Music & Cognition

11/14

www.hum.uva.nl/mmm (see under 'Related Courses')

Today

- Homework Evaluation
- Application of Probability to Music research
- A Gentle Introduction to Probability

Who's this bloke?

- Researcher on the EmCAP project with Olivia and Henkjan.
- http://www.science.uva.nl/~lsmith

EU Project: *Emergent Cognition through Active Perception (EmCAP)*

(European Commission FP6-IST, contract 013123)

- The study of how cognitive behaviour in artificial systems can emerge through interacting with a musical environment.

- Neuroimaging innate vs. learned auditory functions.
- Perception of musical form.
- Prefrontal cortical function controlling attention and STM.
- Spectrotemporal response fields in the thalamocortical system.
- Perception and categorisation of rhythmic patterns.
- Active perception, relative pitch and emergence of tonality.
- Interactive music system: *The Music Projector*.

Information Society Technologies · University of Plymouth · Universitat Pompeu Fabra · MTA Pszichológiai Kutatóintézet · Universiteit van Amsterdam

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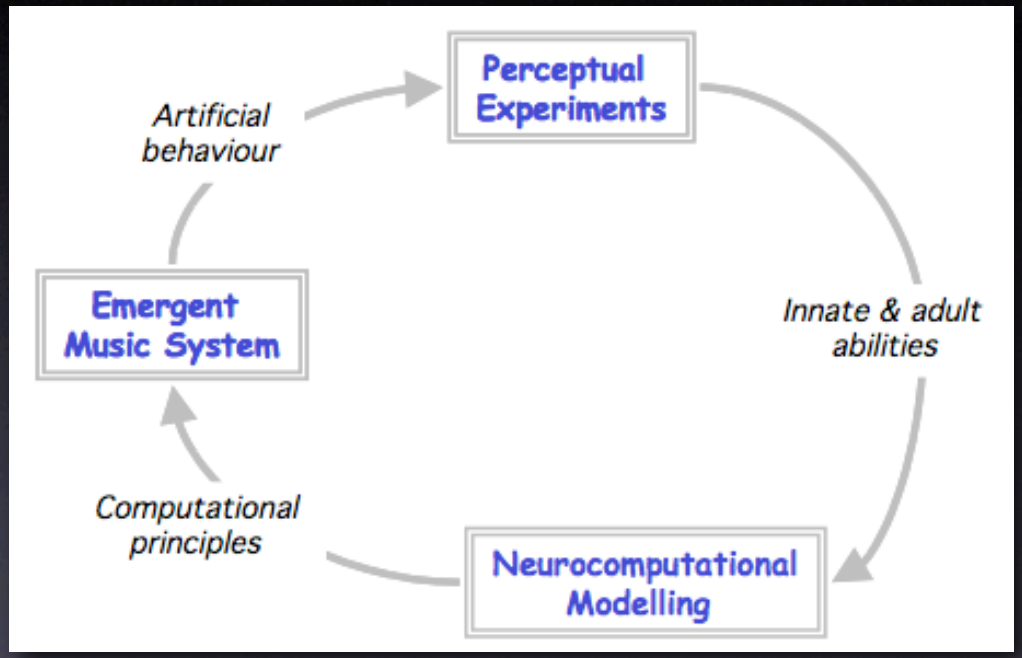

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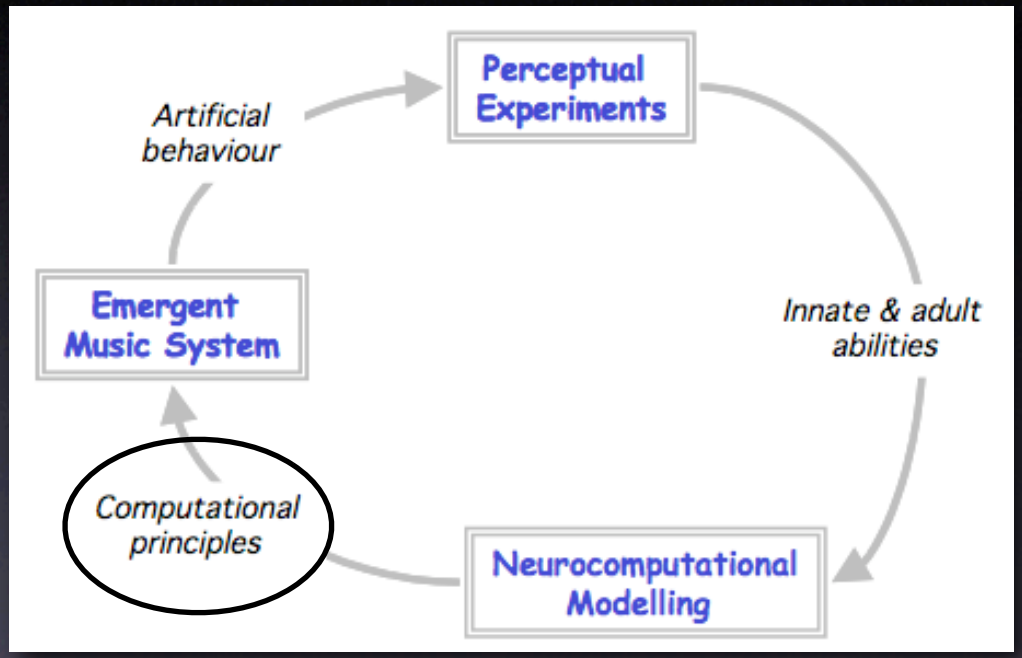

