ISMIR

ISMIR 2019 Tutorial [T3]


# Audiovisual Music Processing

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(* authors in alphabetical order)



Delft, The Netherlands

# Motivation

- Music is a multi-modal art form

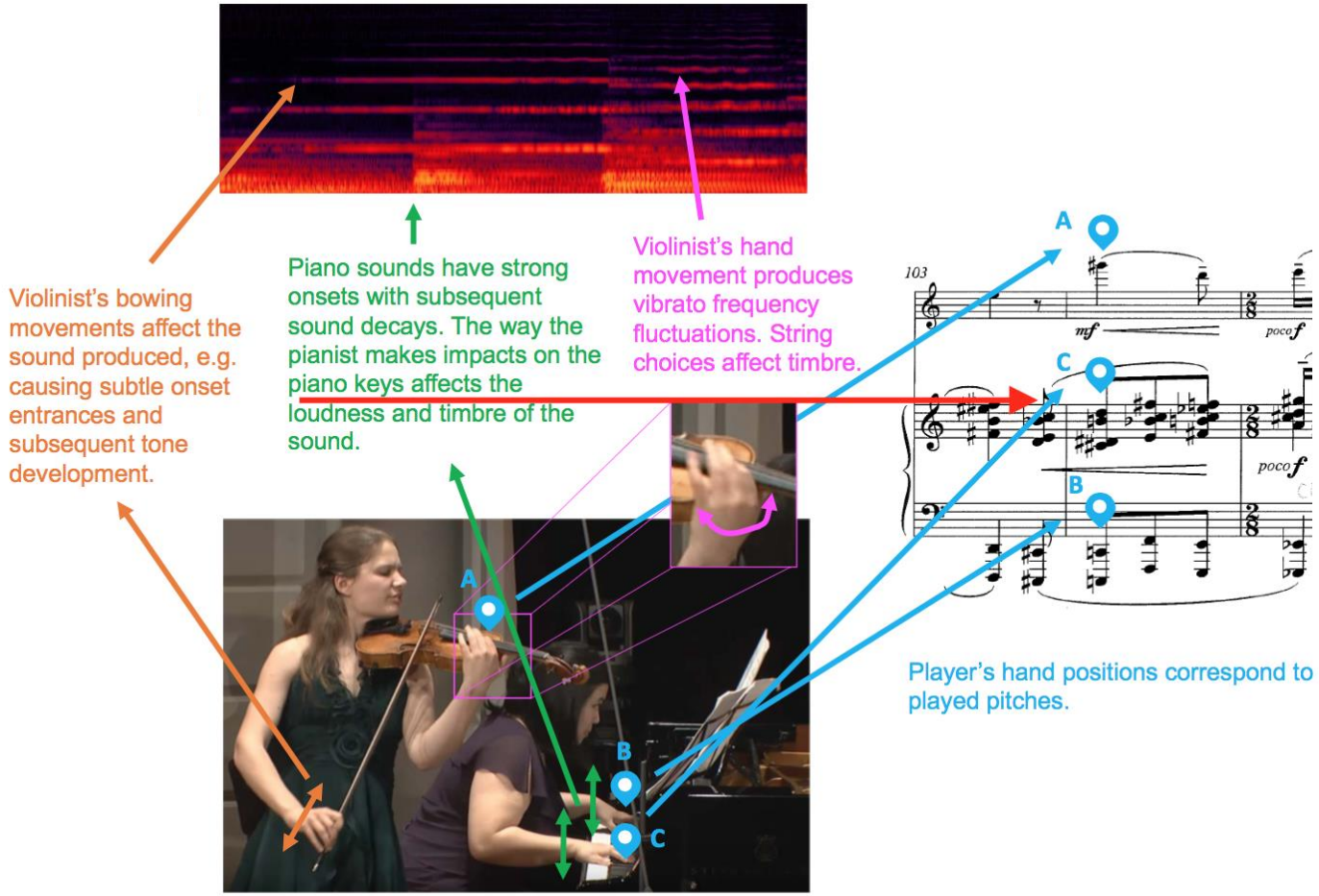
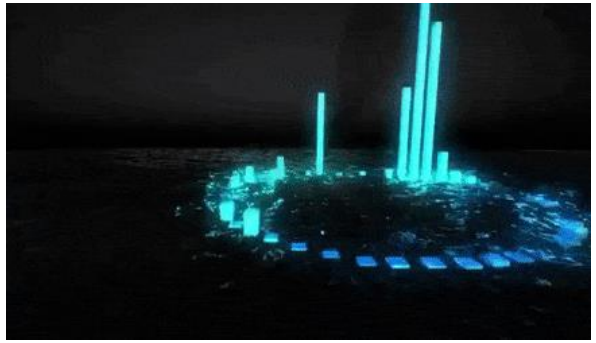



Figure from (Duan et al., 2018)

# Motivation

- Audiovisual expressions of ideas and emotions



# Motivation

- Musicians use audiovisual cues to coordinate with each other

# Motivation

- Audiences enjoy audiovisual expressions

Divje Babe Flute
(43,400 – 67,000 yrs ago)

Phonograph
(Edison, 1877)

Vinyl record
(Victor, 1931)

Compact Disc
(Phillips & Sony, 1982)

Spotify®
(2006)

MP3 (1997)

Cassette tape
(Phillips, 1962)

The audience could only enjoy live music; they would watch instead of just listen.

# Motivation

- Audiences enjoy audiovisual expressions
  - Music video streaming services become popular





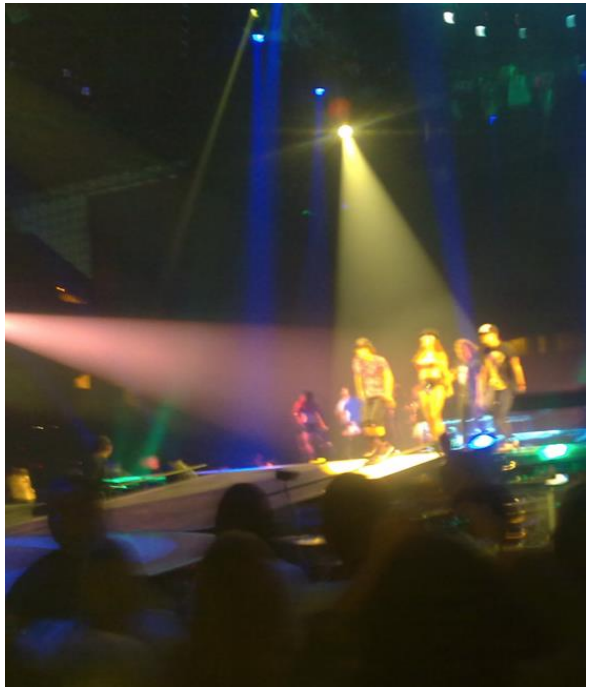

- Visual aspect is an important factor in the communication of meanings (Platz & Kopiez, 2012)
- Sight over sound in the judgement of music performance (Tsay, 2013)

# Intellectual Merit

- Broadens the scope of music signal processing research
- Connects with other areas such as image processing, computer vision and multimedia
- Creates a path towards emerging areas such as music VR/AR
- Serves as a controlled testbed for multimodal data analysis

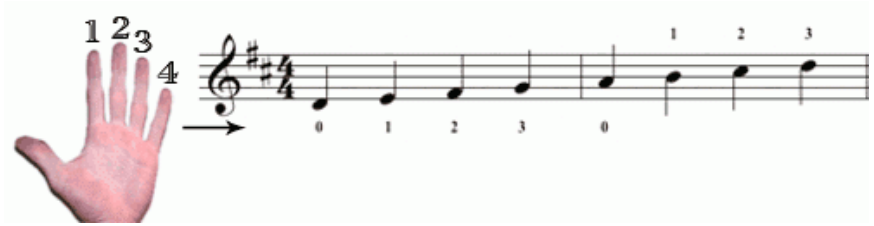
# Applications

- Concerts
  - Automatic camera/light/sound control
  - Augmented concerts with visual displays
  - Virtual concerts




# Applications

- Music Education
  - Pose analysis and feedback
  - Automatic visual demonstration
  - Automatic fingering annotation

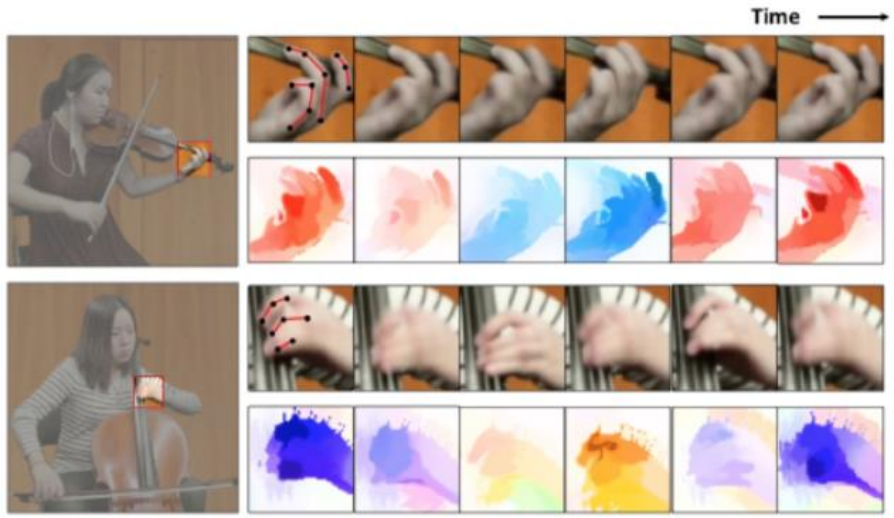


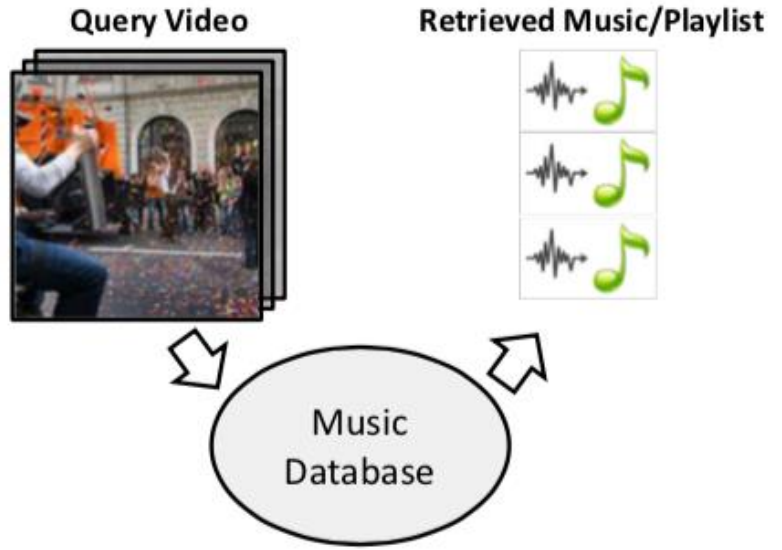

# Applications

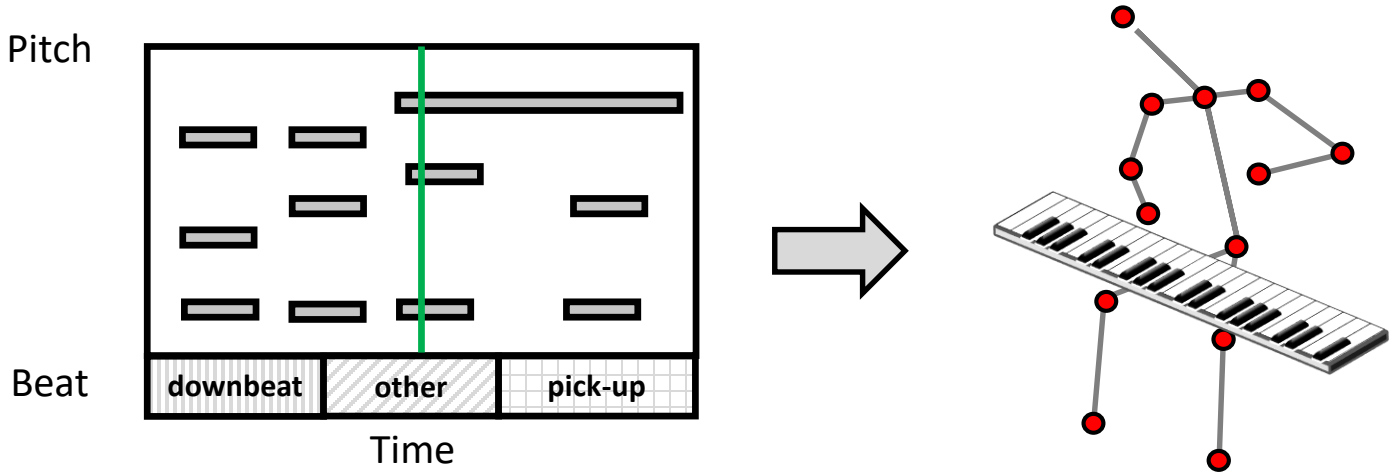
- Music Interaction
  - Human-computer collaborative music making
  - Visually informed automatic accompaniment

# Problem Categorization

- Analysis
  - Association
  - Transcription
  - Separation
- Classification & Retrieval
  - Genre classification
  - Mood recognition
  - Audiovisual matching
  - Recommendation
- Generation
  - Audio/music generation
  - Visual generation



# Tutorial Outline

- **Introduction**
- Audiovisual Music Performance Analysis
  - Overview of Analysis Tasks
  - Audiovisual Co-Factorization for Source Separation
  - Hands-on Case Study #1: Motion Informed Audio Source Separation
- Audiovisual Content Based Classification and Retrieval
  - Genre Classification
  - Emotion Analysis
  - Cross-Modal Retrieval
  - Instrument Classification
- Audiovisual Music Generation
  - Hands-on Case Study #2: Skeleton Plays the Piano
- Datasets, Tools and Other Resources
- Challenges, Opportunities and Conclusions

# Tutorial Goals

- Stimulate interests in audiovisual research in MIR
- Present a comprehensive overview of existing research
  - Research topics
  - Datasets and tools
  - Bibliography
- Provide a taste hands-on experience in two tasks
- Collect ideas and inspirations from YOU, the audience

Please interrupt us whenever you have a question or comment!

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- Datasets, Tools and Other Resources
- Challenges, Opportunities and Conclusions

# Task Categorization

Table adapted from (Duan et al., 2019)

| Visual | Is Critical | | Is Significant | | | | |
|---|---|---|---|---|---|---|---|
| **Tasks** | **Fingering** | **Association** | **Play/Nonplay** | **Onset** | **Vibrato** | **Transcription** | **Separation** |
| Percussion | N/A | - | PP | - | N/A | PT | - |
| Piano | PF | - | - | - | N/A | - | - |
| Guitar | GF | - | - | - | - | GT | GS |
| Strings | SF | SA | SP | SO | SV | ST | SS |
| Wind | - | WA | WP | WO | - | - | WS |
| Singing | N/A | - | - | - | - | - | - |

**PF:** (Gorodnichy & Yogeswaran, 2006)
(Oka & Hashimoto, 2013)
**GF:** (Burns & Wanderley, 2006)
(Kerdvibulvech & Saito, 2007)
(Scarr & Green, 2010)
(Paleari et al., 2008)
**SF:** (Zhang & Wang, 2009)

**SA:** (Li et al., 2017a)
(Li et al., 2017b)
(Li et al., 2019)
**WA:** (Li et al., 2019)

**PP:** (Bazzica et al., 2016)
**SP:** (Bazzica et al., 2016)
(Dinesh et al., 2017)
**WP:** (Bazzica et al., 2016)

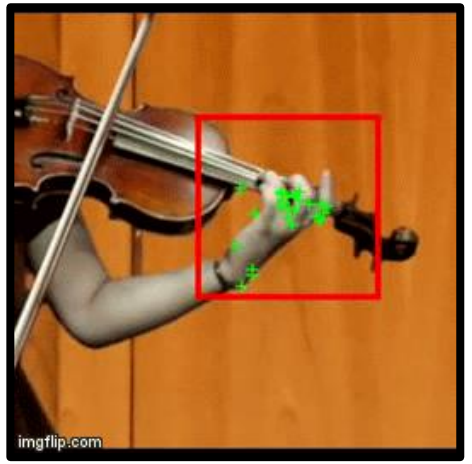
**SO:** (Li et al., 2017b)
**WO:** (Bazzica et al., 2017)
**SV:** (Li et al, 2017c)

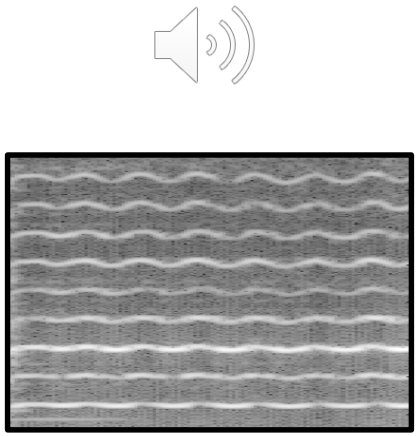
**PT:** (McGuinness et al., 2007)
**GT:** (Paleari et al., 2008)
**ST:** (Zhang & Wang, 2009)
(Dinesh, et al., 2017)
**GS/WS:** (Zhao et al., 2018)
(Zhao et al., 2019)
**SS:** (Parek et al., 2017)
(Zhao et al., 2018)
(Zhao et al., 2019)

# Audiovisual Correspondence

- Static
  - Fixed image ←→ Audio frame
  - E.g., Posture of a flutist ←→ Play/Nonplay activity
  - E.g., Piano fingering ←→ Music transcription

- Dynamic, instrument specific
  - Dynamic movement ←→ Audio feature fluctuation
  - E.g., Guitarist's strumming hand ←→ Rhythmic pattern
  - E.g., Violinist rolling left hand ←→ Vibrato

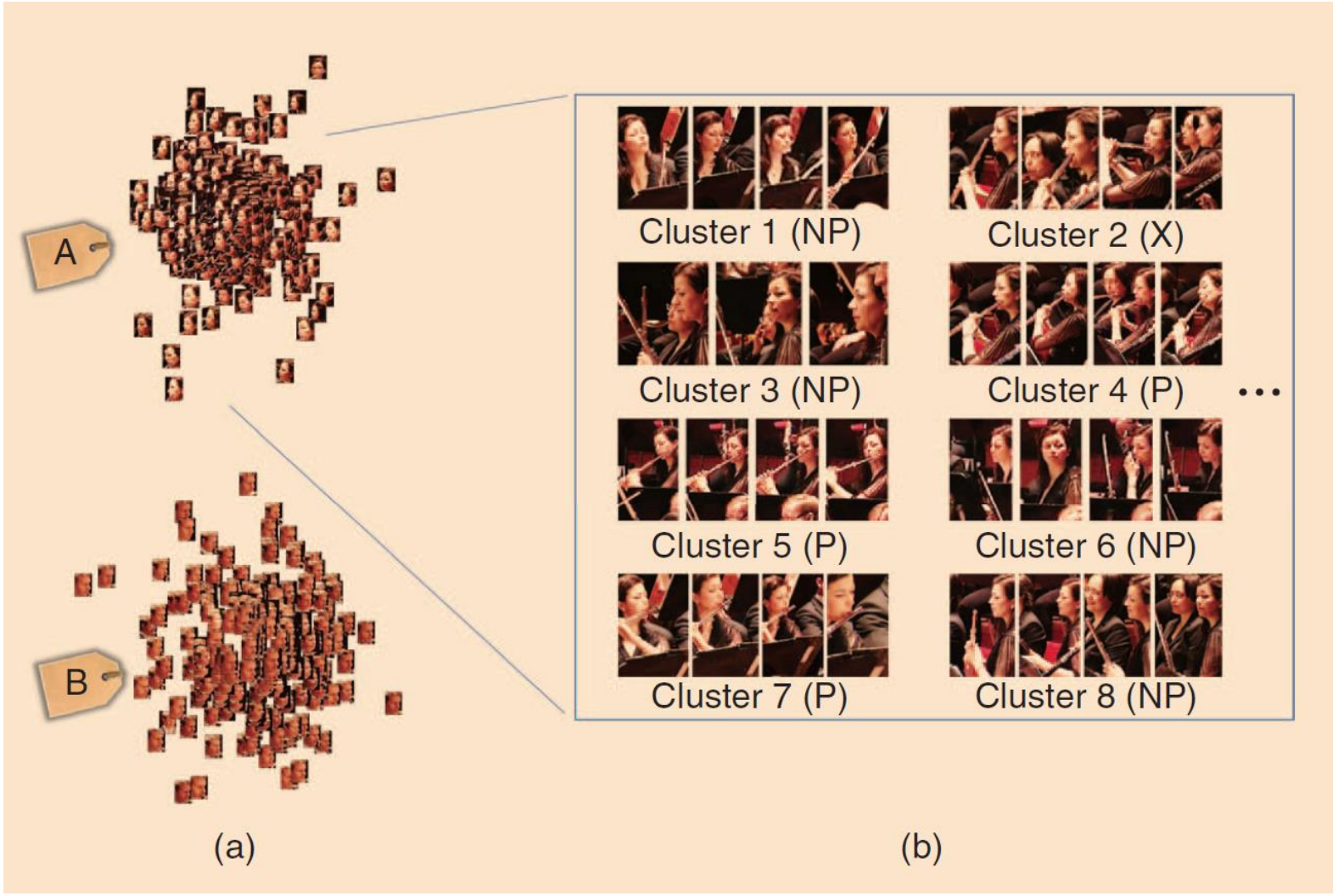


- Dynamic, general
  - Co-factorization of audio/visual fluctuations
  - Learning audiovisual embeddings

# Static Audiovisual Correspondence

- Play/Nonplay Activity Detection
  - Hierarchical clustering
    - (a) cluster musicians
    - (b) cluster P/NP activities

