INVoluntary Musical Imagery

-Investigating Musical Features that Predict ‘Earworms’-

Sebastian Finkel, Sagar Jilka, Victoria Williamson, Lauren Stewart, Daniel Müllensiefen

Correspondence to: finkel.sebastian@googlemail.com
“Roadmap”

• Introduction
  – Terminology
  – Previous findings
  – The idea behind this study

• Methods

• Results

• Conclusion and Discussion
“Roadmap”

• Introduction
• Methods
  – How to find genuine earworms
  – How to analyze InMI tunes
• Results
• Conclusion and Discussion
“Roadmap”

- Introduction
- Methods
- Results
  - The earworm formula!? 
- Conclusion and Discussion
“Roadmap”

- Introduction
- Methods
- Results
- Conclusion and Discussion
  - How to interpret the found features
  - How to shape future research
• Involuntary musical imagery (InMI)
  – Liikkanen (2008)
  – Song in Your Head Phenomenon
  – Spontaneously, Repeatedly, Involuntarily

• Earworm
  – Derived from ‘Ohrwurm’ (German)
Previous findings

• Liikkanen (2008)
  – 90% experience earworms daily
  – Only 15% describe them disturbing

• Beaman & Williams (in press)
  – Earworm episode less than 24 hours
  – Earworm itself longer than short term memory capacity would suggest

• Hemming (2008)
  – Importance of genre and lyrics
The idea behind this study

• No study has dealt with musical features of earworms yet.
  – Are earworms different?

• De la Motte (1993)
  – Analyzed his personal earworms:
    – repetitive motif, harmonically appealing, only 3-5 tones

• Müllensiefen & Kopiez (in press)
  – Musical features can predict success of cover songs
How to find genuine earworms

• Online Survey
• **1014** participants
  – 35.6 years (SD= 13.4 years; range 13–76 years)
  – 572 females and 441 males
• Recent earworm <-> Frequent earworms
  – Artist, song title, exact part
• **1449** usable earworm tracks
• Top earworm list -> **75** songs (6%)
  – Named more than once
  – In total: 227 (16%)
• **14.000** files MIDI Corpus
## Top 5 earworms

<table>
<thead>
<tr>
<th>artist</th>
<th>song</th>
<th>incs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lady Gaga</td>
<td>Bad romance</td>
<td>13</td>
</tr>
<tr>
<td>Journey</td>
<td>Don't stop believing</td>
<td>11</td>
</tr>
<tr>
<td>Lady Gaga</td>
<td>Alejandro</td>
<td>11</td>
</tr>
<tr>
<td>Katy Perry</td>
<td>California gurls</td>
<td>10</td>
</tr>
<tr>
<td>Kylie Minogue</td>
<td>Can't get you out of my head</td>
<td>7</td>
</tr>
</tbody>
</table>
How to find genuine earworms

- Using UK chart data to control for:
  - Popularity (exposure)
  - Recency effects
  - 52 songs left

- Predictors
  - hi.entry: Highest chart position
  - exit.date: Days from end of study to last chart appearance
  - weeks: Number of weeks in the charts
  - entry.date: Days from end of study to first chart appearance

- Response
  - incs: Number of namings
How to find genuine earworms

Poisson Model

| Estimate     | Std. Error | z value | Pr (>|z|) |
|--------------|------------|---------|-----------|
| (Intercept)  | 1.2076e+00 | 9.4763e-02 | 12.7431 | 0.0000 *** |
| hi.entry     | -2.0764e-02 | 5.9391e-03 | -3.4961 | 0.0005 *** |
| exit.date    | -4.3372e-05 | 1.2294e-05 | -3.5278 | 0.0004 *** |

Wald’s Chi-square test:
\[ \chi^2 (2, N = 110) = 19.218, p < 0.001 \] ***
How to find genuine earworms

- Positive residual deviance
  - More often named than expected from the model
- Named more than once
  - More likely to be genuine
- 29 earworms
How to analyze InMI tunes

- Findings matching non-earworms
- Random draw from MIDI corpus
  - 150 (UK chart data available)
  - Not named as earworms
- Gower’s Dissimilarity coefficient
Gower’s Dissimilarity

• Measuring similarity between two objects, using numeric and character variables

• We are using:
  – hi.entry
  – entry.date
  – exit.date
  – weeks
  – genre
  – artist

• Matrix -> lowest value for each earworm
You never gonna get this song....
How to analyze InMI tunes

