Using Visualizations for Music Discovery

ISMIR 2009

Justin Donaldson
Paul Lamere

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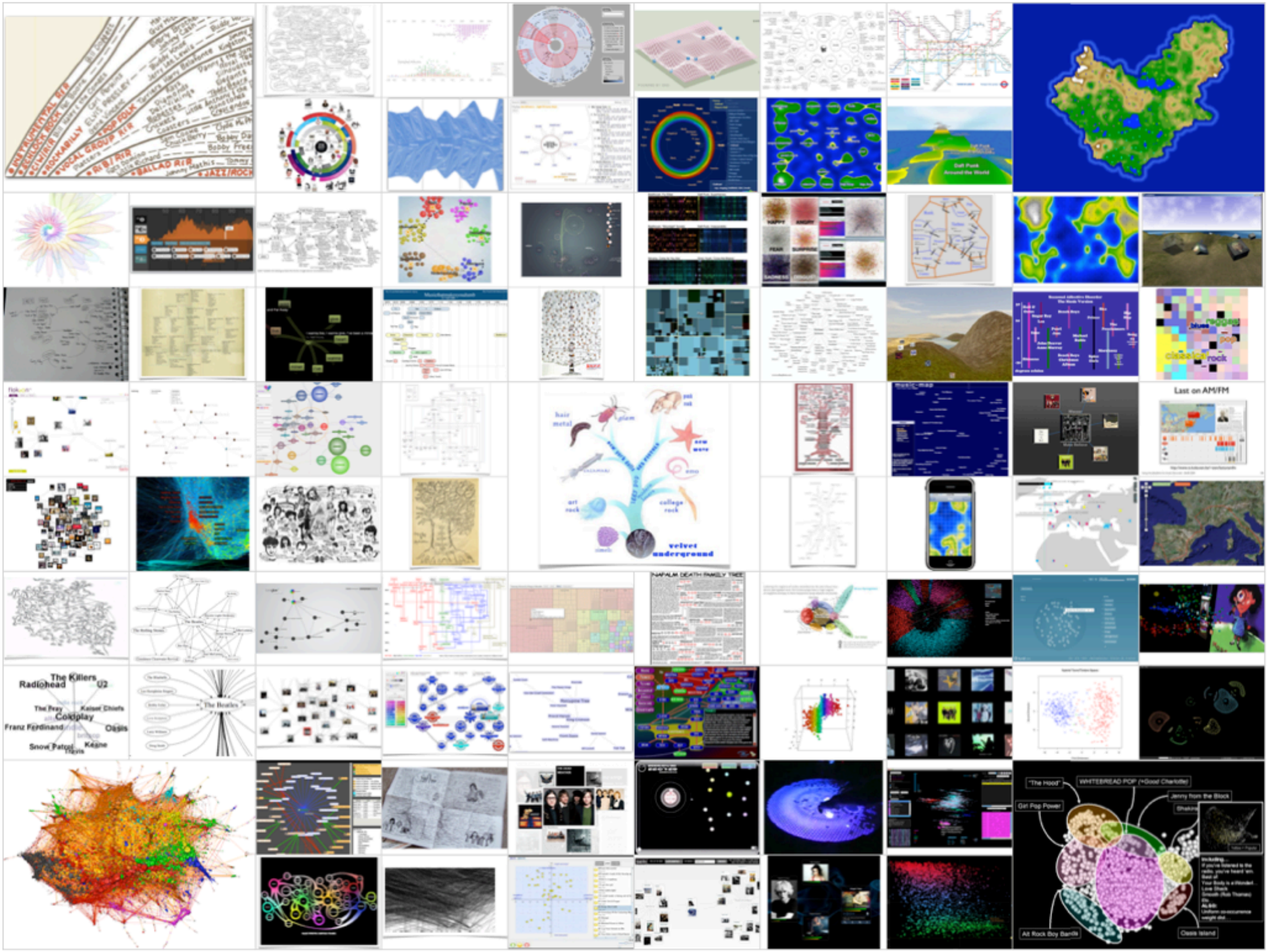
Or ...

85 ways to visualize your music



Speakers

Justin Donaldson is a PhD candidate at Indiana University School of Informatics, as well as a regular research intern at Strands, Inc. Justin is interested with the analyses and visualizations of social sources of data, such as those that are generated from playlists, blogs, and bookmarks.

Paul Lamere is the Director of Developer Community at The Echo Nest, a research-focused music intelligence startup that provides music information services to developers and partners through a data mining and machine listening platform. Paul is especially interested in hybrid music recommenders and using visualizations to aid music discovery. Paul also authors 'Music Machinery' a blog focusing on music discovery and recommendation.

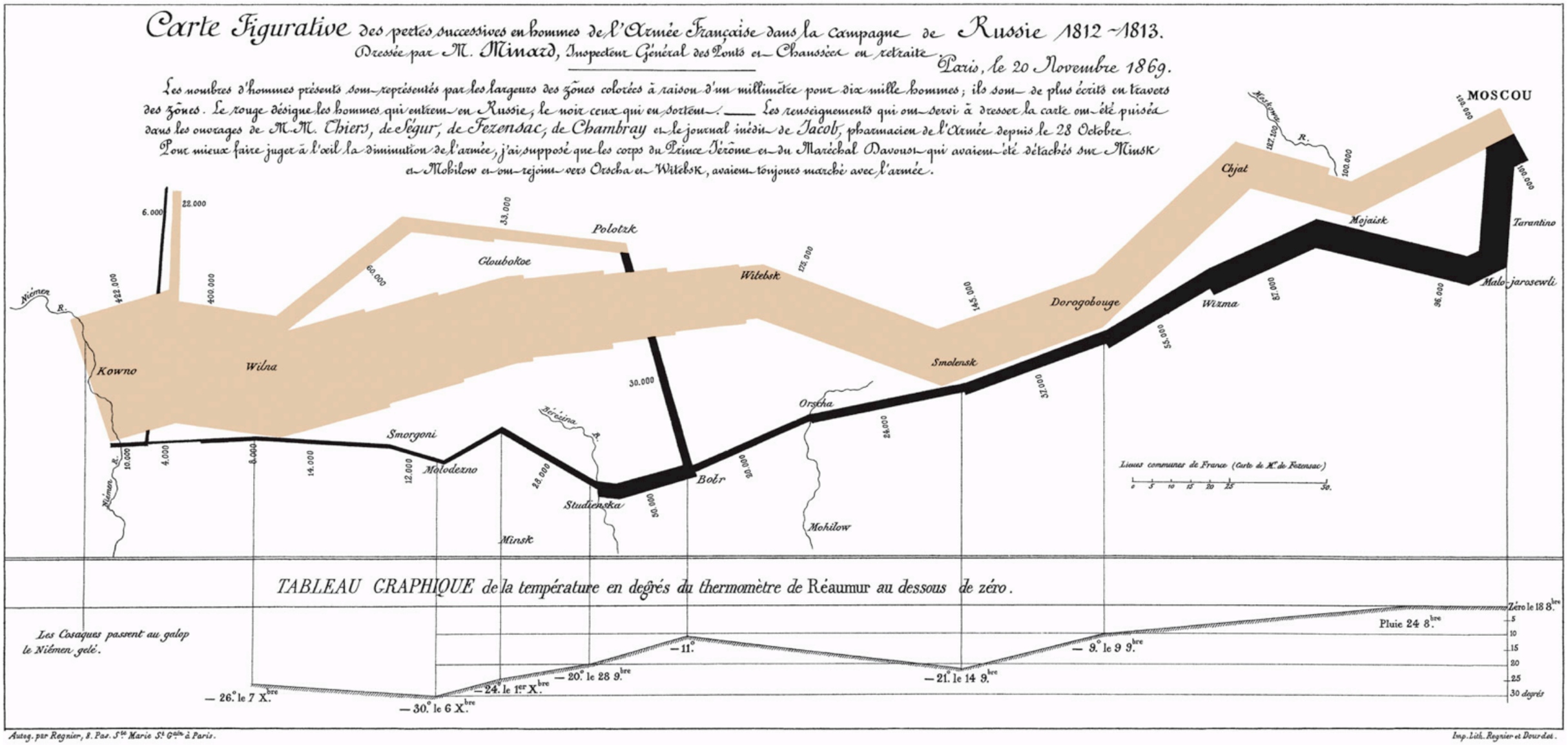
Outline of the talk

- Why visualize
- Some history
- Core concepts
- Survey of Music Visualizations
- Tools / Resources
- Conclusions

Music Discovery Challenge

- Millions of songs
- We need tools
  - Recommendation
  - Playlisting
  - **Visualization**

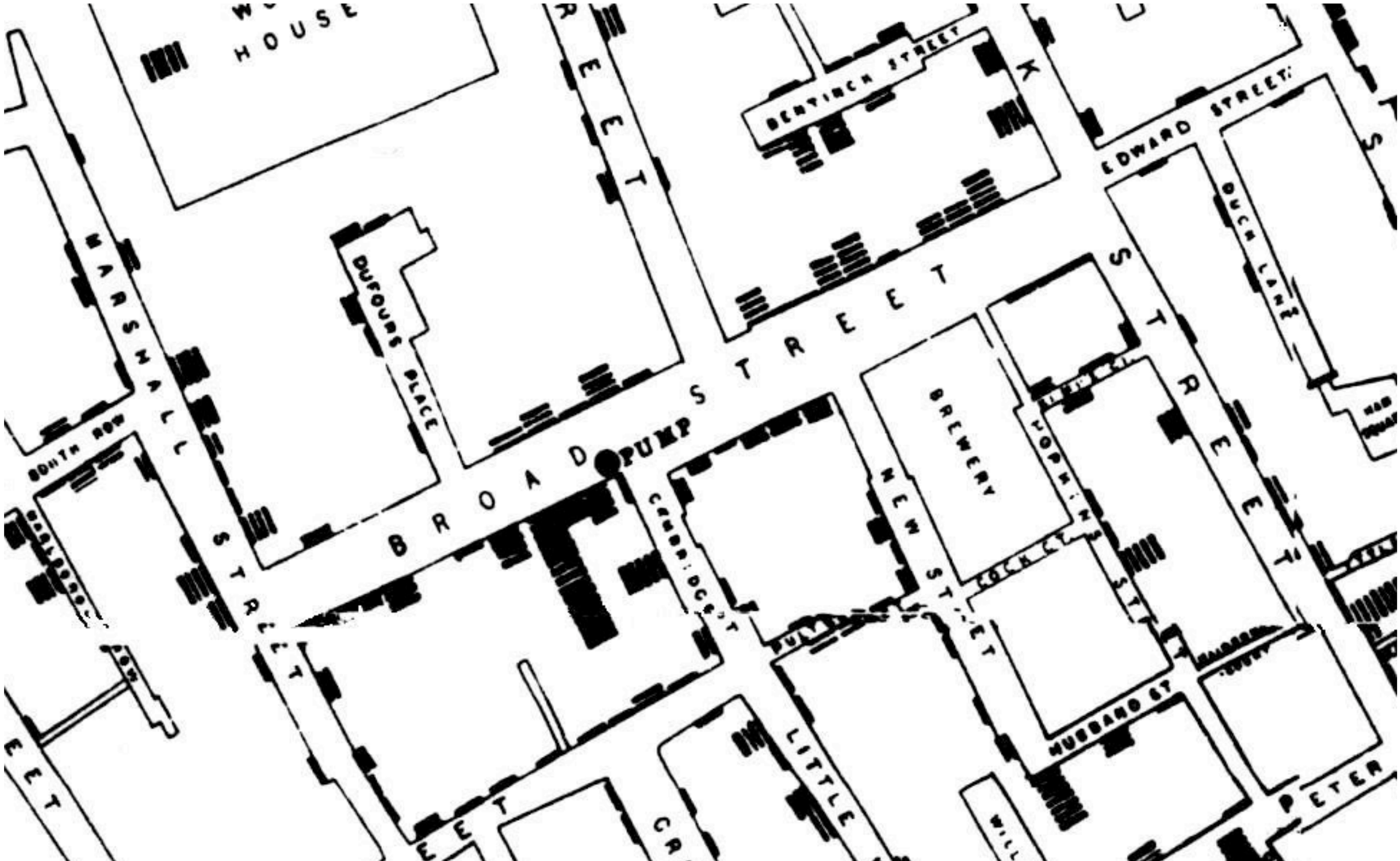
Why Visualize?



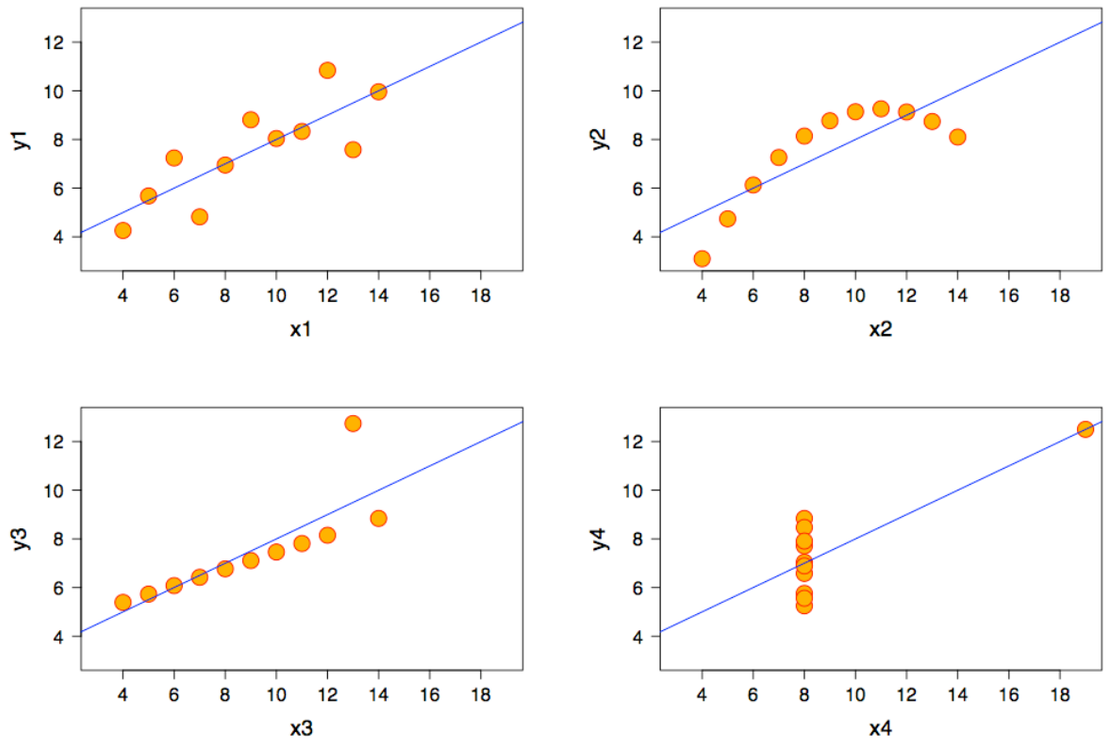
Visualizations can tell a story

Why Visualize?

Visualizations can engage our pattern-matching brain



Why Visualize?



property	value
x mean	9
x var	10
y mean	7.5
y var	3.75
x y cor.	0.816
linear reg.	y = 3 + .5x

- Anscombe's "Quartet"
- Each distribution has equivalent summary statistics
- Means, correlations, variance: Sometimes one number summaries are deceiving.

http://en.wikipedia.org/wiki/Anscombe%27s_quartet

Semantic Pattern Mappings

Graphical Code		Semantics
Small shapes defined by closed contour, texture, color, shaded solid.		Object, idea, entity, node.
Spatially ordered graphical objects.		Related information or a sequence. In a sequence the left-to-right ordering convention borrows from the western convention for written language.
Graphical objects in proximity.		Similar concepts, related information.
Graphical objects having the same shape, color, or texture.		Similar concepts, related information.
Size of graphical object Height of graphical object.		Magnitude, quantity, importance.

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Semantic Pattern Mappings

Graphical Code		Semantics
Shapes connected by contour.		Related entities, path between entities.
Thickness of connecting contour.		Strength of relationship.
Color and texture of connecting contour.		Type of relationship.
Shapes enclosed by a contour, or a common texture, or a common color.		Contained entities. Related entities.
Nested regions, partitioned regions.		Hierarchical concepts.
Attached shapes.		Parts of a conceptual structure.

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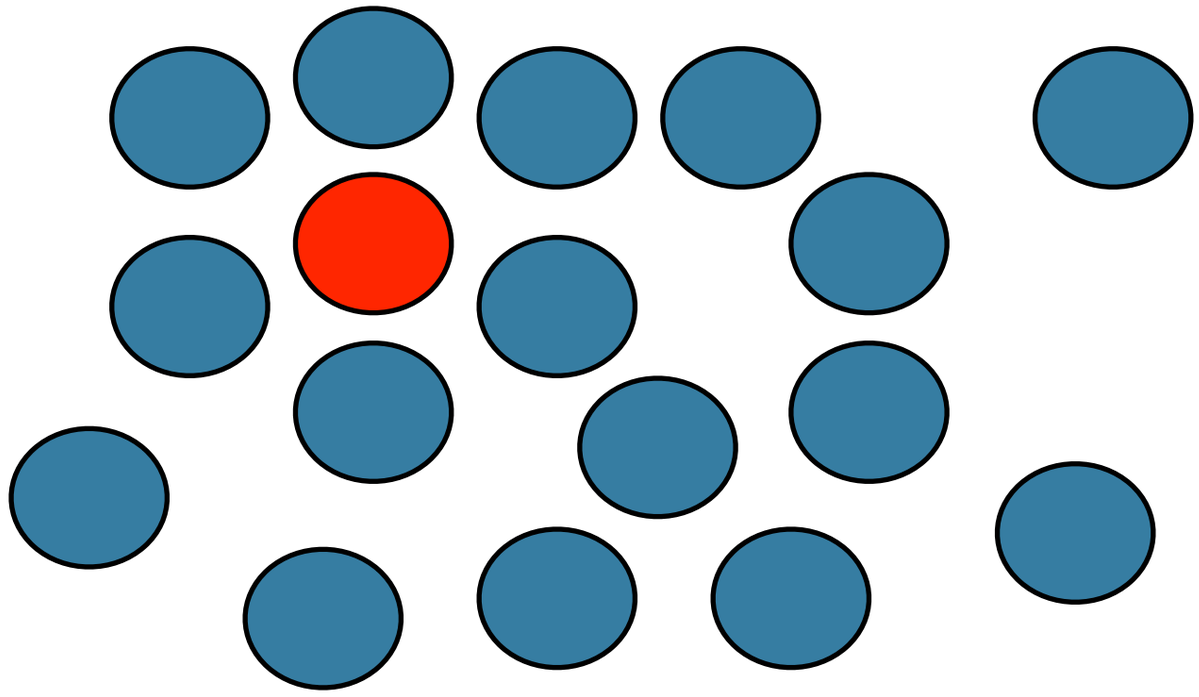
Basic Popout Channels



Color

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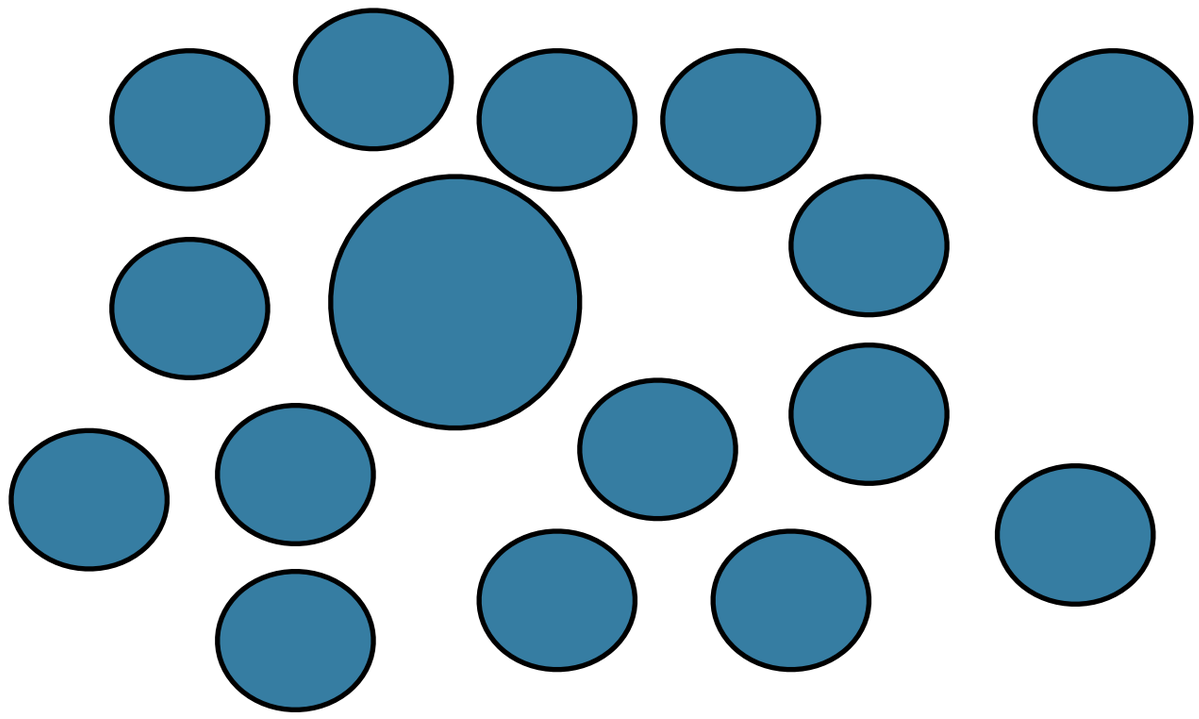
Basic Popout Channels



Size

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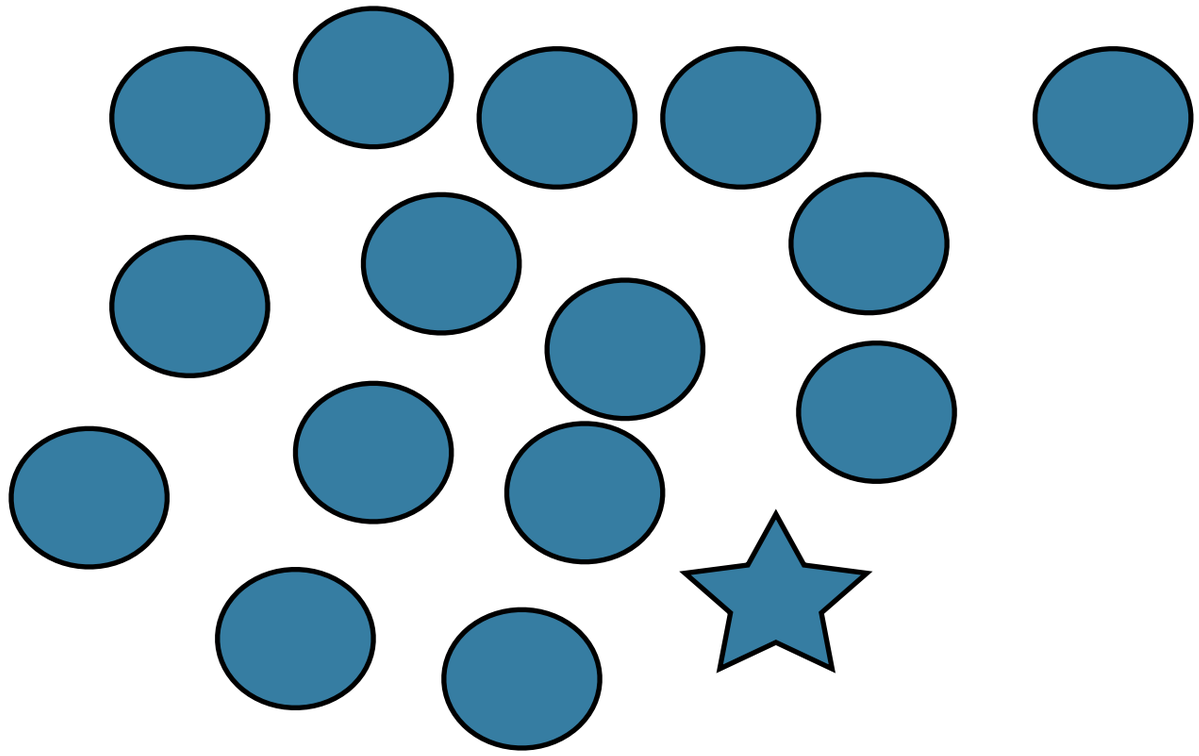
Basic Popout Channels



Shape

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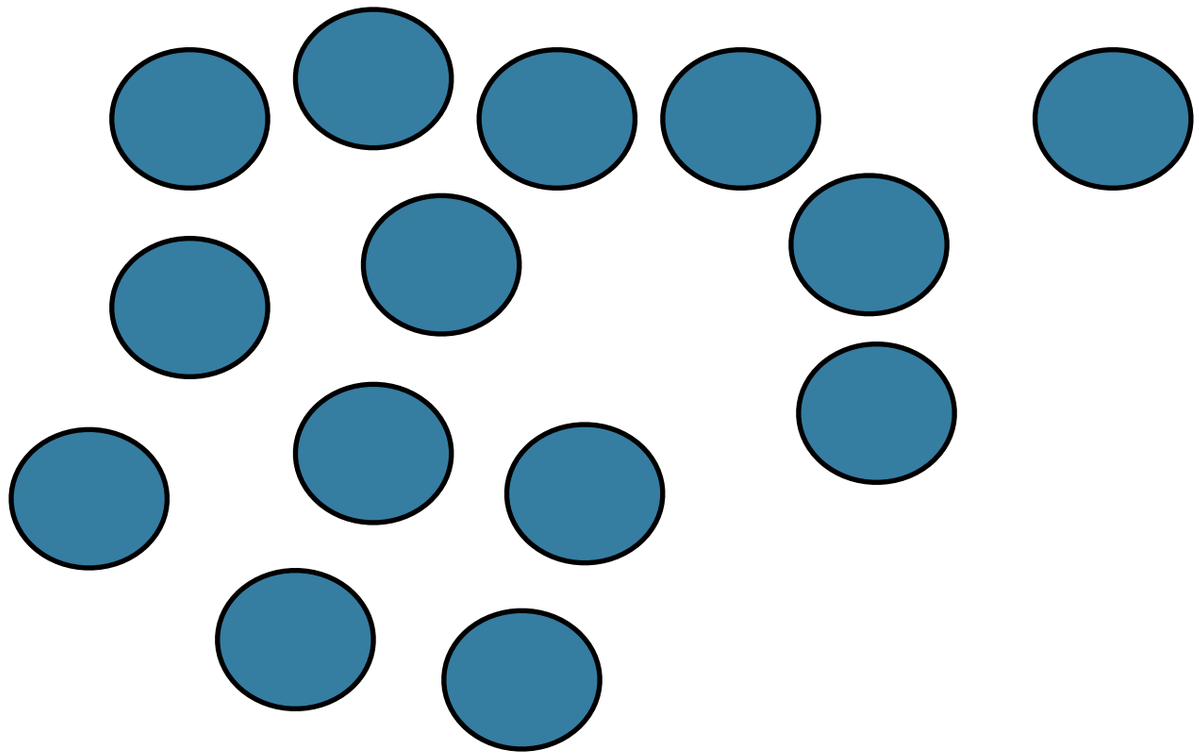
Basic Popout Channels



Motion

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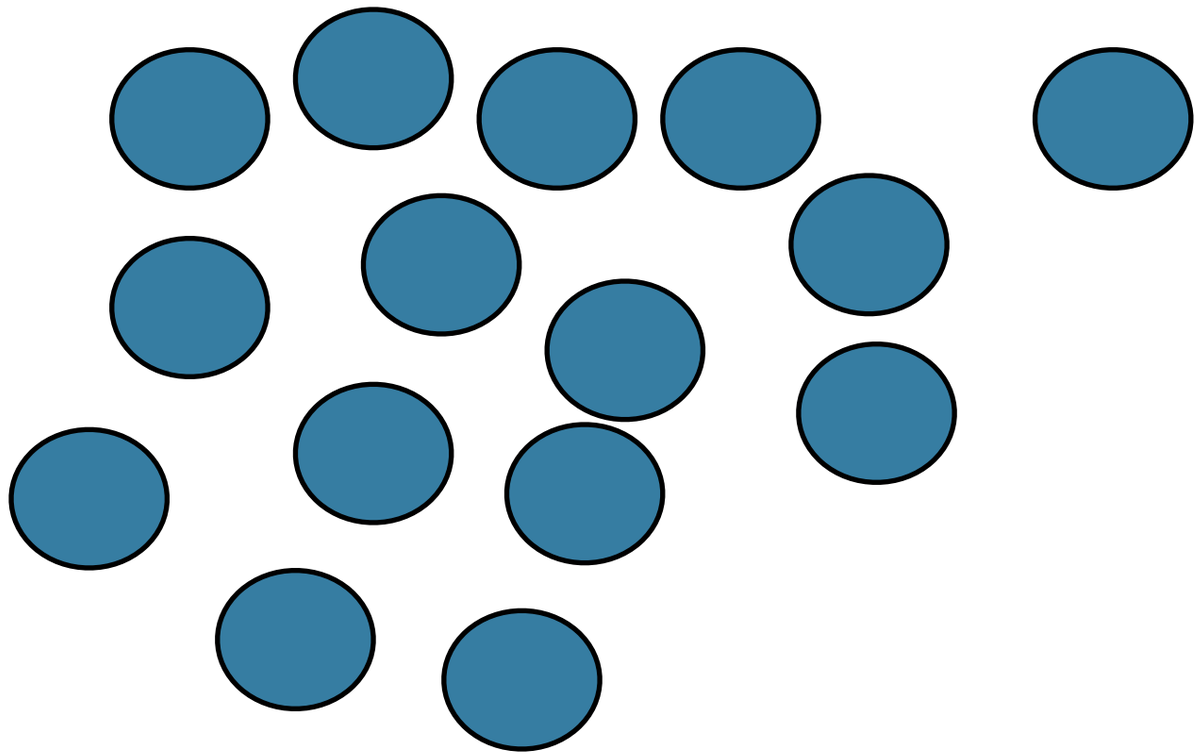

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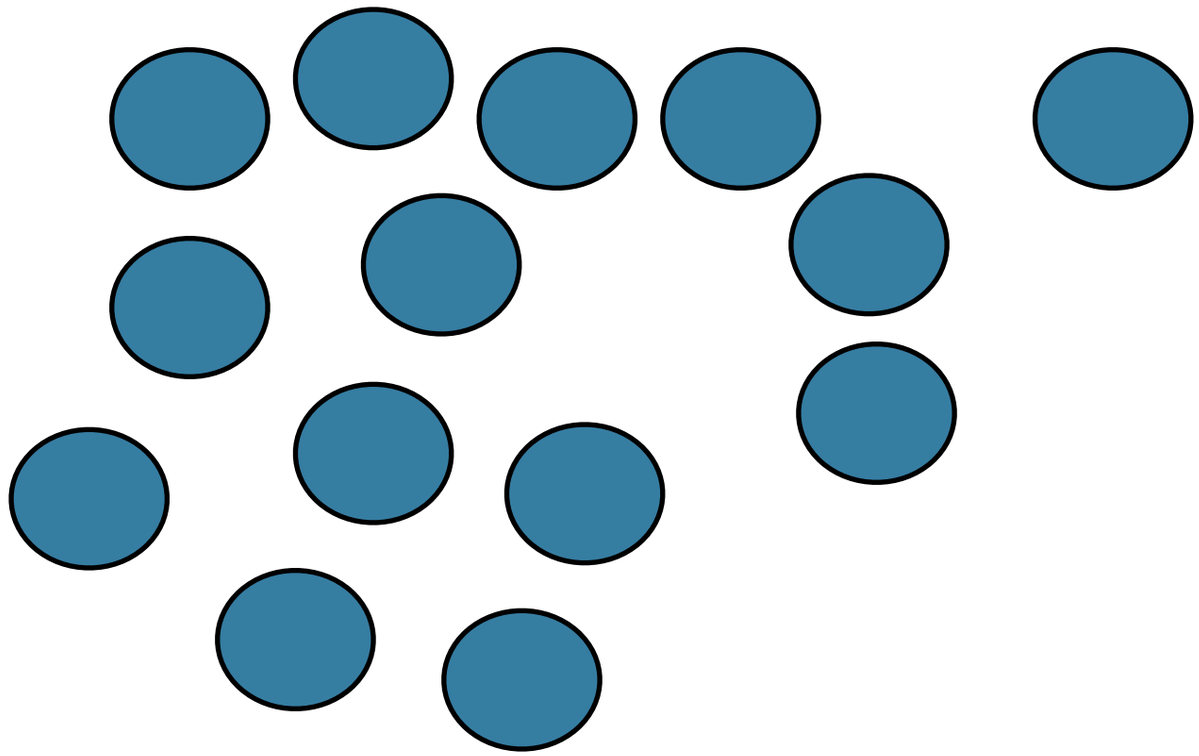

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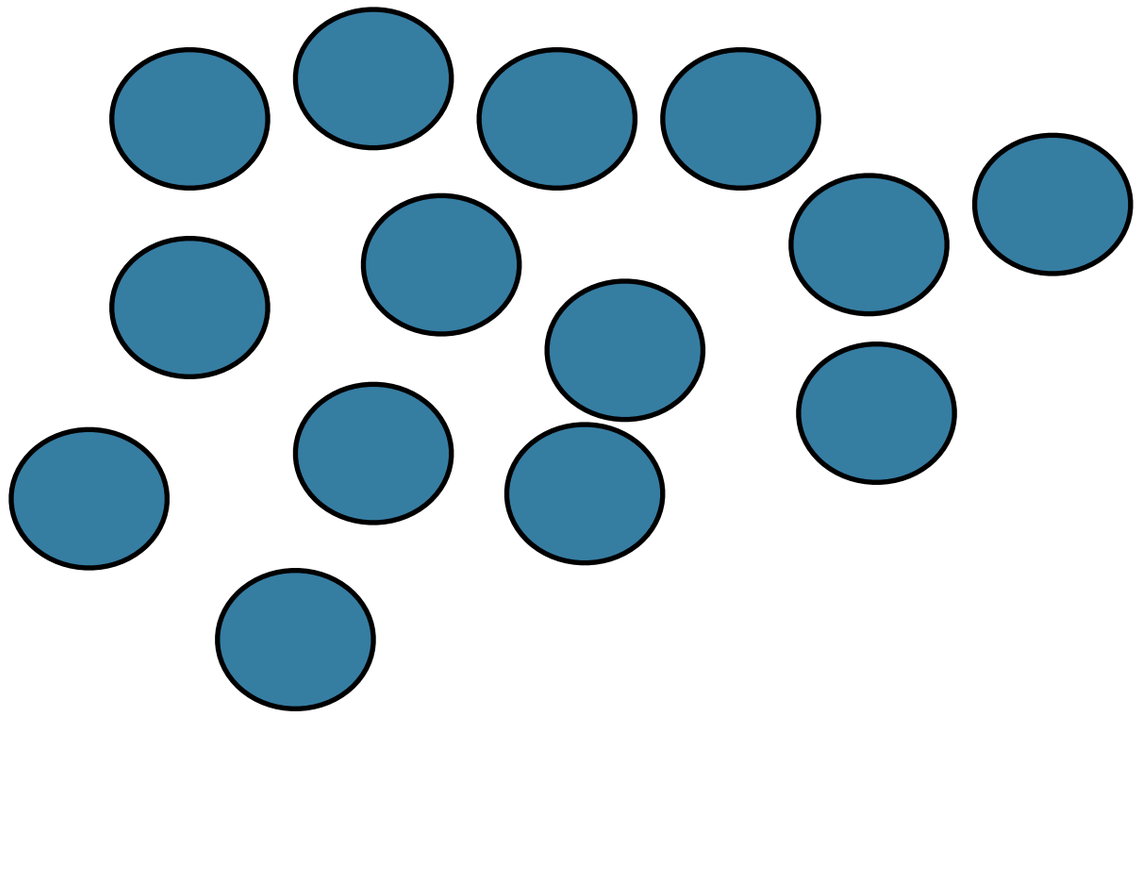

Spatial Grouping

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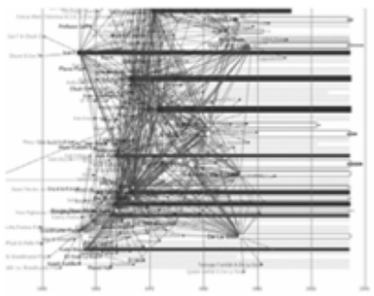
Overloading the channels

Flickr photo by Stéfan

Visualization of Visualizations

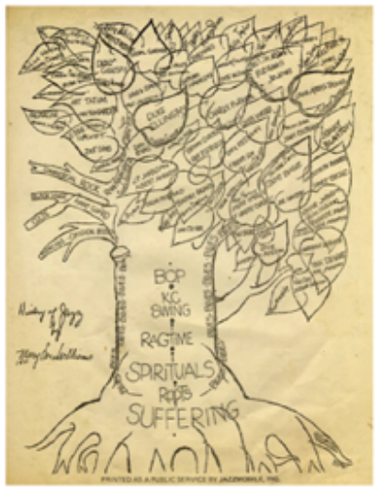
History/Geneaology

Cuban Music Genealogy



musician map

Garofalos' genealogy



History of Jazz

Michael Jackson Samples

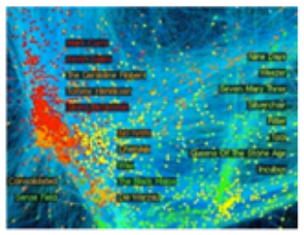
ishkur's guide

Authoritative/Researcher/Historian

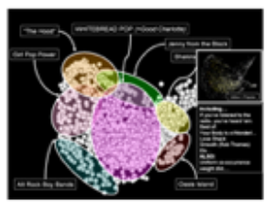
Casual/Consumer

(Not many here...)

(dozens more here)



World of Music



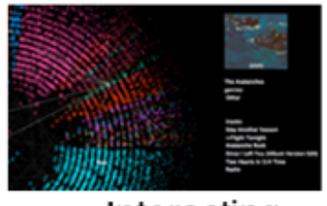
ZMDS

SITM

ESOM MusicMiner

London Tube Map

Last.fm Artist Map



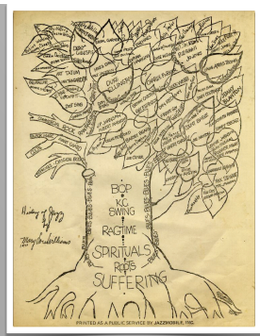
Interacting...

Acoustic/Social Similarity

Visualization Name

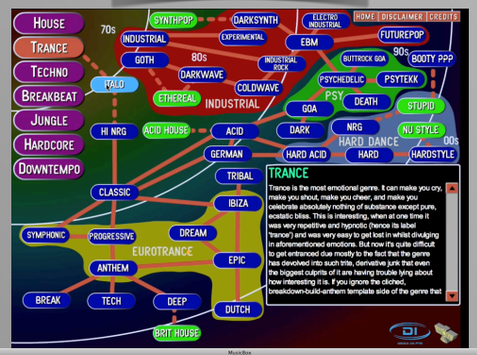
Types of visualizations

Tree

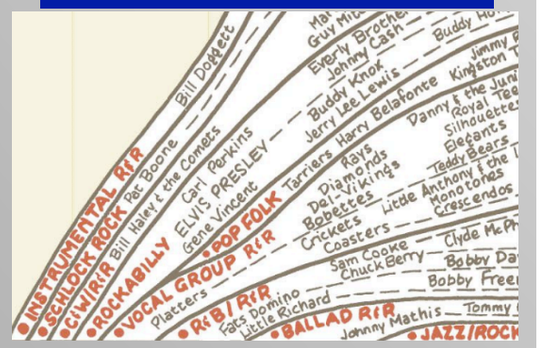


Map

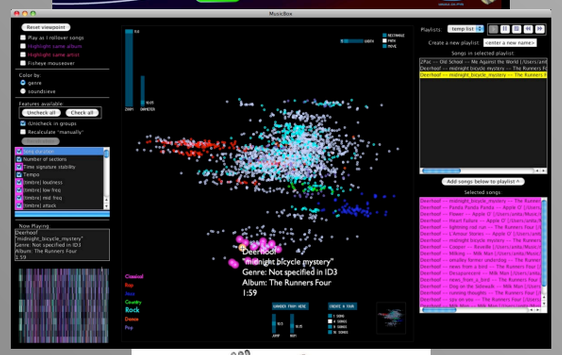
Graph



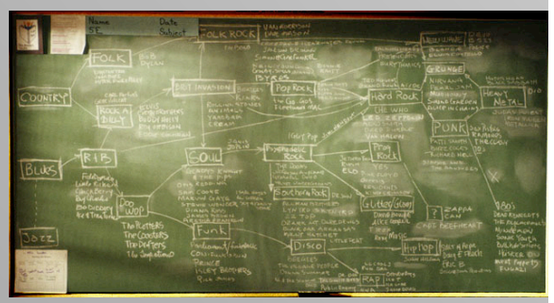
Time Series



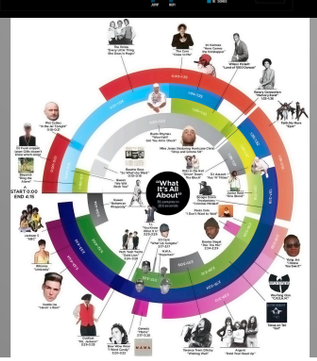
Scatter



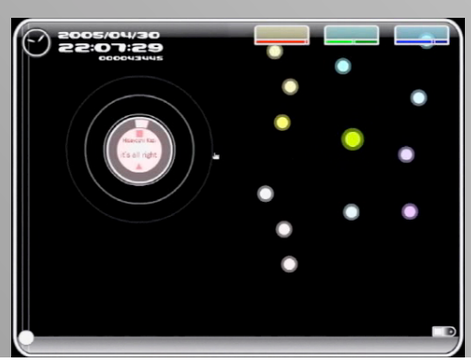
Hybrid



Connections



Interactive



Objects to be discovered

	human	machine
Artists	23	37
Albums	0	6
Tracks	3	17
Samples	3	0
Playlists	0	0
Ordered	0	9
Concerts	0	0
Blogs	0	0
Music	0	0

	human	machine
Genre	18	14
Users	0	4
Radio	0	2
DJs	0	1
Games	0	0
Commu	0	0
Venues	0	0
Taste	2	2
Labels	1	0

26 Human rendered 55 Machine rendered visualizations

Features Used

Content	Beat, tempo, timbre, harmonic content, lyrics
Cultural	web and playlist co-occurrence, purchase/play history, social tags, genre, text aura, expert opinion, appearance, popularity
Relational	member of, collaborated on, supporting musician for, performed as, parent, sibling, married, same label, produced
Mood	happy, sad, angry, relaxed, autumnal
Location	city, country, lat/long,
Time	the hits from the 60s, 70s 80s and today, recent play history
Misc	IQ, Temperature, Name morphology

More features

A scene from High Fidelity

More features

A scene from High Fidelity

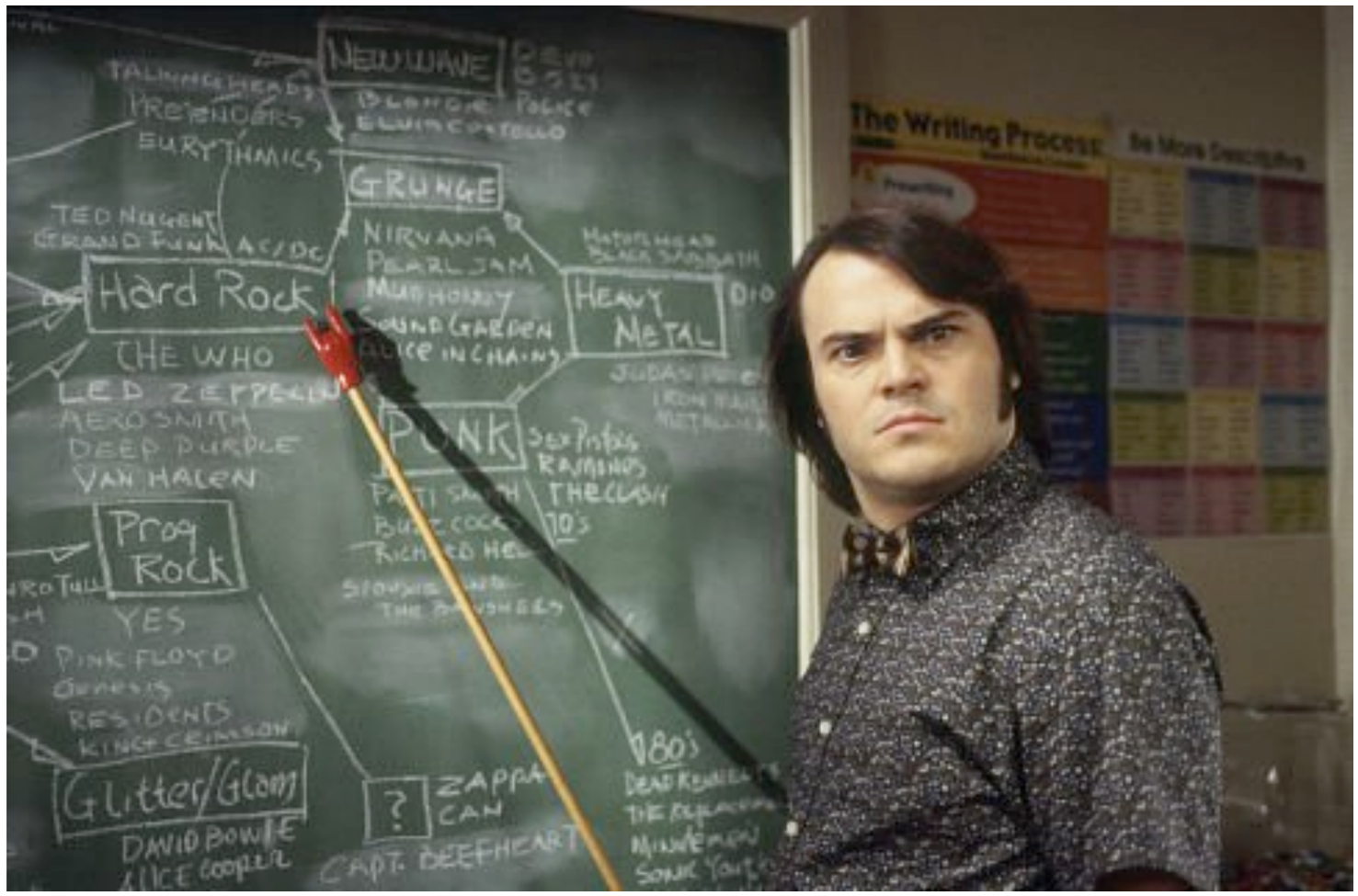
Human rendered visualizations

Human rendered visualizations
Some common techniques

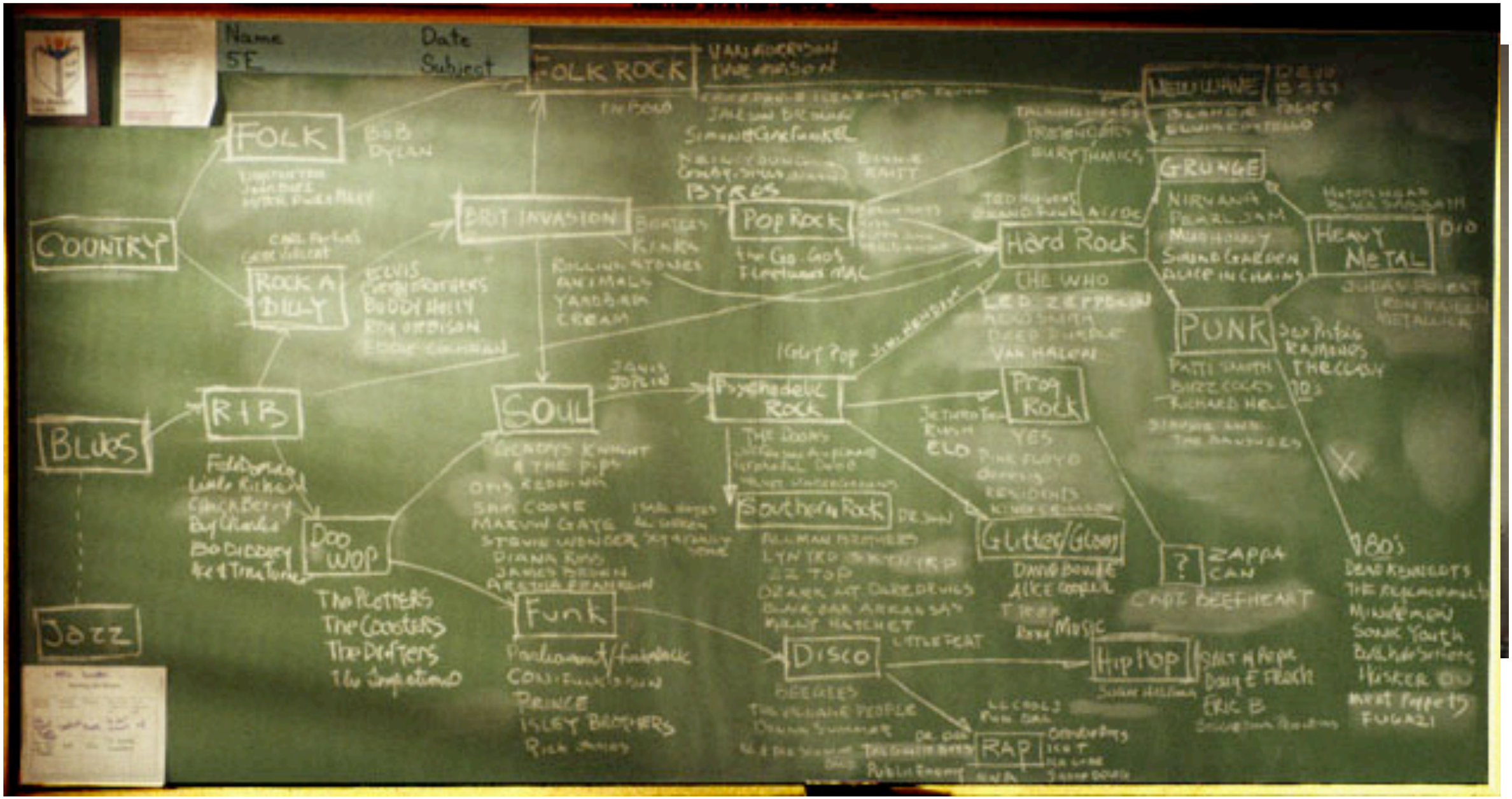
- The Flow
- The Map
- The Tree
- The Graph

Human rendered visualizations
Some common techniques

- History
- Influences
- Similarity
- Popularity

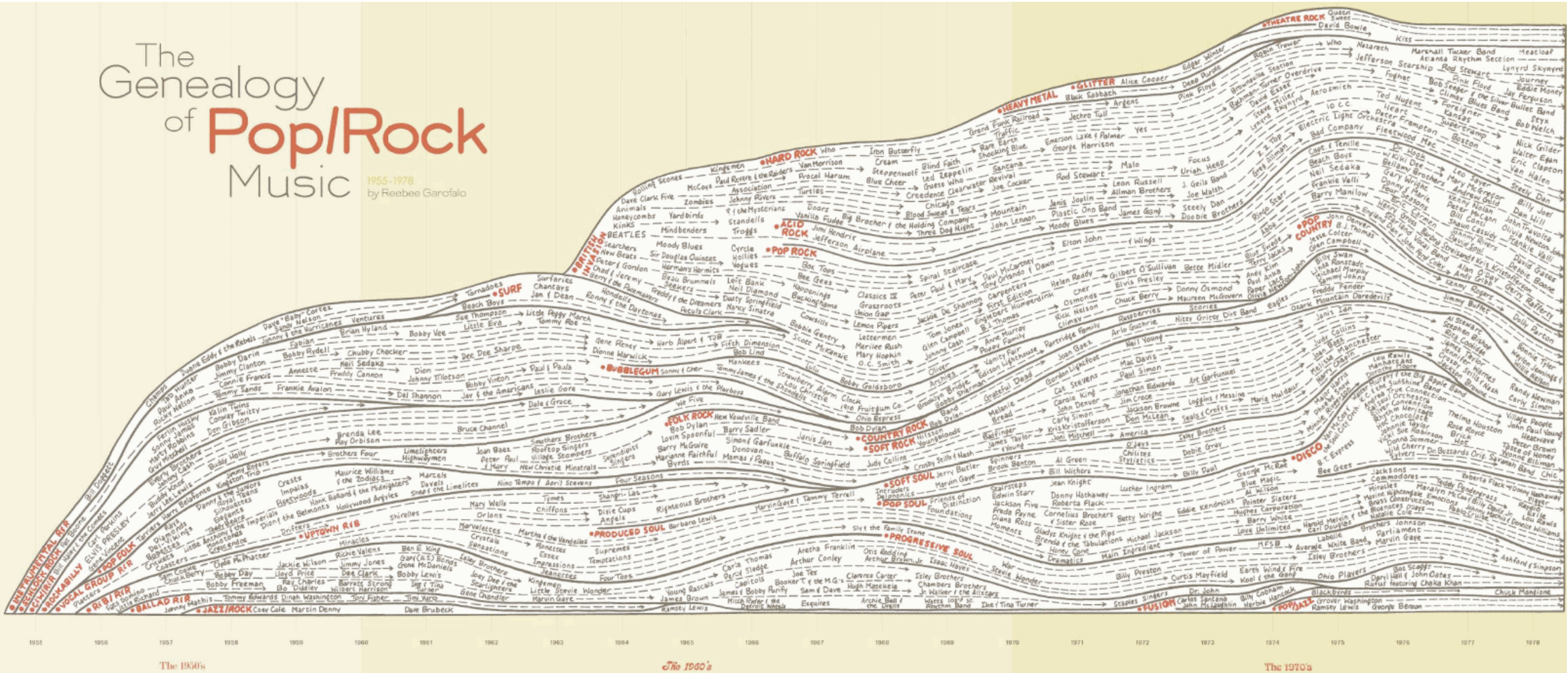


Human rendered visualizations
Some common techniques



Human rendered visualizations
Some common techniques

Genealogy of Pop and Rock Music



Genealogy of Pop and Rock Music - Reebee Garofalo

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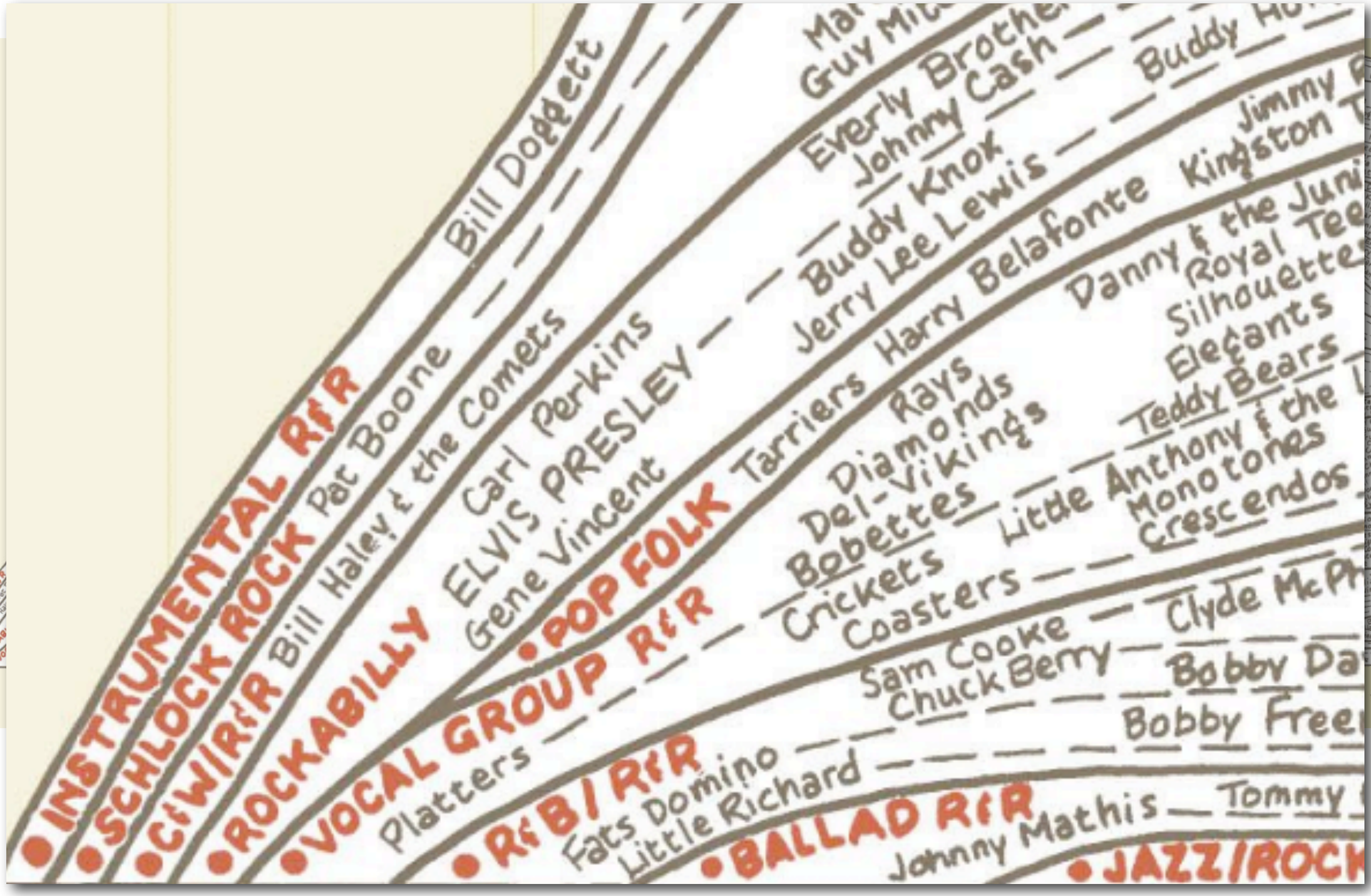

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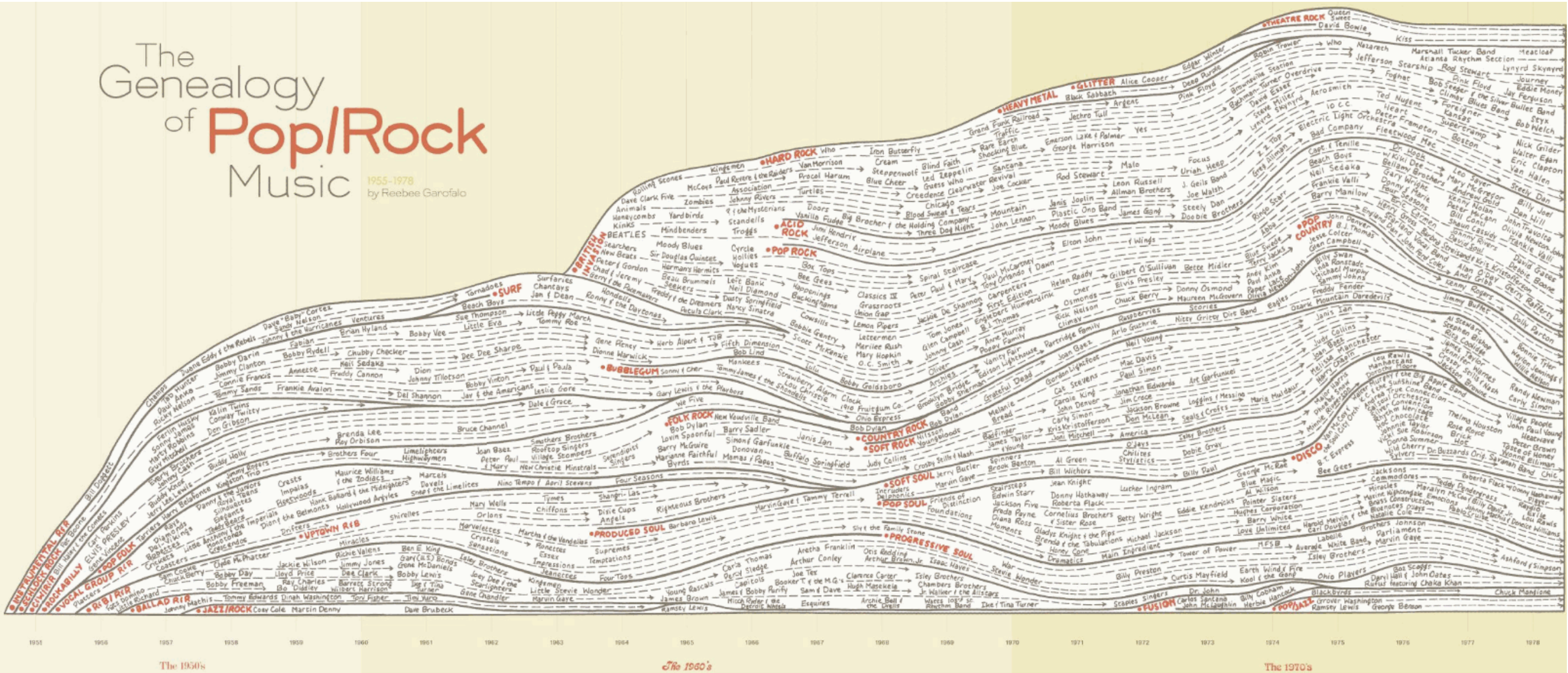

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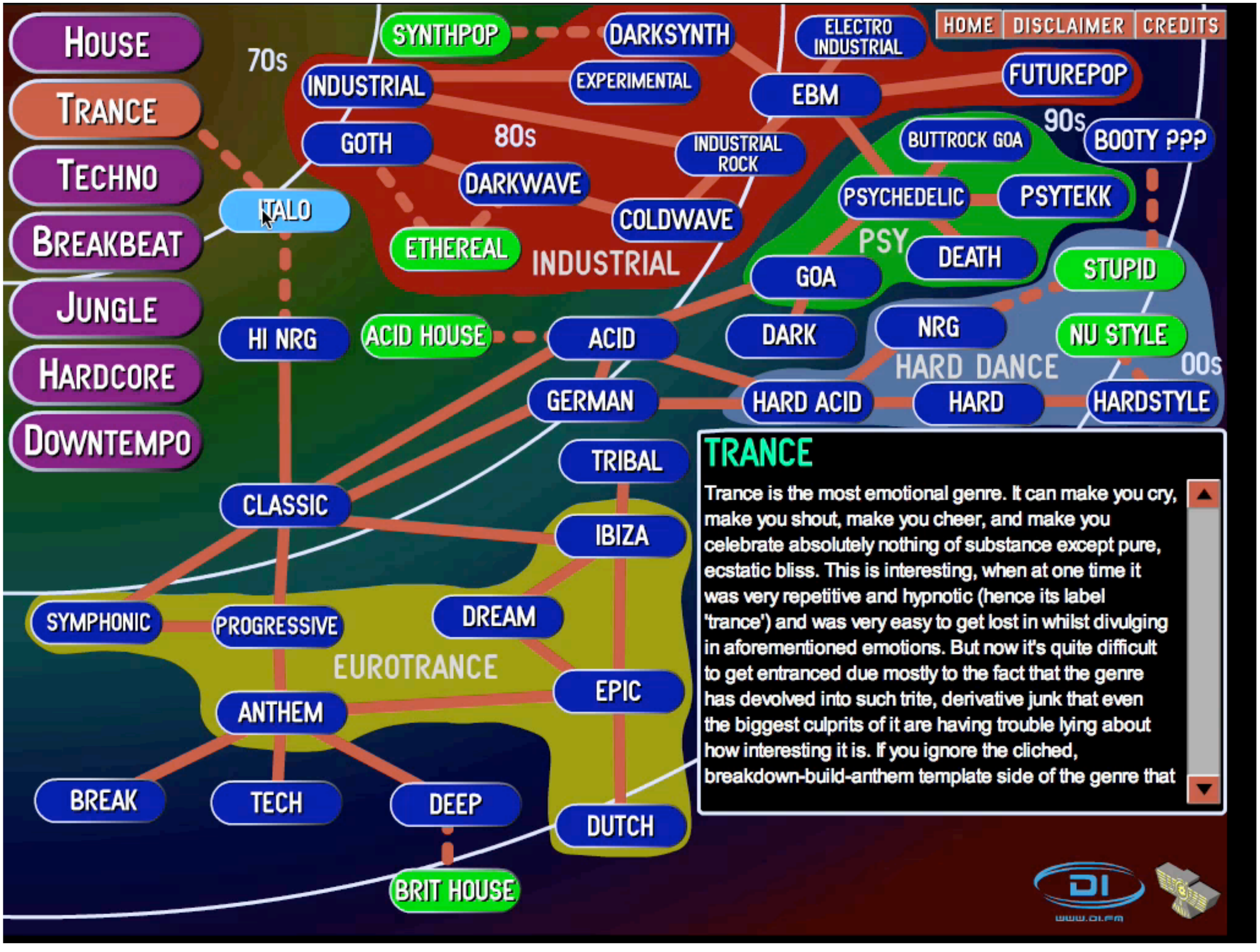
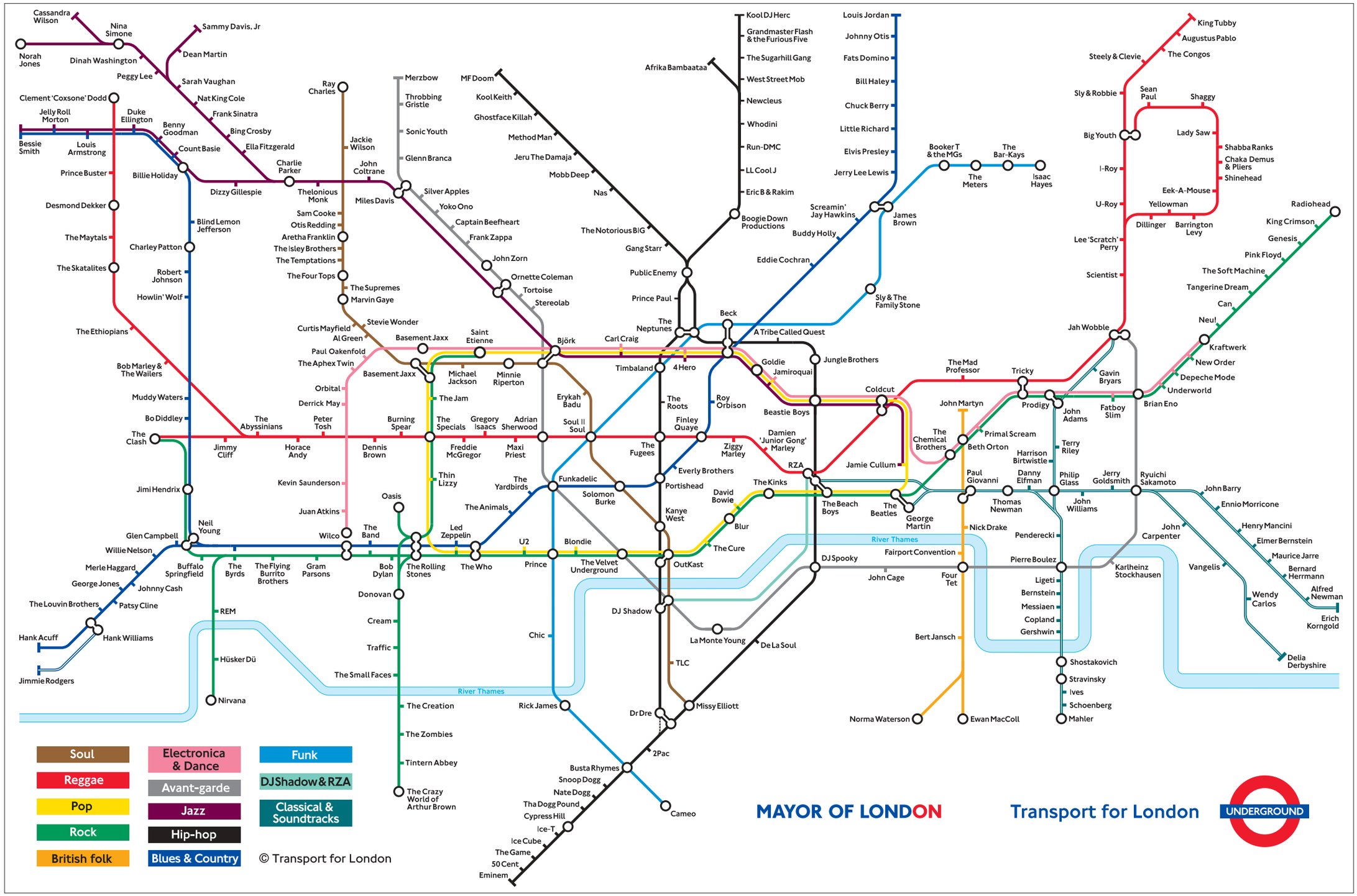
Ishkur's Guide to Electronic Dance Music

Ishkur's Guide to Electronic Dance Music

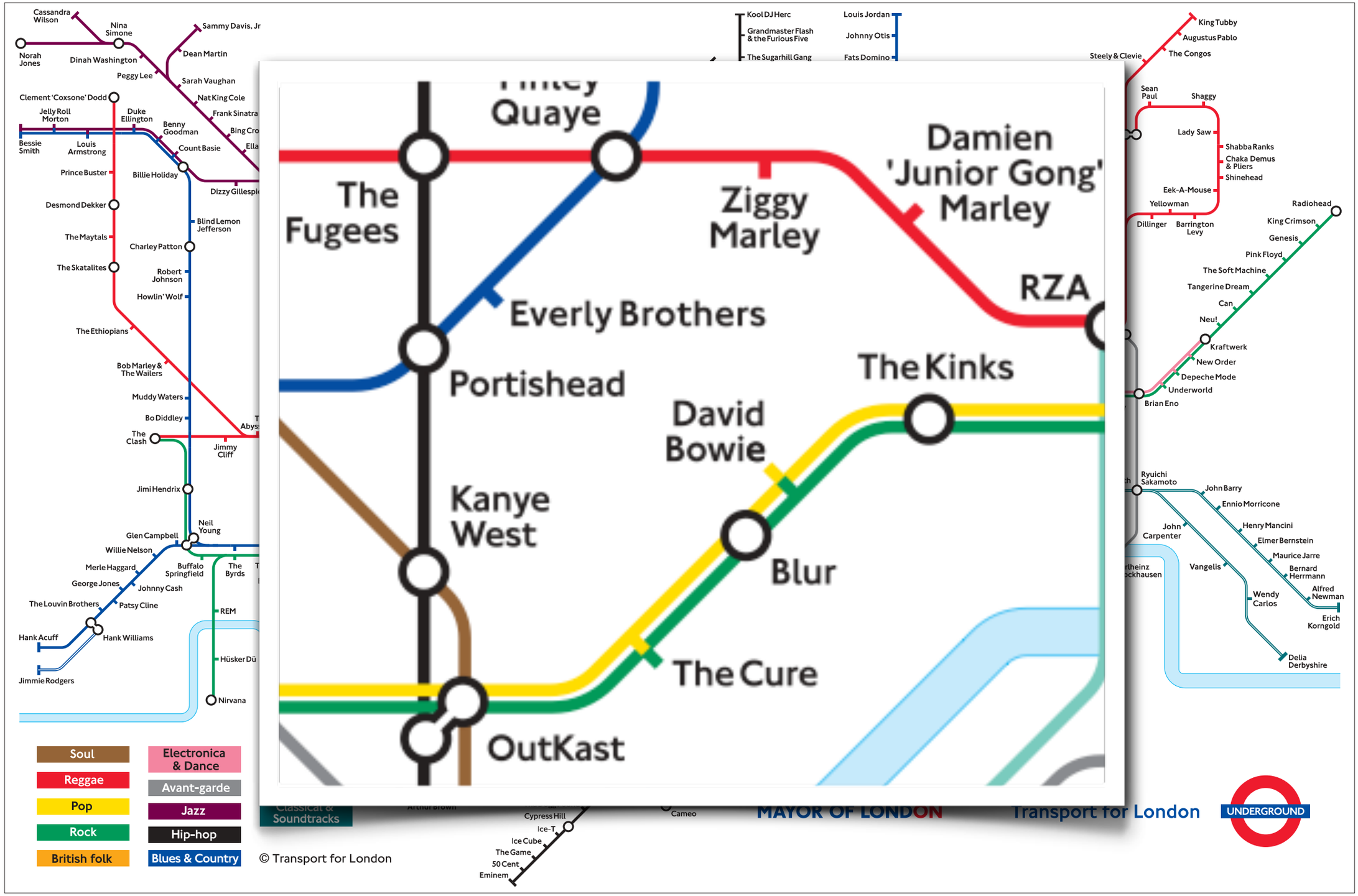


Music History as a London Tube Map



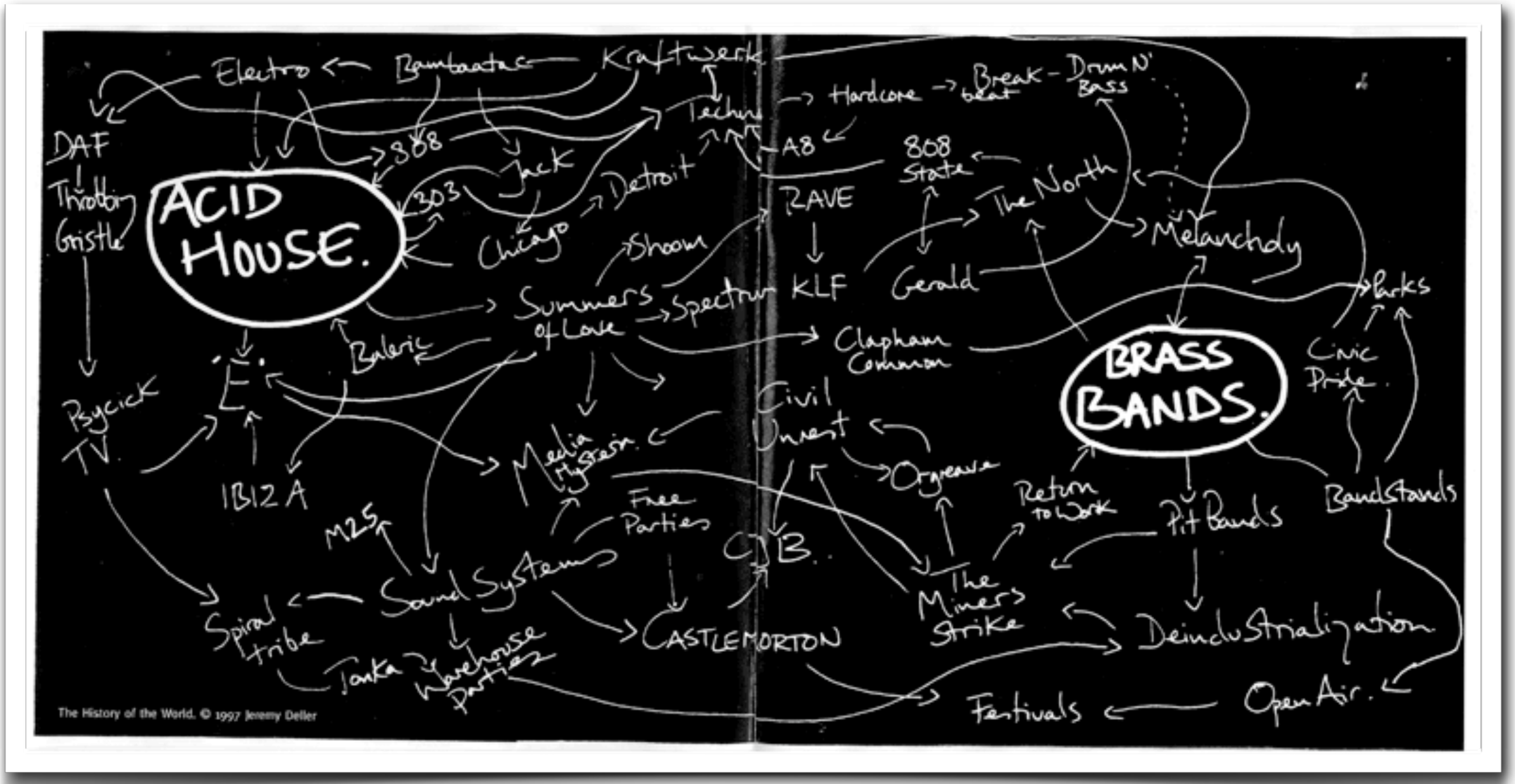
Dorian Lynskey - The Guardian

Music History as a London Tube Map



Dorian Lynskey - The Guardian

Visualizations as a graph



Visualizations as a graph

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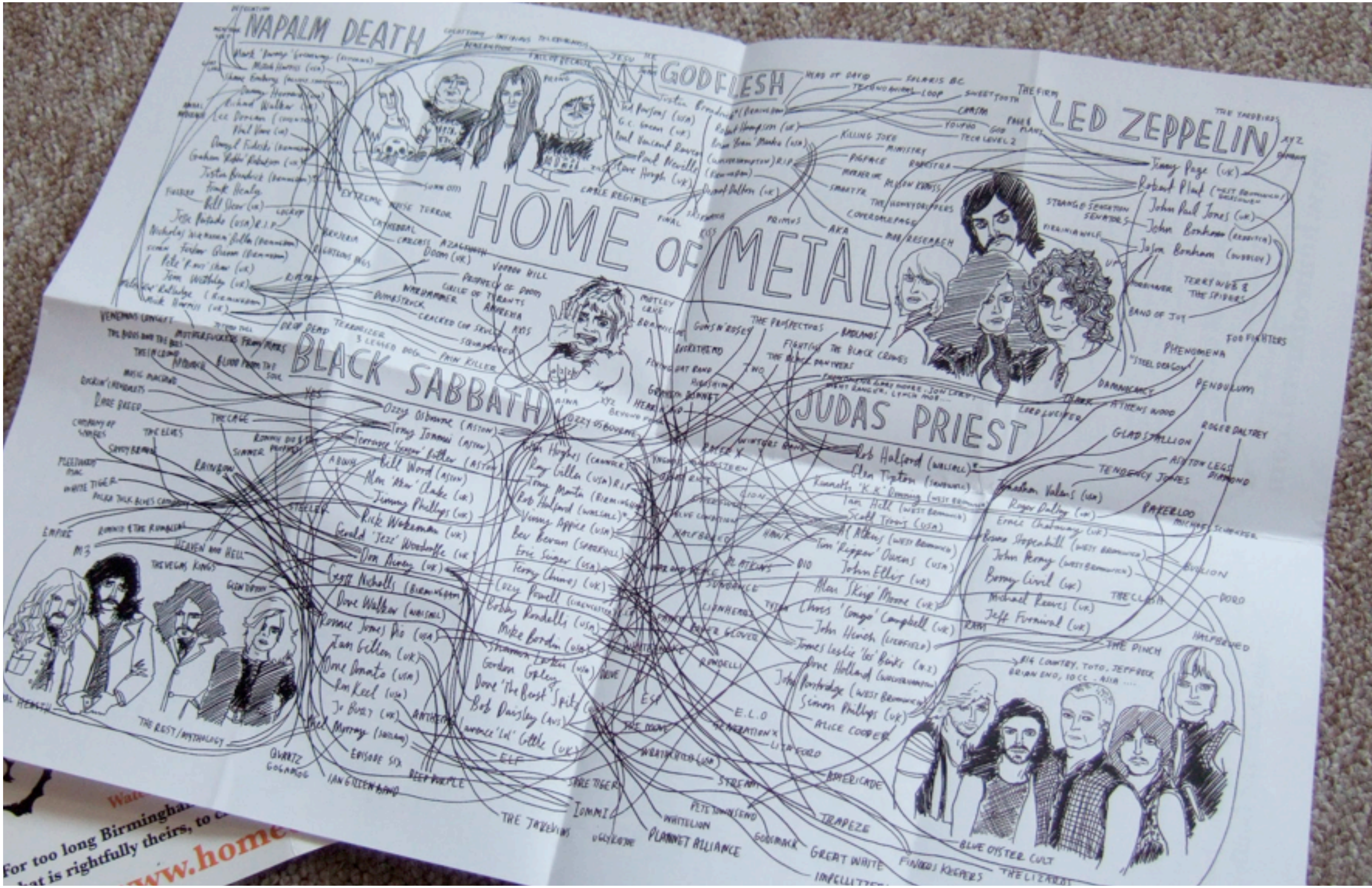

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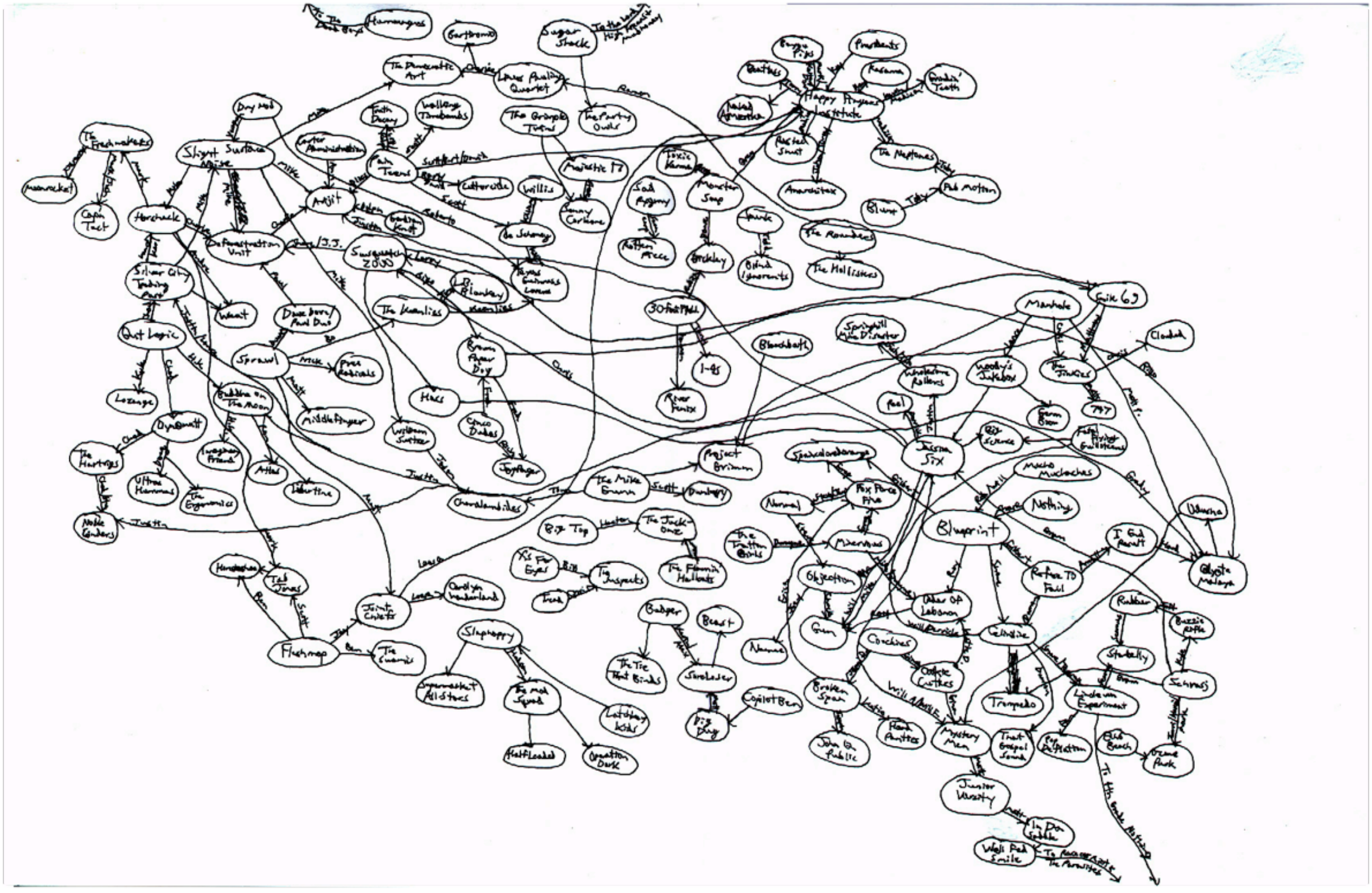

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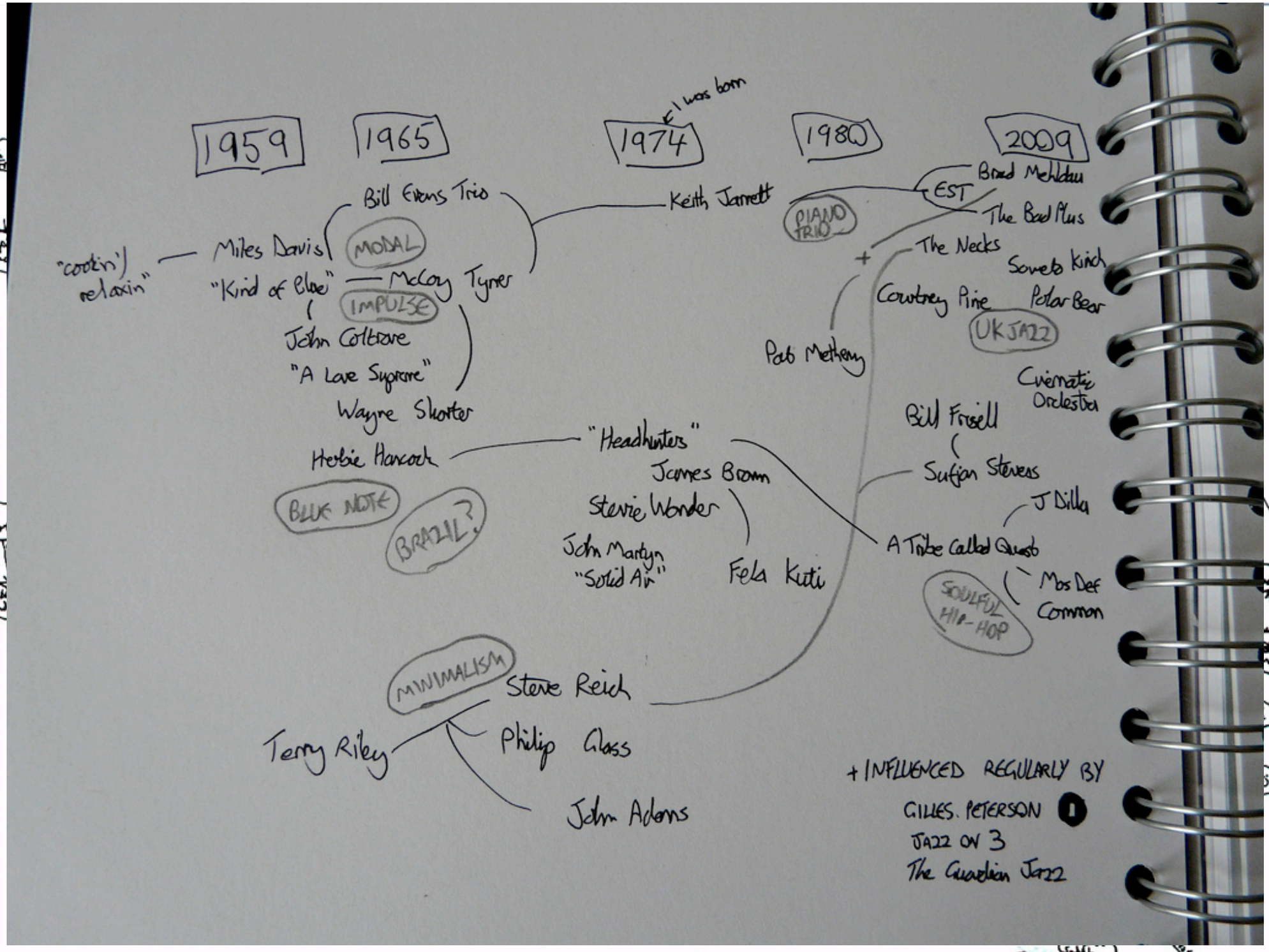

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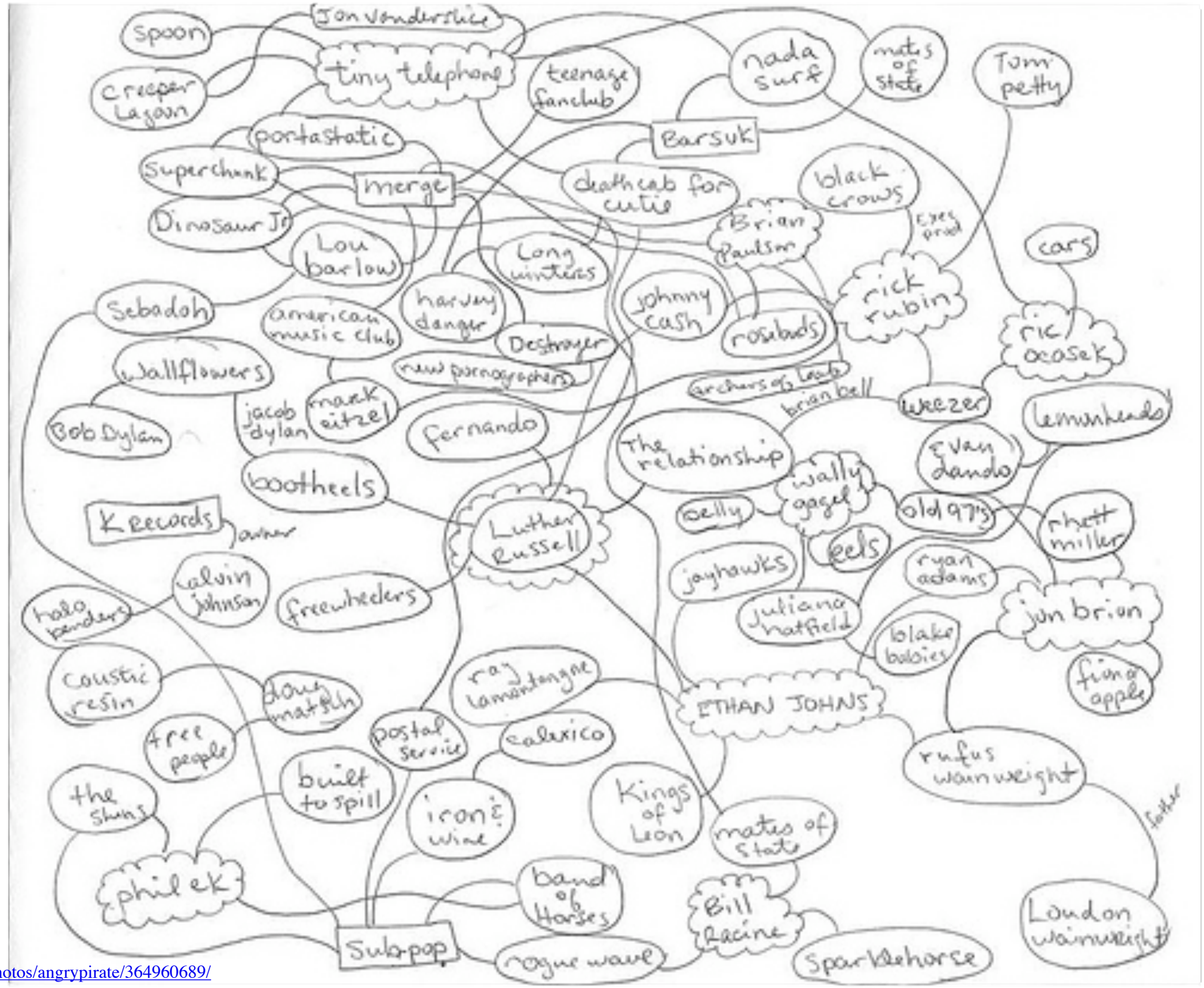
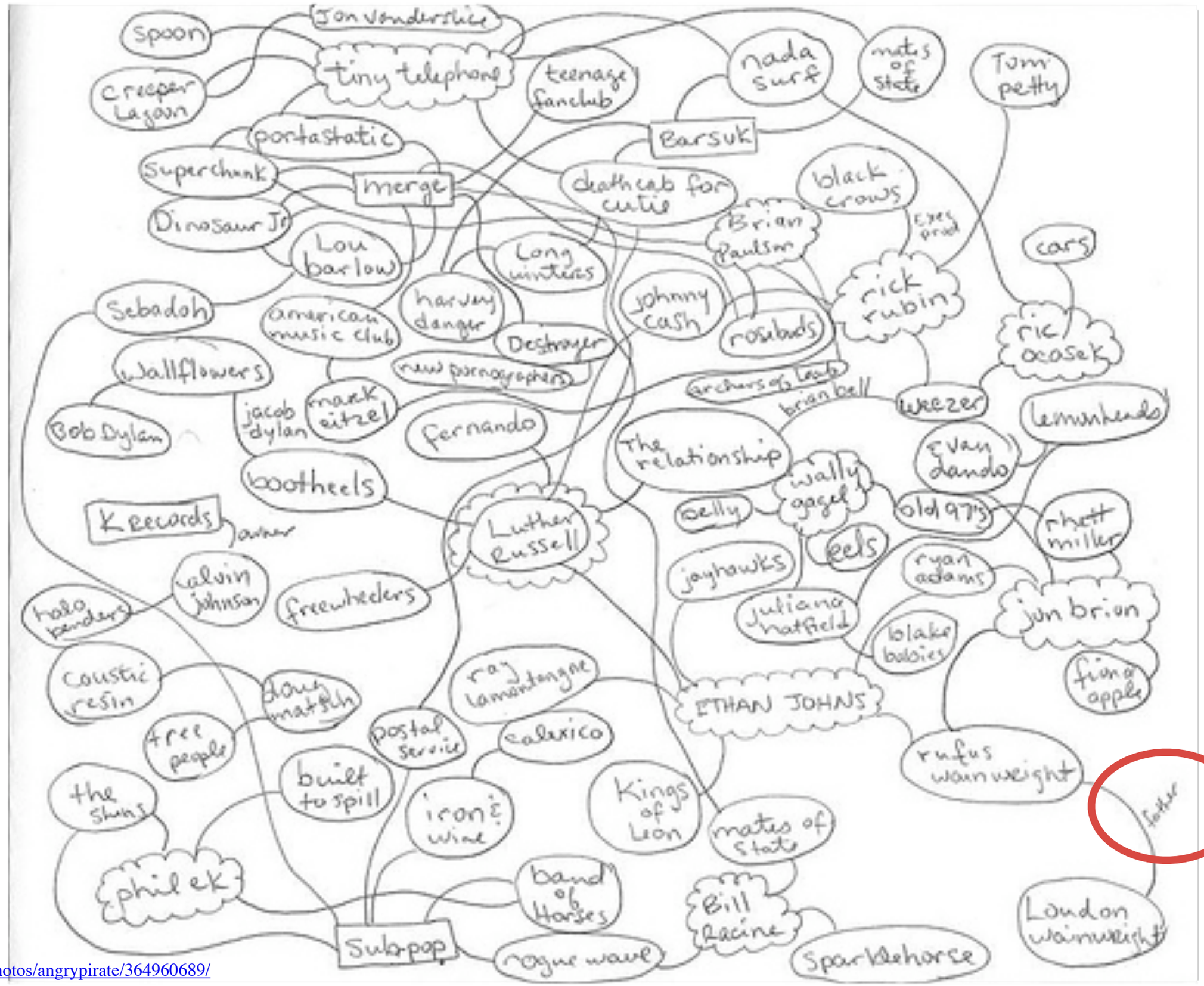


www.flickr.com/photos/angrypirate/364960689/

Visualizations as a graph



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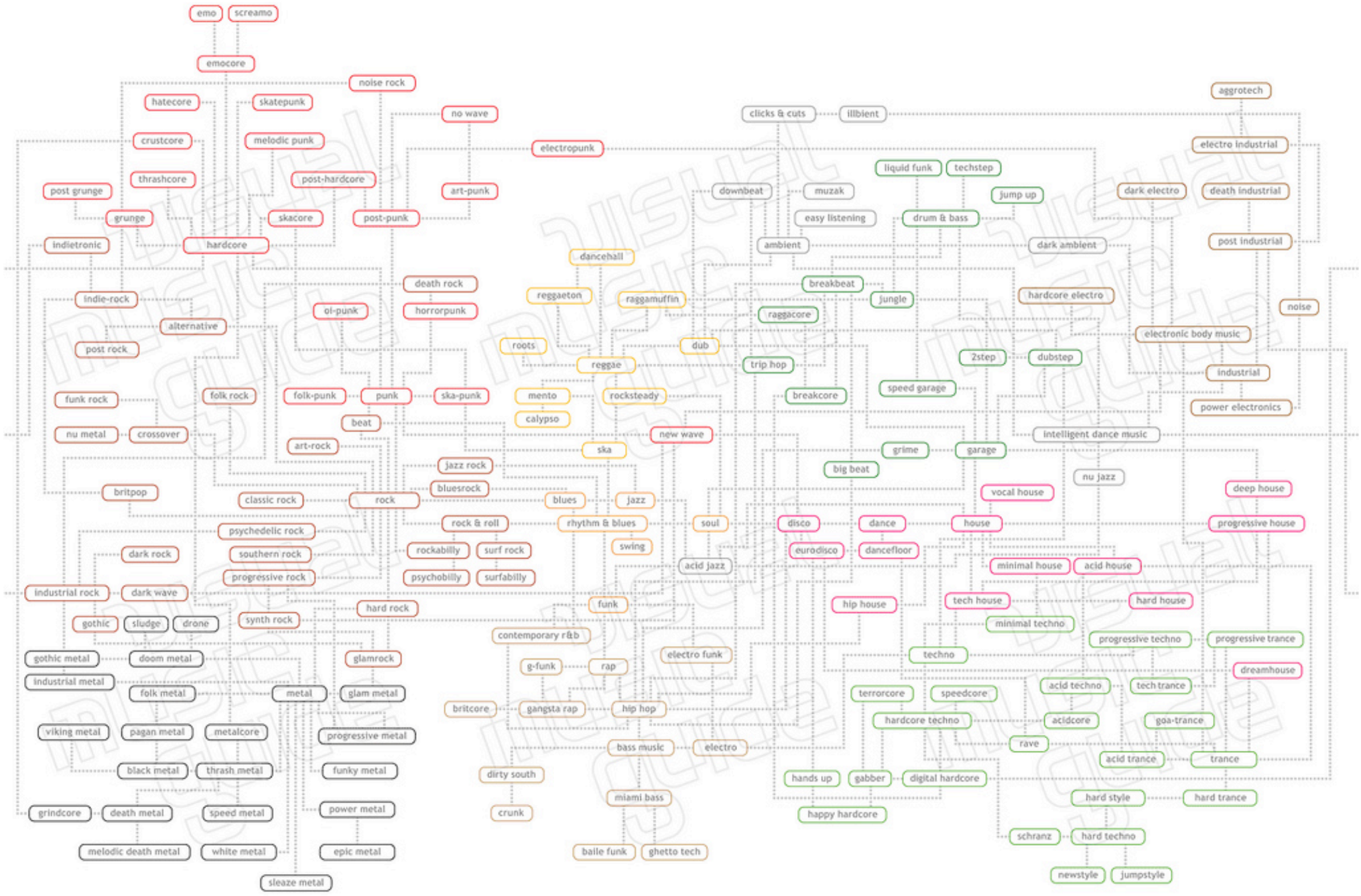
Visual Music Guiden



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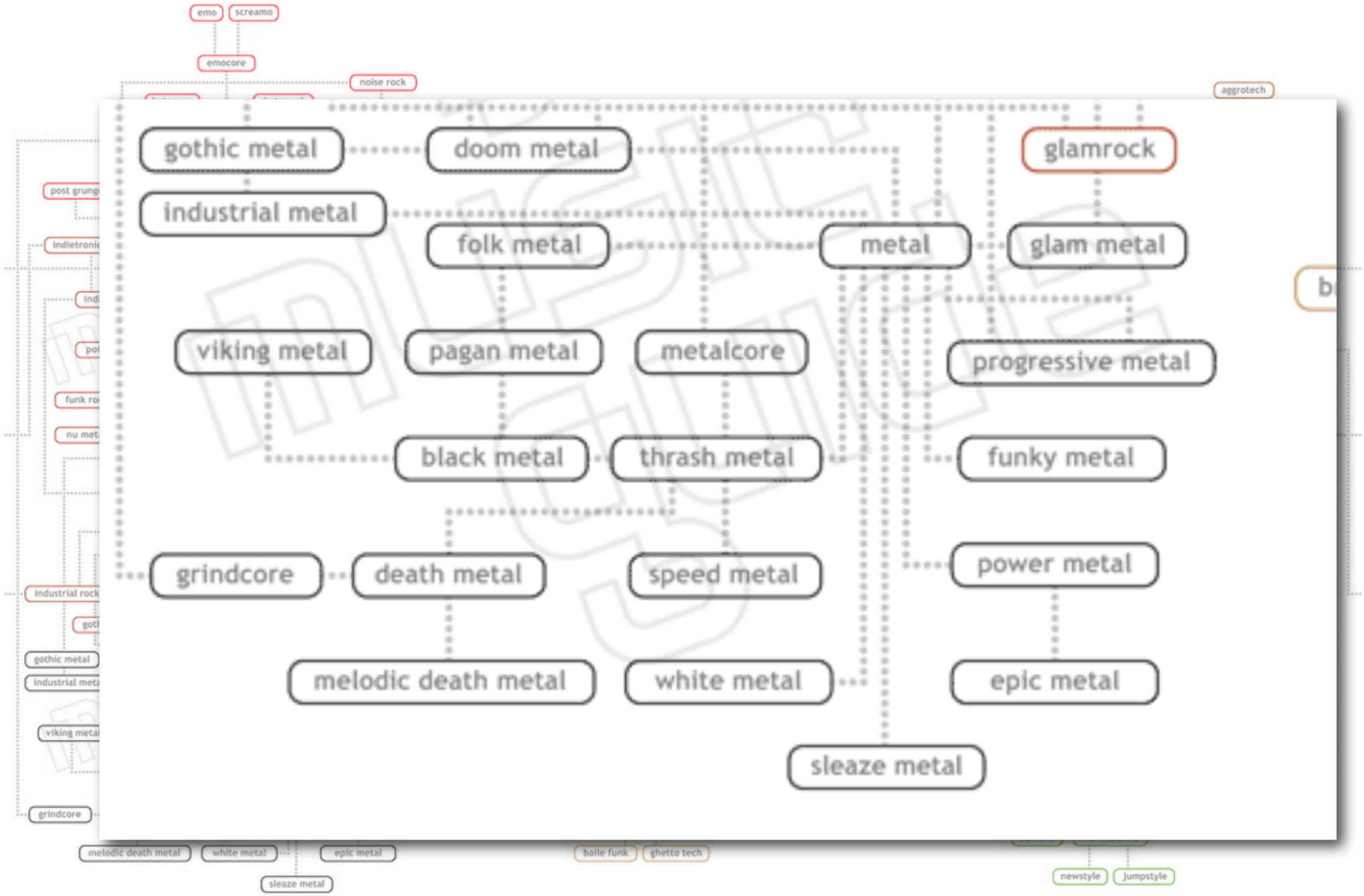
Fabian Schneidmadel - http://www.firutin.de/blog/

Visual Music Guiden



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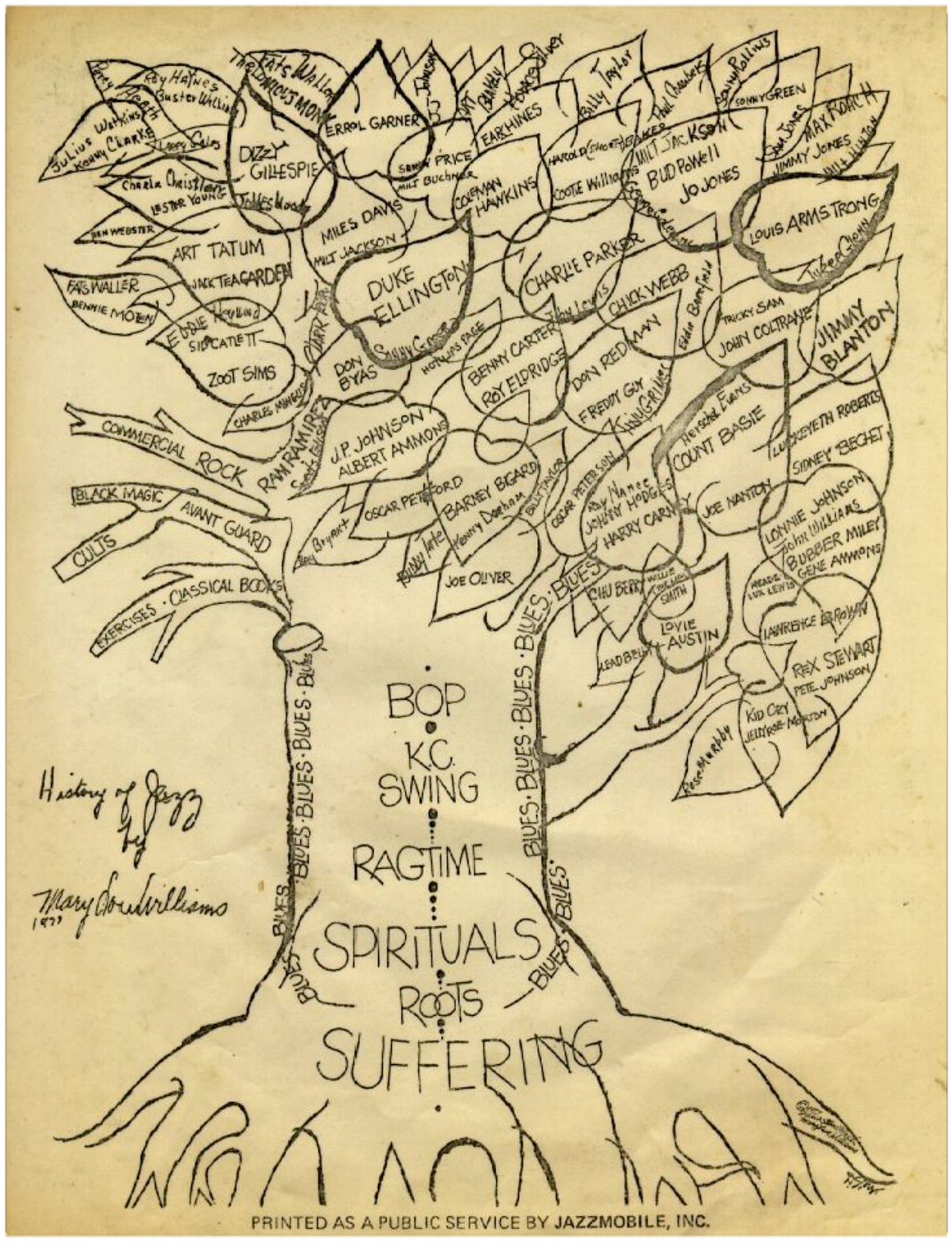
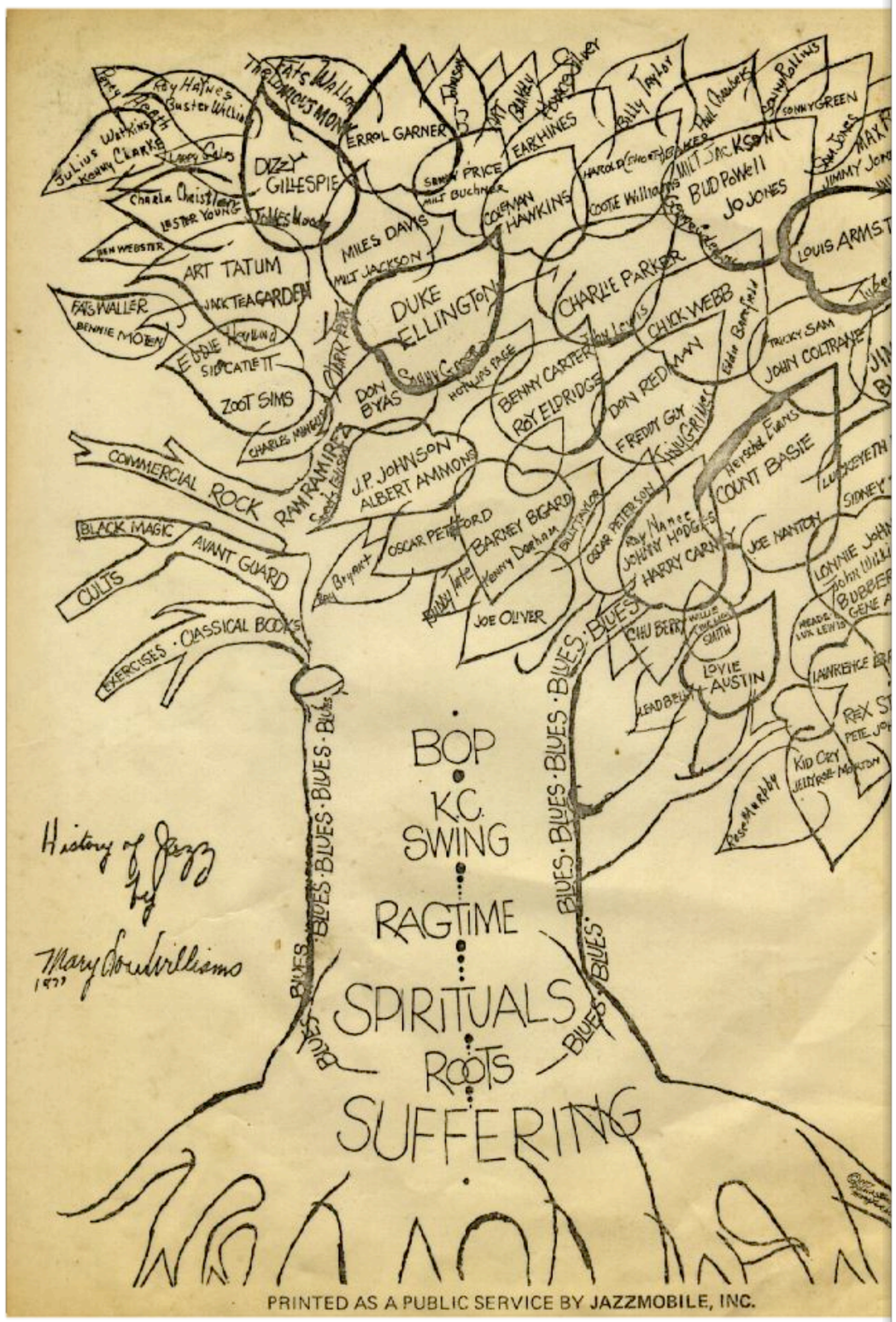
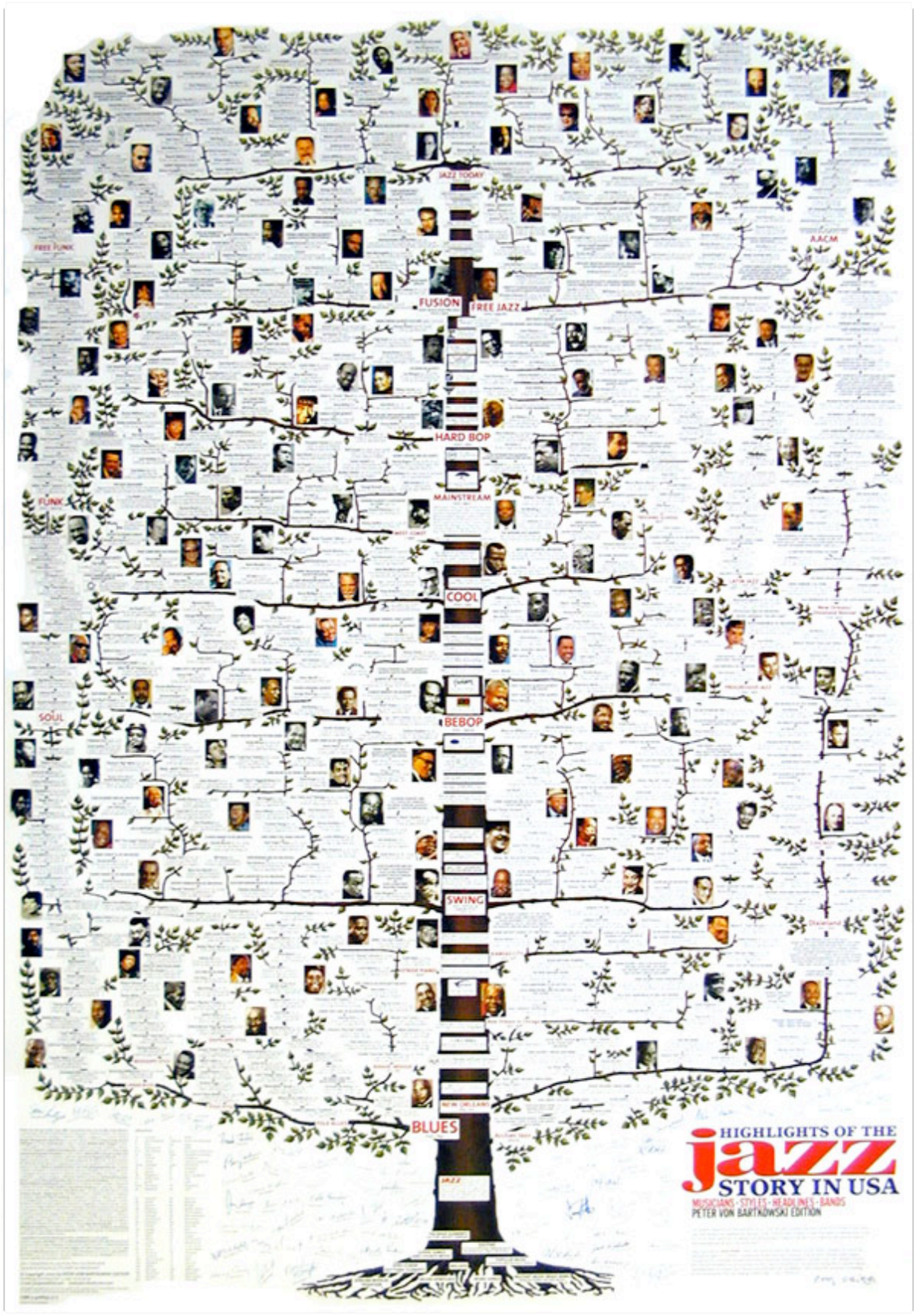
Visualizations as a tree

Visualizations as a tree



Visualizations as a tree





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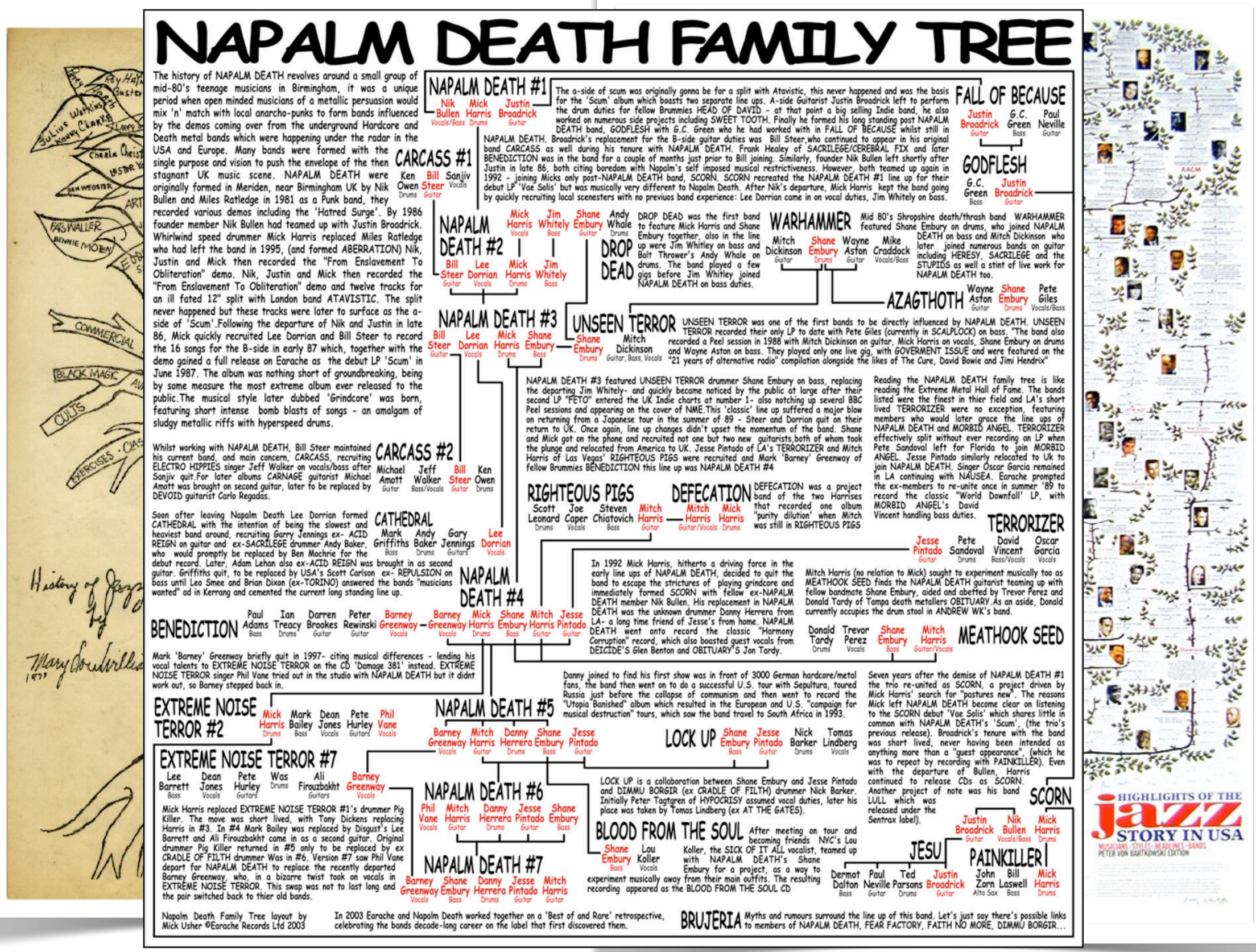

Handmade Genre Maps and Trees

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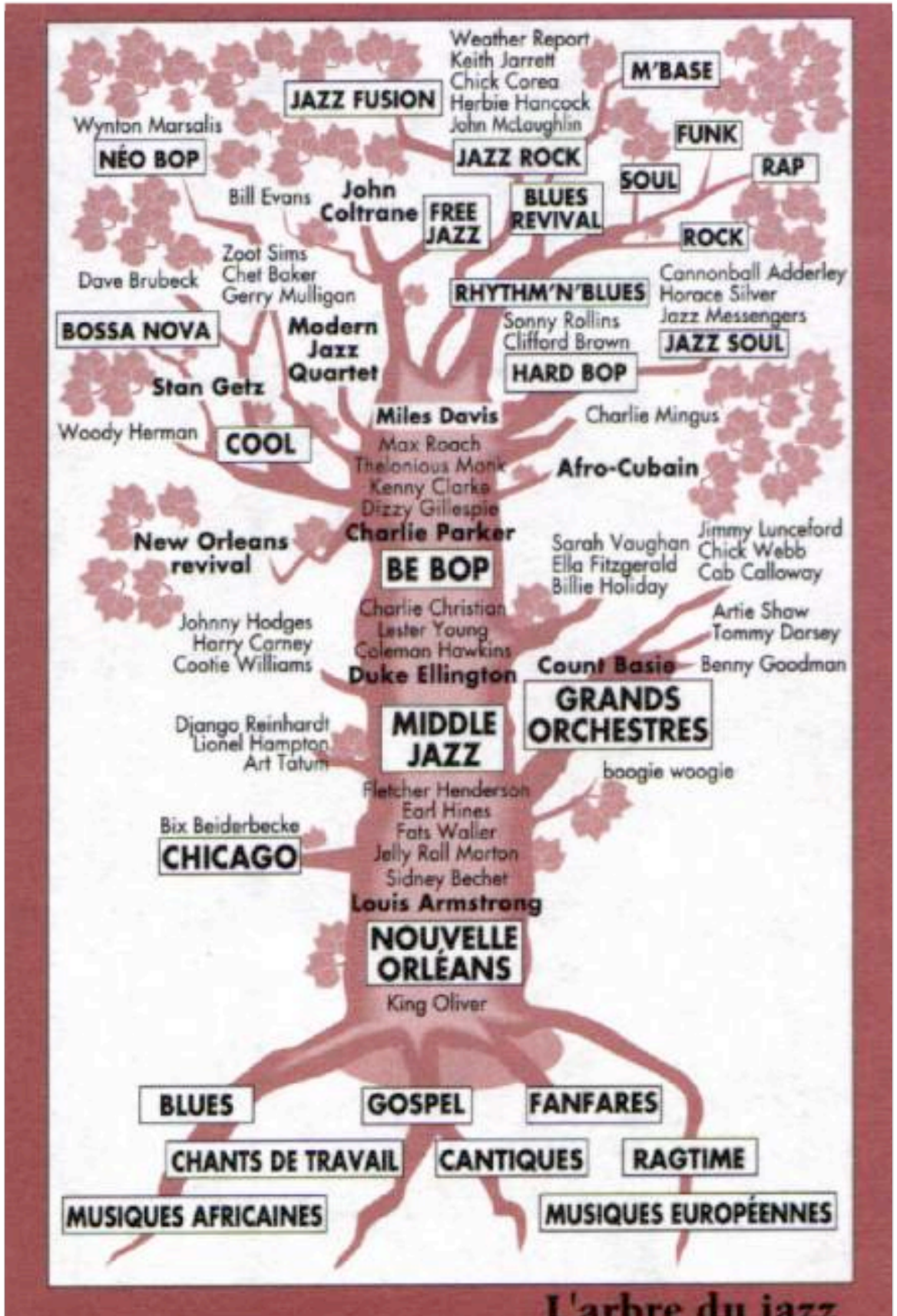
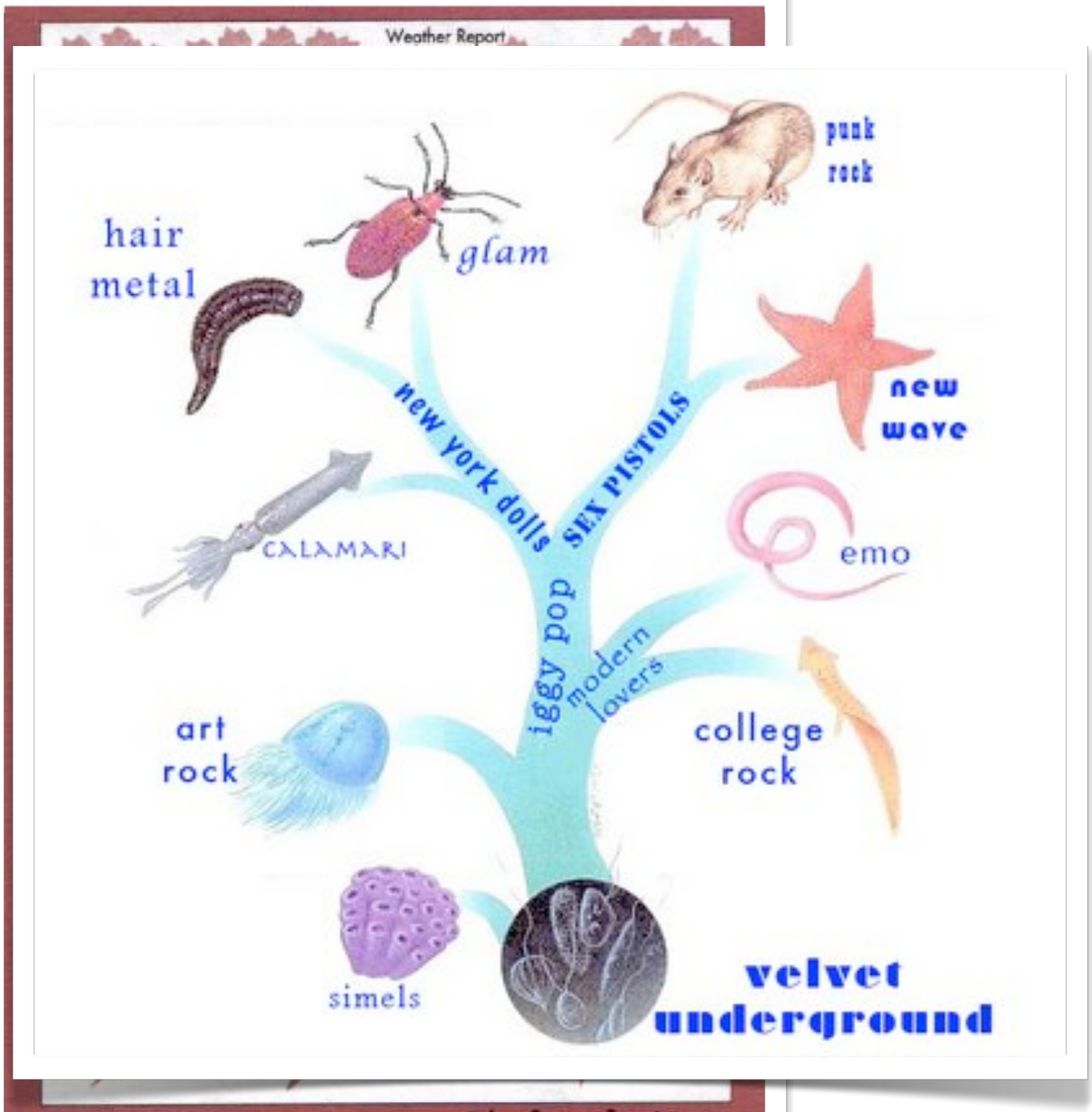


L'arbre du jazz

Handmade Genre Maps and Trees



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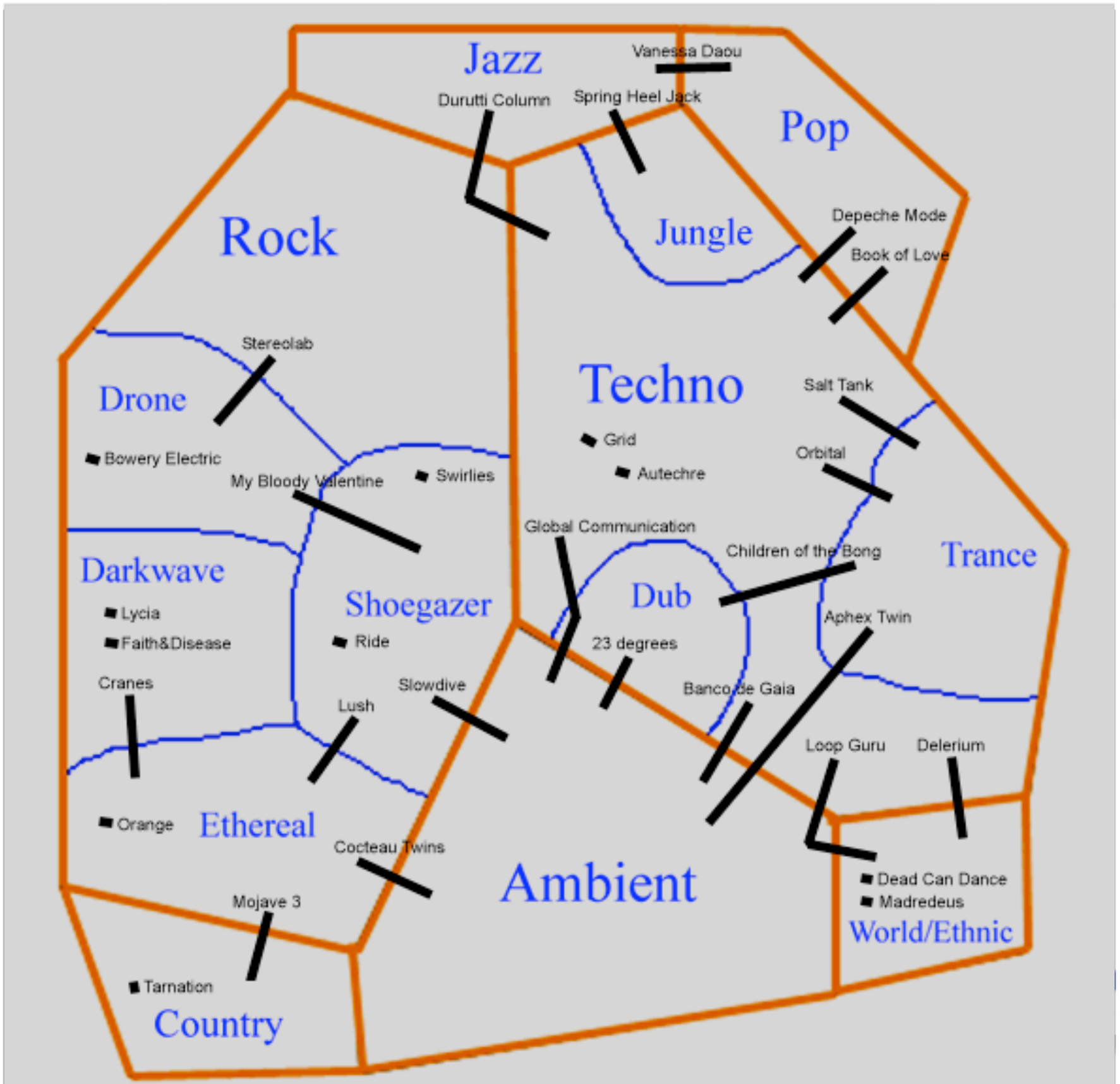

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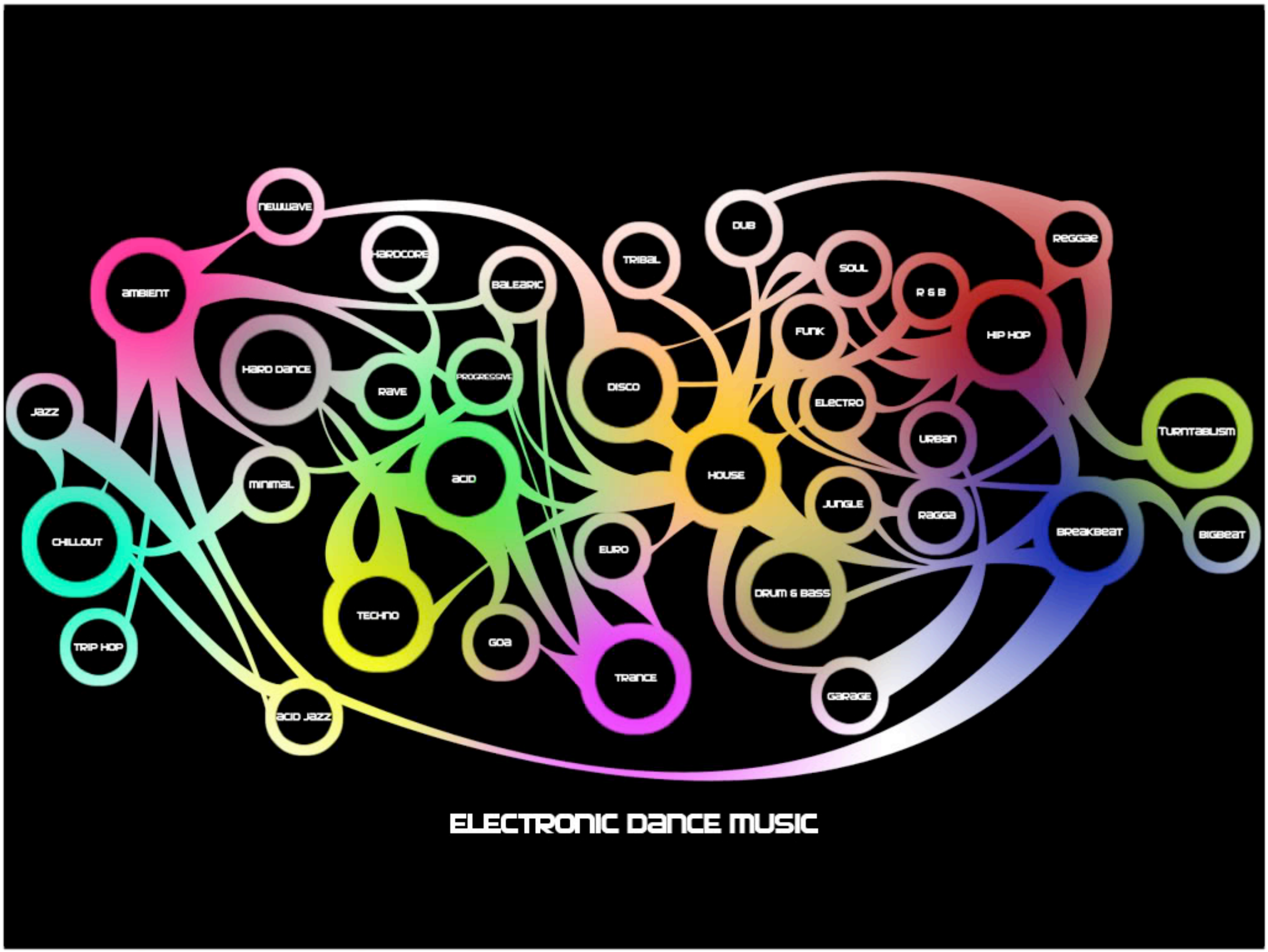

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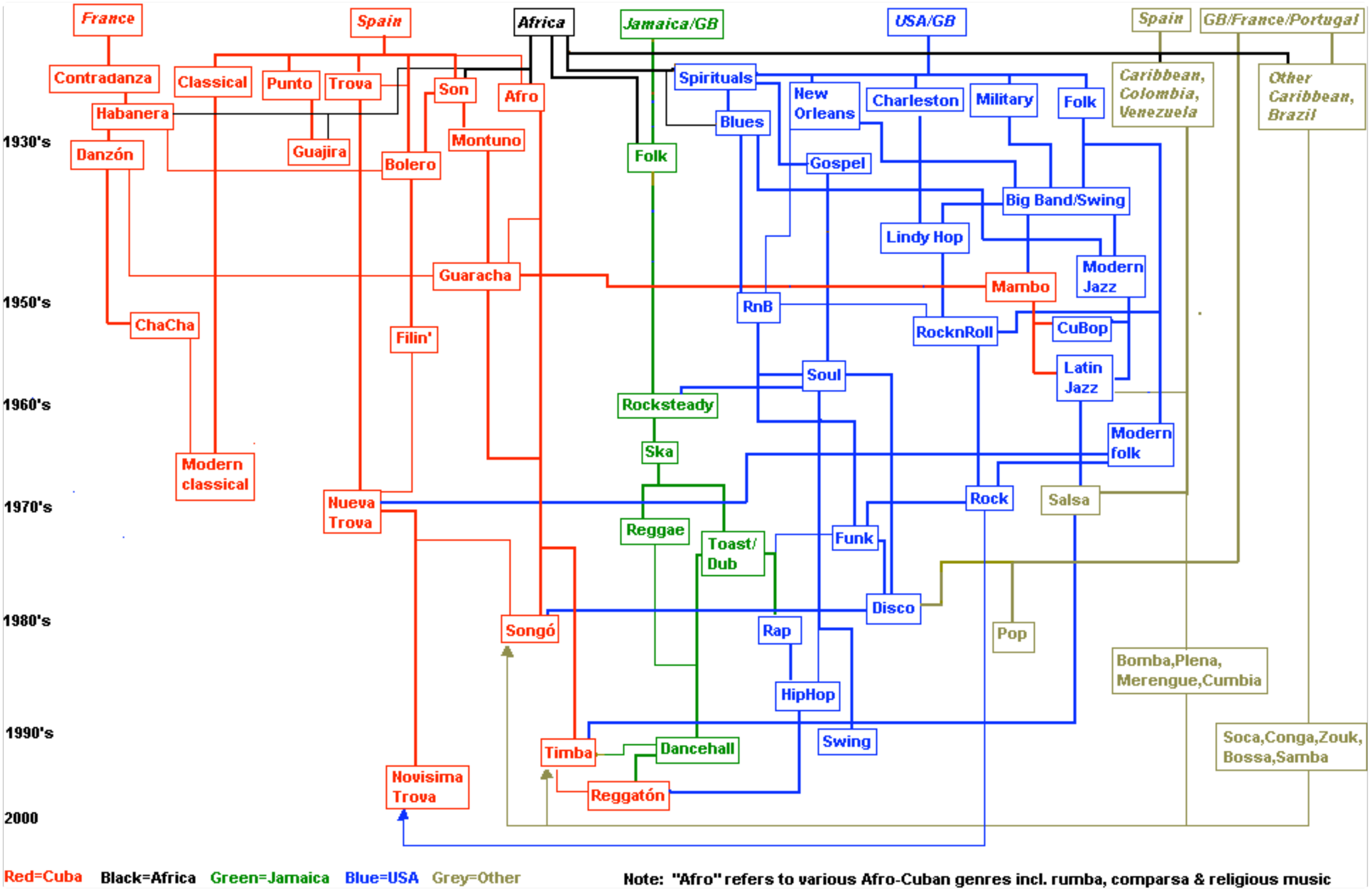
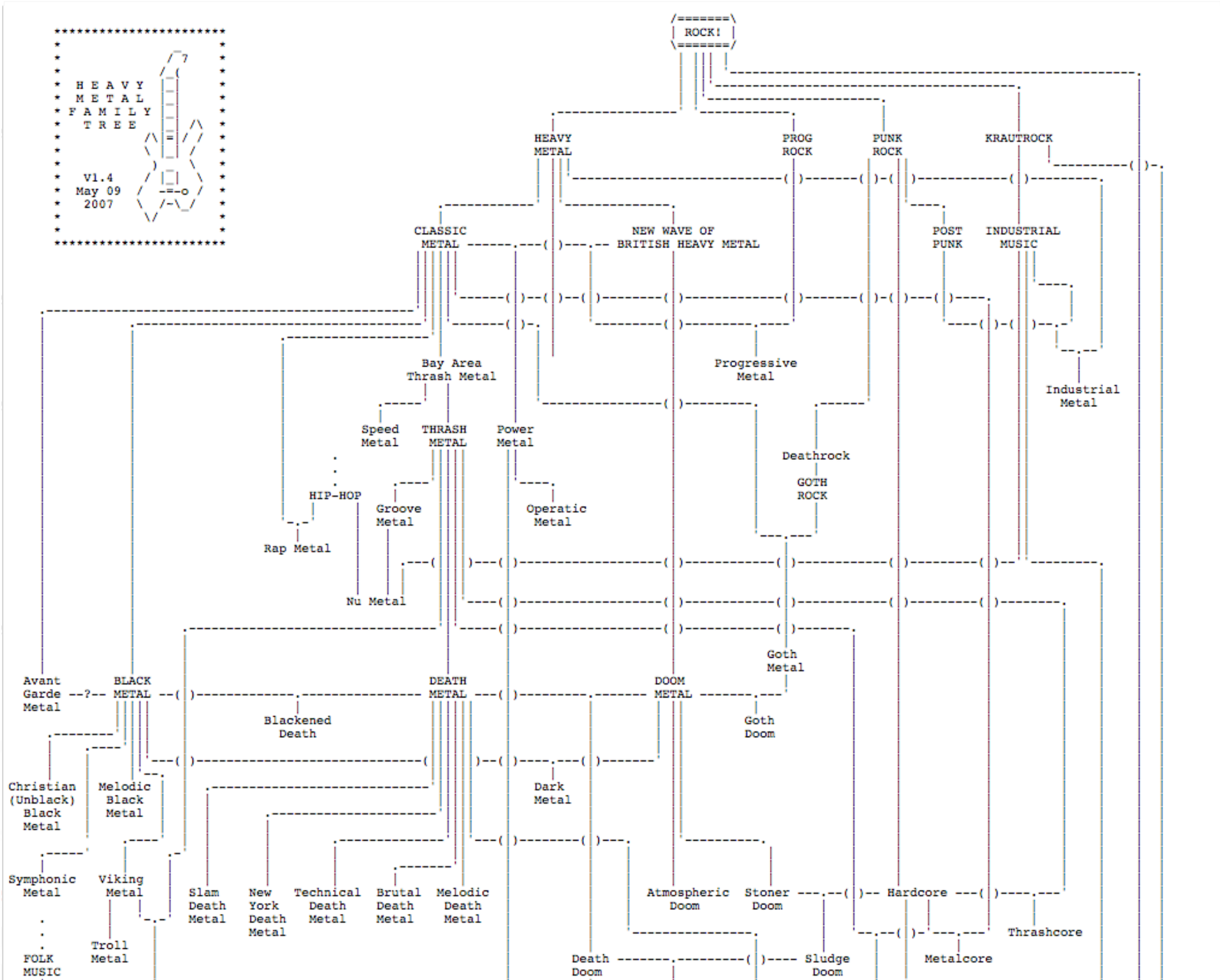
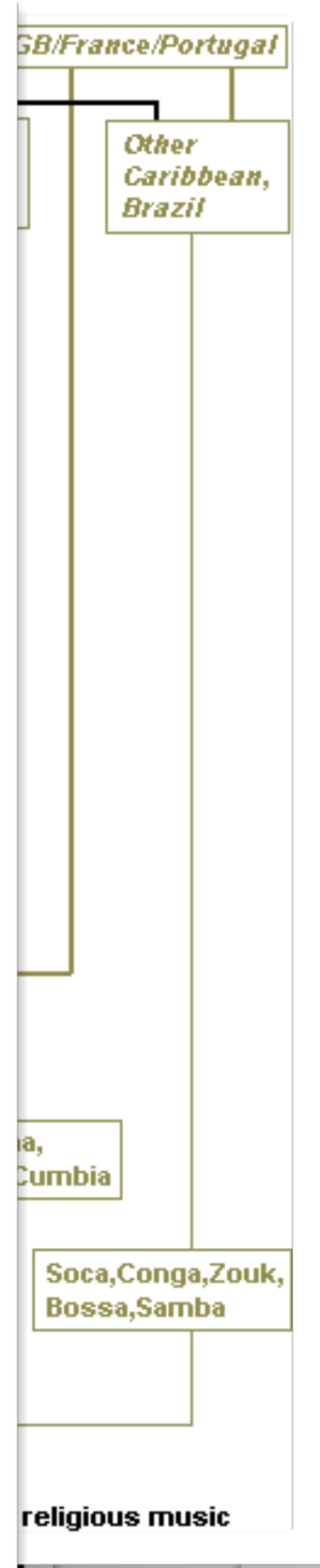


Handmade Genre Maps and Trees





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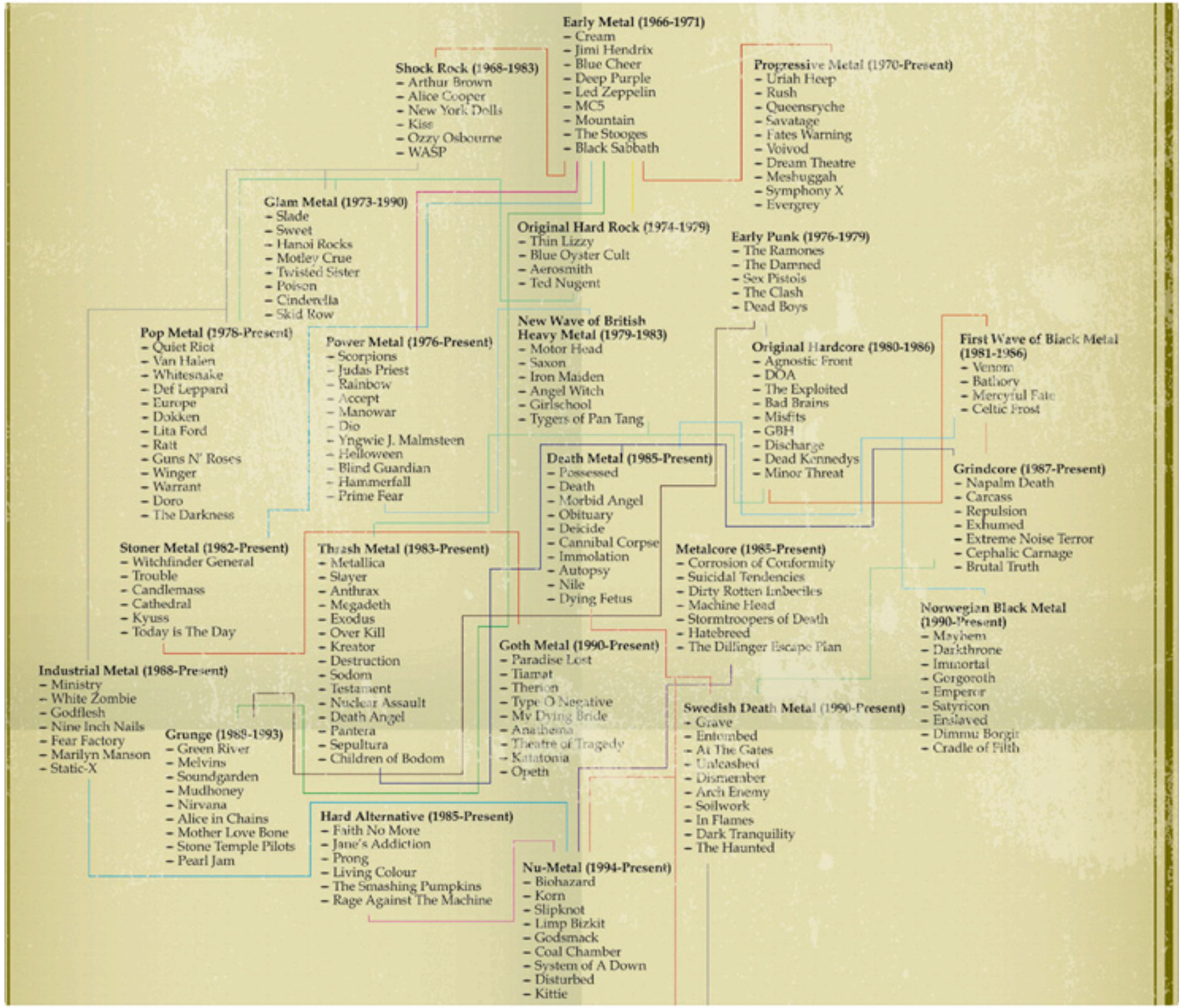
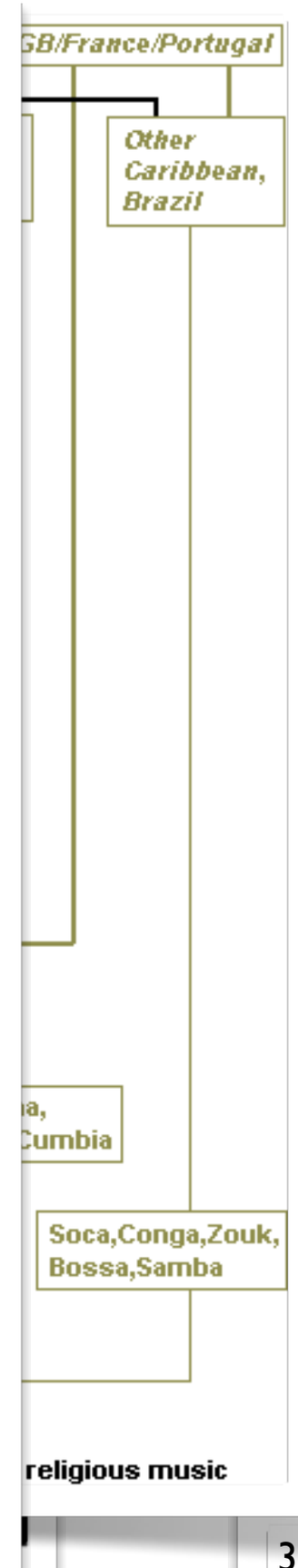
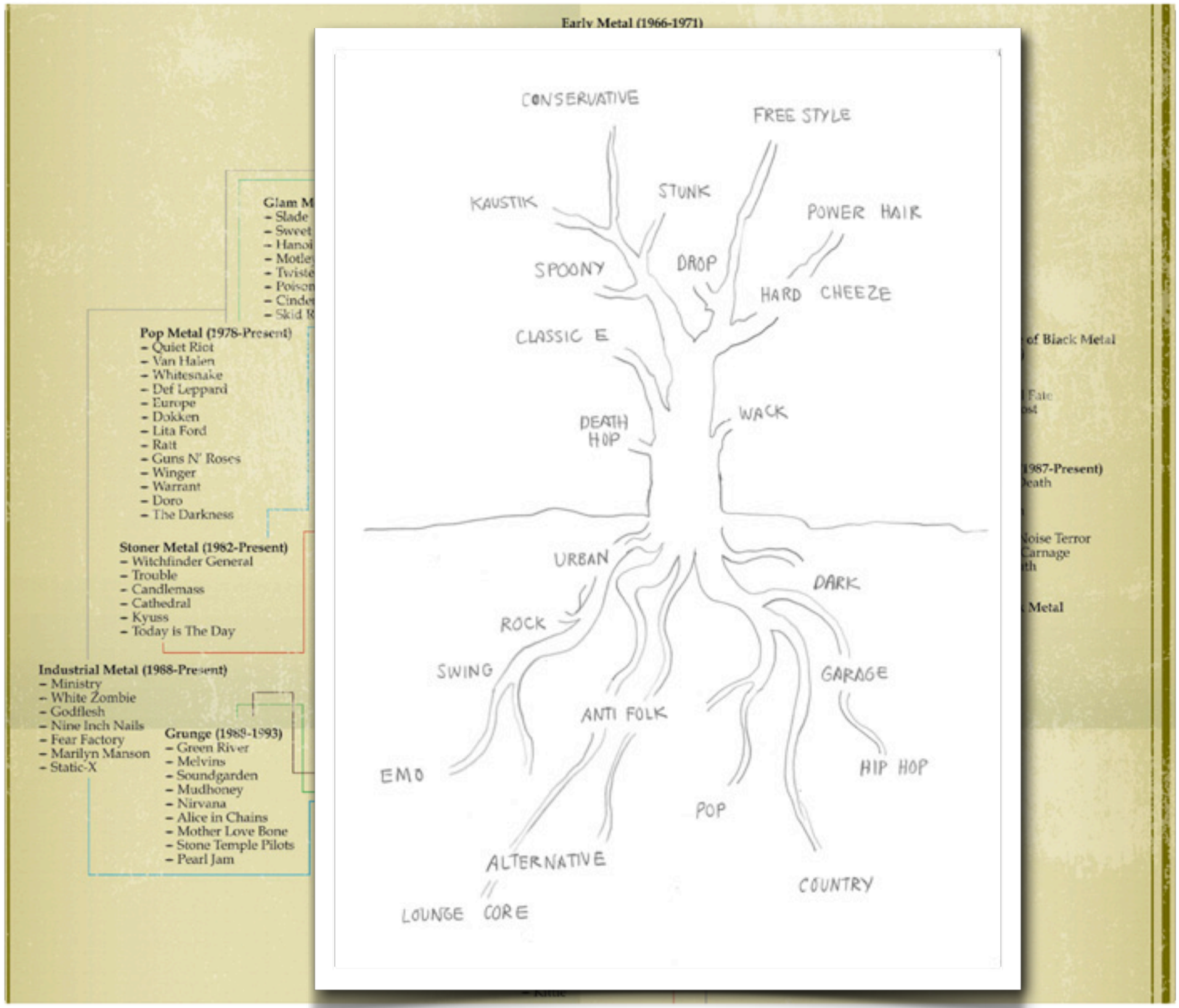
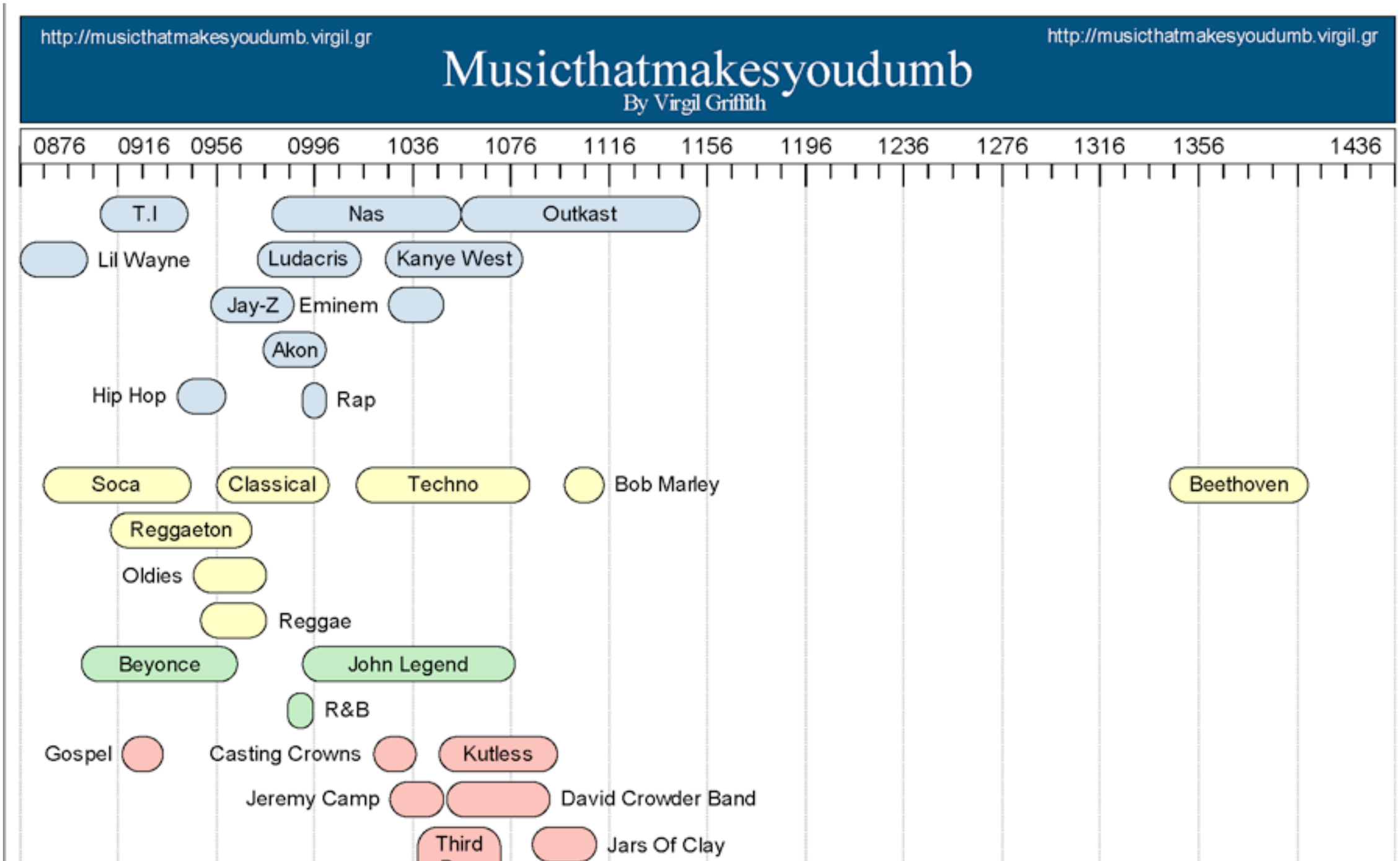




Handmade Genre Maps and Trees



Other types of visualizations



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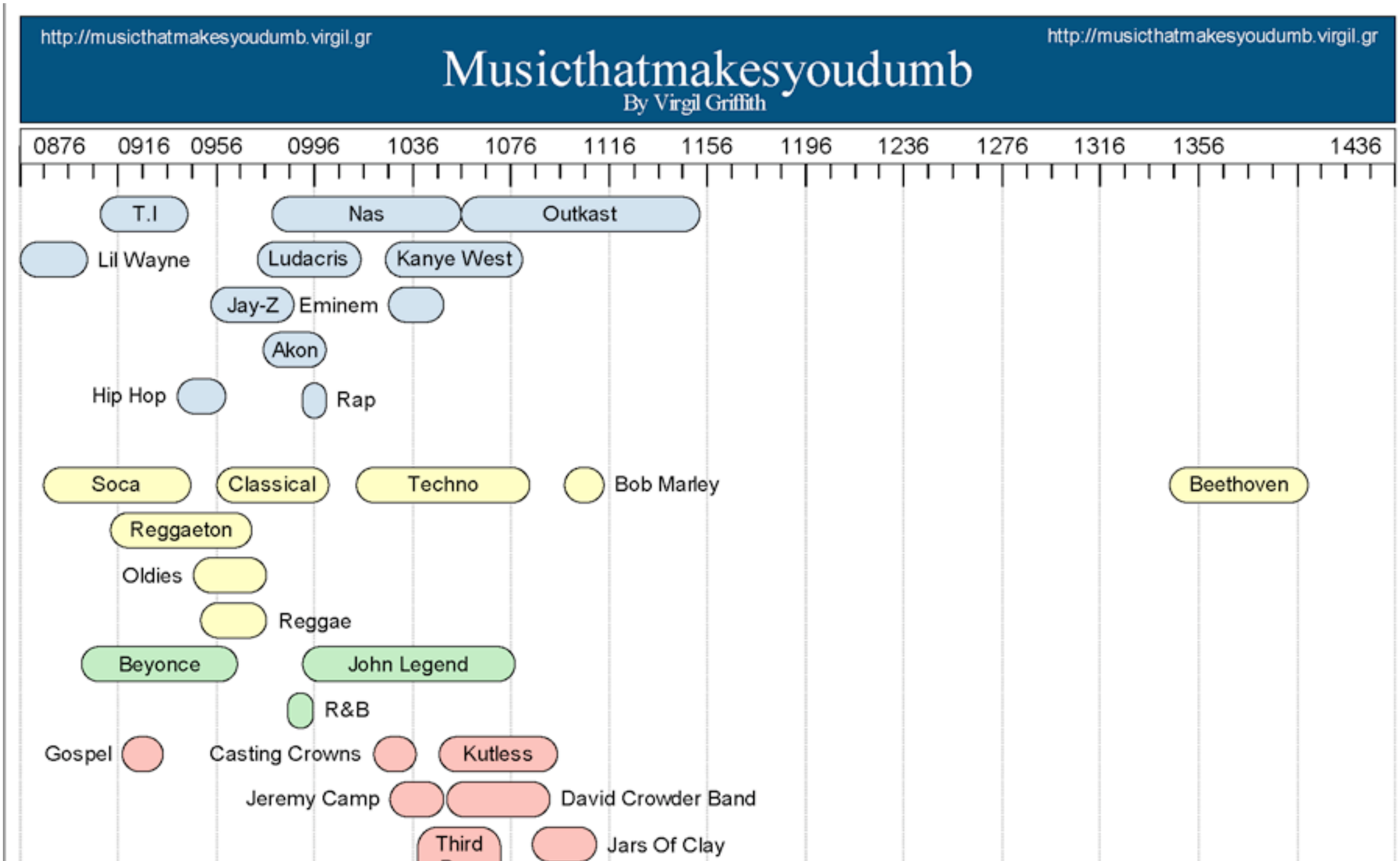

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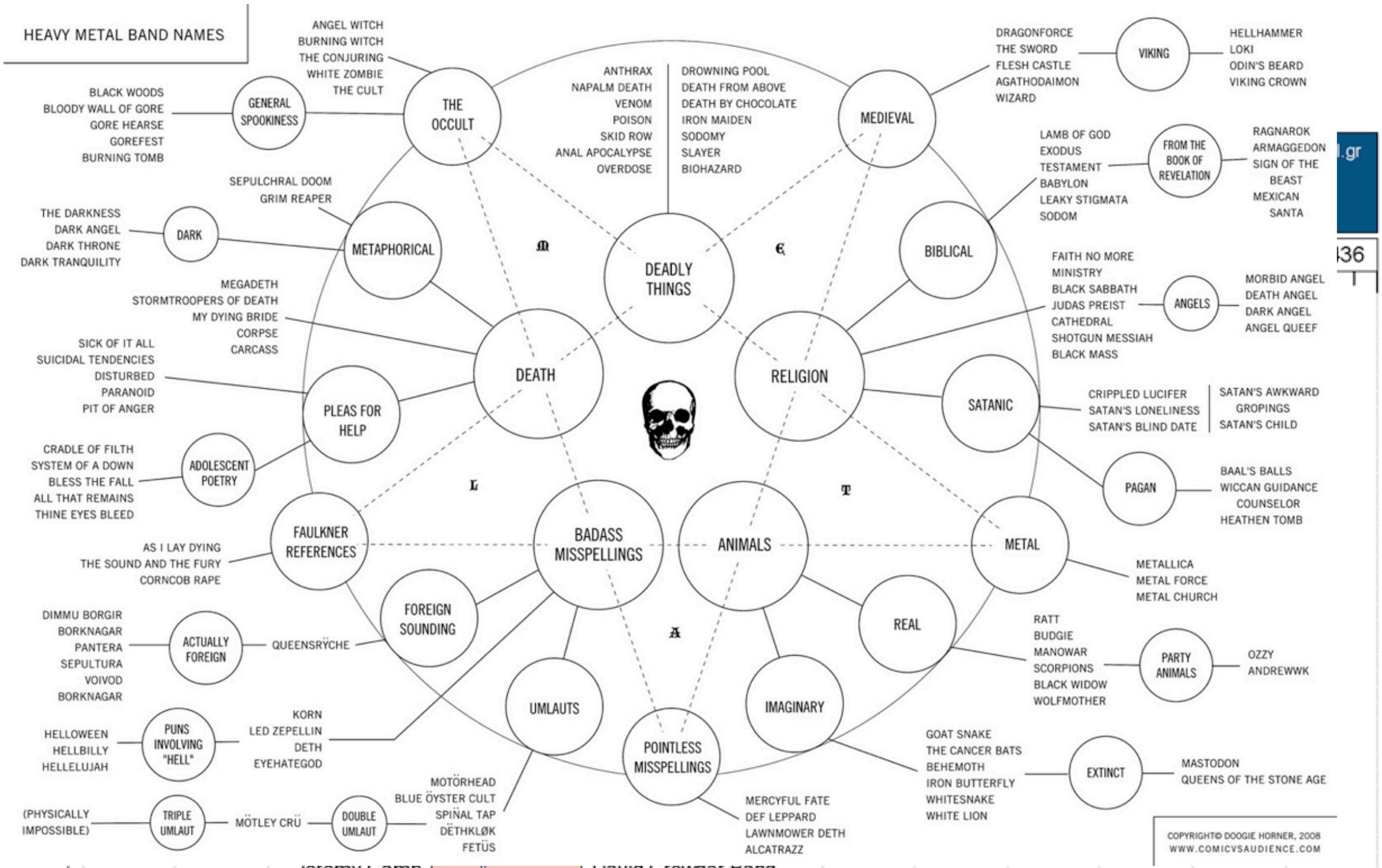

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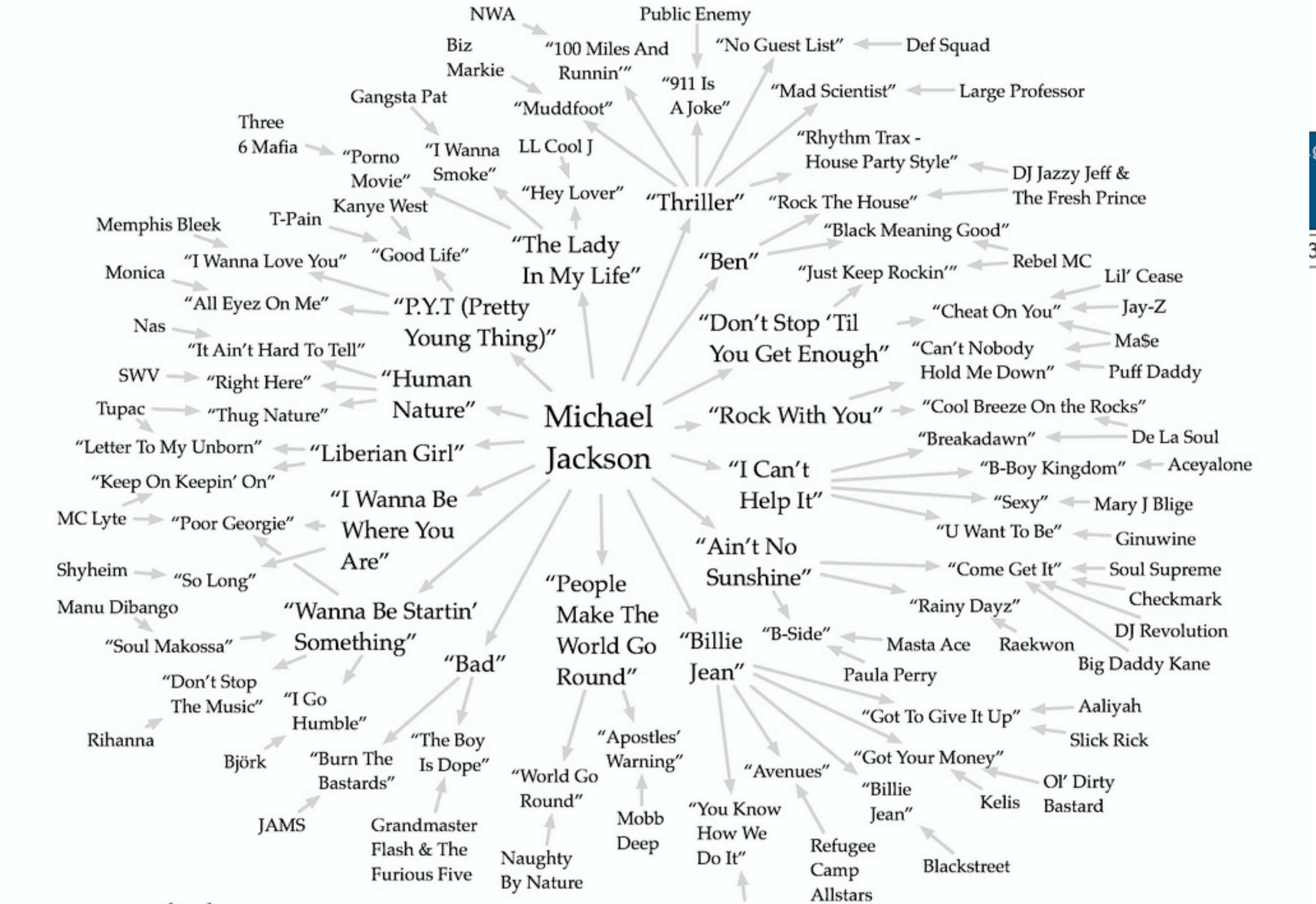