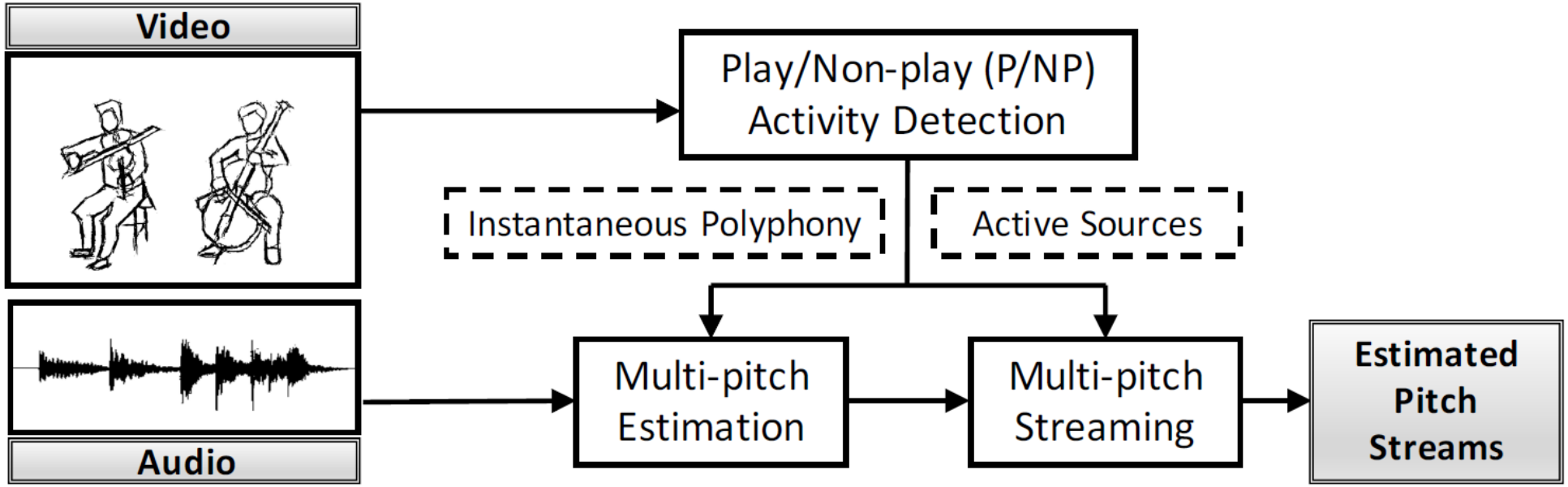



(Bazzica et al., 2016)

# Static Audiovisual Correspondence

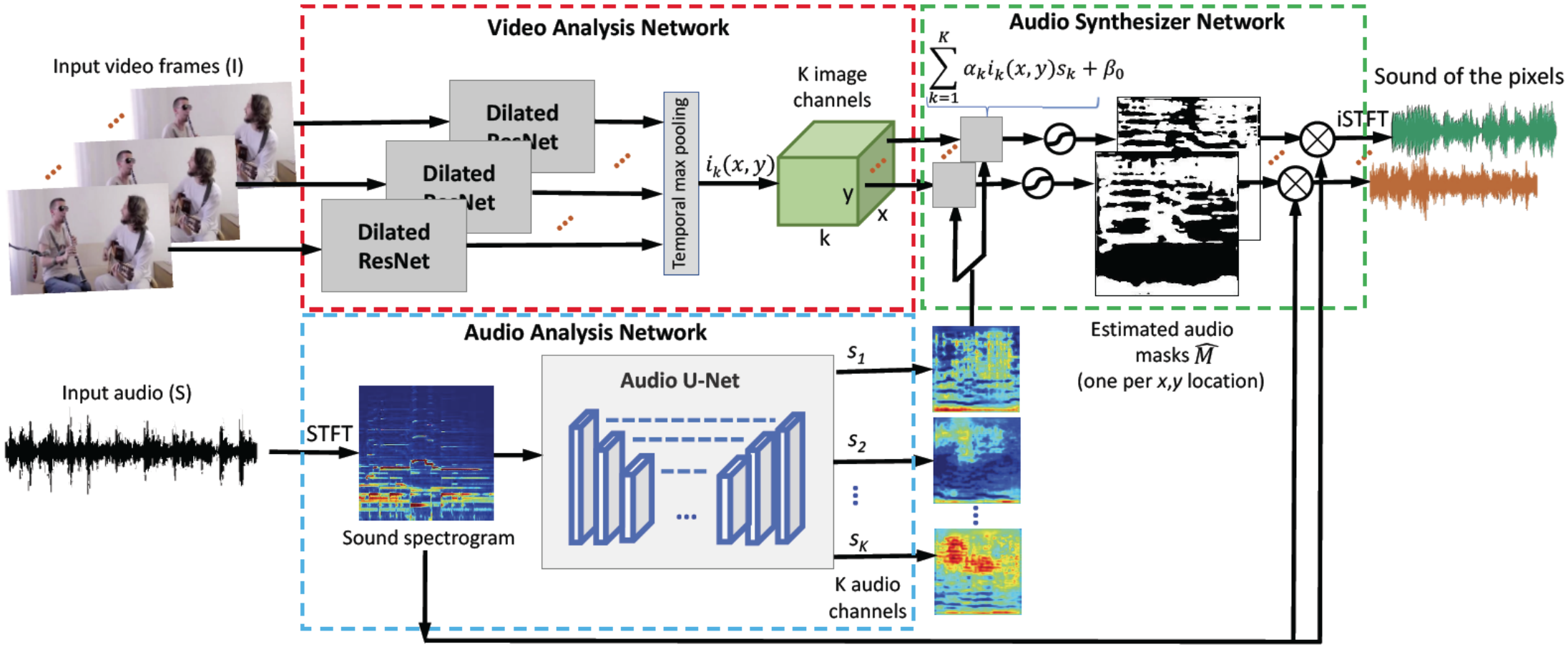
- P/NP information improves multi-pitch analysis and music transcription

(Dinesh et al., 2017)



# Static Audiovisual Correspondence

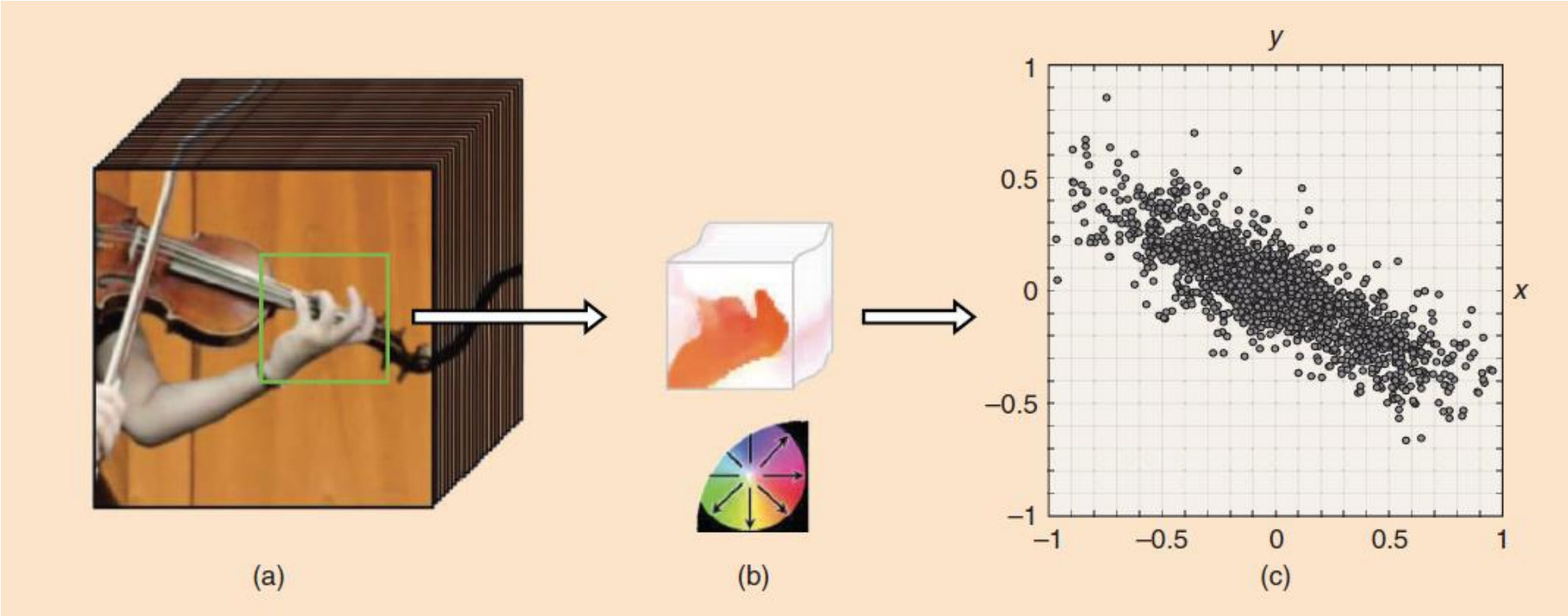
- Audiovisual Music Separation
  - The Sound of Pixels (Zhao et al., 2018)



# Dynamic Audiovisual Correspondence

- Vibrato Analysis (for strings)
  - Correlate left-hand rolling motion with pitch fluctuation

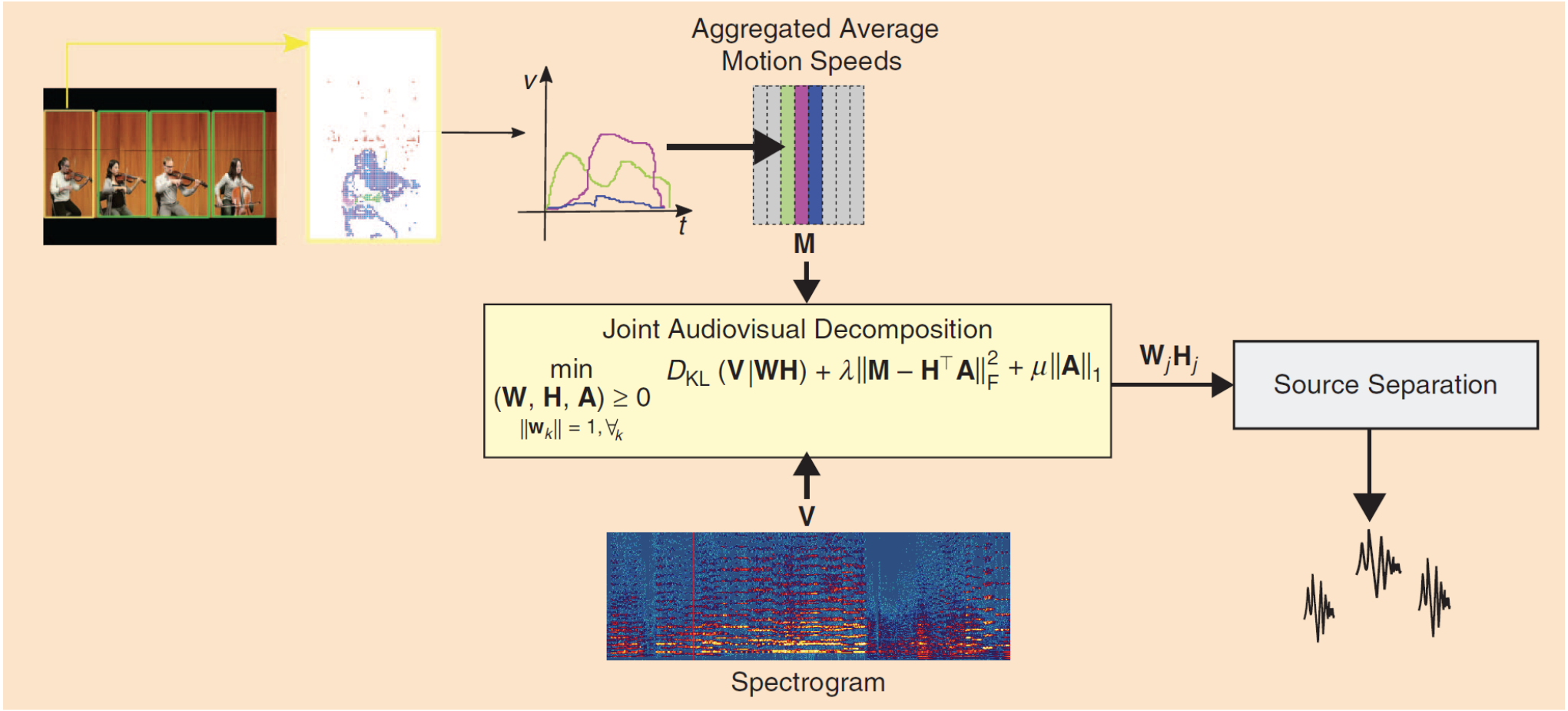
(Li et al., 2017)



# Dynamic Audiovisual Correspondence

- Co-factorization of motion data and spectrogram

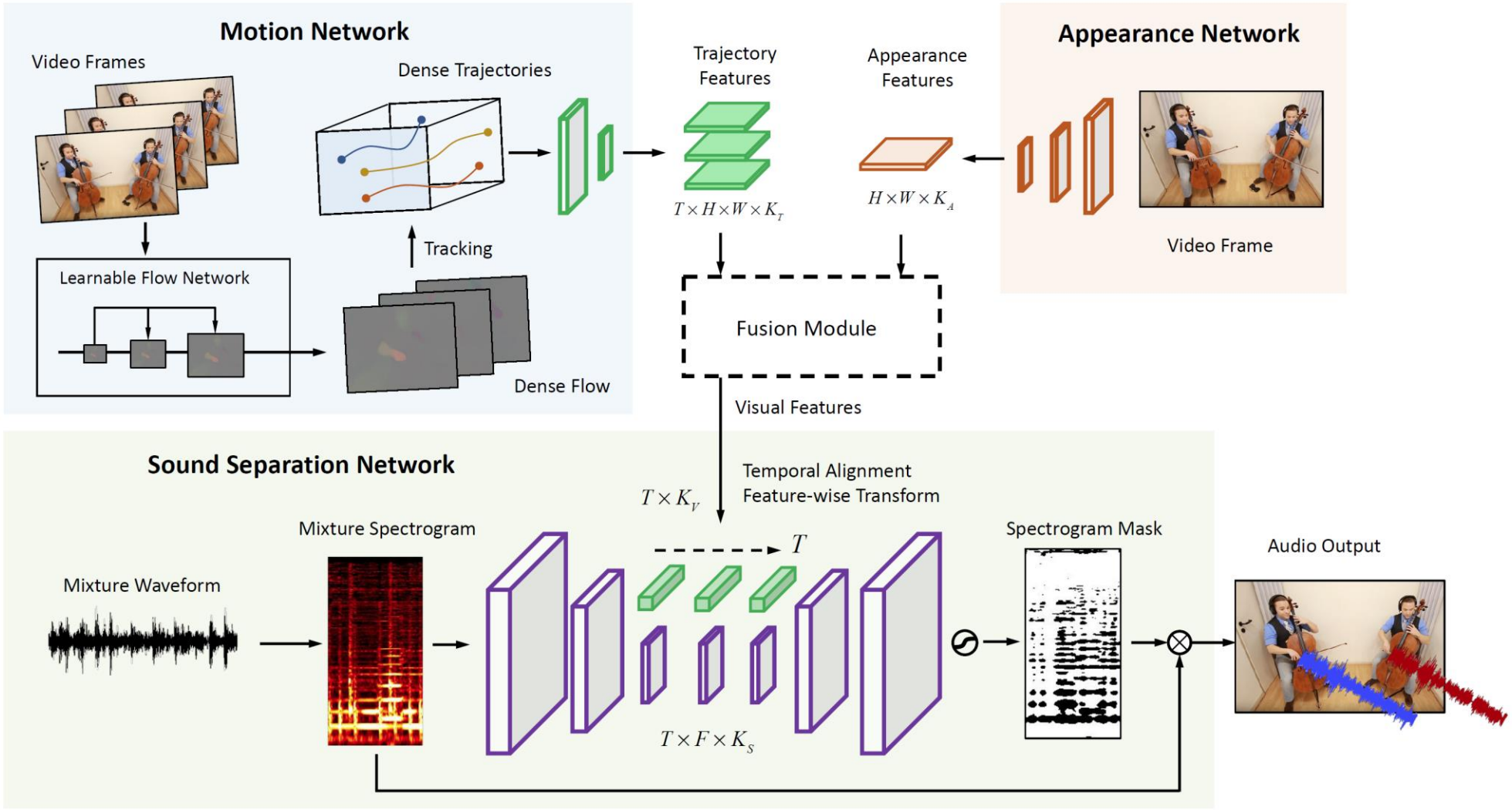
(Parekh et al., 2017)



# Dynamic Audiovisual Correspondence

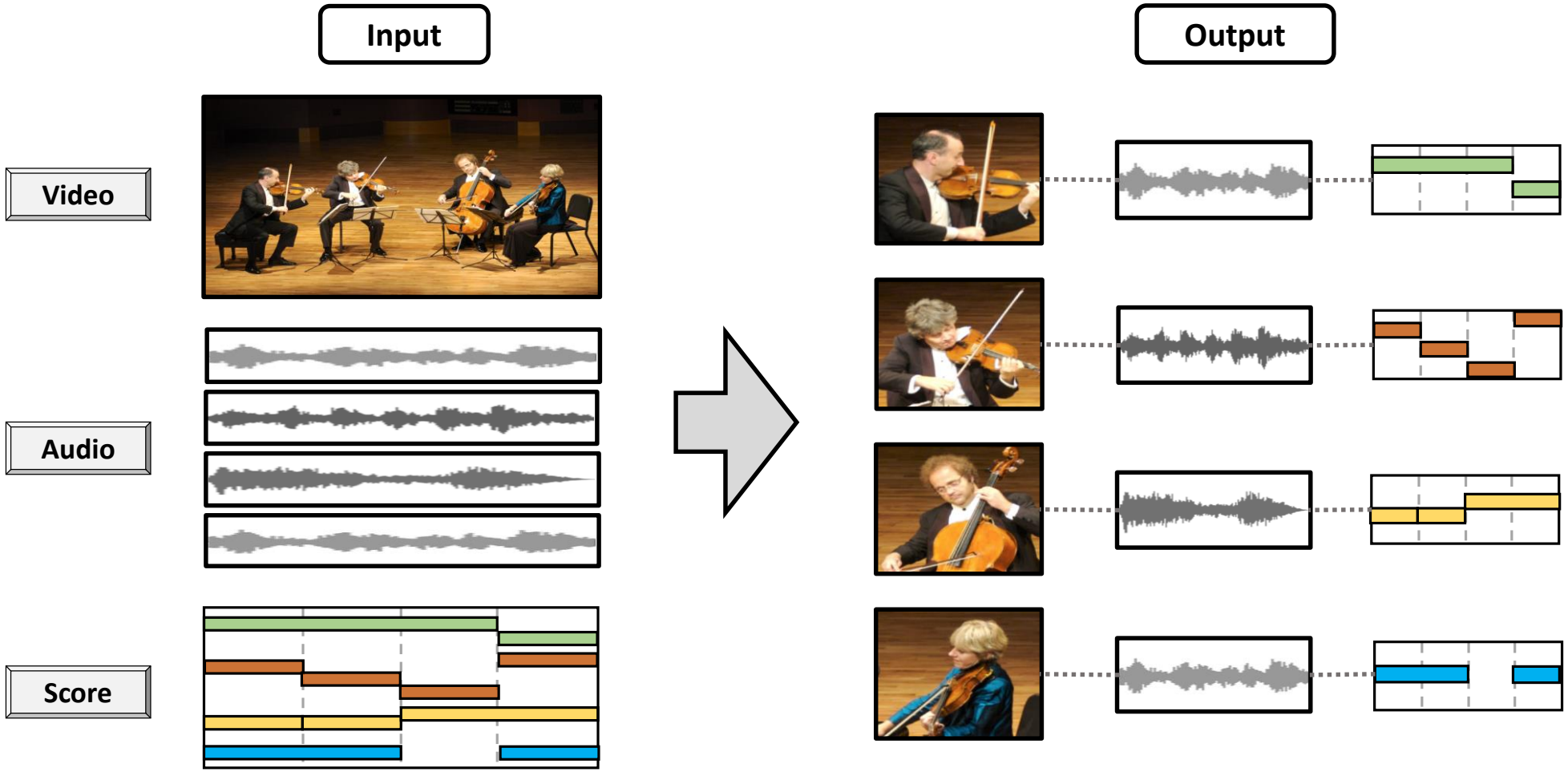
- The Sound of Motions

(Zhao et al., 2019)



