

Mining Rules for Cadences in Dutch Folk-Song Melodies

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Background



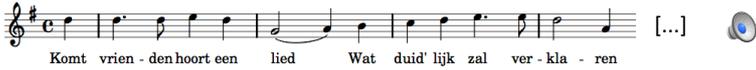
At the **Meertens Institute**
(Amsterdam):

Onder de groene linde: c. 7000
recordings from the Netherlands.
Recorded 1950s – 1980s by Will
Scheepers and Ate Doornbosch.






Example









Background






NLB004456_01.lwc

Meta	Signature	Score	Header	Footer	Comments	Excel	Script
r4	r4	g4	g2	g4	g2	g4	g2
		hst	voe--	dtr	toort	den	s--
a/4	a	bes	c2	bes4	g	a2	g2.
		ghes--	sel	en	last	daer	be--
r4	r4	g4	g2	g4	g2	g4	g2.
		Den	krocht	dat	ty	hem	at--
a/4	a	bes	c2	bes4	g	a2	g2.
		die	sy	hem	brooc	ook	gha--

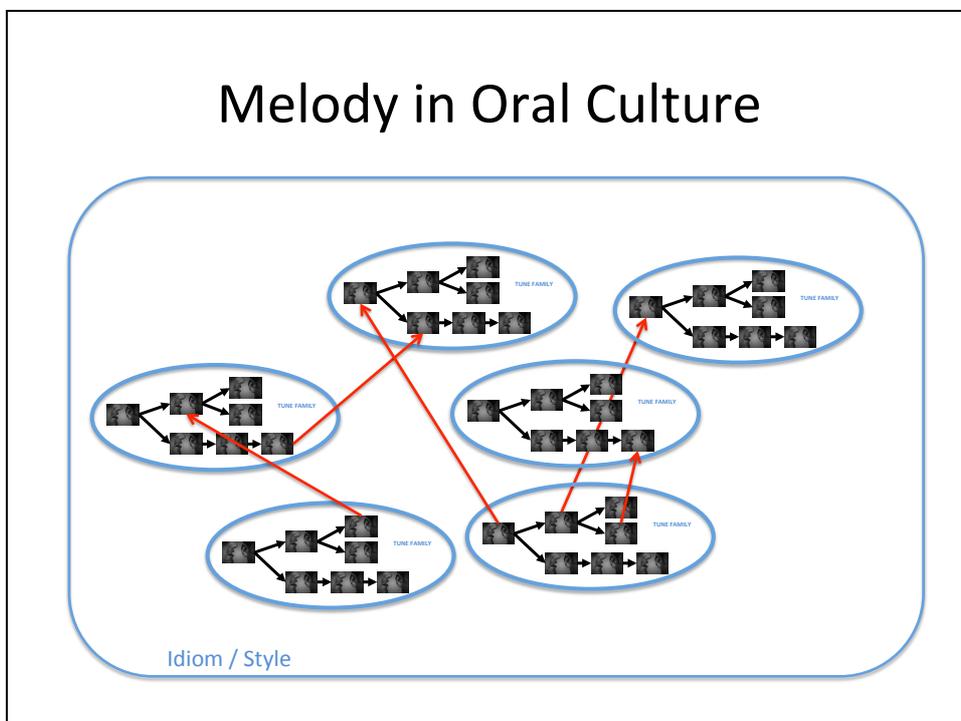
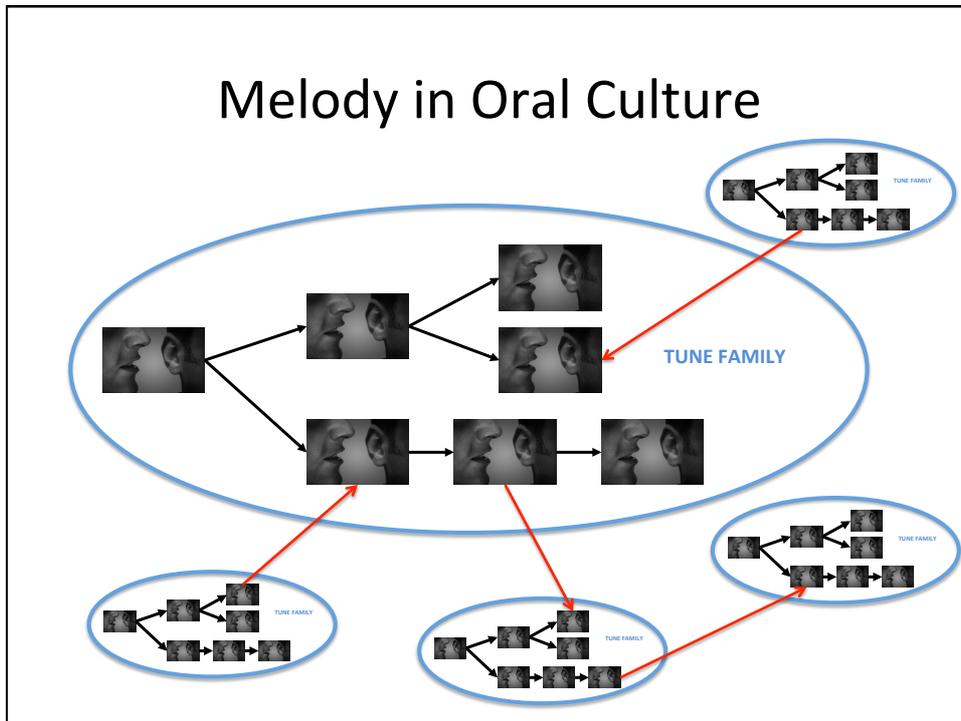






Accessible at: <http://www.liederenbank.nl>

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Cadence

The image shows a musical score in G major, 6/8 time, with four staves of music. The lyrics are: "Sol - daat kwam uit den oor - log en hoe - ra", "Sol - daat kwam uit den oor - log en hoe - ra", "hij had er ge - te - kend voor zes jaar", and "Hij nam z'n pak voortnaar A - mersfoort en hoe - ra." A red box highlights the final two measures of the second staff, which correspond to the lyrics "log en hoe - ra".

Cadence

Related Topics

- Closure (music perception)
- Segmentation (music information retrieval)
- Tonic (music theory)
- Final (music theory)

Main Approaches in Modelling

Gestalt Principles -> rule based model

Narmour (1992): Implication-Realization model

Lehrdal & Jackendoff (1983): GTTM

Cambouropoulos (2001): LBDM

Statistical Learning -> Probabilistic model

Huron (2006): Expectation (ITPRA)

Pearce et al. (2010): IDyOM

Juhász (2004): EBLM

Bod (2001): Data oriented parsing

Gestalt Principles

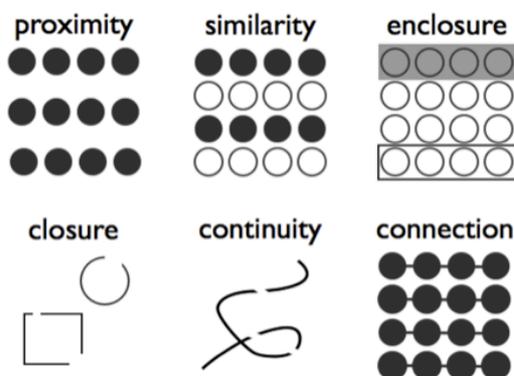


Figure by Farooq Ali

Main Approaches in Modelling

Gestalt Principles -> rule based model

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Lehrdal & Jackendoff (1983): GTTM

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Current Approach

- Data-driven rather than theory-driven
- No pre-defined rules
- No strong theoretic grounding
- Method: Automatic Rule Discovery

if 4 wheels and engine => car

if 2 wheels and pedals => bicycle

if 2 wheels and engine => motorcycle

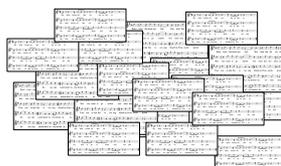
Procedure

Procedure:

- Obtain symbolic representation (notes)
- Extract all trigrams from the melody
- Extract features from the trigrams
- Perform rule-mining algorithm (RIPPER)
- Study and adapt the rules

Data Set

- 4121 Dutch folk songs
- Symbolic representation (*kern)
- Phrase endings are annotated
- Key is annotated
- Lyrics included in digitization



Trigrams

Cadence

In Eng - land woont een koop - man rijk en mach - tig

³ Die had een doch - ter, was wel - be - roemd op d'aard

⁵ Die be - min - d'een [...]

Features

In Eng - land

PITCH

scaledegree first	1
scaledegree second	2
scaledegree third	3
ambitus	2
contains leap	FALSE

CONTOUR

is ascending	TRUE
arrive ascending	TRUE
is descending	FALSE
arrive descending	FALSE

METRIC FEATURES

time signature	'4/4'
metric weight first	1.0
metric weight second	0.25
metric weight third	0.125

Rule Mining

RIPPER (Cohen, 1995)

Basic procedure:

1. split data into two folds
2. grow rules using the one fold
3. prune rules using the other fold
4. remove covered items from data
5. size(data) == 0 ? stop : goto 1

Results on Dutch Songs

On balanced dataset (c. 25,000 cadence, and c. 25,000 nocardence)
70 rules found.

2/3 train, 1/3 test:

	Precision	Recall	F-measure
cadence	0.723	0.754	0.738
nocardence	0.759	0.729	0.744
weight. avg.	0.741	0.741	0.741

Evaluation on full dataset (c. 25,000 cadence, c. 98,000 nocardence):

	Precision	Recall	F-measure
cadence	0.445	0.741	0.556
nocardence	0.926	0.777	0.845
weight. avg.	0.832	0.77	0.789

Results on Dutch Songs

RULE 1

scaledegree third == 1
 arrive descending == TRUE
 metric weight third >= 0.5
 => class=cadence (5940/821)

RULE 3

scaledegree third == 1
 scaledegree second == 7
 metric weight third == 1
 => class=cadence (1050/153)

RULE 2

scaledegree third == 5
 is descending == TRUE
 metric weight third >= 0.5
 => class=cadence (2323/433)

Examples



RULE 1

scaledegree third == 1
 arrive descending == TRUE
 metric weight third >= 0.5

RULE 2

scaledegree third == 5
 is descending == TRUE
 metric weight third >= 0.5

RULE 3

scaledegree third == 1
 scaledegree second == 7
 metric weight third == 1

Examples

The first example consists of three staves of music in 3/4 time. The first staff has notes G4, A4, B4, C5, B4, A4, G4, F4, E4, D4, C4. Fingerings are 1, 2, 1. The second staff starts at measure 6 with notes C4, D4, E4, F4, G4, A4, B4, C5, B4, A4, G4, F4, E4, D4, C4. Fingerings are 2, 1. The third staff starts at measure 12 with notes C4, D4, E4, F4, G4, A4, B4, C5, B4, A4, G4, F4, E4, D4, C4. Fingerings are 1, 1, 1.

RULE 1
 scaledegree third == 1
 arrive descending == TRUE
 metric weight third >= 0.5

RULE 2
 scaledegree third == 5
 is descending == TRUE
 metric weight third >= 0.5

RULE 3
 scaledegree third == 1
 scaledegree second == 7
 metric weight third == 1

Examples

The second example consists of two staves of music in 3/4 time. The first staff has notes G4, A4, B4, C5, B4, A4, G4, F4, E4, D4, C4. Fingerings are 1, 2. The second staff starts at measure 6 with notes C4, D4, E4, F4, G4, A4, B4, C5, B4, A4, G4, F4, E4, D4, C4. Fingering is 2.