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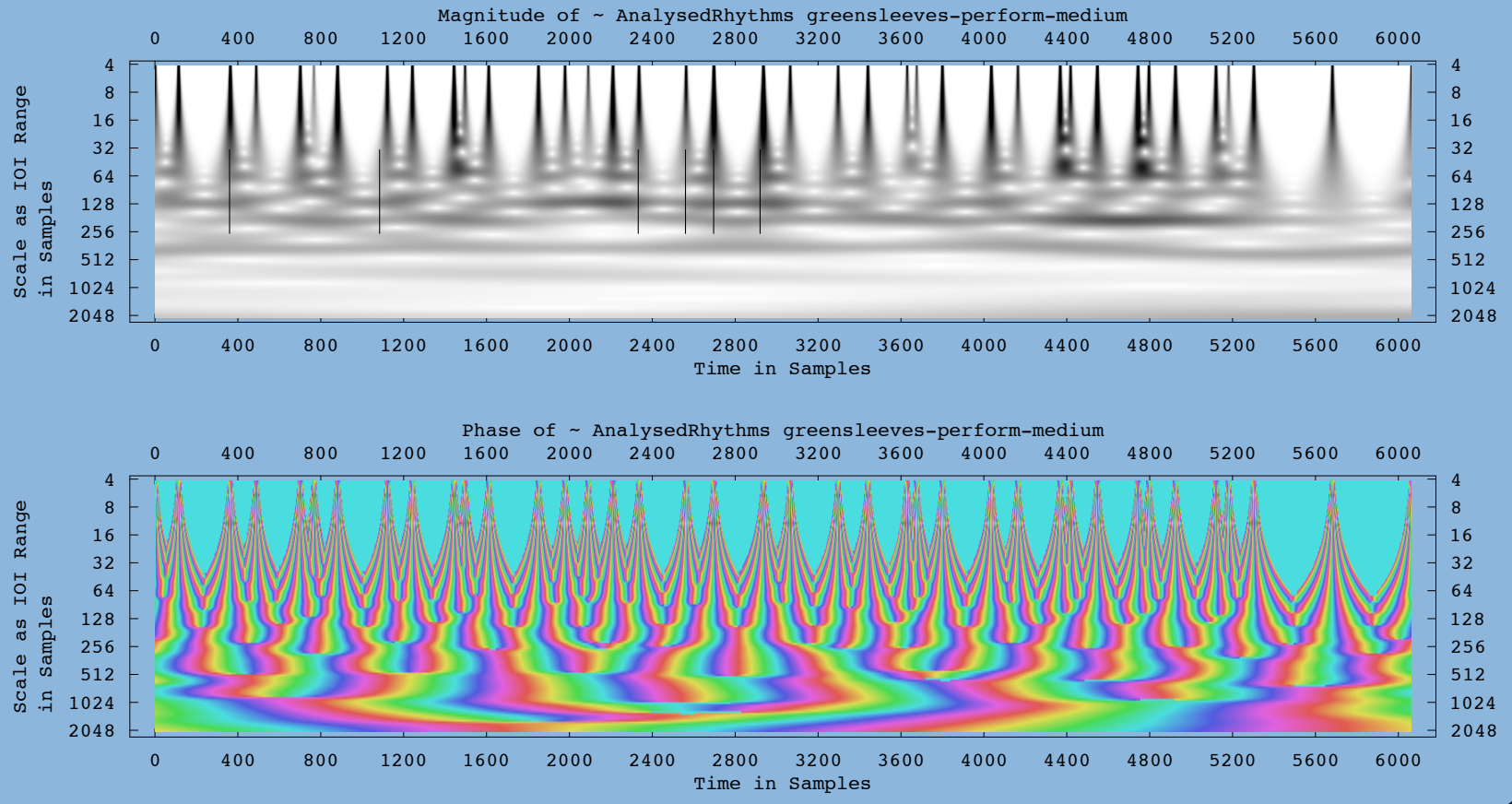
My Research

- Computational modelling of rhythmic expectancy using *wavelet* analysis.

"Greensleeves"



Past Lives...

...with hair...

...in infrared at Comp. Sci. robotics & vision lab at Uni. of Western Australia...

Music and Probability

Music and Probability

- Why consider the two disciplines together?

?

Composition

- Historically, there is a long tradition of composers using chance and automation in composition.
- For example:
  - Guido d'Arezzo (1094) method of chant generation.
  - Serialism (Schoenberg, Webern, Berg, Babbitt, Carter) (1911).
  - W.A. Mozart's musical dice game (*Musikalisches Würfelspiel,* 1787).

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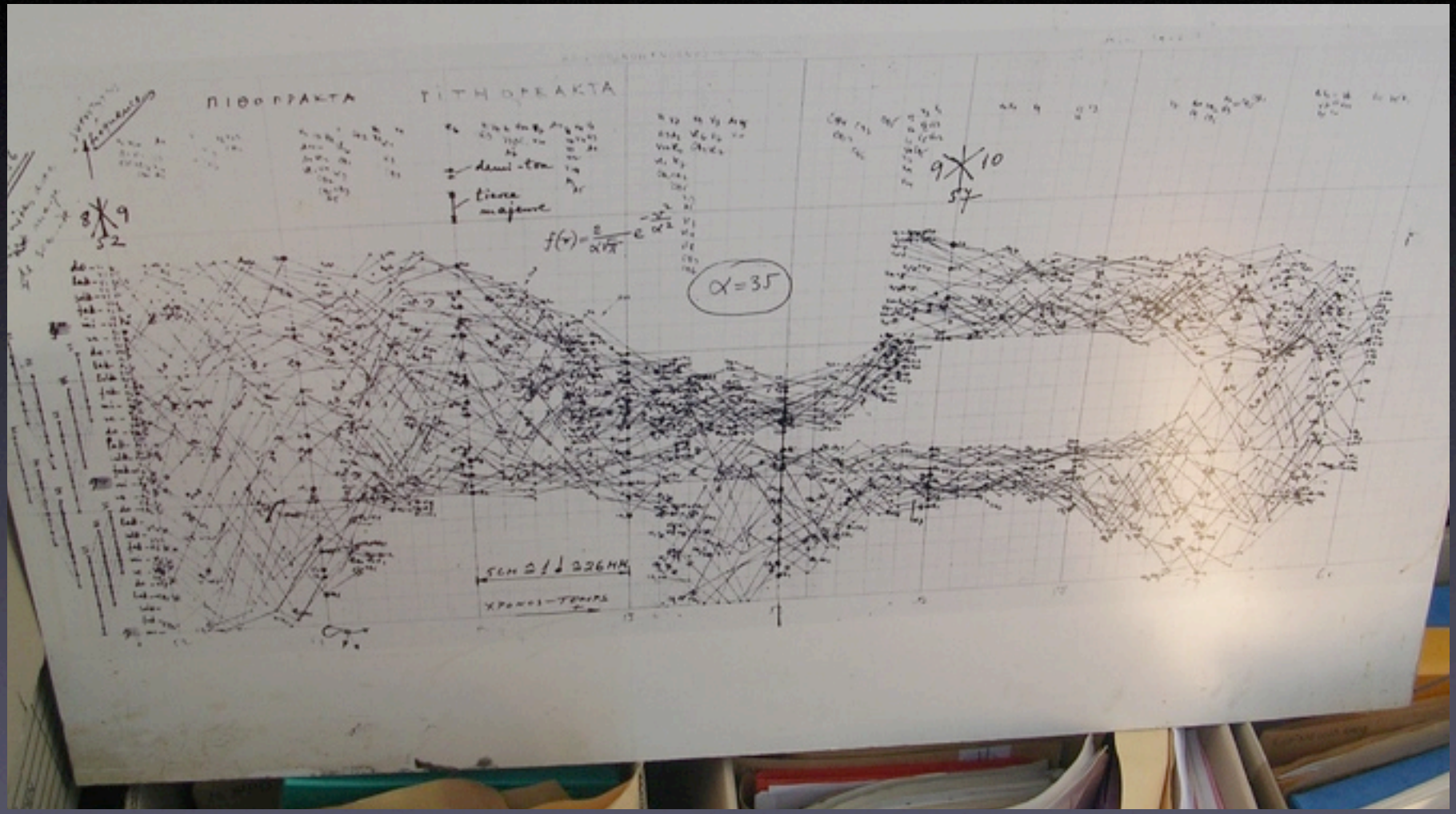
- “Formalised Music” Indiana University Press, 1971.

Pithoprakta (1956)



“Akrata” (1964-5)

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- ST-X Ensemble conducted by C.Z. Bornstein 1996, Mode Records

Recent Applications

- Computer composition (Hiller & Isaacson 1959).
- Computer accompaniment (Winkler 1998).
- Improving musician/software interaction (Rowe 2001).
- Computer collaboration in improvisation.
  - e.g. STEIM http://www.steim.nl
- Musical games.
- Music accompaniment to computer games.
  - Reacting to a dynamically changing game context.
- Dance and Music interaction (e.g. Merce Cunningham).

Music Analysis

- Probabilistic models have been applied to various musical applications.
- Common analyses:
  - Melody
  - Rhythm

Gentle Introduction to Probability

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- **Probability**: Enables quantifying the confidence of a decision or conclusion.

Examples of Uses

- **Coin/dice tossing:**
  - e.g Is the coin fair (balanced)?
- **Sampling for quality:**
  - e.g picking a bunch of fruit at the market, or products off an assembly line to assess the quality of many more.
- **Risk assessment:**
  - e.g financial speculation, medical diagnosis etc.
- **Interpretation of experimental results.**

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- Can be considered as percentage chance of occurrence.

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- $P(X = 3) = 1/6$.

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- What is the probability of a total of 12 being thrown on 2 dice?
- 12 = '6' & '6'
  - $\Rightarrow$ 1 in 6 chance (first throw) ***and***
  - 1 in 6 chance (second throw)

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- 1/36 = 2.77% likely.

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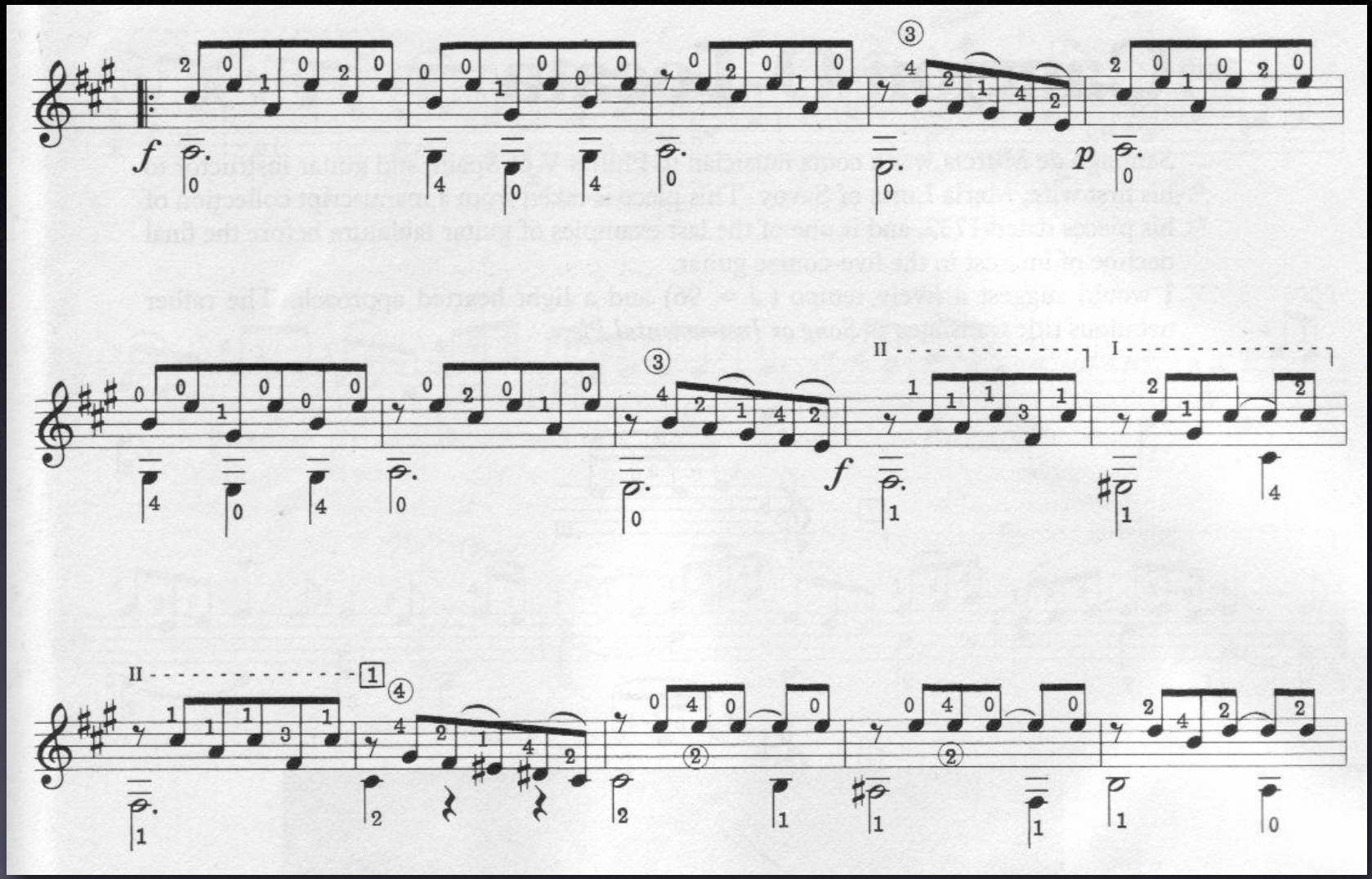
- "Approximately 11.11% likely"