# Audiovisual Source Association

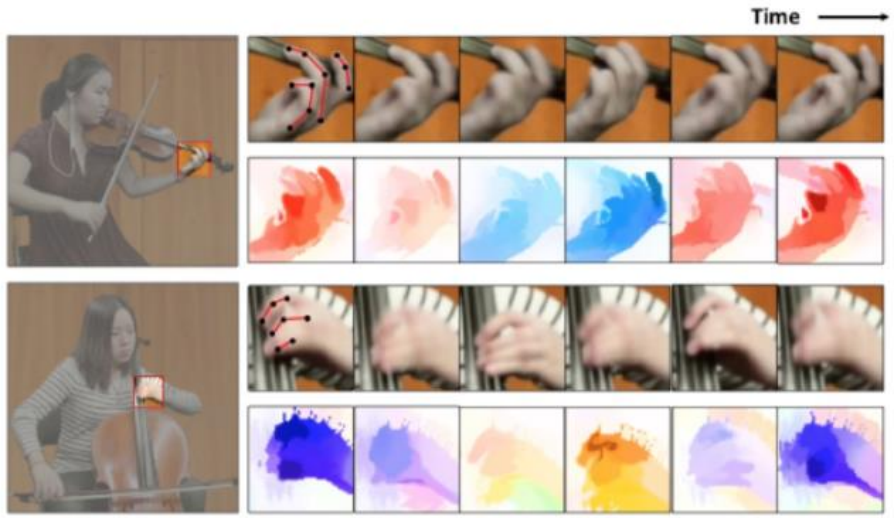
- A novel task

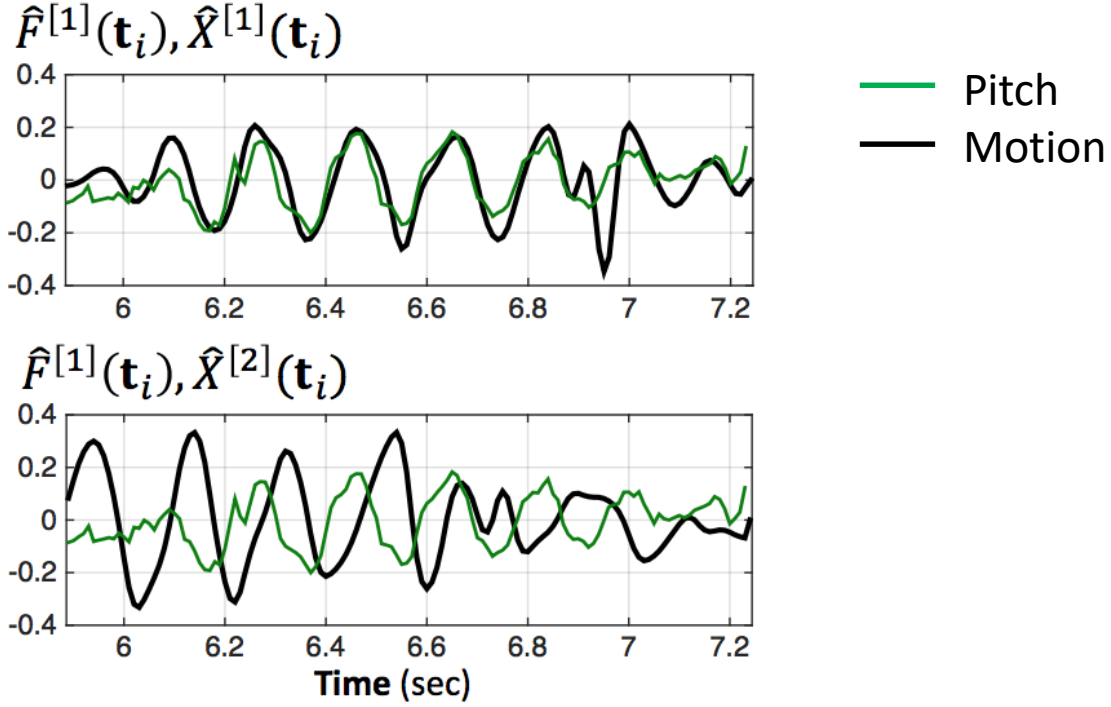


# Hand Rolling Motion ←→ Vibrato Pitch Fluctuation

- Works for strings
  - Hand tracking with OpenPose
  - Fine motion extraction with optical flow estimation
  - Pitch contour estimation with score-informed pitch estimation

(Li et al., 2017b), (Li et al., 2019)

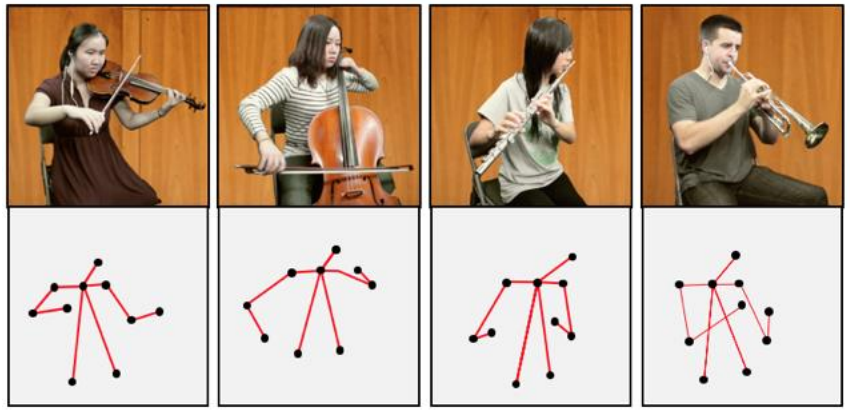


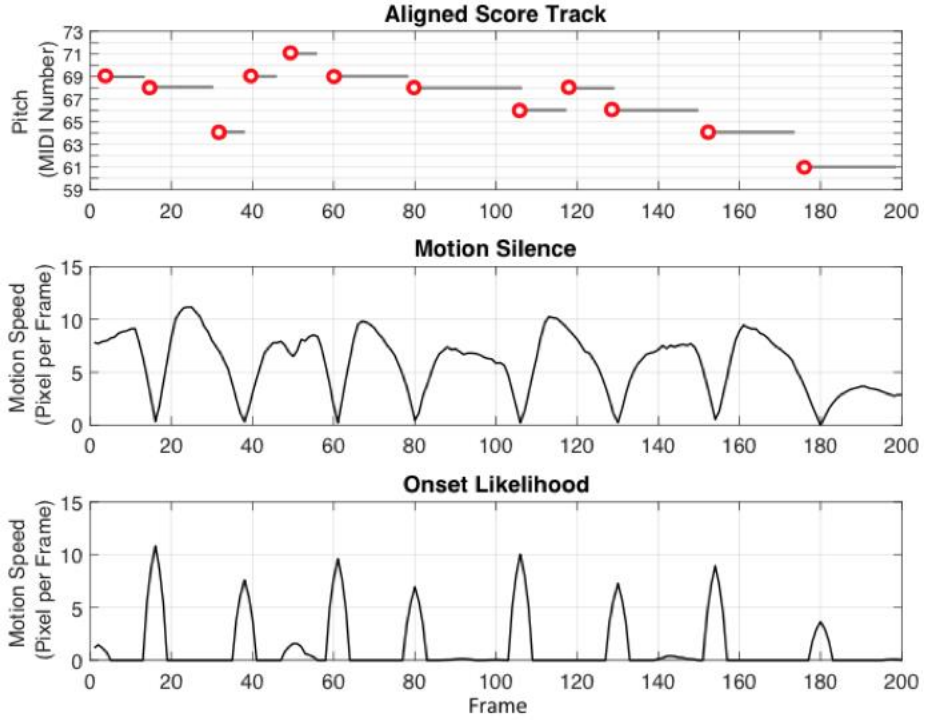



# Body Motion ←→ Note Onsets

- Works for strings
  - Body joint extraction with OpenPose
  - Detect principal motion with PCA
  - Derive onset likelihood curve from principal motion

(Li et al., 2017a), (Li et al., 2019)

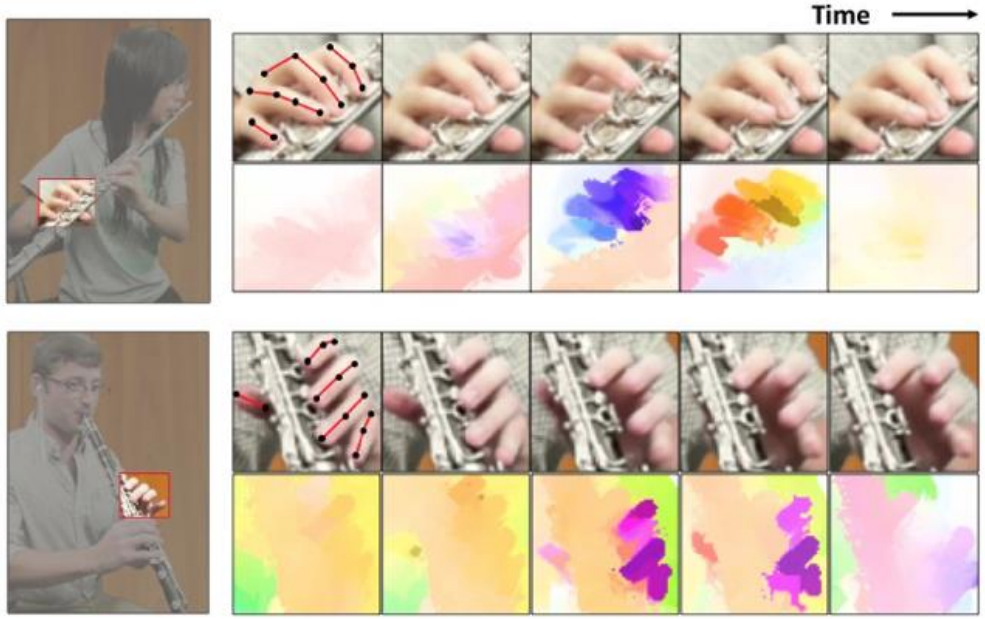


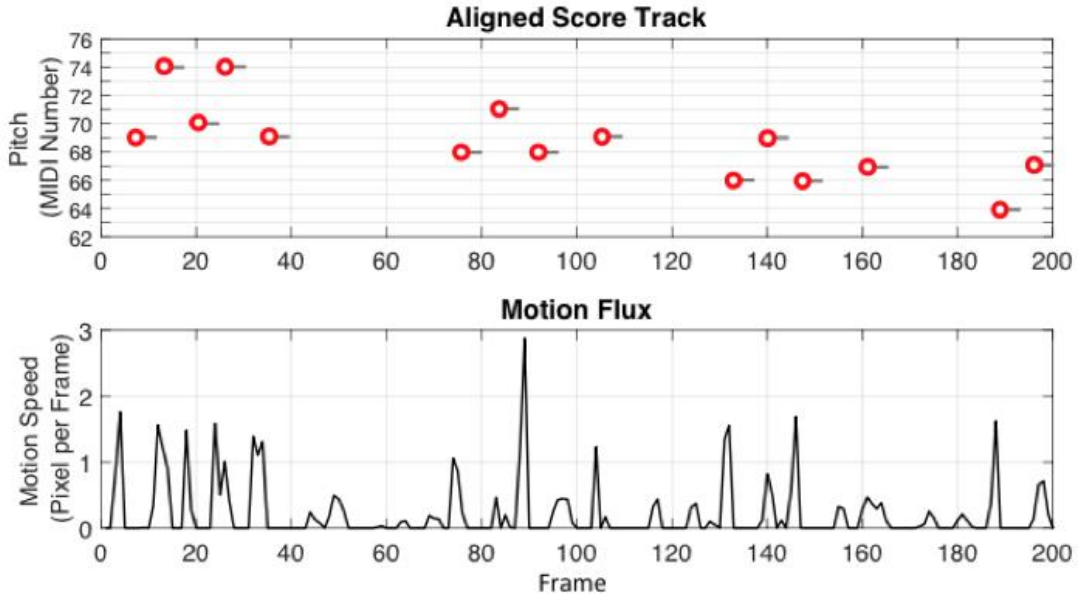


# Fingering Motion ←→ Note Onsets

- Works for woodwind/brass
  - Hand tracking with OpenPose
  - Finger motion flux extraction with optical flow estimation

(Li et al., 2019)

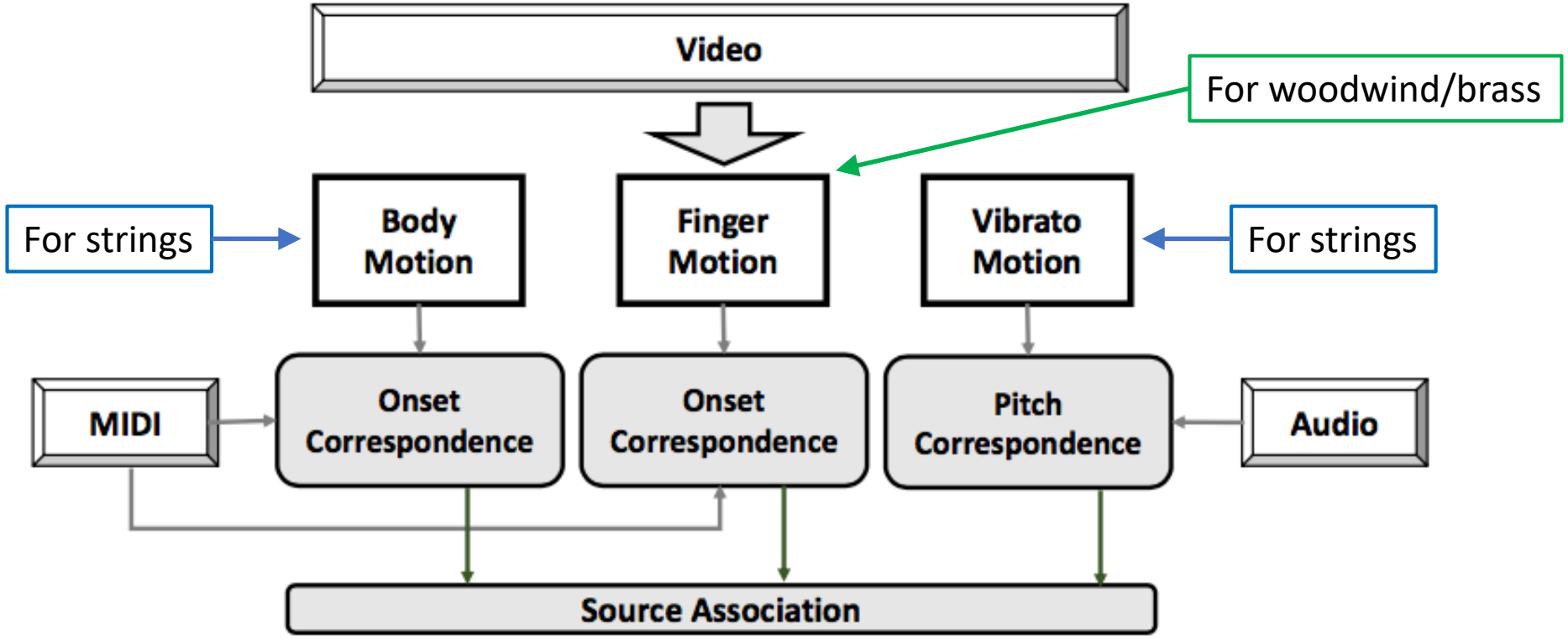


# Integrating All Components

- Linear combination with adaptive weights

(Li et al., 2019)

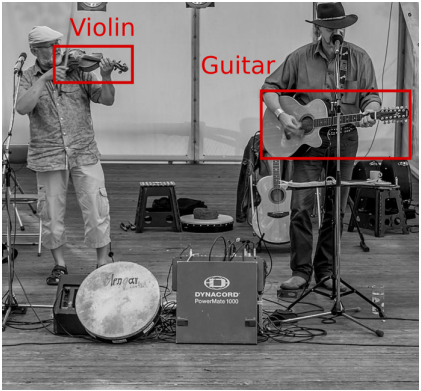


# Tasks

# Tasks

## Recognition and Detection

(Arandjelović and Zisserman, 2017; Slizovskaia et al., 2017; Parekh et al., 2019)



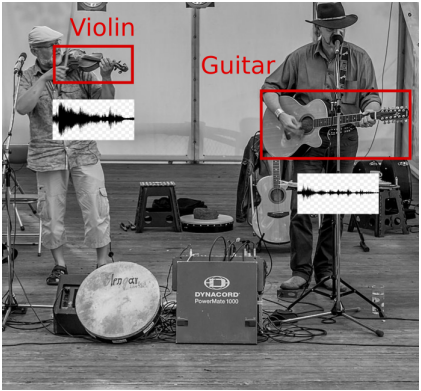
# Tasks

## Recognition and Detection

(Arandjelović and Zisserman, 2017; Slizovskaia et al., 2017; Parekh et al., 2019)

## Association and Separation

(Li et al., 2017c; Parekh et al., 2017a; Gao and Grauman, 2019b)



# Tasks

## Recognition and Detection

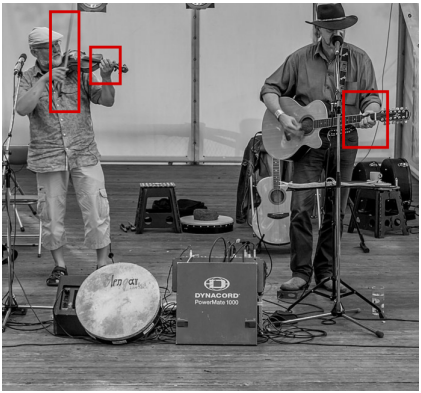
(Arandjelović and Zisserman, 2017; Slizovskaia et al., 2017; Parekh et al., 2019)

## Association and Separation

(Li et al., 2017c; Parekh et al., 2017a; Gao and Grauman, 2019b)

## Player activity analysis

- Onsets - (Bazzica et al., 2016; Li et al., 2017a)
- Fingering analysis - (Burns and Wanderley, 2006)



# Tasks

## Recognition and Detection

(Arandjelović and Zisserman, 2017; Slizovskaia et al., 2017; Parekh et al., 2019)

## Association and Separation

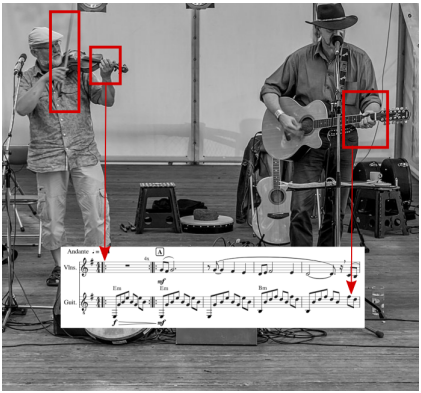
(Li et al., 2017c; Parekh et al., 2017a; Gao and Grauman, 2019b)

## Player activity analysis

- Onsets - (Bazzica et al., 2016; Li et al., 2017a)
- Fingering analysis - (Burns and Wanderley, 2006)

## Transcription

(Gillet and Richard, 2005; Paleari et al., 2008; Dinesh et al., 2017)

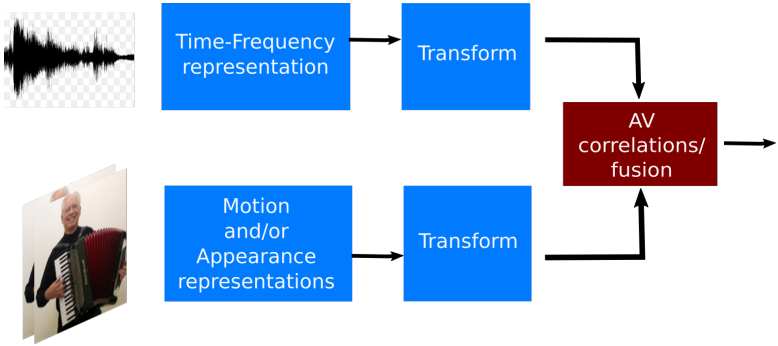


# Tasks

| Visuals | Critical | | Significant | | |
|---|---|---|---|---|---|
| | Fingering | Association | Player activity | Transcription | Separation |
|  | | | | | |
|  | | | | | |
|  | NA | | | | |
|  | | | | | |

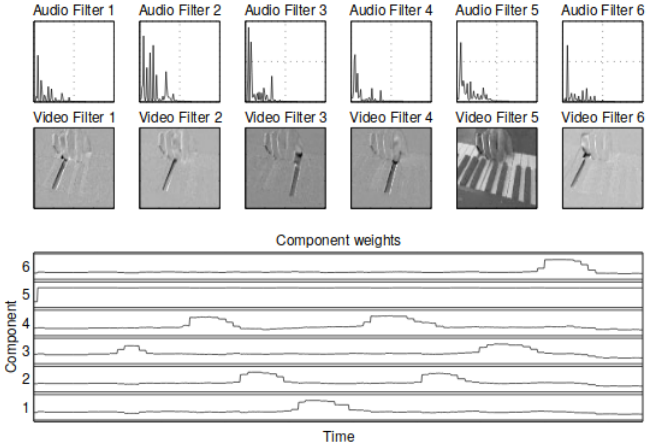
- Other tasks: Conductor gesture analysis - (Sarasúa and Guaus, 2014);
  Dance scene analysis - (Shiratori et al., 2004; Essid et al., 2012; Dremeau and Essid, 2013)

# General Framework



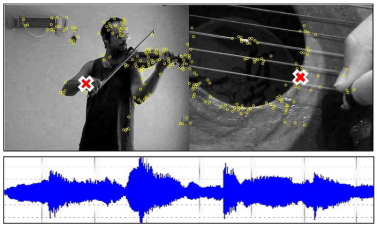

- Audio / visually informed tasks
- Simultaneous learning for other downstream tasks such as classification, detection, transcription etc.

# Illustrative examples

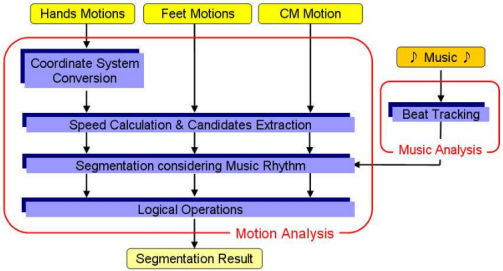



Audio Visual independent component analysis (Smaragdis and Casey, 2003)

# Illustrative examples



(Barzelay and Schechner, 2007)

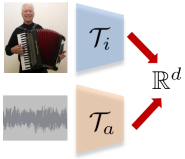



(Shiratori et al., 2004)

Audio-visual onsets co-incidence

# Modeling cross-modal dependence

- Joint subspace learning
  - Mutual Information, CCA, ICA (Fisher et al., 2001; Kidron et al., 2005)
  - Deep learning based variants (Ngiam et al., 2011; Andrew et al., 2013)
  - Misc. - cosine products, bilinear pooling (Barzelay and Schechner, 2007)




$$\mathcal{T}_i^*, \mathcal{T}_a^* = \underset{\mathcal{T}_i, \mathcal{T}_a}{\text{argmax}}\ S(\mathcal{T}_i(I)\mathcal{T}_a(A))$$

- $S$ can be correlation, covariance, mutual information
- $\mathcal{T}_i, \mathcal{T}_a$ can be modeled using deep architectures

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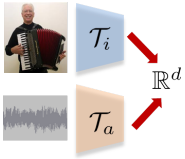


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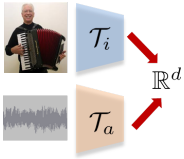
# Modeling cross-modal dependence

- Joint subspace learning
  - Mutual Information, CCA, ICA (Fisher et al., 2001; Kidron et al., 2005)
  - Deep learning based variants (Ngiam et al., 2011; Andrew et al., 2013)
  - Misc. - cosine products, bilinear pooling (Barzelay and Schechner, 2007)

**Focus of this section**

Matrix co-factorization / cross-modal transformations

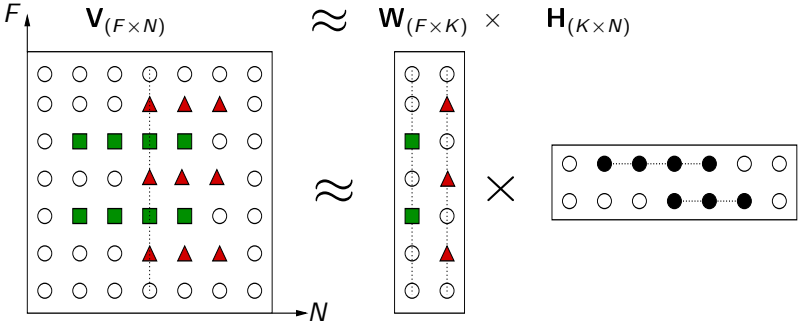



$$\mathcal{T}_i^*, \mathcal{T}_a^* = \underset{\mathcal{T}_i, \mathcal{T}_a}{\text{argmax}}\ S(\mathcal{T}_i(I)\mathcal{T}_a(A))$$

- $S$ can be correlation, covariance, mutual information
- $\mathcal{T}_i, \mathcal{T}_a$ can be modeled using deep architectures

# Explaining data by factorisation

## General formulation

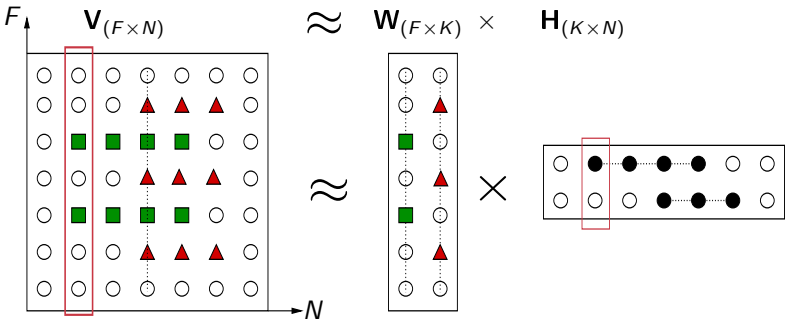



$$\mathbf{V} = [v_{fn}], \qquad \mathbf{W} = [w_{fk}] \qquad \text{and} \qquad \mathbf{H} = [h_{kn}]$$

*Based on an illustration by C. Févotte*

# Explaining data by factorisation

## General formulation

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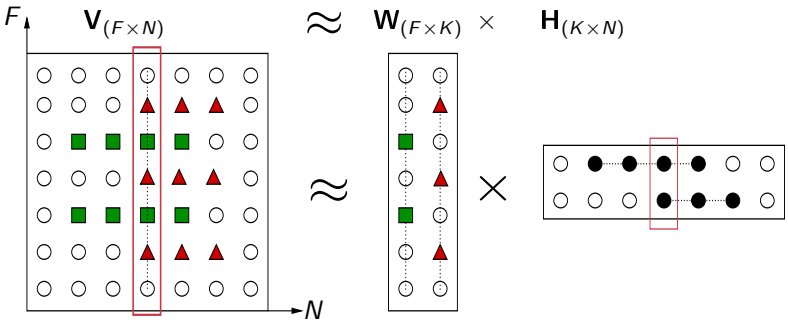


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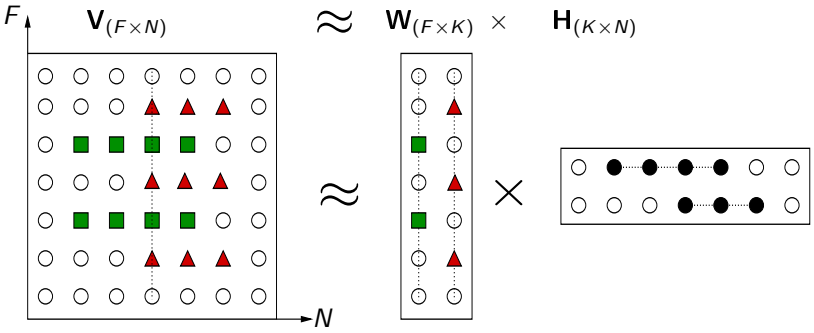
*Based on an illustration by C. Févotte*

# Explaining nonnegative data by factorisation

A more interpretable model: **Nonnegative Matrix Factorisation (NMF)**




$$\mathbf{V} = [v_{fn}],\ v_{fn} \geq 0, \quad \mathbf{W} = [w_{fk}],\ w_{fk} \geq 0 \text{ and } \mathbf{H} = [h_{kn}],\ h_{kn} \geq 0$$

# NMF outputs

## Audio example

NMF produces **part-based** representations of the data:

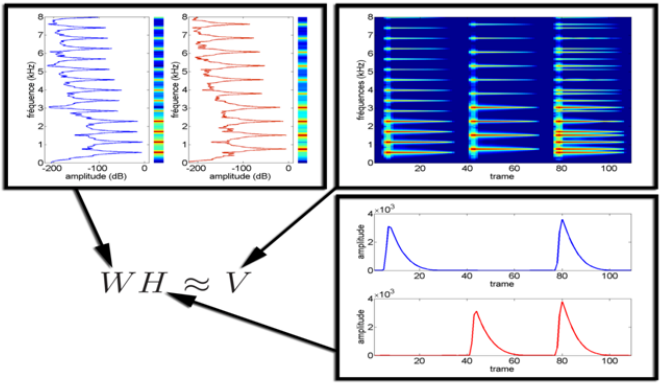
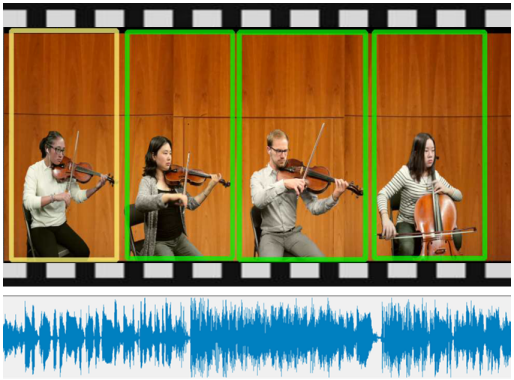



*Illustration by R. Hennequin.*

# MF for multiview data analysis

## Motivation

Consider **multimodal source classification/separation** in music videos



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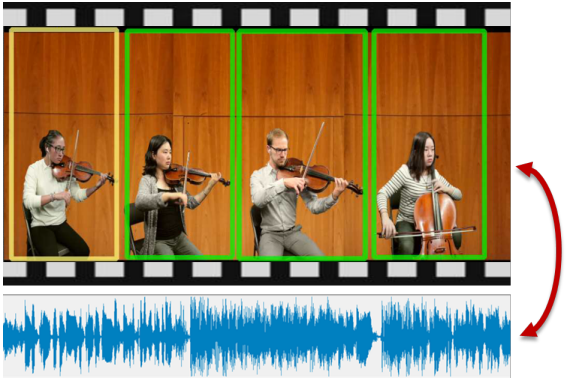

- The audio and visual streams are related...

# MF for multiview data analysis

## Possible approaches I

- Concatenate the feature observations:

$$\mathbf{V} = \begin{bmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \end{bmatrix} \approx \mathbf{WH}$$

→ same cost functions used for different modalities: not always optimal.

# MF for multiview data analysis

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$\rightarrow$ same cost functions used for different modalities: not always optimal.

# MF for multiview data analysis

## Possible approaches II

- Another idea: perform **hard co-factorisation** constraining the activations to be the same:

$$\begin{cases} \mathbf{V}_1 \approx \mathbf{W}_1\mathbf{H} \\ \mathbf{V}_2 \approx \mathbf{W}_2\mathbf{H} \end{cases} \quad \text{solving:} \quad \min_{\mathbf{W}_1,\mathbf{W}_2,\mathbf{H}} D_1(\mathbf{V}_1, \mathbf{W}_1\mathbf{H}) + \beta_2 D_2(\mathbf{V}_2, \mathbf{W}_2\mathbf{H})$$

Does not account for possible local discrepancies across modalities.

→ Constrain the audio and visual data factorisations to be "**related**": temporal activations relating to these two streams of data should be **close**, not necessarily equal.

# MF for multiview data analysis

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# Soft matrix co-factorisation

(Seichepine et al., 2014)

Consider:

$$\begin{cases} \mathbf{V}_1 \approx \mathbf{W}_1\mathbf{H}_1 \\ \mathbf{V}_2 \approx \mathbf{W}_2\mathbf{H}_2 \\ \mathbf{H}_1 \approx \mathbf{H}_2 \end{cases}$$

Solve the problem:

$$\min_{\mathbf{W}_1,\mathbf{H}_1,\mathbf{W}_2,\mathbf{H}_2} D_1(\mathbf{V}_1 \,|\, \mathbf{W}_1\mathbf{H}_1) + \beta_2 D_2(\mathbf{V}_2 \,|\, \mathbf{W}_2\mathbf{H}_2) + \beta_c P(\mathbf{H}_1, \mathbf{H}_2)$$

- $D_1$ and $D_2$ are resp. **measures of fit** for the first and second modality
- $\beta_2$ and $\beta_c$ are weighting **hyperparameters**
- $P(\mathbf{H}_1, \mathbf{H}_2)$ is a **penalization term** coupling factorizations for the first and the second modality. e.g., $P(\mathbf{H}_1, \mathbf{H}_2) = \|\mathbf{H}_1 - \mathbf{H}_2\|_p$

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# Solving the problem

- We have devised a **block-coordinate majorisation-minimisation algorithms** updating $\mathbf{H}_1$, $\mathbf{H}_2$, $\mathbf{W}_1$, $\mathbf{W}_2$ and $\mathbf{S}$ sequentially
- Update rules have thus been determined for:
  - **Kullback-Liebler** and **Itakura-Saito** cost functions;
  - $\ell_2$ and $\ell_1$-**coupling penalties**;

  see (Seichepine et al., 2014) for more details
- Scripts are available online:
  http://www.telecom-paristech.fr/~essid

# Successful applications

The soft co-factorisation scheme has proven effective for various tasks:

- **Multimodal speaker diarisation** ("Who Spoke When?") on videos (Seichepine et al., 2014)
- **Multi-channel speech source separation** in stereo recordings (Seichepine et al., 2014)
- **Multimodal speech separation** with lip surface data (Sedighin et al., 2017)
- **Multimodal audio source separation** in music videos (Parekh et al., 2017b,a)

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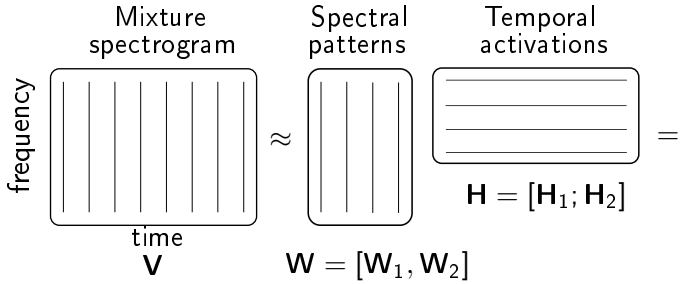
# NMF-based source separation

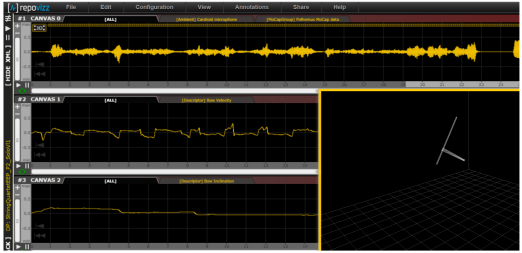
## Background



# Multiview source separation: Task specification

Motion informed source separation

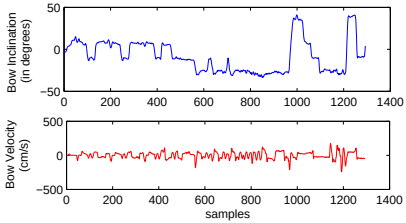
- Exploit information about the causes of vibration of each source, obtained from **motion capture**




EEP Dataset Example Video

# Motion representation

- Motion capture data from sensors placed on the instrument
- We use bow inclination and velocity




Bow inclination and velocity data for violin

Bow velocity: computed along bow direction

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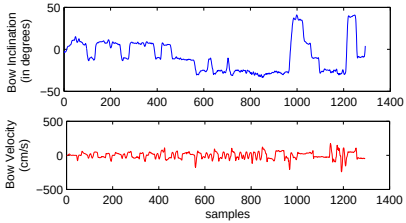


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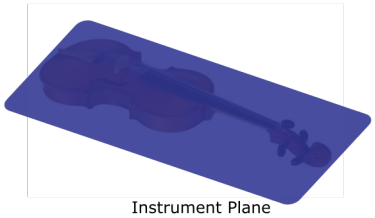


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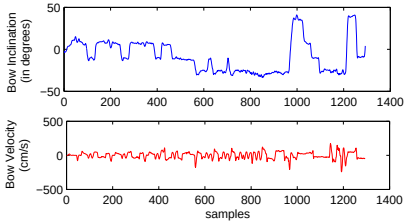


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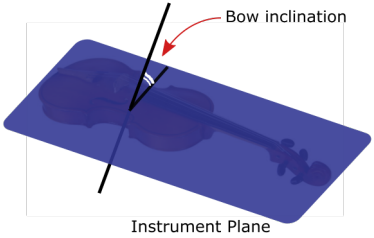


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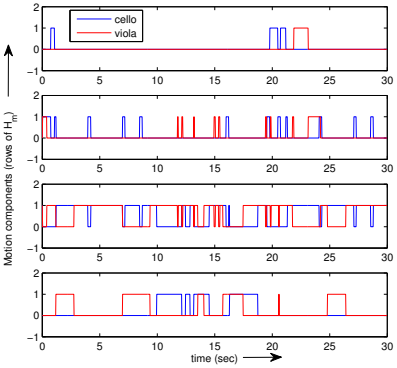
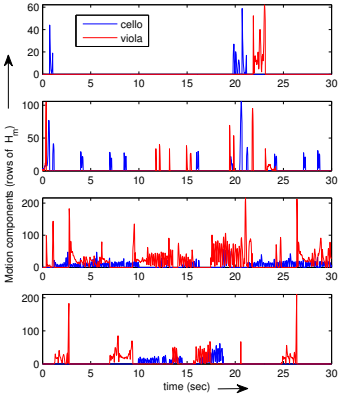



Quantized bow inclination




Quantized components multiplied with bow velocity: $\mathbf{H}_m \in \mathbb{R}_+^{K_m \times N}$

# Model specification

Variant of soft non-negative matrix co-factorization (sNMcF) (Seichepine et al., 2014):

$$\underset{\mathbf{W},\mathbf{H},\mathbf{S}}{\text{minimize}} \Bigg[ \underbrace{D_{KL}(\mathbf{V}|\mathbf{WH})}_{\text{spectogram factorization}} + \underbrace{\alpha\|\Lambda_a\mathbf{H} - \mathbf{S}\mathbf{H}_m\|_1}_{\text{Coupling}} + \underbrace{\beta \sum_{k=1}^{K}\sum_{n=2}^{N}(h_{kn} - h_{k(n-1)})^2}_{\text{temporal smoothing}} \Bigg]$$

$$\text{subject to } \mathbf{W} \geq 0, \mathbf{H} \geq 0.$$

Notation: $\mathbf{W} = (w_{fk})_{f,k} \in \mathbb{R}_+^{F\times K}$ , $\mathbf{H} = (h_{kn})_{k,n} \in \mathbb{R}_+^{K\times N}$, $\mathbf{S}$ - scaling diagonal matrix, $\Lambda_a$ is a diagonal matrix with $k^{th}$ diagonal coefficient $\lambda_{a,k} = \sum_f w_{fk}$, $\alpha$ and $\beta$ are hyperparameters

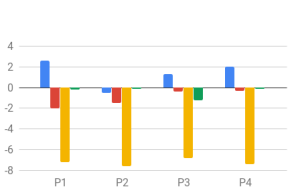
Cost function minimized using a majorization-minimization (MM) algorithm

# Dataset

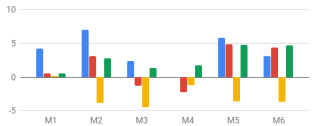
- Ensemble Expressive Performance (EEP) dataset (Marchini et al., 2014) - multimodal recordings of string instrument performances for 4 excerpts of Beethoven's Concerto


- We consider different duos and trios involving Violin, Viola and Cello

# Results and Discussion

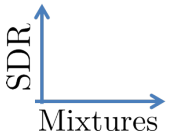



(a) 3-source mixtures



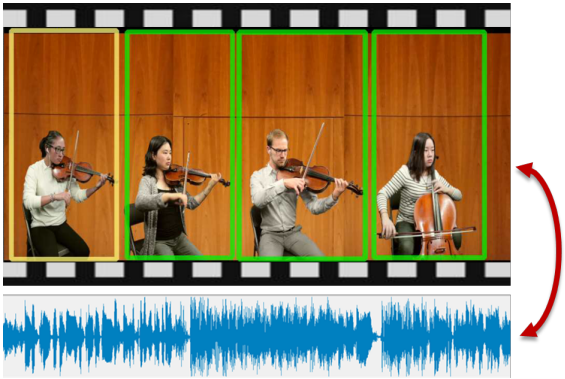

(b) 2-source mixtures


(c) same-source mixtures




Same instrument mixtures. Motion is crucial for disambiguation

# Source separation in music videos



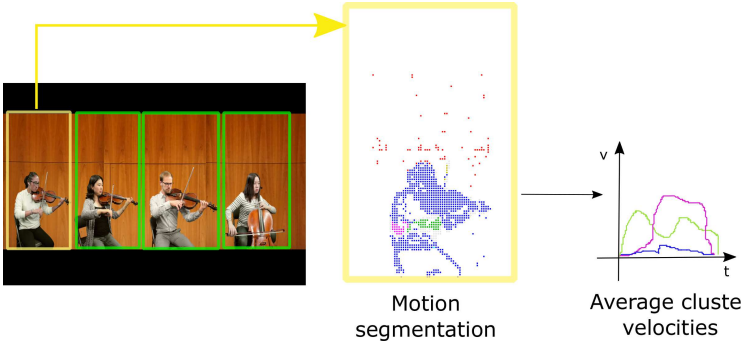
- **Difficulty:** motion representation no longer straightforward

# Cross-modal regression

(Parekh et al., 2017a)

▶ **Solution:**

1. Extract **motion clusters** (Keuper et al., 2015) in each performer's bounding box and represent them by average cluster velocities



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▶ **Solution:**

1. Extract **motion clusters** (Keuper et al., 2015) in each performer's bounding box and represent them by average cluster velocities
2. **Jointly factorise** audio spectrogram and **regress** the audio activations against cluster velocities:

$$\underset{\substack{(\mathbf{W},\mathbf{H},\mathbf{A})\geqslant 0\\ \|\mathbf{w}_k\|=1,\ \forall k}}{\text{minimize}} \quad D_{KL}(\mathbf{V}|\mathbf{WH}) + \lambda\|\mathbf{M}-\mathbf{H}^\top\mathbf{A}\|_F^2 + \mu\|\mathbf{A}\|_1$$

- $\mathbf{M} \in \mathbb{R}_+^{N\times C}$: velocity signals, stacked column-wise; $C$: total number of motion clusters
- $\mathbf{A} = [\boldsymbol{\alpha}_1, \ldots, \boldsymbol{\alpha}_C]$: nonnegative linear combination coefficient matrix

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(Parekh et al., 2017a)

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2. **Jointly factorise** audio spectrogram and **regress** the audio activations against cluster velocities:

- **Results:** Challenging case of two violins!

# Summary

- **Co-factorisation** schemes are well suited to **multiview, esp. multimodal data** analysis tasks
  - they allow for flexibly binding together related factors across different views
- **Stable** (MM) algorithms for different choices of divergences, and coupling/smoothing penalties
- Models have proven effective for **diverse multimodal applications** (music, video and physiological data)

▶ Great potential for other applications in **multiview music analysis**

# Tutorial Outline

- Introduction
- Audiovisual Music Performance Analysis
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  - Audiovisual Co-Factorization for Source Separation
  - Hands-on Case Study #1: Motion Informed Audio Source Separation
- **Audiovisual Content Based Classification and Retrieval**
  - Genre Classification
  - Emotion Analysis
  - Cross-Modal Retrieval
  - Instrument Classification
- Audiovisual Music Generation
  - Hands-on Case Study #2: Skeleton Plays the Piano
- Datasets, Tools and Other Resources
- Challenges, Opportunities and Conclusions

# Audiovisual Music Genre Classification

- Motivation - Visual modality conveys genre information

**Music Videos**


Jazz


Country


Rock


Pop


Classical


Heavy Metal

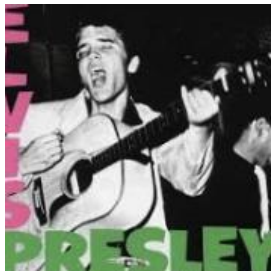
**Album Covers**

Country

New Age

Jazz


Heavy Metal



Rock

Pop

# Existing Work

- Genre tagging and artist similarity calculation from album covers and promotional photos (Libeks and Turnbull, 2011)
  - Color (RGB, HSV and LAB histograms), texture (Gabor and Haar features)
  - Distance calculation and nearest neighbor tag vector averaging

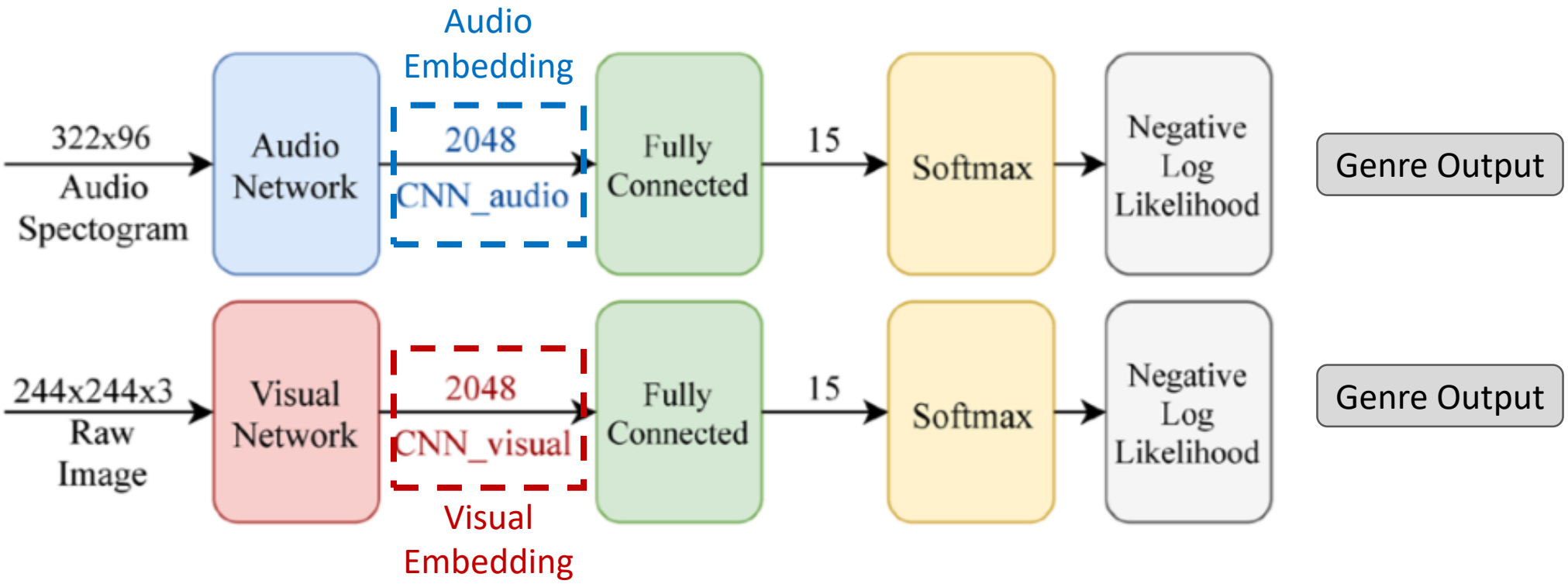
- Genre classification from music videos (Schindler and Rauber, 2015)
  - Audio feature: psychoacoustic music descriptors, MFCCs
  - Visual (color) features: color statistics, emotion values, colorfulness, Wang emotional factors, Itten's contrast, color names, lightness fluctuation patterns
  - Classifiers: SVM, KNN, Random Forest, Naïve Bayes

- Genre classification from audio, album covers, and text reviews (Oramas et al., 2018)
  - Deep neural networks for audio, visual and text representation learning, fusion and multi-label classification

# Multimodal Representation Learning and Fusion

(Oramas et al., 2018)

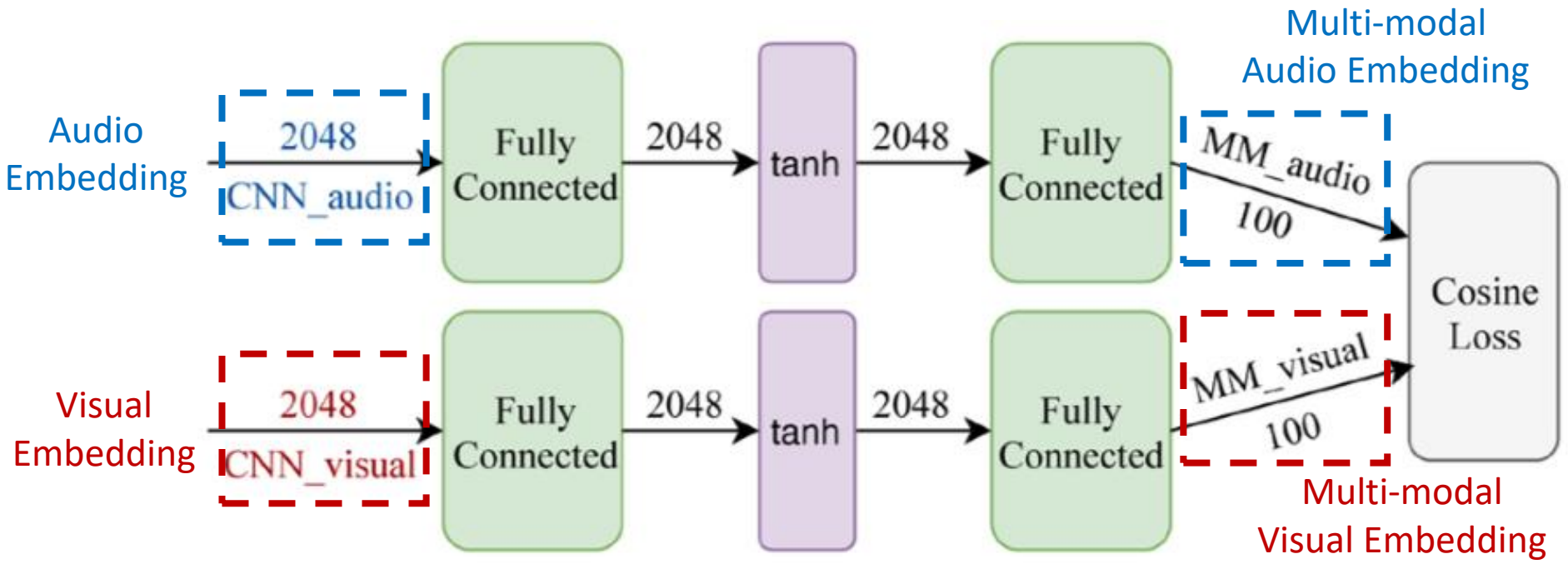
- Training Phase 1: learning single modal features through genre classification



# Multimodal Representation Learning and Fusion

(Oramas et al., 2018)

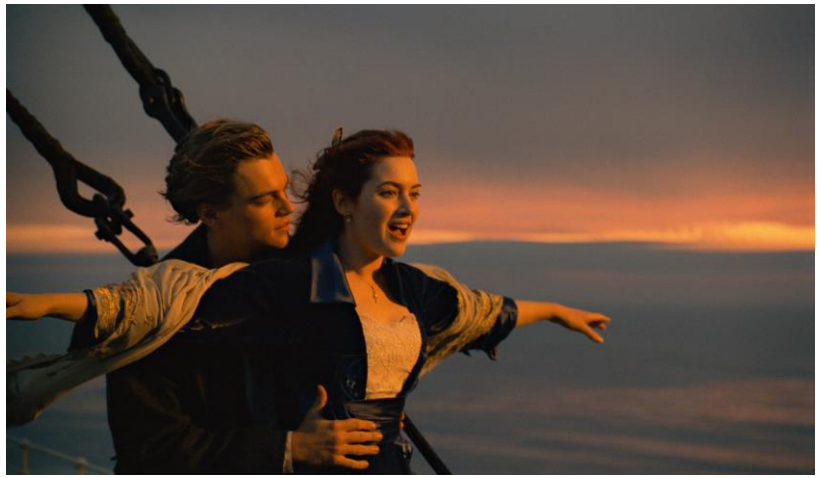
- Training Phase 2: learning multi-modal features through distance minimization



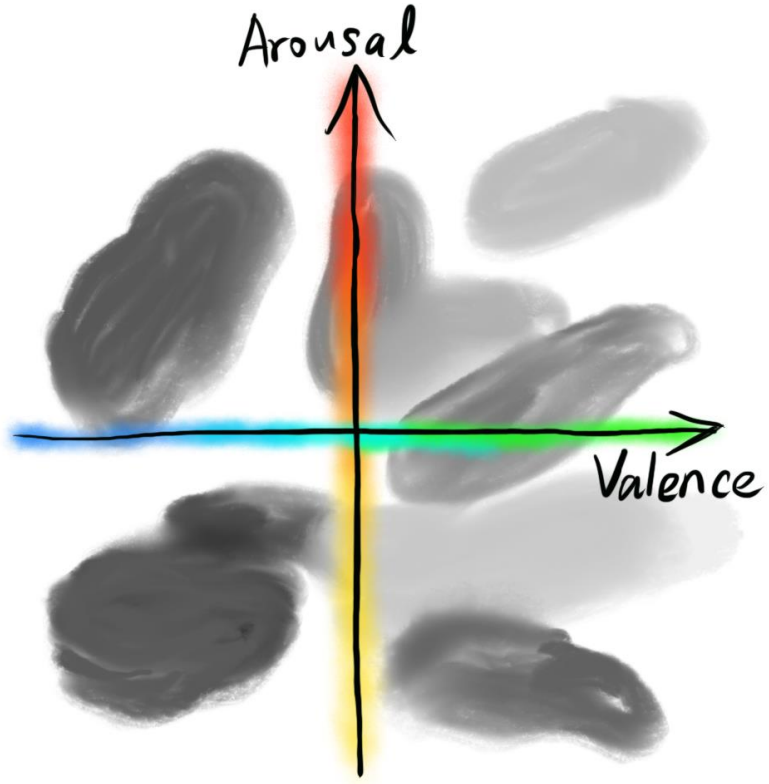

- Training Phase 3: training a feedforward network for multi-label genre classification based on a concatenation of the pre-learned multi-modal features

# Audiovisual Music Emotion Analysis

- Motivation
  - Visual information influences emotional experience of music listening
    - (Coutinho and Scherer, 2017), (Boltz et al., 2009)
  - Music is used to heighten the emotional impact of movie scenes
    - (Parke et al., 2007)
- Emotionally Relevant Factors
  - Audio: tempo, rhythm, pitch, mode, dissonance, articulation, instrument, etc.
  - Video: color, saturation, brightness, motion, action, event, instrument, etc.



# Emotion Representations


- Categorical
  - More categories: ambiguous and subjective (Juslin and Laukka 2004)
  - Fewer categories: not enough
- Dimensional
  - Typically two dimensions
  - Difficult to represent some sentiments/emotions, e.g., nostalgia, awkward, envy, disgust, etc.

# Single-Modality Emotion Analysis Work

- Using **categorical** emotion representations

| Approach | | # Emotion Categories | Data Type |
|---|---|---|---|
| Audio | (Lu et al., 2006) | 4 | Classical music |
| | MIREX 2010 (Hu and Downie, 2007) | 5 | Pop music |
| | (Wu and Jeng, 2006) | 8 | Pop music |
| | (Skowronek et al., 2007) | 12 | 12 music genres |
| | (Leman et al., 2005) | 15 | Pop music |
| | MIREX 2016 | 18 | 7 music genres (80% Pop) |
| Visual | (Kahou et al., 2016), (Kaya et al., 2017) | 7 | Video of facial expressions |
| | (Zhao et al., 2014) | 8 | Unconstrained photos |
| | (Xu et al., 2016) | 8 (3 variations on each) | Unconstrained videos |
| | (Cowen and Keltner, 2017) | 27 | Unconstrained videos |

# Single-Modality Emotion Analysis Work

- Using **dimensional** emotion representations

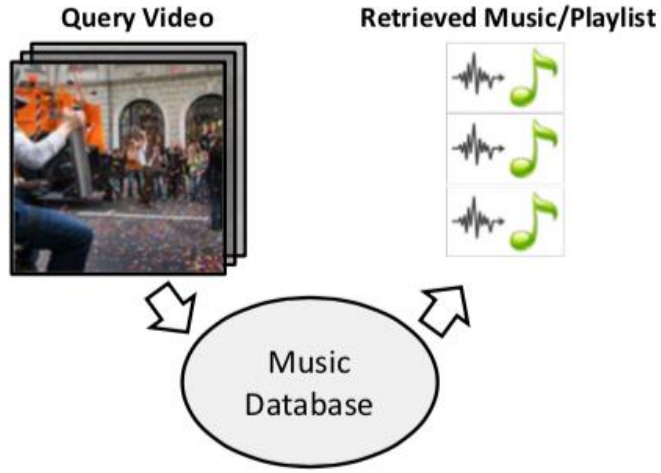
| Approach | | Dimensions | Data Type |
|---|---|---|---|
| Audio | (Wang et al., 2015) | Arousal-Valence | Music |
| | (Soleymani et al., 2013) | Arousal-Valence | Music (8 genres) |
| | (Yang et al., 2008) | Arousal-Valence | Pop Music |
| Visual | (Baveye et al., 2015) | Arousal-Valence | Movie scenes |
| | (Hanjalic and Xu, 2005) | Arousal-Valence-Dominance | Unconstrained videos |
| | (Koelstra et al., 2011) | Arousal-Valence-Dominance | Music videos |

# Cross-Modality Emotion Analysis Work

- Predicting emotions that can induce in people from music videos (Yazdani et al., 2011)
  - Audio features: zero-crossing rate, energy, silence ratio, pitch, MFCC, LPC, spectral centroid
  - Video features: lighting, key frame and shot boundary, color, motion vectors
  - Concatenation, normalization, PCA and kNN classification

- Affective visualization and retrieval (Zhang et al., 2010)
  - Arousal features: audio - *zero cross rate, tempo, beat strength*; video - *motion intensity, shot switch rate*
  - Valence features: audio - *rhythm regularity,* and *pitch;* video - *lighting*, *saturation*, *color energy*
  - Personalized affective analysis using Support Vector Regression

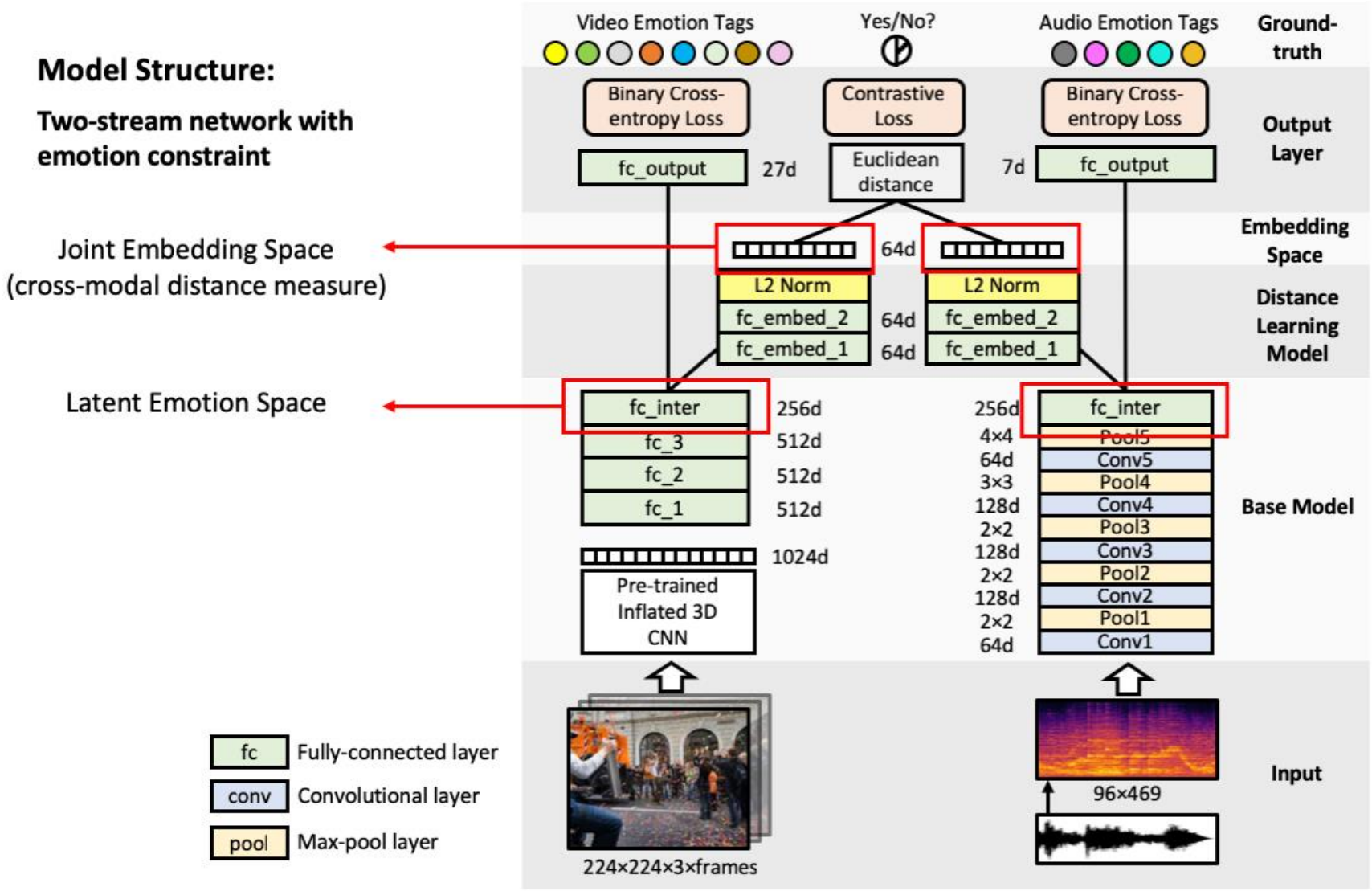
- Retrieving emotionally relevant music using video query (Li & Kumar, 2019)
  - Learning a shared latent emotion space through emotion tagging and distance constraints



# Learning Cross-Modal Latent Emotion Space

**Model Structure:**

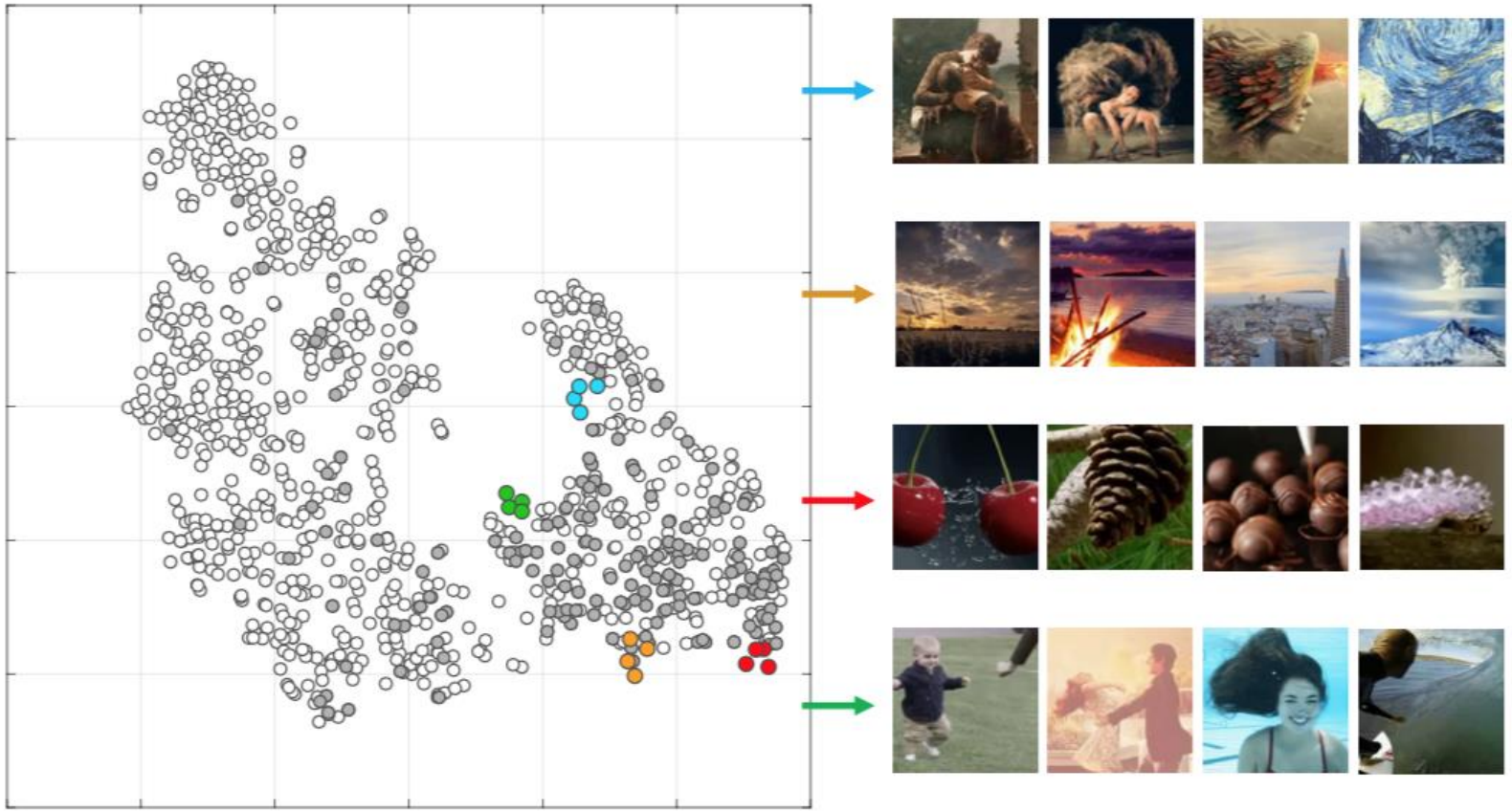
**Two-stream network with emotion constraint**




(Li and Kumar, 2019)

# Cross-Modal Emotion Representation

- Cross-modal emotion representations
  - A latent emotion space from cross-modal joint training

