Can the Computer Learn to Play Music Expressively?

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Biography

- Solo with orchestra at the age of 17
- Played principal oboe-Santa Cruz Symphony
- Professor in Department of Mathematics and Statistics at the University of Massachusetts, at Amherst

Music Plus One (MPO)

- Real-time musical accompaniment for a live soloist
- Non-improvised music
- Bayesian belief network-joint distribution on the times for Solo and Accompaniment
- Hidden variables
- Provide a computationally decision-making engine to utilize information to produce a flexible accompaniment

Input

- Acoustic signal
- Generated by live player
- Construct the accompaniment ,using interpretations
- Learned from examples

Accompaniment problem

- Listen
- Play

Listen

- Input= the acoustic signal of the solo
- Using hidden Markov Model (HMM)
- Performs a real-time analysis of the signal
- Output =identifies note boundaries in the solo part and communicate these events with variable latency

Hidden Markov Model (HMM): strengths

- Automatic trainability
- Computational efficiency
- Accuracy

Play

- Bayesian belief network consist of hundreds of Gaussian random variables
- Belief network trained in rehearsal phase
- Model soloist and accompanist
- The model used in performance to compute in real time the optimal course of action, by available data

Knowledge Sources

- Musical Score
- The output of the Listen component
- Solo performances and human renditions of the accompaniment part

Bayesian belief network

- Probabilistic model developed
- To represents all three knowledge sources
- Through a jointly Gausian distribution
- Contains hundreds of random variables
- Observable variables: Estimated soloist note onset times produced by Listen, and observable times for the accompaniment notes.

Unobservable Variables:

- Hidden variables to describe unobservable quantities : local tempo, change in tempo, rhythmic stress

The Solo Model

- Define random vector of time and tempo for each of the solo notes
- Model sequence of random vectors through a random difference equation:

$$\begin{pmatrix} t_{n+1} \\ s_{n+1} \end{pmatrix} = \begin{pmatrix} 1 & l_n \\ 0 & 1 \end{pmatrix} \begin{pmatrix} t_n \\ s_n \end{pmatrix} + \begin{pmatrix} \tau_n \\ \sigma_n \end{pmatrix}$$

- The distribution will tend to Zero
- Expresses the notion that tempo changes are gradual
- Negative mean show where the soloist speeding up
- Positive mean show where the soloist slowing-down
- Low variance shows the tempo changes are deterministic
- High variance shows the tempo changes are quite variable
- Means and covariance are expressed by vectors

Solo Model

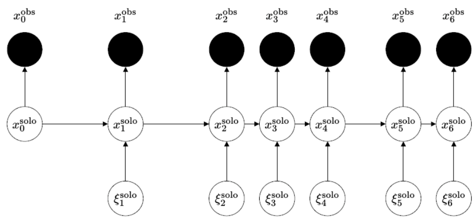
$$x_{n+1}^{\text{solo}} = A_n x_n^{\text{solo}} + \xi_n^{\text{solo}}$$

Training the Solo Model

- Revolves the estimation of the Gaussian random vectors
- These vectors can not observed directly
- Missing data problem
- N-th note estimate produced by Listen

$$x_n^{\text{obs}} = B x_n^{\text{solo}} + \xi_n^{\text{obs}}$$

Dependency structure expressed in the directed acyclic graph (DAG)



Dependency structure of Variables

- Variables with no parents are mutually independent
- Trained using EM algorithm

Training the Solo Model

- To predict the future evolution of the solo part
- Adjust the accompaniment accordingly

Adding the Accompaniment

- Generated through the MIDI protocol
- Accompaniment note is described by three parameters:
  - An onset time
  - A damping time
  - An initial velocity

Accompaniment Model

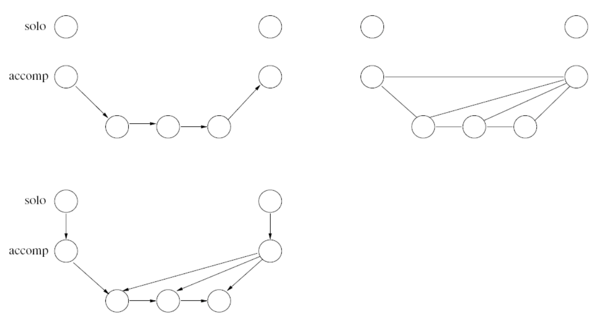
- Mutually independent Gaussian vectors that express the accompaniment's rhythmic interpretation
- The means and co-variances learned from MIDI performances of the accompaniment using EM algorithm

$$x_{m+1}^{\text{accom}} = C_m x_m^{\text{accom}} + \xi_m^{\text{accom}}$$

Combine Solo and Accompaniment Models

- Into joint model containing the variables of both parts
- Solo and Accompaniment play asymmetric roles
- Conditional distribution of the accompaniment part given the solo part
- Integrates the rhythmic interpretation of the accompaniment

Solo combine with Accompaniment



- Round massage passing
- Obtain the equilibrium representation
- Joint distribution :

$$\frac{\prod_{C \in \mathcal{C}} \phi_C}{\prod_{S \in \mathcal{S}} \phi_S}$$

Conditional distribution of the Accompaniment given the Solo

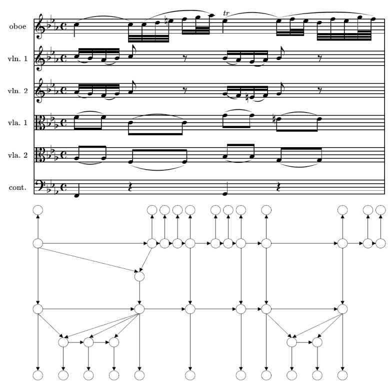
$$x^{\text{cond}}_{m_l} = x^{\text{solo}}_{n(m_l)} + \xi^{\text{cond}}_{m_l}$$

$$x^{\text{cond}}_{m_r} = x^{\text{solo}}_{n(m_r)} + \xi^{\text{cond}}_{m_r}$$

Special situation

- Accompaniment notes can not be sandwiched between a pair of coincident solo notes

Sinfonia J.S. Bach's Cantata 12



- Posterior distribution depends:
  - The score
  - Currently observed solo and accompaniment note times
  - Predicted evolution of future solo note times learned during the training phase
  - Learned rhythmic interpretation of the accompaniment

Discussion & Conclusion

- Real-time accompaniment algorithm
- Computation of marginal distribution by the message-passing algorithm
- Limited by passing only the messages necessary to compute the marginal distribution on the pending accompaniment note.
- Messages moving “away” from the variable marked “hot”
- Message passed marked “ cold”
- Computing the distribution on the pending accompaniment note –only hot messages are passed.

Can the computer learn to play expressively?

- The level of musically attained by this system is truly surprising.
- Why dehumanize music with the cold and unfeeling computers?
- Questions?