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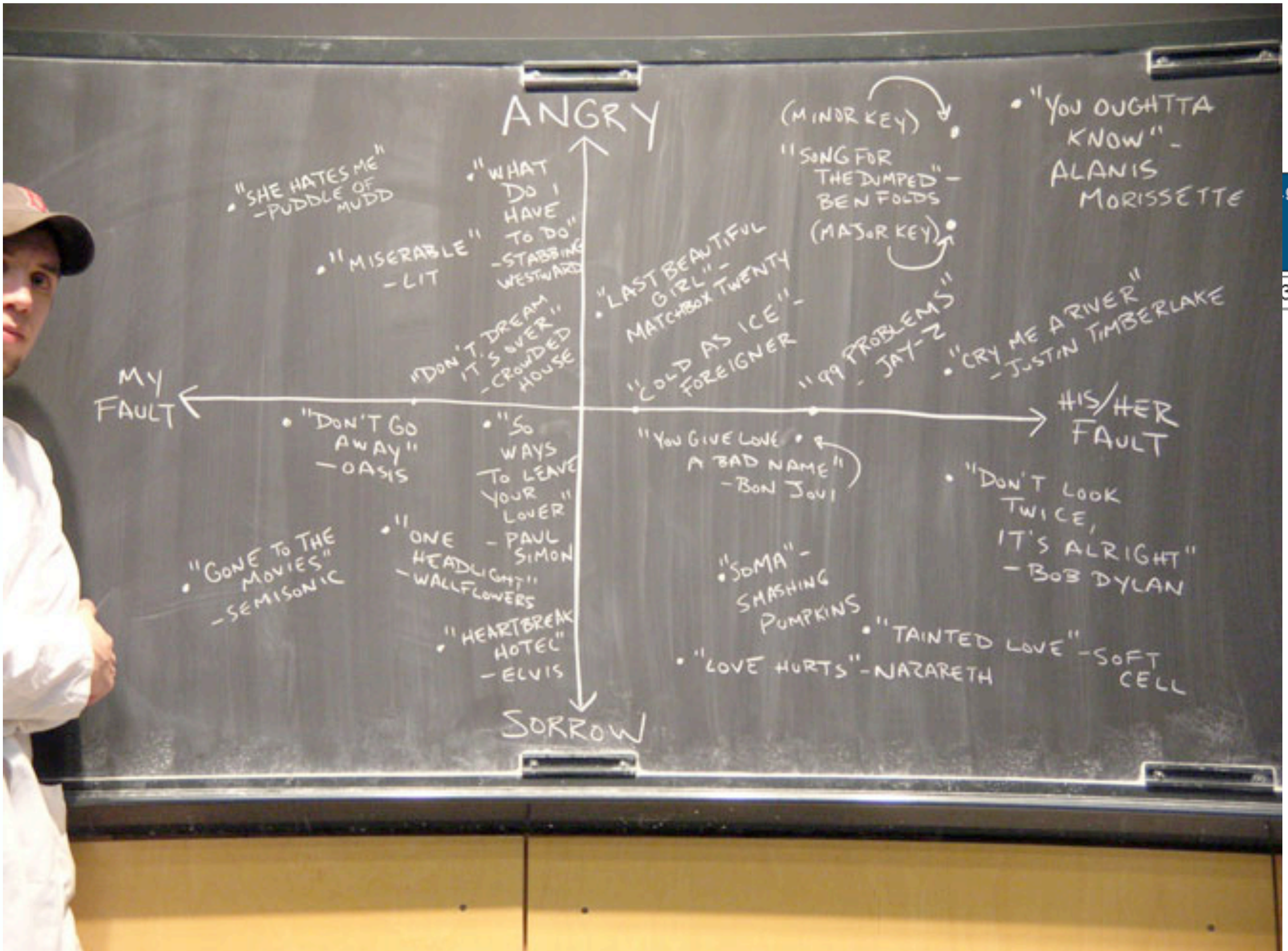
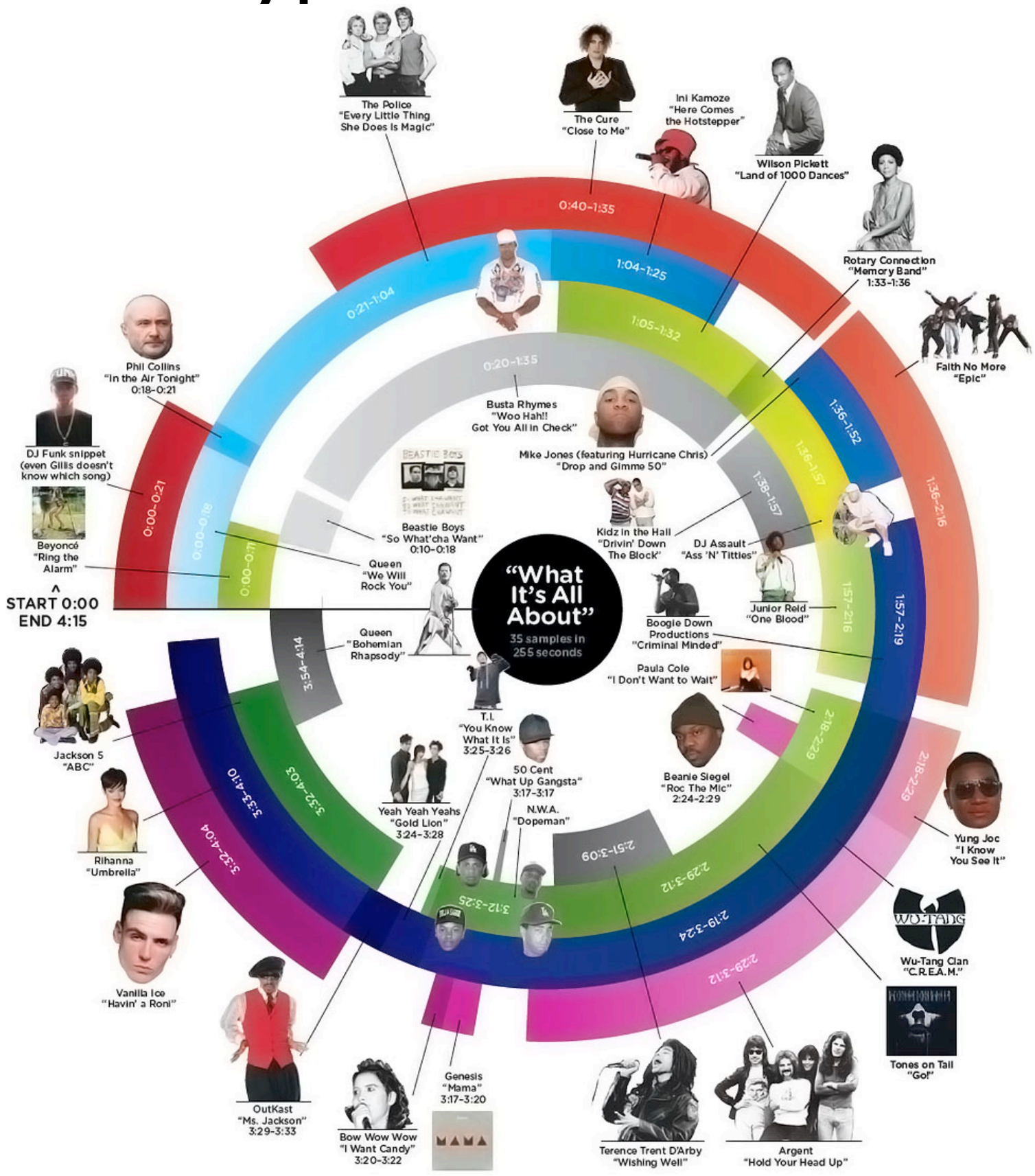
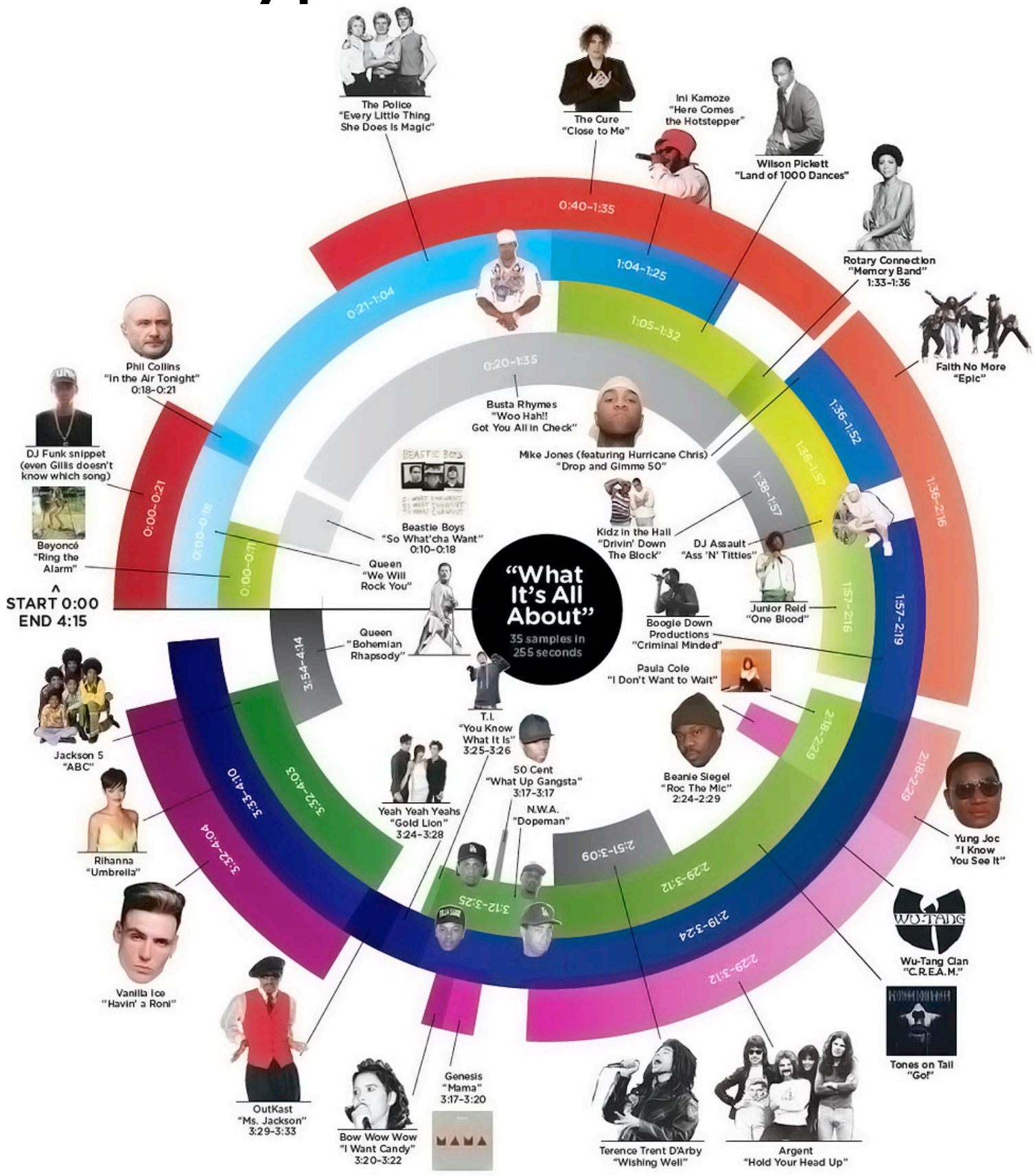


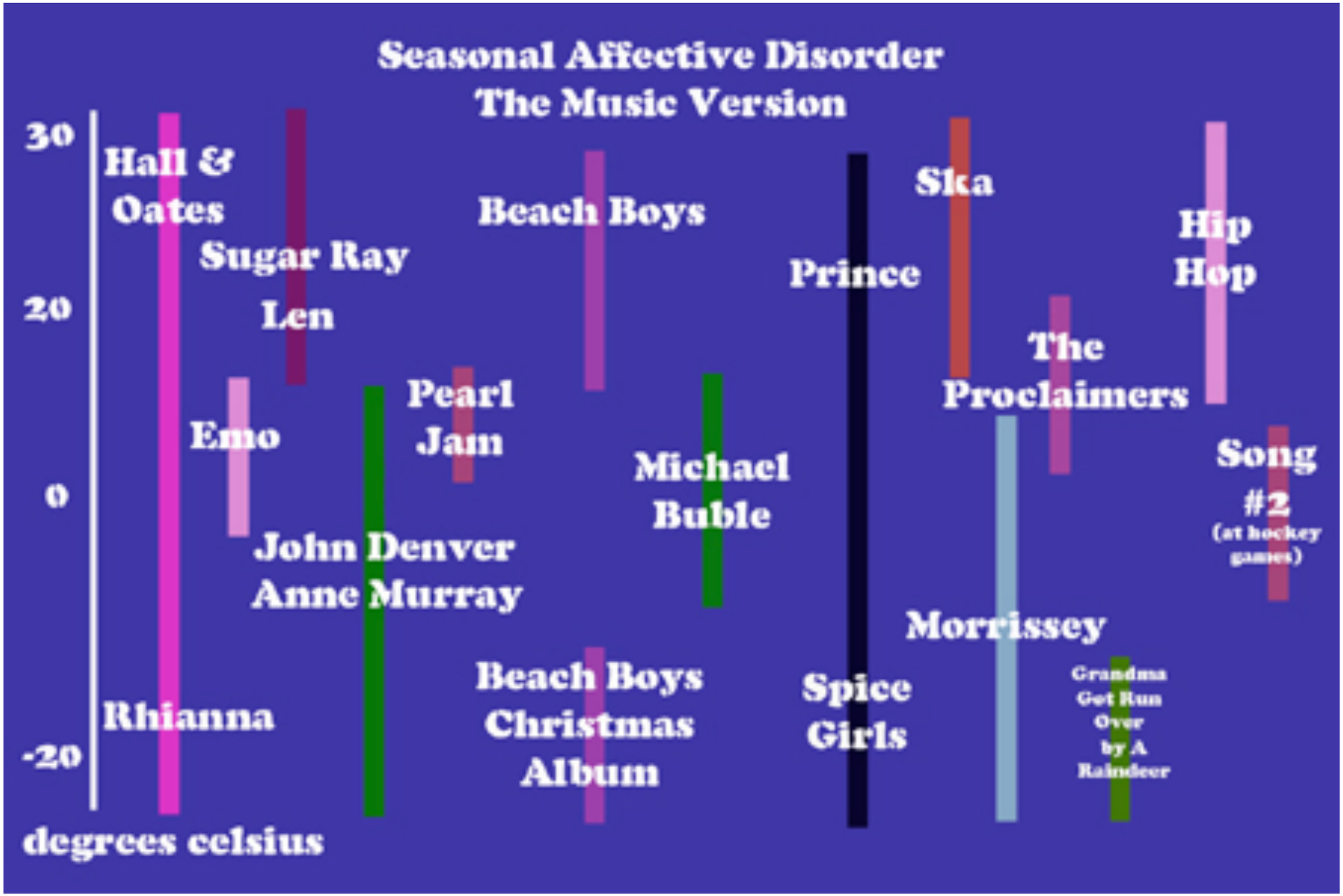
Other types of visualizations



Other types of visualizations



Artist as a function of temperature



ISMIR Tutorial 2005

Visualization for Music IR

Tutorial II,part 2

ISMIR2005 London UK

Stephan.Baumann@dfki.de

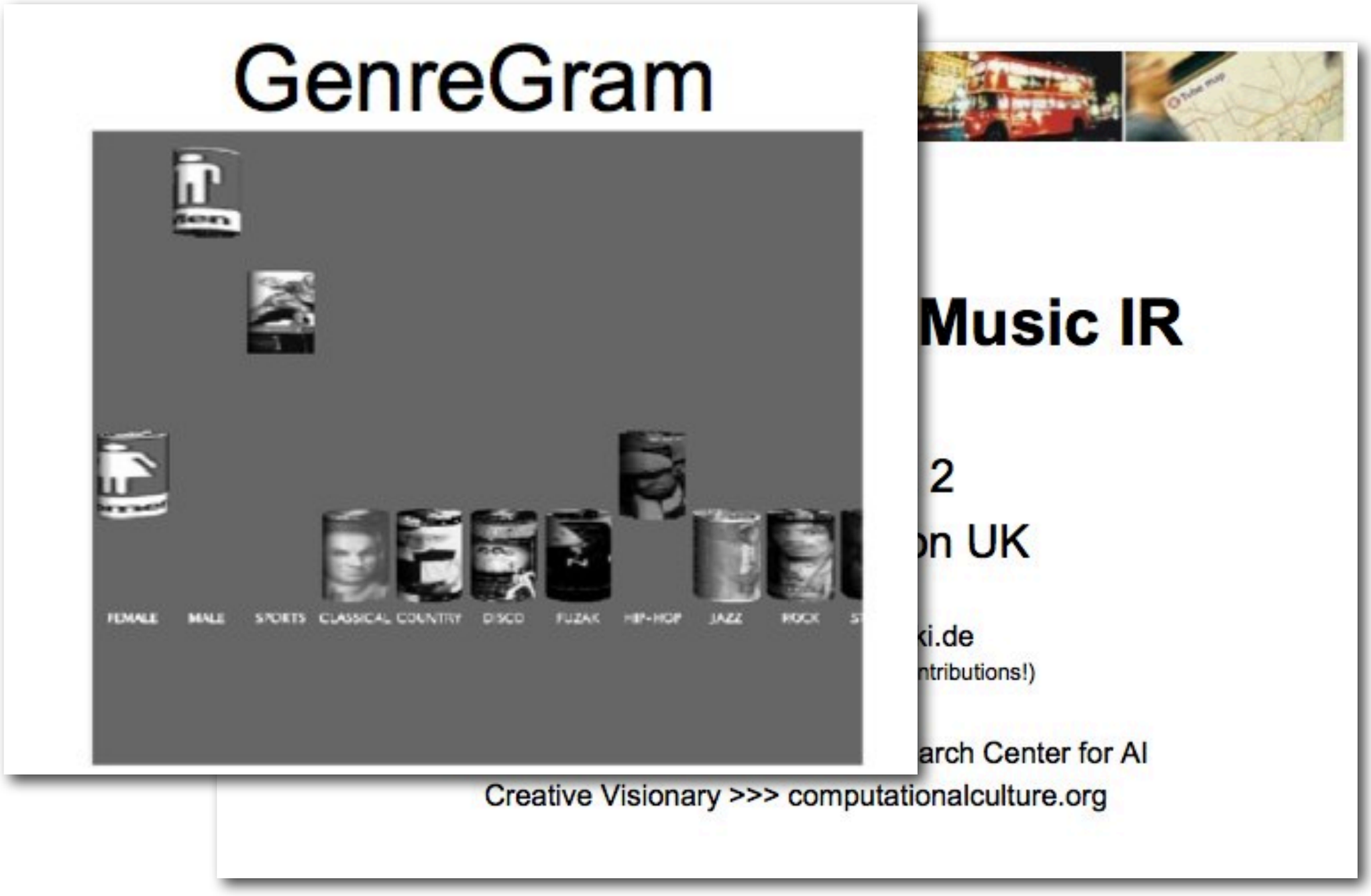
(Thanks to the authors of original contributions!)

Senior Researcher >> German Research Center for AI

Creative Visionary >>> computationalculture.org

Stephan Bauman -Senior Researcher - German Research Center for AI

ISMIR Tutorial 2005



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ISMIR Tutorial 2005

GenreGram

Powerwall of Tzanetakis

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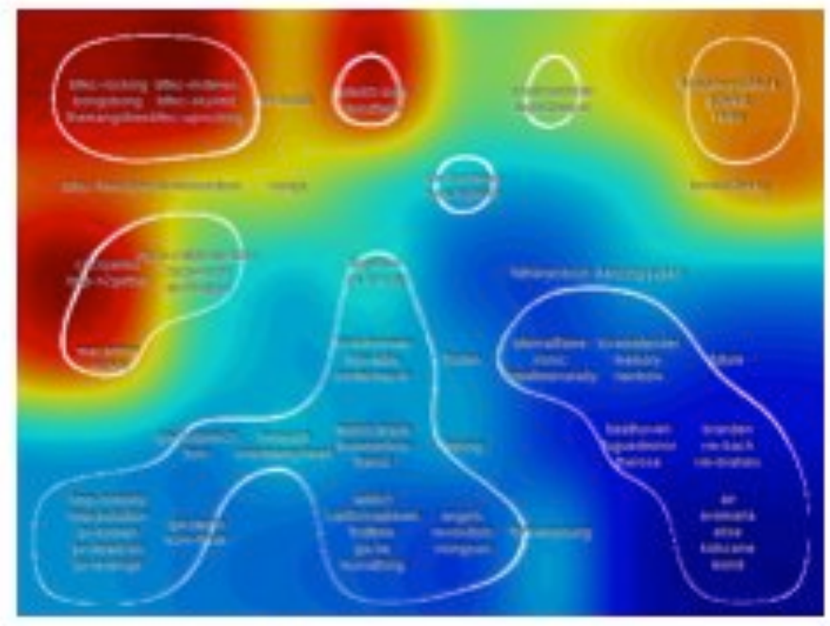
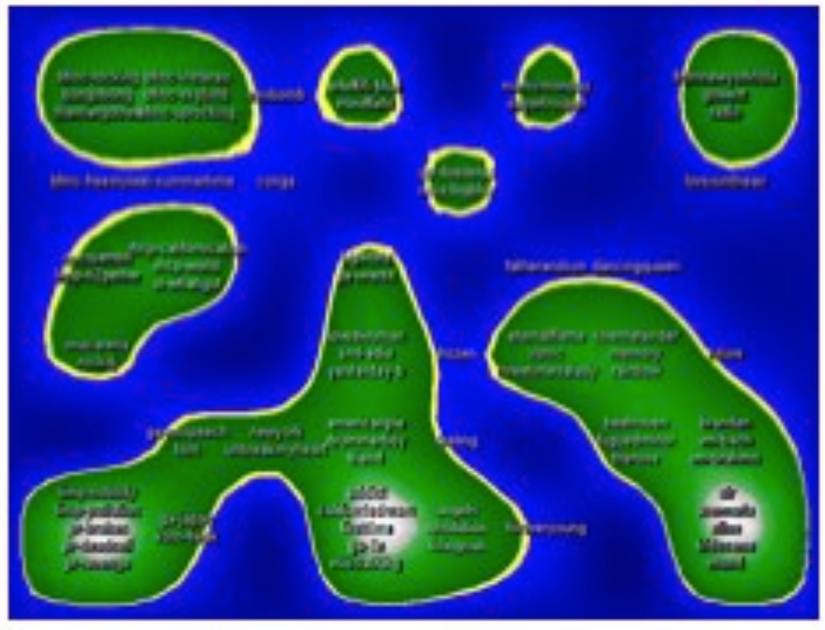
ISMIR Tutorial 2005

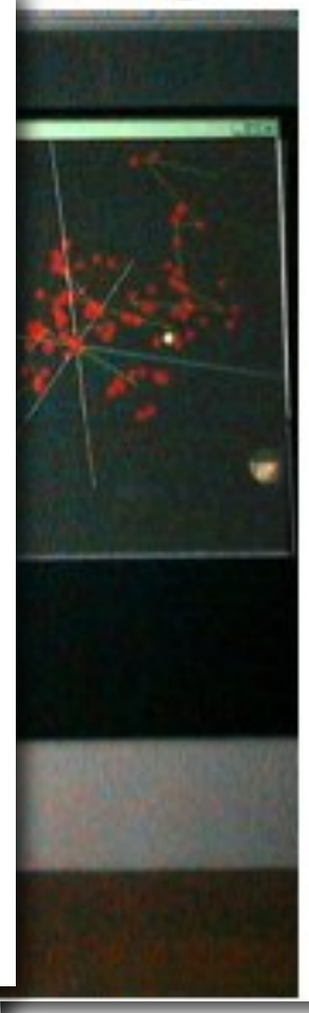
GenreGram

Powerwall of Tzanetakis

Weathercharts, Islands of Music







Stephan Bauman -Senior Researcher - German Research Center for AI

ISMIR Tutorial 2005

GenreGram

Weath

Visualization tool for ESOMs

MusicMiner

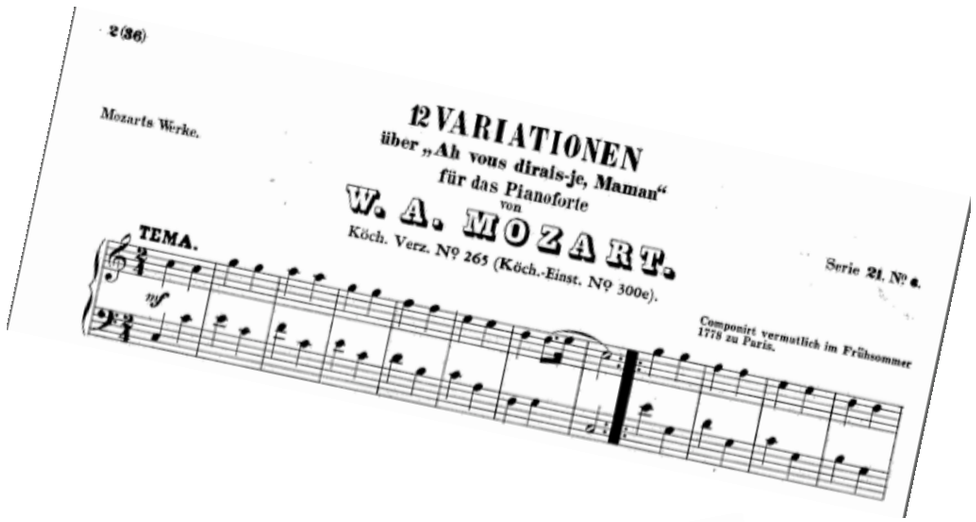
Kis

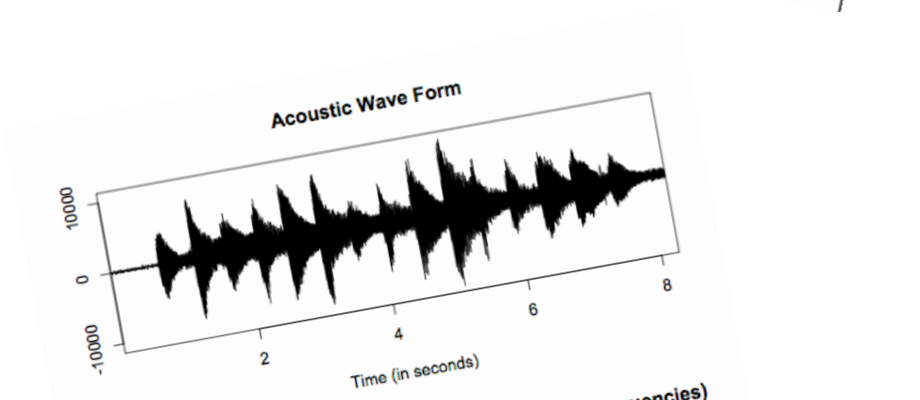
Stephan Bauman -Senior Researcher - German Research Center for AI

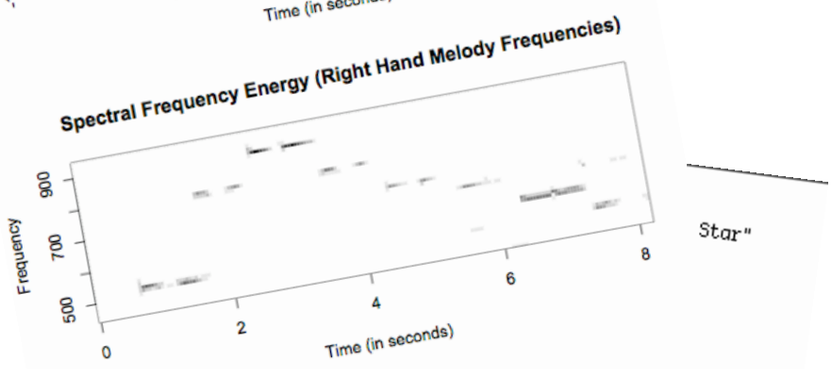
Core Concepts

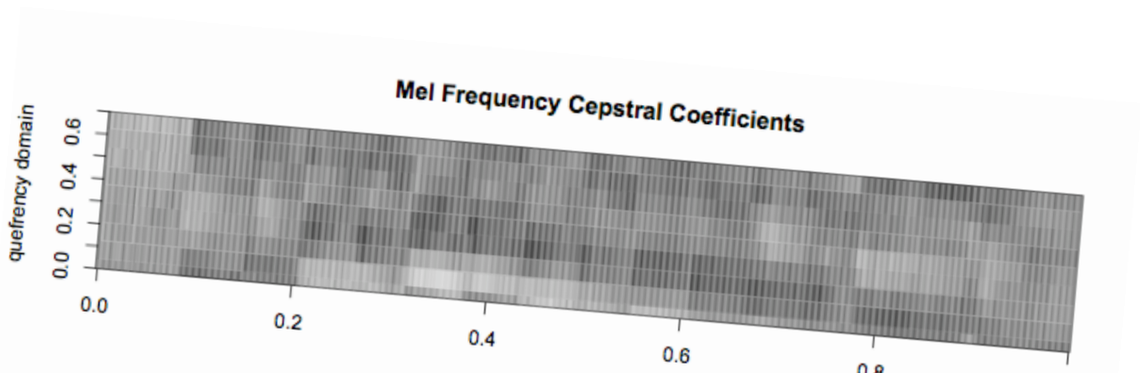
How do computers represent music?

- Score - As MIDI data
- Signal - As digital wave form
- Association - Through associations with tags, people, or other songs







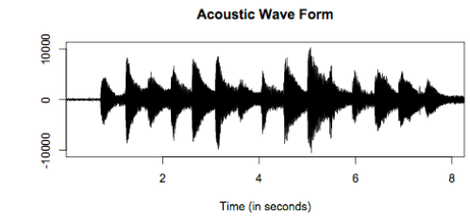


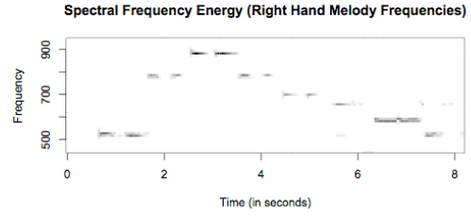
(a brief note on) Symbolic score data

- Typically provides an explicit compositional structure, and sometimes even explicit performance directions.
- “Easy” to analyze/extract meaningful musicological features (time signature, key, etc.)
- Scores are typically not present for most music, so other forms of representation are becoming popular.
- ***We won’t cover score based representations of music today.***

Acoustic Data

- Easy (and even occasionally legal) to find digital wave form representations of music
- New techniques, methods, and even services for music signal analysis.

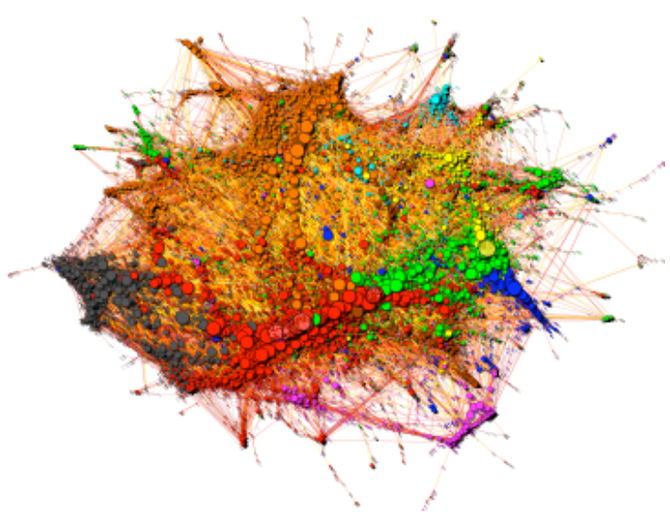


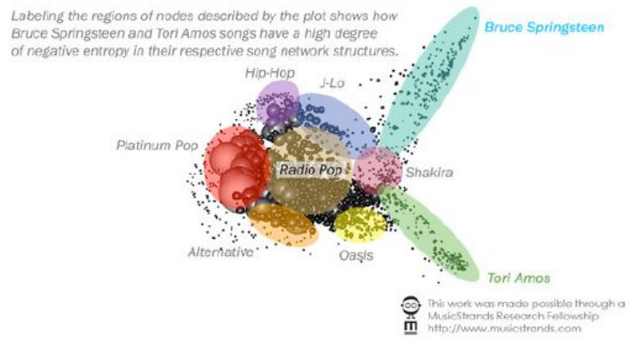


http://www.echonest.com/ http://www.magnatune.com/

Association Data

- Relatively new form of music analysis
- New methods/services as well
- What connections/ associations/relationships does music share with tags, people, playlists, other music?





http://www.last.fm
http://sixdegrees.hu/last.fm/
http://www.flickr.com/photos/scwn/153098444/
http://manyeyes.alphaworks.ibm.com/manyeyes/visualizations/matchbox-20-song-lyrics-tag-cloud

Representing "Lots of Songs"

- Many different types of music-related information.
- Problems of sparsity, noise, data set size.
- We need a common appropriate *format of representation* and *method of comparison.*
- We would like to work with matrices.

Song	Feature1	Feature2
"Love me do"	0.4	0.9
"Hound Dog"	3.2	1.4
"Paint it Black"	3.4	1.5

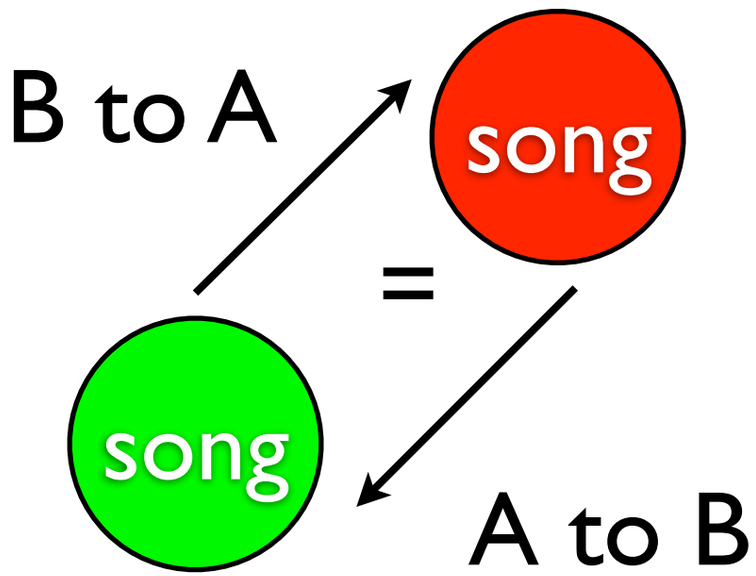
Distances and Similarity

- To form a two/three dimensional visualization, we will need to express a *distance* or *dissimilarity** between the songs in vector form.

- Distance *must be* symmetric in order to represent a metric space.

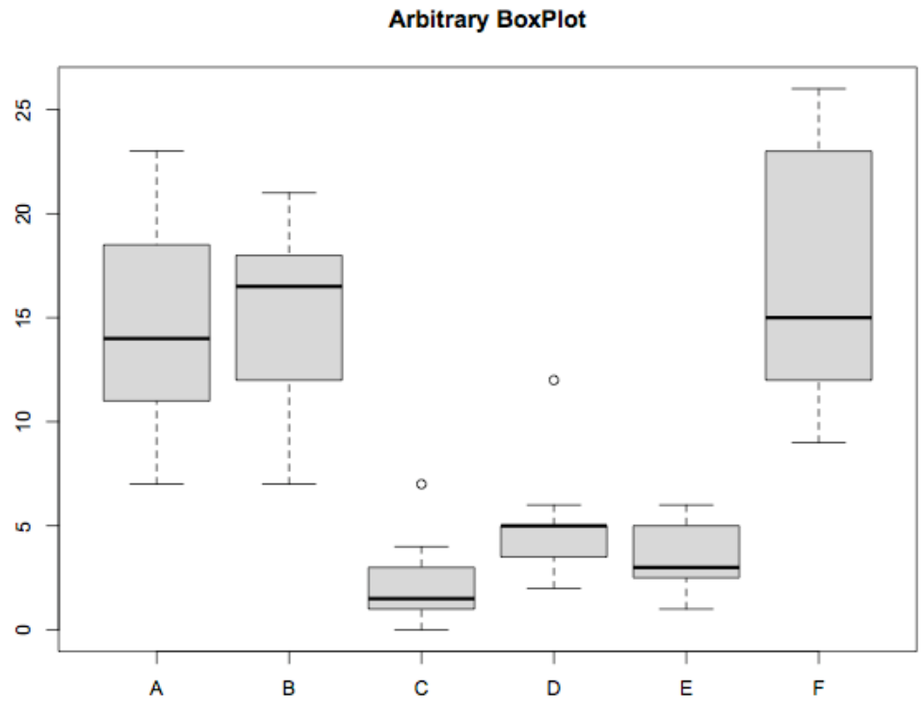
- Distance must be "non-degenerate" (distance from song A to song A == 0)

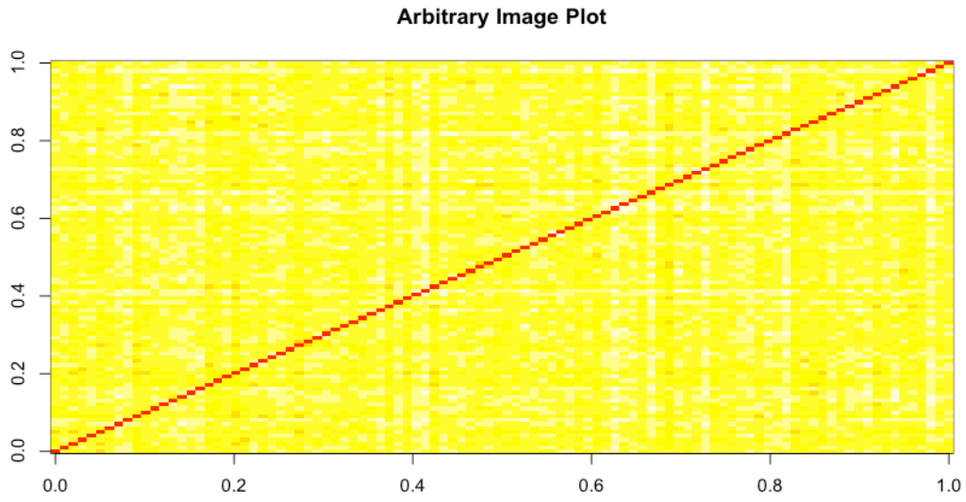
Song	"Love me do"	"Hound Dog"	"Paint it Black"
"Love me do"	n/a	3.2	3.4
"Hound Dog"	3.2	n/a	1.5
"Paint it Black"	3.4	1.5	n/a

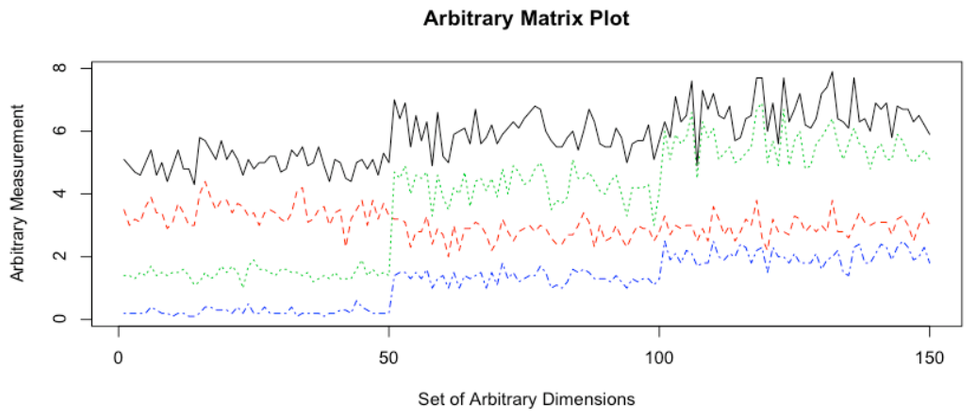


"Big Picture" Visualization

- A couple of "simple" visualizations help to assess variance, etc. across the relevant dimensions.
- Boxplots, matrix plots, image plots, etc.
- Selectively normalizing data at this point to have more control, and removing obvious outlier (points/dimensions).





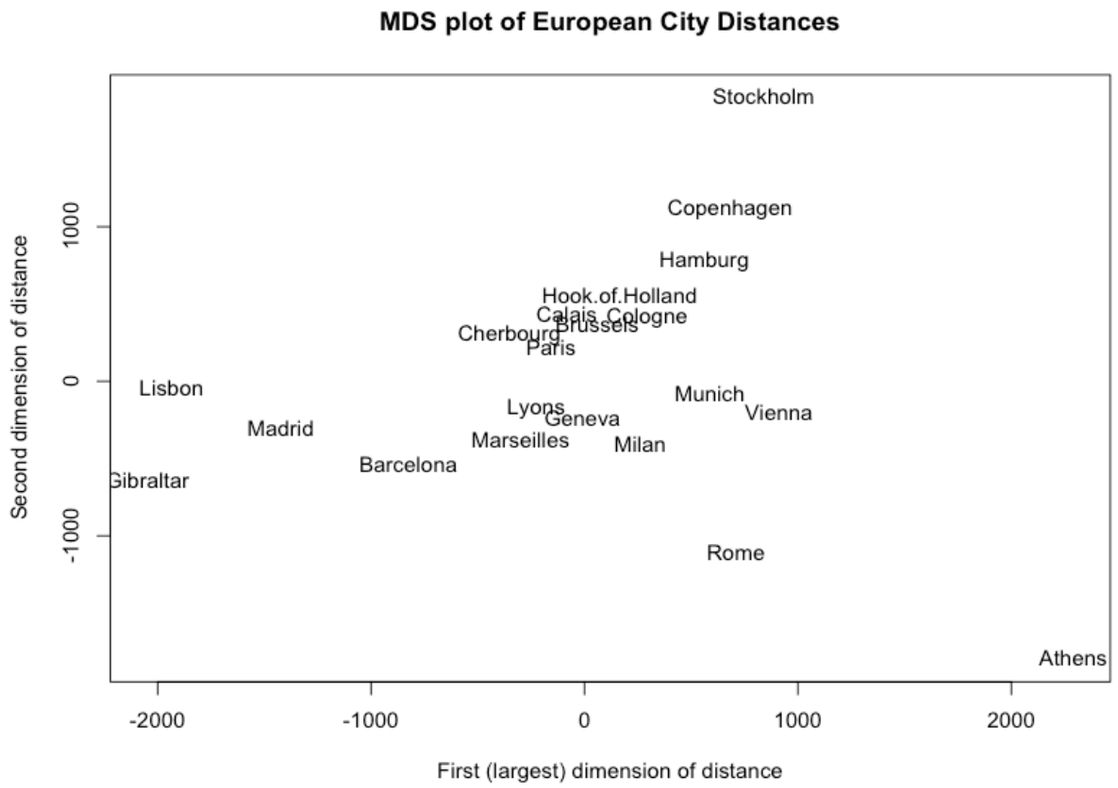


Multidimensional Scaling

- *Reducing* the number of dimensions of the music vector.

	Athens	Barcelona	Brussels	Calais	Cherbourg
Athens	0	3313	2963	3175	3339
Barcelona	3313	0	1318	1326	1294
Brussels	2963	1318	0	204	583
Calais	3175	1326	204	0	460
Cherbourg	3339	1294	583	460	0
Cologne	2762	1498	206	409	785

- Similar to "rotating" the data to find large dimensions of variation/ dissimilarity in the data.



http://www.mathpsyc.uni-bonn.de/doc/delbeke/delbeke.htm

DEMO

Demo: Acoustic Feature Vectors

- Working with *Magnatagatune dataset*
- Combination of:
  - Magnatune creative commons licensed songs (clips)
  - Tagatune project data
  - **Echo Nest feature data**
- Freely available

The dataset consists of the following files:

clip_info_final.csv.bz2	audio clips information, such as title, artist, album, url, start and end time, download URL for the mp3 file (entire song), and path to the mp3 clip.
annotations_final.csv.bz2	tags associated with each audio clip, and path to the clip mp3 file.
comparisons_final.csv.bz2	similarity judgments (number of people who voted that a particular clip is the most different) associated with a tuple of audio clips, and paths to the mp3 clips.
clips.tar	TAR archive with all the audio clips as 16kHz, 32kbps, mono mp3.
mp3_echonest_xml.zip	The Echo Nest analysis of each of the clips in XML format.

http://tagatune.org/Magnatagatune.html

Demo: Feature Vector

Echonest data includes:

- loudness
- tempo
- segments with:
  - pitch information
  - timbre information


```
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        – <pitches>
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            <pitch class="2">0.061</pitch>
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          </timbre>
```


http://tagatune.org/Magnatagatune.html

Demo: Feature Vector

Demo motivation

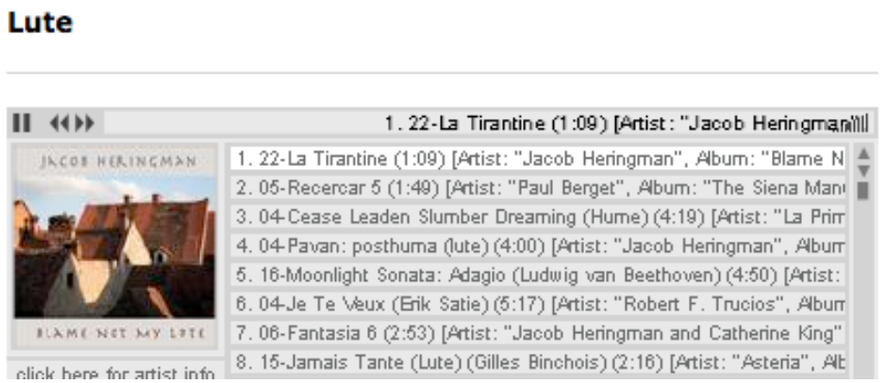
- Genre classification has become a prominent trend in the IR community. Explore the data pertaining to such systems.
- Current approaches can identify "textural" properties of acoustic sound, but can lack cultural or structural properties of music. West & Lamere note that:
  "...a common example might be the confusion of a classical lute timbre, with that of an acoustic guitar string that might be found in folk, pop, or rock music..."

K. West and P. Lamere, "A model-based approach to constructing music similarity functions," *EURASIP Journal on Advances in Signal Processing* 2007 (2007).

Demo: Feature Vector

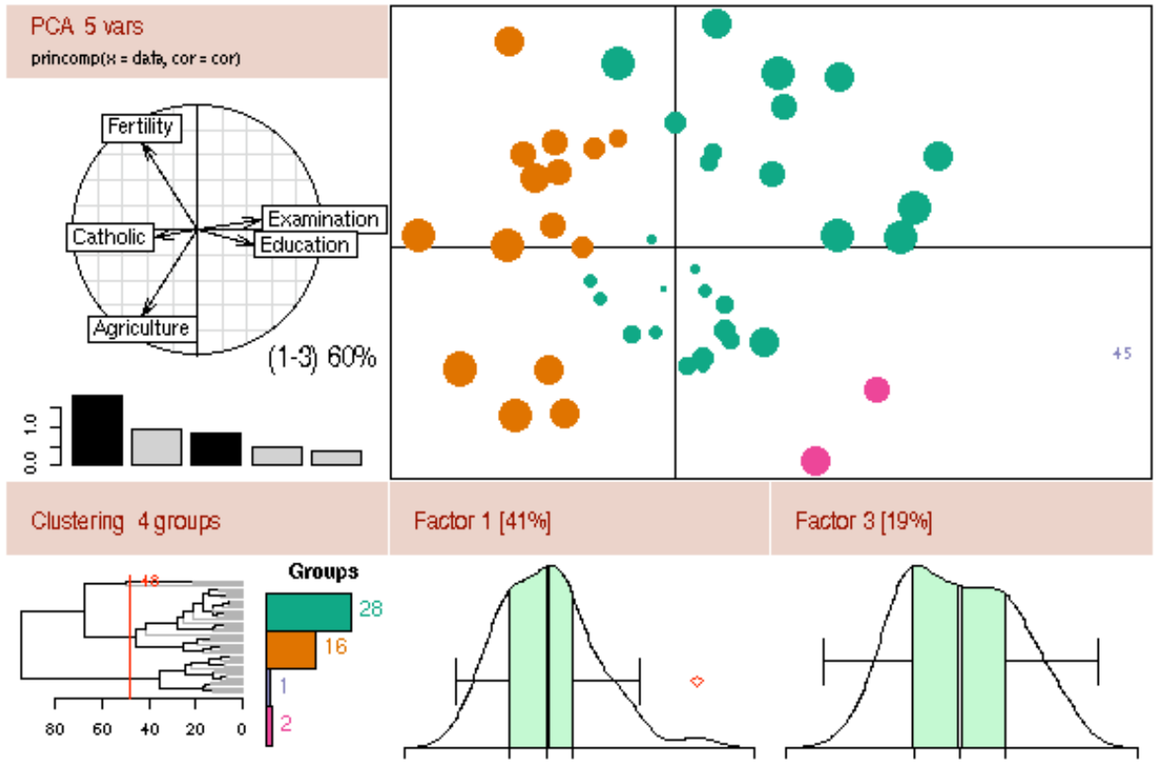
Demo motivation

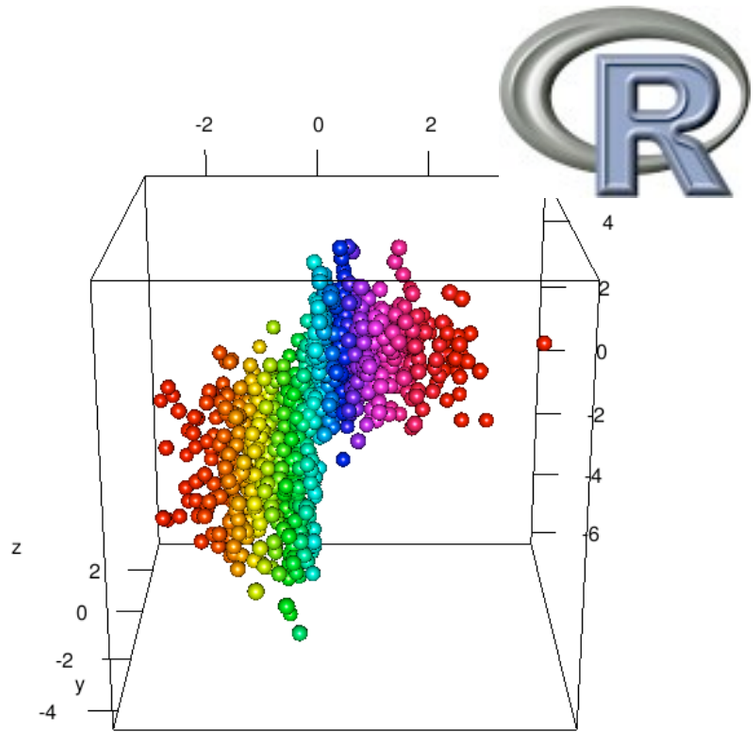
- Magnatagatune happens to have a large amount of Classical music, and Classical Lute music to boot.
- We'll try to visualize this part of the magnatagatune data set, along with folk music.



Tools

Tools: Feature Vector





- Download Data
- Use **R** to process, analyze, and visualize data
- Free! (Libre!)

http://cran.r-project.org/

http://www.cyclismo.org/tutorial/R/

http://cran.r-project.org/doc/manuals/R-intro.html

Demo: Feature Vectors

Demo: Feature Vector

Basic Echo Nest Features

- (overall) loudness
- tempo
- pitch means (12) *
- pitch stdev (12) *
- timbre means (12) *
- timber stdev (12) *


```
– <analysis decoder="Quicktime" version="0x7608000">
  – <track duration="29.12331" endOfFadeIn="0.00000" startOfFadeOut="29.12331"
    mode="1" modeConfidence="1.000">
    + <meter></meter>
    + <sections></sections>
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            <pitch class="2">0.061</pitch>
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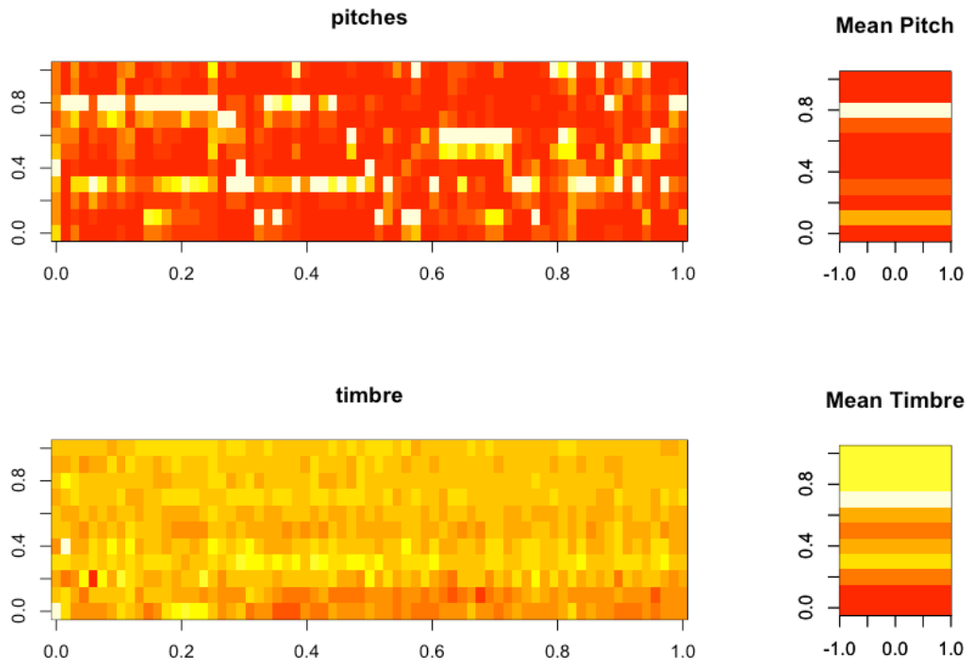
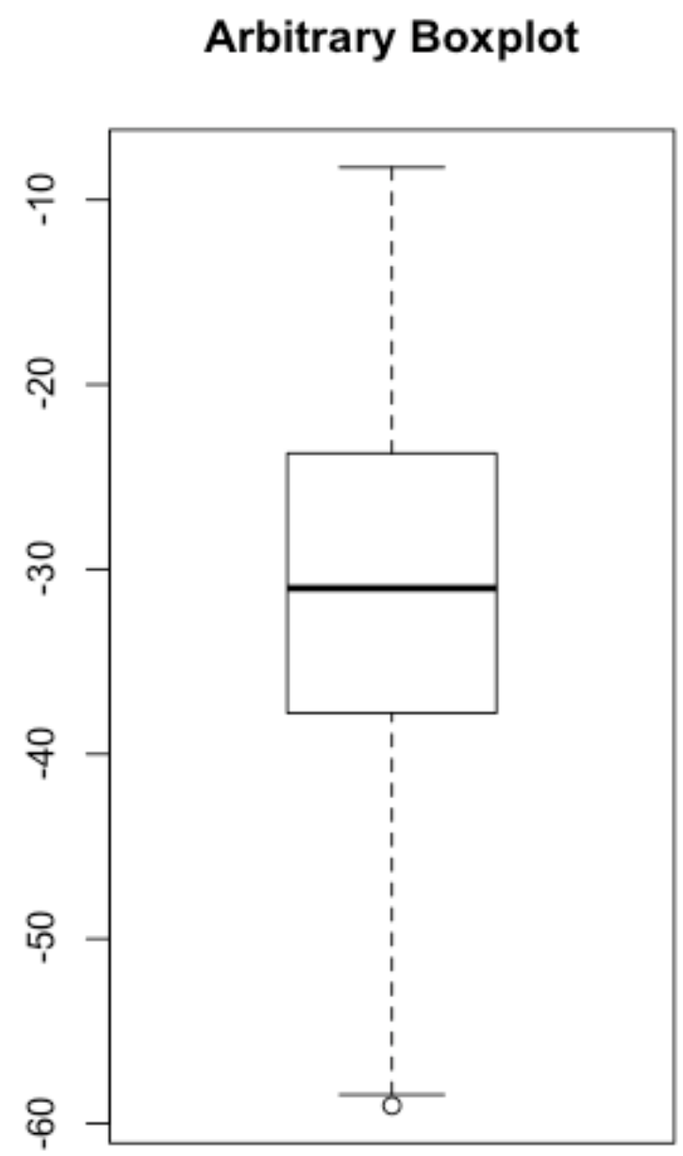


* weighted by segment *onset* loudness

Boxplots

Boxplots show the *five-number summaries* of a distribution:

- sample maximum
- upper quartile
- median
- lower quartile
- sample minimum
- (outliers)



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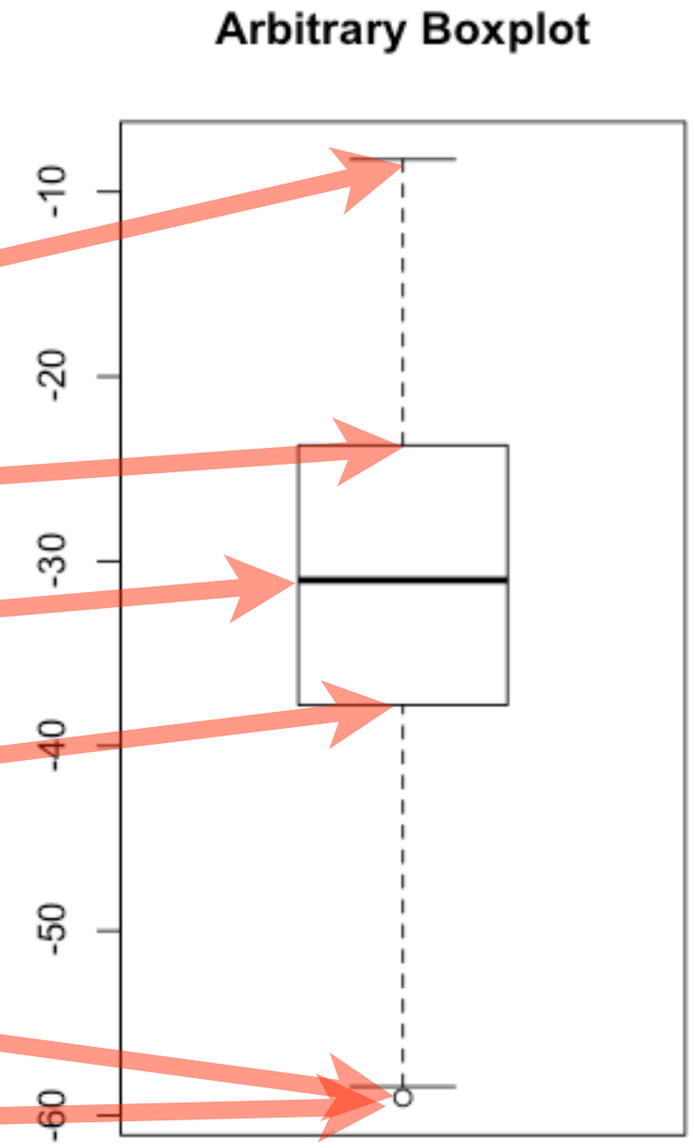
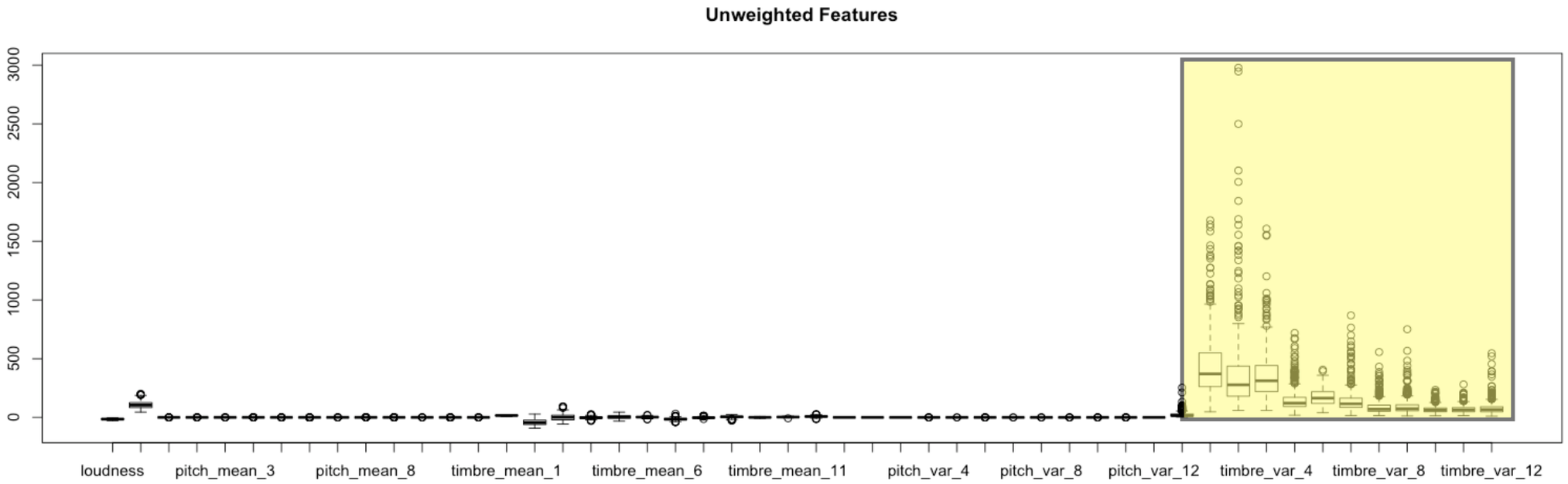


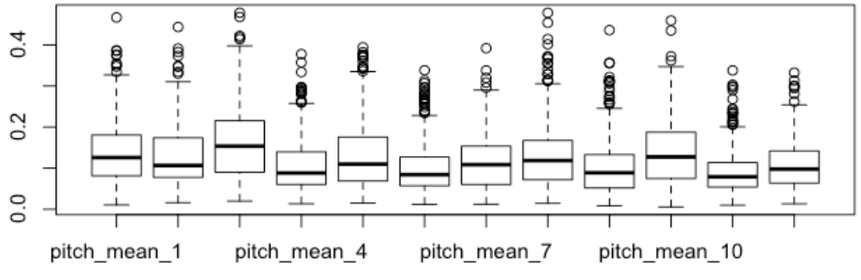
Demo: Feature Vector

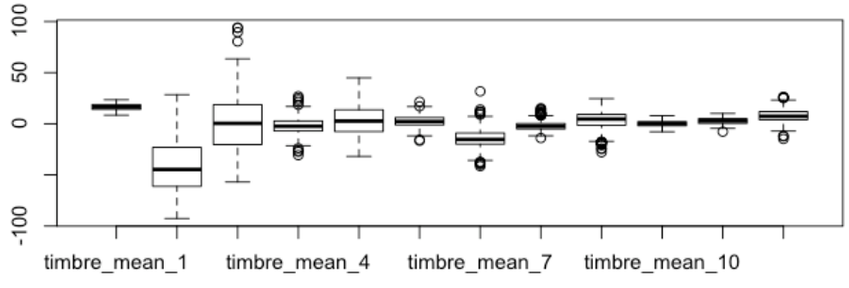


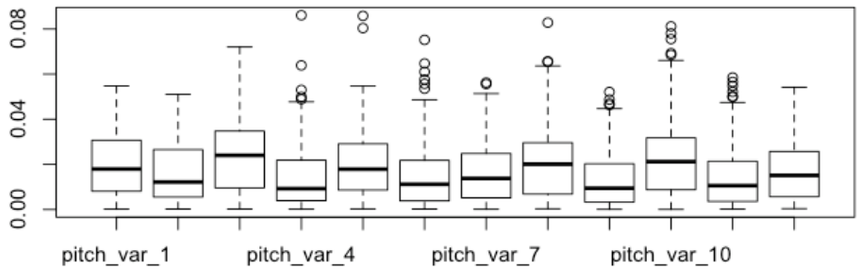
Raw Feature Boxplots...

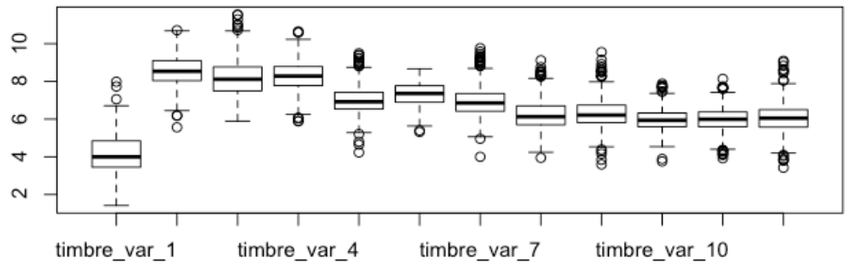
- Are these all normal distributions?
- Are all of these weighted evenly?
- Scaling becomes important... why?

Demo: Feature Vector





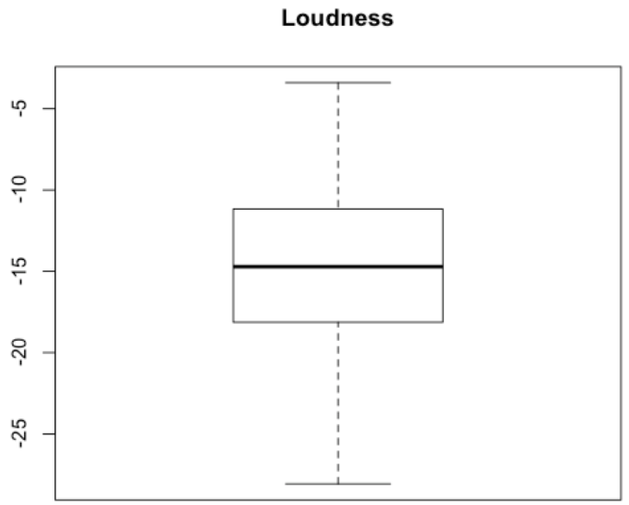


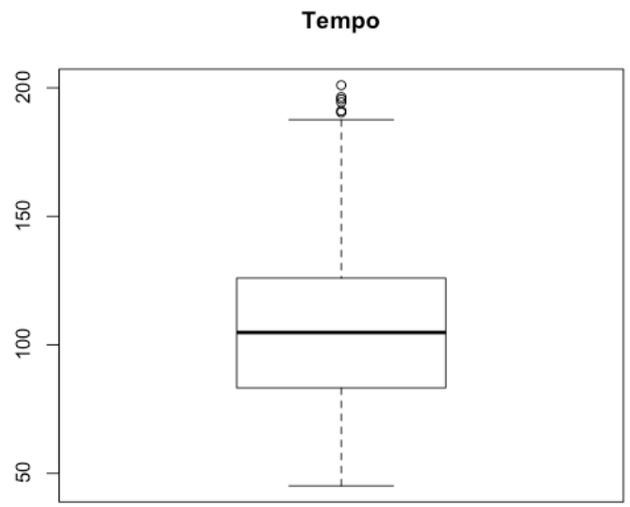


Looking at scaled summary statistics

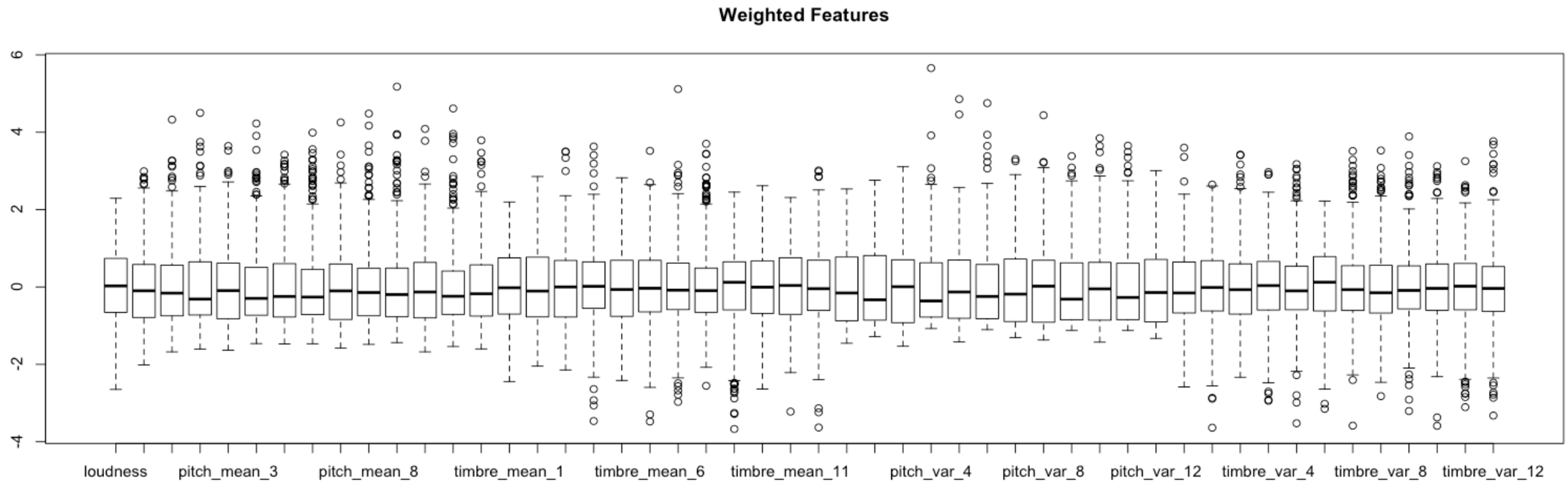
These are the 'expected' values for any song, so they're 'normal' for a song.

We want to enhance relationships between songs that *differ from the norm*.





Demo: Feature Vector

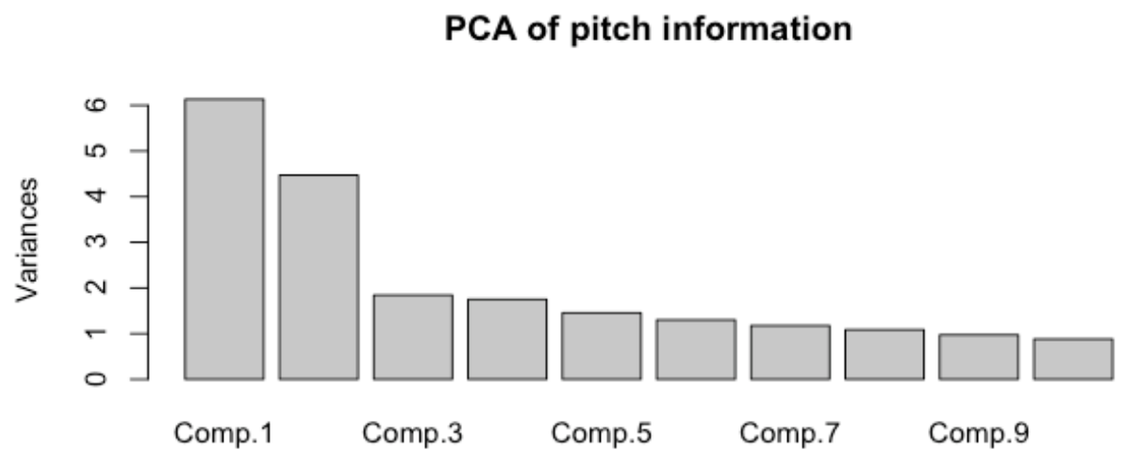


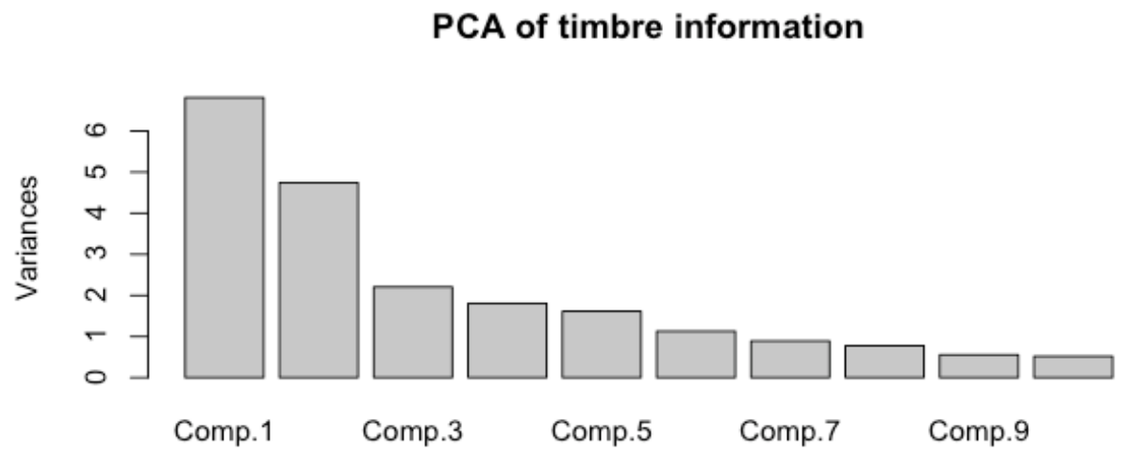
Weighted Feature Boxplots...

- Standard normalized data. All means are 0, all standard deviations are 1.
- We can find 'interesting' relationships between songs better this way. Distances can be understood in terms of *standard deviations from the mean.*
- However... 24 pitch and 24 timbre features, vs. just 1 tempo...

Demo: Feature Vector

Principle Component Analysis (PCA) of timbre and pitch information reveal a high degree of covariance.





Demo: Feature Vector

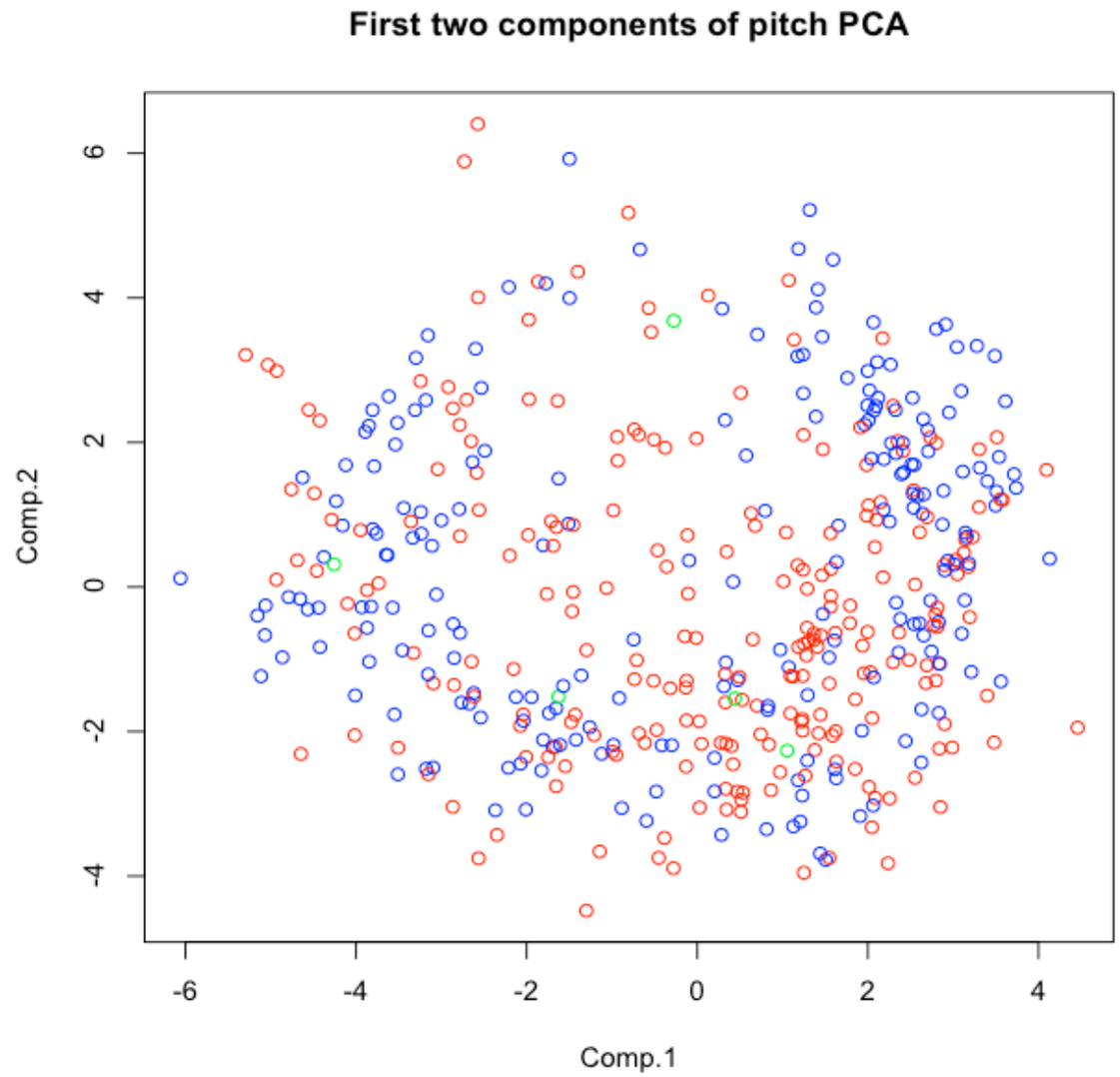
Plotting the PCA loadings show the 'structure' of how the pitch profiles co-vary across the music.

Blue = "Classical Guitar"
(almost entirely lute music)

Red = "Folk"

Green= "Both"

(flips and rotations)

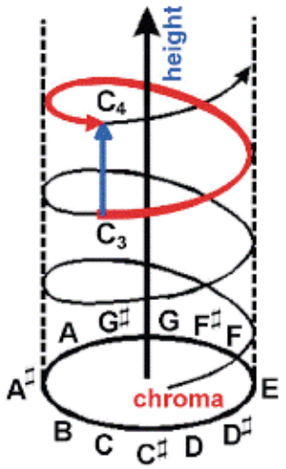


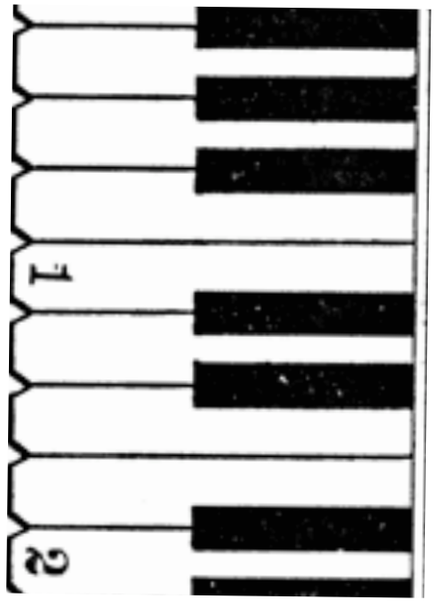
Demo: Feature Vector

Performing a Factor analysis shows evidence of "musicological" factors.

(alternating positive/negative loadings for both means and variances, indicating certain "keys" are followed for songs)

Should pitch profile distances be figured another way?