• 29 earworm tracks

<table>
<thead>
<tr>
<th>artist</th>
<th>song</th>
<th>incs</th>
<th>hi.entry</th>
<th>weeks</th>
<th>entry.date</th>
<th>exit.date</th>
<th>genre</th>
</tr>
</thead>
<tbody>
<tr>
<td>lady gaga</td>
<td>bad romance</td>
<td>13</td>
<td>1</td>
<td>38</td>
<td>261</td>
<td>15</td>
<td>pop</td>
</tr>
<tr>
<td>lady gaga</td>
<td>alejandro</td>
<td>11</td>
<td>7</td>
<td>10</td>
<td>253</td>
<td>183</td>
<td>pop</td>
</tr>
<tr>
<td>journey</td>
<td>don’t stop believing</td>
<td>11</td>
<td>6</td>
<td>47</td>
<td>477</td>
<td>149</td>
<td>rock</td>
</tr>
<tr>
<td>katy perry</td>
<td>california gurls</td>
<td>10</td>
<td>1</td>
<td>6</td>
<td>43</td>
<td>1</td>
<td>pop</td>
</tr>
<tr>
<td>queen</td>
<td>bohemian rhapsody</td>
<td>7</td>
<td>1</td>
<td>17</td>
<td>12699</td>
<td>12580</td>
<td>rock</td>
</tr>
</tbody>
</table>

• 29 non-earworm tracks

<table>
<thead>
<tr>
<th>artist</th>
<th>song</th>
<th>incs</th>
<th>hi.entry</th>
<th>weeks</th>
<th>entry.date</th>
<th>exit.date</th>
<th>genre</th>
</tr>
</thead>
<tbody>
<tr>
<td>gorillaz</td>
<td>feel good inc.</td>
<td>0</td>
<td>2</td>
<td>39</td>
<td>1940</td>
<td>1667</td>
<td>pop</td>
</tr>
<tr>
<td>jessica</td>
<td>these boots are</td>
<td>0</td>
<td>4</td>
<td>10</td>
<td>1800</td>
<td>1730</td>
<td>pop</td>
</tr>
<tr>
<td>simpson</td>
<td>made for walkin’</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>stereophonics</td>
<td>handbags and gladrag</td>
<td>0</td>
<td>4</td>
<td>15</td>
<td>3164</td>
<td>3059</td>
<td>rock</td>
</tr>
<tr>
<td>nelly</td>
<td>my place</td>
<td>0</td>
<td>1</td>
<td>11</td>
<td>2164</td>
<td>2087</td>
<td>pop</td>
</tr>
<tr>
<td>elvis presley</td>
<td>way down</td>
<td>0</td>
<td>1</td>
<td>13</td>
<td>12054</td>
<td>11963</td>
<td>rock</td>
</tr>
</tbody>
</table>
Logistic Regression

- Predictor variables:
  - 40 musical features
  - 12 clusters
- Response variable
  - Binary earworm status
  - (1 = yes, 0 = no)

Step AIC

- Stepwise algorithm for model selection
- Using Akaike information criterion
- Simplifying the logistic regression
Results

- Logistic regression model:
  - Using 4 features

|                | Estimate | Std. Error | z value | Pr (>|z|) |
|----------------|----------|------------|---------|-----------|
| (Intercept)    | - 7.7520 | 4.1703     | 0.9386  | 0.0630    |
| d.median       | 0.0767   | 0.0373     | 2.0613  | 0.0393 *  |
| tonal.clarity  | 5.9946   | 3.4817     | 1.7218  | 0.0851    |
| int.cont.grad.std | - 0.3878 | 0.1989     | - 1.9597| 0.0512    |
| i.leaps        | 41.8001  | 20.3481    | 2.0543  | 0.0399 *  |

- Predicts 72% of the data set correctly
- \( \chi^2 (4, N = 58) = 8.7476, p = .0677 \)
How to interpret the features

- **d.median**
  - the median of the average duration of all notes
- **int.cont.grad.std**
  - standard deviation of interpolation contour measure
- **tonal.clarity**
  - how clear is the tonality of the melody
  - Auhagen (1994)
- **i.leaps**
  - average number of leaps larger than a 5th
  - Rauhe (1987) “Activation structures”
Conclusions

• Songs that appear often as earworms can be distinguished from other pop songs
  – Model predicts 72% correctly
  – Using only musical features
  – Excluding contextual & subject-related variables
How to shape further research

- Better ways to control for exposure
  - Airplay charts, API queries (lastfm)
  - Hurdle and negative binomial models
- Increasing number of possible matches
- Different earworm types?
  - Decision tree models
  - Corpus features
- Including context and subject-related variables
• Have we found the ultimate pop song formula?
• Are successful songs earworm OR earworms commercially bestselling?
• Can we learn something about musical memory?
  – Müllensiefen & Halpern (submitted)
    • Musical features predict implicit and explicit memory for melodies
How to shape further research

Project is ongoing!!!
Any ideas are welcome!
Thank you for your attention

This project was supported by: