A MAXENT MODEL OF TONE-TUNE ASSOCIATION IN TOMMO SO SONGS

Laura McPherson, UCLA
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TONE-TUNE ASSOCIATION

- Do speakers of a tone language map musical melody to linguistic tone (or vice versa) when singing?
- Recent surveys (e.g. Schellenberg 2012) show varying degrees of adherence across languages and styles.
  - Cantonese (Wong and Diehl 2002) stricter than Shona (Schellenberg 2009).
  - Traditional songs and recitations stricter than popular music.

TODAY’S TALK

- Novel test case: Tommo So (Dogon, Mali) folk music
- Tommo So has a high degree of tone-tune association, but higher within words than across word boundaries.
- Research question: Is this correlation deliberate (=artistic) or an accidental property of the linguistic and musical structure?
- Using the language sample method (Tarlinskaja 1976, Hall 2006), I developed three corpora of fake songs to test this question.

THREE TEST CORPORAS

1. Real melodies matched with randomly selected prose
   - Tests whether melodies are biased to match Tommo So linguistic structure.
2. Real lyrics matched with randomly generated melodies
   - Tests whether Tommo So lyrics are biased to match the pentatonic scale
3. Real melodies and lyrics, scrambled
   - Tests whether Tommo So lyrics and melodies are biased to match each other
ASSESSING ASSOCIATION

- Logistic regression/maximum entropy grammar (Goldwater and Johnson 2003, Hayes and Wilson 2008):
  - Constraints on tone-tune association are able to distinguish between lines from the real corpus and the three artificial corpora.
  - Word-bounded: Constraints on two note sequences within words sequences are stronger than constraints on sequences across word boundaries.

LANGUAGE AND DATA

- Tommo So

  - Dogon (Niger-Congo) language spoken in Mali by ~60,000 people (McPherson 2013).
  - Original data based on fieldwork from 2008-2012.

TONE SYSTEM

- Two phonemic tones, H and L, plus surface underspecified syllables (Ø, McPherson 2011).
- Three main lexical melodies:
  - /H/, as in dàmmá ‘village’
  - /LH/, as in dàmmá ‘hoe’
  - (/HL/, as in pǎllă ‘cloth strip’)
- Tone also used grammatically (replacive overlays in verb conjugation and between words in an NP, Heath and McPherson 2013, McPherson in prep).
  - {L} in possession, as in Sǎndà dàmmá ‘Sana’s village / hoe’
ABOUT THE SONGS

- Preliminary data from four women’s folk songs recorded in Tédié, Mali in 2012.
- Songs consist of call and response.
  - Basic melody and lyrics are set, but are subject to improvisation in performance.
- Major pentatonic scale, with the following intervals:
  - Eb F (G) Ab Bb C    (1 2 (3) 4 5 6)
- Polyrhythmic: singing and percussion are in different time signatures.

“AN ELEPHANT GAVE BIRTH”
Right to left: Tepama Ouologuem, Roukiatou Djebukile, Kunjay Ouologuem
Chorus lyrics: An elephant gave birth, there was so much colostrum, an elephant gave birth. Come here, whoever is thirsty for milk, come and suckle.

METHODOLOGY

- Musically transcribed four songs totaling about 6 minutes of singing from a total of an hour and a half.
- Lyrics transcribed and translated with the help of Sana ‘M. le Maire’ Ouologuem.
- Coded these 96 musical lines (ranging from 3 to 24 syllables) in Excel, noting the tone, note of the scale, and boundary strength for each syllable.

TRANSCRIPTION AND EVALUATION
EXAMPLE

Text:  L-H     H=0                  H-L-L      (L-H)
      kùwⁿá náy=le               píyè-d  "(kùwⁿá)
      crane  cousin=ASSOC  cry-IMPF (crane)
      ‘Crane is crying with her cousin’

PRELIMINARY CHECKING

- I hand-checked words with lexical tone (/H/, /LH/, /HL/) to see how they were mapped to musical melody (level, rising, falling).

<table>
<thead>
<tr>
<th></th>
<th>Level</th>
<th>Rising</th>
<th>Falling</th>
</tr>
</thead>
<tbody>
<tr>
<td>/H/</td>
<td>37 (23%)</td>
<td>2 (3%)</td>
<td>22 (54%)</td>
</tr>
<tr>
<td>/LH/</td>
<td>122 (74%)</td>
<td>71 (96%)</td>
<td>2 (5%)</td>
</tr>
<tr>
<td>/HL/</td>
<td>5 (3%)</td>
<td>1 (1%)</td>
<td>17 (41%)</td>
</tr>
</tbody>
</table>

(Percentages summed across melodies/columns)

- Chi-squared test on this table yields $p < .001$

TESTING THE HYPOTHESIS

- Question: Are these findings significant?
- Method: Language sample (“Russian”) method of metrics (Tarlinskaja 1976, Hall 2006) compares the real corpus to a randomly generated corpus based on actual musical/linguistic forms.
- The input for the model consists of the set of real lines of music and a corresponding fake set:
  1. Prose (paired with real melodies) (288 tokens)
  2. Random melodies (paired with real lyrics) (192 tokens)
  3. Scrambled (melodies and lyrics) (192 tokens)

CONSTRAINTS

- Coded the data for a series of tone-tune association constraints, of the format: [Tonal movement, tune movement].
  
  - **Association** constraints and **anti-association** constraints.
  
  - E.g. $+$ToneRise,$+$TuneRise, $+$ToneRise,$-$TuneFall; $+$ToneFall,$-$TuneFall, $+$ToneRise,$+$TuneFall, etc.

  - Two basic versions: word-bounded and boundary.

  - Third version: Blind constraint (combines word-bounded and boundary violations)
Maxent/Logistic Regression

- I use these constraints to predict whether a line in the corpus is real (0) or fake (1).
- In a case with binary outputs (as in 0/1), the math of a maximum entropy model is formally identical to the math of logistic regression.
- I first ran logistic regression models in R to find the best constraints.
- Weights shown here are all positive, as in maxent (association constraints penalize fake candidate; anti-association constraints penalize real candidate)

Significant Constraints

- Out of 12 constraints for each version, 3 proved highly significant.
  - +ToneRise,+ToneRise ; +ToneRise,+TuneFall ; +ToneFall,-TuneFall

- One general constraint was also significant:
  - X0,TuneRise: Assess a violation if any sequence X0 (0-0, L-0, H-0) is realized on a rising melody.
  - Phonetically grounded: rising interpolation avoided on underspecified syllables.

Results
BASIC FINDINGS

- For all corpora, no significant difference between a model with word-bounded vs. blind constraints (looking at the AIC).
- Both significantly better than a model with only word boundary constraints.
- However, word-bounded + boundary is marginally better.
- Allows the model to weight violations for each condition differently.

+ToneRise,+TuneRise

- An association constraint, whose structural description is met when a L-H sequence is sung on a rising sequence of notes.
- Penalizes fake lines.
- Example: kùwáá/L-H/3-4 ‘crane’ (from Line 74)

<table>
<thead>
<tr>
<th>Model</th>
<th>Word-bounded weight</th>
<th>Boundary weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prose</td>
<td>0.97 ***</td>
<td>0.9 *</td>
</tr>
<tr>
<td>Scrambled</td>
<td>1.13 ***</td>
<td>1.72 **</td>
</tr>
</tbody>
</table>

+ToneRise,+TuneFall

- An anti-association constraint, whose structural description is met when a L-H sequence is sung on a falling sequence of notes.
- Penalizes real lines.
- Example: ìmbáá/L-H/3-2 ‘here’

<table>
<thead>
<tr>
<th>Model</th>
<th>Word-bounded weight</th>
<th>Boundary weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prose</td>
<td>1.67 ***</td>
<td>0.63</td>
</tr>
<tr>
<td>Scrambled</td>
<td>1.78 ***</td>
<td>0.03</td>
</tr>
</tbody>
</table>

+ToneFall,-TuneFall

- An anti-association constraint, whose structural description is met when a H-L sequence is sung on a falling sequence of notes (sung on either level or rising).
- Penalizes real lines.
- Example: píyè-de/H-L-L/3-3 ‘she cries’

<table>
<thead>
<tr>
<th>Model</th>
<th>Word-bounded weight</th>
<th>Boundary weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prose</td>
<td>1.07 ***</td>
<td>0.20</td>
</tr>
<tr>
<td>Scrambled</td>
<td>0.98 **</td>
<td>0.16</td>
</tr>
</tbody>
</table>
x0,+TuneRise

- An anti-association constraint, whose structural description is met when an X-0 sequence is sung on a rising sequence of notes.
- Penalizes real lines.
- Example:  ámb=m = gL-H=0/3-4 ‘the men’

<table>
<thead>
<tr>
<th>Model</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prose</td>
<td>2.12***</td>
</tr>
<tr>
<td>Scrambled</td>
<td>1.03</td>
</tr>
</tbody>
</table>

PREDICTIONS

- For each model, we can look at the average predicted probability of being fake.
- A perfect model would predict 0 for real and 1 for fake.

<table>
<thead>
<tr>
<th></th>
<th>Real</th>
<th>Fake</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prose</td>
<td>0.36</td>
<td>0.75</td>
</tr>
<tr>
<td>Scrambled</td>
<td>0.29</td>
<td>0.72</td>
</tr>
</tbody>
</table>

RANDOM MELODIES

- A different set of constraints does a better job for the random melody corpus.
- Constraints and weights:

<table>
<thead>
<tr>
<th>Word-bounded weights</th>
<th>Boundary weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>+ToR,+TuR</td>
<td>+ToR,+TuR</td>
</tr>
<tr>
<td>1.60</td>
<td>1.60</td>
</tr>
<tr>
<td>+ToR,-TuR</td>
<td>+ToR,-TuR</td>
</tr>
<tr>
<td>0.77</td>
<td>2.44</td>
</tr>
<tr>
<td>-ToR,+TuR</td>
<td>-ToR,+TuR</td>
</tr>
<tr>
<td>3.7</td>
<td>2.46</td>
</tr>
<tr>
<td>X0Rising</td>
<td></td>
</tr>
<tr>
<td>3.49</td>
<td></td>
</tr>
</tbody>
</table>

- Average predicted probability for real lines: .19
- Average predicted probability for fake lines: .87

DISCUSSION

- Model makes the strongest predictions with the randomly generated melodies.
- All constraints focus on +/-Rise for melodic movement.
- Natural Tommo So melodies follow a downward progression; randomly generated melodies include more rising sequences.
- Tone-tune association restricts rising melodies to occurring with rising tones; more instances in the database allow more cases of mismatch to be found.
CONCLUSIONS

MAIN FINDINGS

- Three different test cases support the hypothesis that musical melody is constrained by lexical tone in Tommo So folk music, beyond an accidental baseline.
- Effect is word-bounded:
  - Strong within words, weak across word boundaries.
- Tommo So shows aspects of both “parallel” and “not opposing” (Schellenberg 2012) tone-tune association:
  - Rising tone sequences should be sung on non-opposing melodies.
  - Falling tone sequences should be sung on parallel (=falling) melodies.

FUTURE DIRECTIONS

- Transcribe and annotate more songs.
- Develop a solid model of tone-tune association, that predicts not just directionality but also interval size.
- Check whether tone-tune association is stronger for lexical tone than grammatical tone.
- Explore tone-tune association in non-native speakers singing in Tommo So.
- Tommo So is the language of song for most of the Dogon area, so this is a natural question.

THANK YOU!

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REFERENCES

Heath, Jeffrey and Laura McPherson. Tonal syntax and reference restriction in Dogon NPs. Language 89.2: 265-296.
An elephant gave birth
There was so much colostrum
Tommo So folk song

Bass

ha koy gwé\textsuperscript{n} nà-lè\textsuperscript{e} èm\textsuperscript{t} ké-mìn-jé sàm-è - è gwé\textsuperscript{n} nà-lè\textsuperscript{e}

B.

nà\textsuperscript{t} yàa\textsuperscript{t} ndó gi-né ú-wà\textsubscript{m} ne gwé\textsuperscript{n} nà-lè\textsuperscript{e} èm\textsuperscript{t} ké-mìn-jé sà-mè\textsuperscript{e}

B.

á-mí-ru ge gi-nè\textsuperscript{è} ge ne gwé\textsuperscript{n} nà-lè\textsuperscript{è} mo èm\textsuperscript{ù} ké-mìn-jé sà-mè\textsuperscript{è}

B.

nòm-báá yèl-èé i-rù\textsuperscript{ù} gi-yè ñ-dè\textsuperscript{è} á-wí-nè nò-nú yèl-èé á-rá-má ye

B.

gwé\textsuperscript{n} nà-lè\textsuperscript{è} ké-mìn-jé sà-mè\textsuperscript{è} gwé\textsuperscript{n} nà-lè\textsuperscript{è} á-mè-ru gi-nàà\textsuperscript{ù}

B.

gwé\textsuperscript{n} nà-lè\textsuperscript{è} èm\textsuperscript{ù} ké-mìn-jé sà-mè\textsuperscript{è} nòm-báá yèl-èé i-rù\textsuperscript{ù} gi-yè á-

B.

wè\textsuperscript{è} yo nòm-báá yèl-èé á-rá-má ye gwé\textsuperscript{n} nà-lè\textsuperscript{è} èm\textsuperscript{ù} ké-mìn-jé sà-

B.

mè\textsuperscript{ù} gwé\textsuperscript{n} nà-lè\textsuperscript{è} tò-gò\textsuperscript{ù} bí lu dá-má é-wò gwé\textsuperscript{n} nà-
An Elephant Gave Birth
(Tepama)
1. Hakoy gwēⁿ nàl¹-è, ém¹ kémínjé sàm¹-è, okay elephant give.birth-PFV.L milk colostrum be.a.lot-PFV.L
   gwēⁿ nàl¹-è
elephant give.birth-PFV.L
‘Okay, an elephant gave birth, there was so much colostrum, an elephant gave birth.’
2. nàà Yààndó giné úwɔ=ỳ = ge, gwēⁿ nàl¹-è,
mother Yaandó house 2SG.POSS = OBJ = COP elephant give.birth-PFV.L
   kémínjé sàm¹-è
colostrum be.a.lot-PFV.L
‘Mother Yaandó (= LM), it was your house, an elephant gave birth, there was so much
colostrum.’
3. Ámèru ginè¹ = ge = ne gwēⁿ nàl¹-è mɔ, èm¹ chief house = DEF = OBL elephant give.birth-PFV.L EMPH milk
   kémínjé sàm¹-è
colostrum be.a.lot-PFV.L
‘An elephant gave birth in the chief’s house! There was so much colostrum.’
suckle-CAUS? oh
‘Come there, whoever is thirsty for milk, oh come here and suckle.’

(Chorus)
5. gwēⁿ nàl¹-è kémínjé sàm¹-è
elephant give.birth-PFV.L colostrum be.a.lot-PFV.L
‘An elephant gave birth, there was so much colostrum.’
6. Àmèru ginè¹ = ne gwēⁿ nàl¹-è, kémínjé sàm¹-è.
   chief house = OBL elephant give.birth-PFV.L colostrum be.a.lot-PFV.L
‘An elephant gave birth in the chief’s house, there was so much colostrum.’
7. mbáá yèl-ée iùrú⁴ gíyé àw²-è-w=yo mbáá yèl-ée árá-mɔ⇒ here come-NF breast hunger catch-PFV.L.2SG = if here come-NF suckle-CAUS
‘Come here if you are thirsty for milk, come here and suckle.’

(Tepama)
8. gwēⁿ nàl¹-è, èm¹ kémínjé sàm¹-è, gwēⁿ nàl¹-è
elephant give.birth-PFV.L milk colostrum be.a.lot-PFV.L elephant give.birth-PFV.L
‘An elephant gave birth, there was so much colostrum, an elephant gave birth.’