```
Loadings:
                Factor1 Factor2
pitch_mean_1    -0.117   0.625
pitch_mean_2     0.576  -0.270
pitch_mean_3    -0.585
pitch_mean_4     0.677   0.126
pitch_mean_5    -0.103  -0.487
pitch_mean_6             0.473
pitch_mean_7     0.332  -0.504
pitch_mean_8    -0.512   0.217
pitch_mean_9     0.527  -0.124
pitch_mean_10   -0.520  -0.274
pitch_mean_11    0.475   0.452
pitch_mean_12    0.216  -0.359
pitch_var_1     -0.318   0.689
pitch_var_2      0.638  -0.377
pitch_var_3     -0.661   0.100
pitch_var_4      0.695   0.289
pitch_var_5     -0.169  -0.536
pitch_var_6              0.658
pitch_var_7      0.363  -0.550
pitch_var_8     -0.660   0.315
pitch_var_9      0.669  -0.104
pitch_var_10    -0.620  -0.213
pitch_var_11     0.385   0.593
pitch_var_12     0.124  -0.399
```

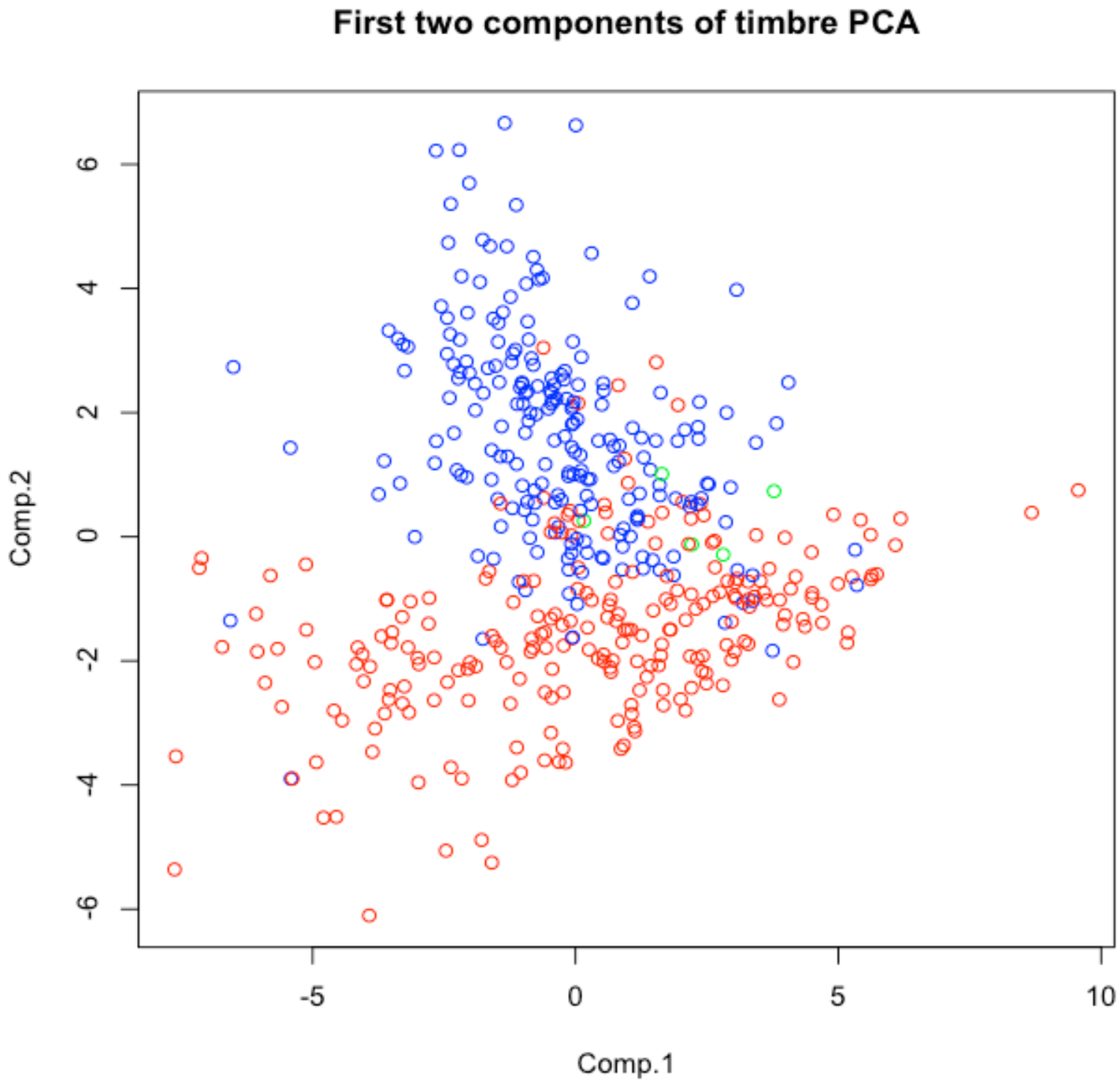
Demo: Feature Vector

Timbre features clearly split the different tags we were concerned with.

Blue = “Classical Guitar”

Red = “Folk”

Green= “Both”



Demo: Feature Vector

Timbral factors are a lot more straightforward. Certain songs have a lot of timbral variance. Other songs simply have strong overall timbral means.

```
Loadings:
                Factor1 Factor2
timbre_mean_1             0.987
timbre_mean_2             0.489
timbre_mean_3   0.151     0.728
timbre_mean_4  -0.139     0.349
timbre_mean_5            -0.570
timbre_mean_6
timbre_mean_7  -0.126     0.248
timbre_mean_8   0.175    -0.556
timbre_mean_9   0.122     0.589
timbre_mean_10  0.257    -0.461
timbre_mean_11 -0.363    -0.238
timbre_mean_12
timbre_var_1    0.582     0.614
timbre_var_2    0.681    -0.286
timbre_var_3    0.822    -0.114
timbre_var_4    0.680    -0.387
timbre_var_5    0.779
timbre_var_6    0.241    -0.690
timbre_var_7    0.810
timbre_var_8    0.712
timbre_var_9    0.792
timbre_var_10   0.591    -0.358
timbre_var_11   0.667    -0.140
timbre_var_12   0.736
```

Demo: Association Data

Demo: Association Data

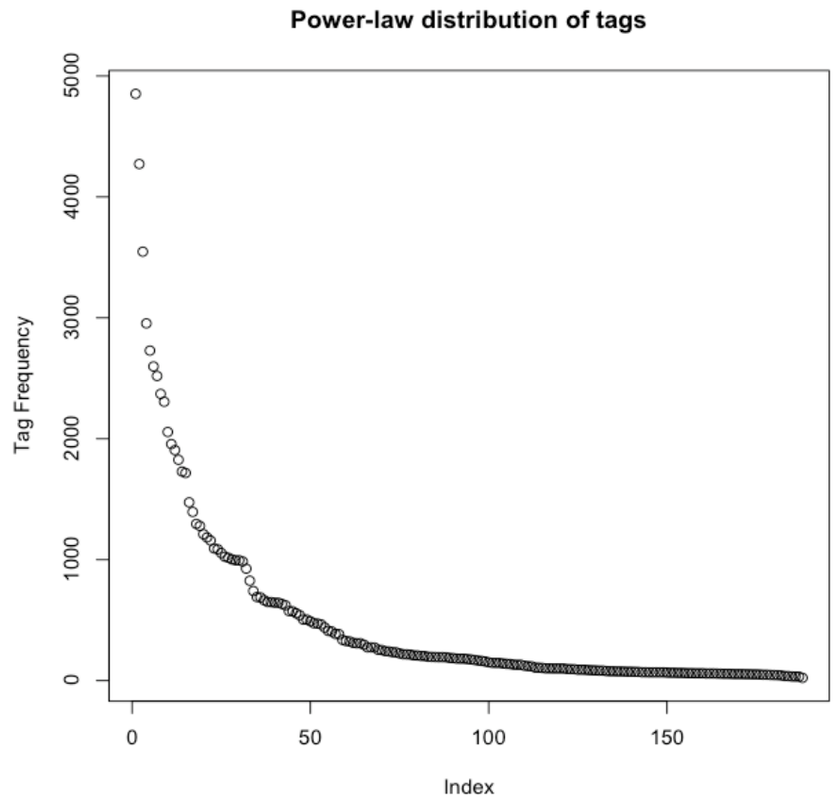
	clip_id	no.voice	singer	duet	plucking	hard.rock	world	bongos	harpsichord	female.singing	classical
1	2	0	0	0	0	0	0	0	0	0	0
2	6	0	0	0	0	0	0	0	1	0	0
3	10	0	0	0	1	0	0	0	0	0	0
4	11	0	0	0	0	0	0	0	0	0	0
5	12	0	1	0	0	0	0	1	0	0	1
6	14	0	0	0	0	0	0	0	0	0	0

- Magnatagatune has ‘tag’ data for songs
- Tags only exist if *two* people used the same tag for the same song
- 188 total tags

Demo: Association Data

guitar	classical	slow	techno	strings	drums	electronic	rock
4852	4272	3547	2954	2729	2598	2519	2371
fast	piano	ambient	beat	violin	vocal	synth	female
2306	2056	1956	1906	1826	1729	1717	1474
indian	opera	male	singing	vocals	no.vocals	harpsichord	loud
1395	1296	1279	1211	1184	1158	1093	1086

- Tags are distributed by a *power-law*
- It's not as meaningful to share a "guitar" tag. A "soprano" tag is far more informative.
- We need to form a comparison of tags based on the *weighted relevance* of the terms.



Demo: Association Data

- TF/IDF (term frequency/document frequency)
- n(i,j) = number of times a term i appears in a ‘document’ j.
- n(k,j) = total number of terms in ‘document’ j.
- |D| = total number of ‘documents’
- {d:...} = total documents containing i
- documents = tags for song

$$\mathrm{tf_{i,j}} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

$$\mathrm{idf_i} = \log \frac{|D|}{|\{d : t_i \in d\}|}$$

http://en.wikipedia.org/wiki/Tf%E2%80%93idf

Demo: Association Data

- Forming a similarity/dissimilarity between weighted tags commonly involves finding the *angle* between two vectors.
- Cosine dissimilarity is one (of many) ways of expressing a distance between vectors.
- A, B = vectors of attributes
- ||A||, ||B|| = magnitudes of vectors

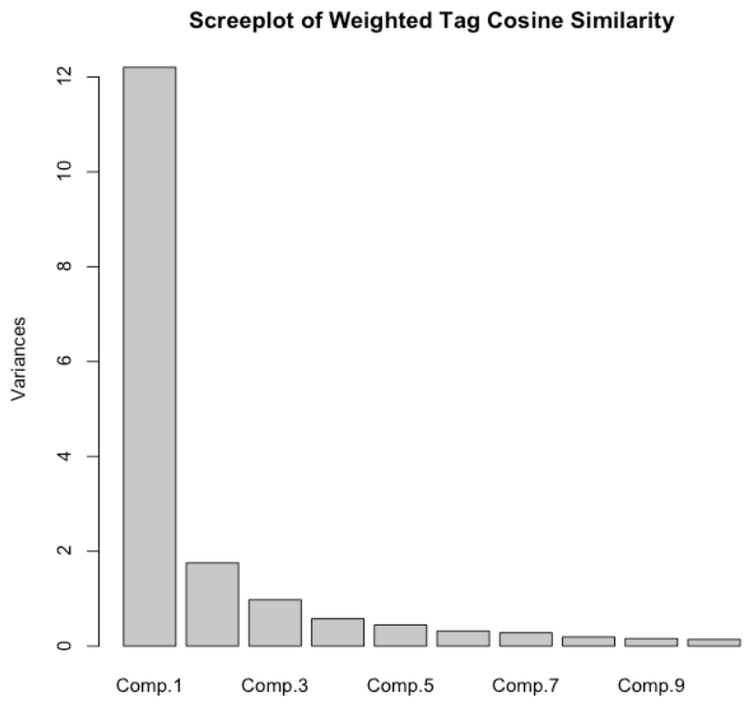
$$\text{similarity} = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|}.$$

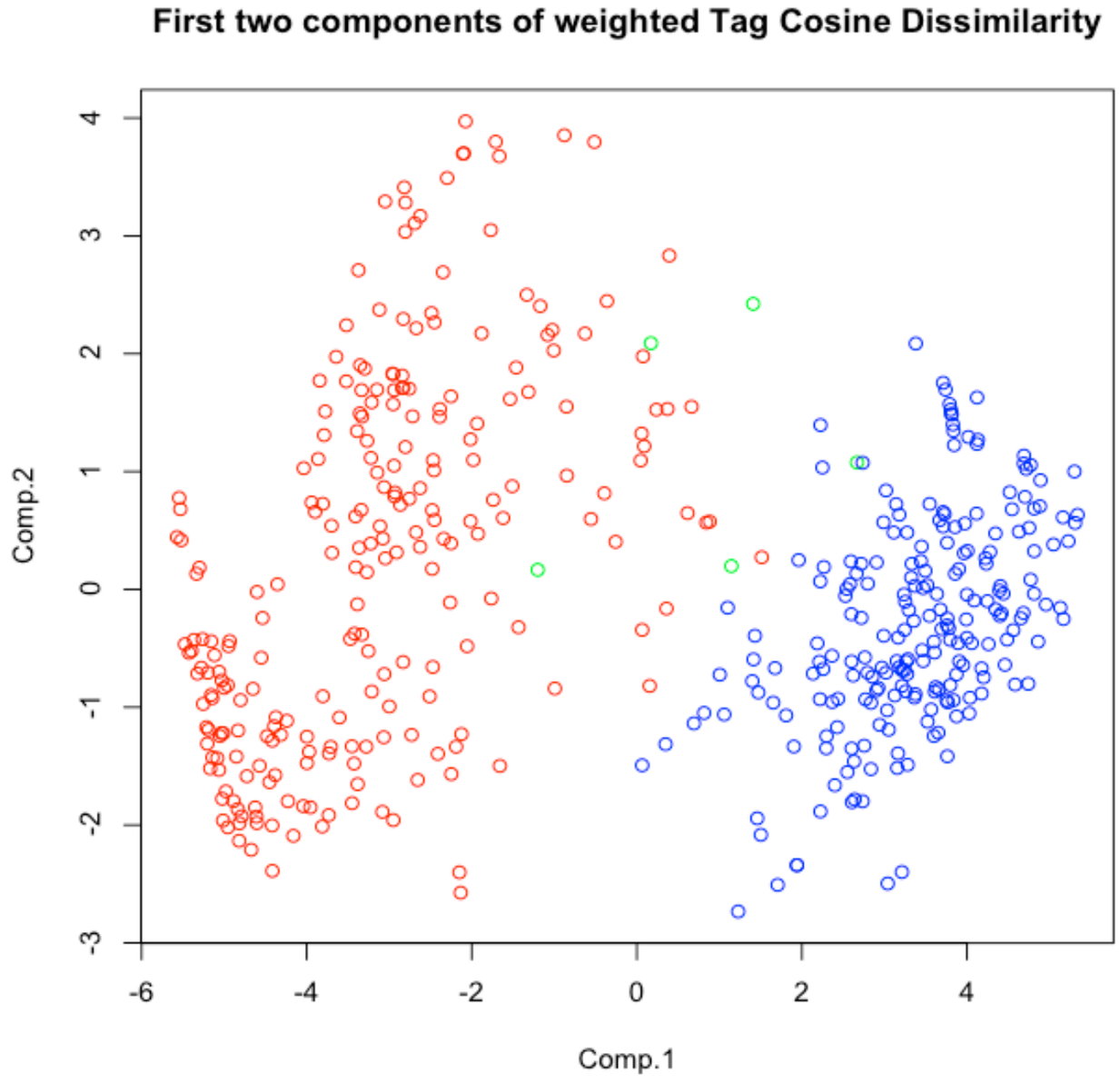
$$\|\mathbf{x}\| := \sqrt{x_1^2 + \cdots + x_n^2}.$$

http://en.wikipedia.org/wiki/Cosine_similarity

Demo: Association Data

Cosine similarity of tags also (not surprisingly) clearly separates the two tags





Demo: Hybrid

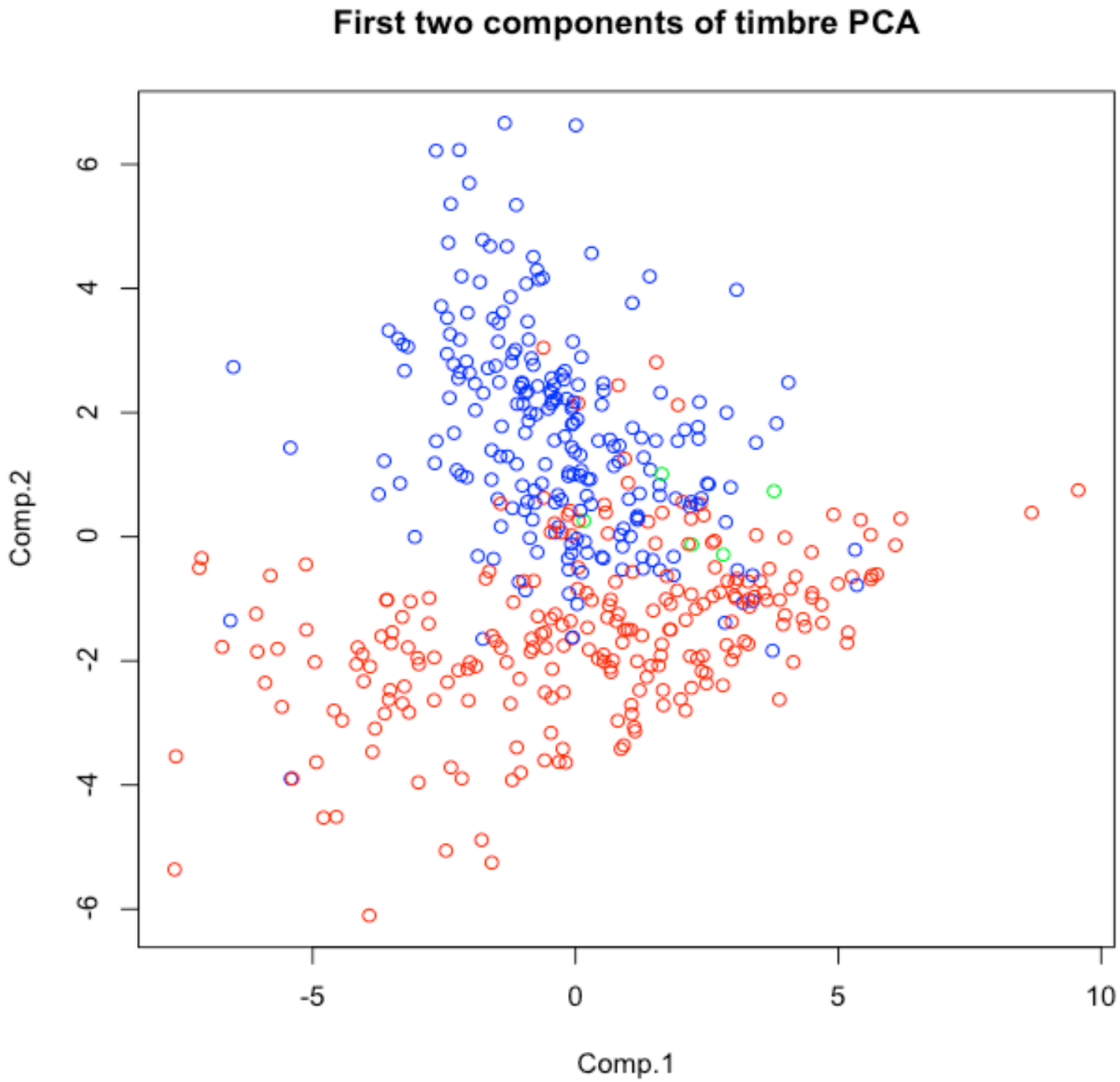
Demo: Feature Vector

Timbre features clearly split the different tags we were concerned with.

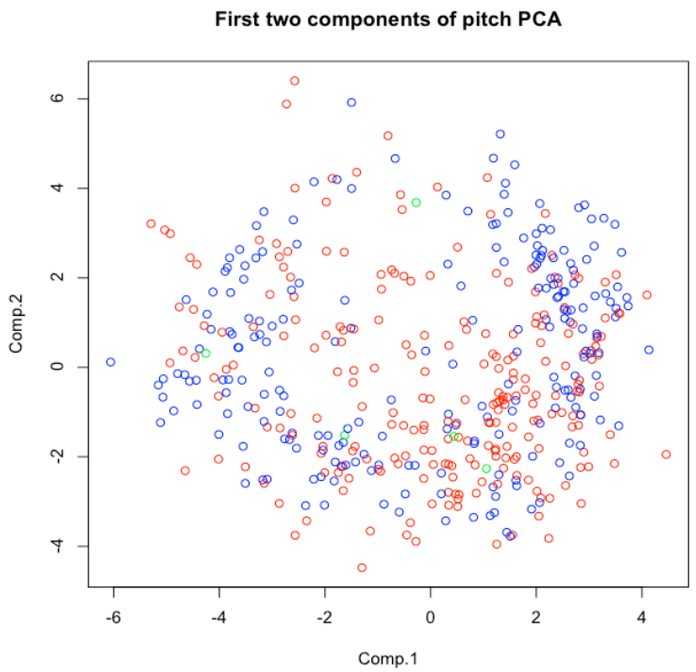
Blue = “Classical Guitar”

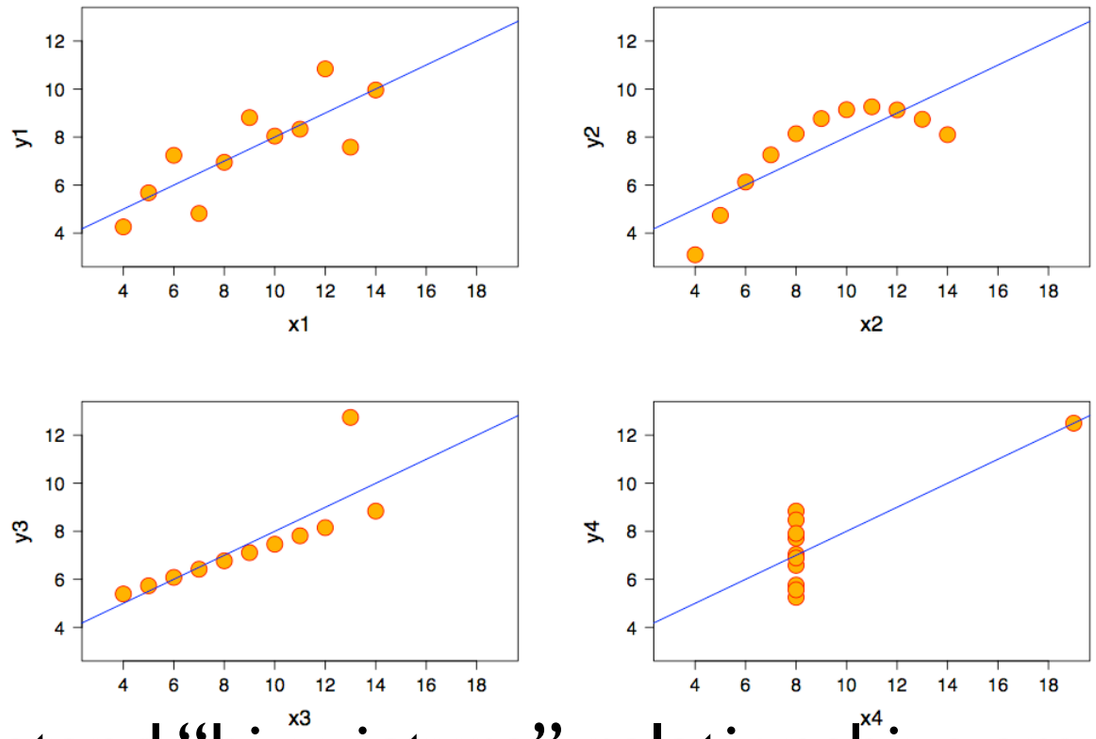
Red = “Folk”

Green= “Both”



Conclusions (demo)

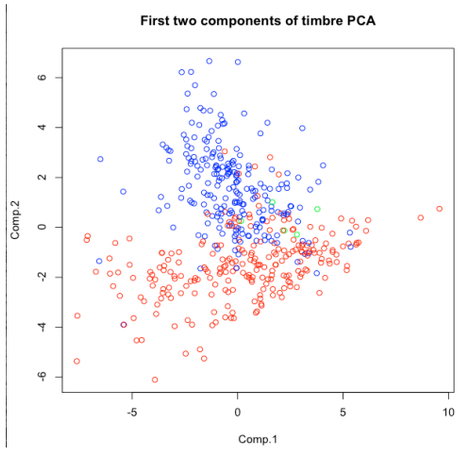




- Visualizations can help understand "big picture" relationships among songs, and support that the relationships are meaningful. (left plot)
- Visualizations can help understand "mismatches" in modeling/clustering/ classification approaches. (x2)
- Visualizations can help detect noise (x1) and outliers. (x3, x4)
- Visualizations can help find a way to *improve the underlying model*.

Opportunity: Hybrid Maps

Mixing information from both timbre & term spaces has a great opportunity for forming a 'better' representation of genre



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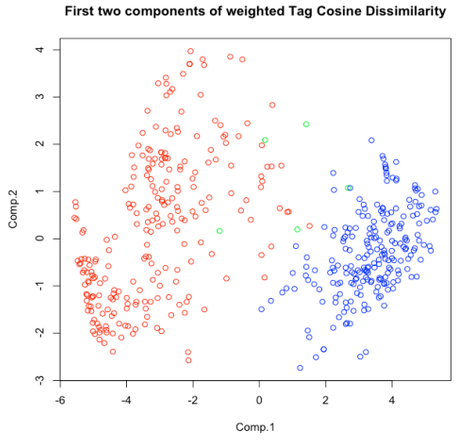

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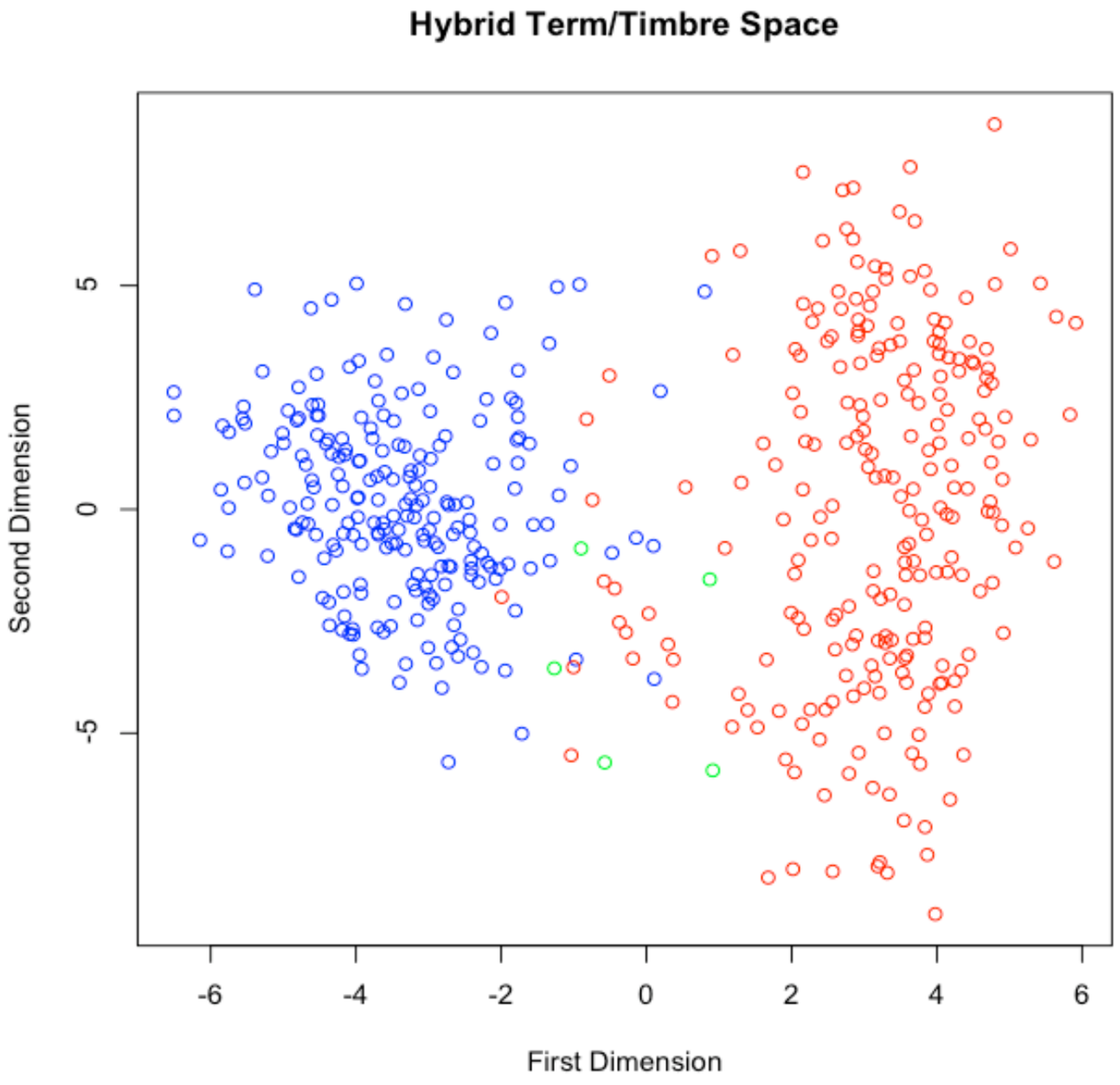
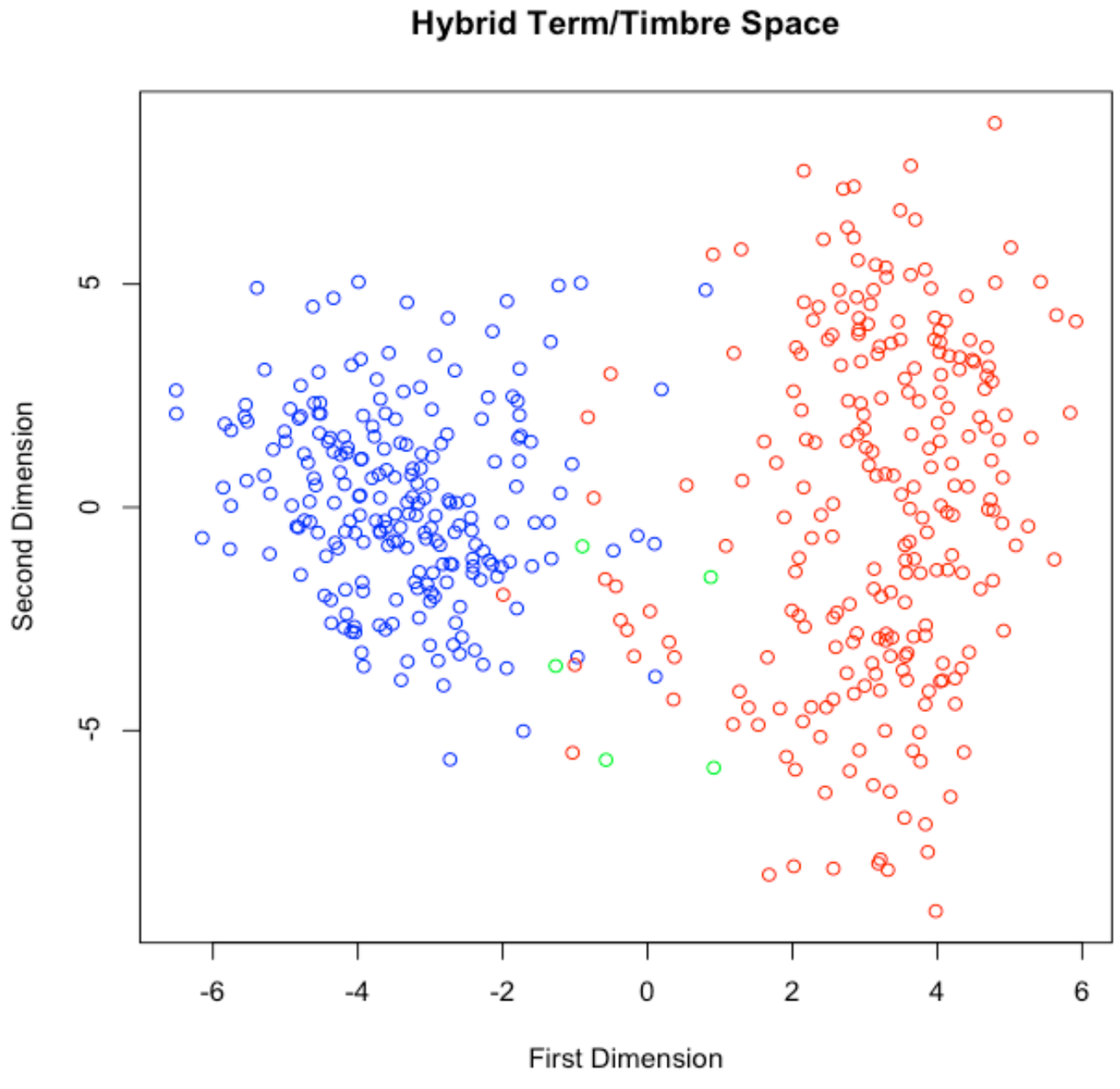


"Reading" Conventional Dimensionality Reductions

- *Large* dissimilarity is preserved over *small dissimilarity.*

- Try to understand the plot in terms of its two biggest *orthogonal* distances. If those don't make sense, then the plot is suspect.

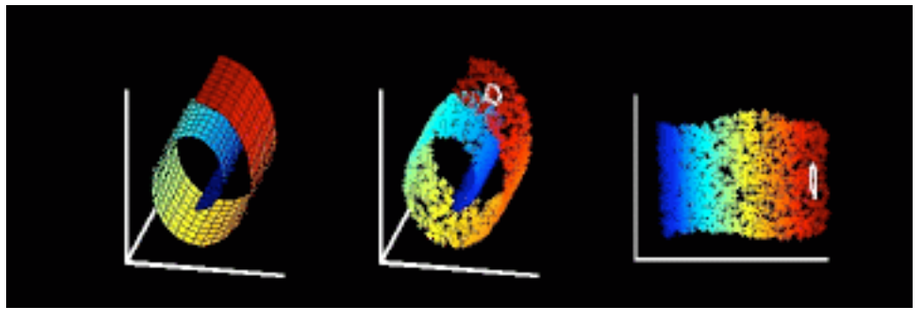
- Next, look for local structure, clustering, etc.



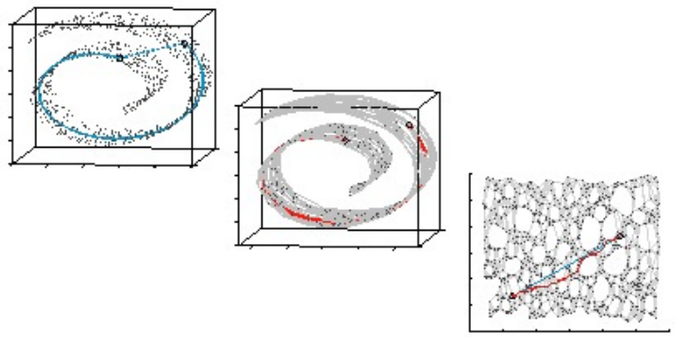
Other Techniques

Other Techniques

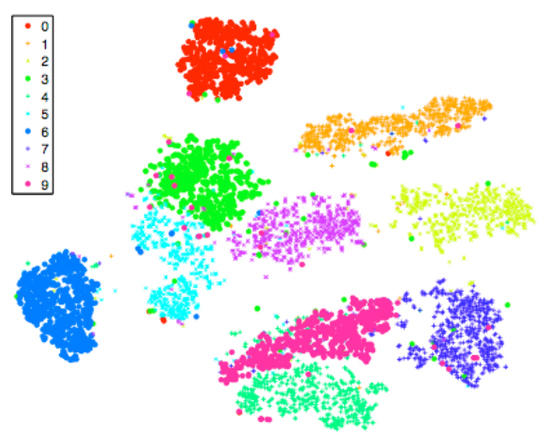
- Locally Linear Embedding : Only consider ‘close’ points in distance matrix. Good at recovering from “kinks”, “folds”, and “spirals” in data (chroma)



- Isomap : Establish geodesic “neighborhood” distances using Dijkstra’s algorithm, and solve with mds.



- T-SNE : Convert neighbor distances to conditional probabilities. Perform gradient descent on Kullback-Leibler Divergence. Good at recovering clusters at different *scales*.



(a) Visualization by t-SNE.

Other Techniques

(observations)

- Many advanced techniques sacrifice "large scale" dissimilarities in order to preserve/enhance "local" features.

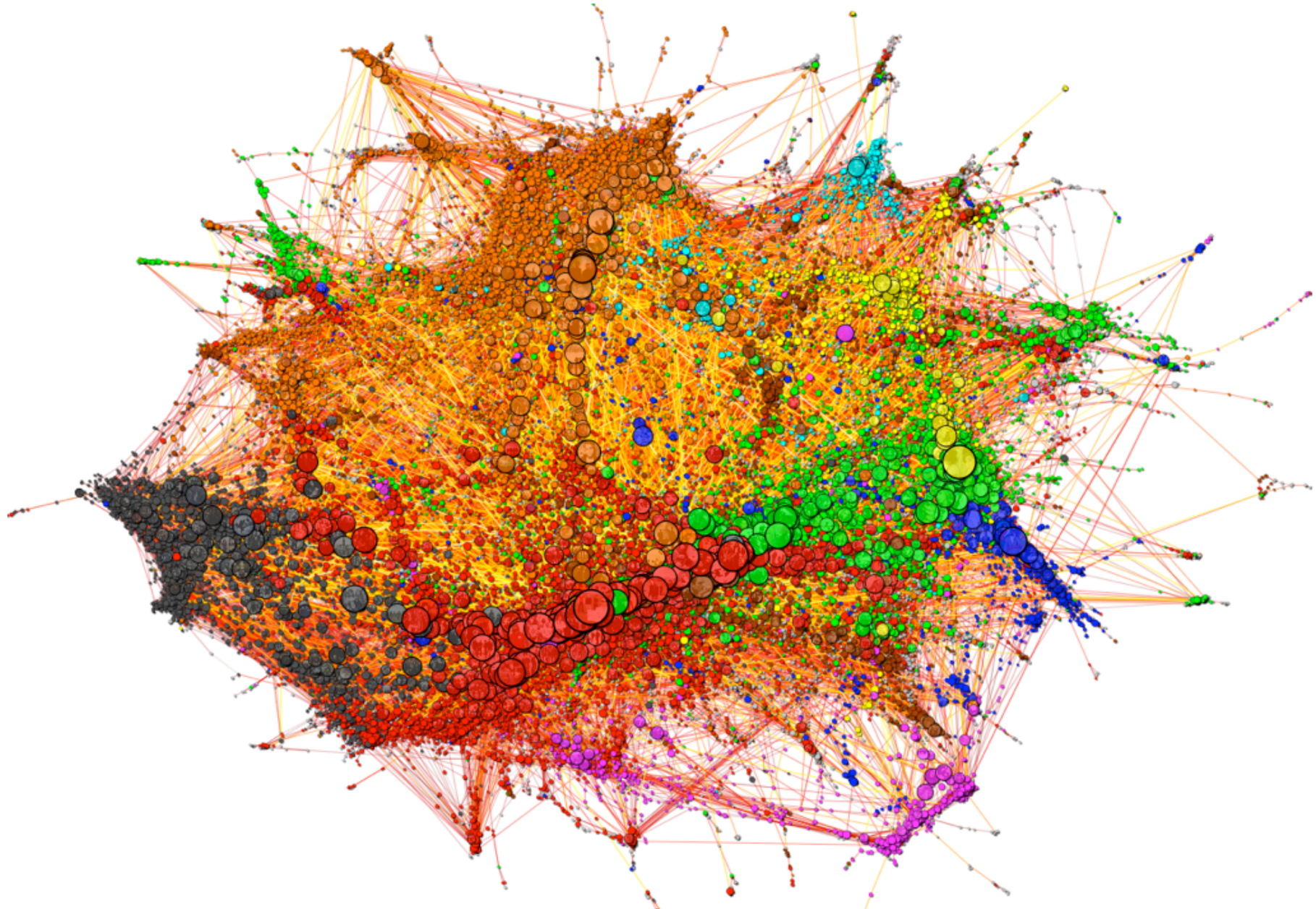
- Sometimes large scale information is useful (to determine if scales are wrong, or if there are significant outliers)

- Interpretation of advanced techniques is much more complicated. (What are the loadings, factors, of features etc.?)

- It can be harder to use advanced dimensionality reduction techniques to inform classifier design.

Building an artist map

The Goal - build an artist graph suitable for music exploration



Problem: The artist space is very complex

The Data

- Crawled The Echo Nest API for:
  - Artist names
  - Artist hotness
  - Artist familiarity
  - 15 most similar artists
- 70,000 artists
- 250,000 artist-artist links
- Available at musicviz.googlepages.com

Version 3
Overview
Data Types
Version History

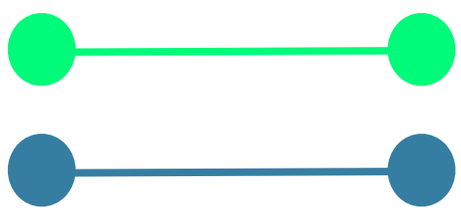
API Methods

Artist:
get_audio
get_biographies
get_blogs
get_familiarity
get_hotttnesss
get_image
get_news
get_profile
get_reviews
get_similar
get_top_terms
get_urls
get_video

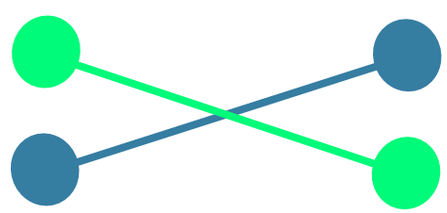
Making a good graph

- Minimize edge crossings, bends and curves

Good

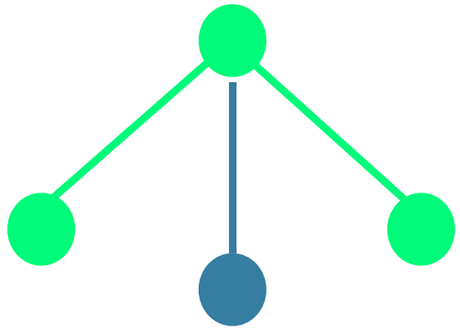


Bad

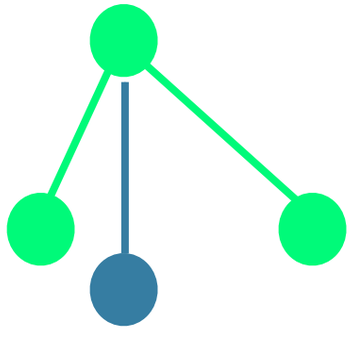


- Maximize angular resolution, symmetry

Good



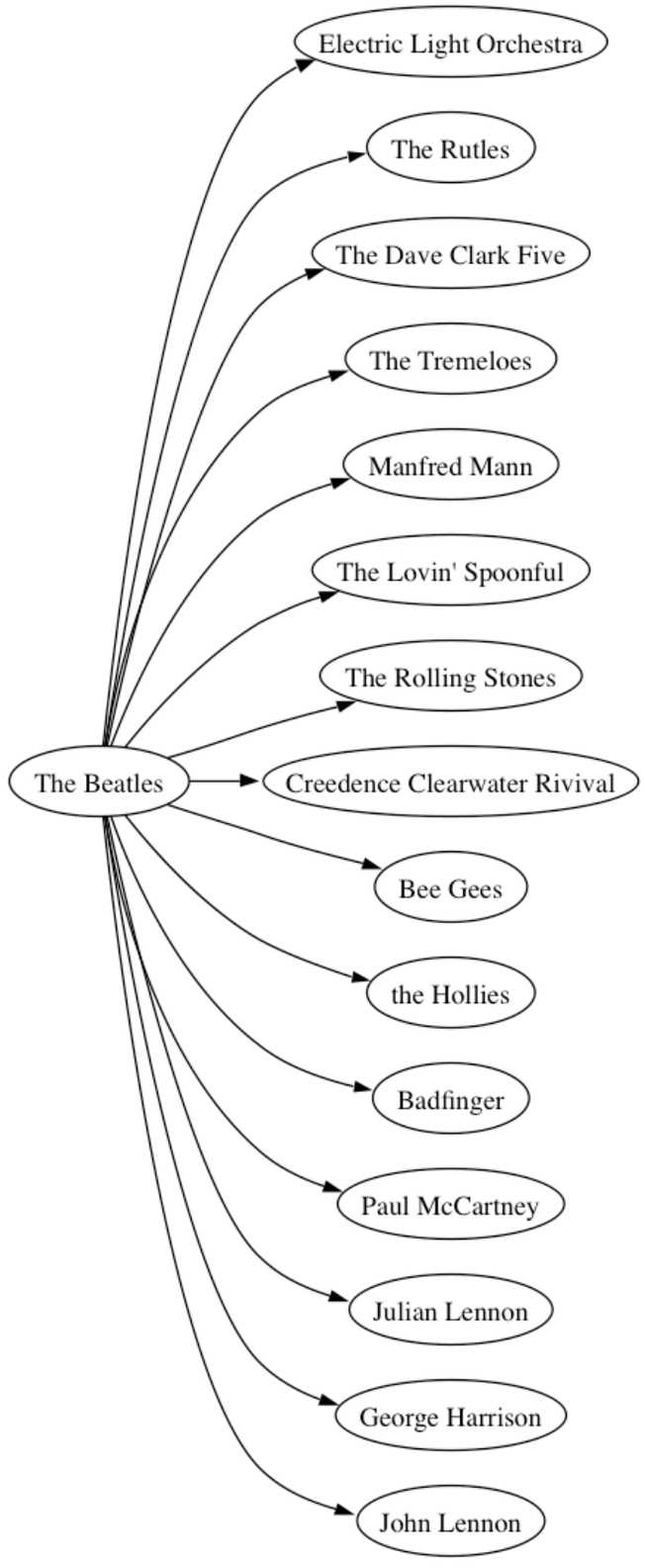
Bad



Cognitive measurements of graph aesthetics, Ware, Purchase, Colpoys, McGill

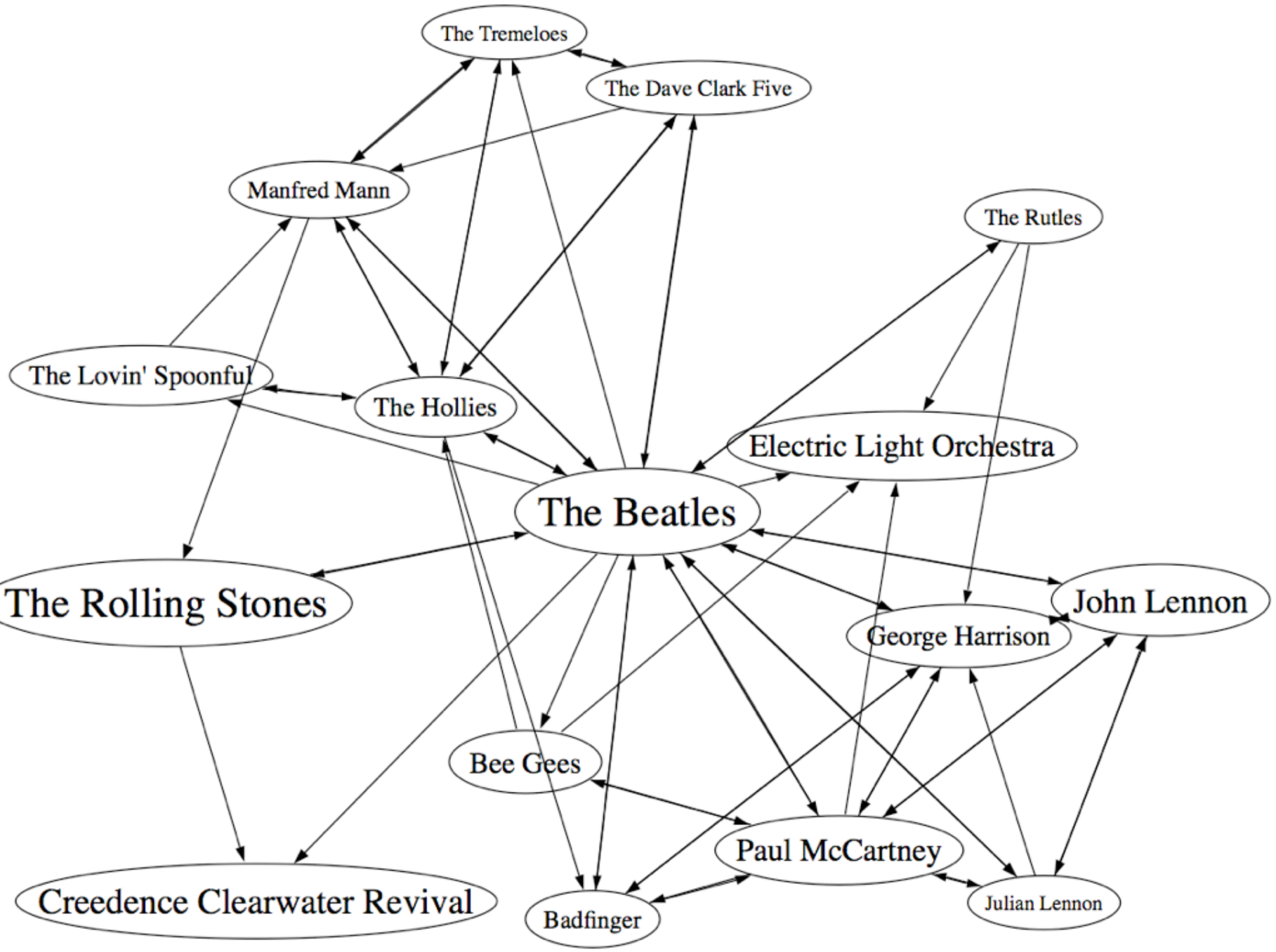
Graphing the Beatles Neighborhood

