ref: Tidhar et al. JNMR 2010; Dixon et al. JASA 2011, to appear)

- For fixed-pitch instruments, tuning systems are chosen which aim to maximise the consonance of common intervals
- Temperament is a compromise arising from the impossibility of satisfying all tuning constraints simultaneously
- We measure temperament to aid study of historical performance
  - Perform "conservative" transcription
  - Calculate precise frequencies of partials (CQIFFT)
  - Estimate fundamental and inharmonicity of each note
  - Classify temperament

	Synthesised	Acoustic (real)
Spectral Peaks	96%	79%
Conservative Transcription	100%	92%

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Application 3: Analysis of Cello Timbre

(Ref: Chudy, Benetos and Dixon, work in progress)

- Expert human listeners can recognise the “sound” of a performer
  - Not just the recording
  - Not just the instrument
- Can this be captured in standard timbral features?
  - Temporal: attack time, decay time, temporal centroid
  - Spectral: spectral centroid, spectral deviation, spectral spread, irregularity, tristimuli, odd/even ratio, envelope, MFCCs
  - Spectrotemporal: spectral flux, roughness
- In order to estimate features, it is necesary to identify the notes (onset, offset, pitch, etc.)
  - As a manual task, this is very time consuming
  - Conservative transcription solves the problem: high precision, low recall
  - System is trained on cello samples from RWC database

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Take-home Messages

- Automatic transcription enables new musicological questions to be investigated
- Many other applications: music education, practice, MIR
- The technology is not perfect but music is highly redundant
- Shift-invariant PLCA is ideal for instrument-specific polyphonic transcription

- Proposed procedure for folk music analysis:
  - Extract templates for desired instruments (e.g. using NMF)
  - Perform shift-invariant PLCA transcription
  - Estimate features of interest
  - Interpret results according to estimates obtained

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Any Questions?

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  - Emmanouil Benetos, Lesley Mearns, Magdalena Chudy: the PhD students who do all the work
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