Probability Summary

- Demonstrated how to make simple calculations of probability of event occurrence.
- References:
  - Prob. & Statistics for Engineers & Scientists 8th Ed(Walpole, Myers & Myers 2006)
  - Music & Probability (Temperley 2007)

Homework



Vivace for Lute, A. Falckenhagen (1697-1761), trans. F. Noad

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- Example: likelihood of words in a sentence, or notes in a melody.
- First order Markov chain: Each note is dependent only on one immediately previous note.
- Second order Markov chain: Each note is dependent on the previous two notes, etc.

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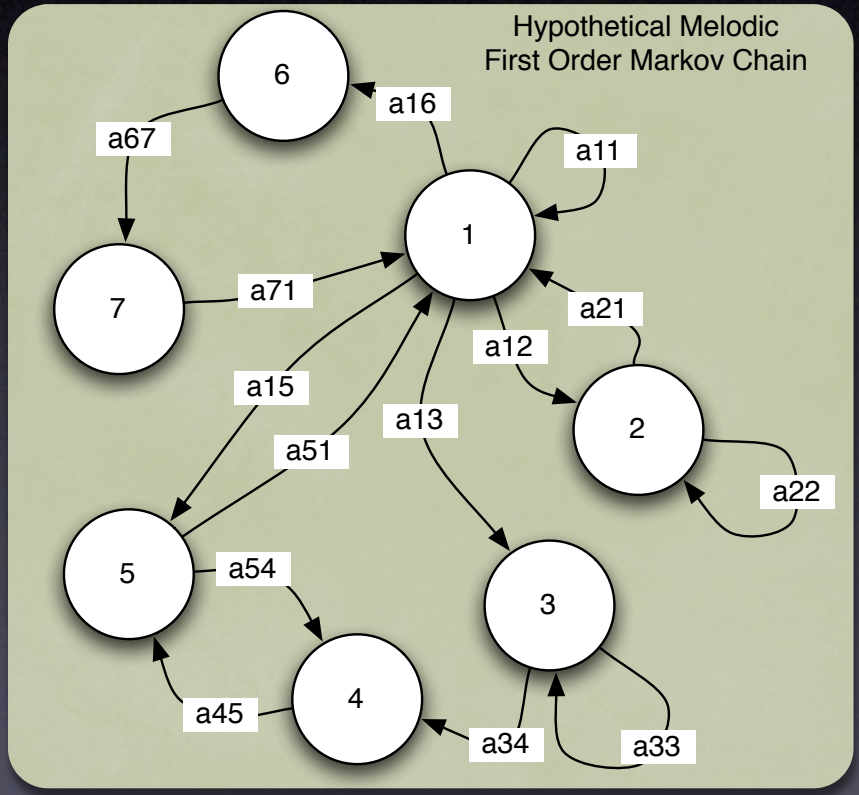