```
digraph {
    "The Beatles" ->  "Electric Light Orchestra";
    "The Beatles" ->  "The Rutles";
    "The Beatles" ->  "The Dave Clark Five";
    "The Beatles" ->  "The Tremeloes";
    "The Beatles" ->  "Manfred Mann";
    "The Beatles" ->  "The Lovin' Spoonful";
    "The Beatles" ->  "The Rolling Stones";
    "The Beatles" ->  "Creedence Clearwater Revival";
    "The Beatles" ->  "Bee Gees";
    "The Beatles" ->  "the Hollies";
    "The Beatles" ->  "Badfinger";
    "The Beatles" ->  "Paul McCartney";
    "The Beatles" ->  "Julian Lennon";
    "The Beatles" ->  "George Harrison";
    "The Beatles" ->  "John Lennon";
}
```



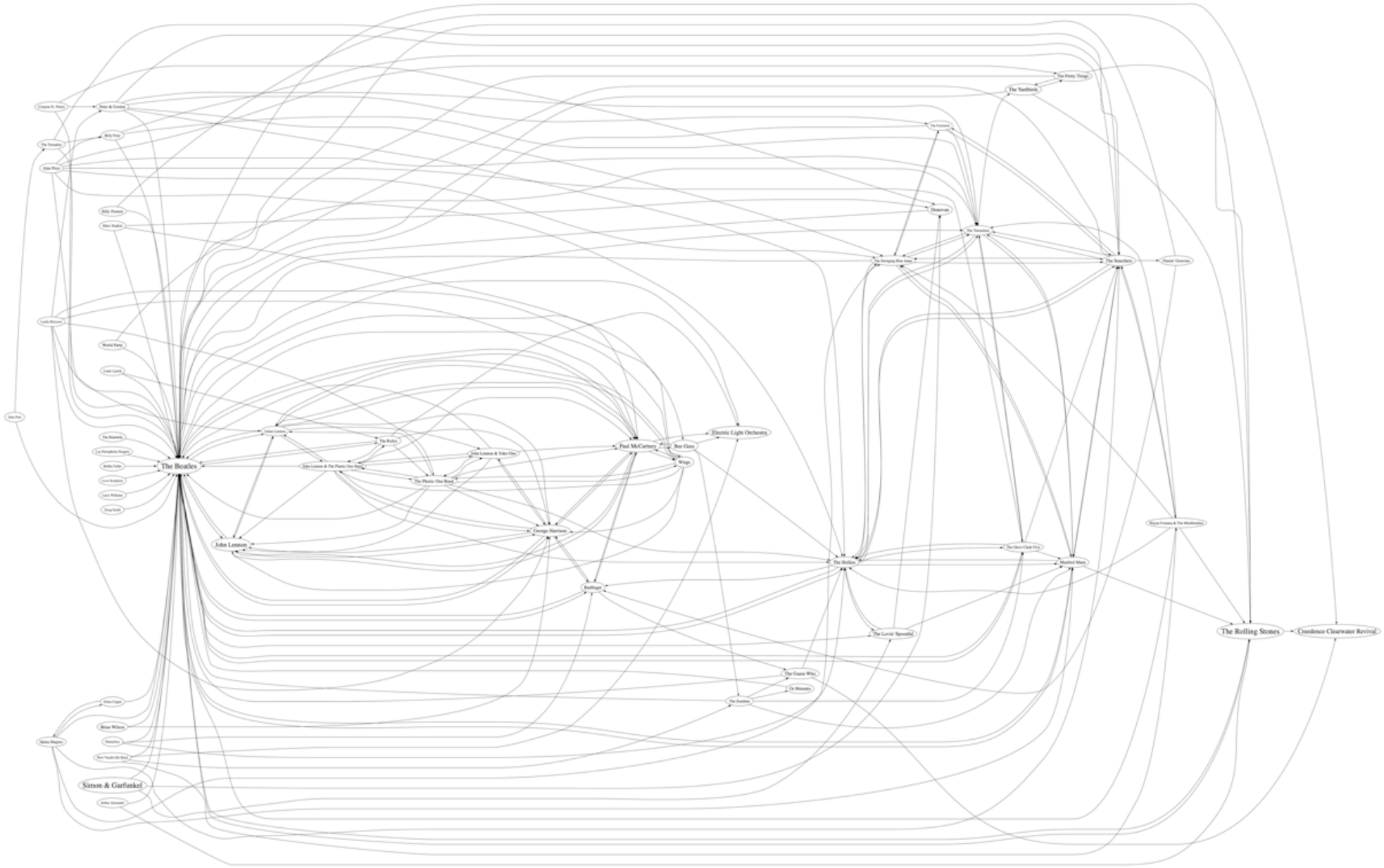
http://www.graphviz.org/

Artist map - level 1 out

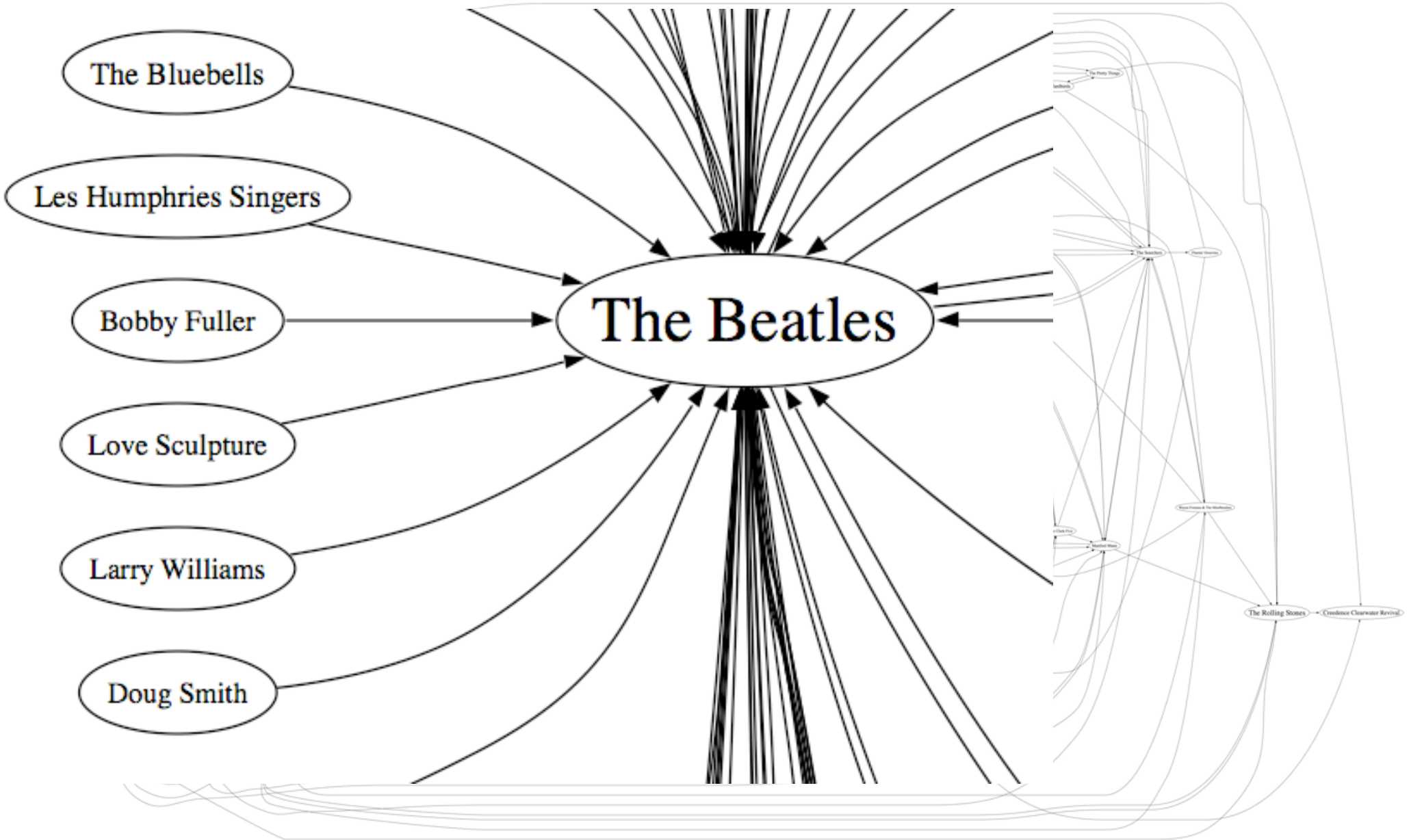


Already interconnections start to overwhelm

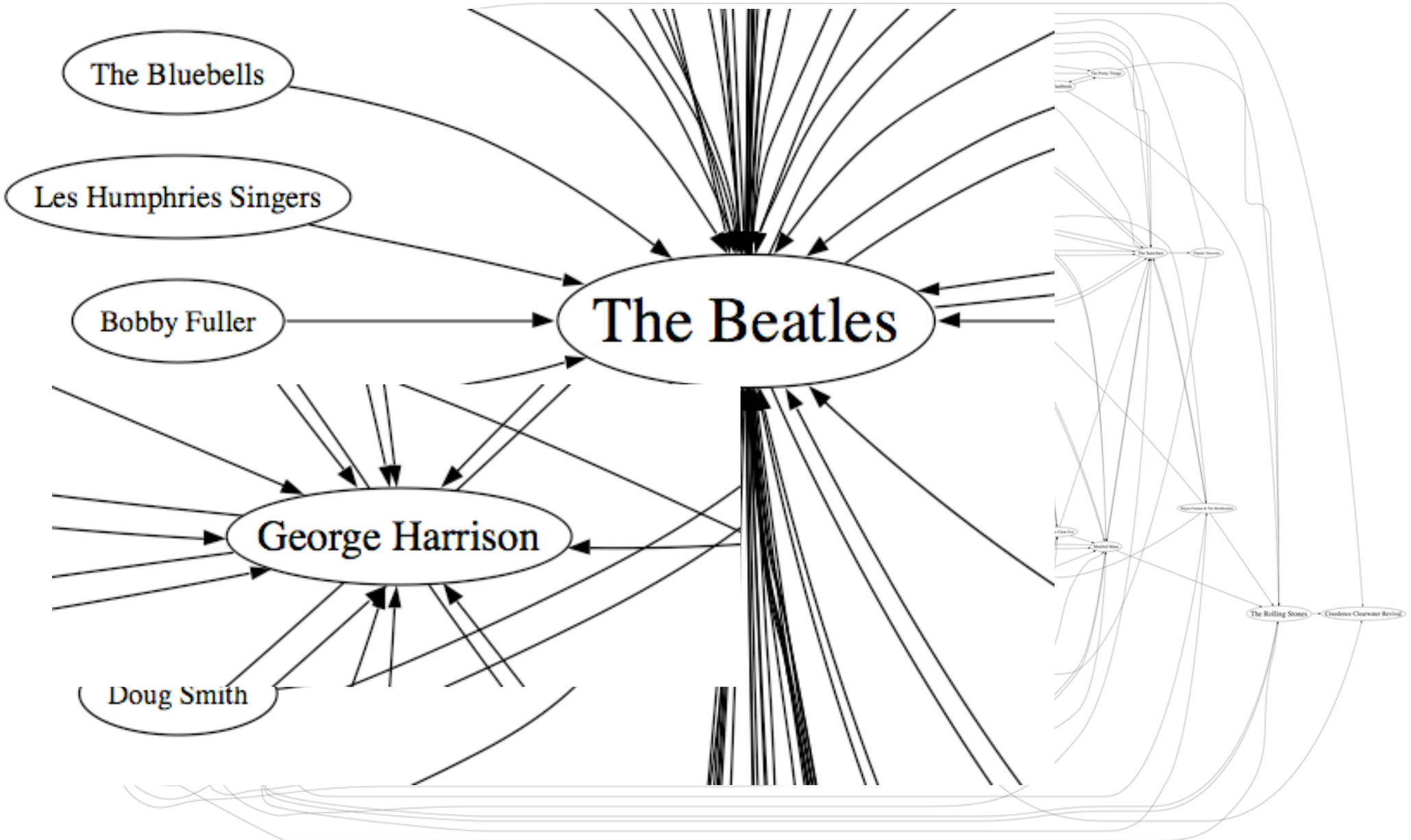
Artist map - level 1 in/out



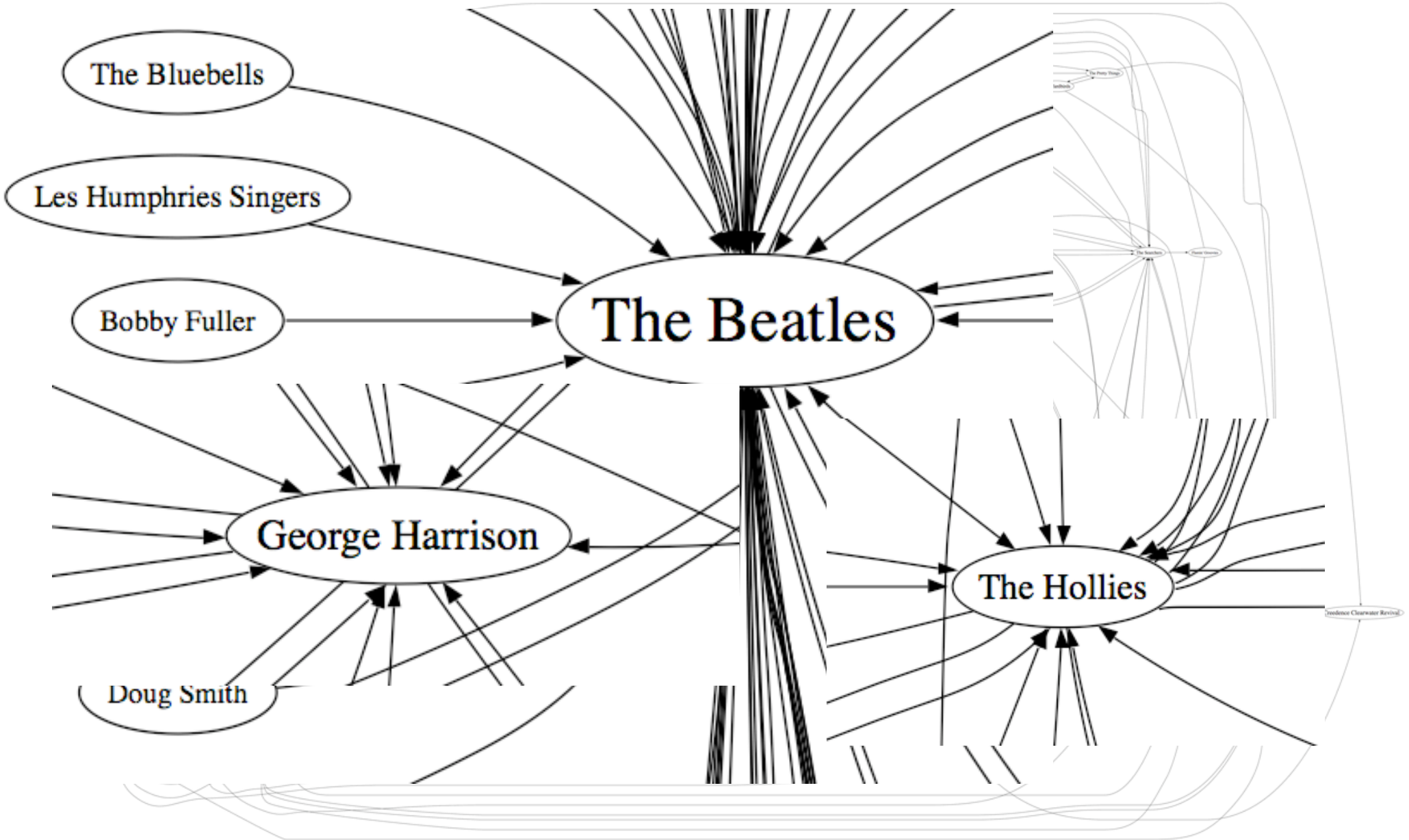
Artist map - level 1 in/out



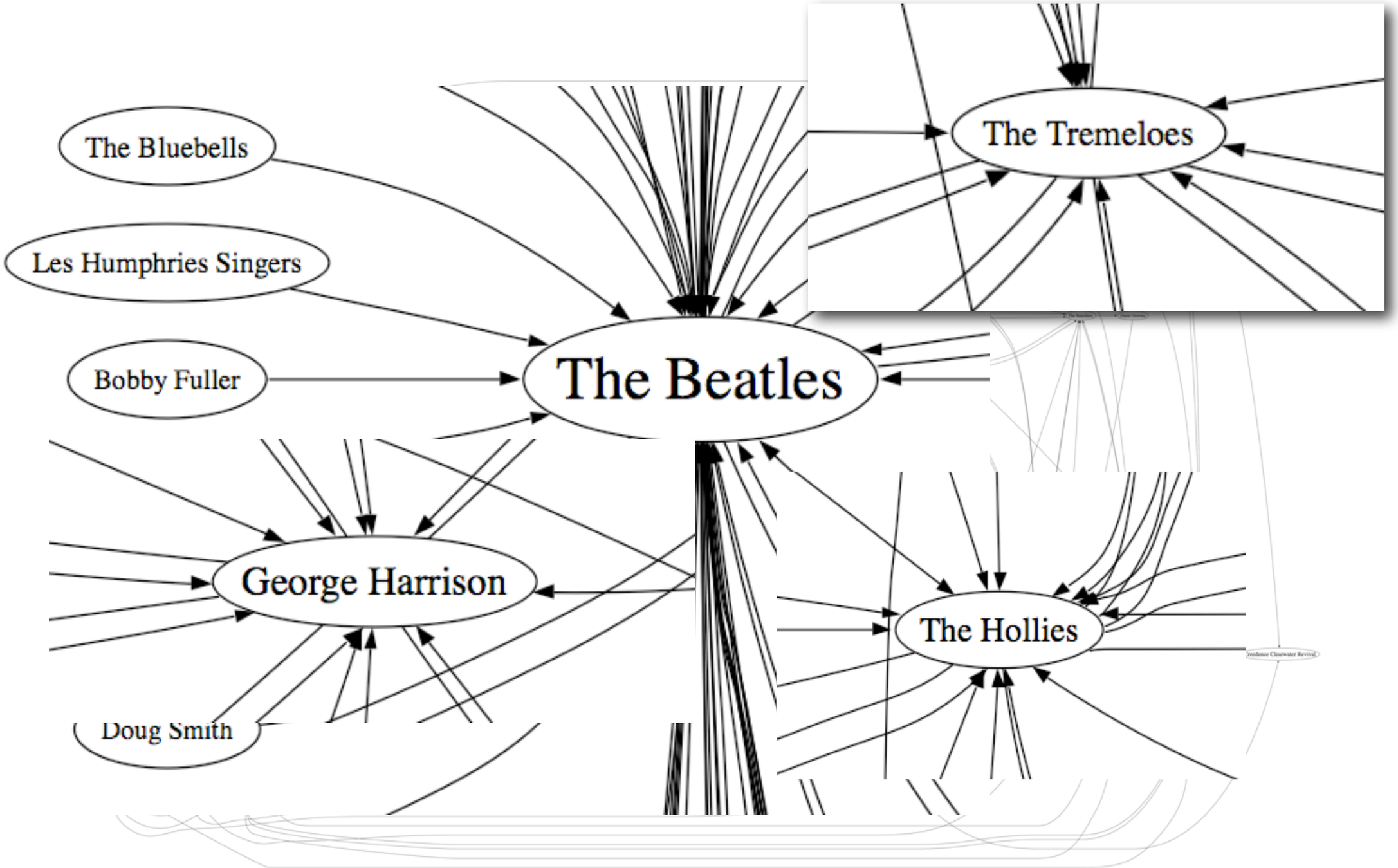
Artist map - level 1 in/out



Artist map - level 1 in/out



Artist map - level 1 in/out



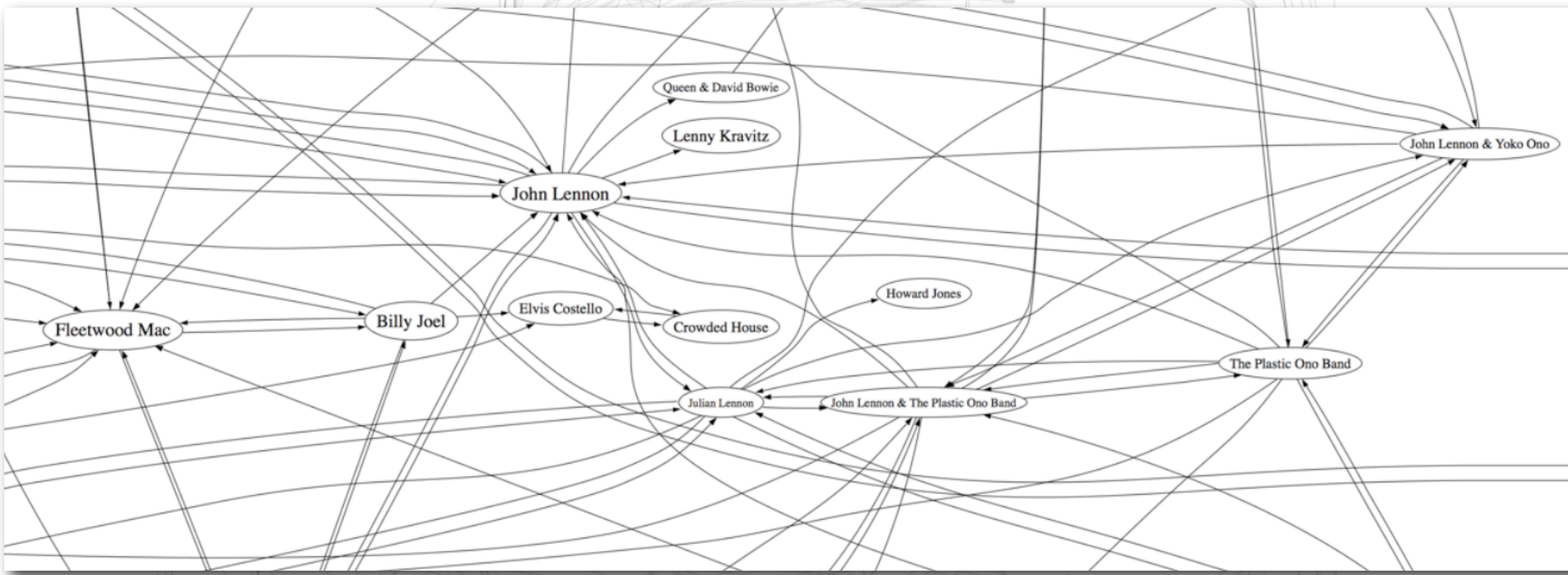
Artist map - level 1 in/out

Artist map - level 1 in/out

Artist map - level 2

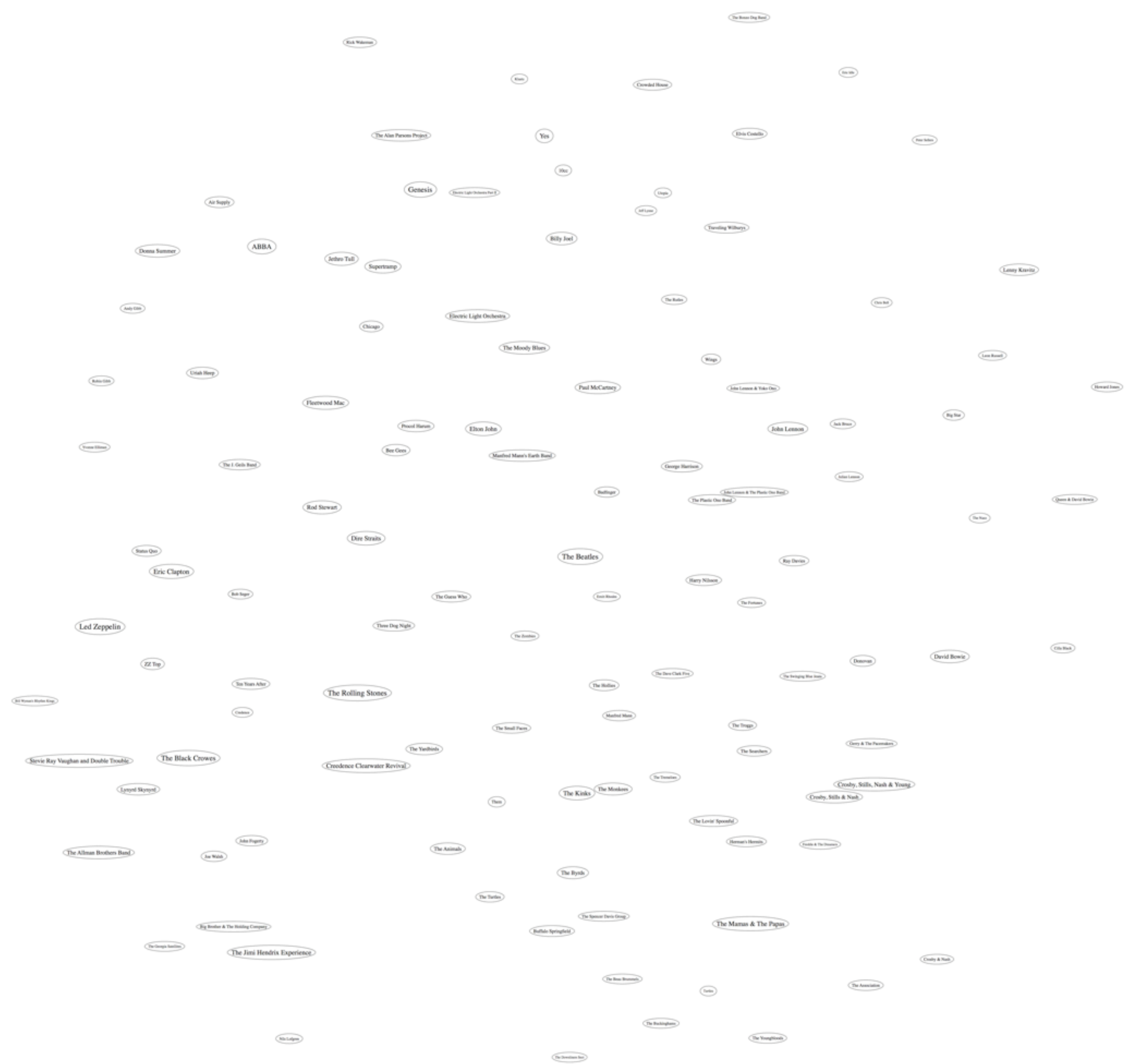
116 artists and 665 edges. We are totally overwhelmed.

Artist map - level 2



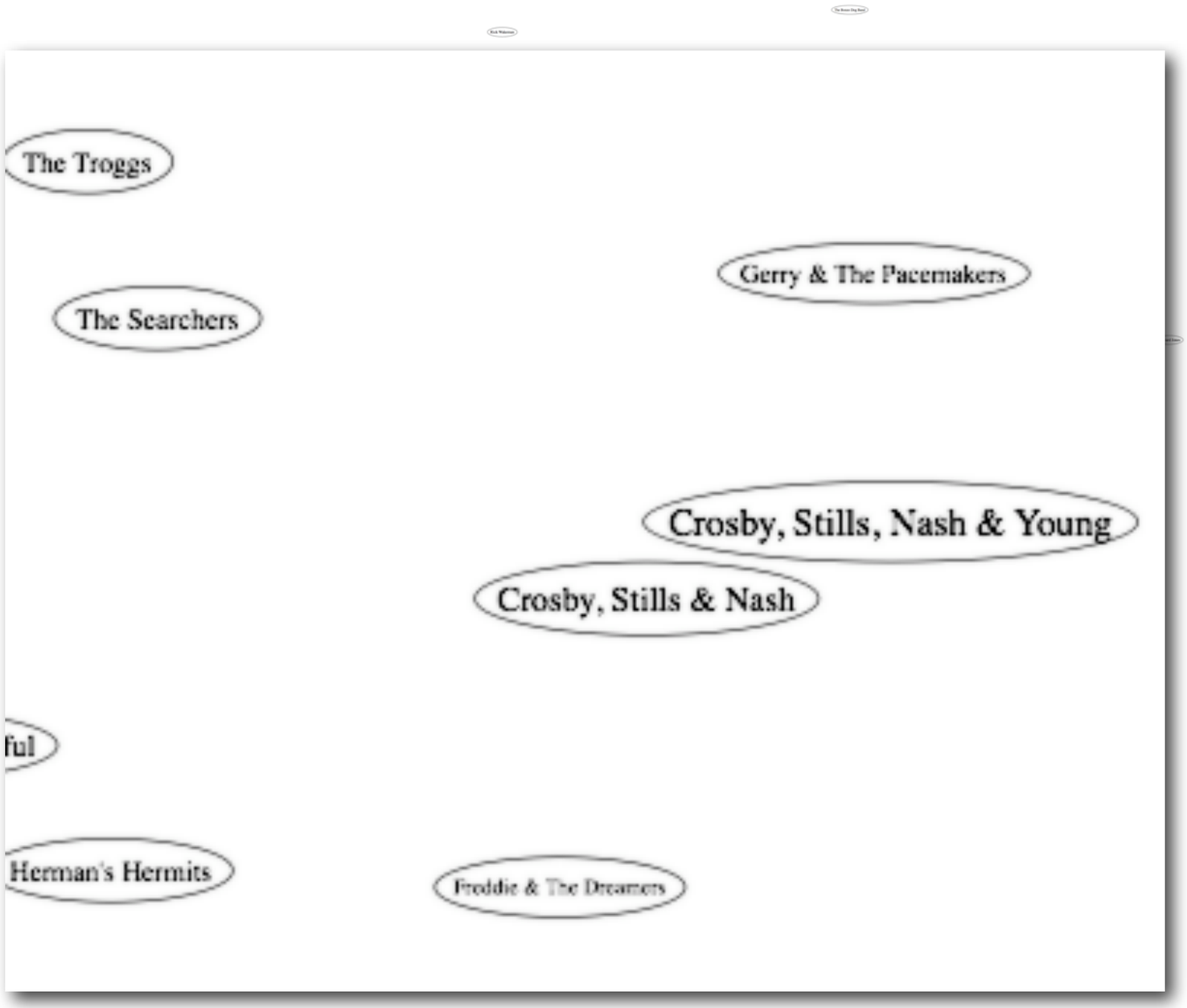
116 artists and 665 edges. We are totally overwhelmed.

Simplifying the graph



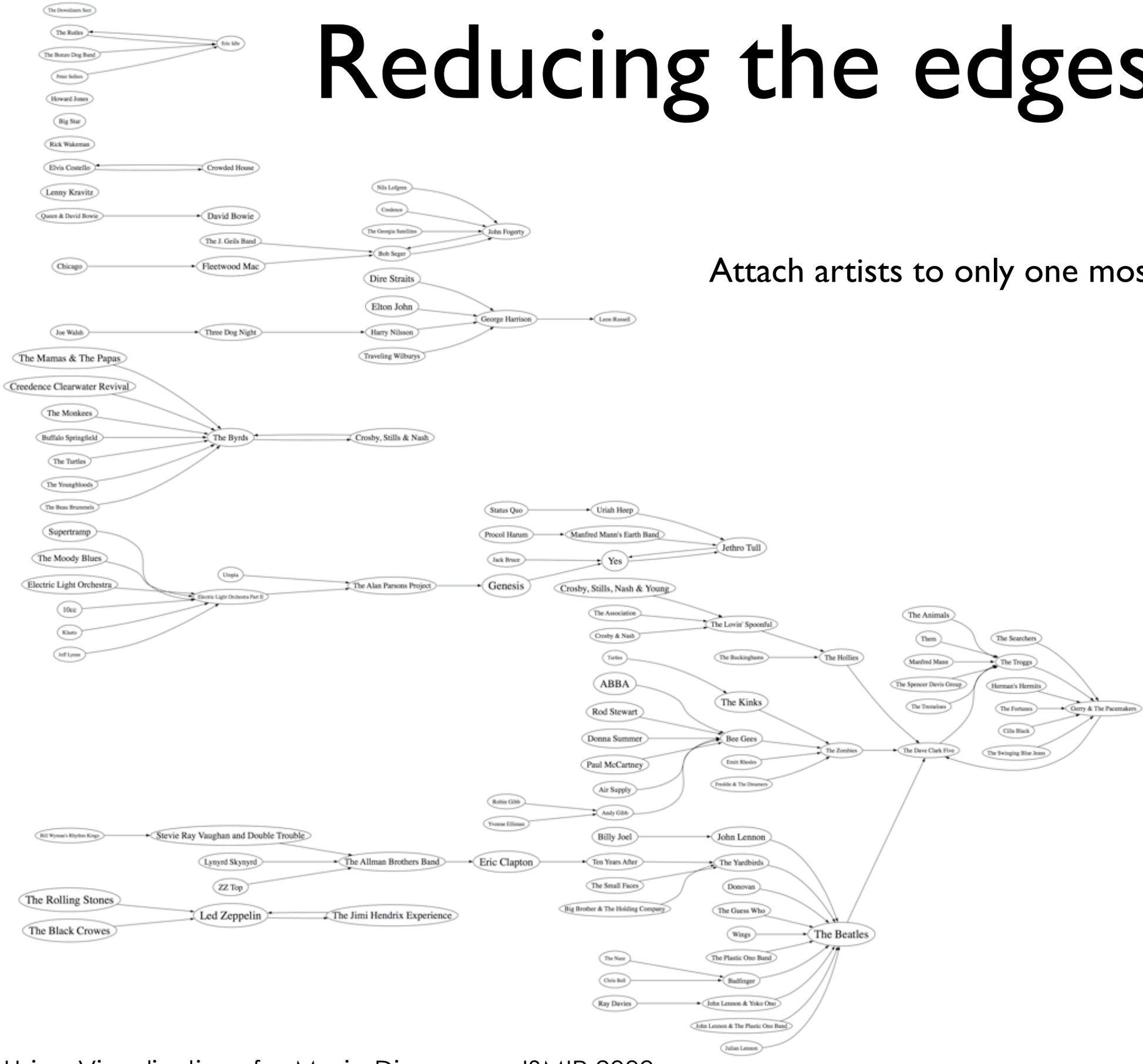
Eliminate the edges and use spring force embedding to position the artists

Simplifying the graph



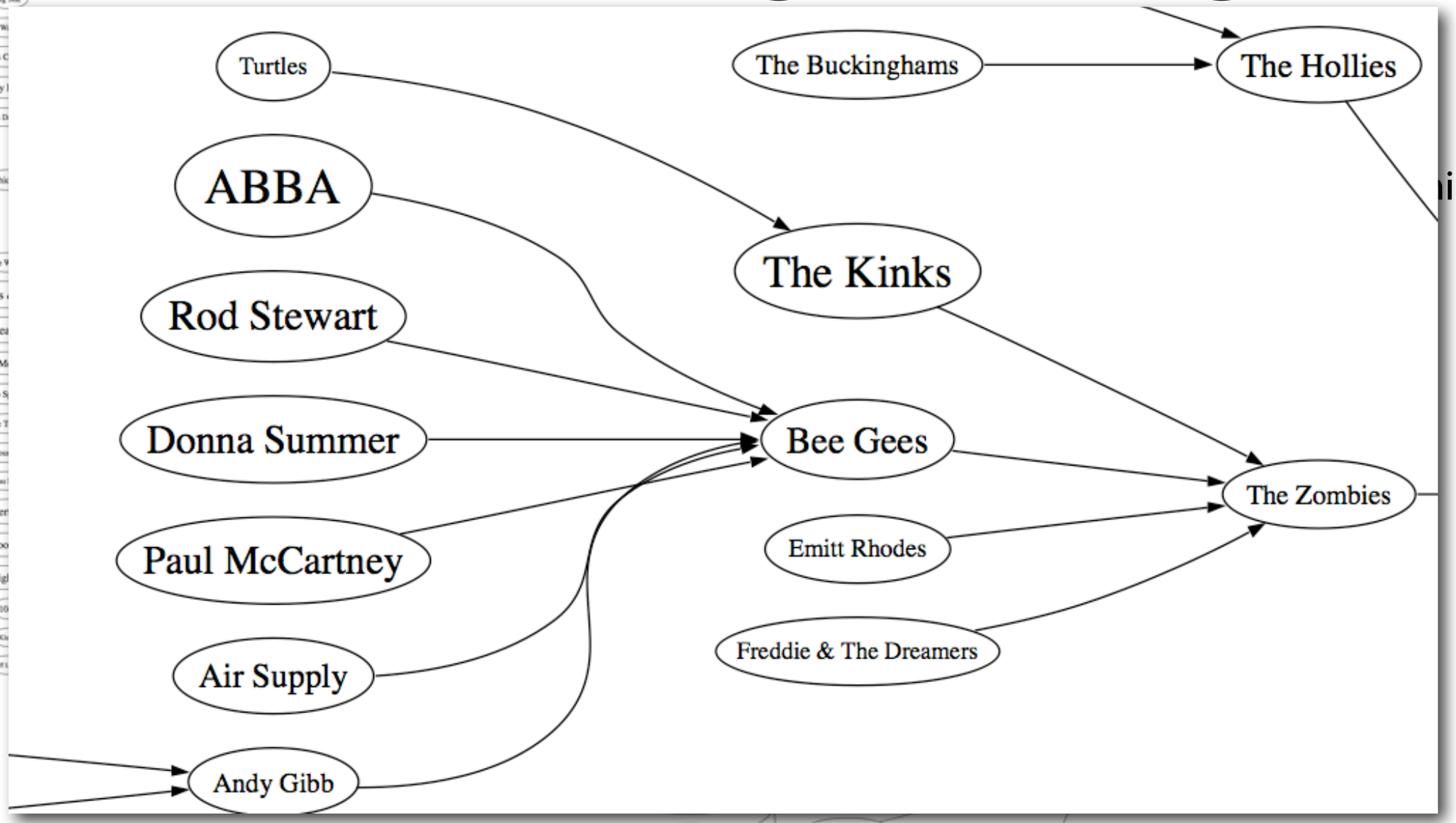
Eliminate the edges and use spring force embedding to position the artists

Reducing the edges



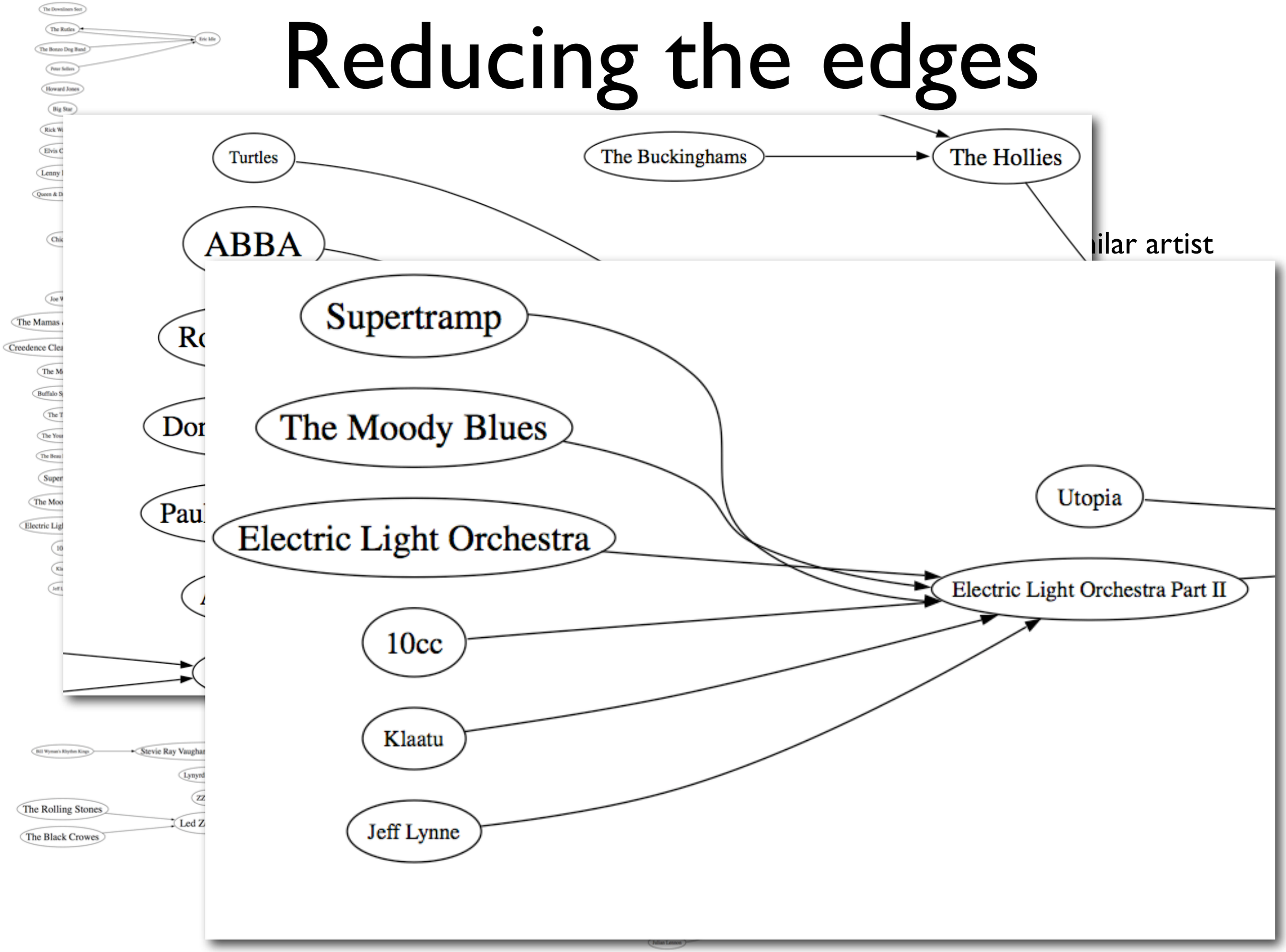
Attach artists to only one most similar artist

Reducing the edges

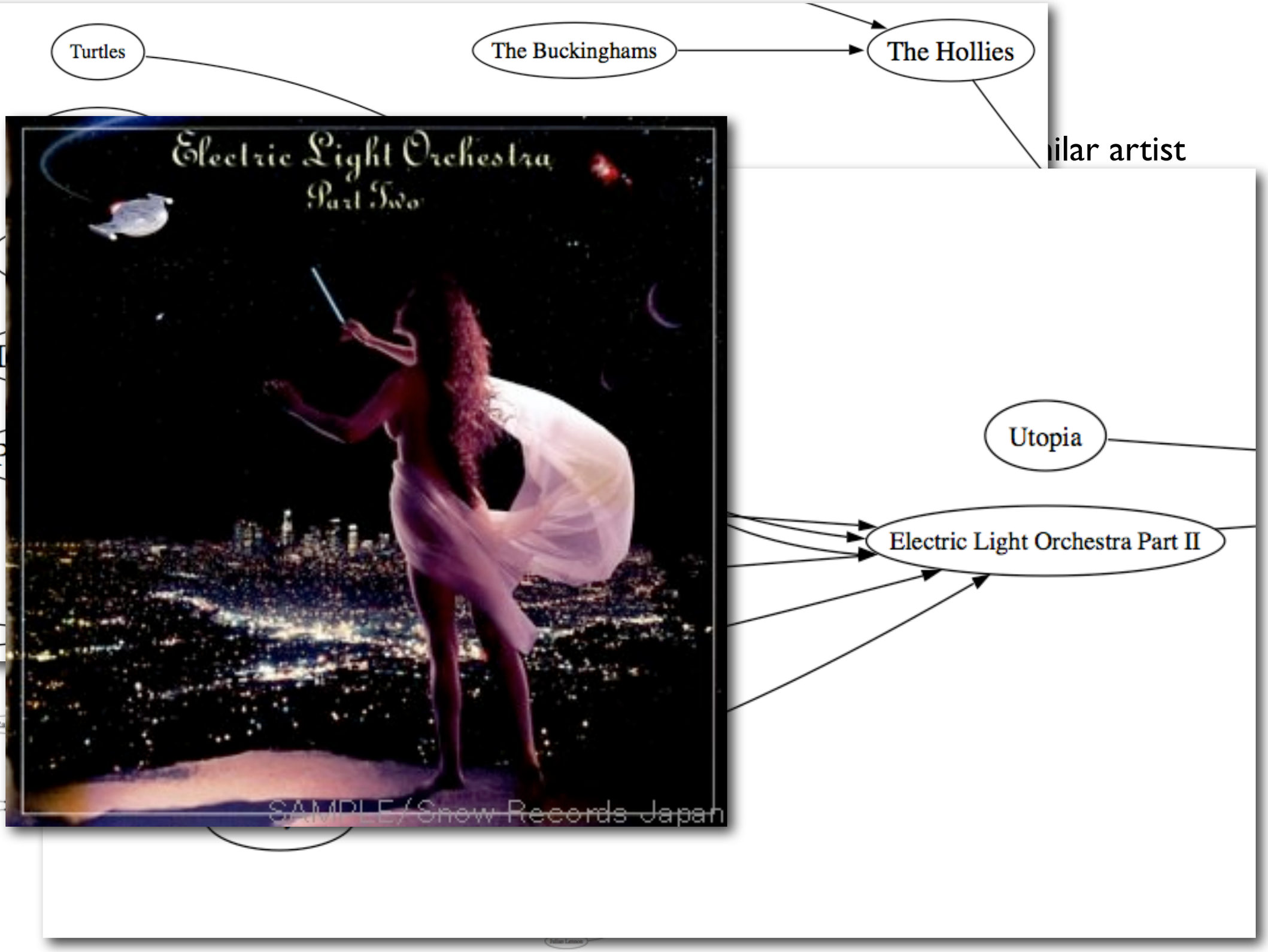


ilar artist

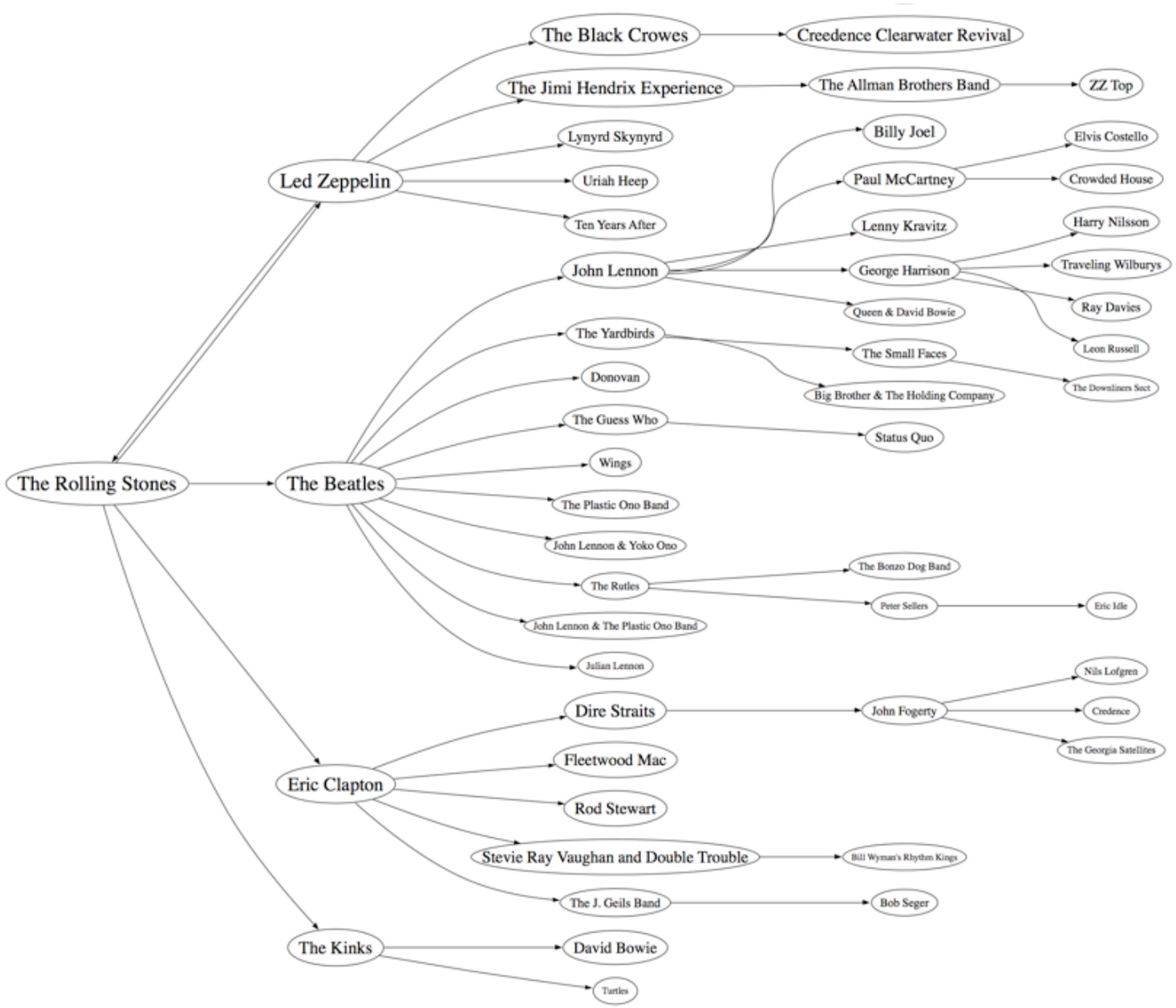
Reducing the edges

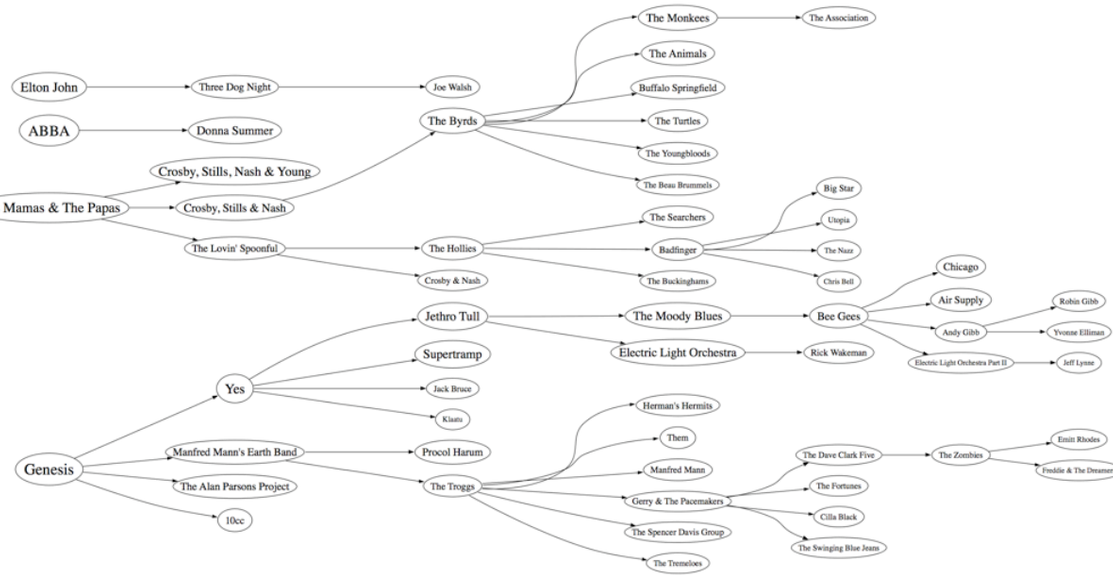


Reducing the edges



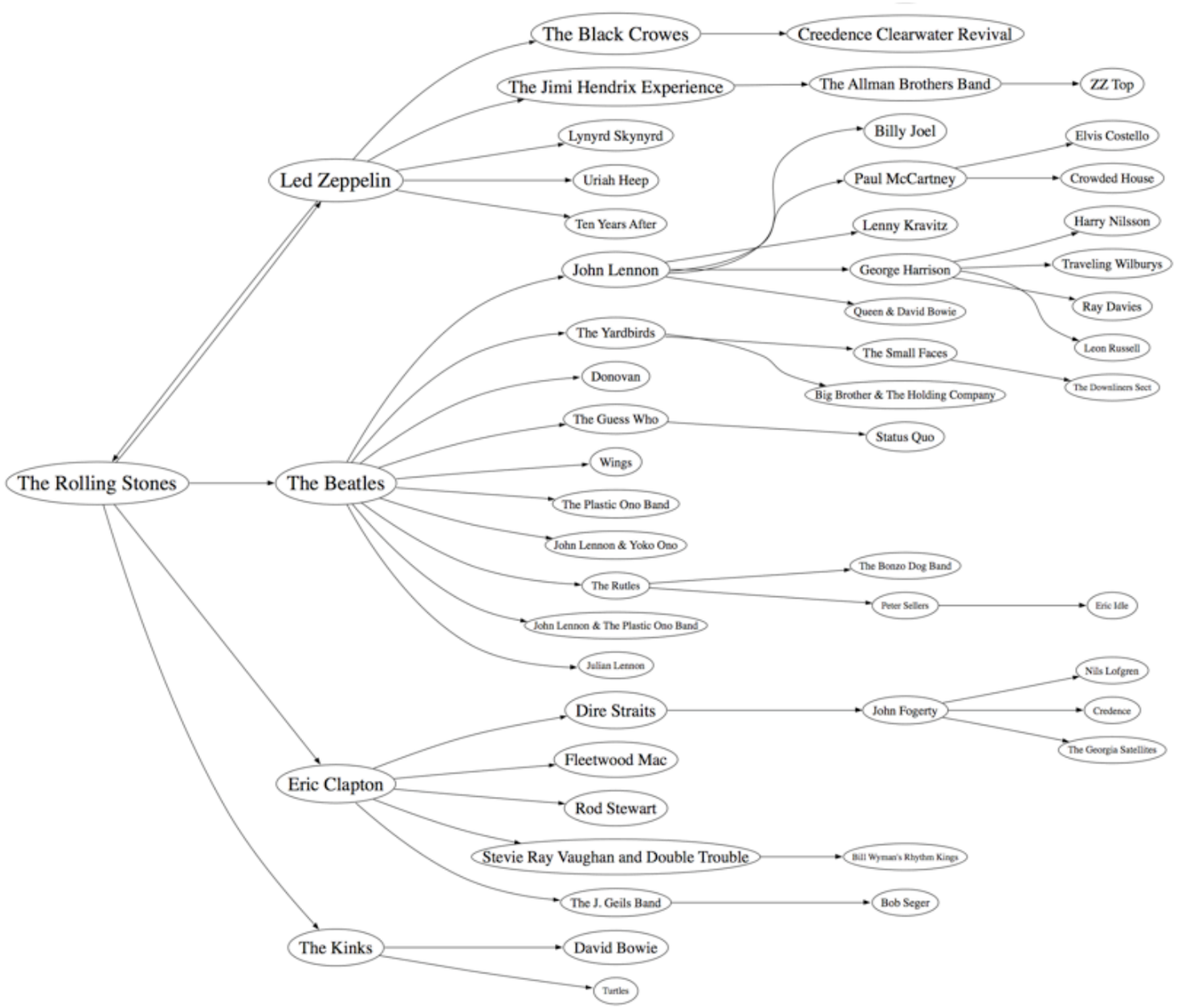
Putting ELO II in its place

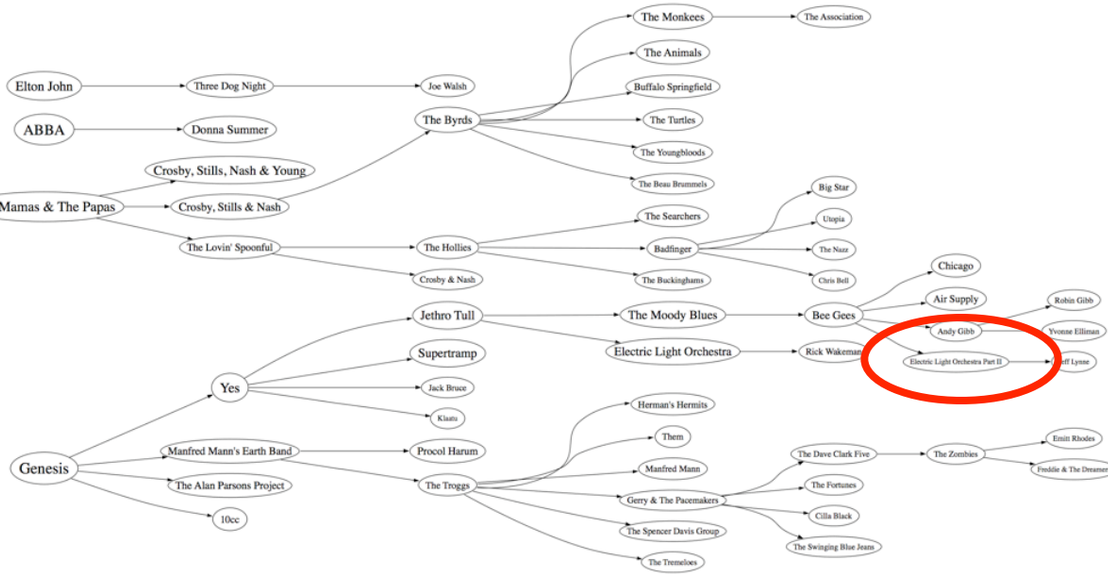




Attach artists to the most similar artist that has greater familiarity

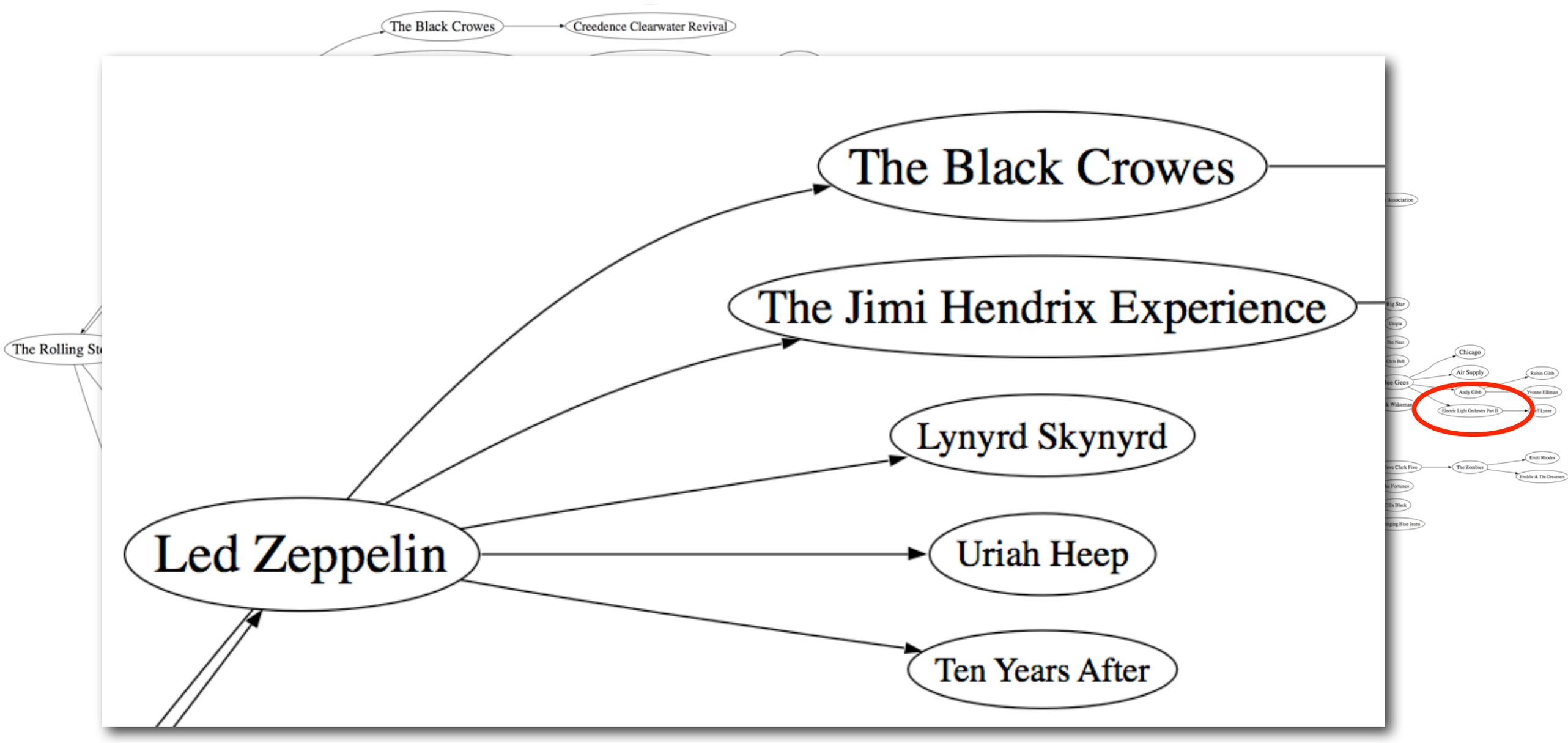
Putting ELO II in its place





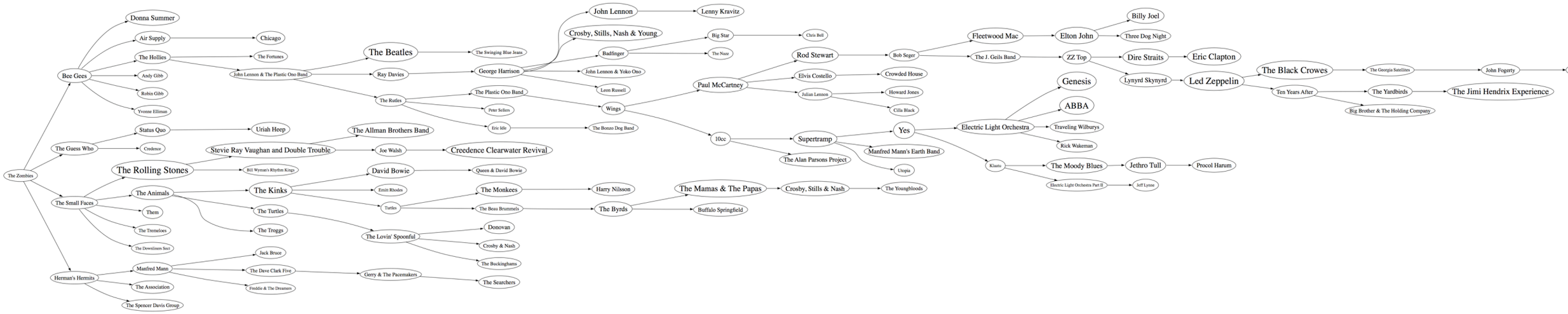
Attach artists to the most similar artist that has greater familiarity

Putting ELO II in its place



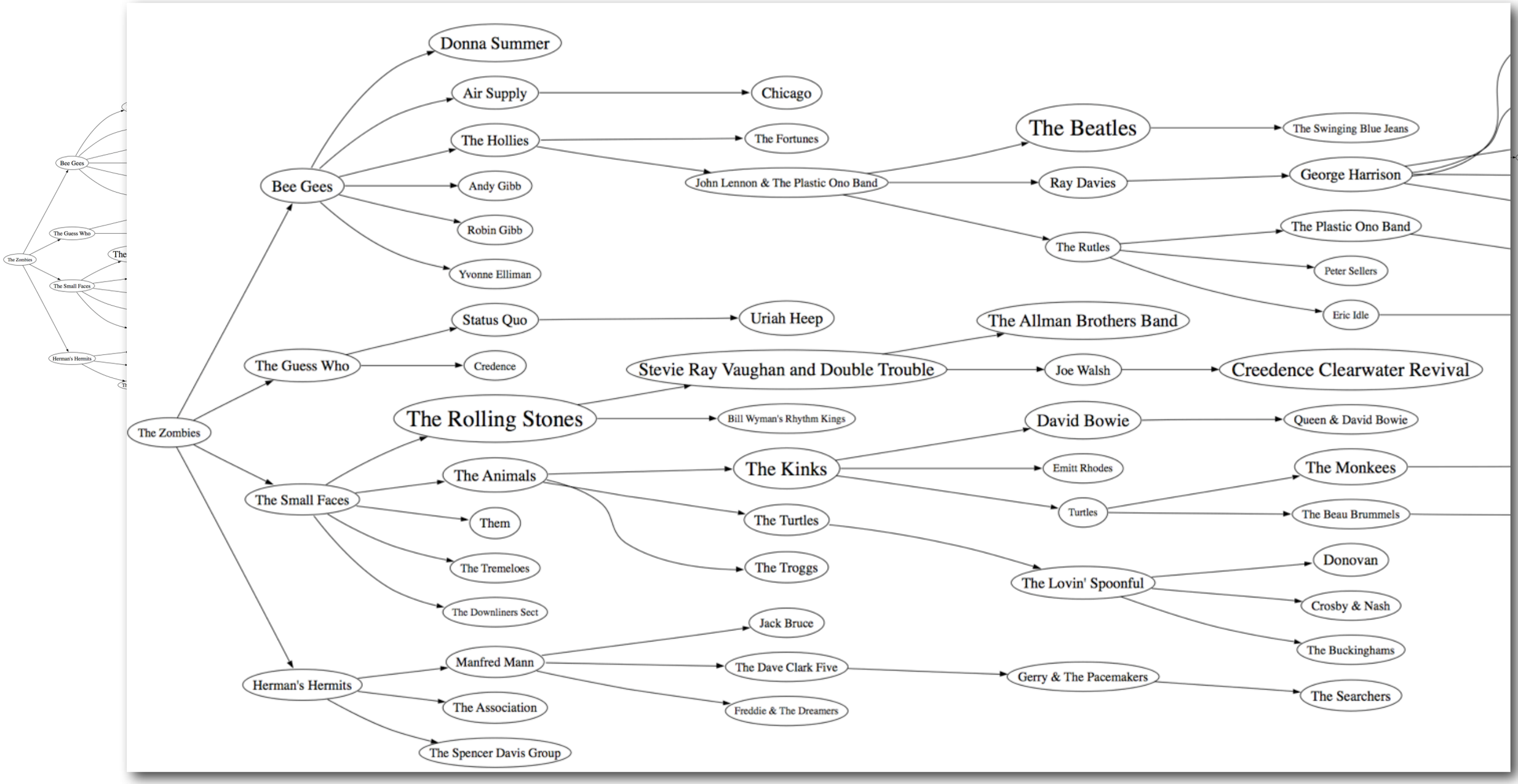
Attach artists to the most similar artist that has greater familiarity

Making the graph connected



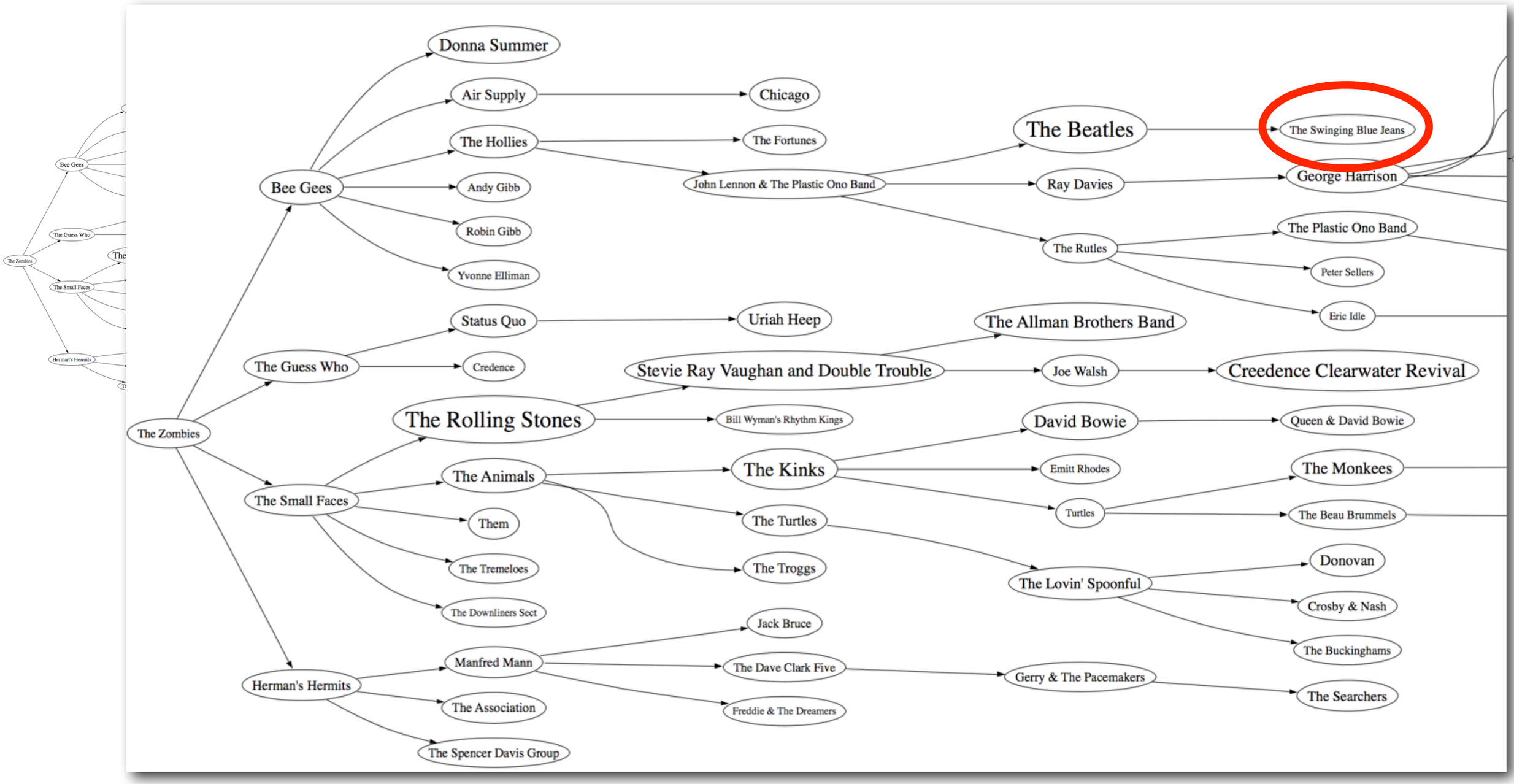
Build a minimum spanning tree from the graph

Making the graph connected



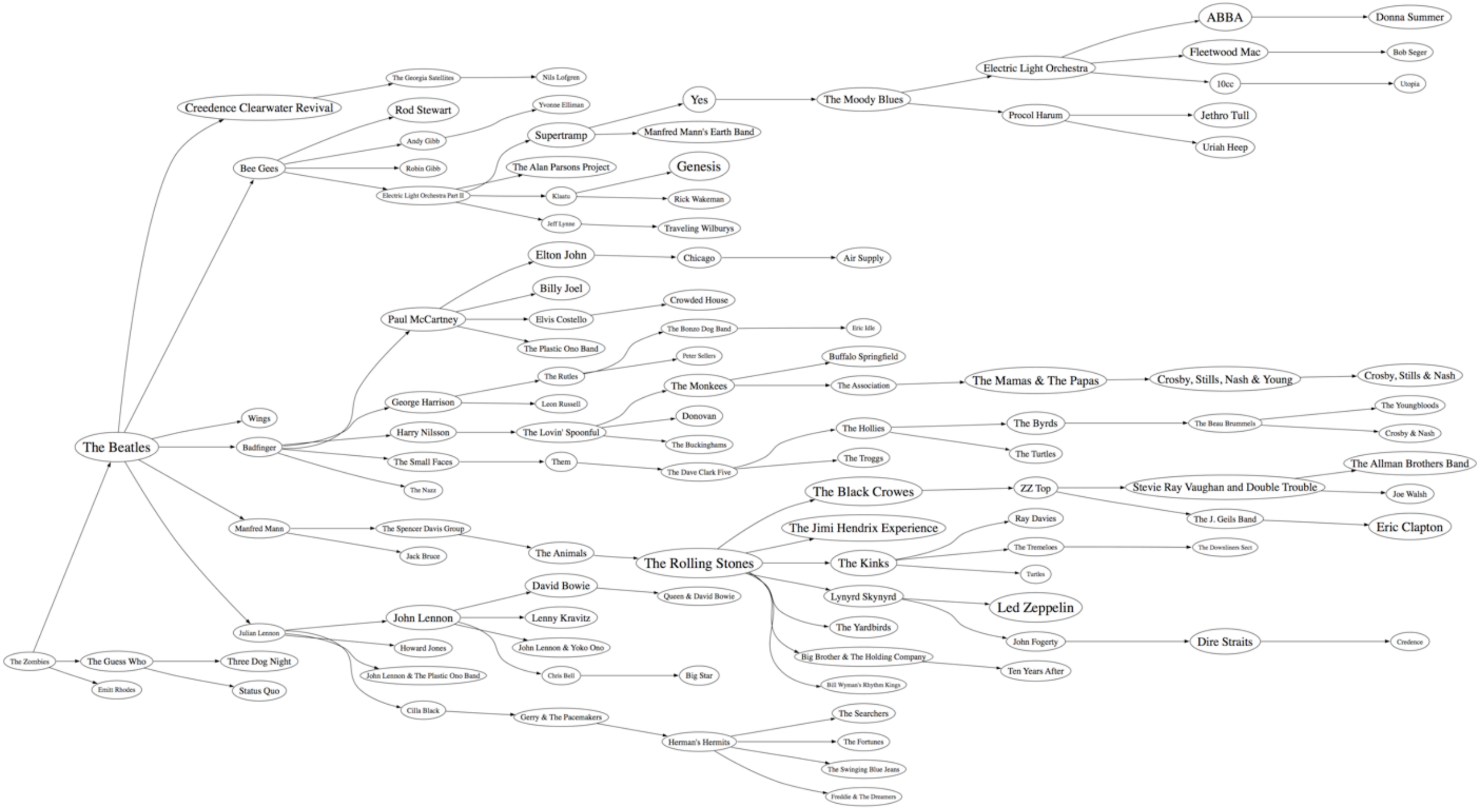
Build a minimum spanning tree from the graph

Making the graph connected



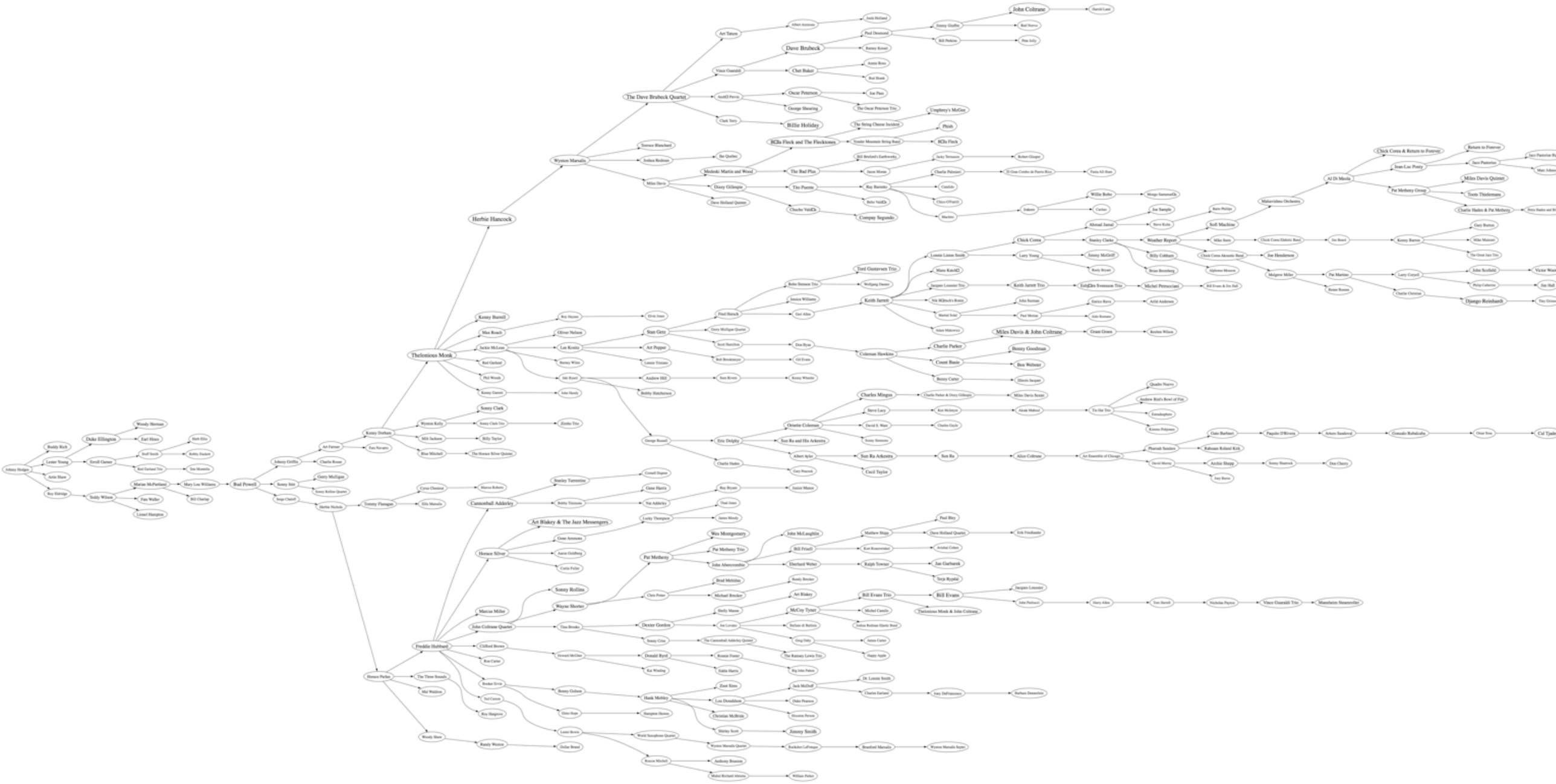
Build a minimum spanning tree from the graph

Fixing the swinging blue jeans problem



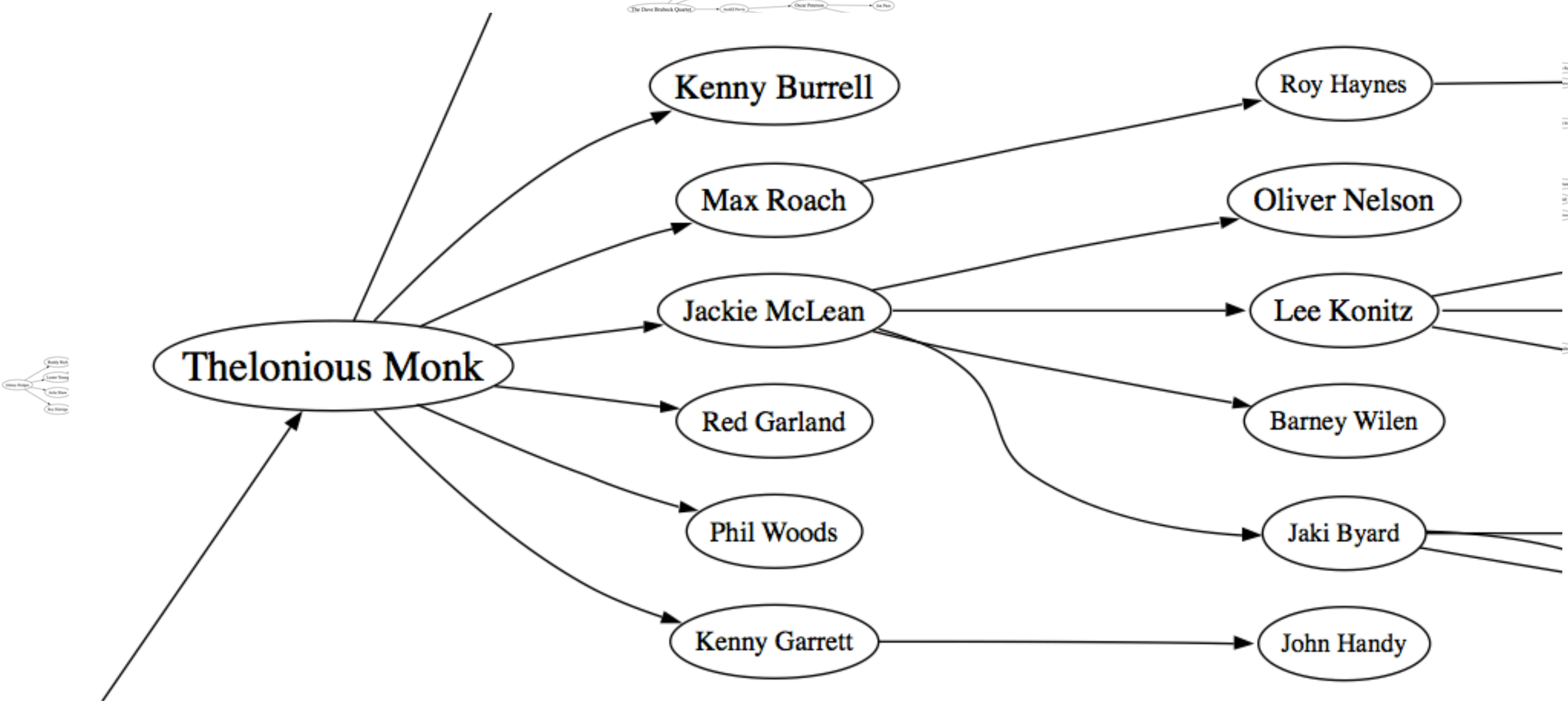
Prefer connections to bands of similar familiarity

Other near-neighbor graphs



Miles Davis

Other near-neighbor graphs

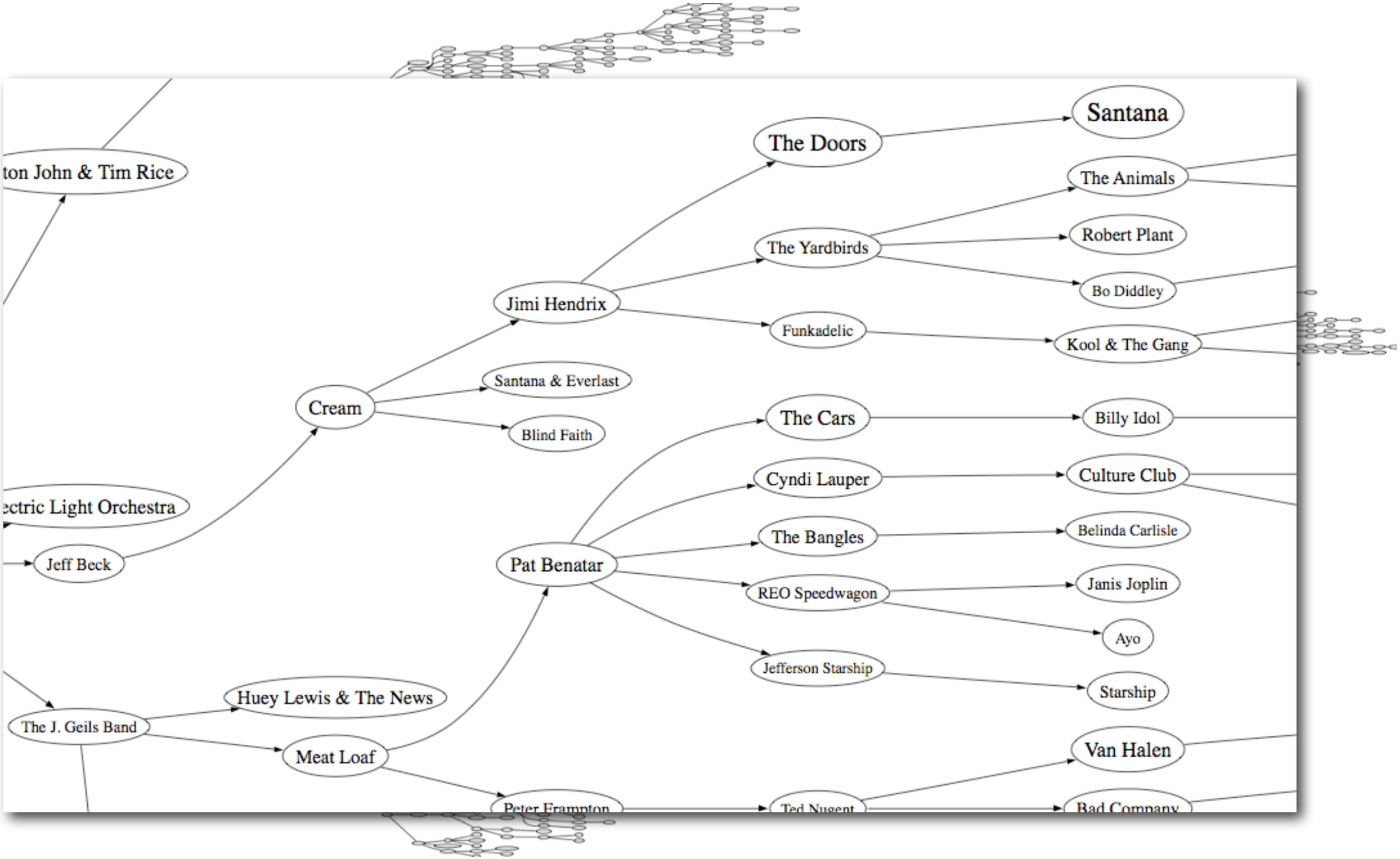


Miles Davis

2K artists

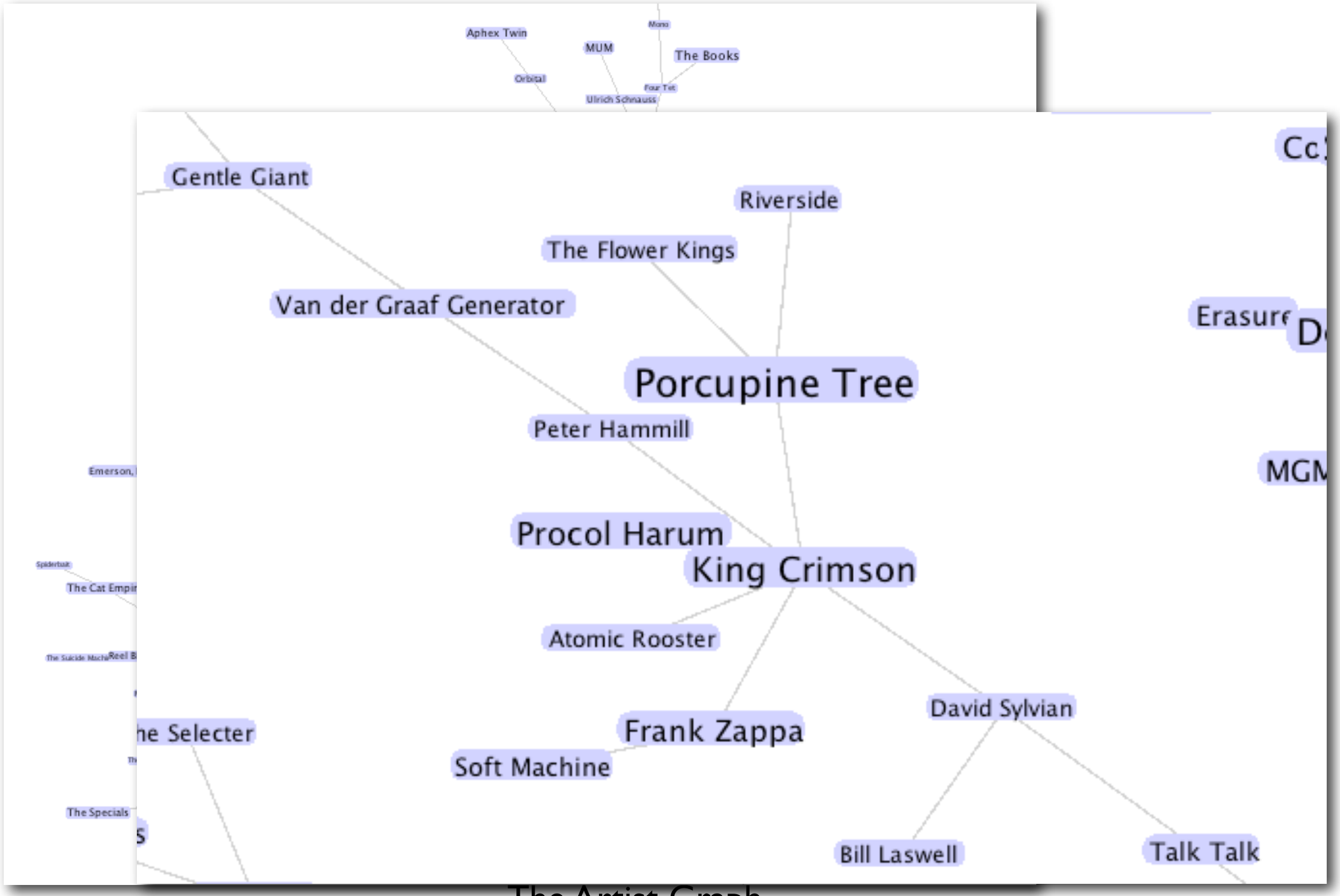
A browsing network for music discovery

2K artists



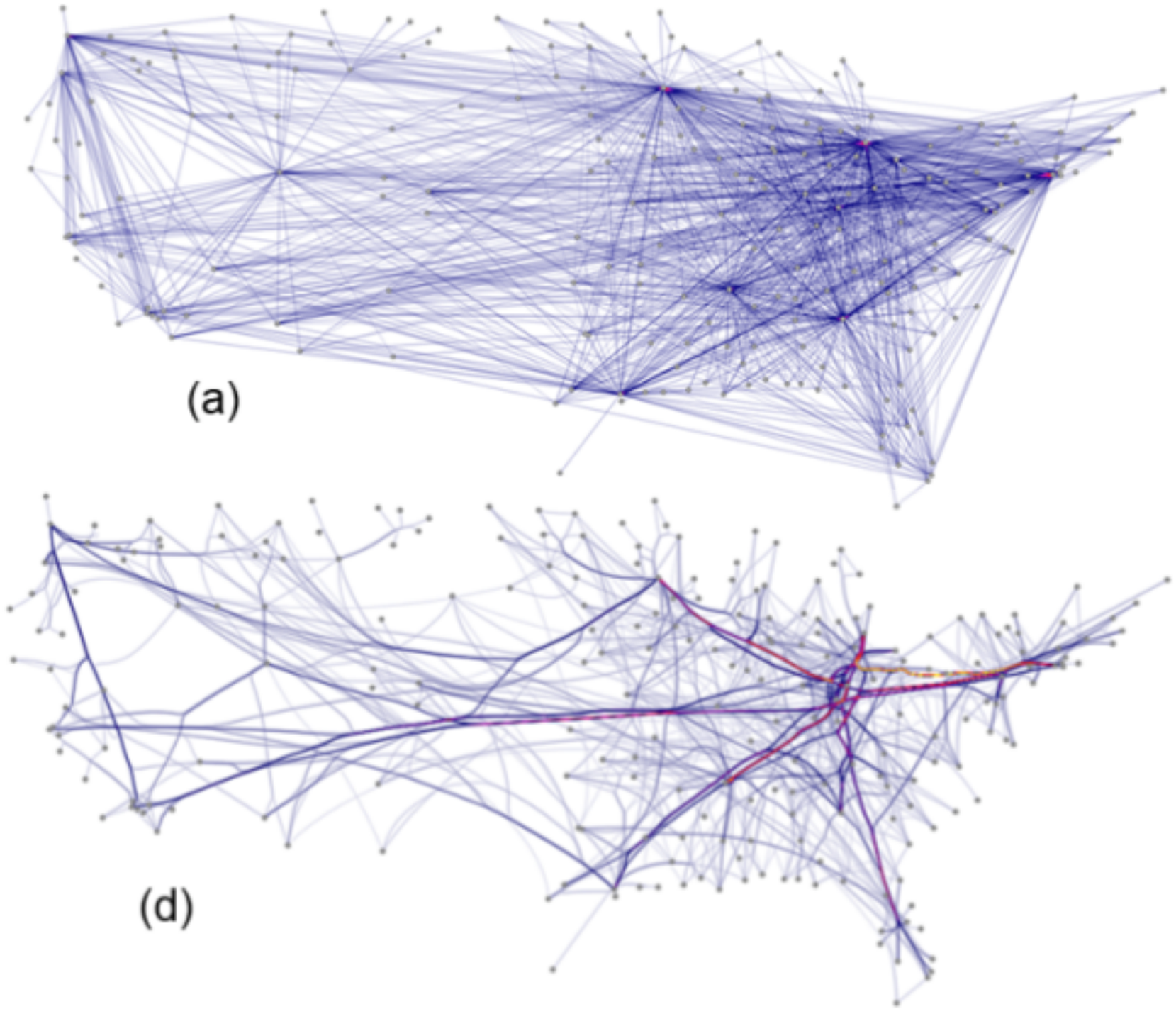
A browsing network for music discovery

Making the graph interactive



The Artist Graph

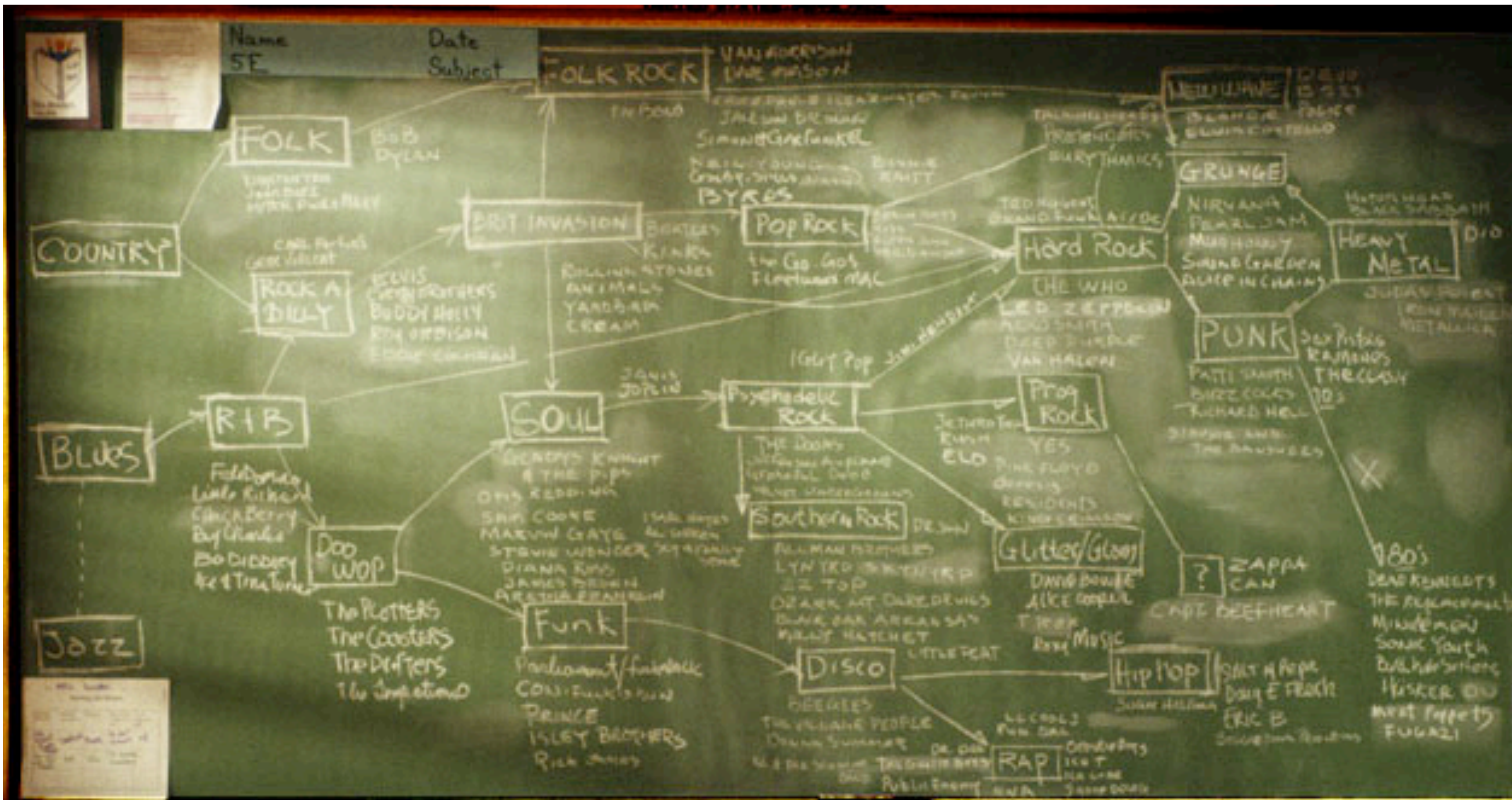
Force-Directed Edge Bundling for Graph Visualization



Danny Holten, Jarke J. van Wijk

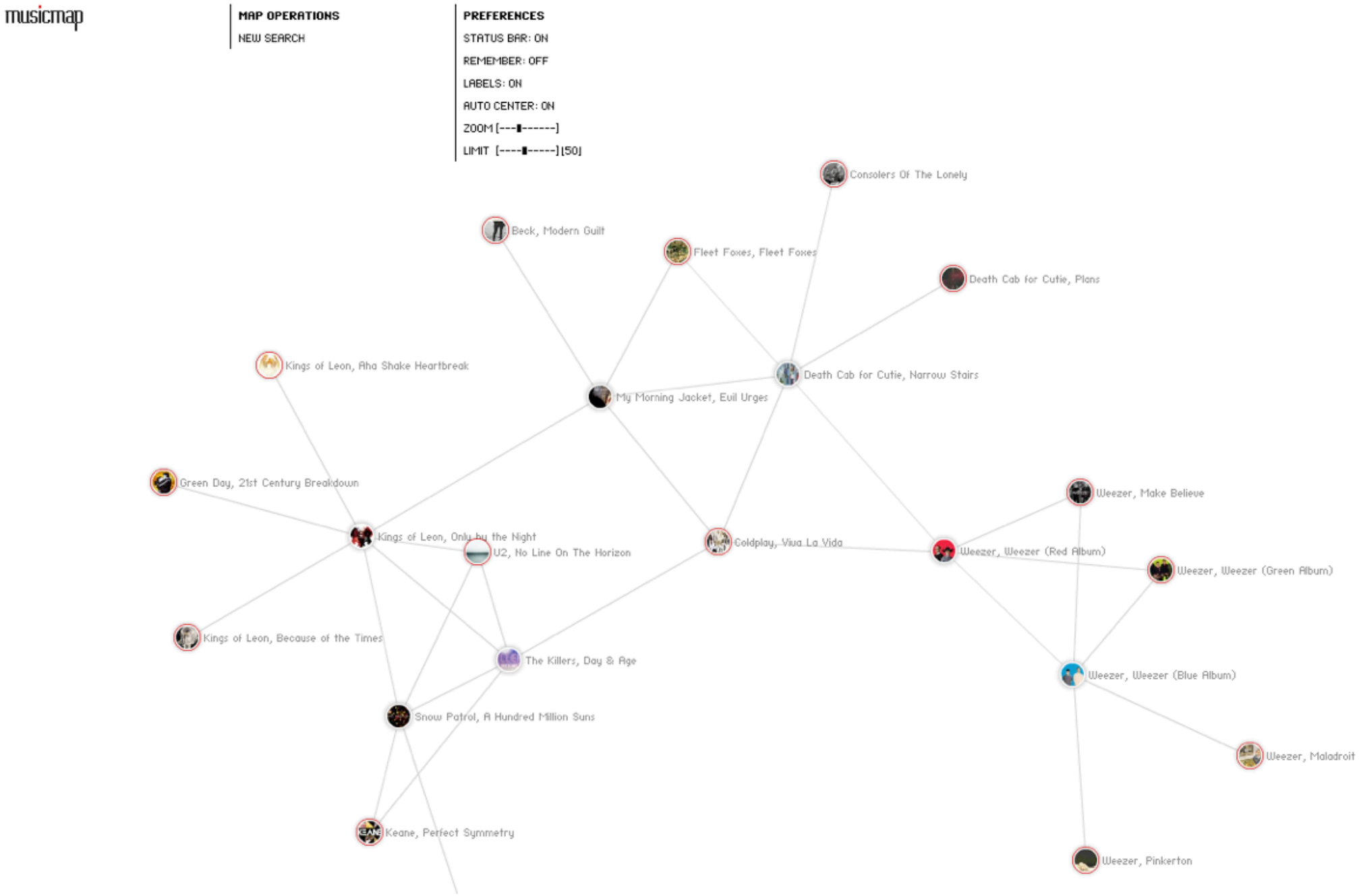
Survey of Music Visualizations

Graphs



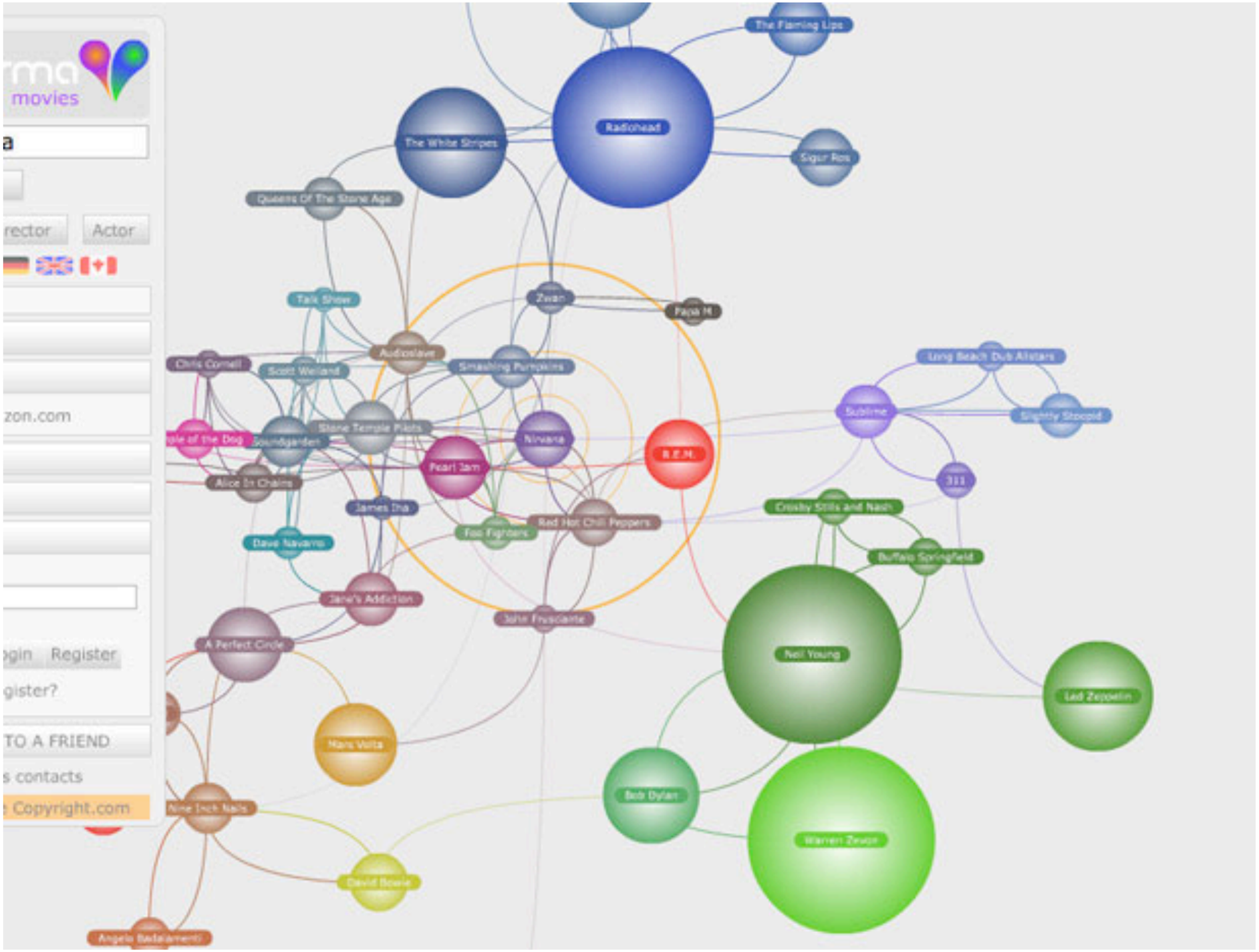
Name
Date
Subject
FOLK ROCK
FOLK
BOB DYLAN
COUNTRY
ROCK A BILLY
ELVIS
BRIT INVASION
BYRDS
Pop Rock
Hard Rock
NEW WAVE
GRUNGE
NIRVANA
PEARL JAM
HEAVY METAL
PUNK
THE WHO
LED ZEPPELIN
VAN HALEN
R+B
BLUES
SOUL
Psychedelic Rock
Prog Rock
YES
PINK FLOYD
Southern Rock
Glitter/Glam
DOO WOP
Funk
DISCO
Hip Hop
RAP
Jazz
ZAPPA
CAN
CAPT BEEFHEART
80's
PRINCE

musicmap



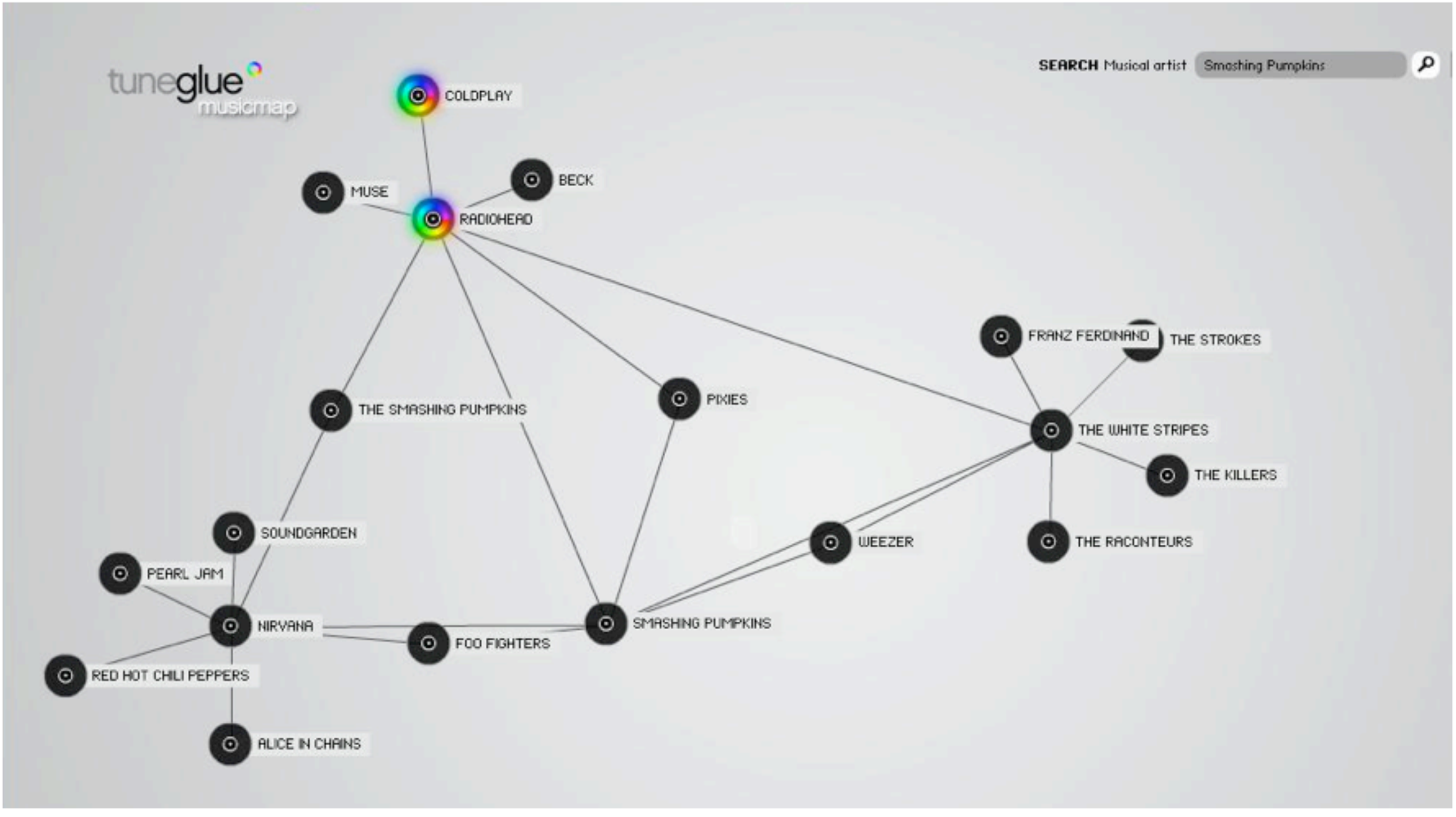
http://www.dimvision.com/musicmap/

Music Plasma



MusicPlasma.com

tuneglue

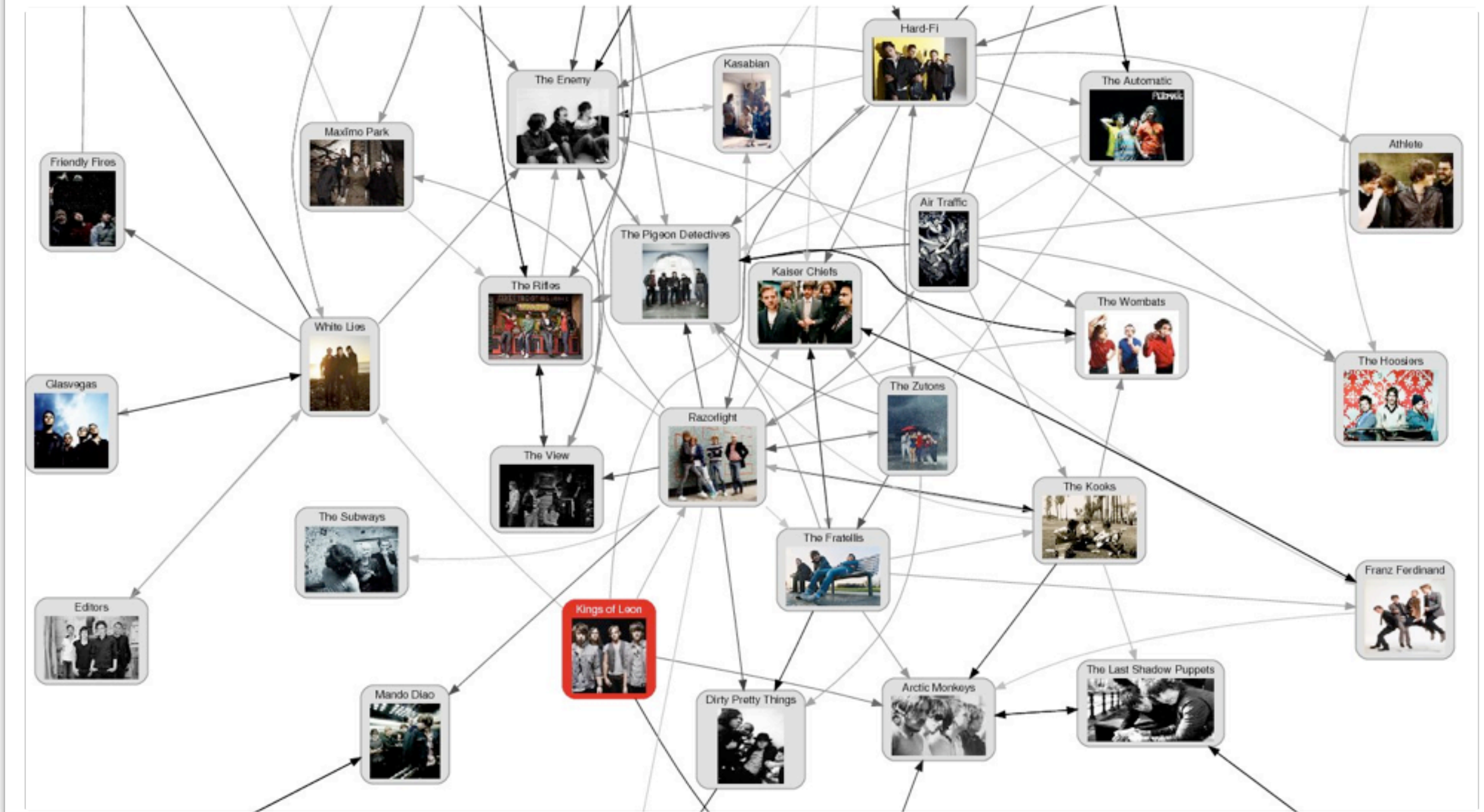


http://audiomap.tuneglue.net/

Last.fm artist map

http://lastfm.dontdrinkandroot.net/

Last.fm artist map



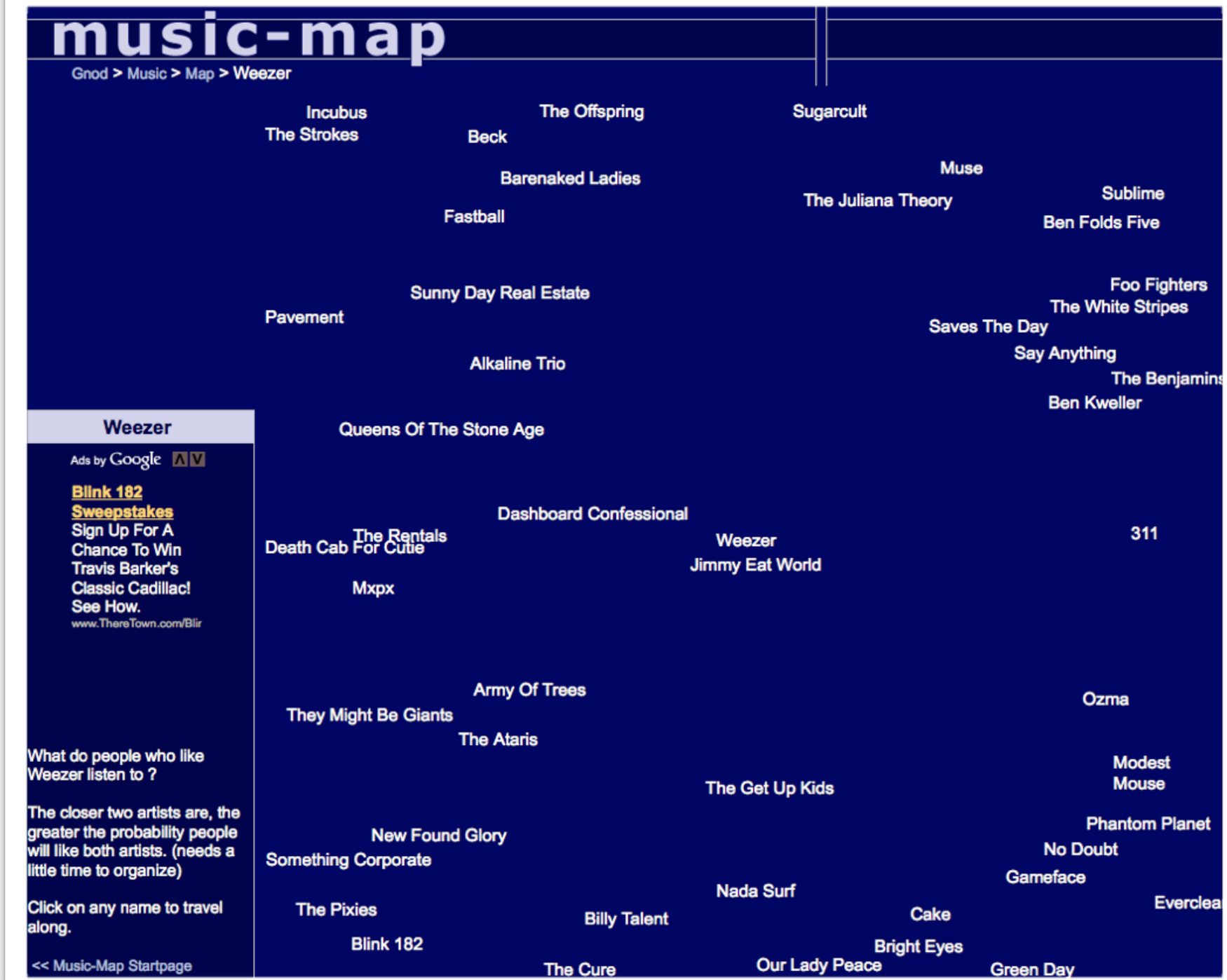
http://lastfm.dontdrinkandroot.net/

RAMA - Relational Artist Maps

Late-Breaking Demo Session

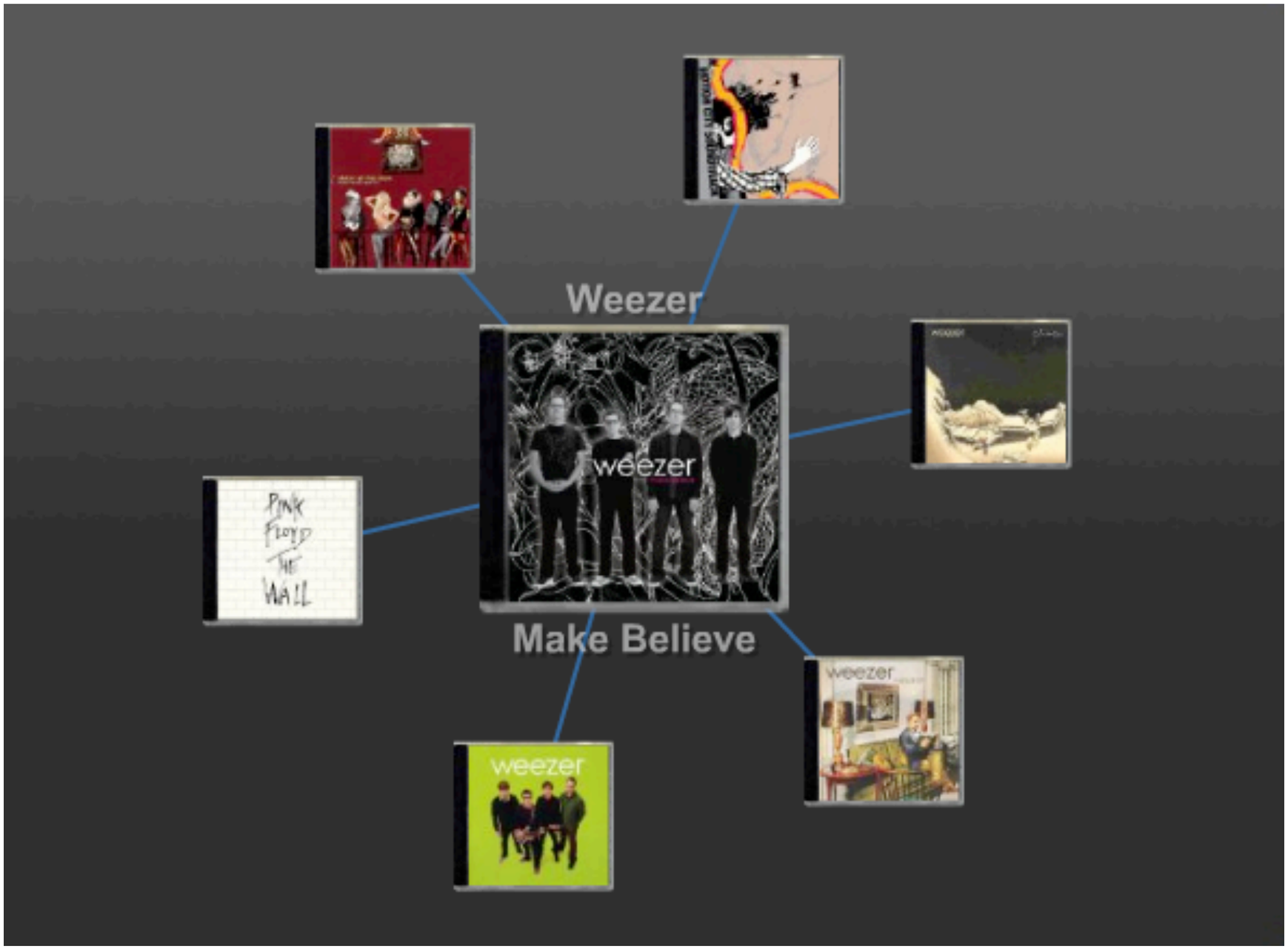
http://rama.inescporto.pt/

gnod music-map



http://www.music-map.com/

musicmesh



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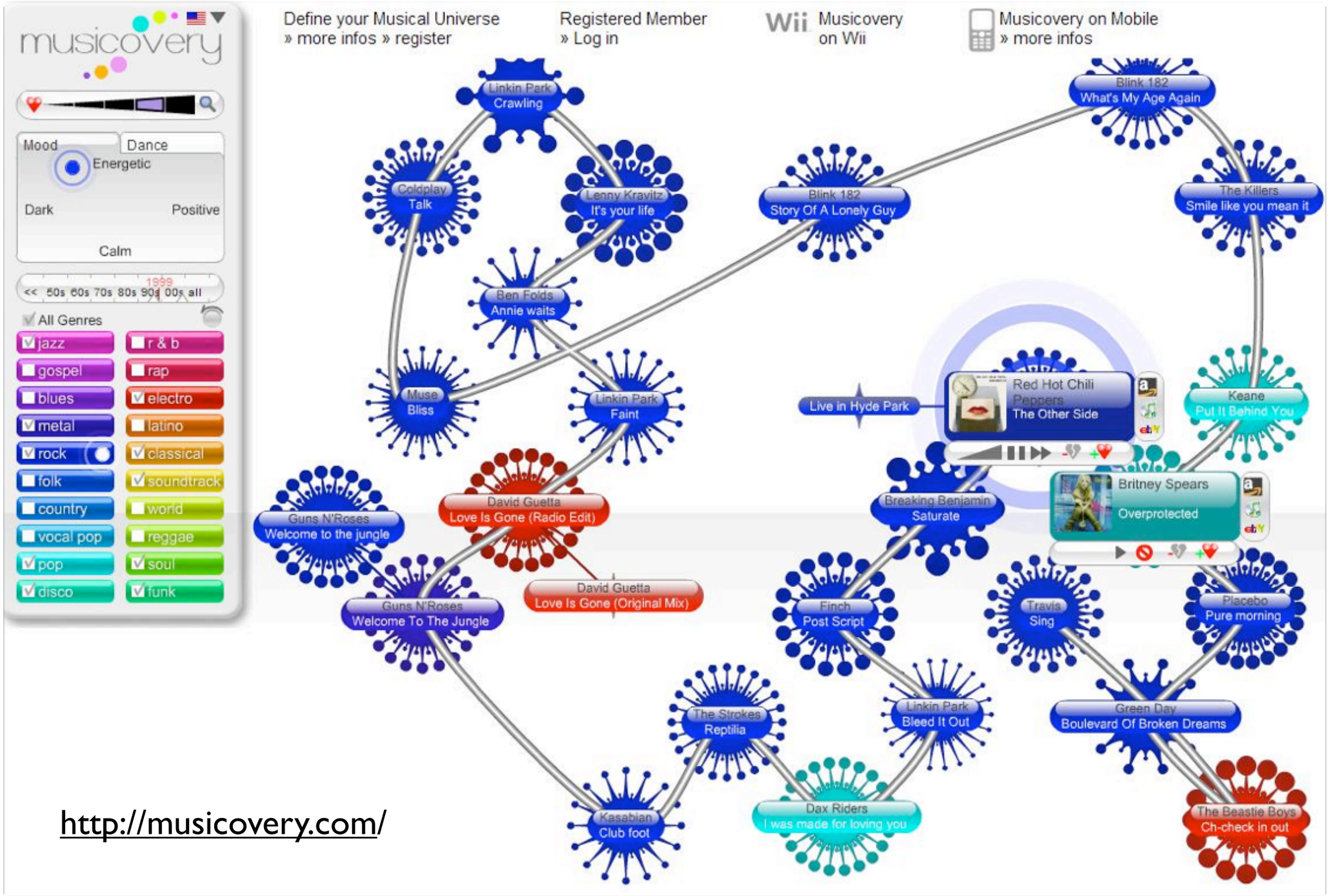
musicovery

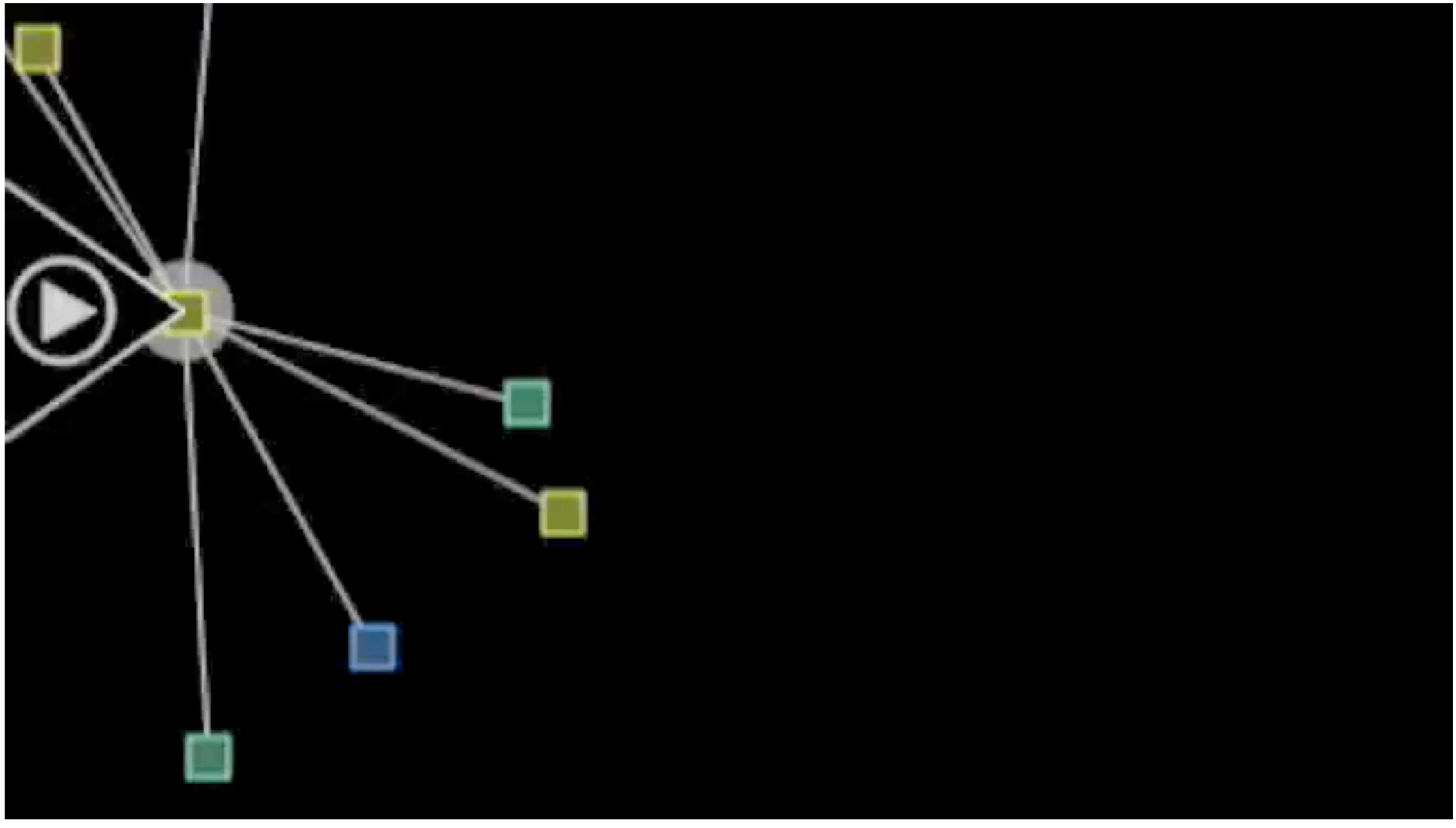


http://musicovery.com/

SoundBite for SongBird

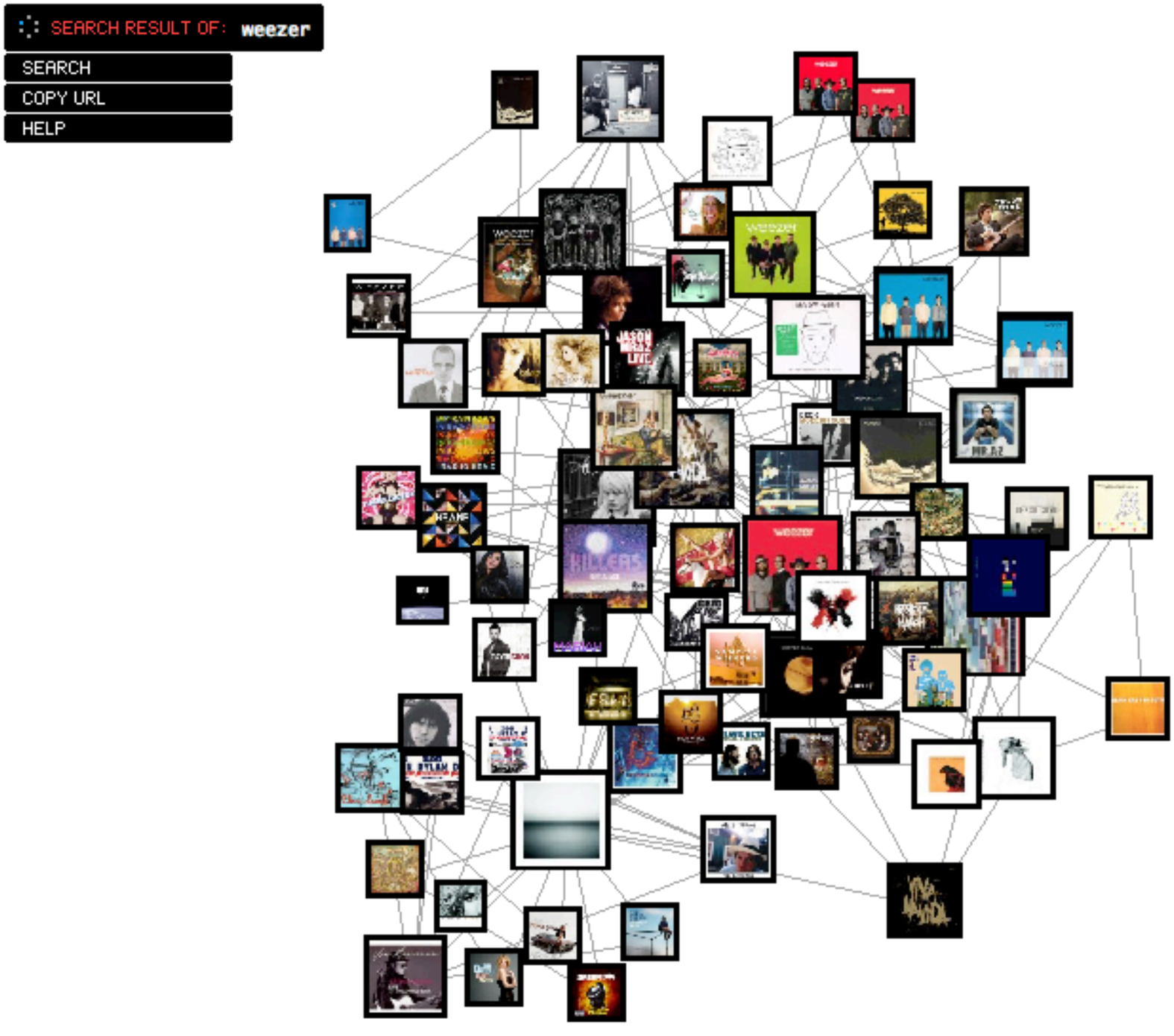
http://www.repeatingbeats.com/thesis.php - Steve Lloyd - QMUL

SoundBite for SongBird



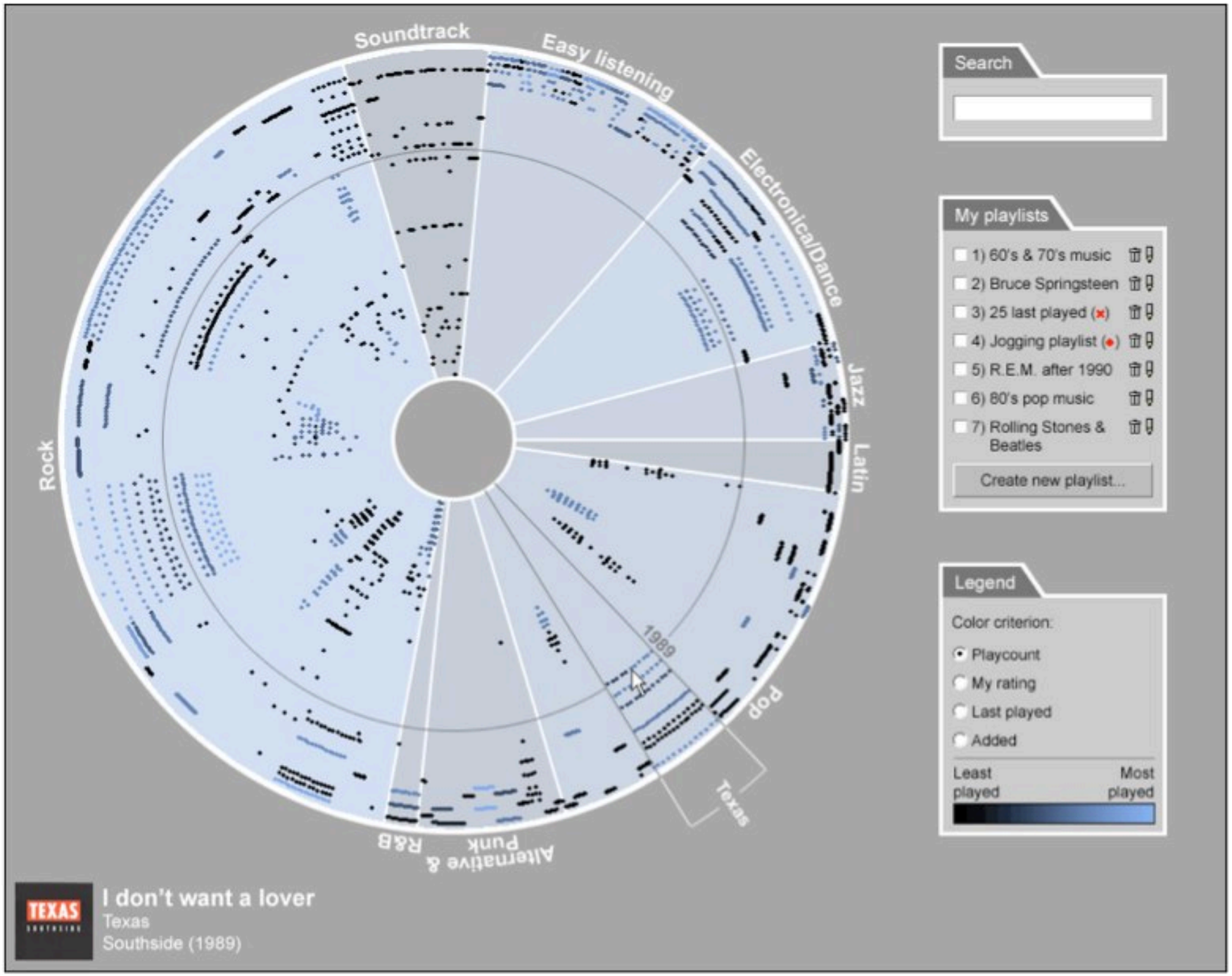
http://www.repeatingbeats.com/thesis.php - Steve Lloyd - QMUL

Amaznode



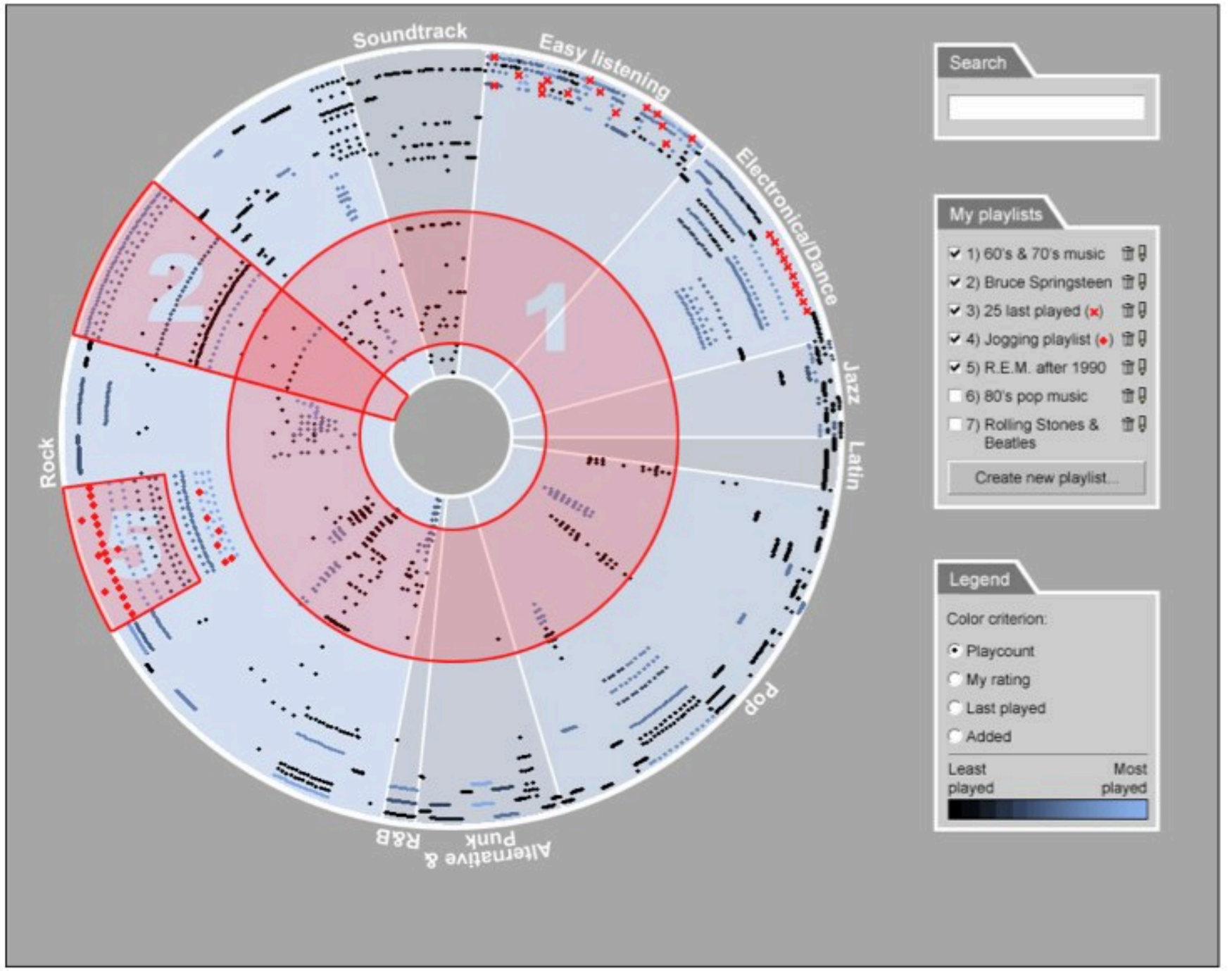
http://amaznode.fladdict.net/

Visualizing and Exploring Personal Libraries



http://torrens.files.wordpress.com/2009/06/ismir.pdf
Torrens, Patrick Hertzog, Josep-Lluís Arcos

Visualizing and Exploring Personal Libraries



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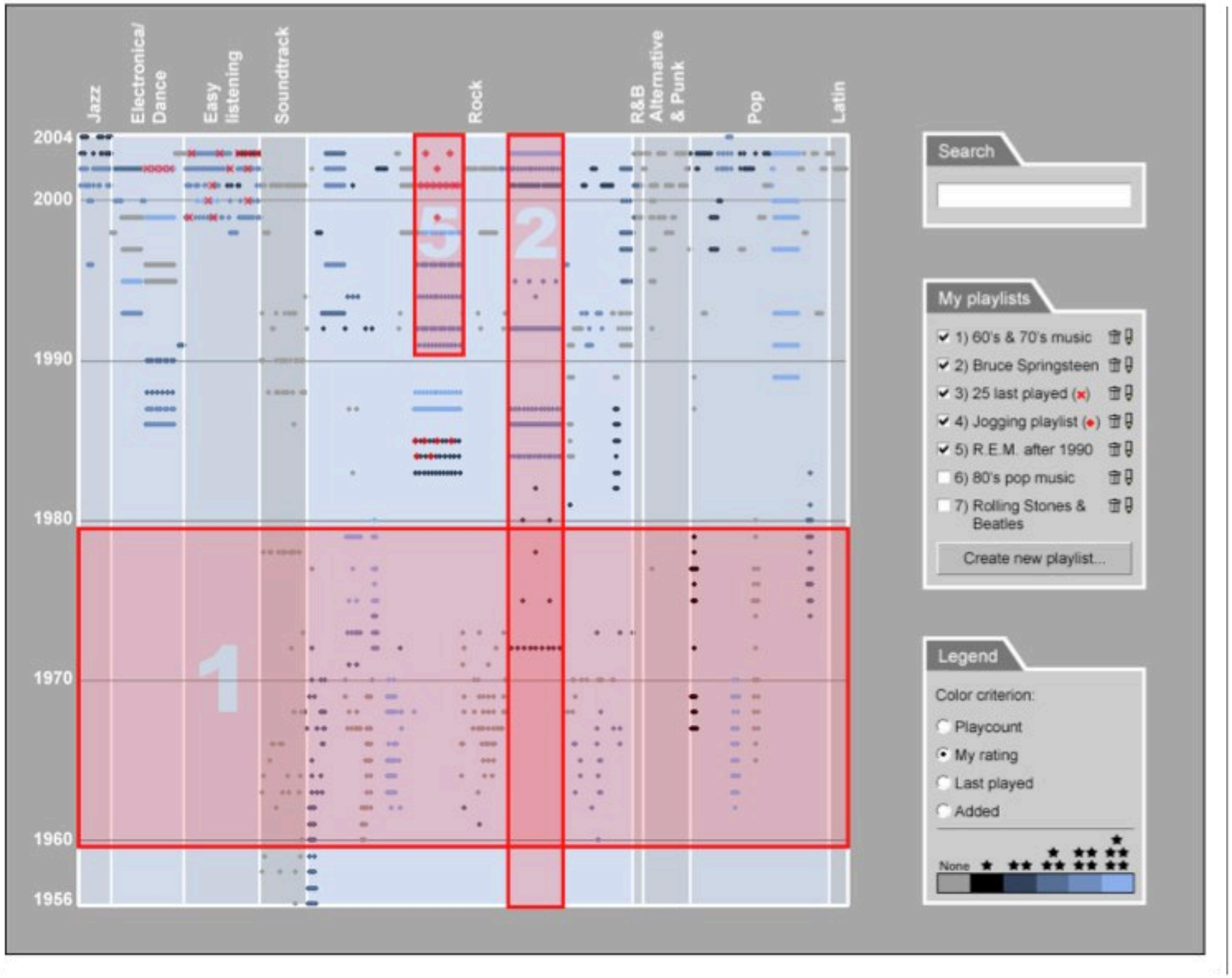

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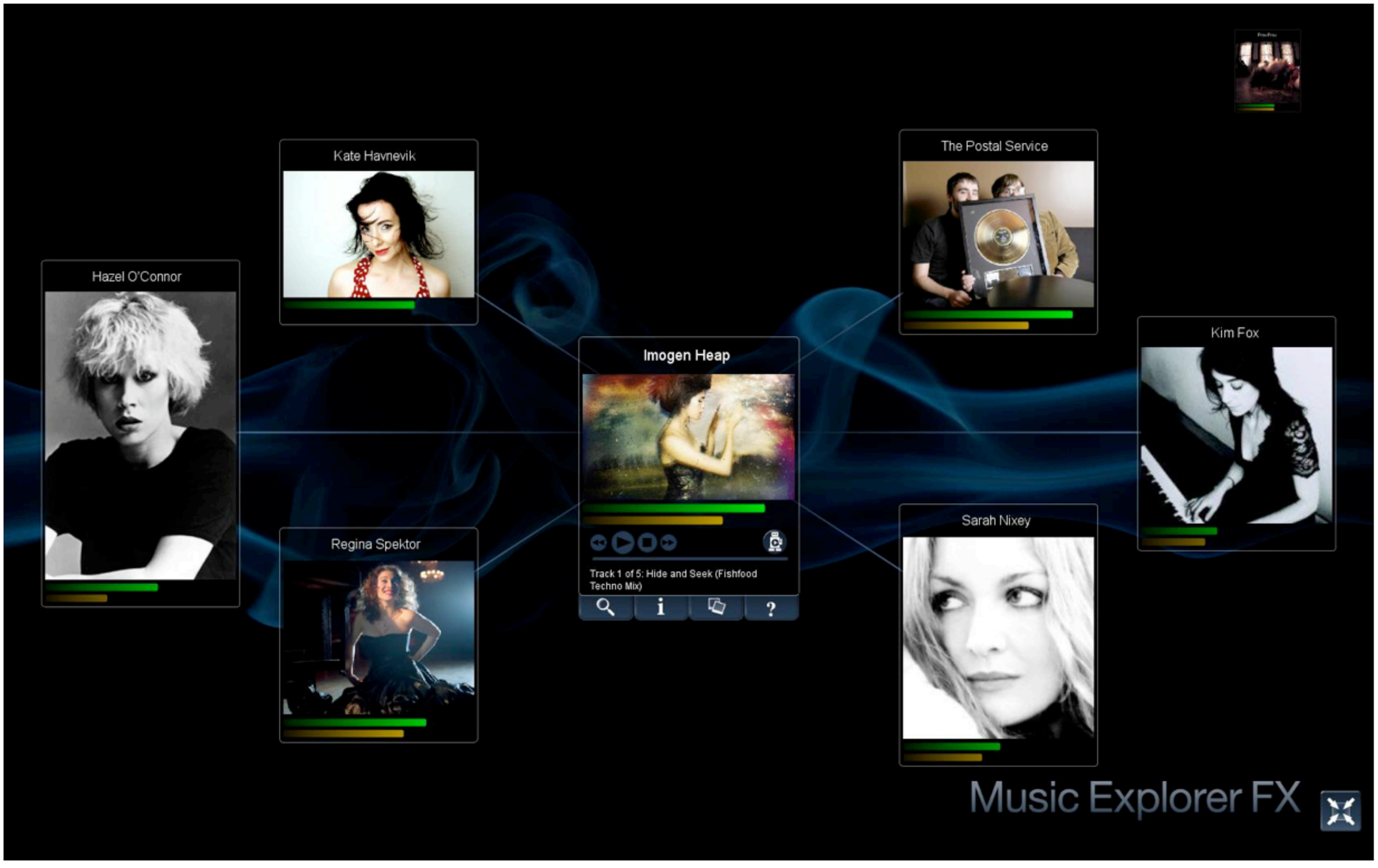
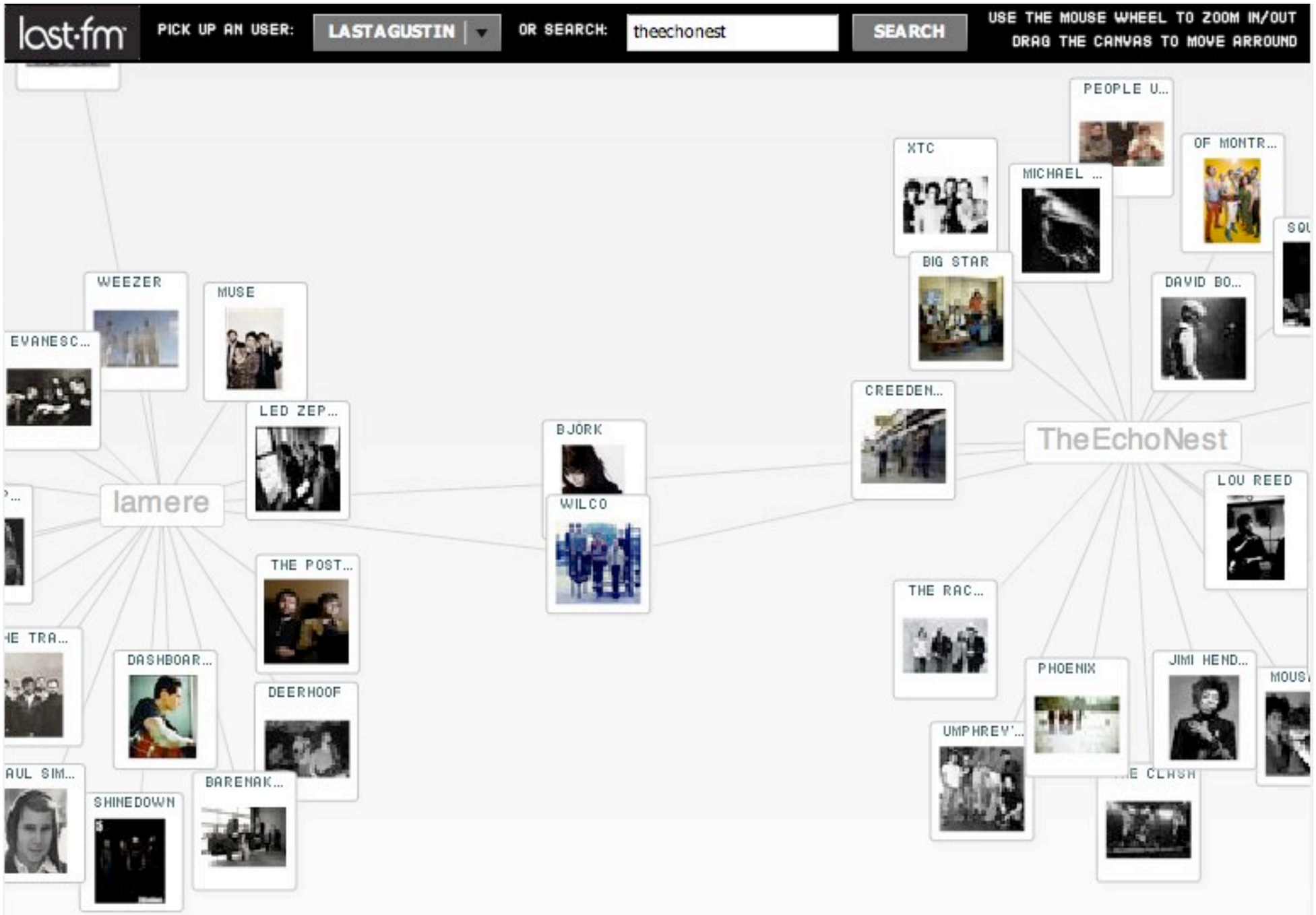
Music Explorer FX



http://musicexplorerfx.citytechinc.com/

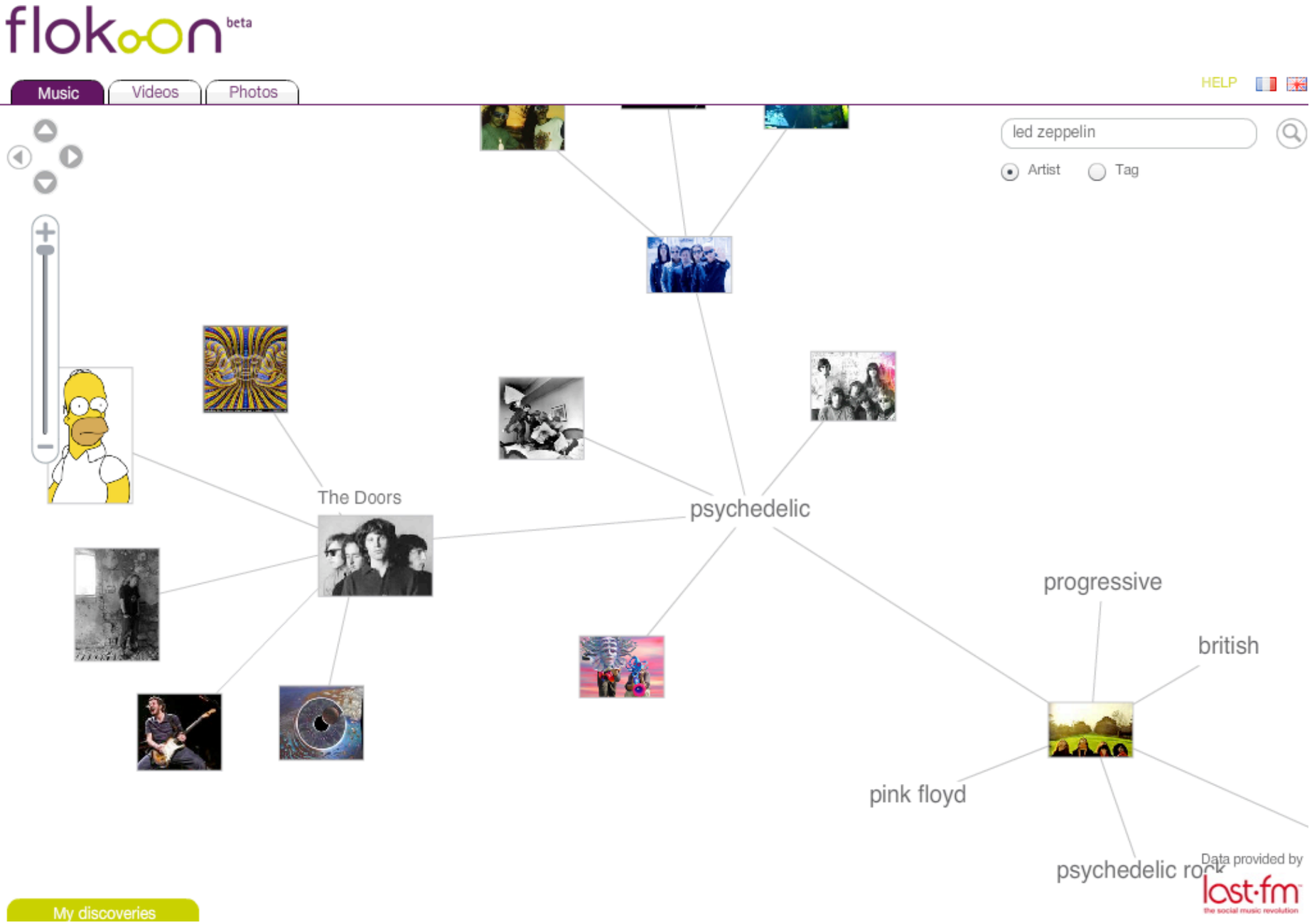
Social Music Discovery



Last FM tasteOgraph

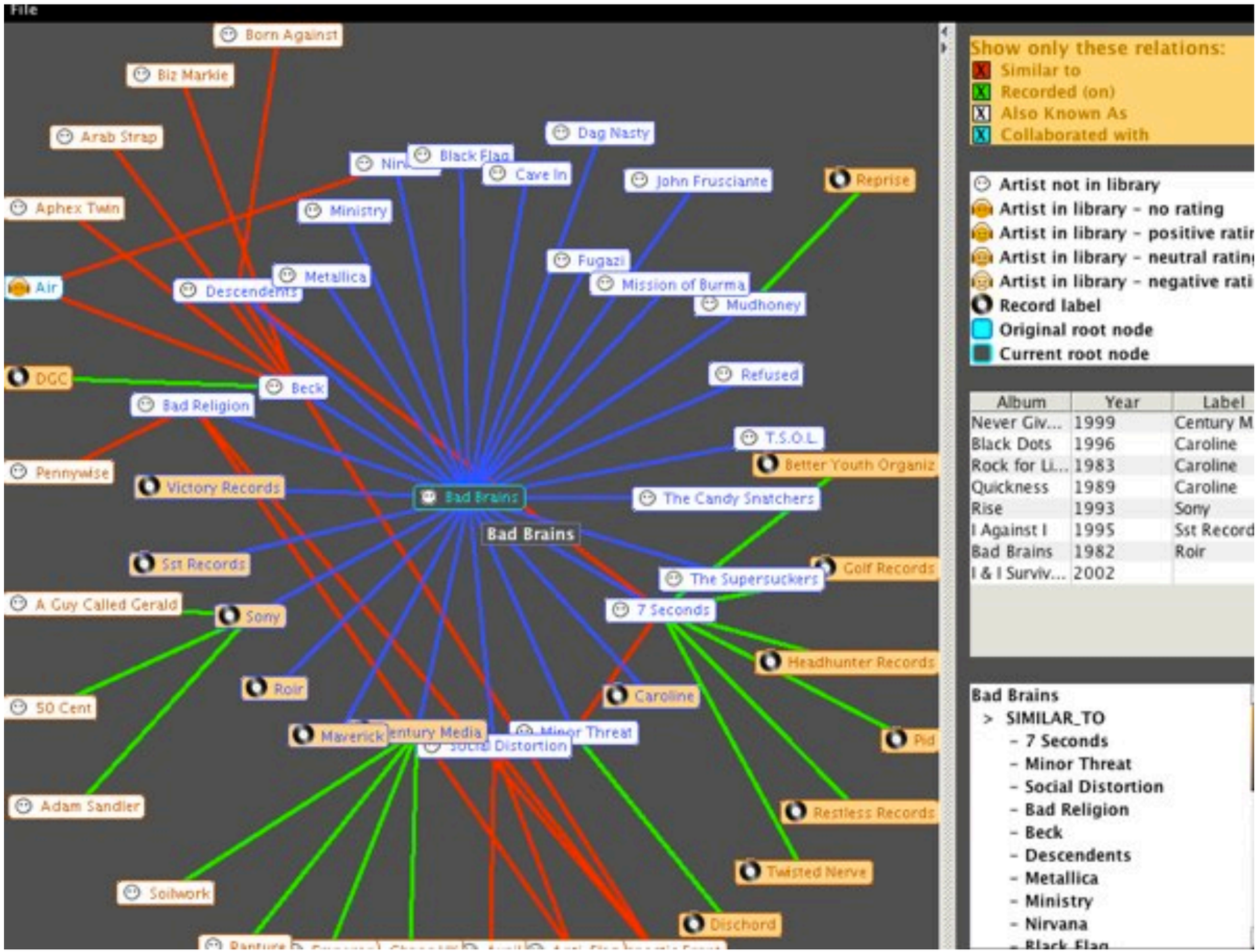
http://geniol.publishpath.com/last-fm-tasteograph

Floko-On



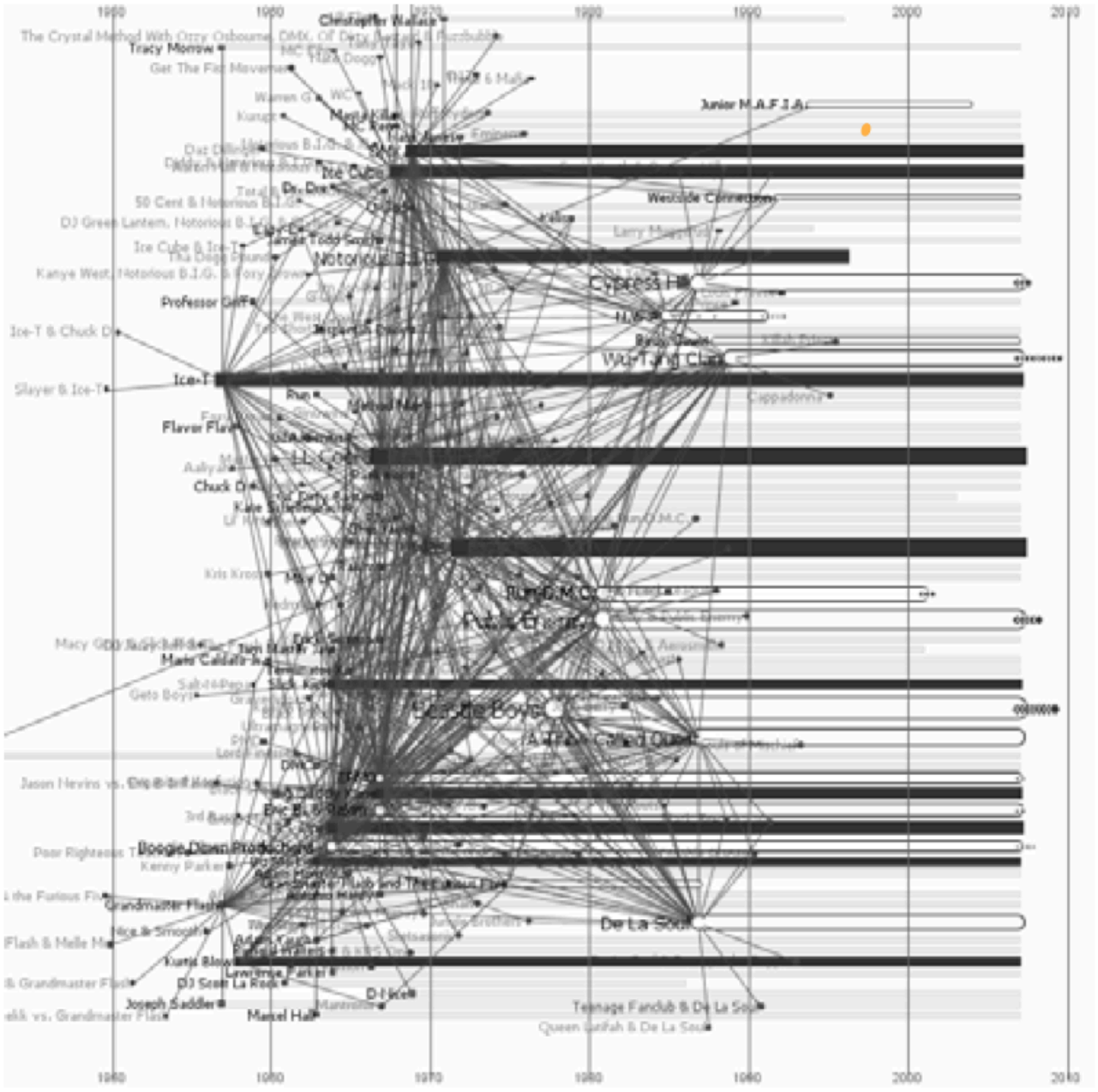
http://www.flokoon.com/#lastfm

Project Orpheus



http://arcus-associates.com/orpheus/

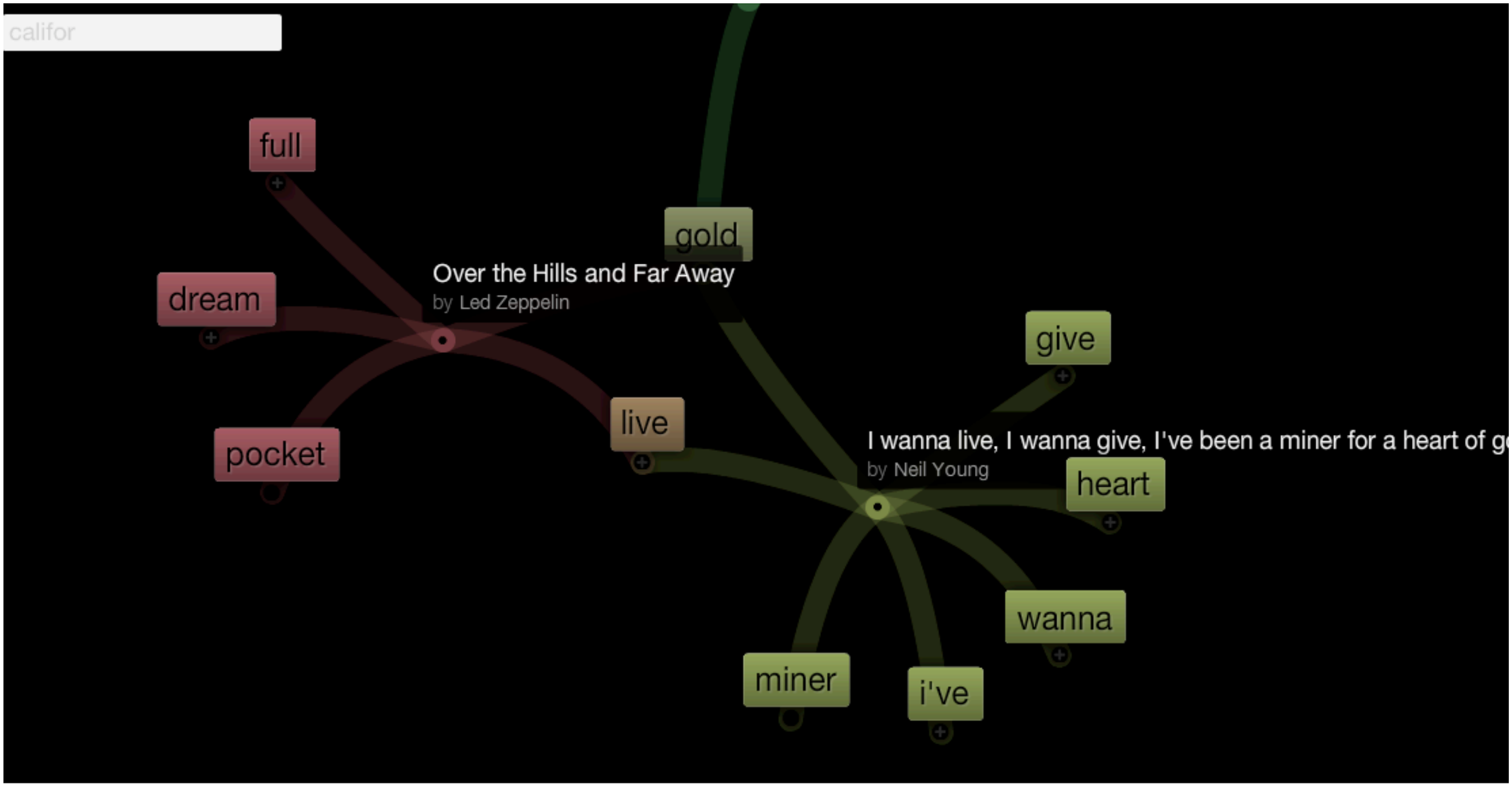
Musician Map: visualizing music collaborations over time



http://www.sfu.ca/~jdyim/musicianMap/

Ji-Dong Yim Chris Shaw Lyn Bartram

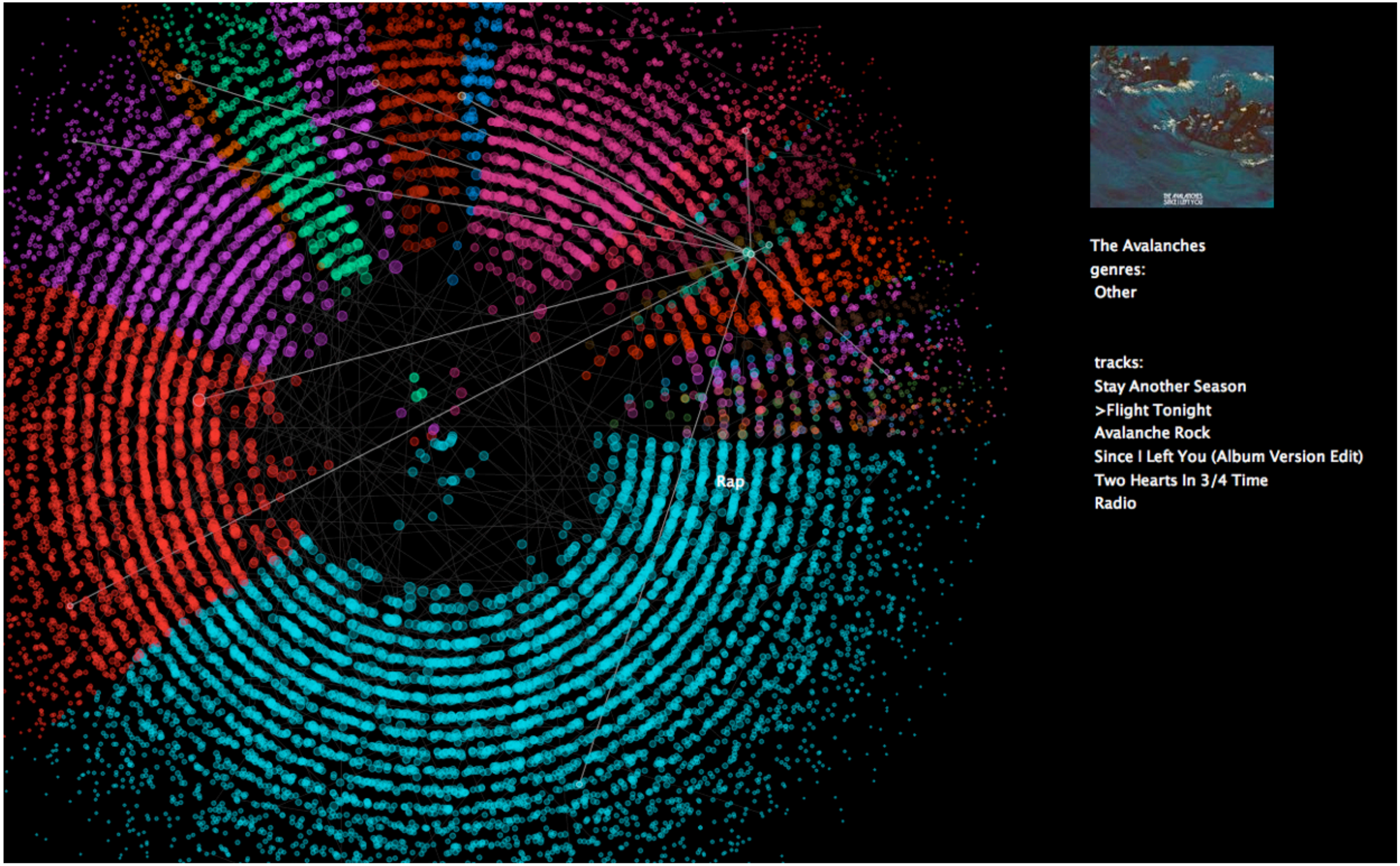
lyric connections



http://www.identitee.com/visualizer.php

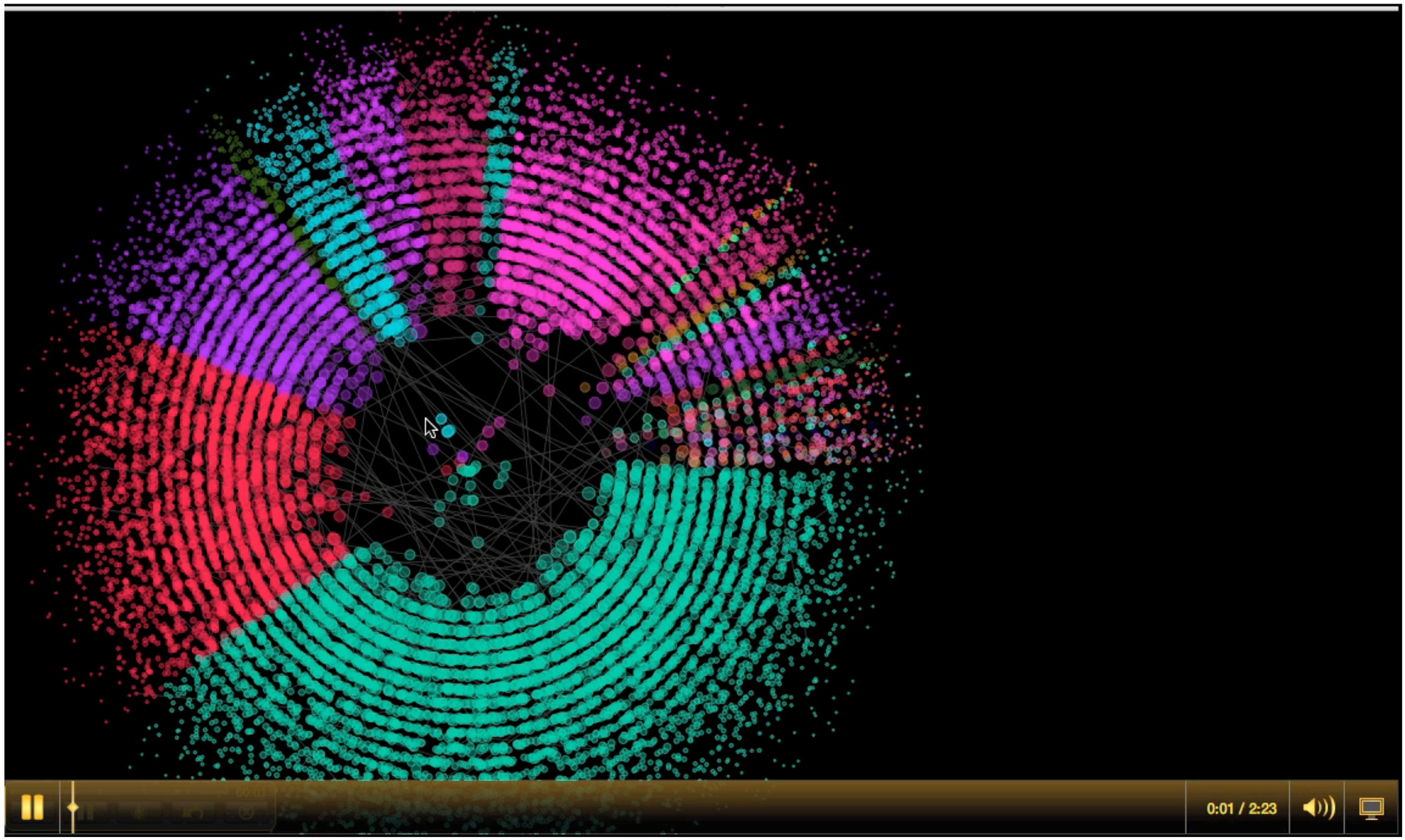
music tees and tee shirts on i/denti/tee

Interacting with linked data about music



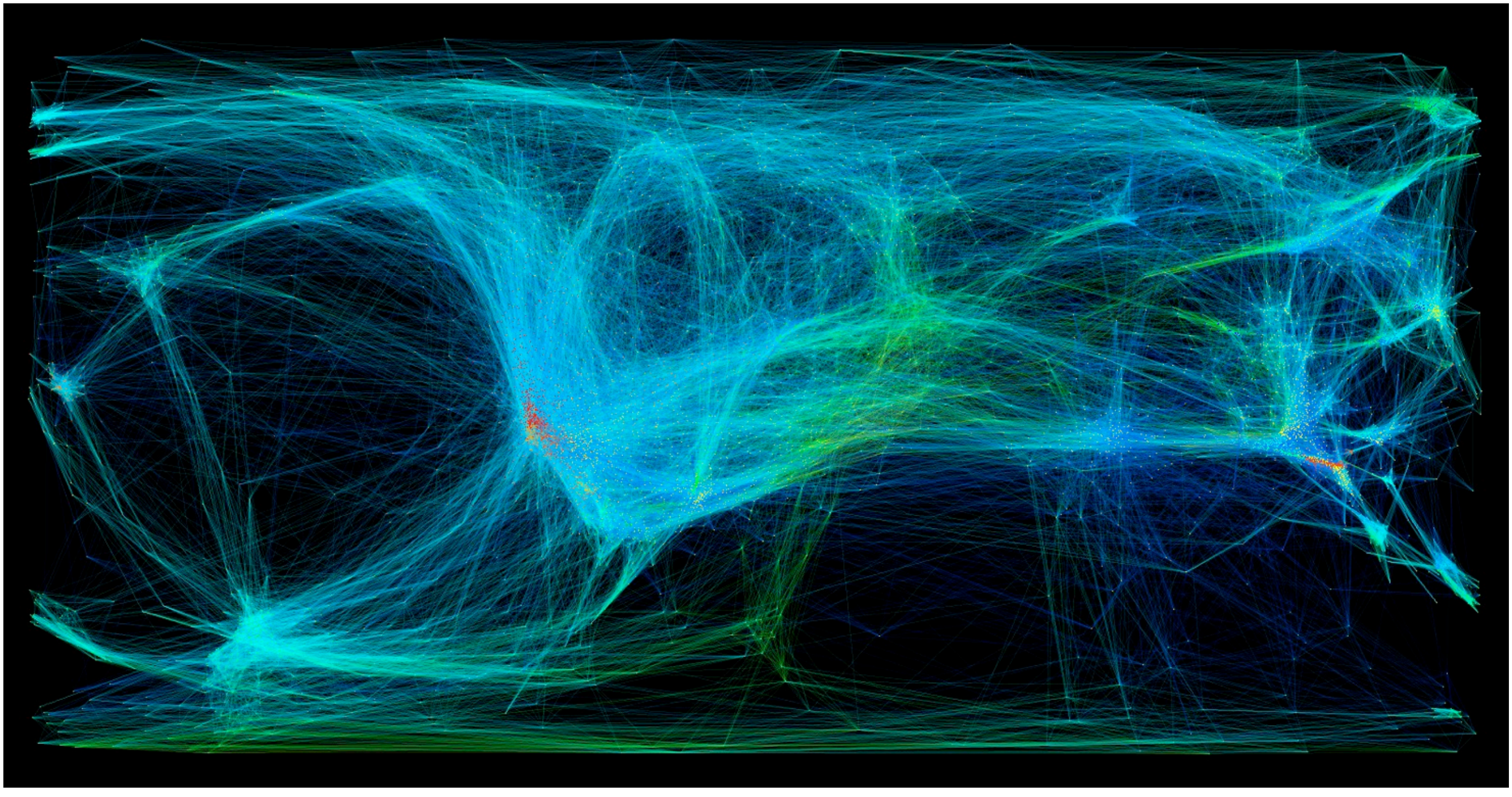
http://journal.webscience.org/110/

Interacting with linked data about music



http://journal.webscience.org/110/

The World Of Music

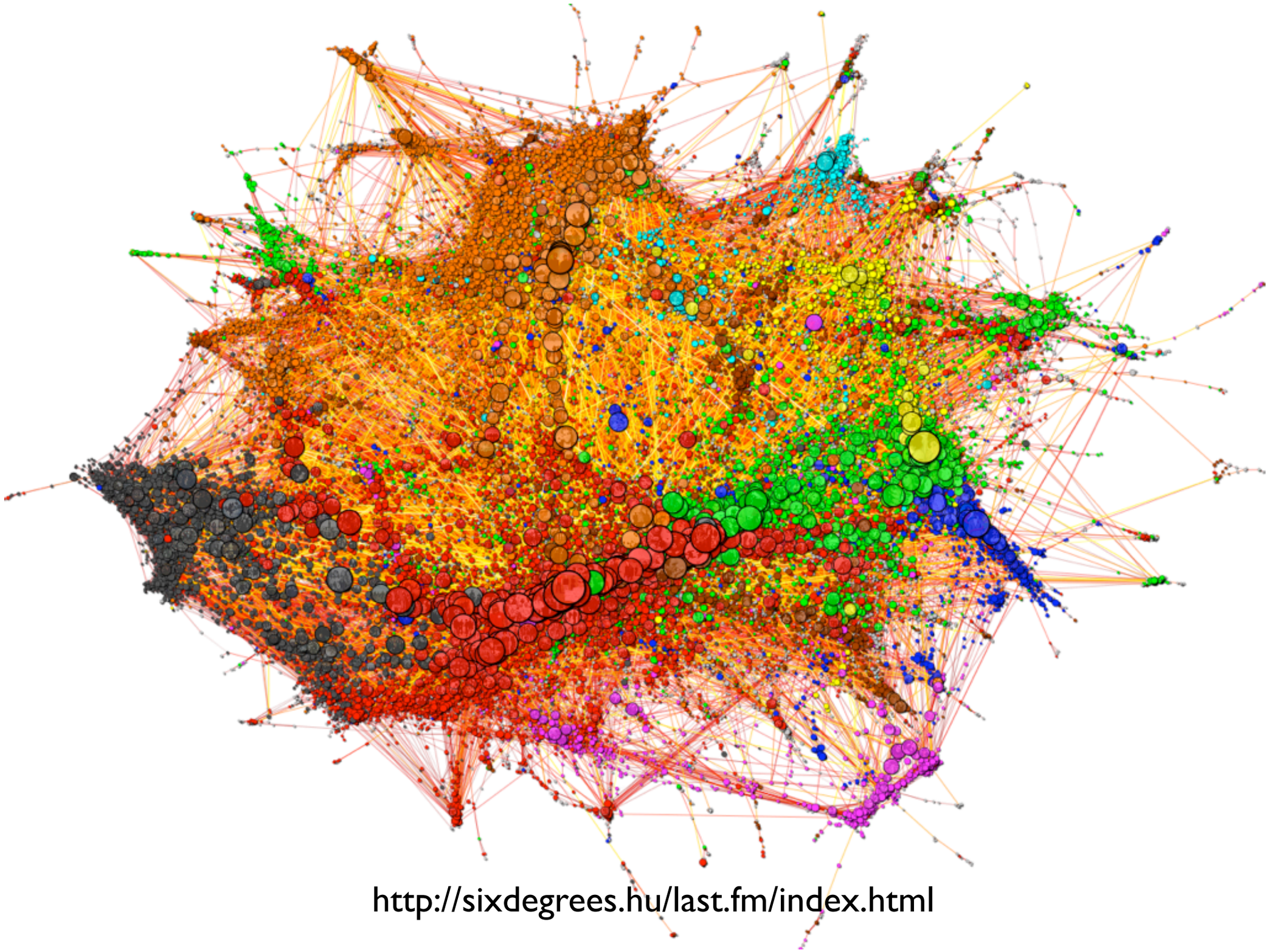


http://www.stanford.edu/~dgleich/demos/worldofmusic/WorldOfMusic.html
David Gleich, Matt Rasmussen, Leonid Zhukov, and Kevin Lang

The World Of Music

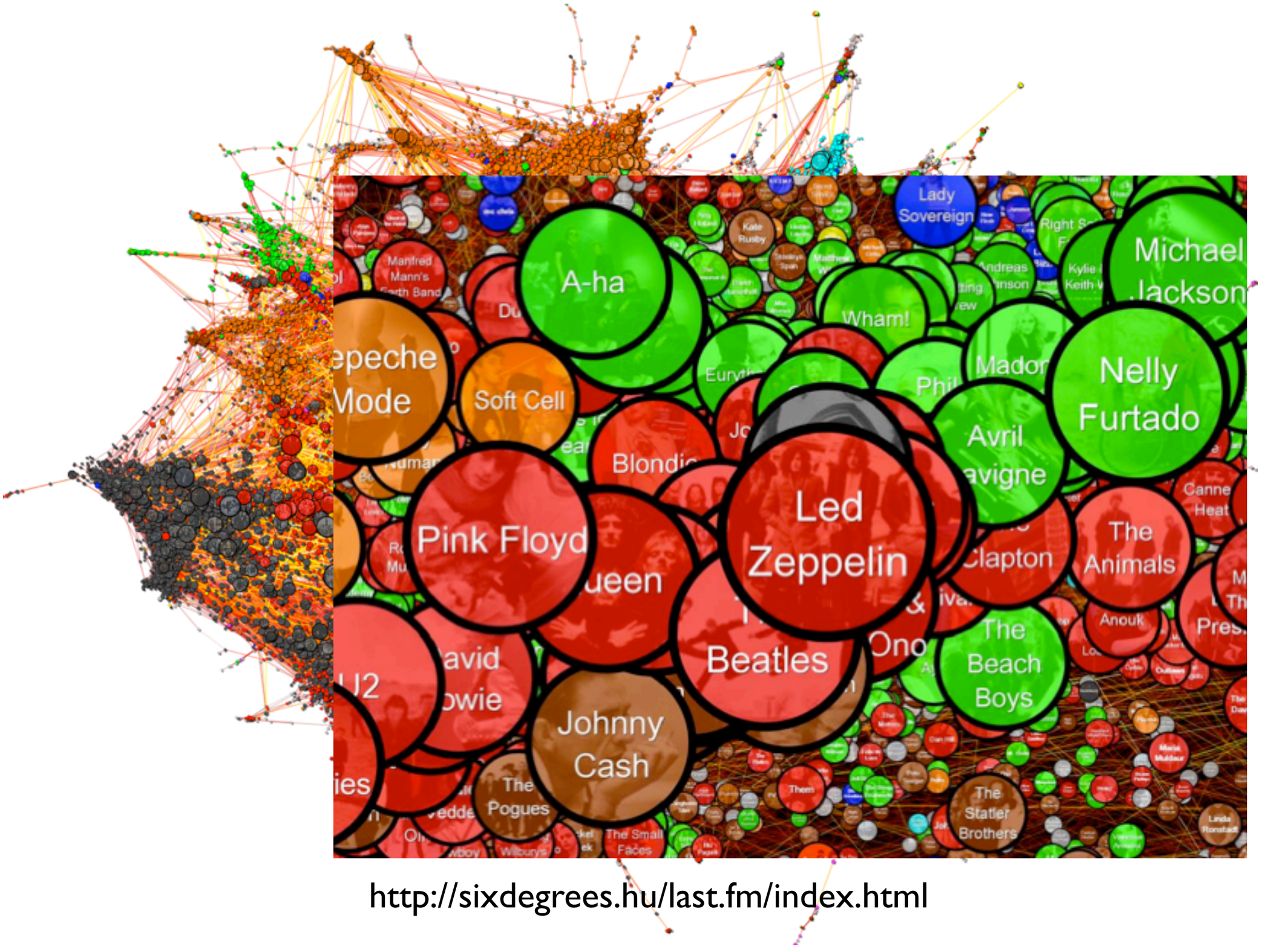
http://www.stanford.edu/~dgleich/demos/worldofmusic/WorldOfMusic.html
David Gleich, Matt Rasmussen, Leonid Zhukov, and Kevin Lang

Last.fm Artist Map



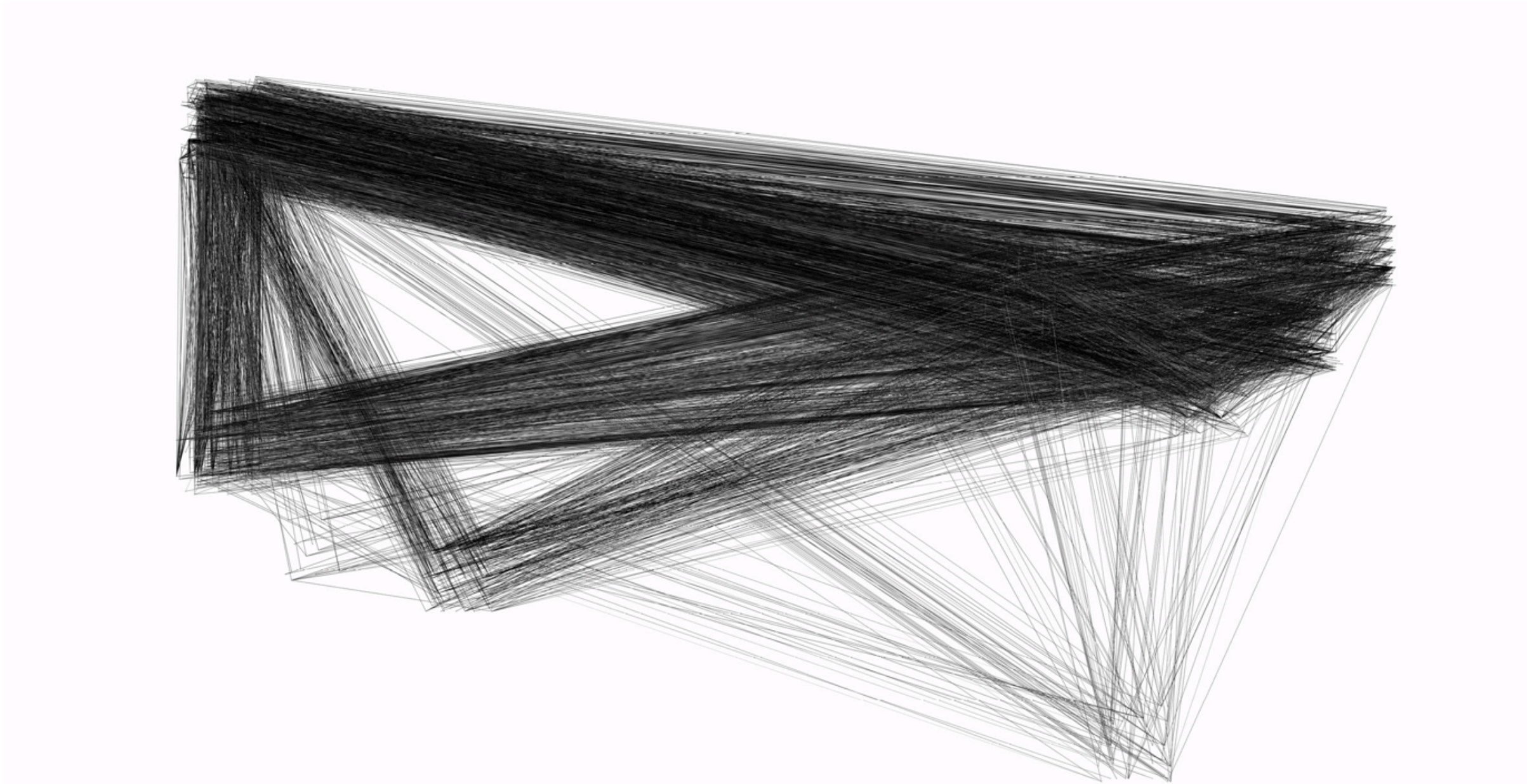
http://sixdegrees.hu/last.fm/index.html

Last.fm Artist Map



http://sixdegrees.hu/last.fm/index.html

Visualizations of the connections amongst geographically located iTunes libraries



http://caleblarsen.com/projects/visualization-of-the-inherent-connections-/#0

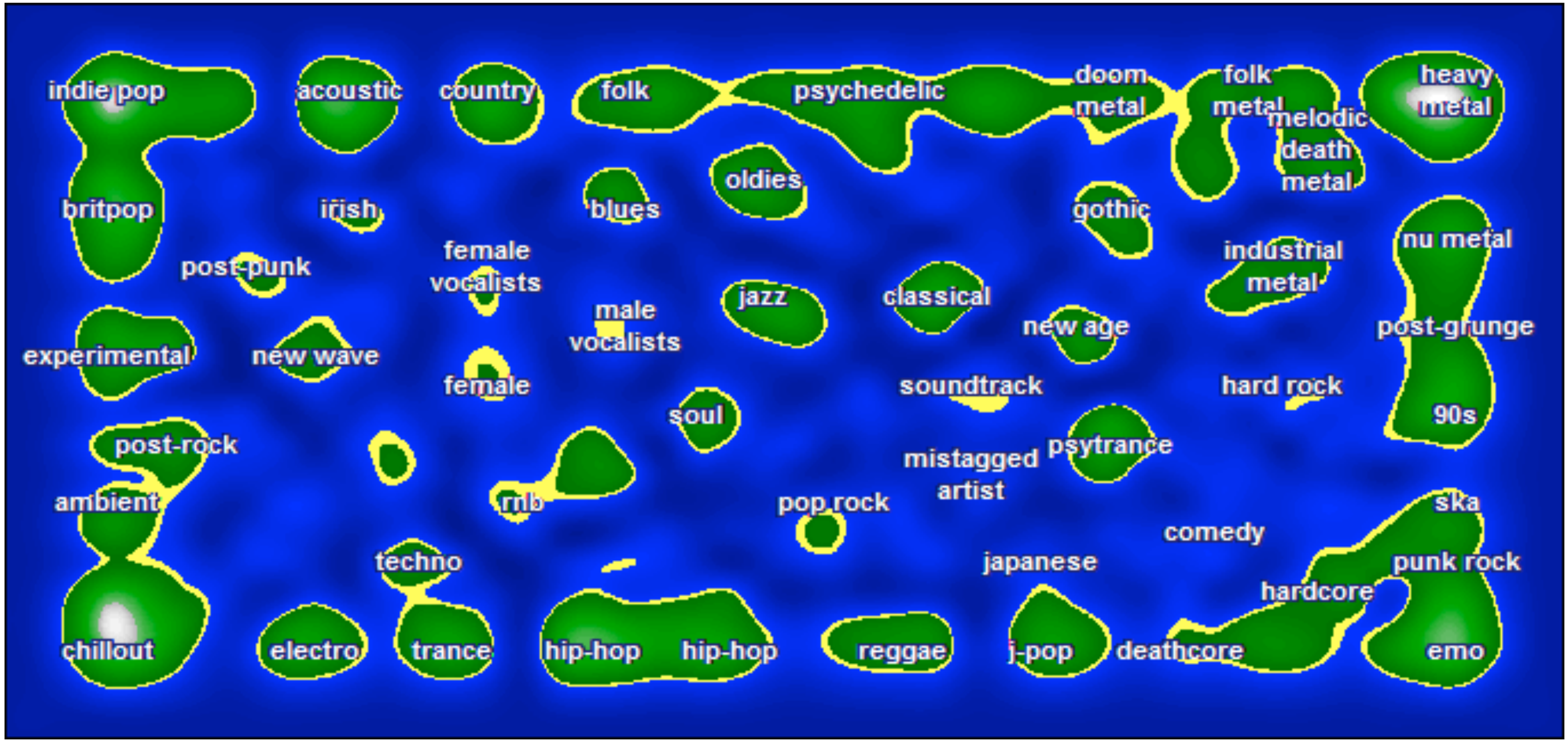
Visualizations of the connections amongst geographically located iTunes libraries

http://caleblarsen.com/projects/visualization-of-the-inherent-connections-/#0

Maps


Quaye
Damien
'Junior Gong'
Marley
The
Fugees
Ziggy
Marley
RZA
Everly Brothers
The Kinks
Portishead
David
Bowie
Kanye
West
Blur
The Cure
OutKast

Maps

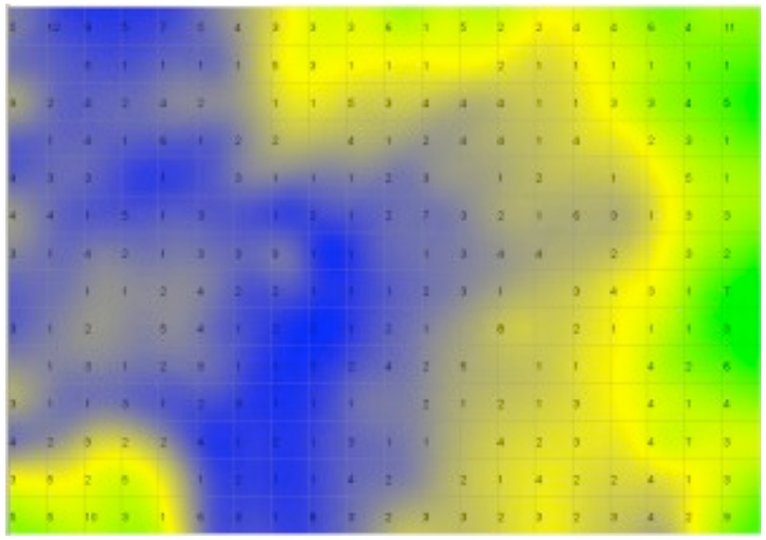


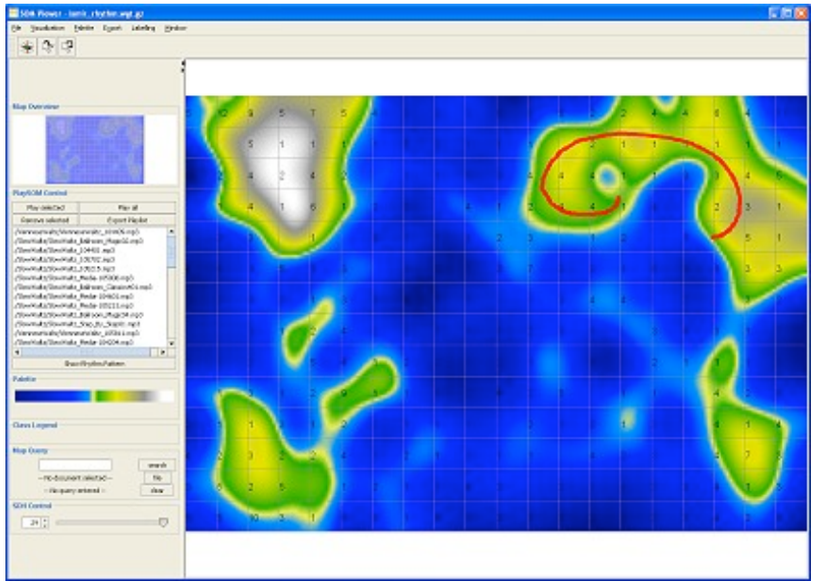
http://playground.last.fm/iom - Islands of Music - Elias Pampalk

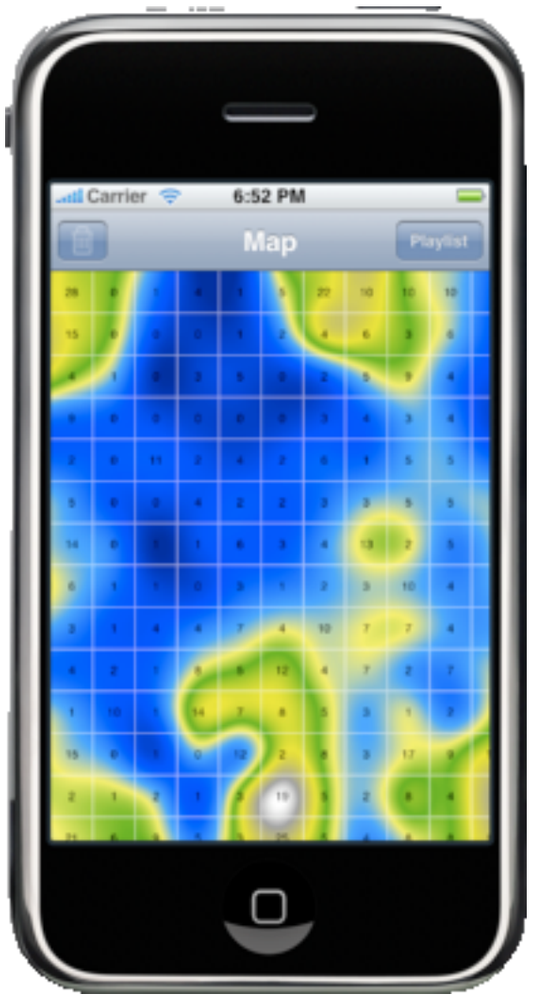
marGrid

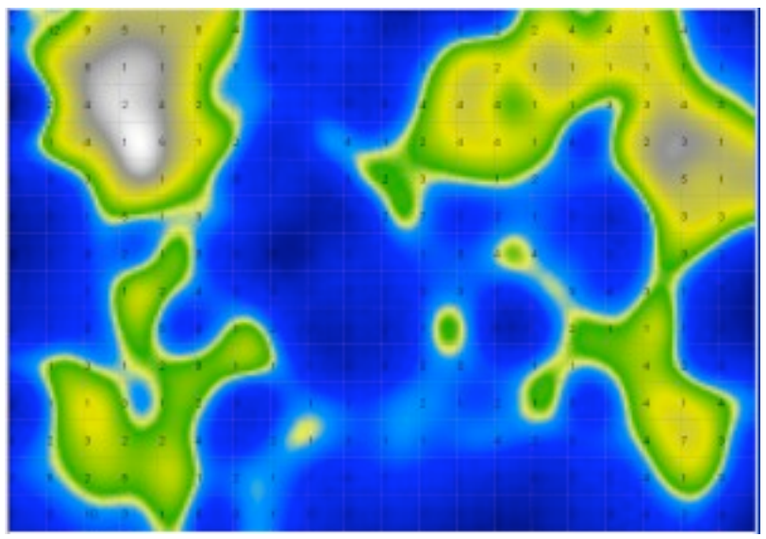
http://margrid.sness.net/