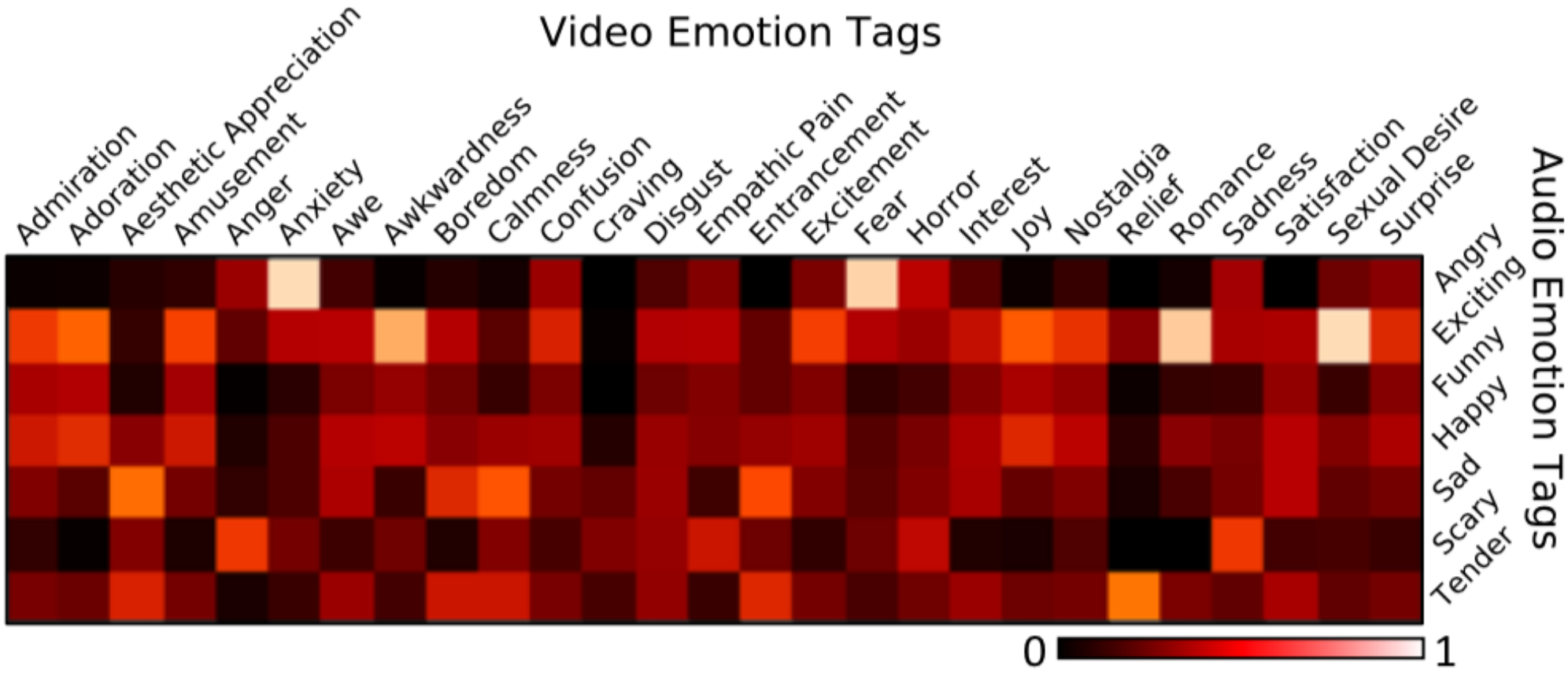


t-SNE visualization of a 64-D latent emotion space with some retrieved video thumbnails

Figure from (Li and Kuman, 2019)

# Audiovisual Emotion Tag Relations

- On crowd annotated 2000 music audio-video pairs (Li and Kuman, 2019)
  - Each audio and each video has its pre-labeled emotion tags
  - Audio-video pairs are annotated while their emotion tags are hidden



# Retrieval Examples

- User uploaded video clips from Instagram
- Retrieve music from 1195 Spotify music clips of the 30 most popular genres


Videos from http://www.ece.rochester.edu/~bli23/projects/query.html

# Audiovisual Cross-Modal Retrieval - Existing Tasks

- Music/playlist recommendation (Li and Kuman, 2019), (Sasaki et al., 2015)
  - Input query image/video, return a song or playlist
  - Recommend from a global connection (e.g., emotion, culture, genre)

- Soundtrack retrieval for videos (Shah et al., 2014), (Shin and Lee, 2017)
  - Pair silent video with proper soundtrack
  - Consider temporal correlation
    - Visual motions → music beats
    - Video shot transition → music phrase boundary

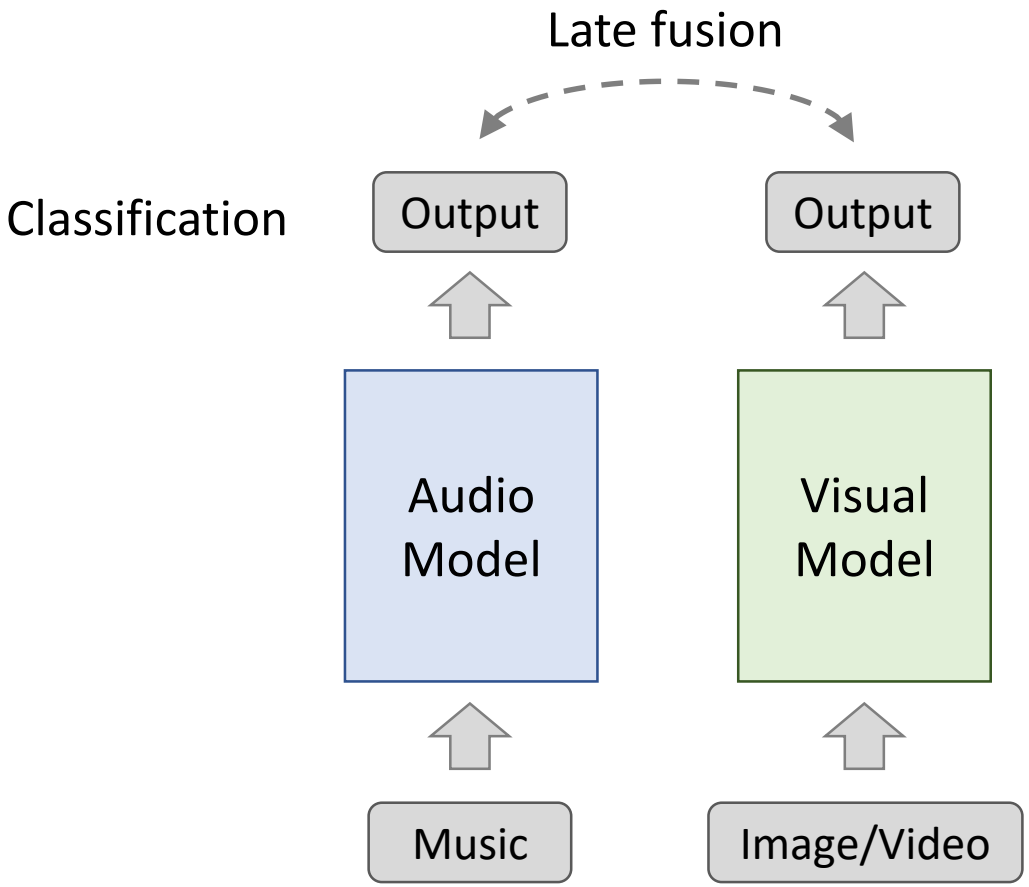
- Video retrieval for MV generation (Lin et al., 2015), (Gross et al., 2019), (Yoon et al., 2009)
  - Input query music, return video shots
  - Detect music phrase boundaries and pair a video scene for each audio segment

# Existing Cross-Modal Connections

- Low-level features
  - (Yoon et al., 2009), (Gross et al., 2019)
- Auxiliary info *(keywords, mood tags, association description, etc.)*
  - (Yu et al., 2012), (Shah and Zimmermann, 2014), (Wu et al., 2016), (Liem et al., 2012)
- Emotion modeling
  - (Chao et al., 2011)
  - Considering temporal correlation: (Wang et al., 2012), (Lin et al., 2015), (Sasaki et al., 2015), (Shin et al., 2017)
- Deep representation from neural networks
  - (Hong et al., 2018), (Li and Kumar, 2019)

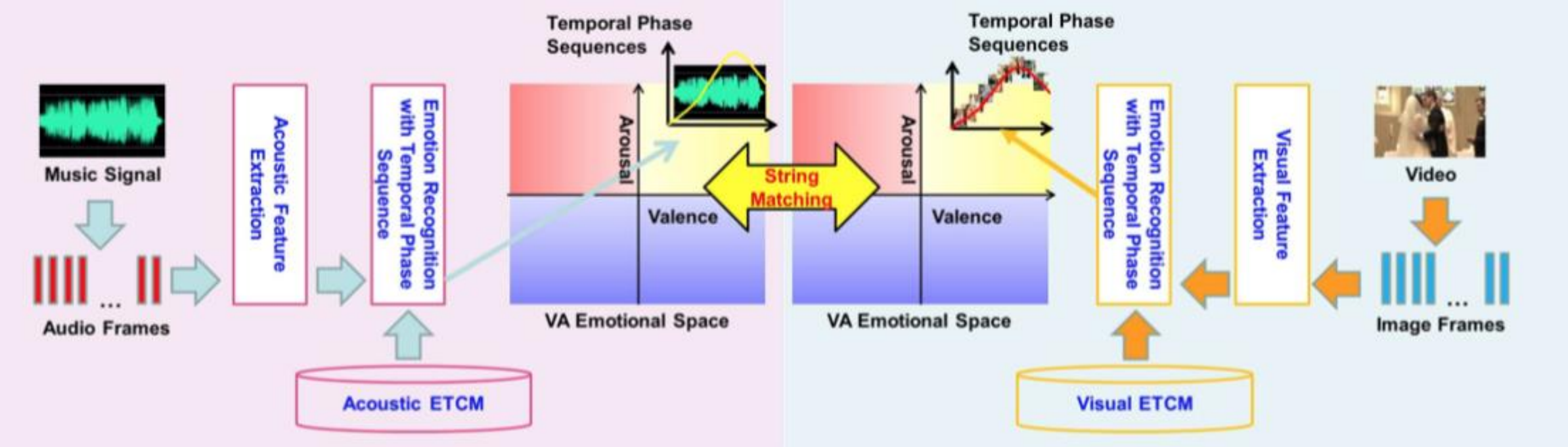
# A Typical Cross Modal Connection Approach

- Cross-Modal Connection through Late Fusion



# Example Cross-Modal Connection

(Lin et al., 2015)

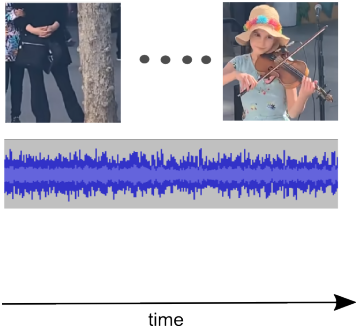



- String matching is replaced by a DNN model in their follow up work (Lin et al., 2016)

# Multimodal instrument classification and extraction

## Motivation

- Identify, locate and separate music instruments in audio and visual modalities
- Useful for various downstream tasks such as music transcription, remixing etc.



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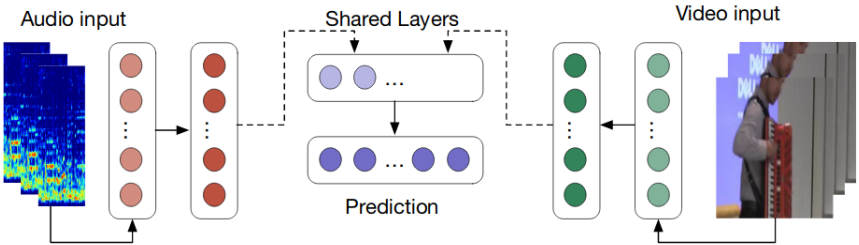
# Multimodal instrument classification and extraction

## Motivation

- Identify, locate and separate music instruments in audio and visual modalities
- Useful for various downstream tasks such as music transcription, remixing etc.

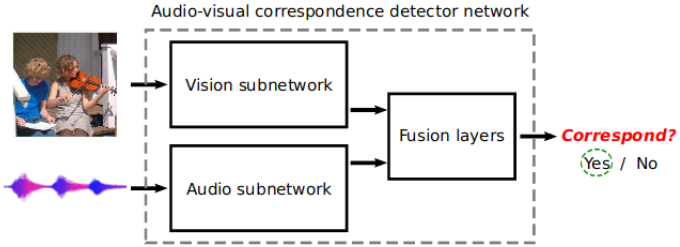

- Little to no supervision available for large-scale datasets

# Example I



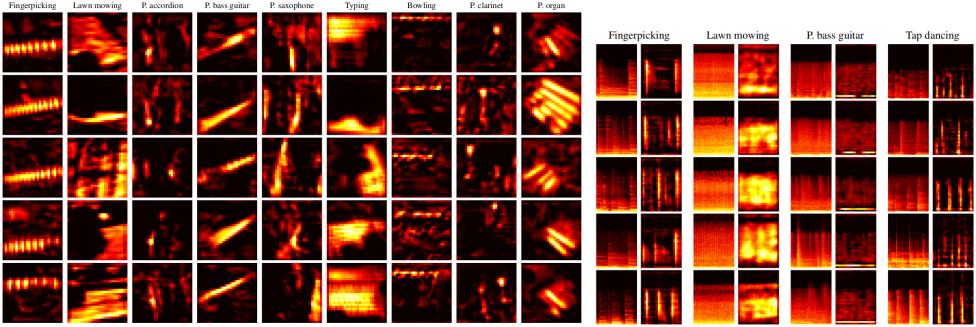

A two-stream approach to recognition
(Slizovskaia et al., 2017)

# Example II



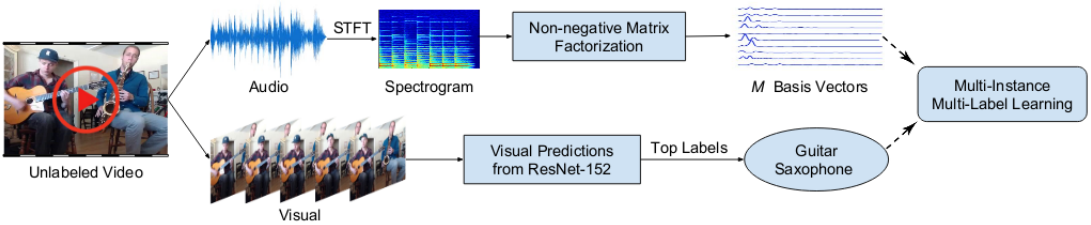

AV correspondence task: unsupervised representation learning, recognition and localization (Arandjelović and Zisserman, 2017)

# Example II




AV correspondence task: unsupervised representation learning, recognition and localization (Arandjelović and Zisserman, 2017)

# Example III

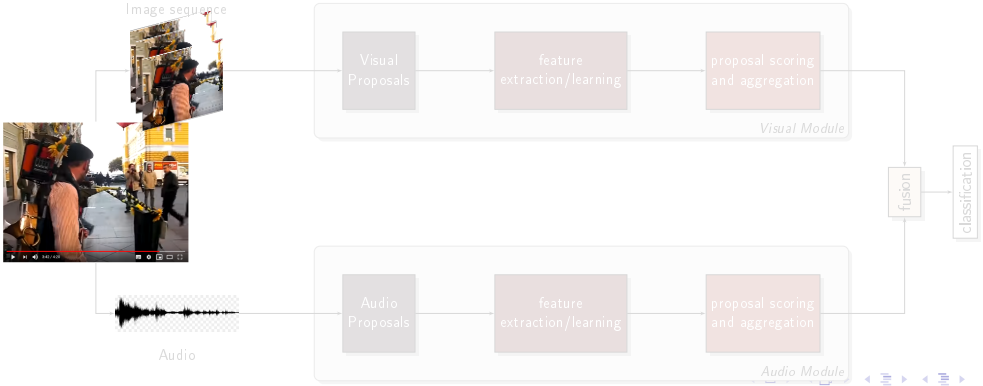



Audio source separation through unsupervised learning (Gao et al., 2018)

# Case study: A multiple instance learning based formulation

**Propose and Learn**

- Consider each video to be a bag of class-agnostic audio and visual proposals
- Extract features and transform them to score each according to their relevance for a particular class



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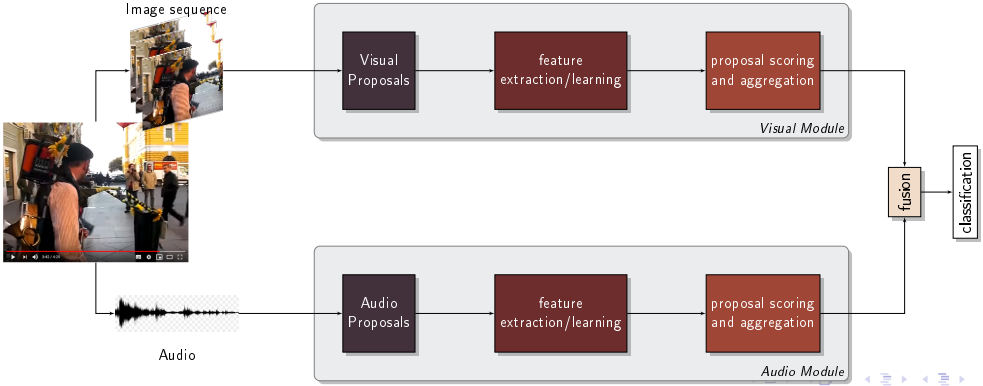
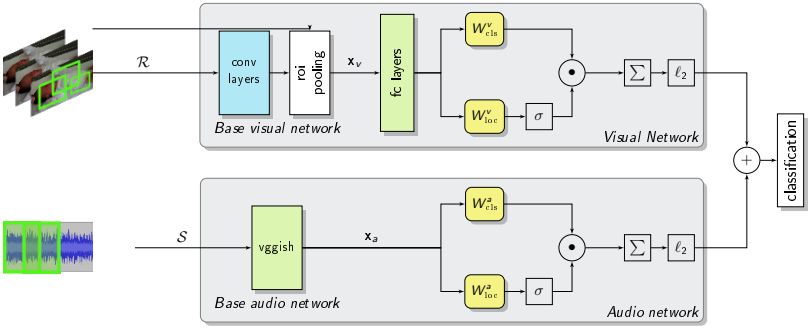
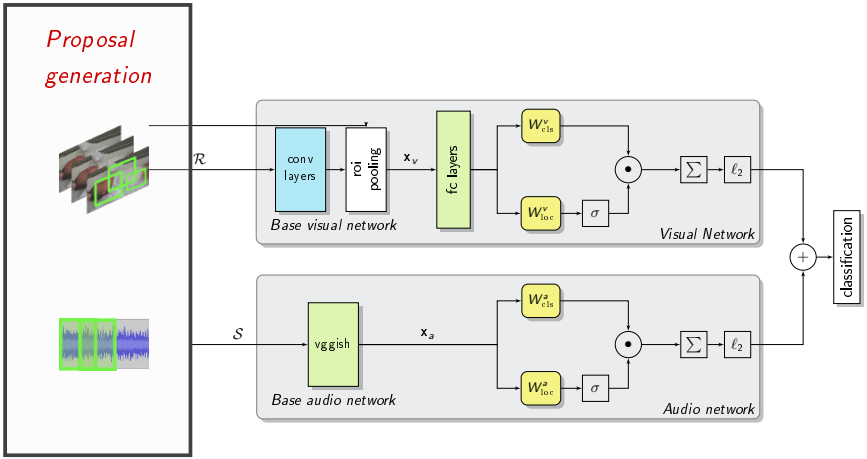


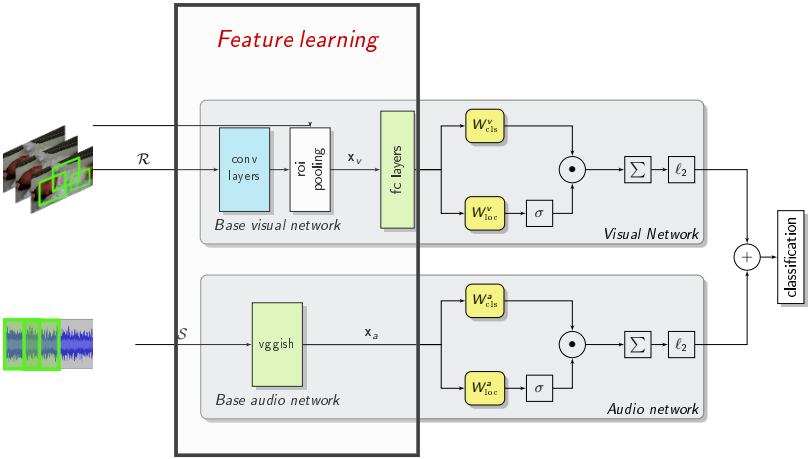
# An instantiation



# An instantiation

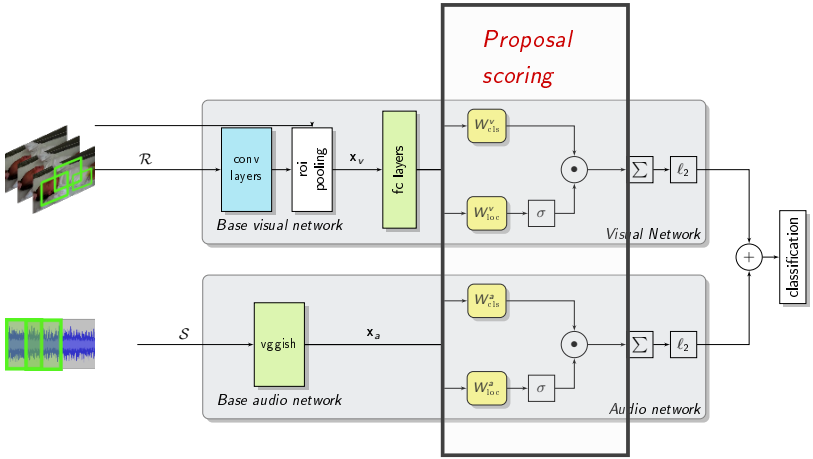


# An instantiation




- *Fine-tuning networks in green*

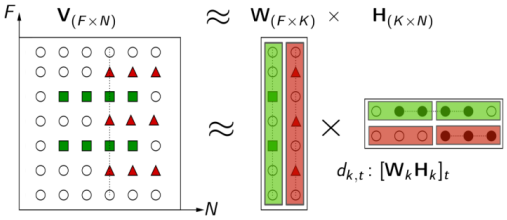
# An instantiation




- *A score for each class and proposal*

# NMF-based audio proposals

## Integrating source enhancement capability




**Source enhancement**

For each $d_{k,t}$ $\xrightarrow{\text{network}}$ $\beta_{k,t}$ $\xrightarrow{\text{pooling}}$ $\alpha_k$ $\xrightarrow{\text{scale}}$ $\alpha'_k$

$$\mathbf{S} = \frac{\sum_k \alpha'_k \mathbf{W}_k\mathbf{H}_k}{\mathbf{WH}}\mathbf{V}, \quad \mathbf{N} = \frac{\sum_k (1-\alpha'_k)\mathbf{W}_k\mathbf{H}_k}{\mathbf{WH}}\mathbf{V}$$

*Figure adapted from C. Fevotte*

# NMF-based audio proposals

## Integrating source enhancement capability

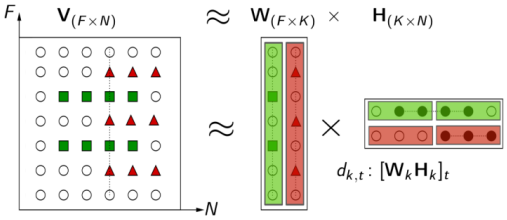



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*Figure adapted from C. Fevotte*