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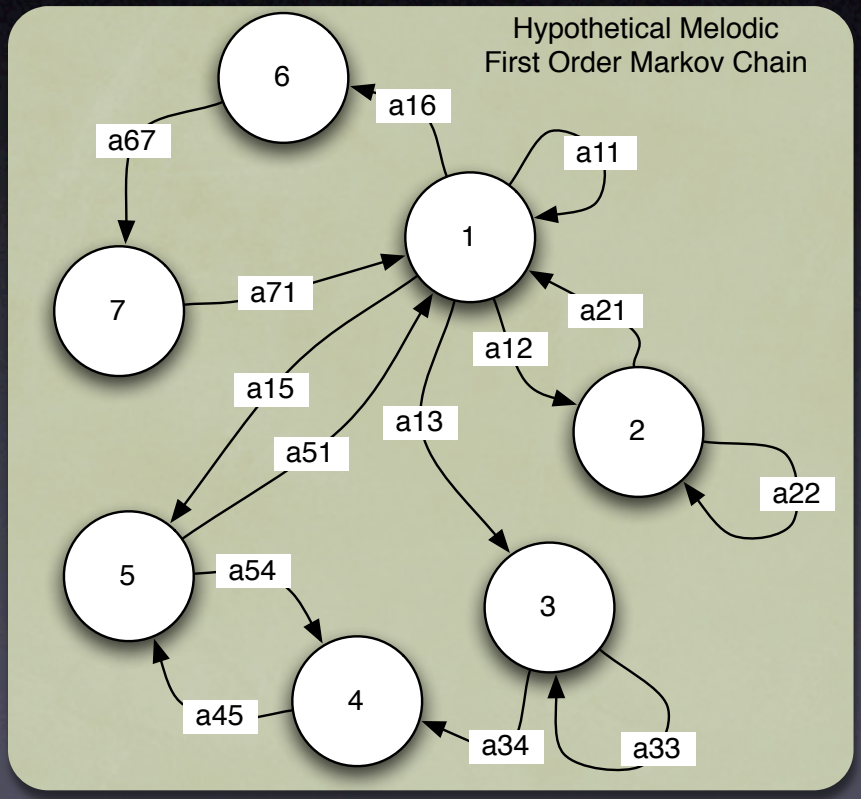
- The state at each moment in time is specified as a probability in terms of the previous state.



First Order Markov Chain

- Represents likelihood of next states (notes) in a table (matrix):

	1	2	3	4	5	6	7
1	0.1	0.3	0.1		0.3	0.2	
2	0.7	0.3					
3			0.5	0.5			
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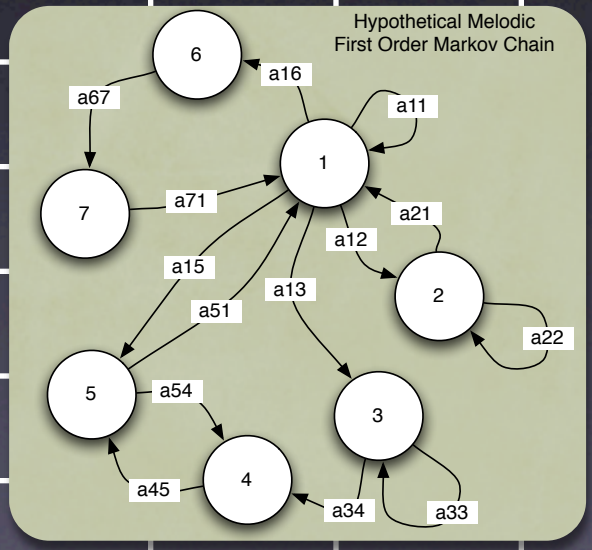

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- The Markov chain is used to generate a melody by deciding which next note to choose from all possible options with a random number generator.

Markov Chain Demo

- Example modified from David Cope's "Experiments in Musical Creativity" project.
  - http://arts.ucsc.edu/faculty/cope/

The Continuator

- Markov melodic improviser (Pachet 2003):

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Claude Barthelemy
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- Tempo tracking: Automated following of the tempo in a performance containing expressive timing and tempo variations. (A. T. Cemgil and B. Kappen and P. Desain and H. Honing 2000)
- Uses Bayesian probabilistic models.