PlaySOM - Intuitive access to Music Archives









http://www.ifs.tuwien.ac.at/mir/playsom.html

Vienna University of Technology

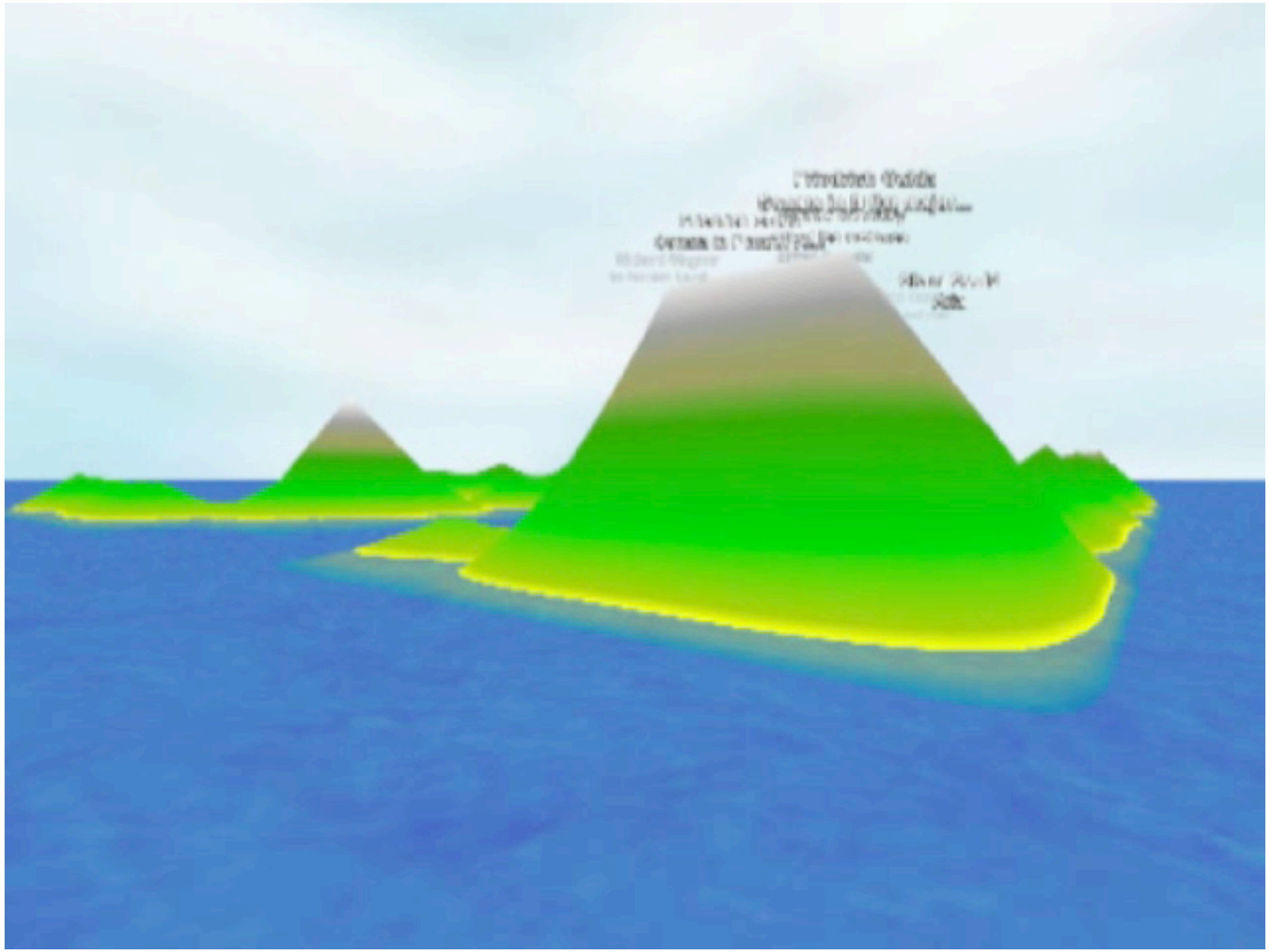
FM4 Soundpark

http://fm4.orf.at/soundpark Martin Gasser, Arthur Flexer

nepTune

http://www.cp.jku.at/projects/nepTune/

nepTune

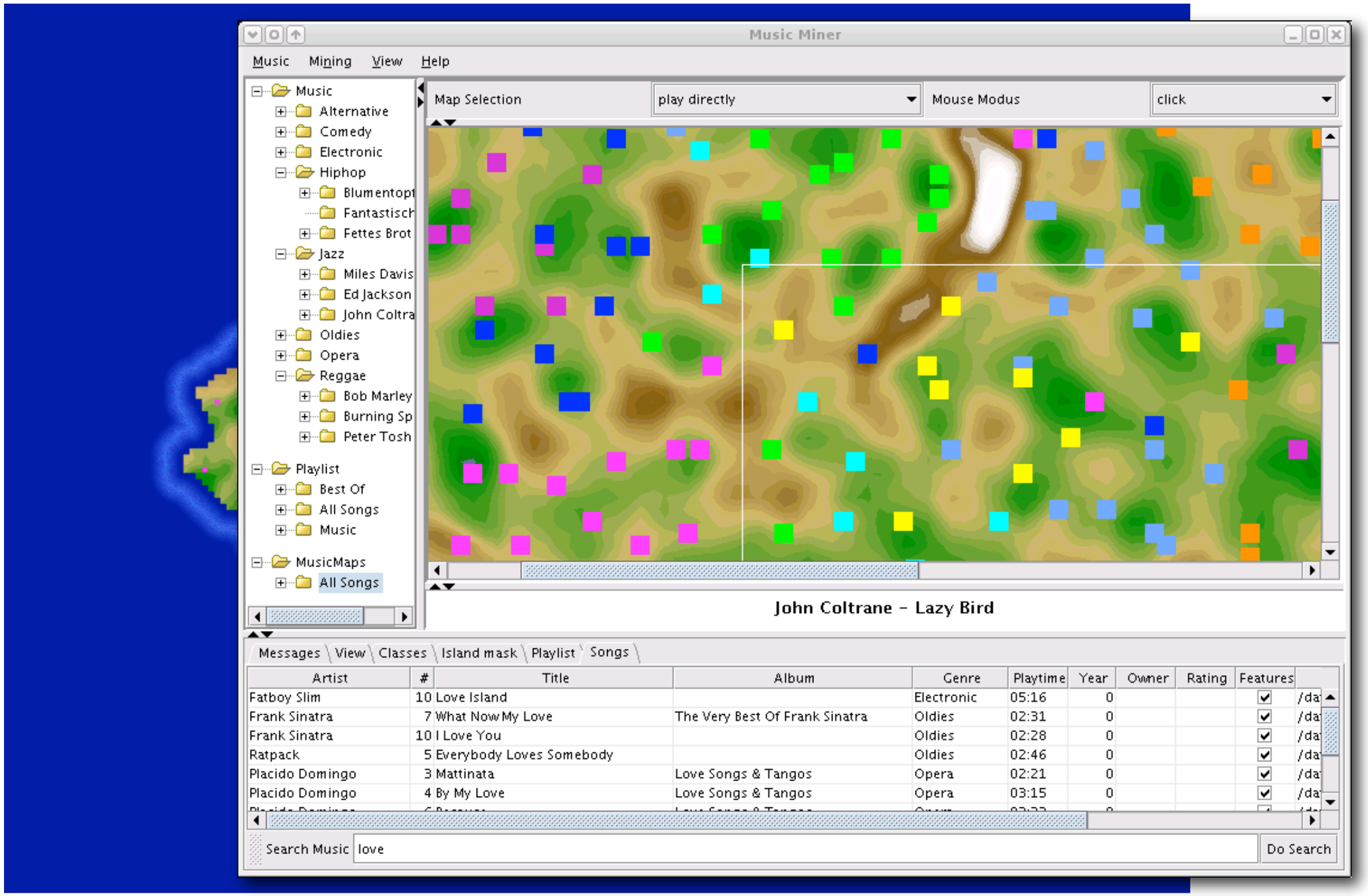


http://www.cp.jku.at/projects/nepTune/

Databionic Music Miner

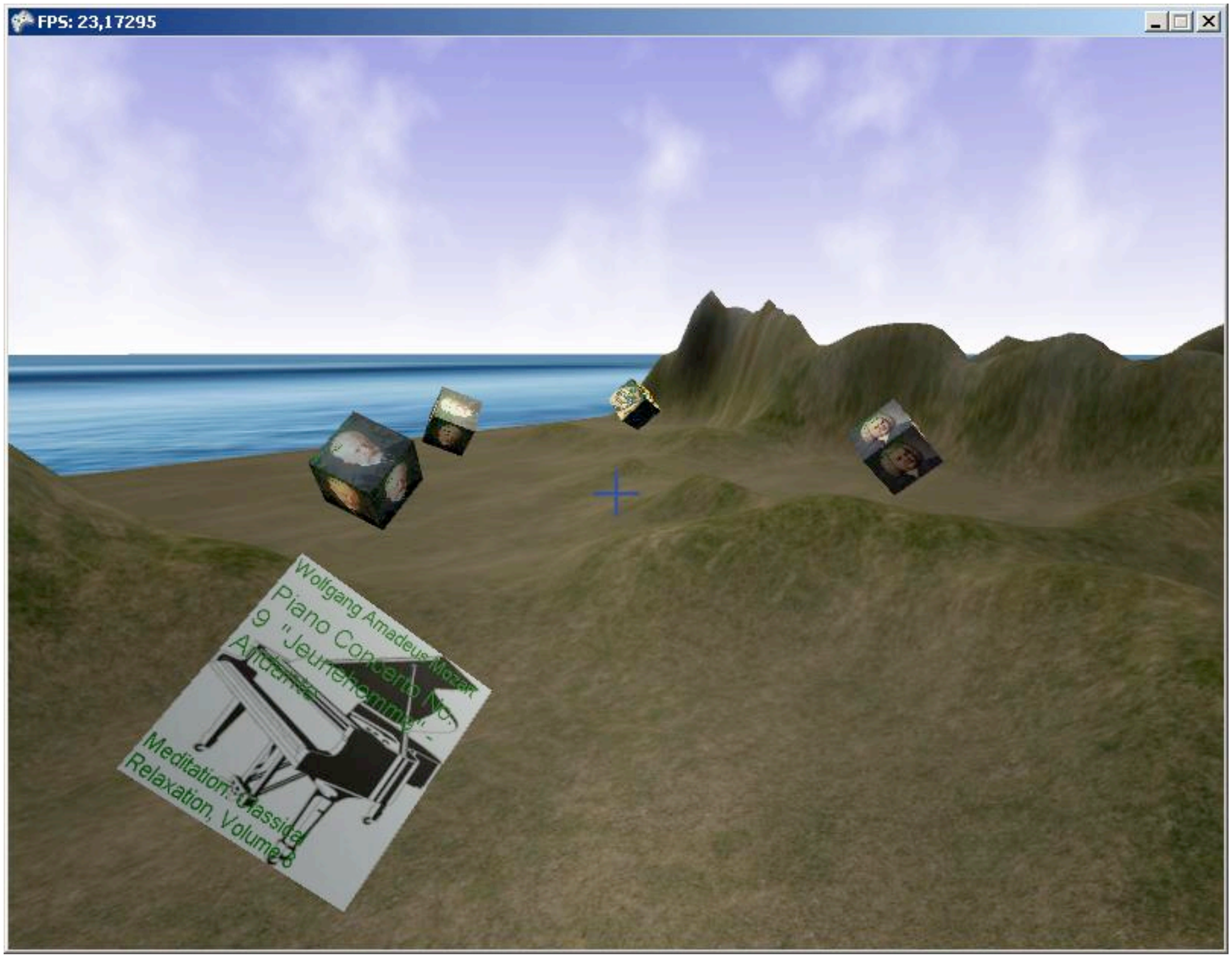
http://musicminer.sourceforge.net/

Databionic Music Miner



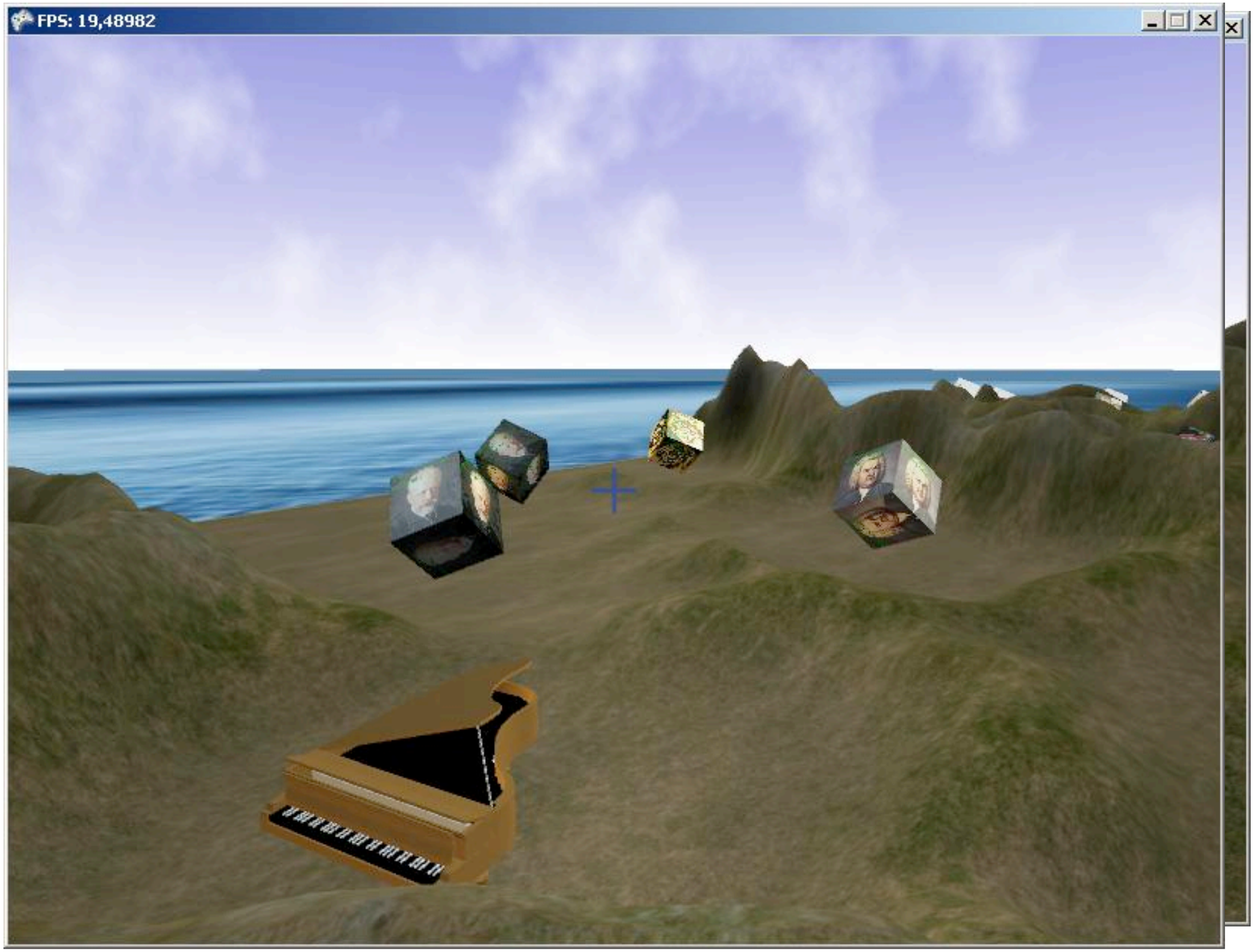
http://musicminer.sourceforge.net/

soniXplorer



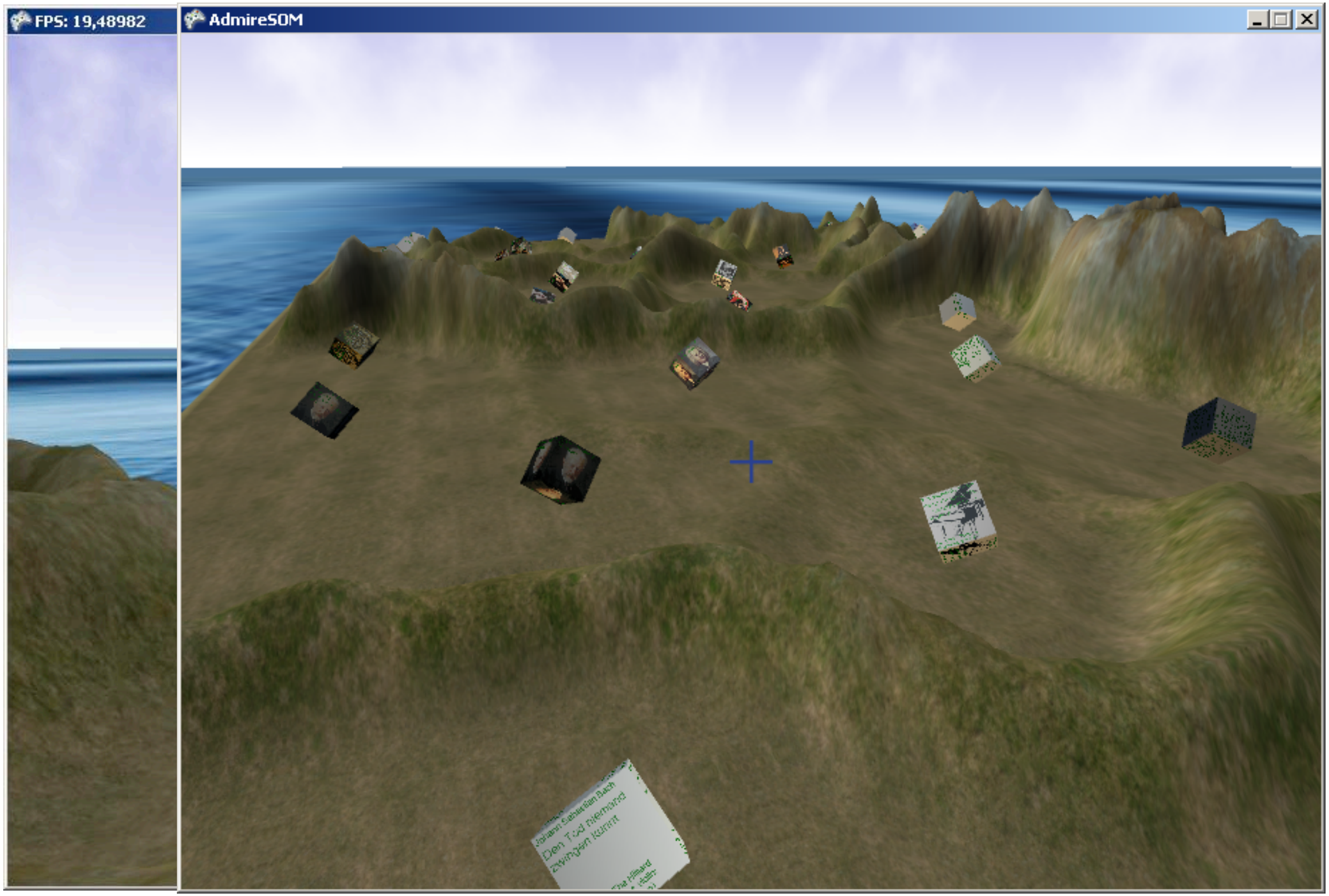
Presented at ISMIR 2009 by Dominik Lübbers

soniXplorer



Presented at ISMIR 2009 by Dominik Lübbers

soniXplorer



Presented at ISMIR 2009 by Dominik Lübbers

soniXplorer

Presented at ISMIR 2009 by Dominik Lübbers

mHashup

http://www.mhashup.com/

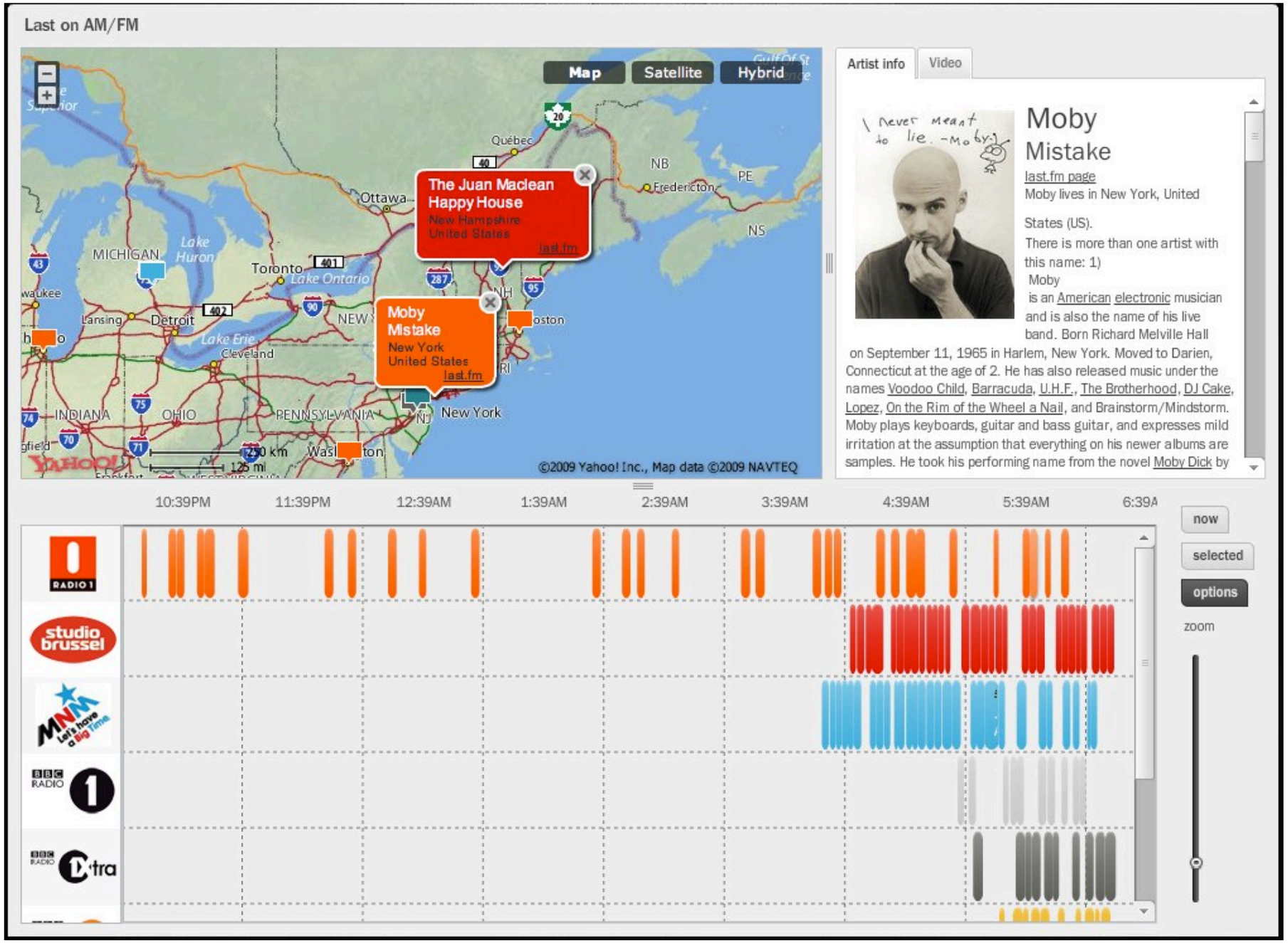
mHashup

http://www.mhashup.com/

GeoMuzik

ISMIR 2008 - Oscar Celma

Last on AM/FM

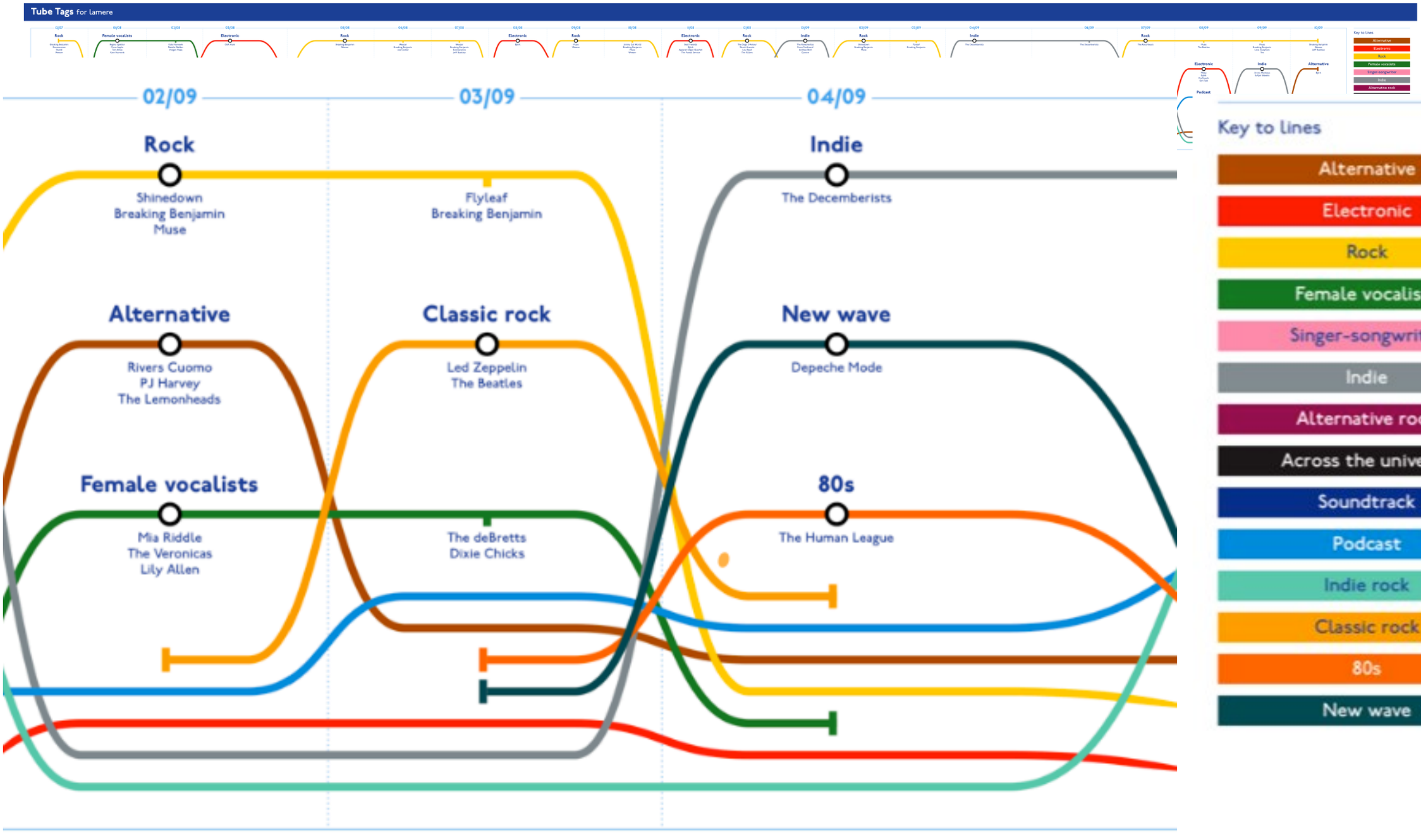


http://www.cs.kuleuven.be/~sten/lastonamfm

Last.fm tube tags

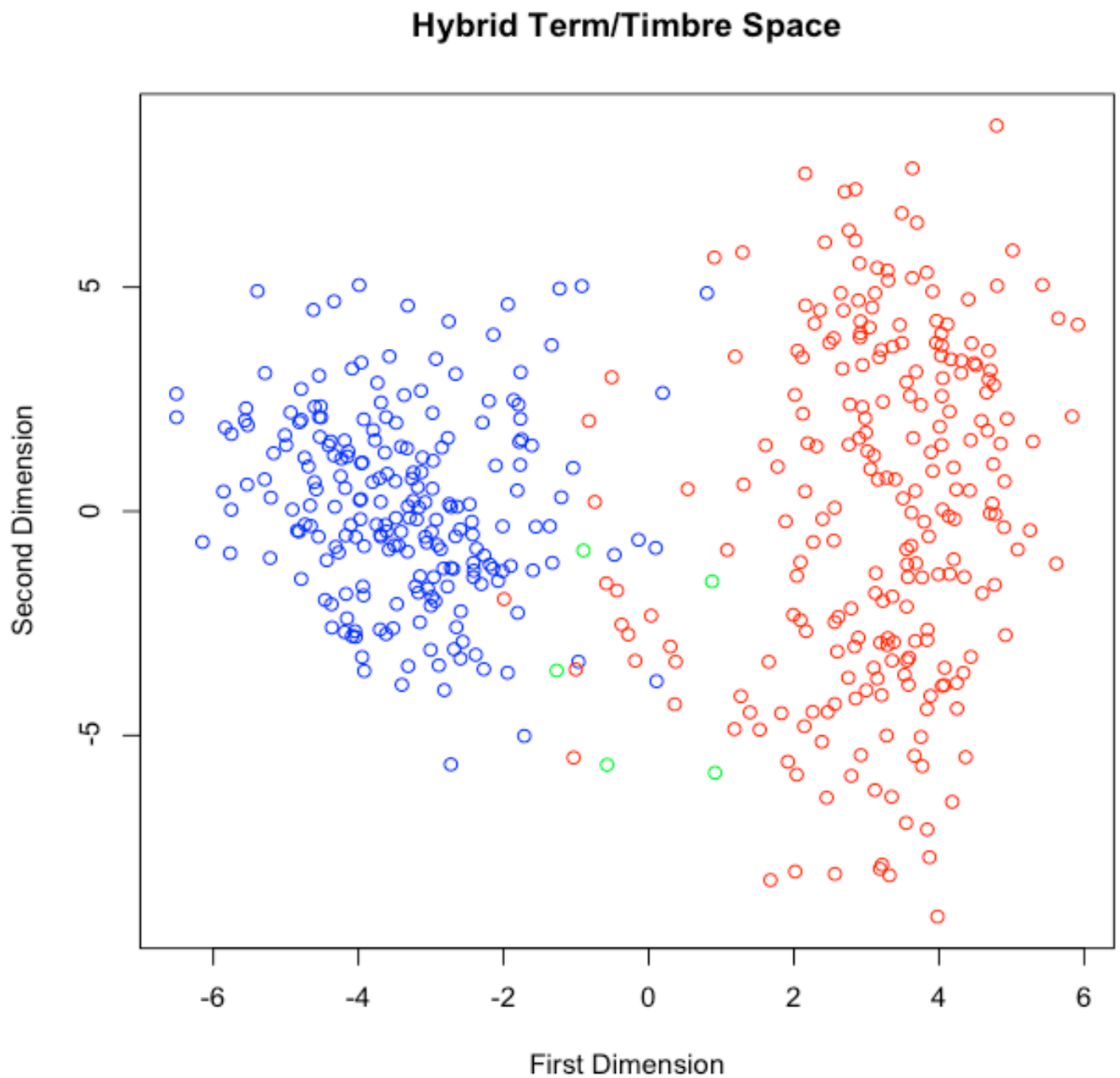
http://playground.last.fm/demo/tagstube

Last.fm tube tags

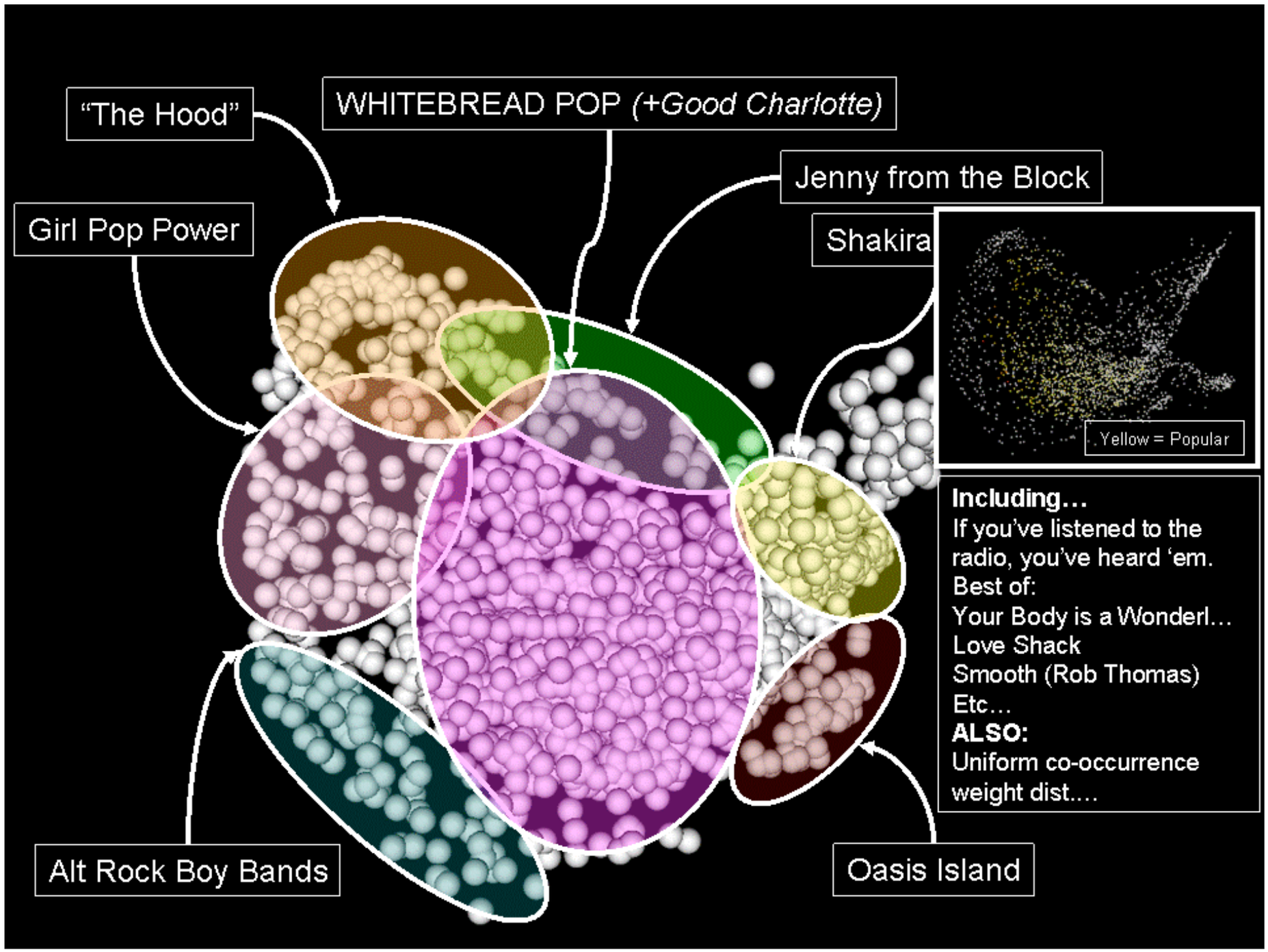


http://playground.last.fm/demo/tagstube

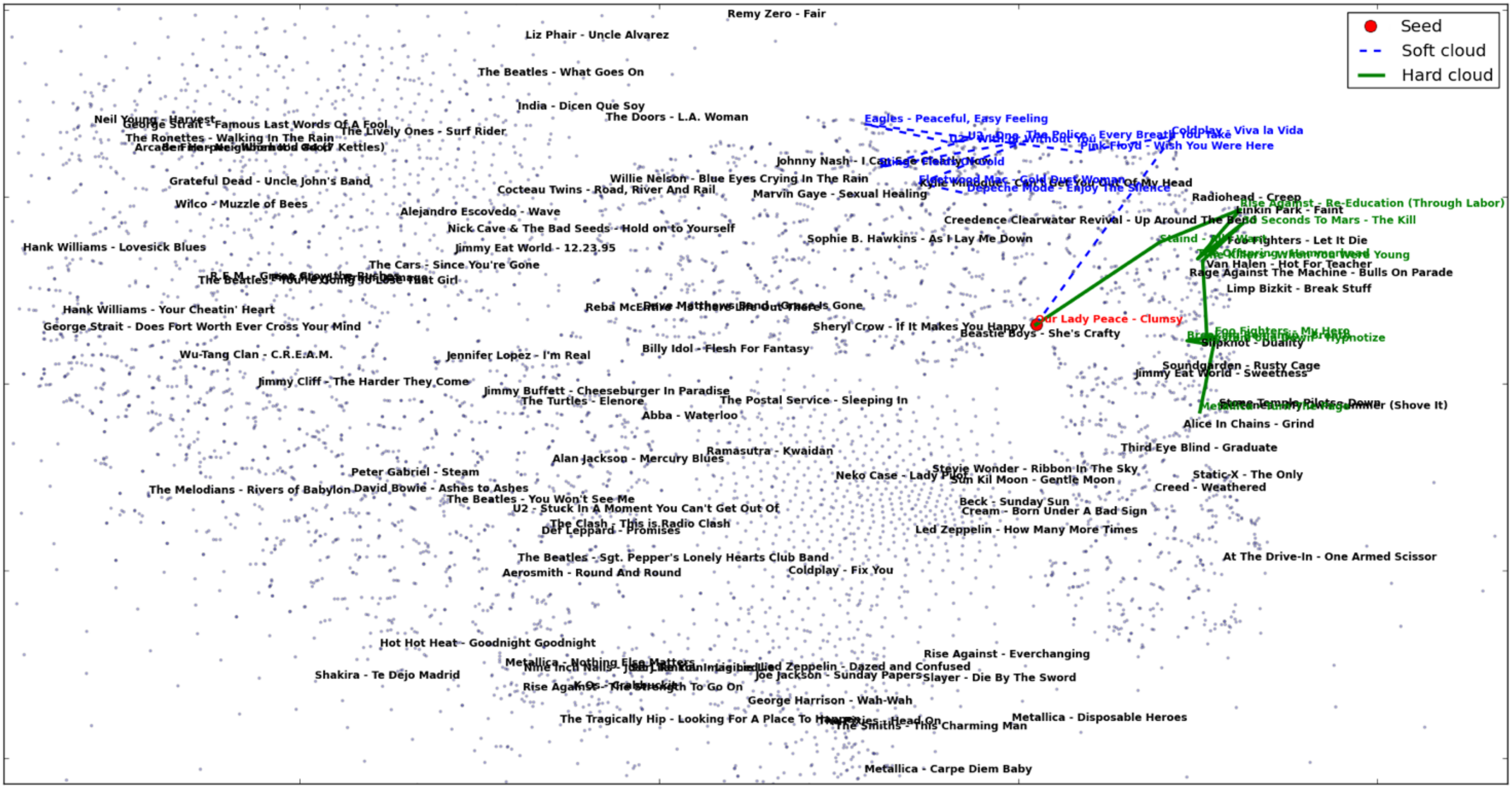
Scatter plots



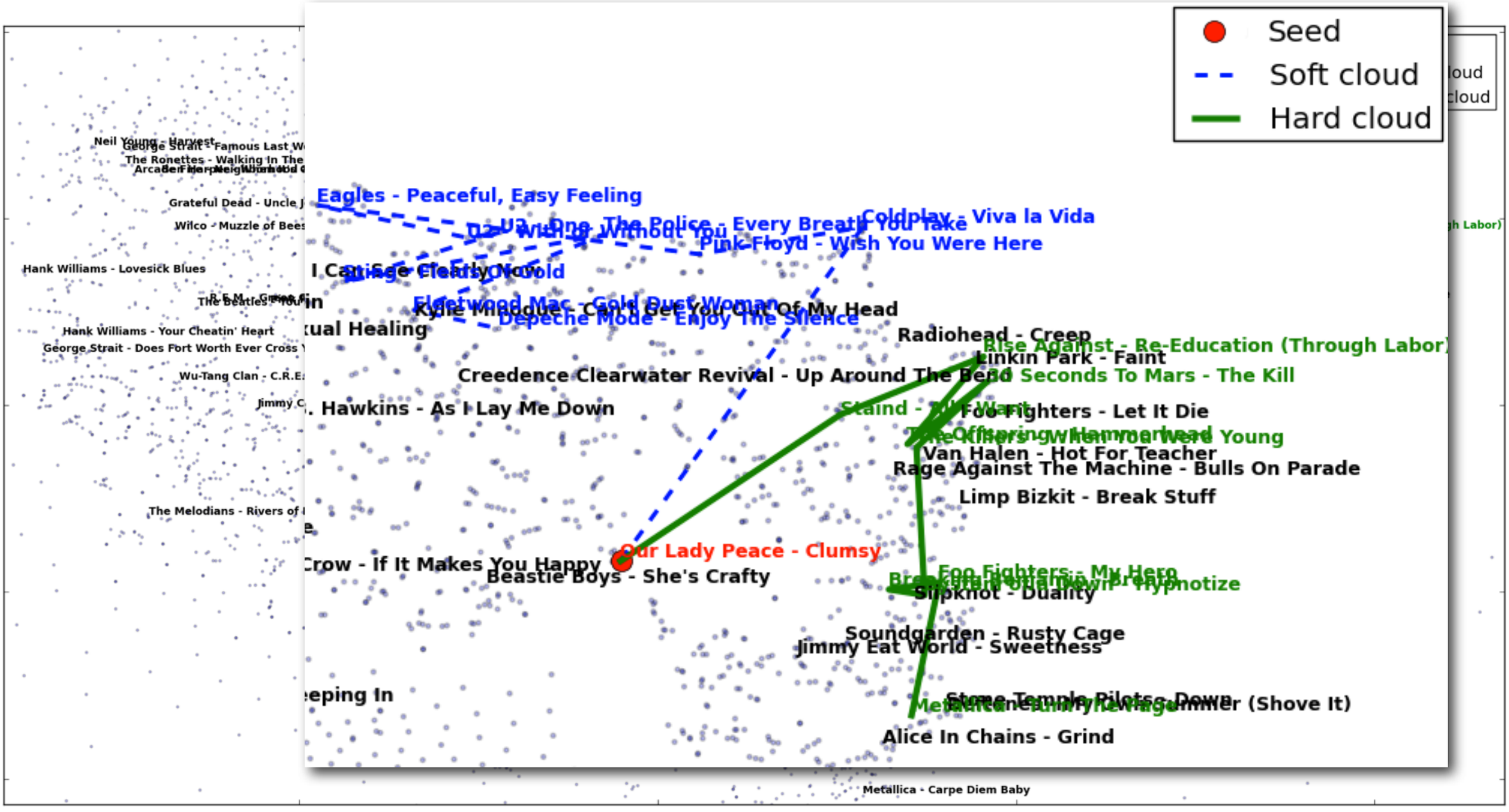
ZMDS Visualization



Justin Donaldson

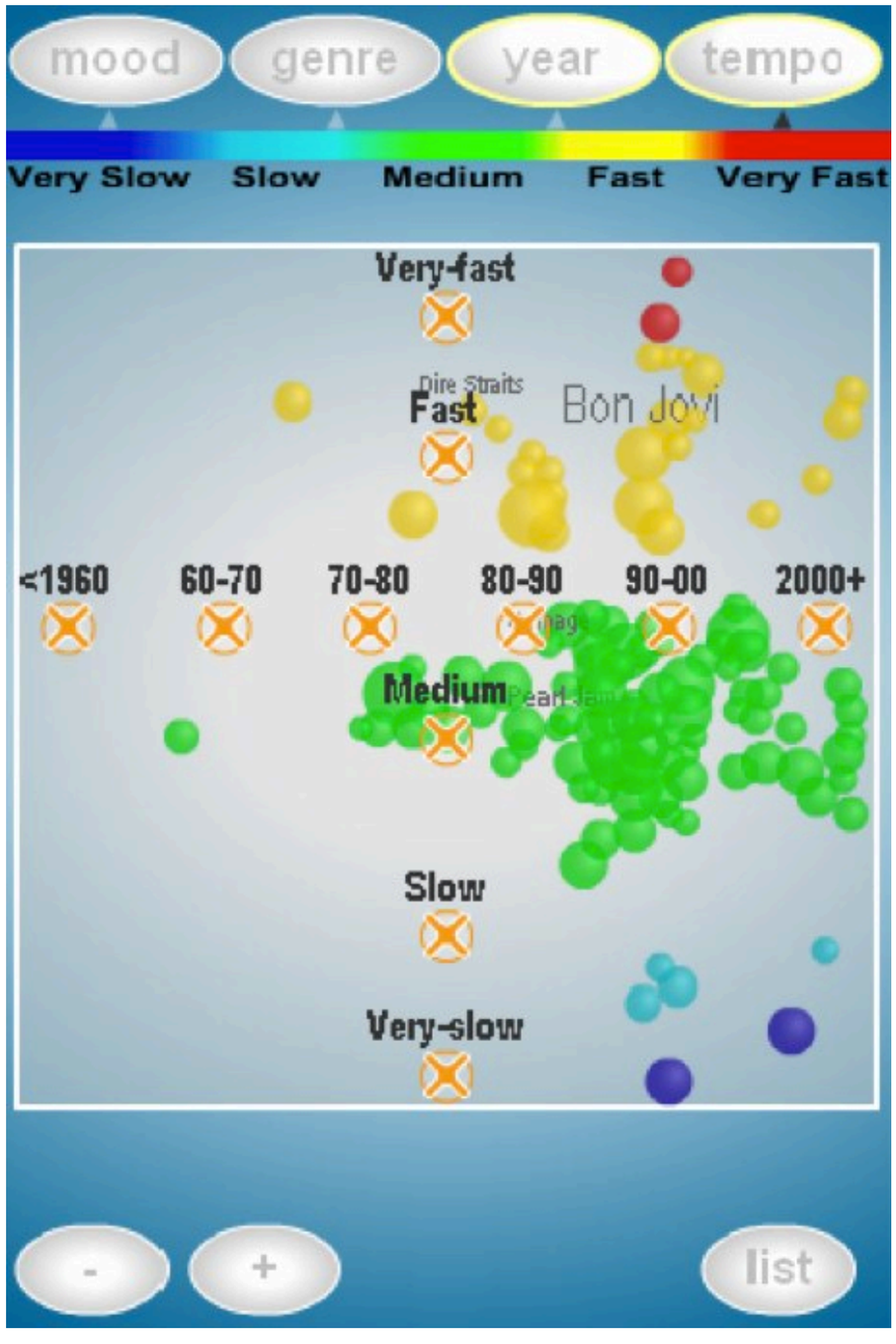


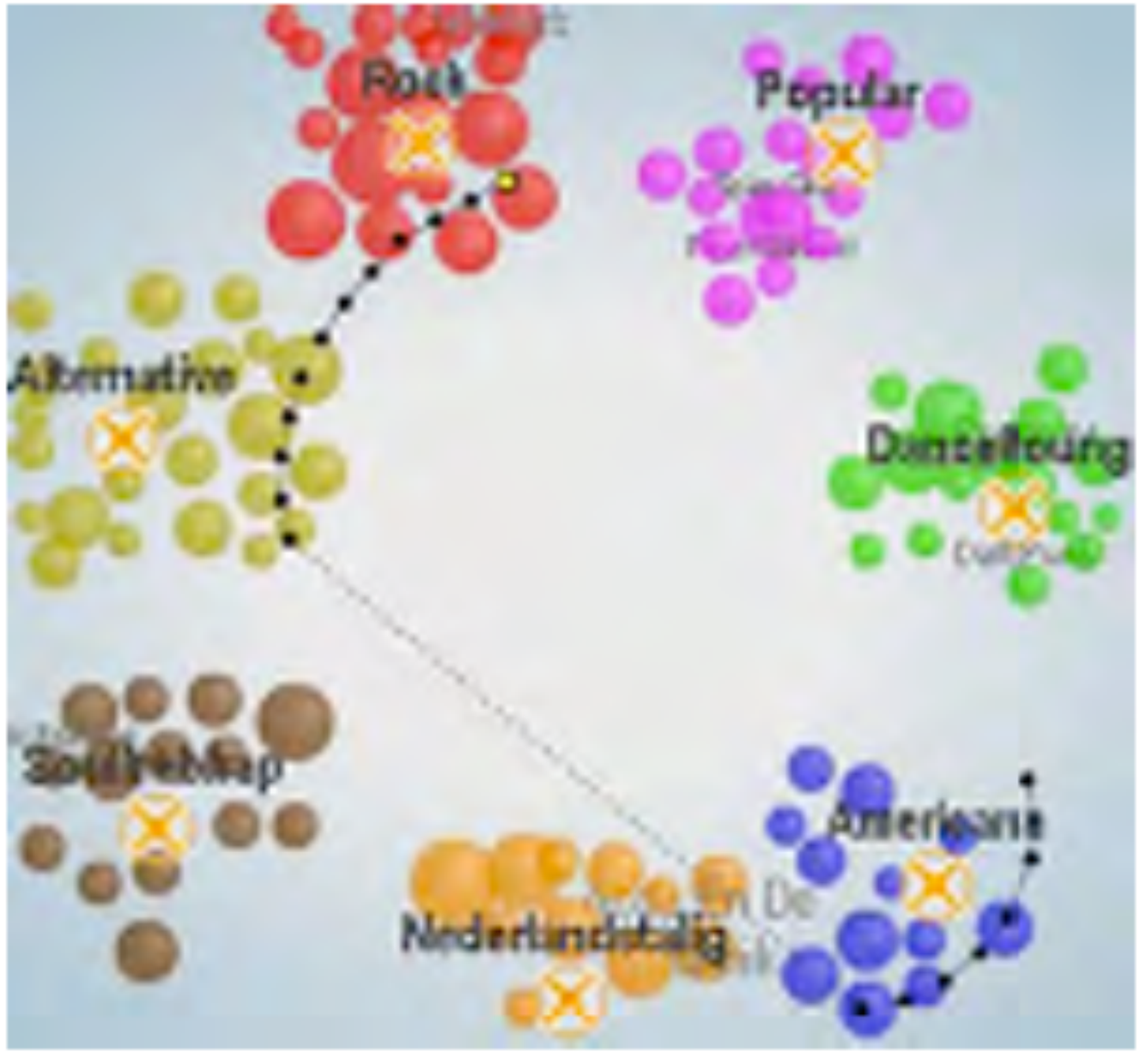
Visualization Name



Visualization Name

Using map for playlist navigation





Visual Playlist Generation on the Artist Map - *Van Gulick, Vignoli*

Mr. Emo: Music Retrieval in the Emotional Plane

http://mpac.ee.ntu.edu.tw/~yihsuan/pub/MM08_MrEmo.pdf

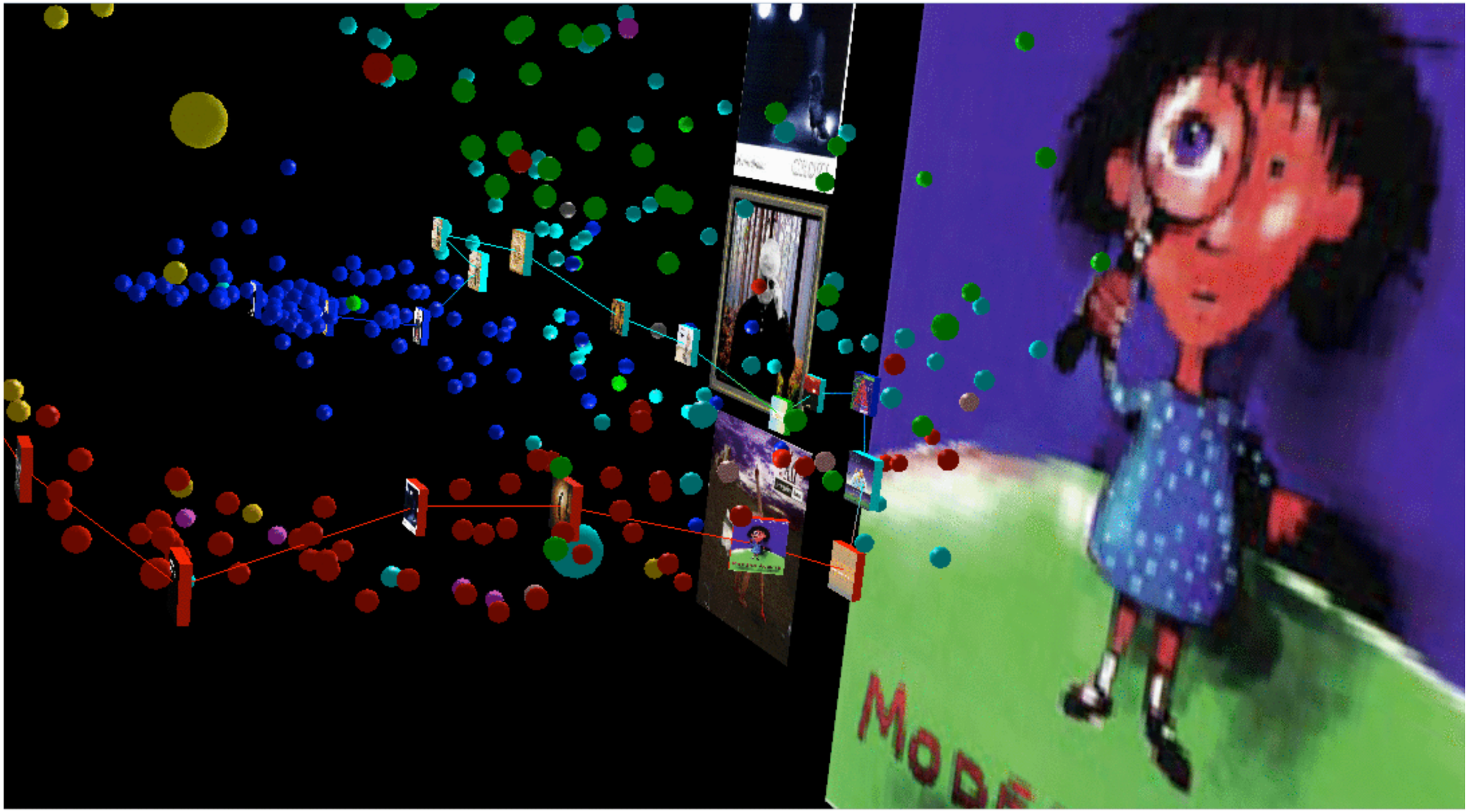
Mr. Emo: Music Retrieval in the Emotional Plane

http://mpac.ee.ntu.edu.tw/~yihsuan/pub/MM08_MrEmo.pdf

Burst Labs

http://www.burstlabs.com/

Search Inside the Music



http://mediacast.sun.com/share/plamere/sitm_final.pdf - Lamere, Eck

3D Track similarity

The Mufin Player

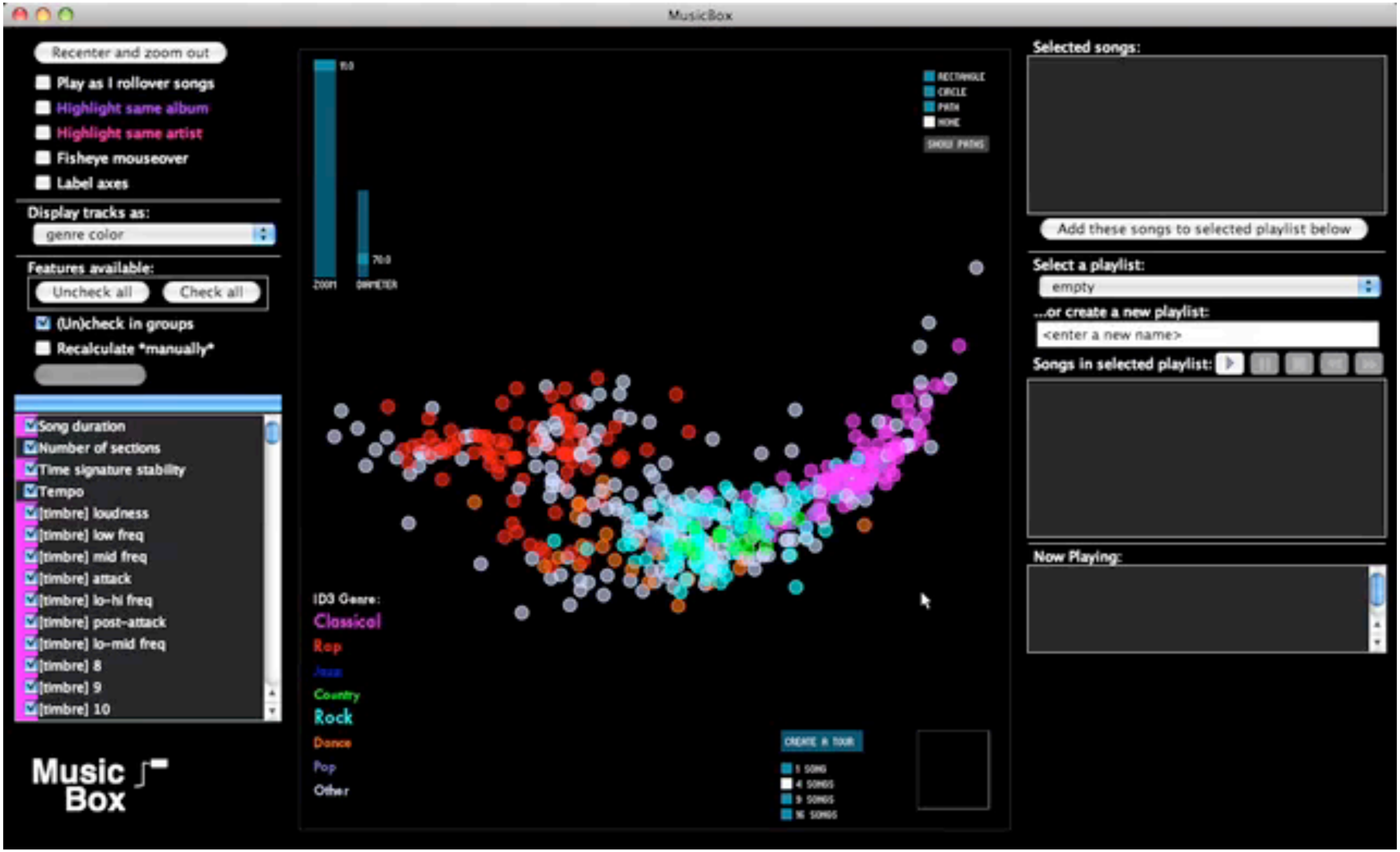
3D Track similarity

The Mufin Player

Music Box

http://thesis.flyingpudding.com/ - Anita Lillie

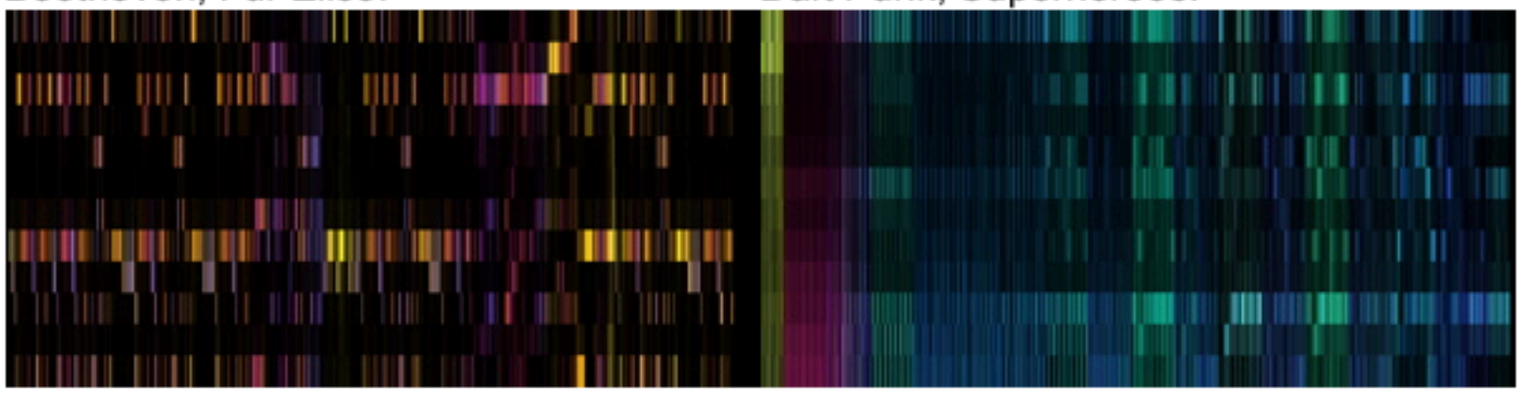
Music Box



http://thesis.flyingpudding.com/ - Anita Lillie

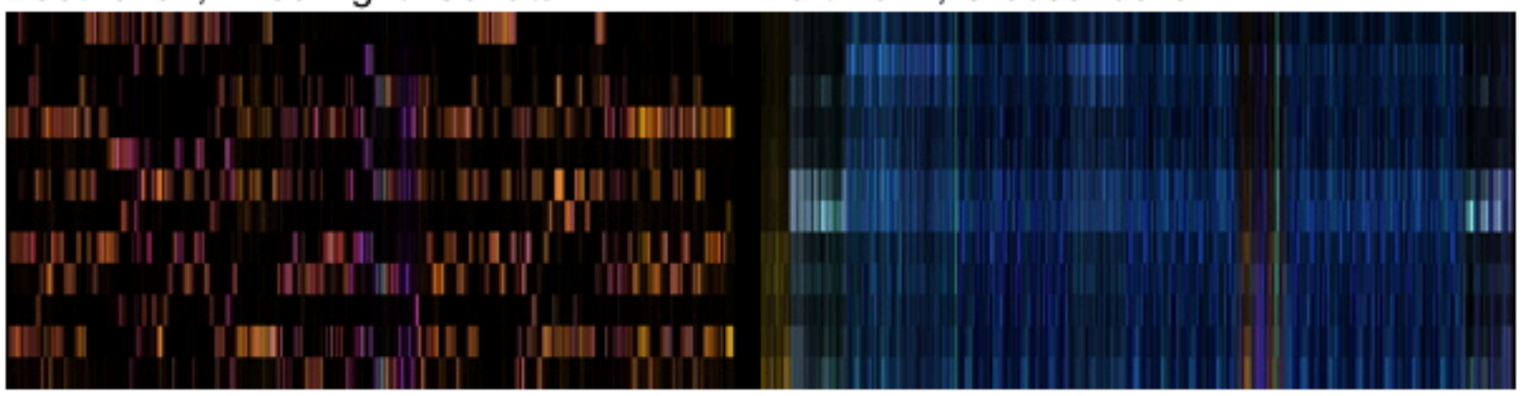
Pictures of Songs

Beethoven, Fur Elise:



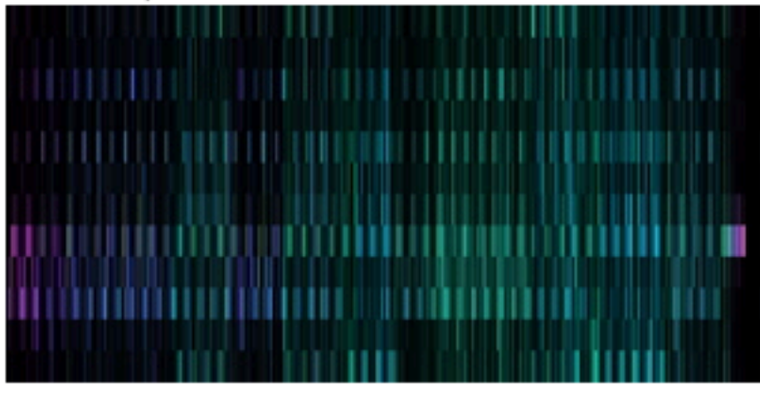
Daft Punk, Superheroes:

Beethoven, "Moonlight" Sonata:

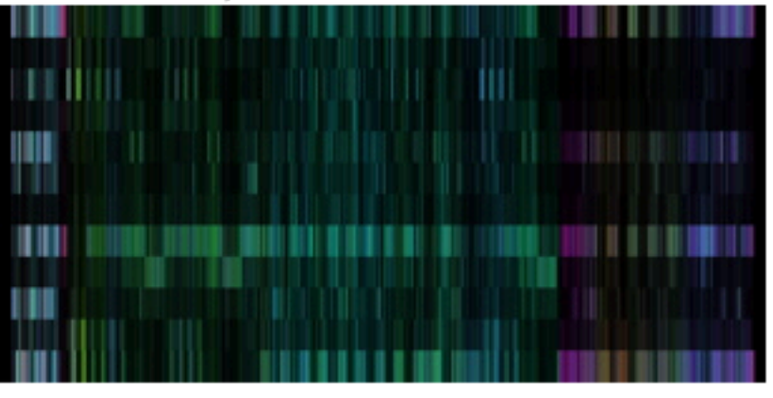


Daft Punk, Crescendolls:

Nirvana, Come As You Are:



Sonic Youth, 'Cross the Breeze:

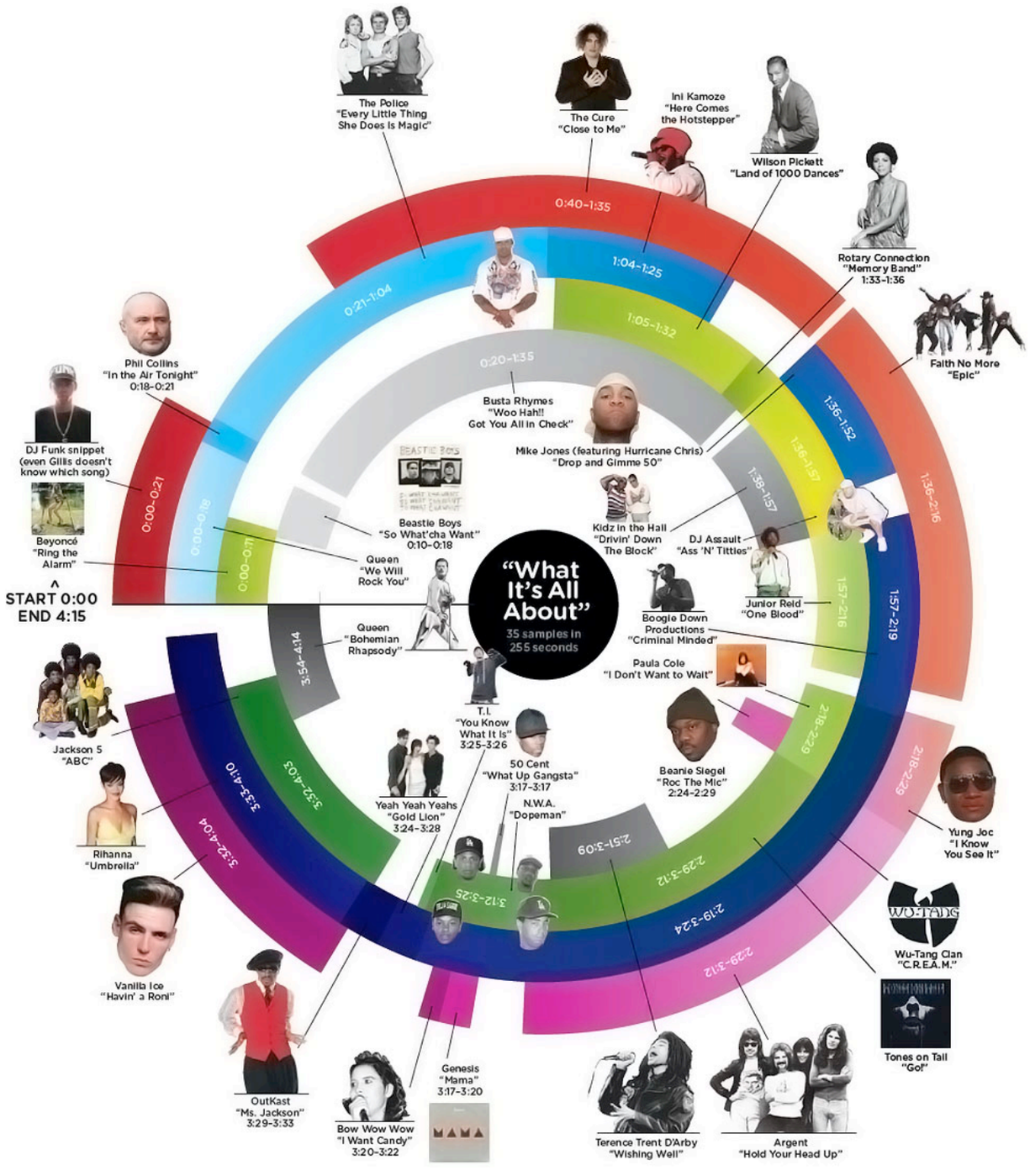


http://www.flyingpudding.com/projects/viz_music/

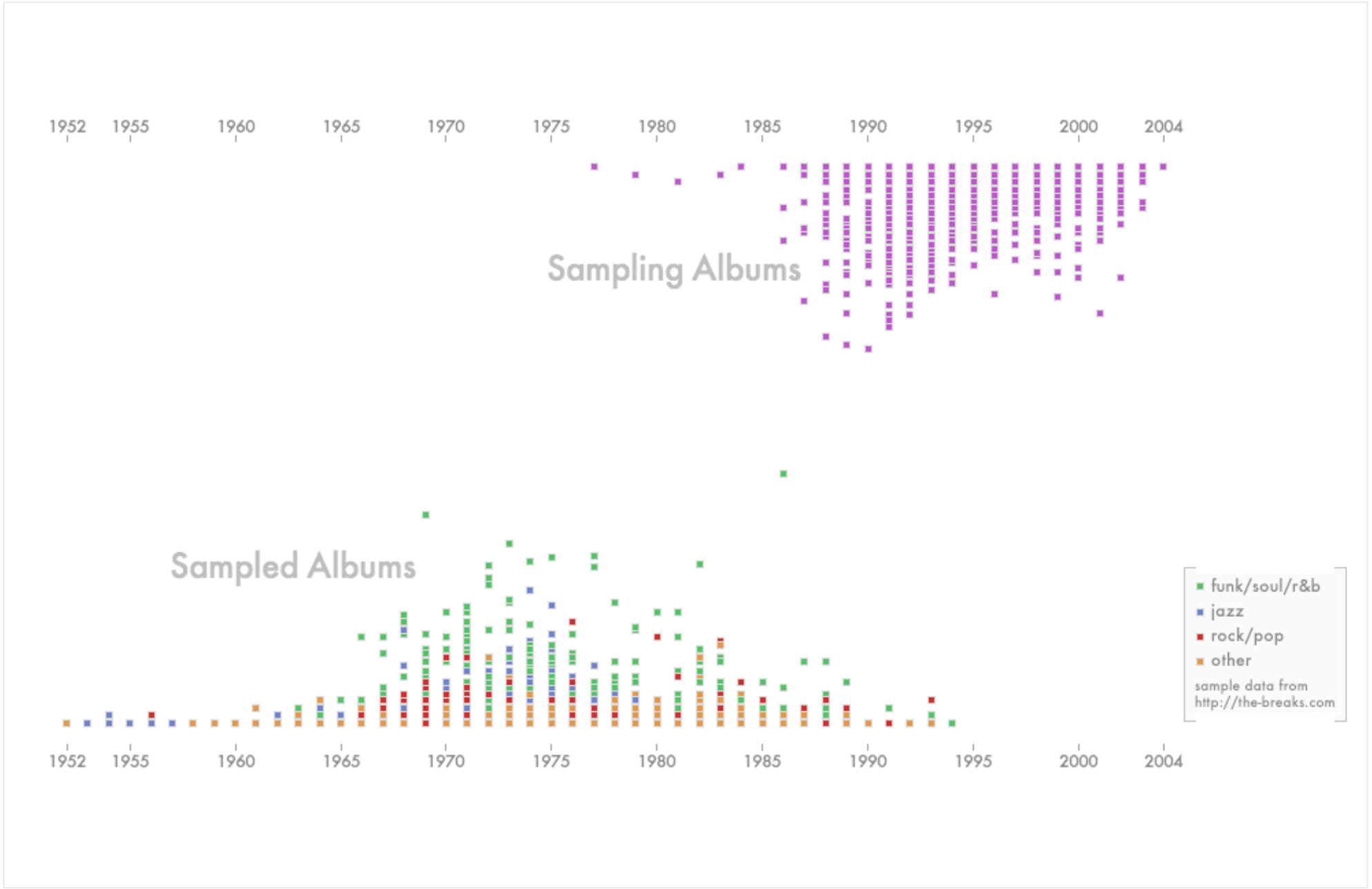
Visualizing Emotion in Lyrics

http://www.cs.kuleuven.be/~jorisk/thrillerMovie.mov

Sampling Connections

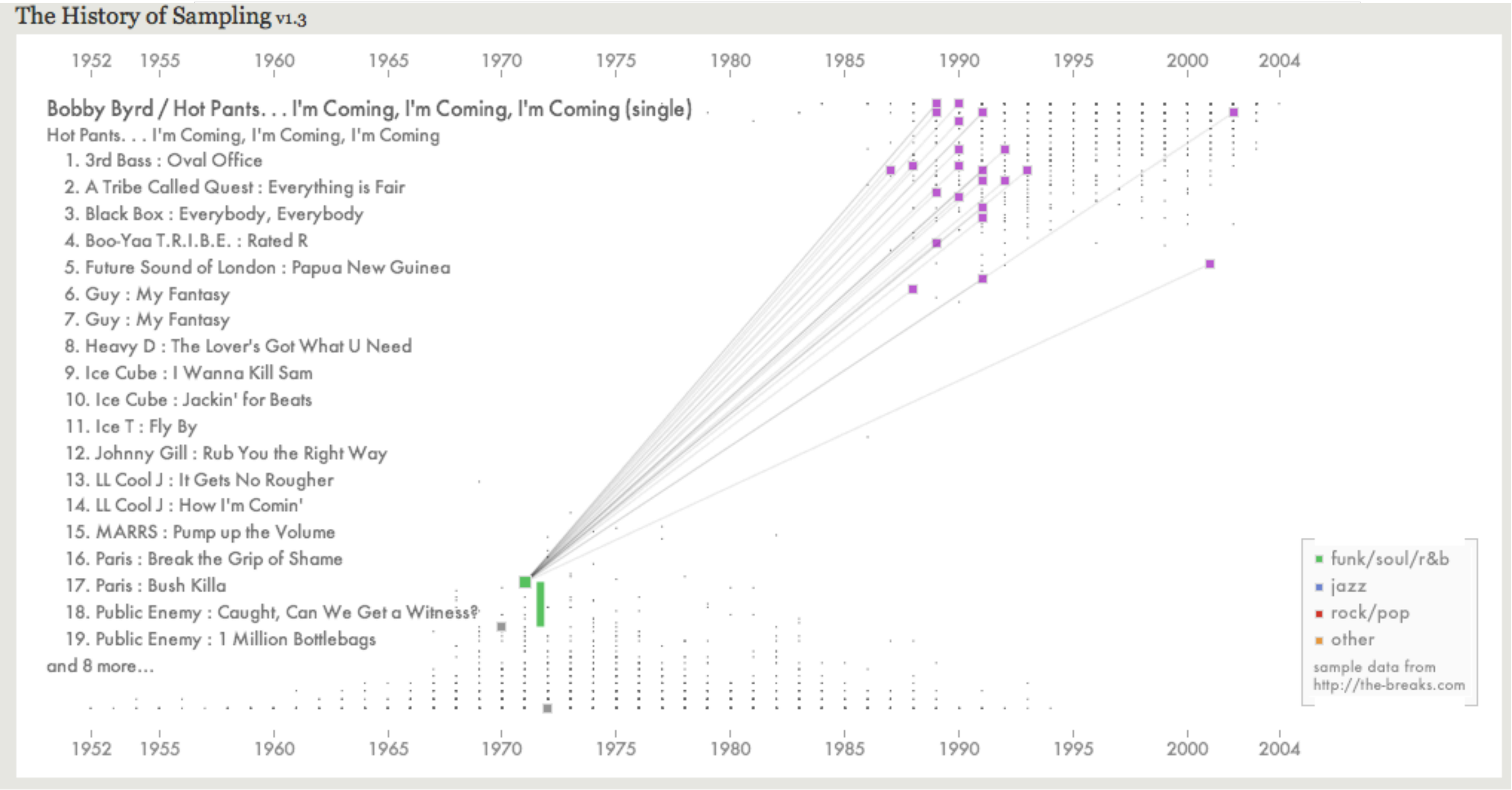


The History of Sampling



http://jessekriss.com/projects/samplinghistory/

The History of Sampling

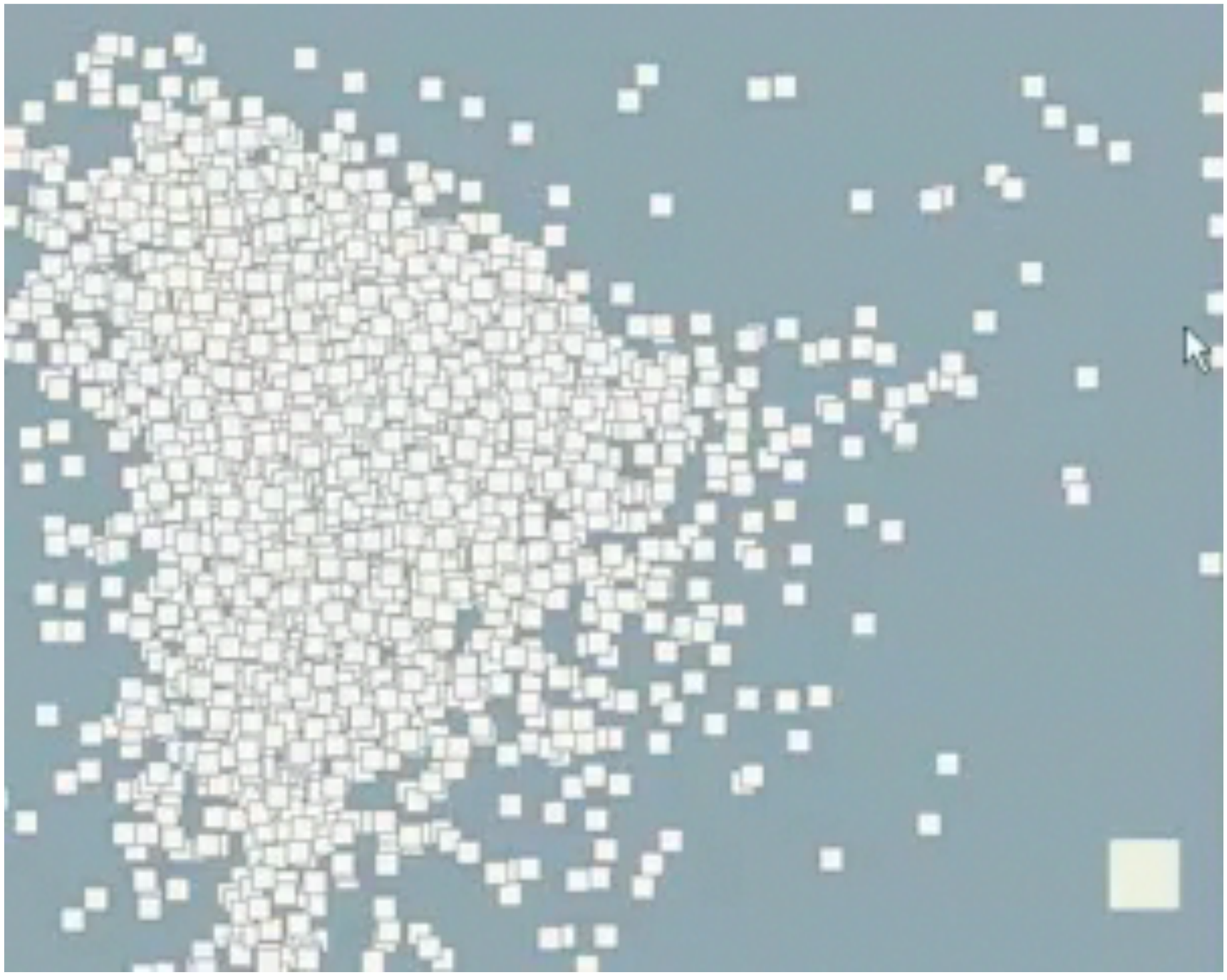


http://jessekriss.com/projects/samplinghistory/

Mused: Navigating the personal sample library

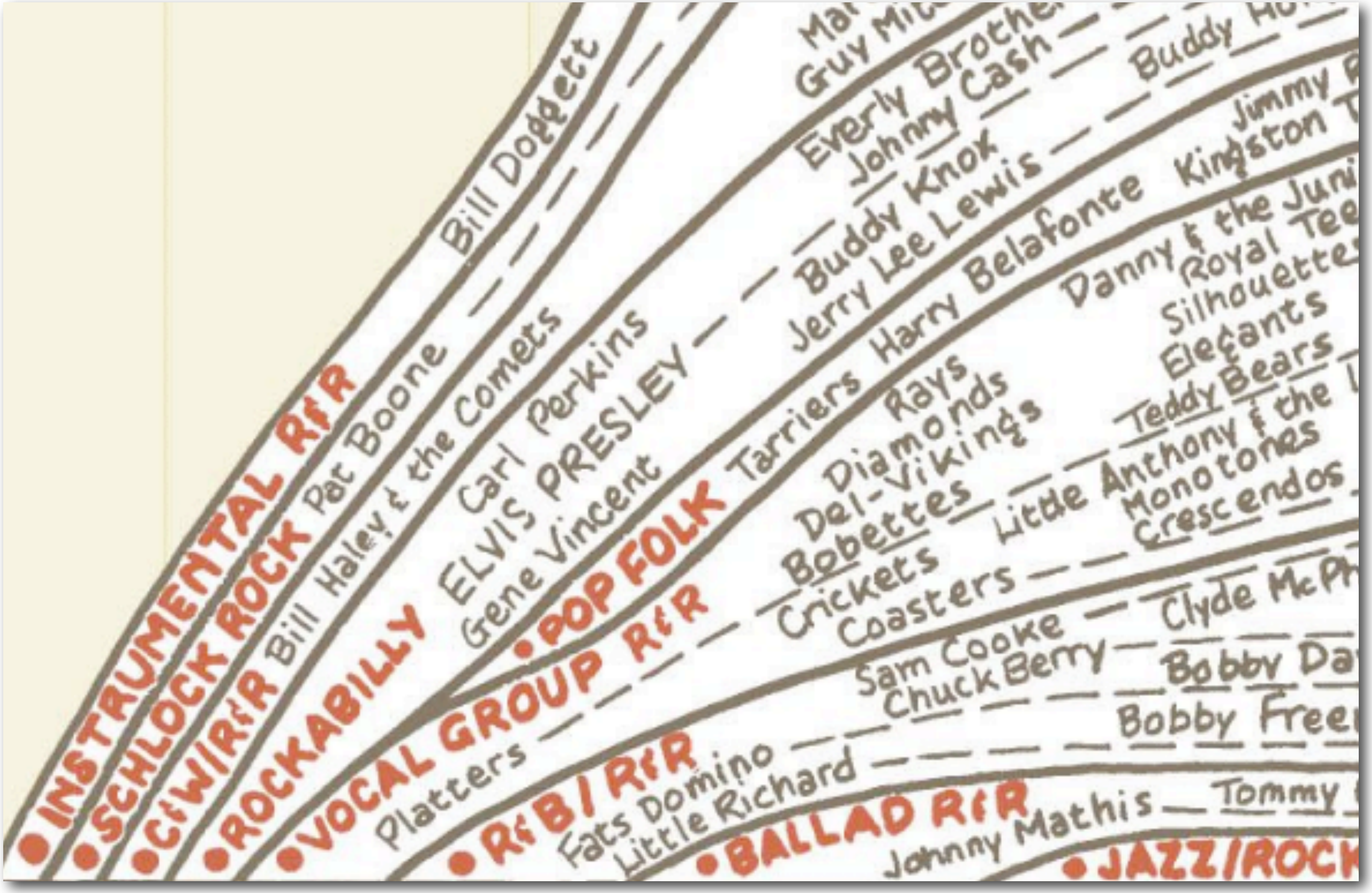
Graham Coleman - http://www.iua.upf.edu/~gcoleman/pubs/mused07.pdf

Mused: Navigating the personal sample library



Graham Coleman - http://www.iua.upf.edu/~gcoleman/pubs/mused07.pdf

Time Series

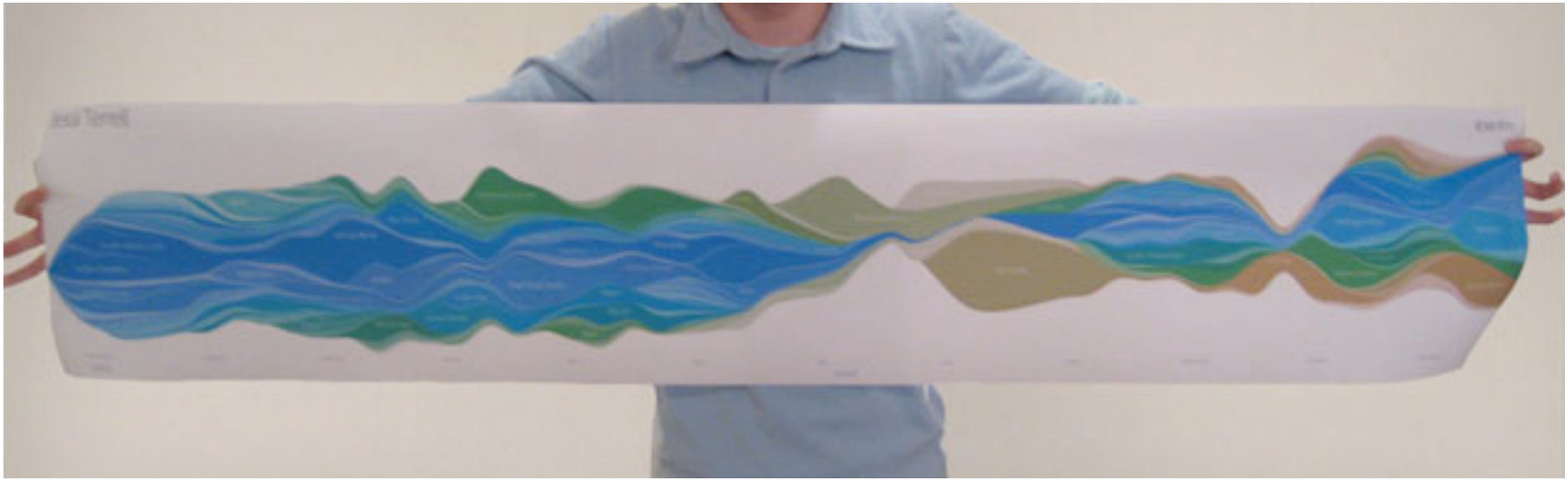


INSTRUMENTAL R&R
Bill Doggett
SCHLOCK ROCK
Pat Boone
C&W/R&R
Bill Haley & the Comets
ROCKABILLY
Carl Perkins
ELVIS PRESLEY
Gene Vincent
Guy Mitc
Everly Brother
Johnny Cash
Buddy Knox
Jerry Lee Lewis
Buddy Ho
POP FOLK
Tarriers
Harry Belafonte
Kingston T
Jimmy
VOCAL GROUP R&R
Platters
Rays
Diamonds
Del-Vikings
Bobettes
Crickets
Coasters
Danny & the Juni
Royal Tee
Silhouettes
Elegants
Teddy Bears
Little Anthony & the