# Case study results

- Promising classification, visual localization and audio source enhancement results on Kinetics Instruments dataset
  - https://perso.telecom-paristech.fr/sparekh/ile2019_supp.html

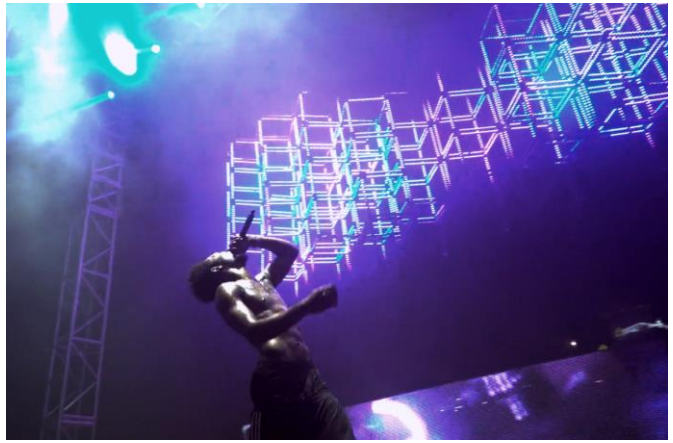
# Tutorial Outline

- Introduction
- Audiovisual Music Performance Analysis
  - Overview of Analysis Tasks
  - Audiovisual Co-Factorization for Source Separation
  - Hands-on Case Study #1: Motion Informed Audio Source Separation
- Audiovisual Content Based Classification and Retrieval
  - Genre Classification
  - Emotion Analysis
  - Cross-Modal Retrieval
  - Instrument Classification
- **Audiovisual Music Generation**
  - Hands-on Case Study #2: Skeleton Plays the Piano
- Datasets, Tools and Other Resources
- Challenges, Opportunities and Conclusions

# Audiovisual Music Generation

# Motivation

- Music visualization / Stage light control



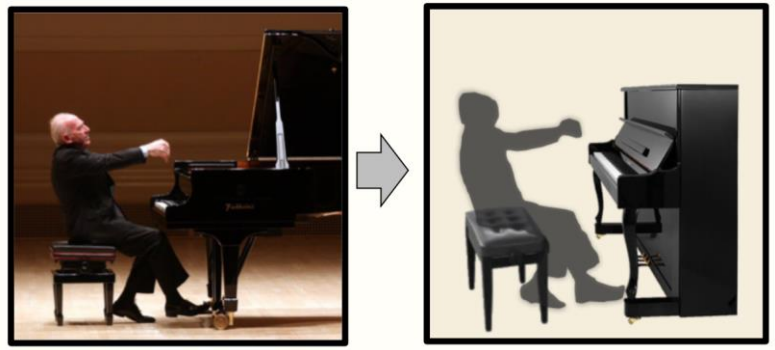
Symmetry Lab

- Education/entertainment tools

Microsoft Hololens

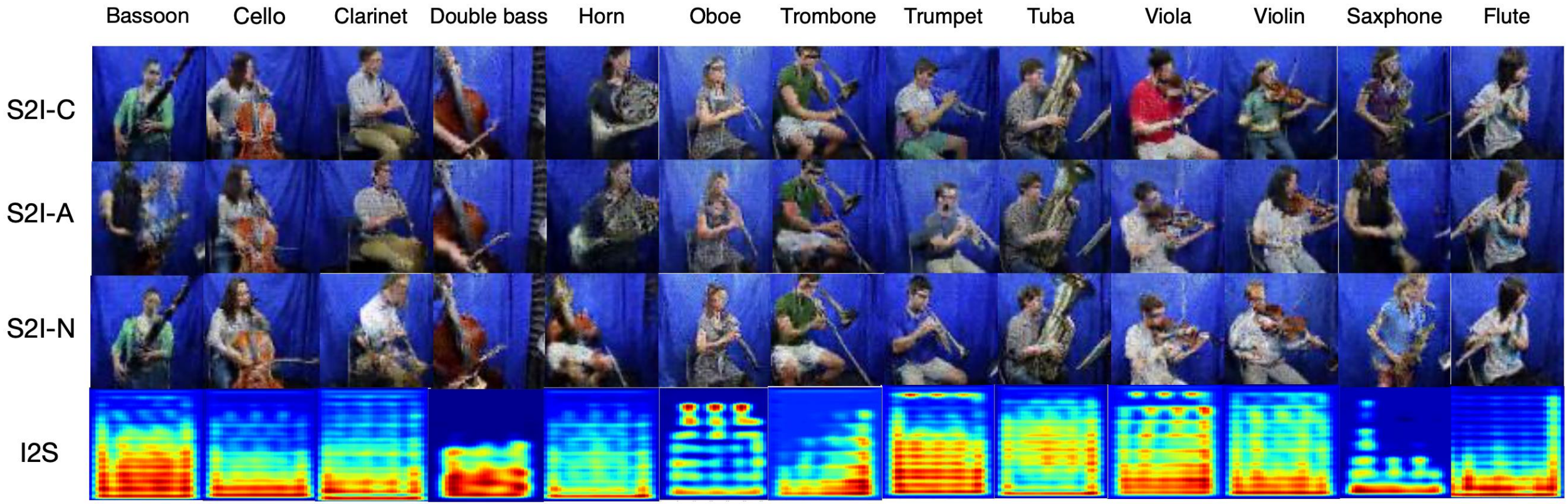
- Expressive robot ensemble

- Immersive music enjoyment



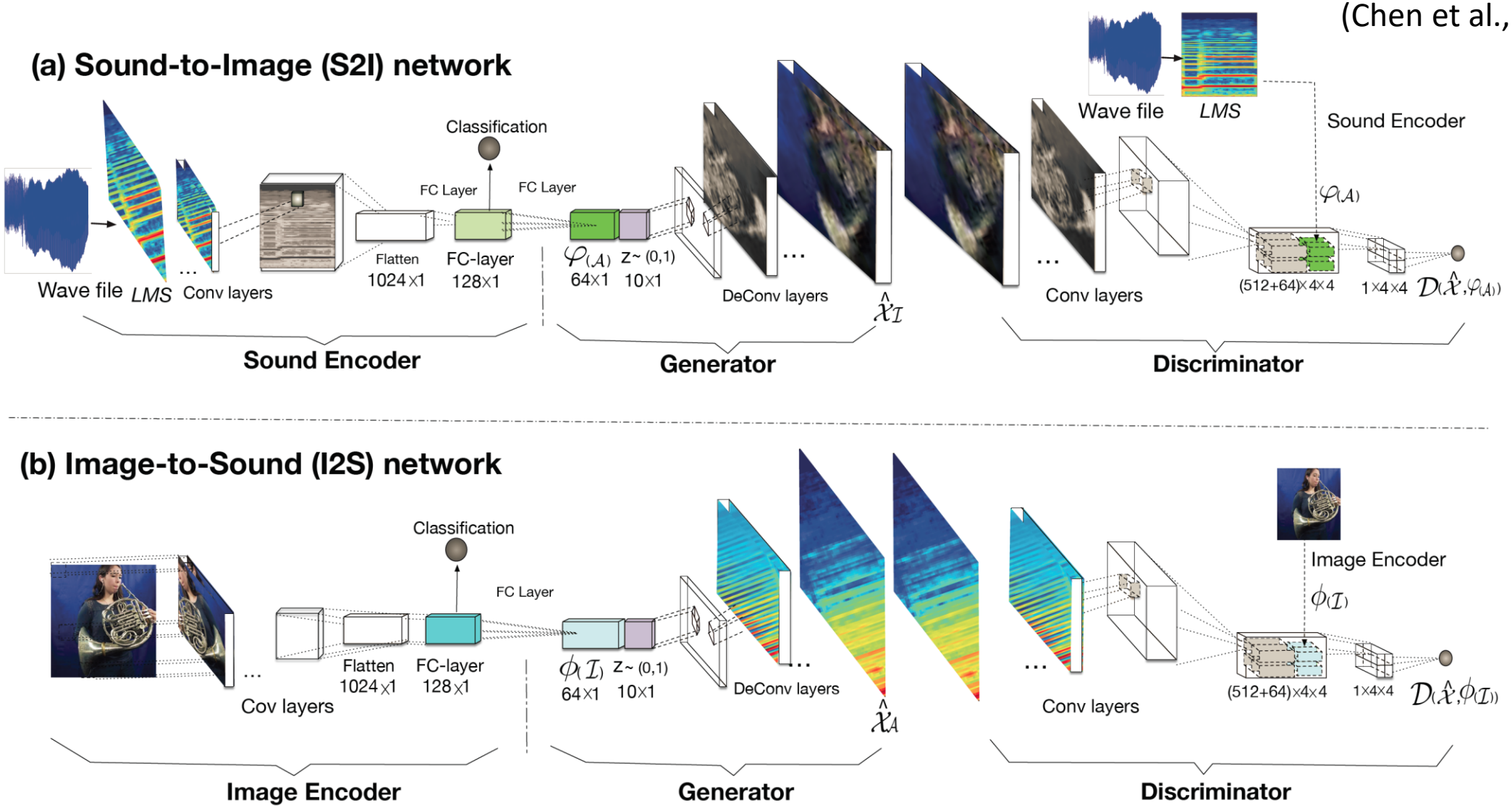
# Image vs. Sound

- Image-sound cross-modal generation for music performance (Chen et al., 2017)
  - Instrument player generation from instrument sound
  - Instrument sound generation from instrument player image
  - Focus on static image and single tone



# Model Structure

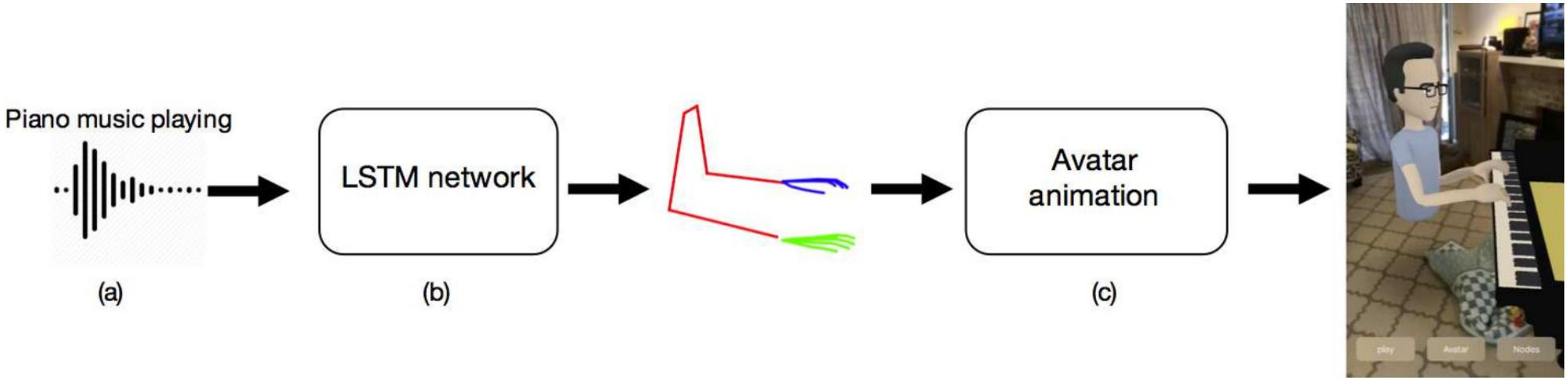
(Chen et al., 2017)



# Audio to Video

- Generate instrumentalists visual movement from music audio
  - Focus on violinist and pianist
  - Input: audio performance; Output: upper body skeleton movements
  - Generate avatar animation using a 3D body model

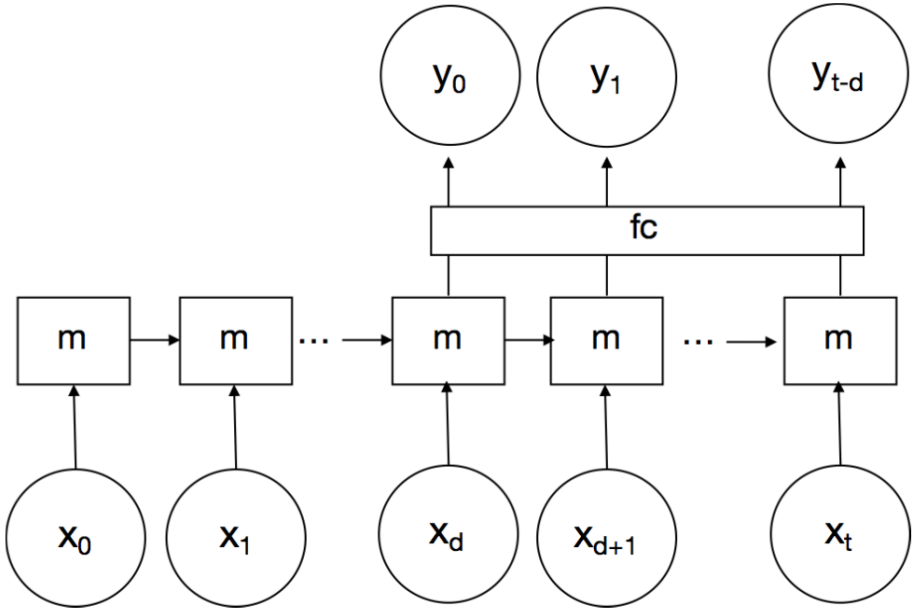
(Shlizerman et al., 2018)



# Audio to Video

- Generate instrumentalists visual movement given music audio
  - Network structure

(Shlizerman et al., 2018)

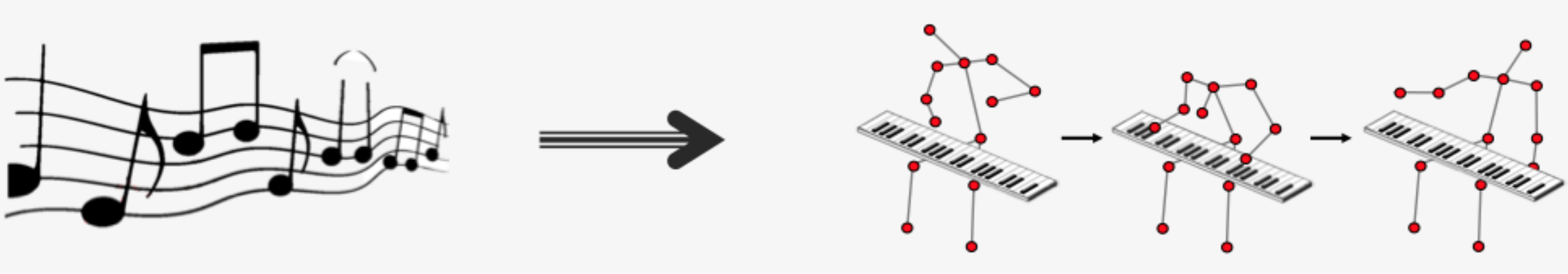



x: PCA coefficients of audio MFCC features
y: PCA coefficients of visual skeleton key points (extracted from OpenPose and MaskRCNN)

# MIDI to Video

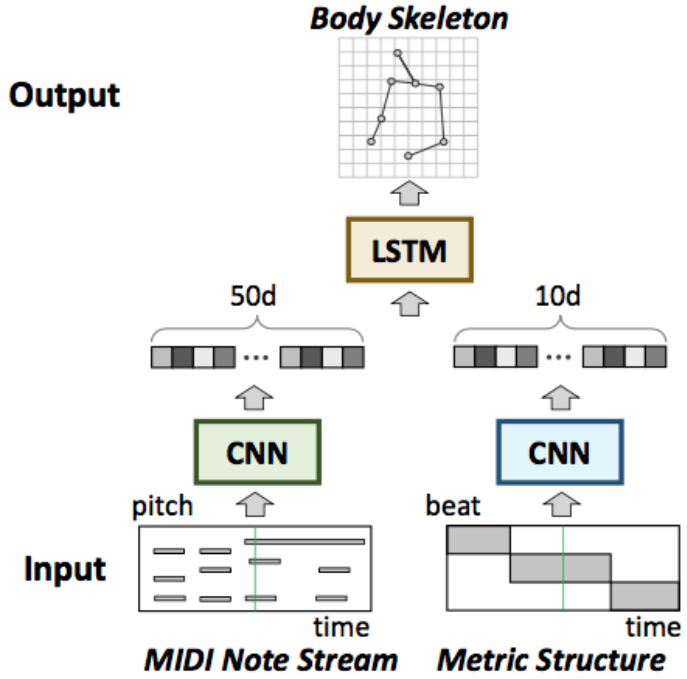
- Generate instrumentalists visual movement from MIDI performance
  - Input: MIDI (pianoroll) performance
  - Output: A sequence of coordinates of upper body skeleton points

(Li et al., 2018)

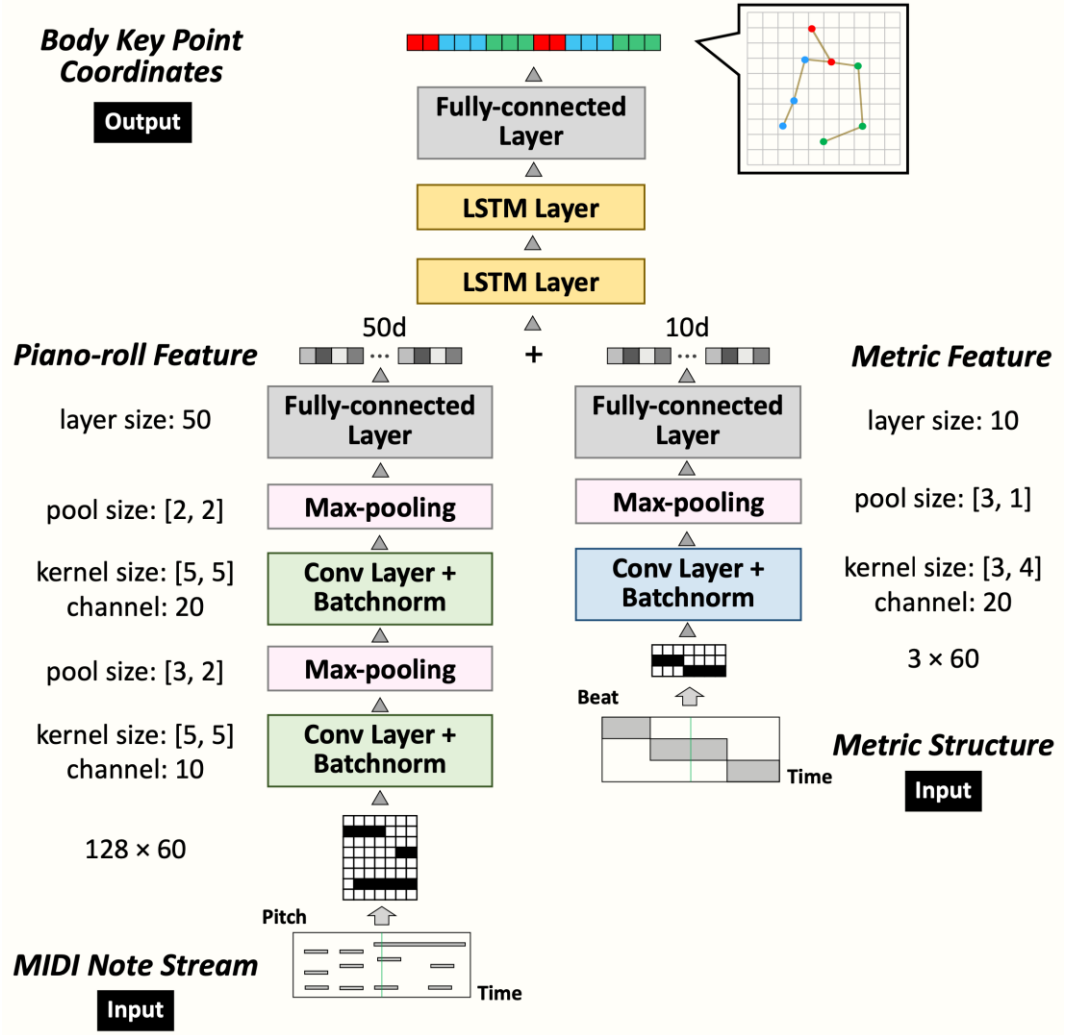


# MIDI to Video

- Generate instrumentalists visual movement given MIDI performance (Li et al., 2018)
  - Network structure



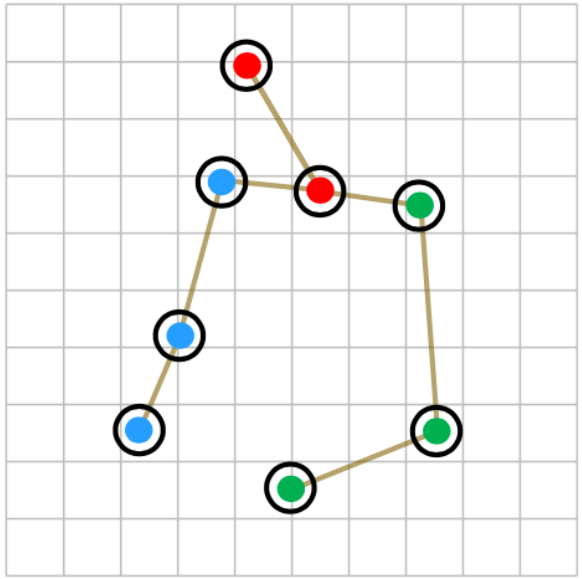

More Details



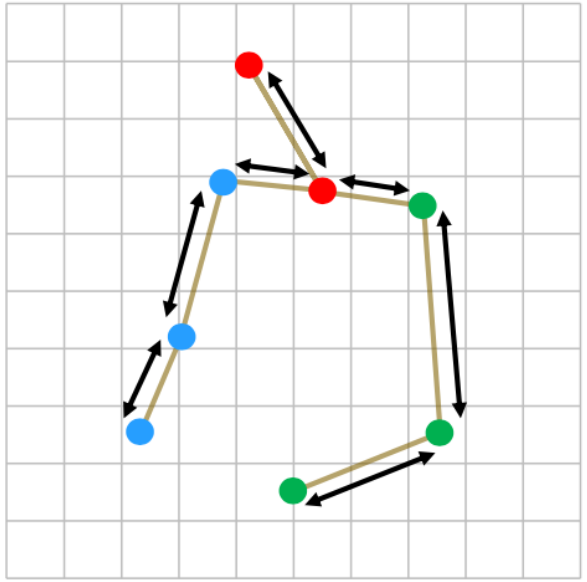
# MIDI to Video

- Generate instrumentalists visual movement given MIDI performance (Li et al., 2018)
  - Training Strategy
    - Loss function: mean absolute error
    - Joint constraint: on each individual body joint (applied in all epochs)
    - Limb constraint: ensure that relative length between adjacent joints is reasonable (applied after 30 epochs)

**Joint Constraint**



**Limb Constraint**



# MIDI to Video

- Generate instrumentalists visual movement given MIDI performance
  - Dataset collection
    - 2 players, 16 different pieces, 74 recordings

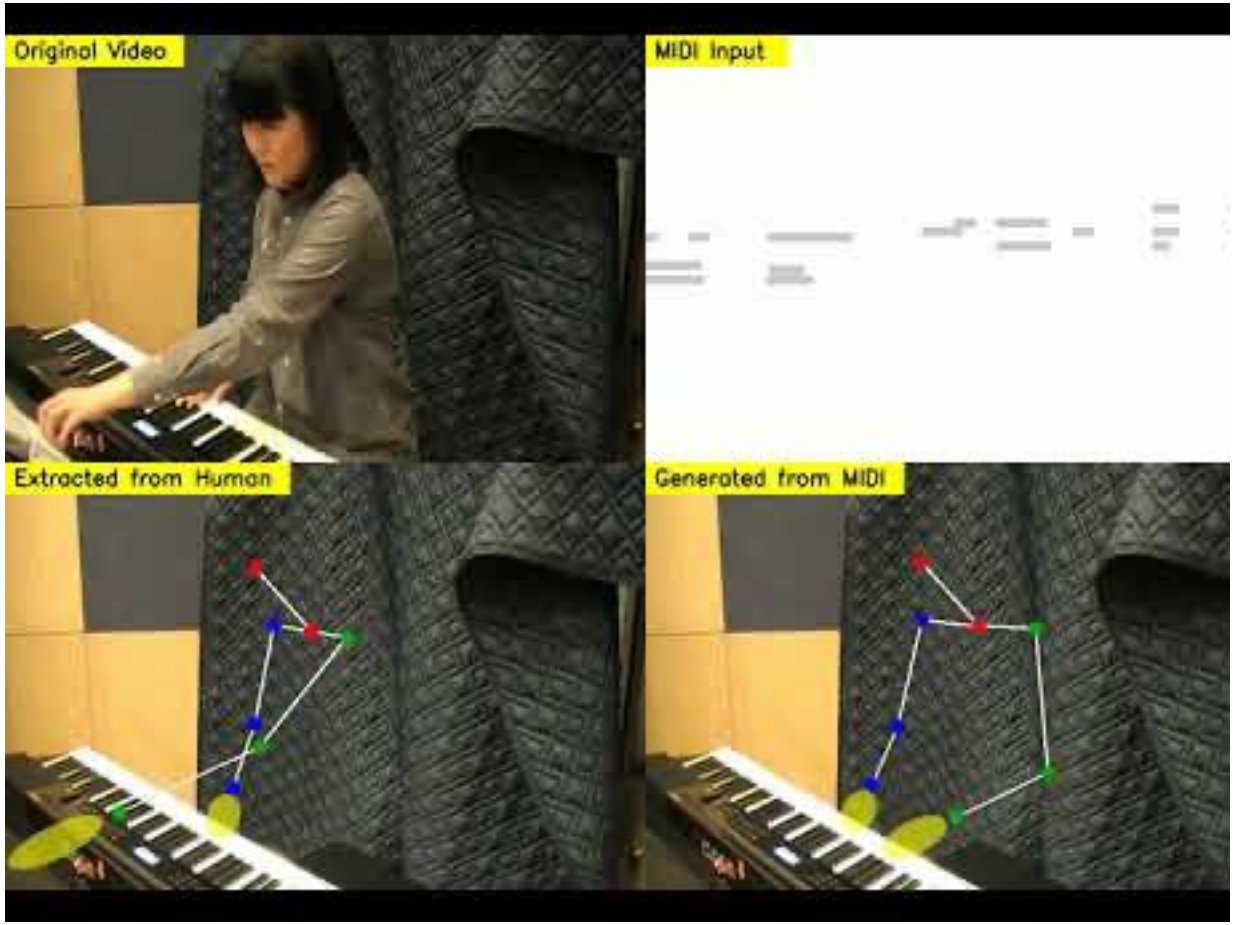
(Li et al., 2018)


Directly from MIDI keyboard

Extracted using OpenPose library

# MIDI to Video

- Generate instrumentalists visual movement given MIDI performance (Li et al., 2018)
  - Example



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# Datasets, Tools, and Resources

# Datasets about Music Performances

- Single-track

| Name | Instrument | # Pieces | Total Duration | Content |
|---|---|---|---|---|
| Multi-modal Guitar (Perez-Carrillo et al., 2015) | Guitar | 10 | 10 m | Audio, video |
| C4S (Bazzica et al., 2017) | Clarinet | 54 | 4.5 h | Audio, video, visual annotations |
| MUSIC (Zhao et al., 2018) | Multi-instrument | 685 | N/A | Audio, video (as Youtube ID) |

# Datasets about Music Performances

- Multi-track

| Name | Instrument | # Pieces | Total Duration | Content |
|---|---|---|---|---|
| ENST-Drums (Gillet and Richard, 2006) | Drum kit | N/A | 3.75 h | Audio, video (multi-camera views) |
| (Abeßer et al., 2011) | Guitar, drum, bass | N/A | 1.2 h | Audio, video (multi-camera views) |
| EEP (Marchini et al., 2014) | String quartets | 23 | N/A | Audio, Note annotation, Bow MoCap data |
| URMP (Li et al., 2018) | Multi-instrument chamber ensembles | 44 | 1.3 h | Audio, Video, Note annotation, Pitch contour |

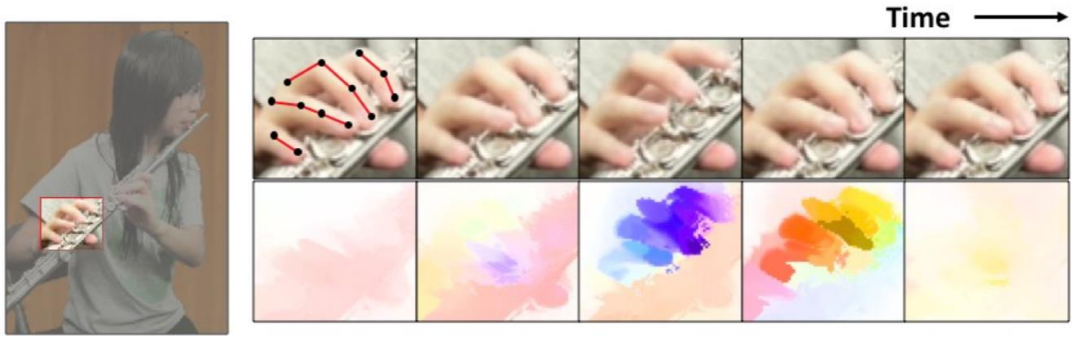
# Datasets about General Music Videos

| Name | Content | Tasks |
|---|---|---|
| (Hong et al., 2018) | Music videos (as Youtube ID) | Cross-modal retrieval |
| (Choi, 2017) | Music videos (as Youtube ID) | Cross-modal retrieval |
| MuMu (Oramas et al., 2017) | Album reviews for Million Song Dataset | Genre classification |
| RAVDESS (Livingstone and Russo, 2018) | Audiovisual recording of speech and singing, emotion labels | Emotion recognition |
| DEAP dataset (Koelstra et al., 2011) | Music videos, emotion annotations, annotators' EEG signal and face recordings | Cross-modal retrieval, multi-modal emotion analysis |

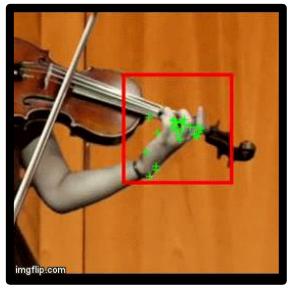
- Other datasets that contain audiovisual music subsets:
  - Audioset, Youtube-8M, Moments in Time, etc.

# Low-Level Video Feature Extractors

- Optical flow
  - Pixel-wise velocity across frames




- KLT tracker
  - Initialize bounding box for the 1st frame
  - Detect feature points
  - Track feature points



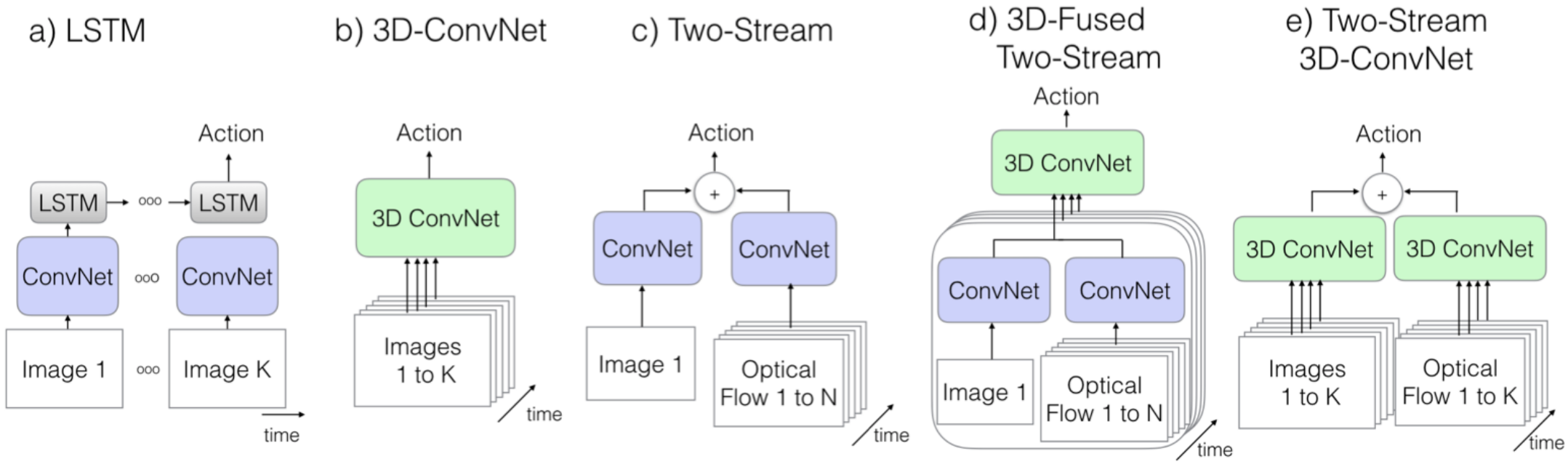
- Supervoxel (Xu et al., 2016)
  - Video temporal-spatial segmentation

# High-Level Video Feature Extractors

- Pretrained image classification models
  - ResNet (He et al., 2016)
  - VGGNet (Carreira and Zisserman, 2017)
  - DenseNet (Huang et al., 2017)
- Network architectures (Image to Video)

Pretrained video processing models

- C3D (Tran et al., 2015)
  - Pretrained on sport activity classification
- I3D (Carreira and Zisserman, 2017)
  - Pretrained on human action recognition
  - SoTA in Kinetics dataset




(Carreira and Zisserman, 2017)

# Open-Source Projects/Code

- Facebook Detectron
  - Object detection
  - Object segmentation
  - Human-object interaction recognition

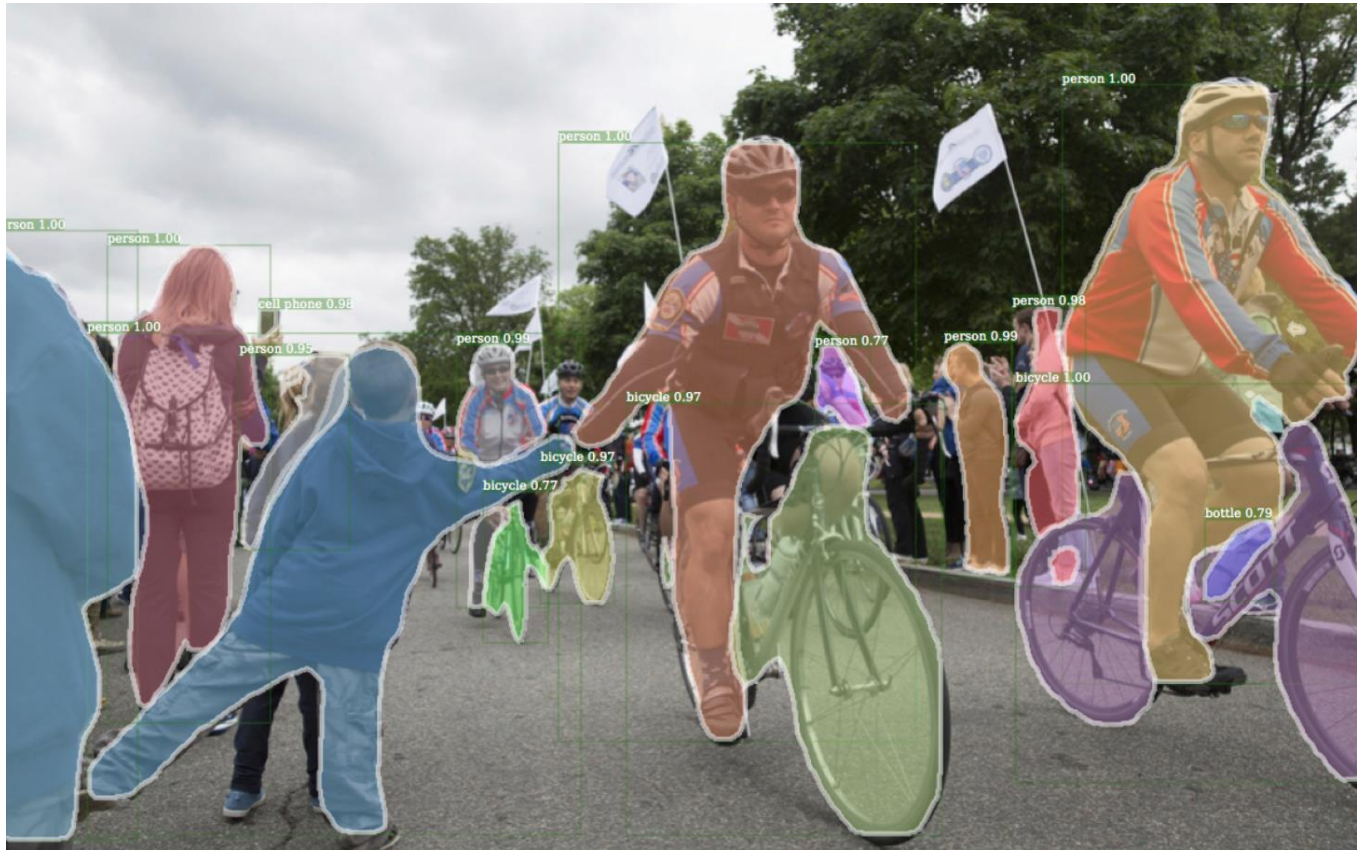



Figure from: https://research.fb.com/downloads/detectron

# Open-Source Projects/Code

- OpenPose
  - Body joint landmark detection
  - Facial landmark detection
  - Finger joint landmark detection
  - Single-person tracking

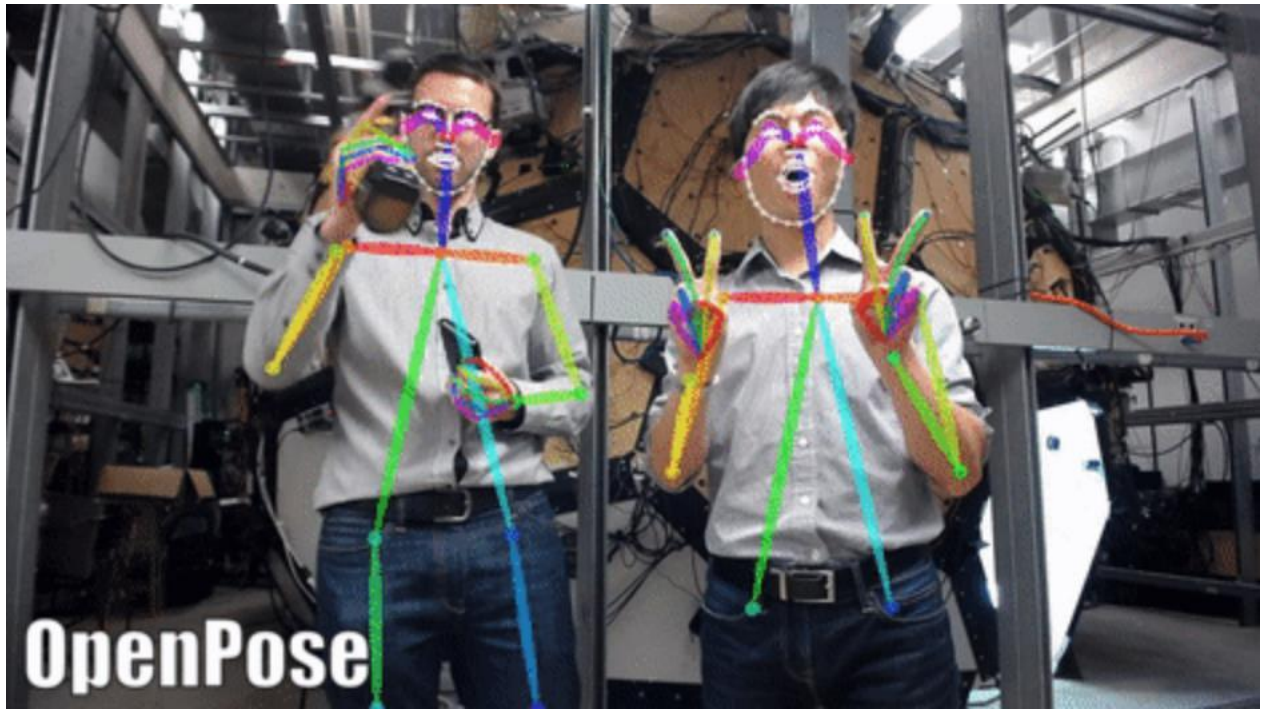



Figure from: https://github.com/CMU-Perceptual-Computing-Lab/openpose

- Introduction
- Audiovisual Music Performance Analysis
- Audiovisual Content Based Classification and Retrieval
- Audiovisual Music Generation
- Datasets, Tools and Other Resources
- Challenges, Opportunities and Conclusions

# Challenges and Opportunities

## Audio-visual correspondence

- Determining the what, where and how of fusion
  - May differ at different spatio-temporal locations!
  - Integration of static and dynamic correpondence models (Owens and Efros, 2018)
- Better modeling of AV associations
  - Often non-linear: exploring deep architectures
  - Distinguishing between cause and correlation
- Complexity of visual analysis
  - Difficult to capture and extract subtle *musically* relevant movements
    *for e.g.* playing hand movement on string instruments
    - Combining other sources of information (e.g. motion capture)

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Cause

Correlation

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# Challenges and Opportunities

## Data

- Scarcity of large-scale clean, annotated datasets
  - Amateurish quality and unconstrained nature of user–generated videos
    - Adapt to changing camera view-points, illumination
  - Artificially edited content (video frames unrelated to audio etc.)
    - Flexibly tackle intermittent or long range correspondences
  - Lack of annotations
    - Towards unsupervised, weakly supervised and semi-supervised methods
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# Challenges and Opportunities

## Tasks and applications

- Audio-visual music synthesis
  - An end goal for artists and users (Owens et al., 2016; Shlizerman et al., 2018; Li et al., 2018b; Zhou et al., 2018)
    - Interactive machine learning (Fiebrink et al., 2016)
    - Assisting those with vision or hearing impairment
  - A tool for analysis
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- Enhancing music education and production
  - Movement, posture and playing style analysis
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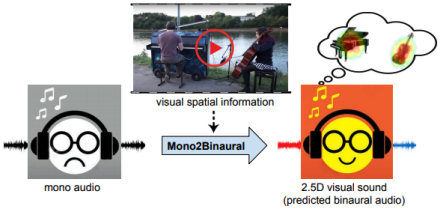


(Gao and Grauman, 2019a)

# Credits

- L. Chen
- K. Dinesh
- A. Kumar
- C. Liem
- X. Liu
- A. Maezawa
- G. Sharma
- C. Xu
- A. Ozerov
- G. Richard
- N. Q. K. Duong
- P. Perez
- C. Févotte
- N. Seichepine
- O. Cappé

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# Soft matrix co-factorisation

(Seichepine et al., 2014)

Solve the problem:

$$\min_{\mathbf{W}_1,\mathbf{H}_1,\mathbf{W}_2,\mathbf{H}_2} D_1(\mathbf{V}_1 \,|\, \mathbf{W}_1\mathbf{H}_1) + \beta_2 D_2(\mathbf{V}_2 \,|\, \mathbf{W}_2\mathbf{H}_2) + \beta_c \|\mathbf{H}_1 - \mathbf{H}_2\|_p$$

- **Remarks:**
  - the initial formulation cannot lead to sensible solutions:
    - there is a scale ambiguity on $\mathbf{W}_1\mathbf{H}_1$ and $\mathbf{W}_2\mathbf{H}_2$;

    → the problem needs to be rescaled
    - $\mathbf{H}_1$ and $\mathbf{H}_2$ are not necessarily directly comparable

    → introduce scaling matrix $\mathbf{S}$

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$$\min_{\mathbf{W}_m,\mathbf{H}_m} D_1(\mathbf{V}_1 \,|\, \mathbf{W}_1\mathbf{H}_1) + \beta_2 D_2(\mathbf{V}_2 \,|\, \mathbf{W}_2\mathbf{H}_2) + \beta_c \left\| \mathbf{\Lambda}_1\mathbf{H}_1 - \mathbf{\Lambda}_2\mathbf{H}_2 \right\|_p$$

$$\mathbf{\Lambda}_1 = \mathrm{diag}(\lambda_{m,1}, \cdots, \lambda_{m,K}) \;;\; \lambda_{m,k} = \textstyle\sum_f w_{m,fk} \;;\; m \in \{1,2\}$$

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# Behavior of the soft co-factorisation

## Using synthetic data