Palmer & Krumhansl

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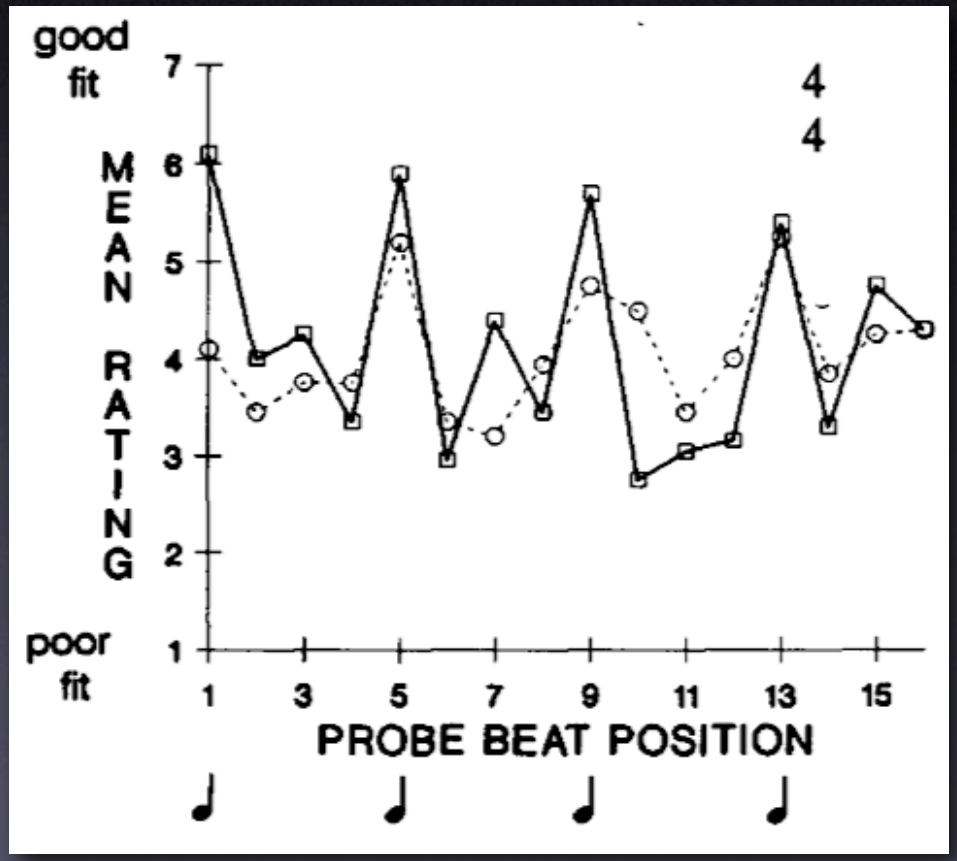
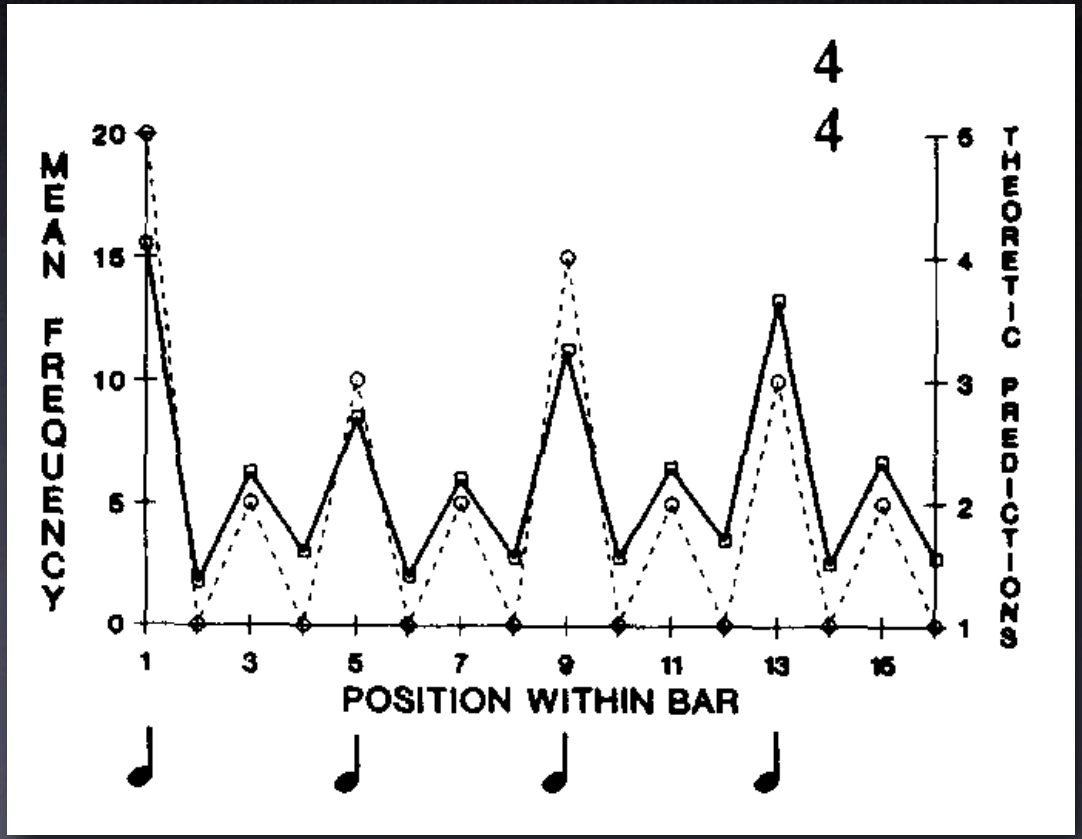


From Palmer & Krumhansl (1990). Mean goodness-of-fit ratings for musicians (solid line) and nonmusicians (dashed line).

Palmer & Krumhansl

- P&K also determined frequency of occurrence of beat positions from composers scores:



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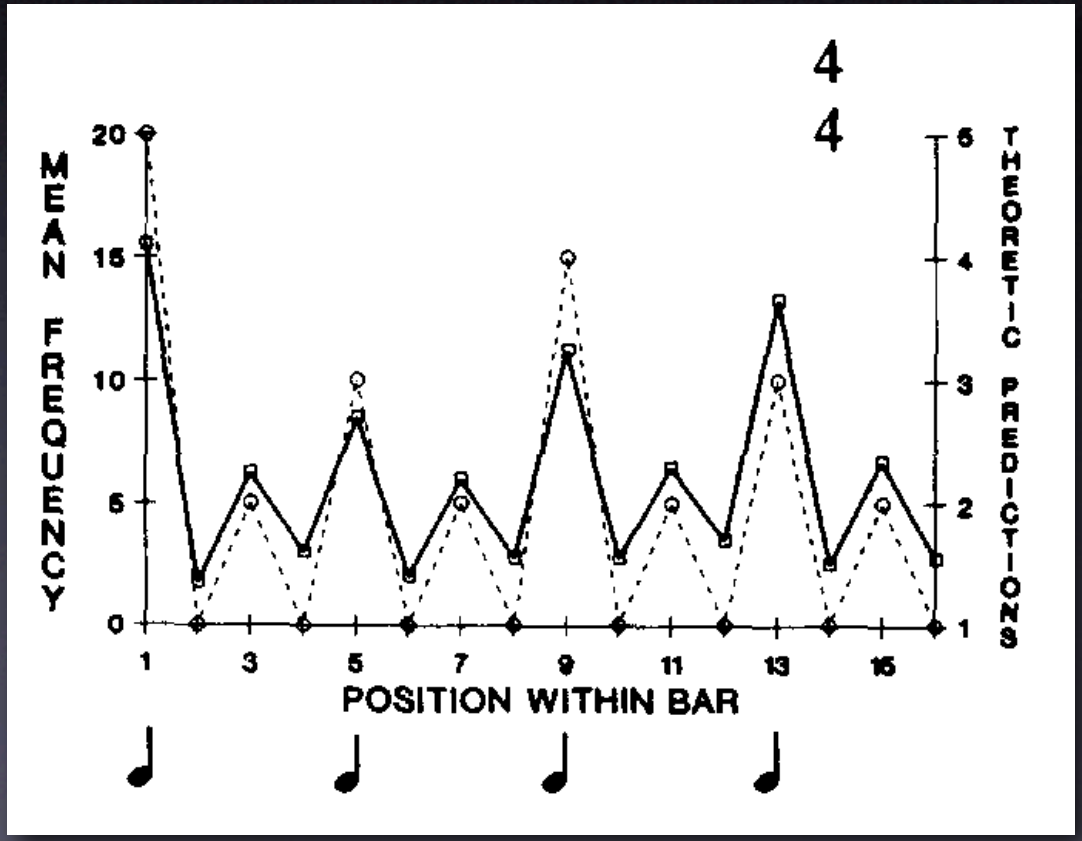

From Palmer & Krumhansl (1990). Mean frequency counts (solid line) vs. theoretical metrical hierarchy (dashed line).

Rhythmic Markov Models

- Exercise: How would a rhythmic Markov chain be constructed? What would be an appropriate order?

Assignment

1) **What is the most funky piece of music you know?**
   1) Bring it, and write down the artist, title, album and year of the piece.
   2) Describe in a half A4, why you consider this piece funky, and what are the features that make it funky (i.e. rhythmical structure, sounds, instruments, timing, etc.)
2) **Find two pieces of music, one that swings and one that doesn't. The swinging song does not have to be a typical jazz song, any song with triplet subdivision as metrical grid will do (this is frequently referred to as shuffle as well).**
   1) Bring them, and write down the artist, title, album and year of the pieces.
   2) Describe in a half A4 why the first song swings and the second doesn't.
3) **Read Honing & Haas (2008). It will help in doing question 2. Prepare questions to bring forward in class (N.B. These do not have to be sent in before-hand).**

References

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