RULE 1
 scaledegree third == 1
 arrive descending == TRUE
 metric weight third >= 0.5

RULE 2
 scaledegree third == 5
 is descending == TRUE
 metric weight third >= 0.5

RULE 3
 scaledegree third == 1
 scaledegree second == 7
 metric weight third == 1

New Results on Dutch Songs

On balanced dataset (c. 25,000 cadence, and c. 25,000 nocadence)
98 rules found.

2/3 train, 1/3 test

	Precision	Recall	F-measure
cadence	0.813	0.818	0.815
nocadence	0.828	0.823	0.826
weight. avg.	0.821	0.821	0.821

Evaluation on full dataset (c. 25,000 cadence, c. 98,000 nocadence):

	Precision	Recall	F-measure
cadence	0.533	0.828	0.649
nocadence	0.952	0.825	0.884
weight. avg.	0.871	0.826	0.839

New Results on Dutch Songs

RULE 1

phrase offset ≥ 7
 scaledegree third == 1
 metric weight third ≥ 0.5
 \Rightarrow class=cadence (2289/90)

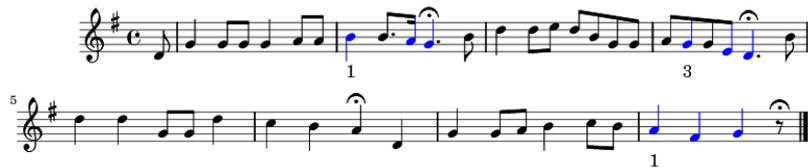
RULE 2

phrase offset ≥ 4
 scaledegree third == 1
 arrivedescending == TRUE
 metric weight third ≥ 0.5
 timesig = 6/8
 \Rightarrow class=cadence (910/51)

RULE 3

phrase offset ≥ 6
 scaledegree third == 5
 isdescending == TRUE
 metric weight third ≥ 0.5
 \Rightarrow class=cadence (1012/47)

Examples



RULE 1
 phrase offset >= 7
 scaledegree third == 1
 metric weight third >= 0.5

RULE 2
 phrase offset >= 4
 scaledegree third == 1
 arrivedescending == TRUE
 metric weight third >= 0.5
 timesig = 6/8

RULE 3
 phrase offset >= 6
 scaledegree third == 5
 isdescending == TRUE
 metric weight third >= 0.5

Examples



RULE 1
 phrase offset >= 7
 scaledegree third == 1
 metric weight third >= 0.5

RULE 2
 phrase offset >= 4
 scaledegree third == 1
 arrivedescending == TRUE
 metric weight third >= 0.5
 timesig = 6/8

RULE 3
 phrase offset >= 6
 scaledegree third == 5
 isdescending == TRUE
 metric weight third >= 0.5

Examples



RULE 1
 scaledegree third == 1
 arrive descending == TRUE
 metric weight third >= 0.5

RULE 2
 scaledegree third == 5
 is descending == TRUE
 metric weight third >= 0.5

RULE 3
 scaledegree third == 1
 scaledegree second == 7
 metric weight third == 1



RULE 1
 phrase offset >= 7
 scaledegree third == 1
 metric weight third >= 0.5

RULE 2
 phrase offset >= 4
 scaledegree third == 1
 arrivedescending == TRUE
 metric weight third >= 0.5
 timesig = 6/8

RULE 3
 phrase offset >= 6
 scaledegree third == 5
 isdescending == TRUE
 metric weight third >= 0.5

Conclusions

- Cadence patterns do obey general rules
- It is possible to derive these general rules from melodic data
- Arrival at the tonic implies a cadence
- This confirms music theory

Future Work

- Add more features
- Incorporate parallelism in the model
- Incorporate relation with lyrics in the model
- Evaluate theories of melody (e.g. IR-model)
- Apply the same method to melodies from other cultures



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