Monotones
Crescendos
R&B/R&R
Fats Domino
Little Richard
Sam Cooke
Chuck Berry
Clyde McPh
Bobby Da
Bobby Free
BALLAD R&R
Johnny Mathis
Tommy
JAZZ/ROCK

last.fm spiral

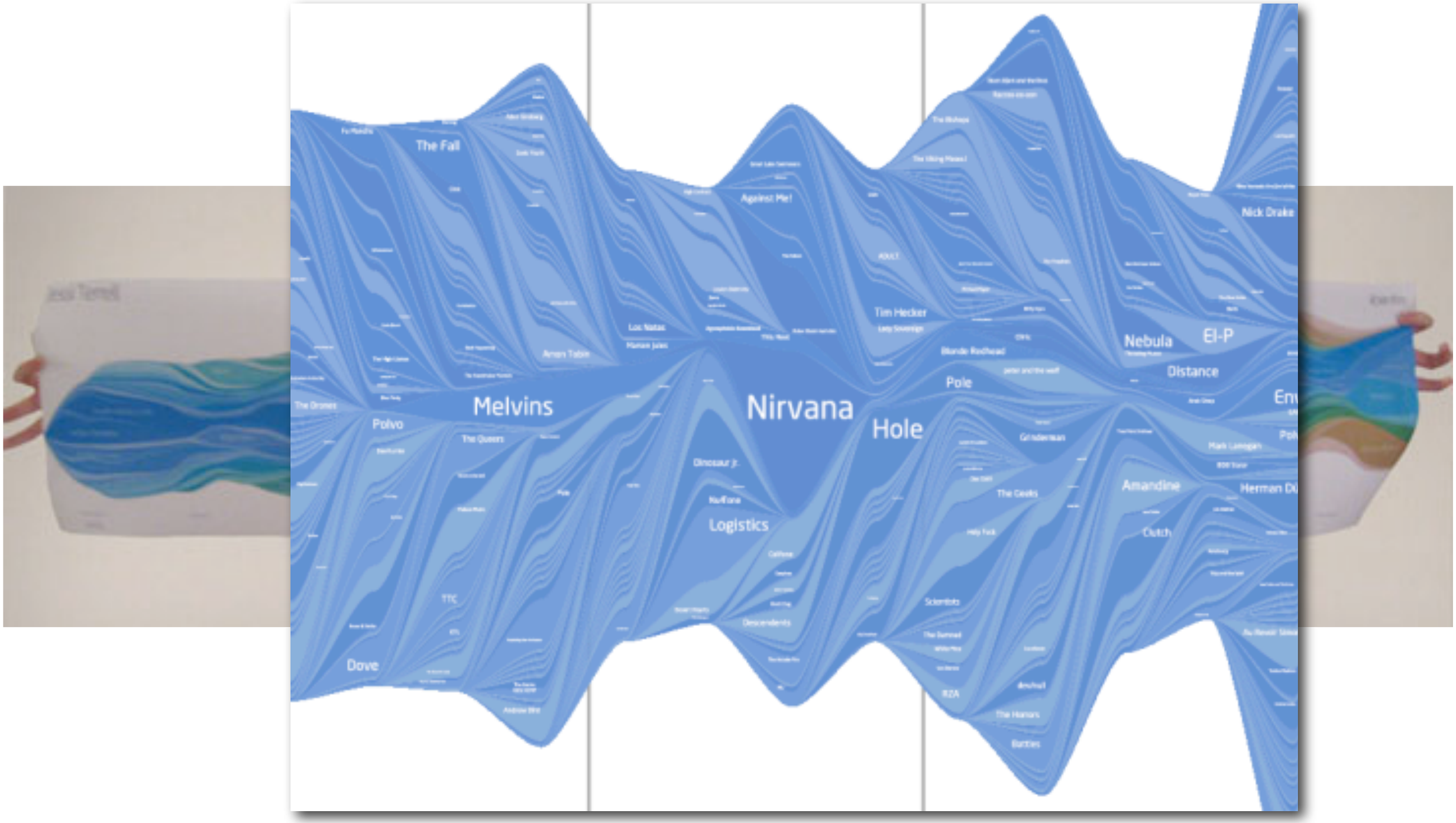
http://www.diametunim.com/muse/

Visualizing Listening History



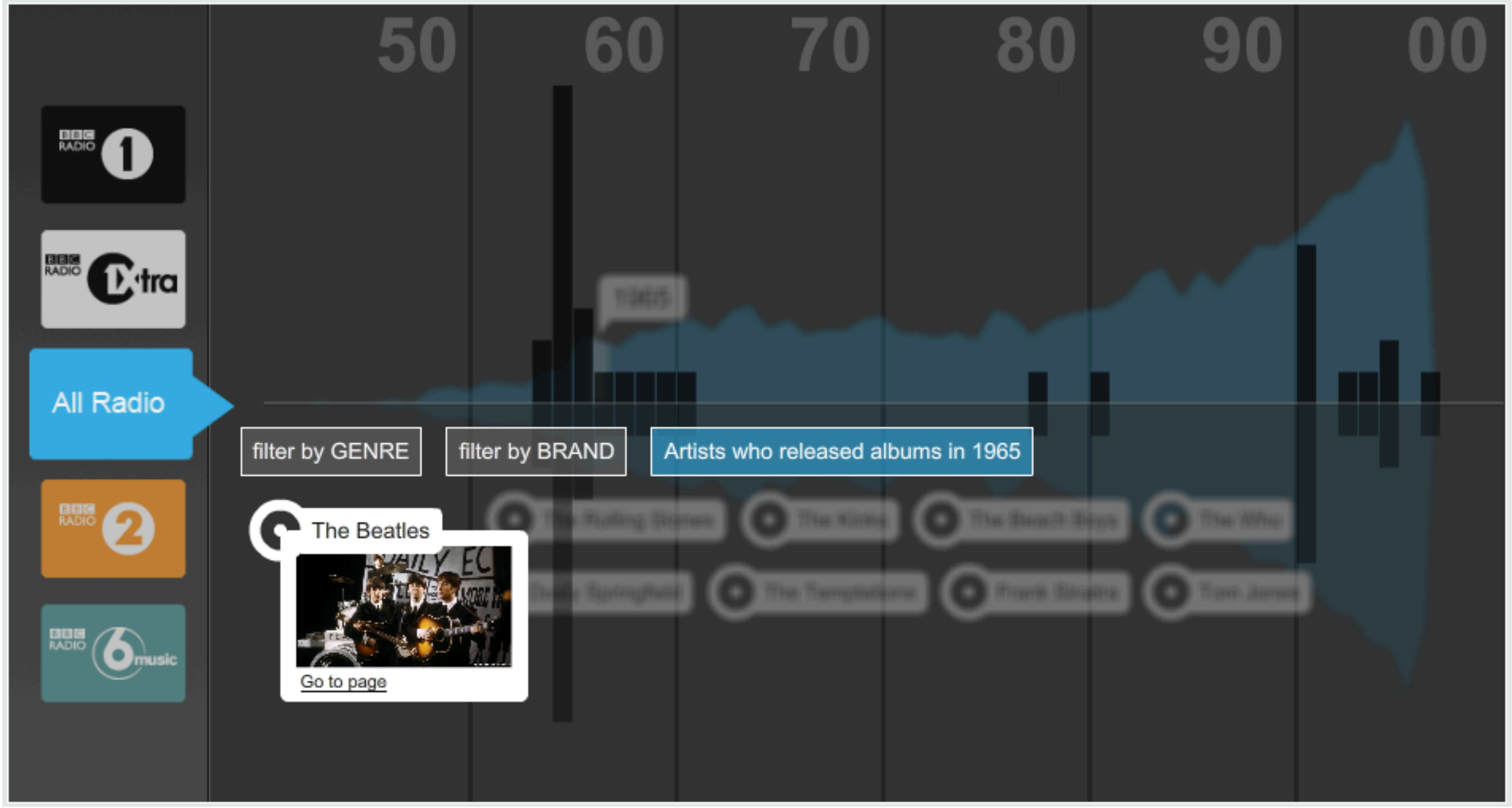
http://www.leebyron.com/what/lastfm/ - Lee Byron

Visualizing Listening History



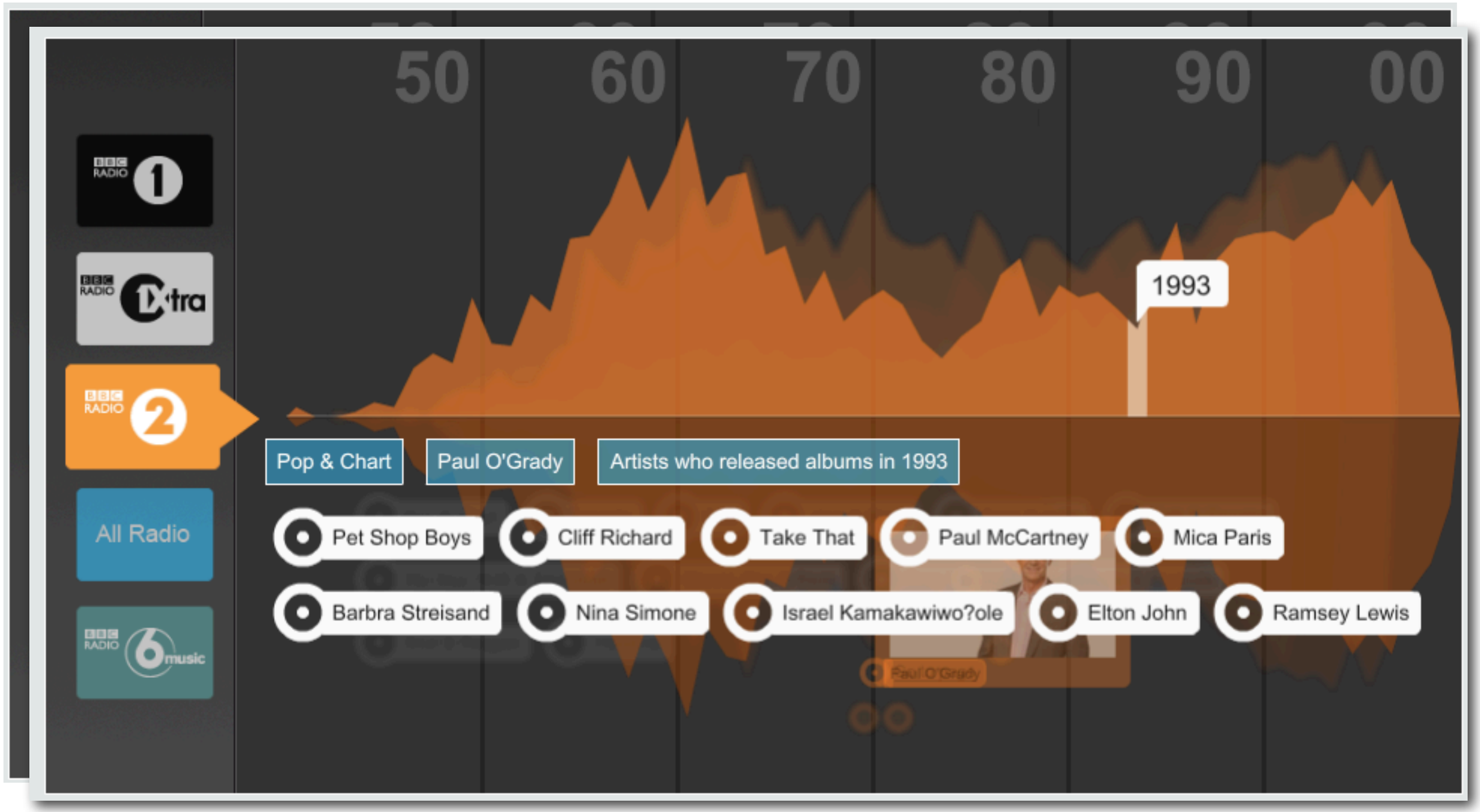
http://www.leebyron.com/what/lastfm/ - Lee Byron

Radio Waves



http://www.bbc.co.uk/radio/labs/radiowaves/

Radio Waves

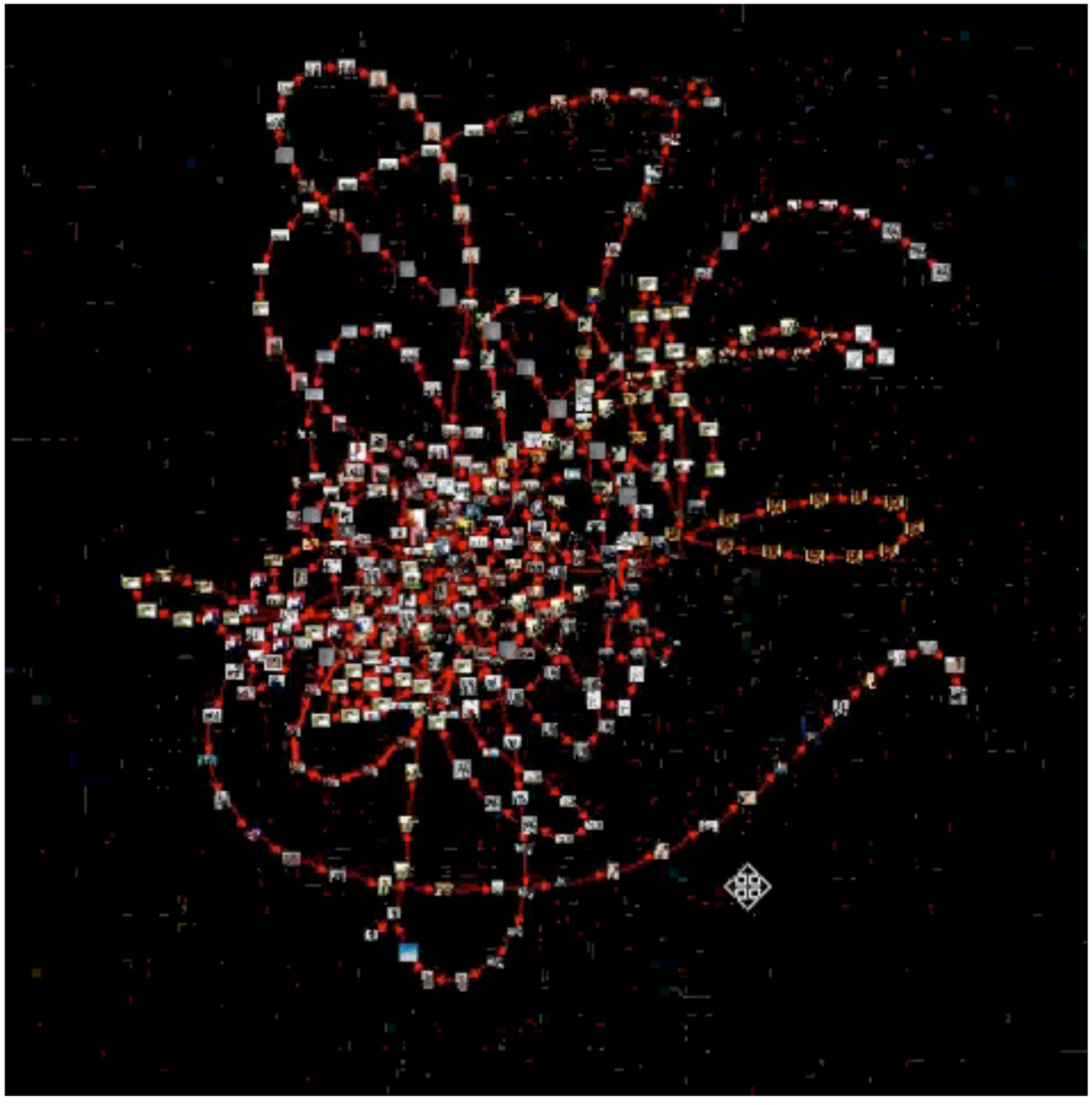


http://www.bbc.co.uk/radio/labs/radiowaves/

Pulling strings from a tangle

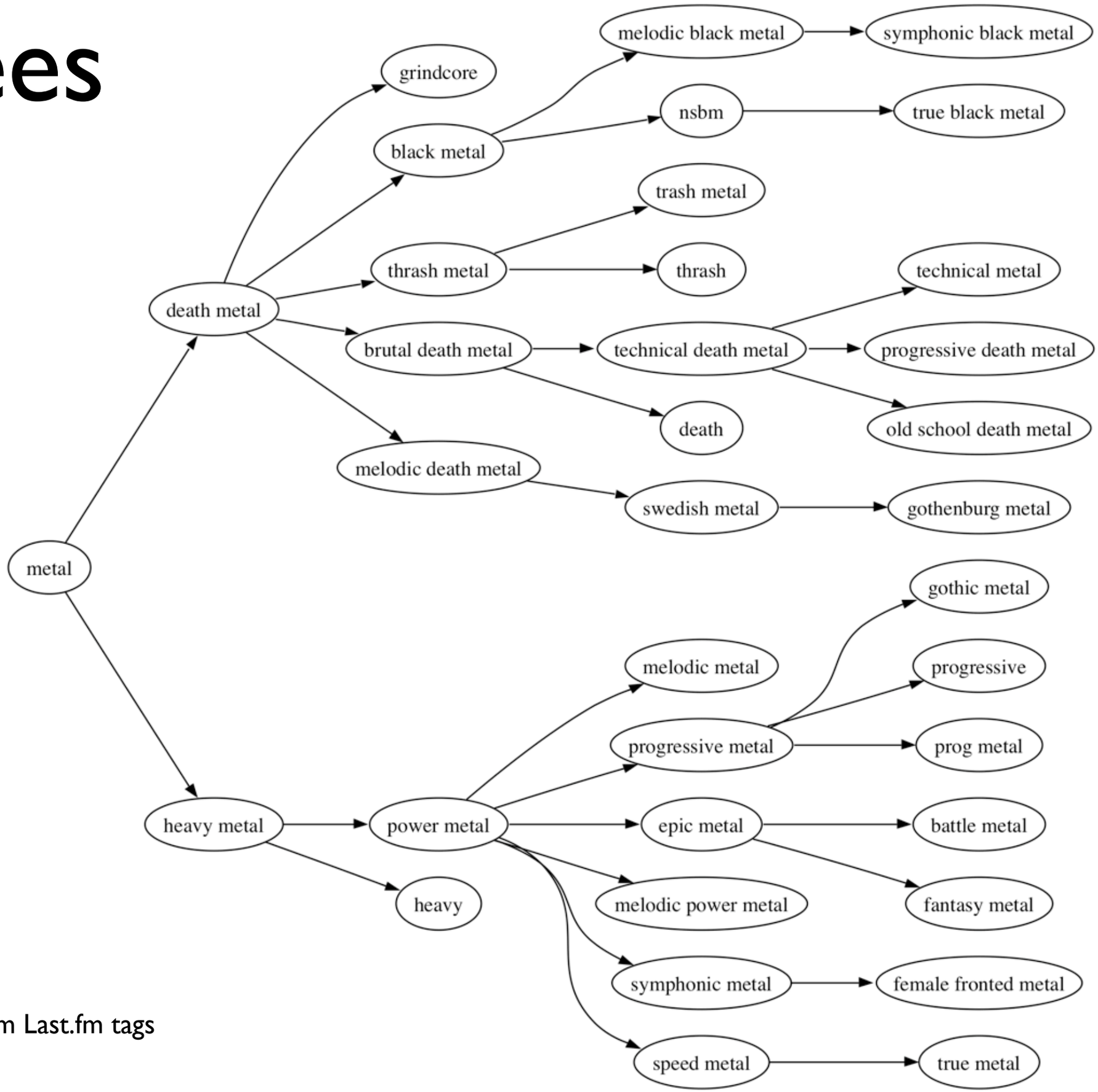
http://bowr.de/blog/?p=49
Dominikus Baur University of Munich

Pulling strings from a tangle



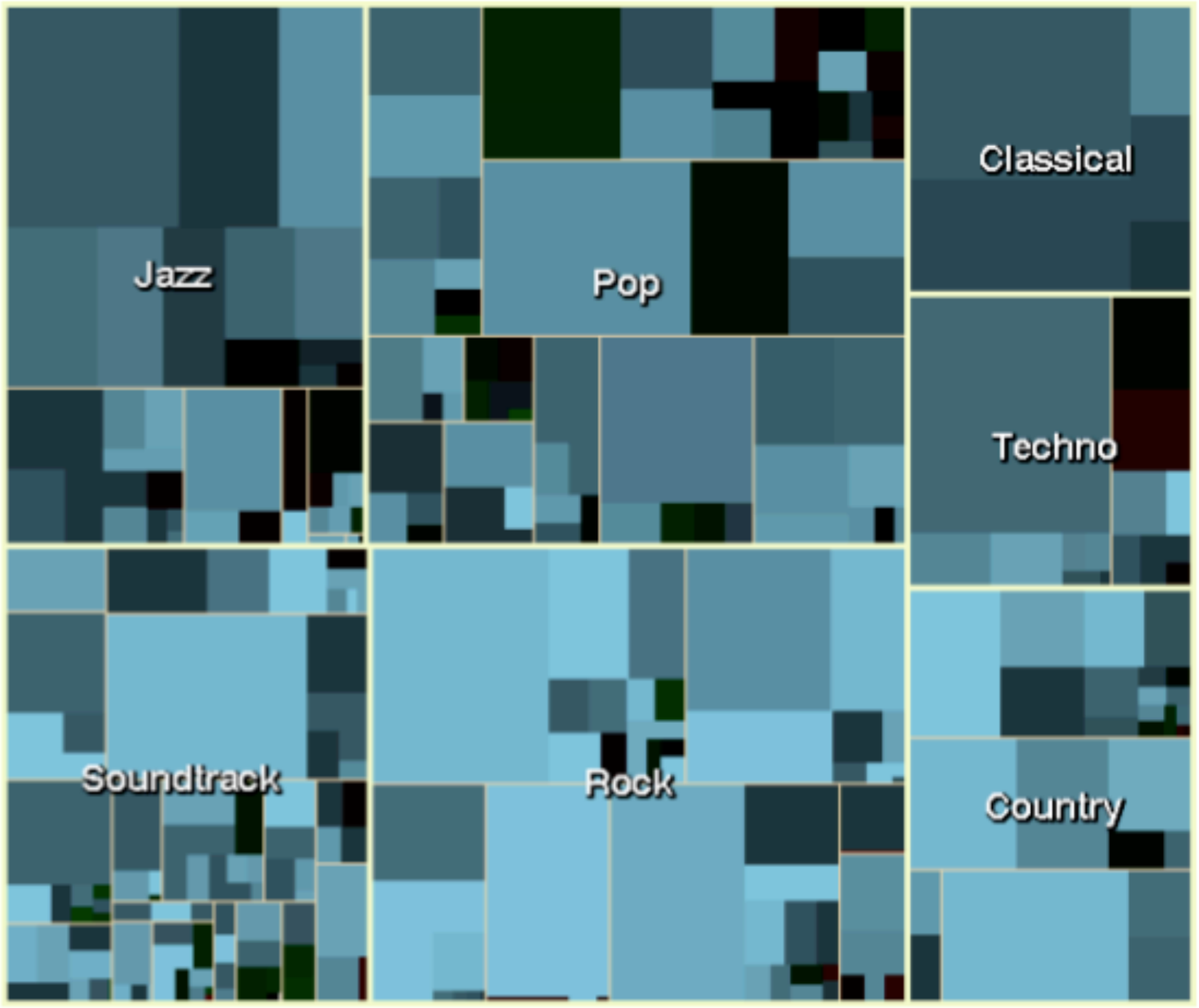
http://bowr.de/blog/?p=49
Dominikus Baur University of Munich

Trees



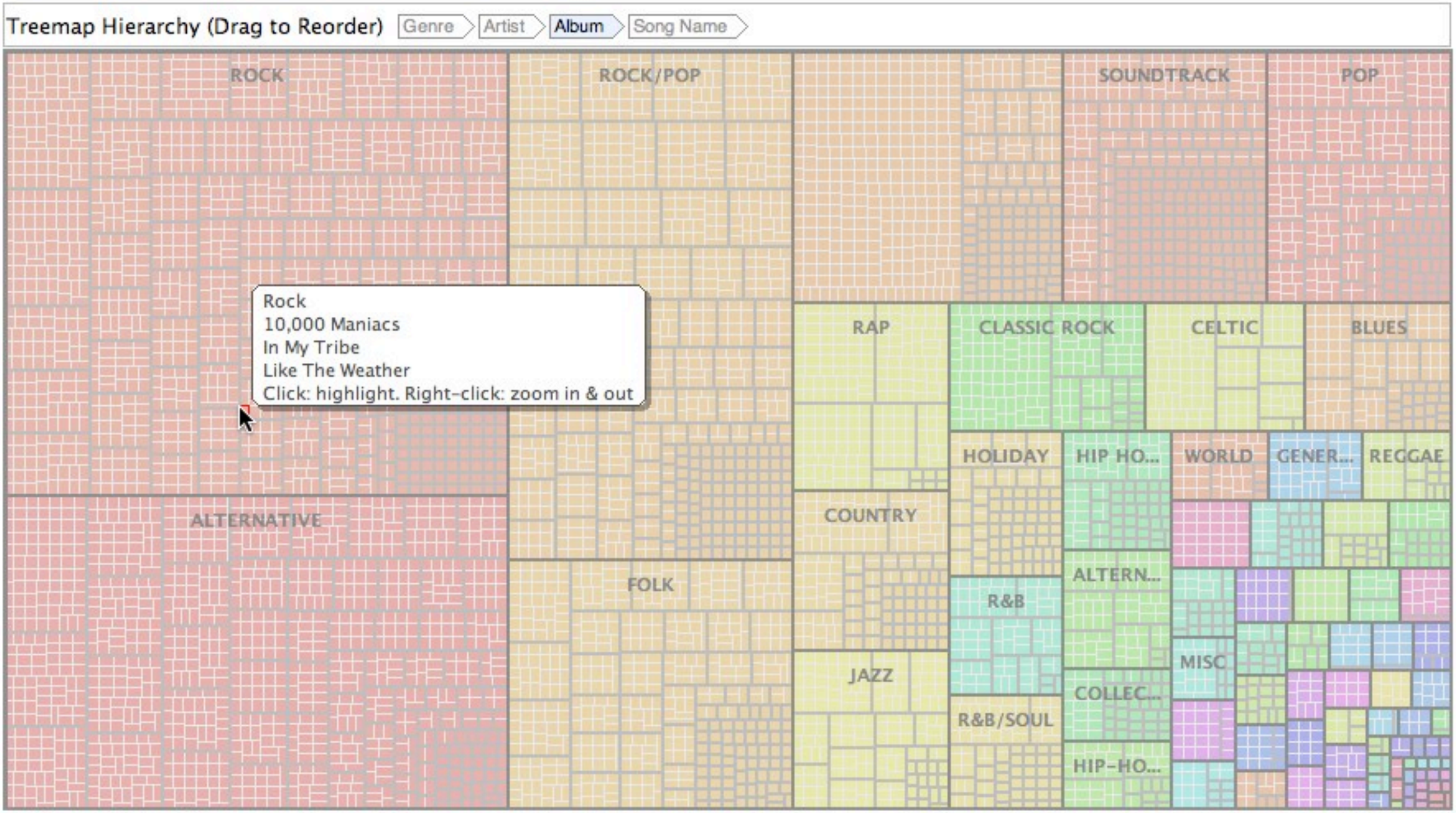
Genre Map derived from Last.fm tags
Lamere

Trees



Visualizing and exploring personal music libraries
Torrens, Hertzog, Arcos

Treemap of a personal music collection



Visualizations : Dave's Music Library Contents

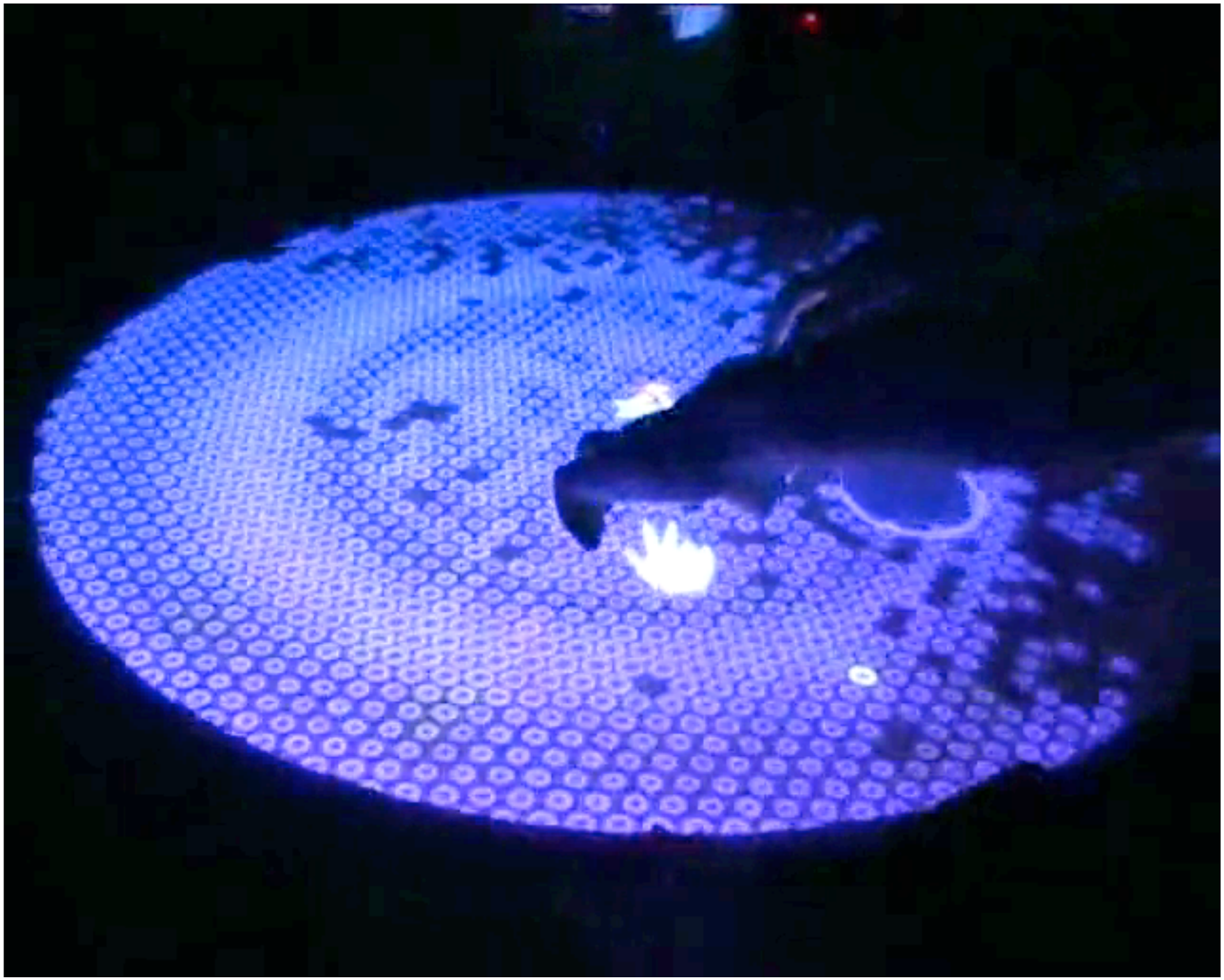
Interactive

Mirrored Radio dial - by thomwatson

SongExplorer

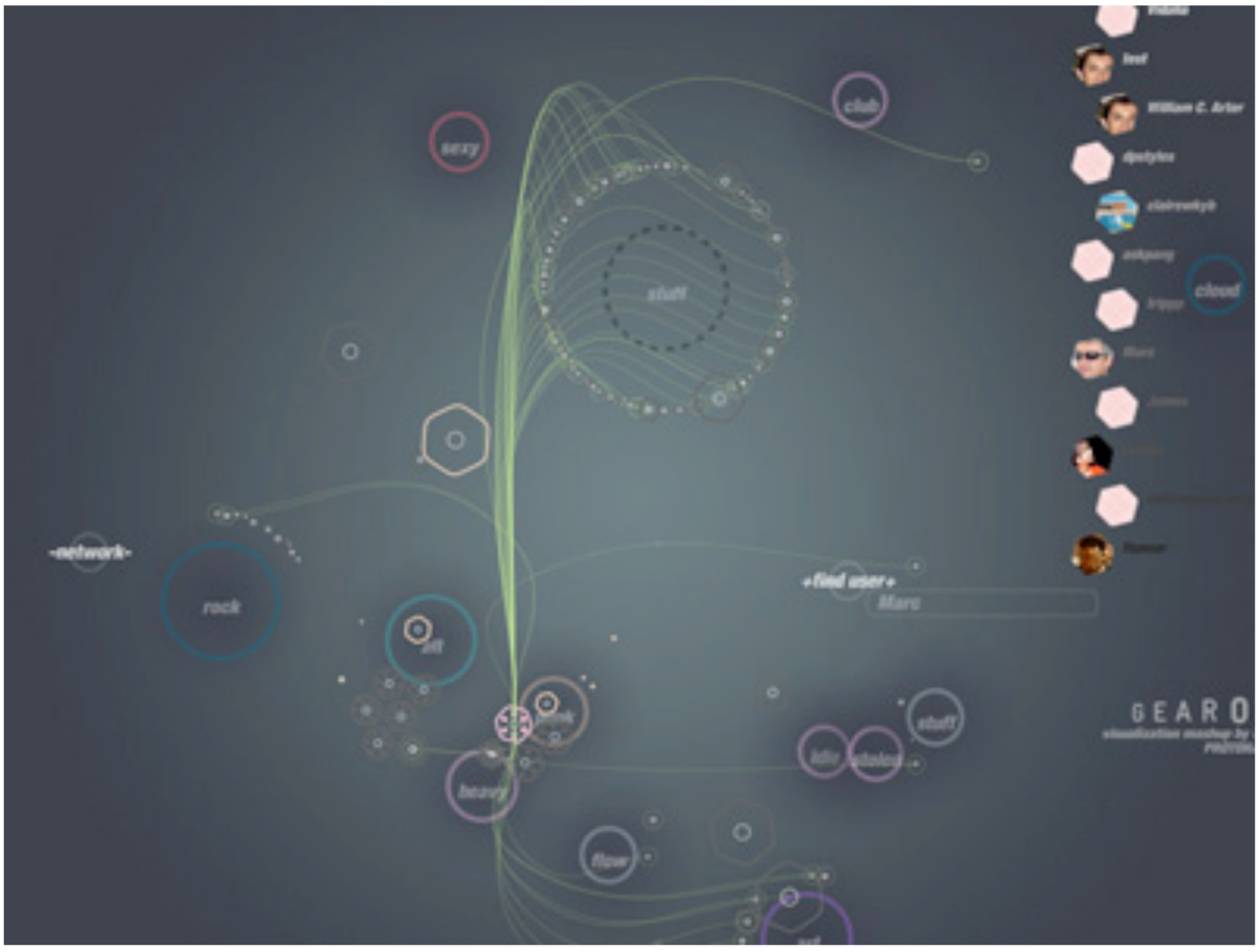
SongExplorer: Exploring Large Musical Databases Using a Tabletop Interface
Carles F. Julià - Music Technology Group - Universitat Pompeu Fabra

SongExplorer



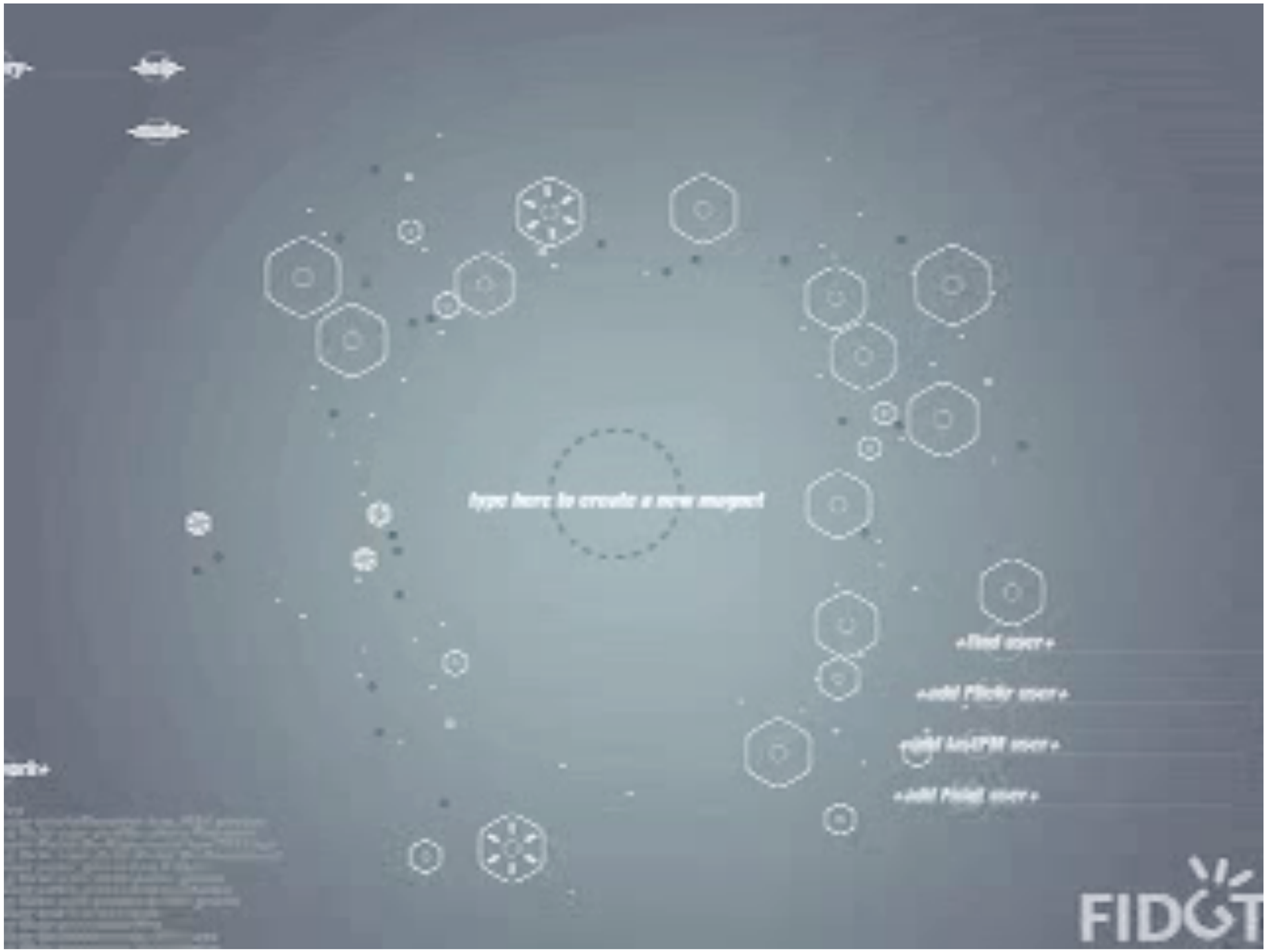
SongExplorer: Exploring Large Musical Databases Using a Tabletop Interface
Carles F. Julià - Music Technology Group - Universitat Pompeu Fabra

Fidgt: Visualize



http://fidgt.com/visualize

Fidgt: Visualize



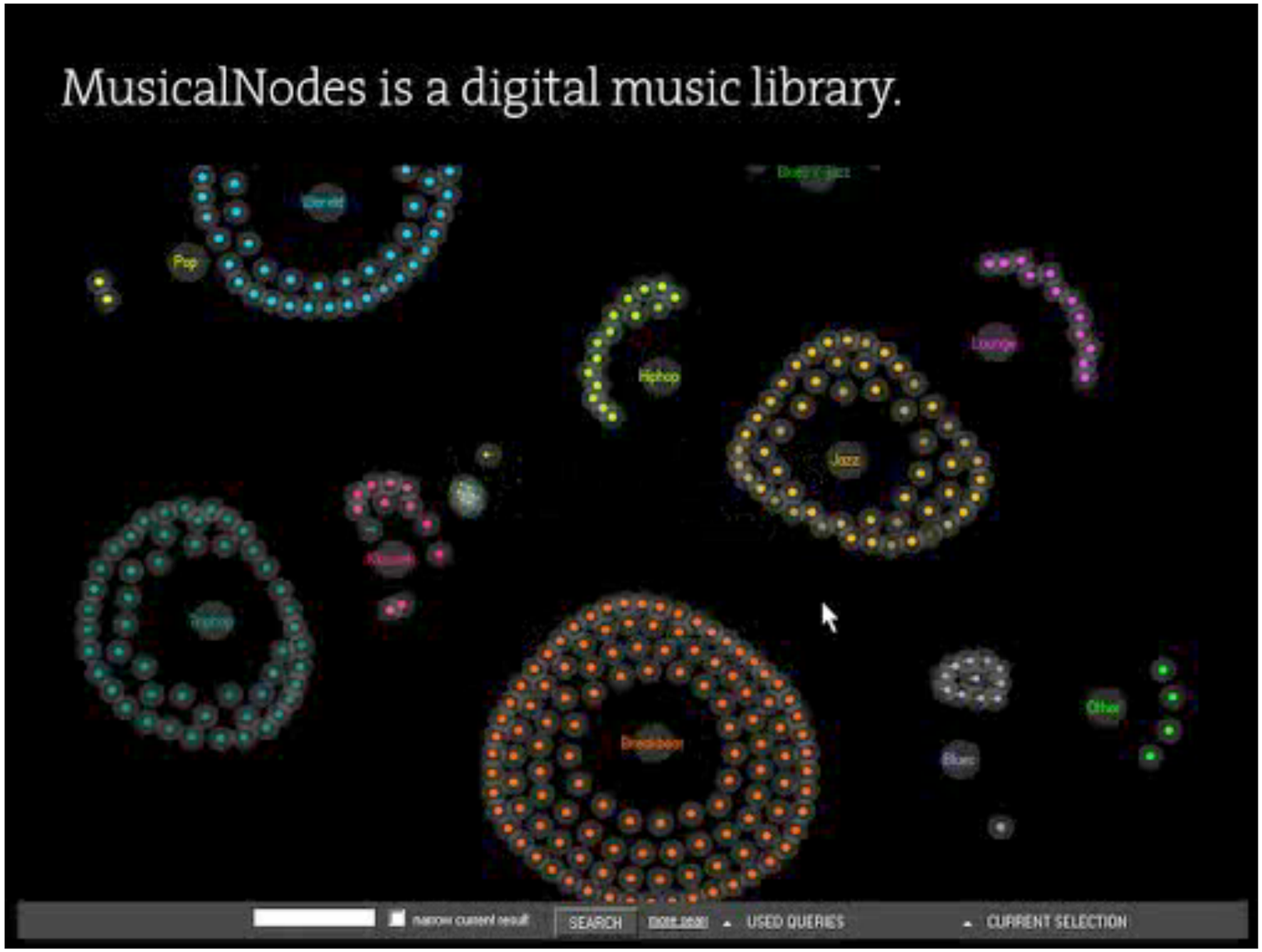
http://fidgt.com/visualize

MusicNodes

http://waks.nl/nl/musicalnodes

Lisa Dalhuijsen, Lieven van Velthoven -LIACS, Leiden University

MusicNodes



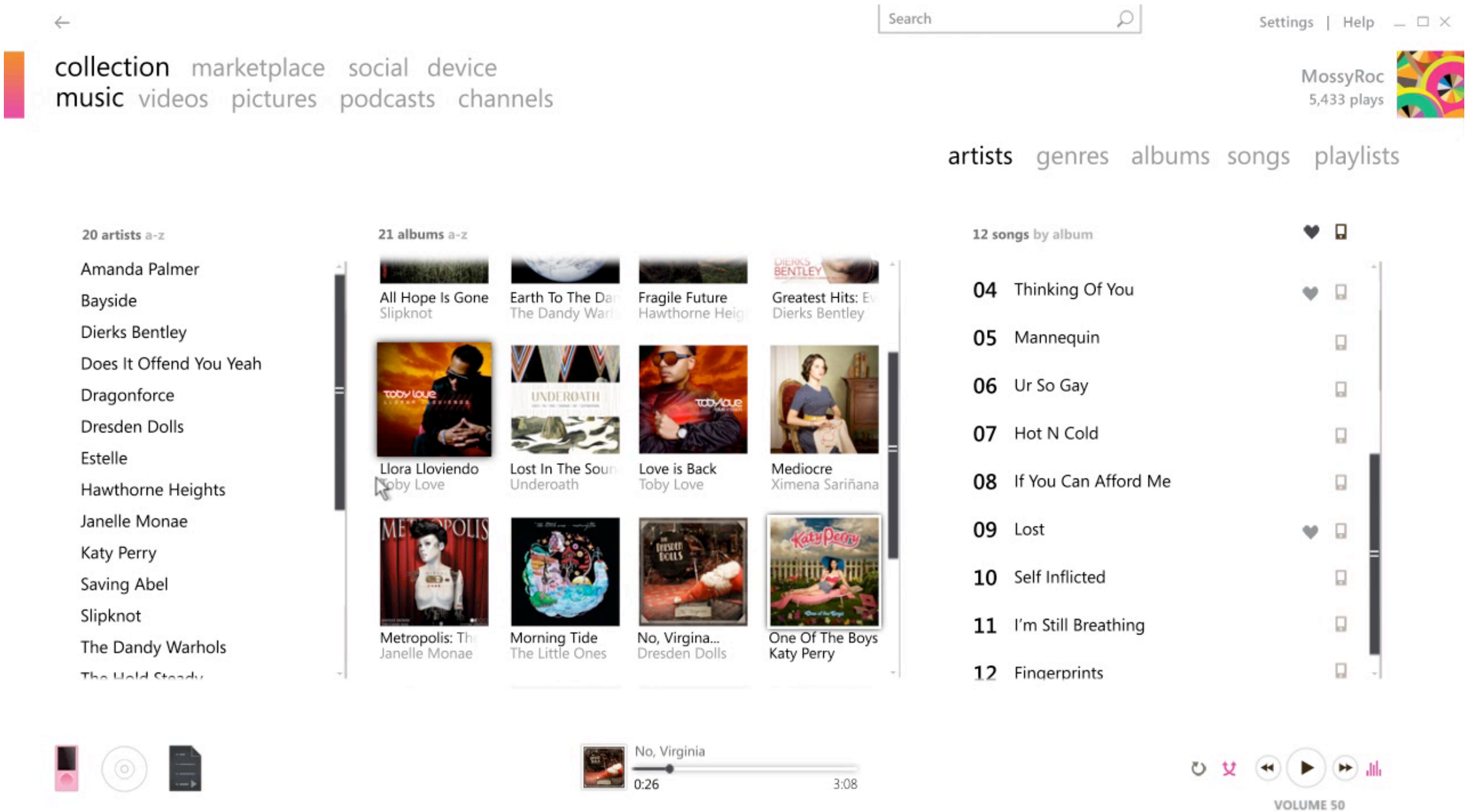
http://waks.nl/nl/musicalnodes

Lisa Dalhuijsen, Lieven van Velthoven -LIACS, Leiden University

Zune MixView

social.zune.net

Zune MixView

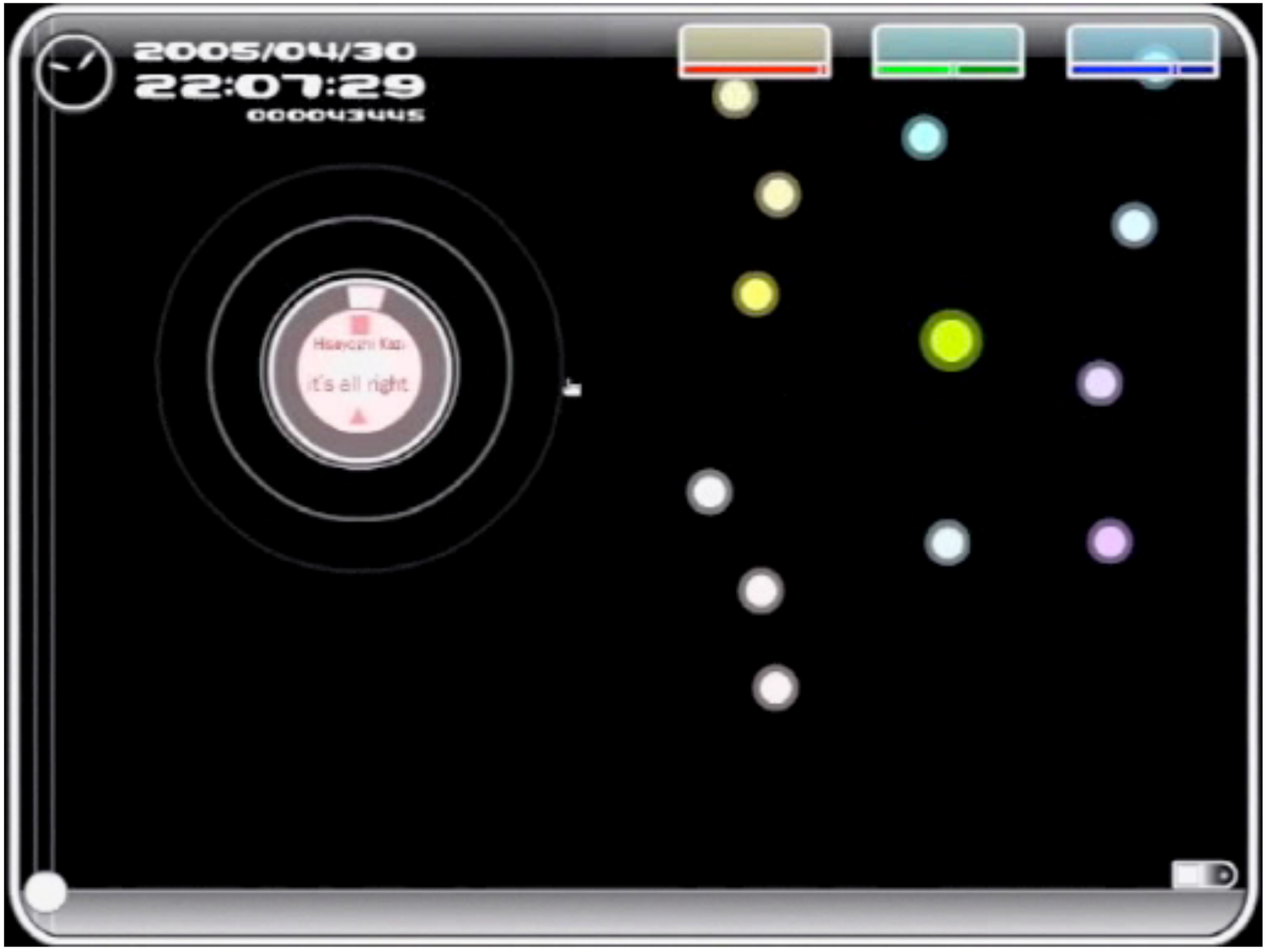


social.zune.net

Musicream

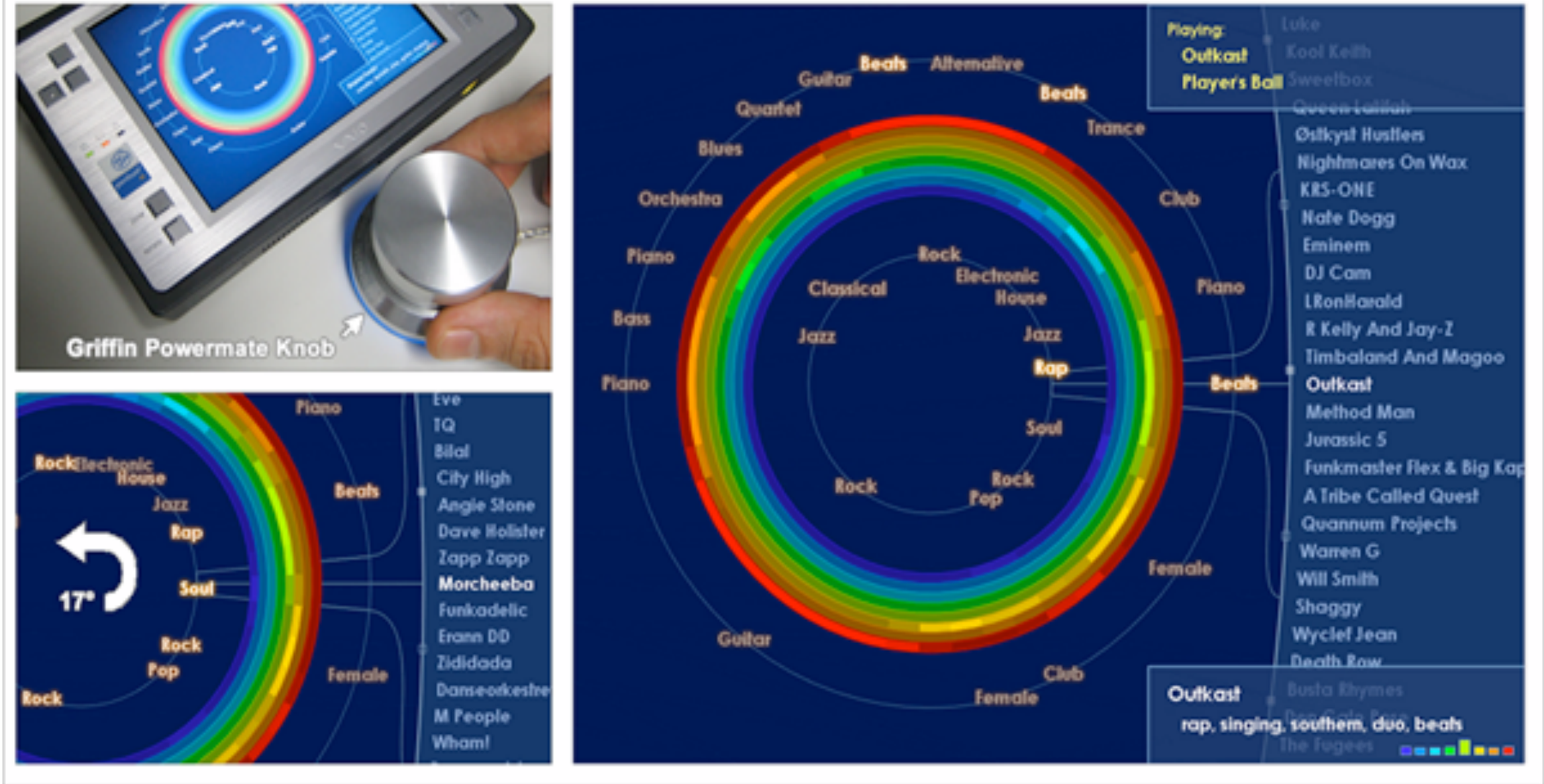
http://staff.aist.go.jp/m.goto/Musicream/ Goto and Masataka Goto.

Musicream



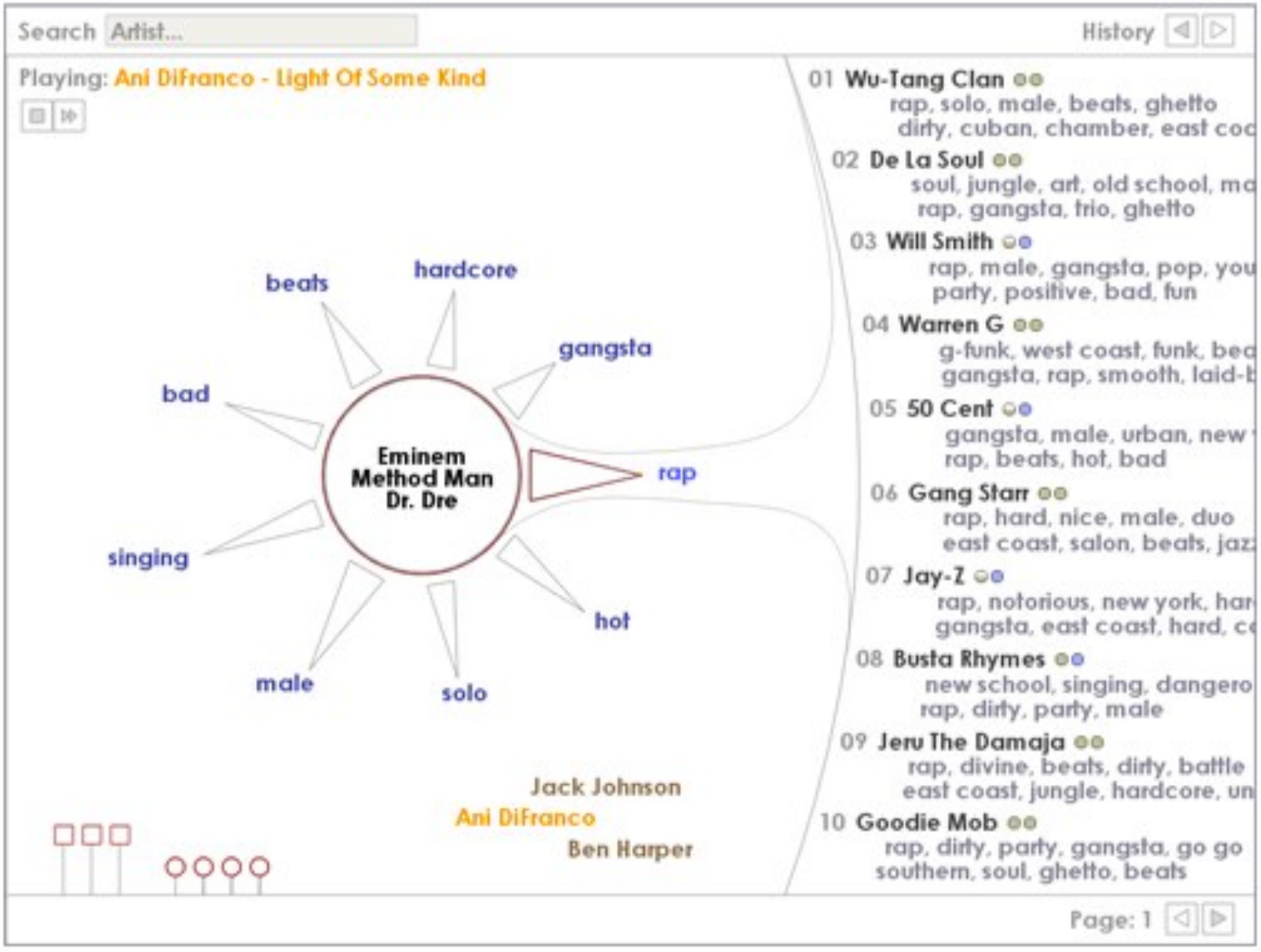
http://staff.aist.go.jp/m.goto/Musicream/ Goto and Masataka Goto.

MusicRainbow



Elias Pampalk & Masataka Goto, "MusicRainbow: A New User Interface to Discover Artists Using Audio-based Similarity and Web-based Labeling

MusicSun

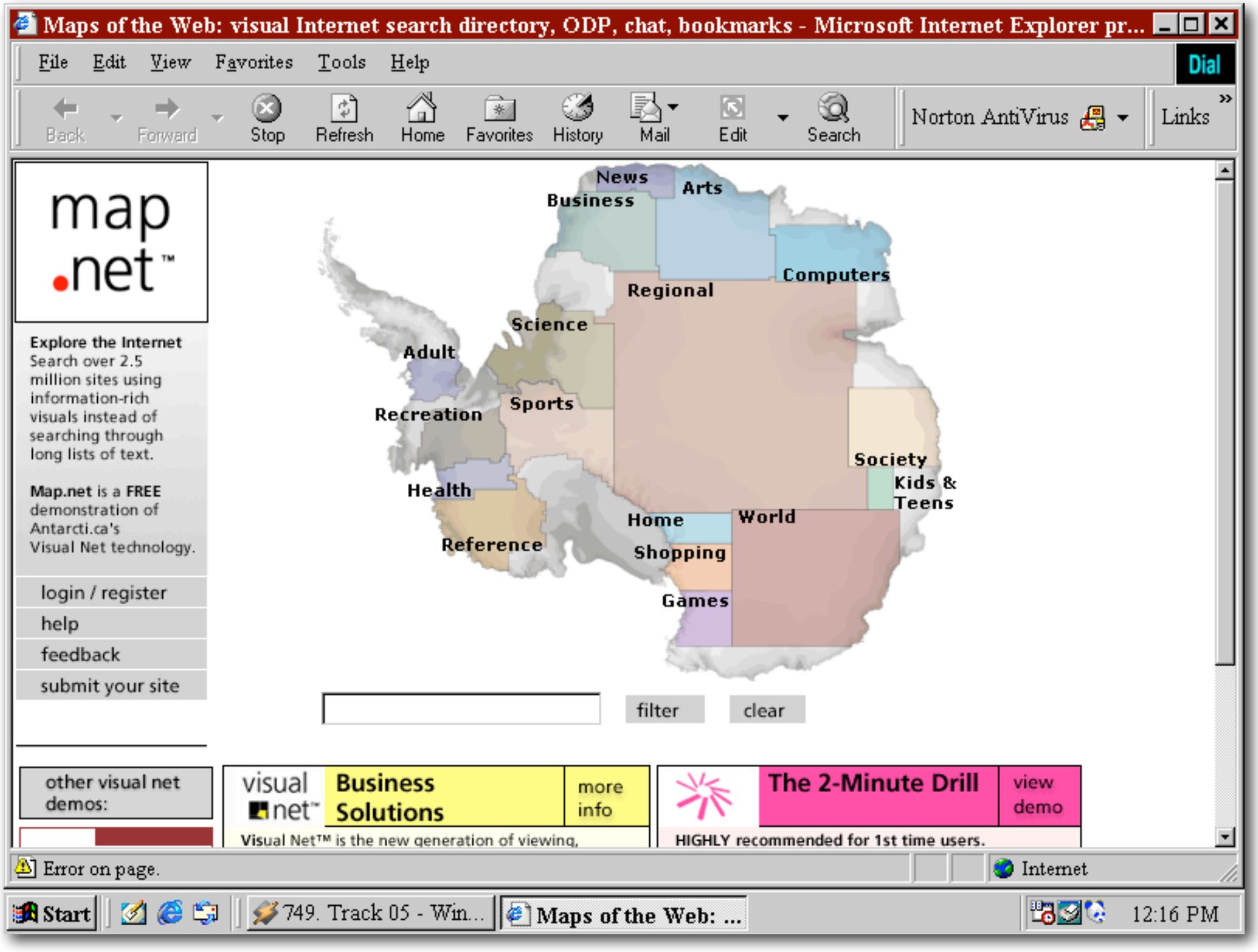


Elias Pampalk & Masataka Goto,
"MusicSun: A New Approach to Artist Recommendation"

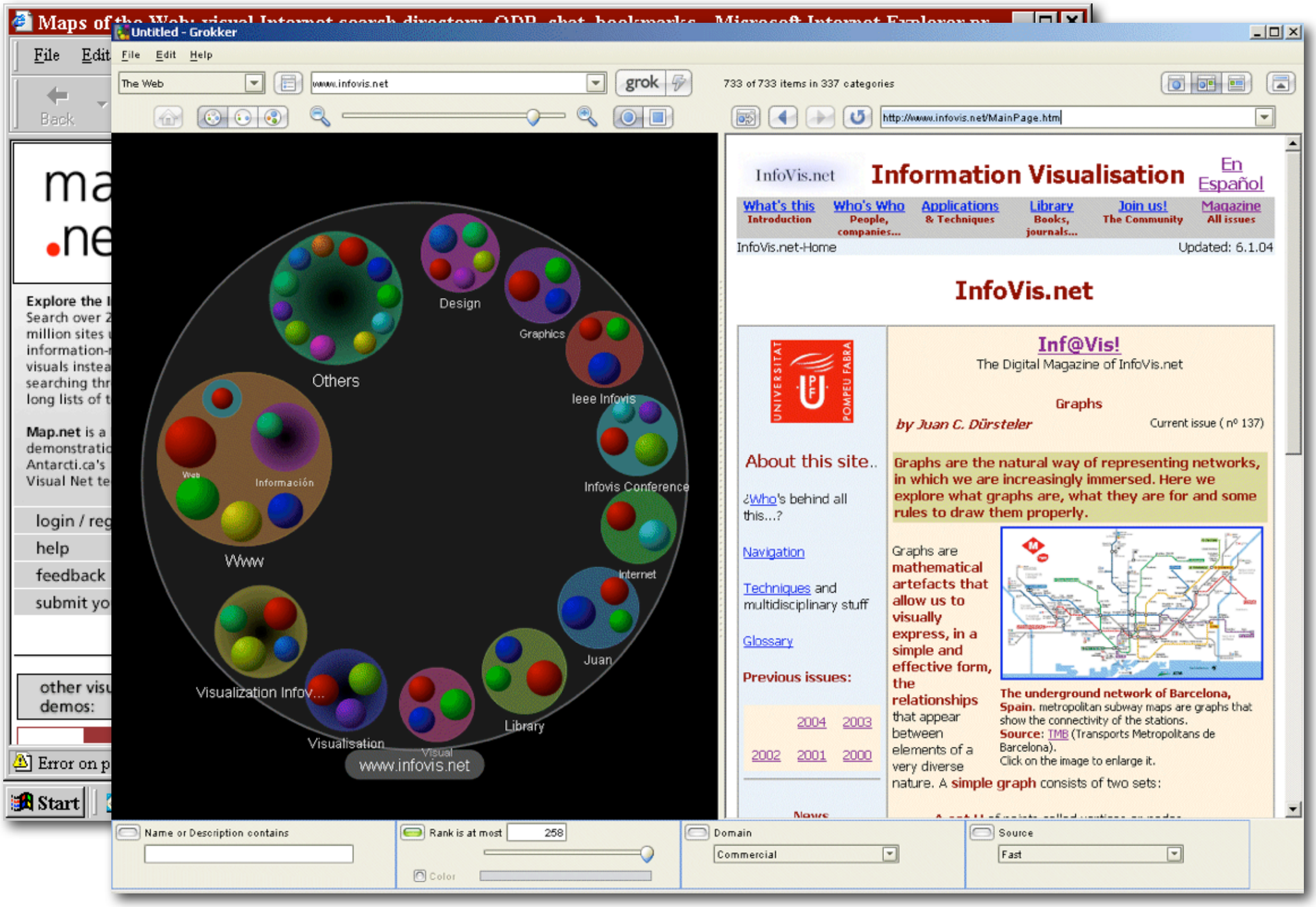
EN Music Explorer

EN Music Explorer

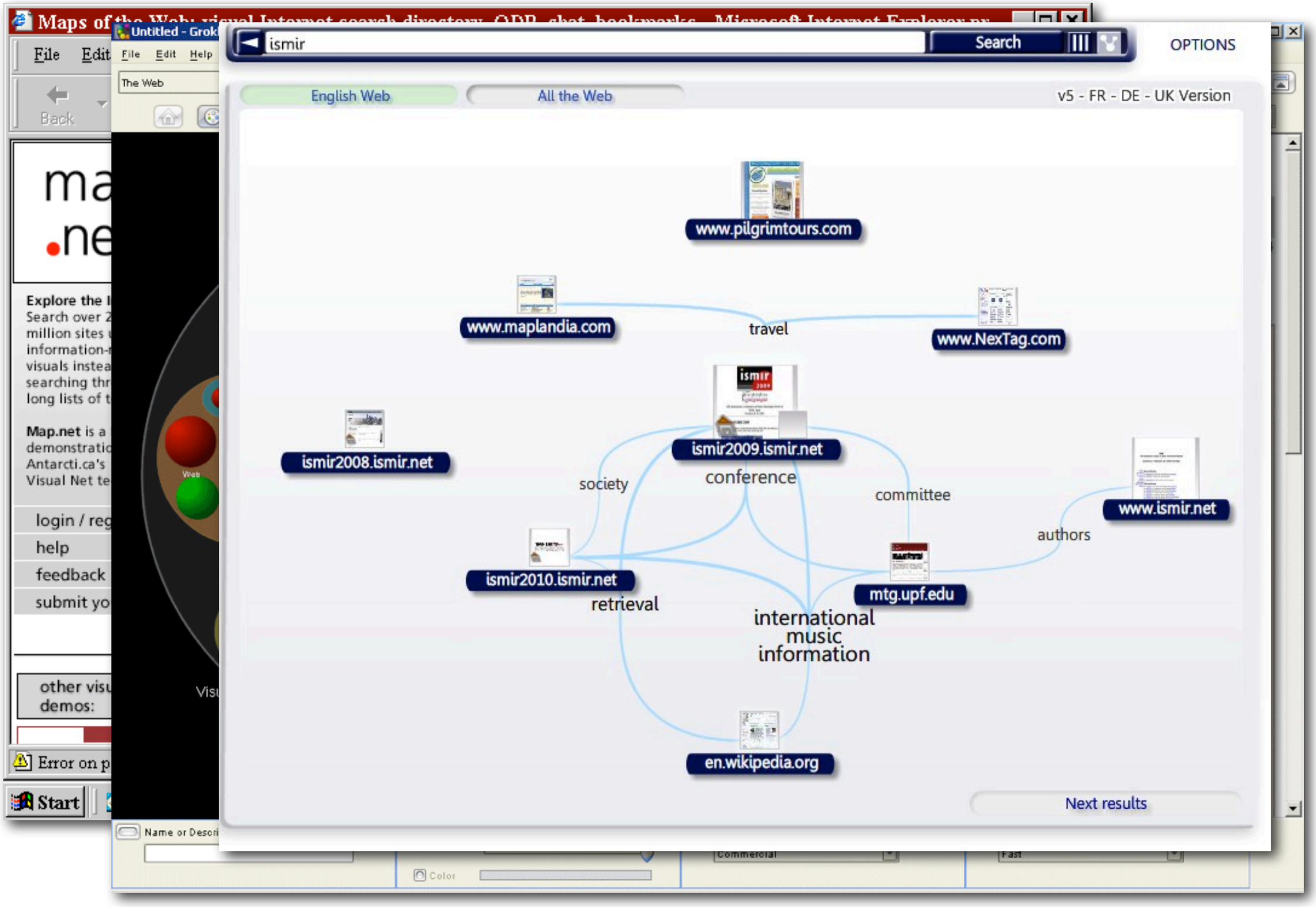
Here be Dragons



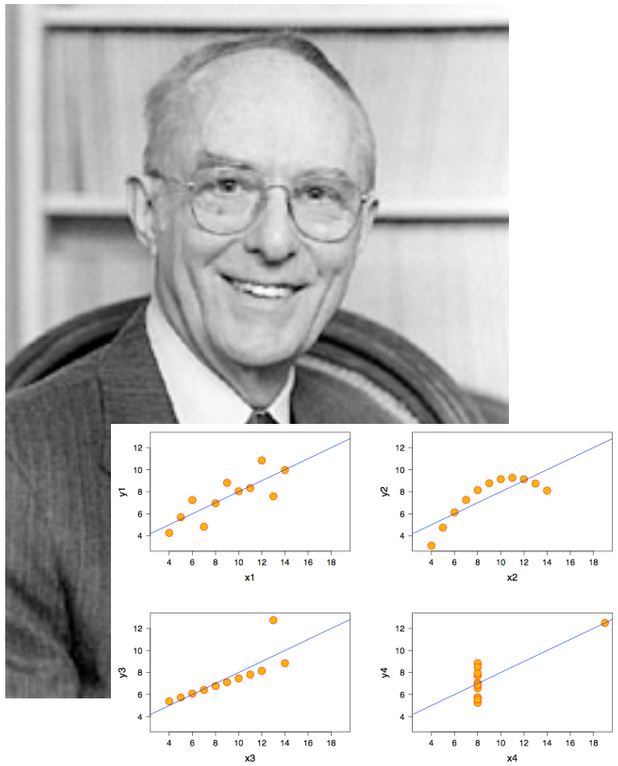
Here be Dragons



Here be Dragons



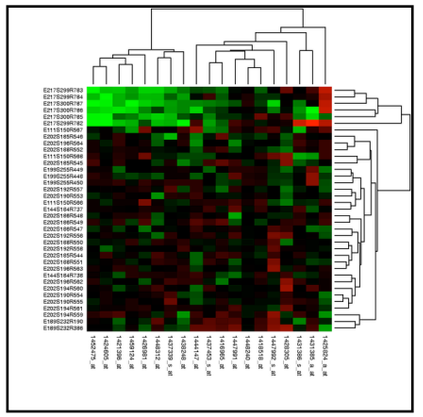
Visualization Proponents (The Yale Club)



F.J. Anscombe
(Anscombe's Quartet)

0 | 0000111111222338
2 | 07
4 | 5
6 | 8
8 | 4
10 | 5
12 |
14 |
16 | 0

John Tukey
(stem/leaf plots)

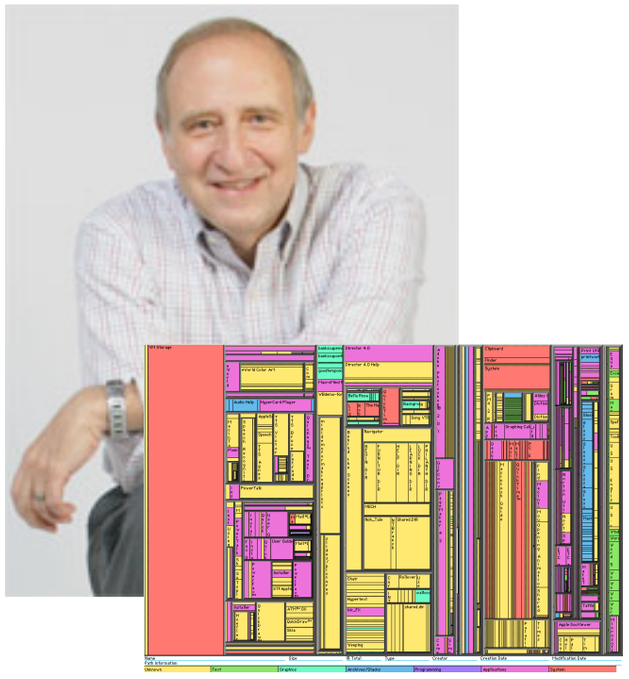


Leland Wilkinsen
(Cluster heat maps)

Edward Tufte
(Sparklines)

http://en.wikipedia.org/wiki/F.J._Anscombe
http://en.wikipedia.org/wiki/John_Tukey
http://en.wikipedia.org/wiki/Leland_Wilkinson
http://en.wikipedia.org/wiki/Edward_Tufte

Interactive Visualization Proponents



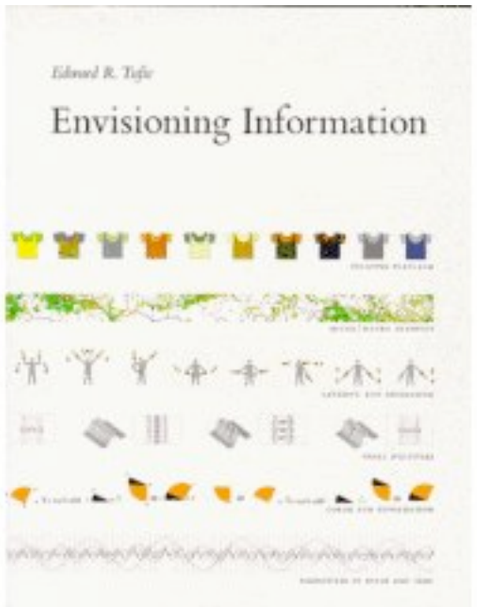
Ben Shneiderman (Treemaps, NSD diagrams)

Steve Deunes (& entire NYT Graphics Department)

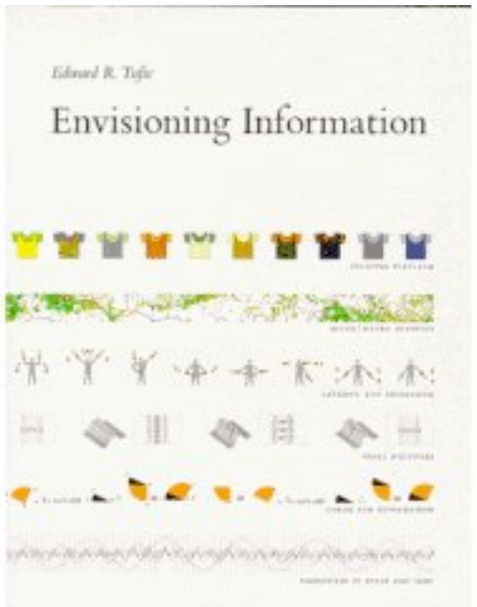
Ben Fry & Casey Reas (Processing)

Resources

Resources



Resources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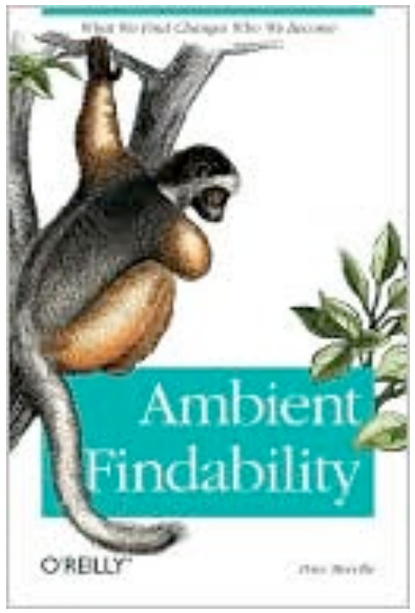
Ambient Findability
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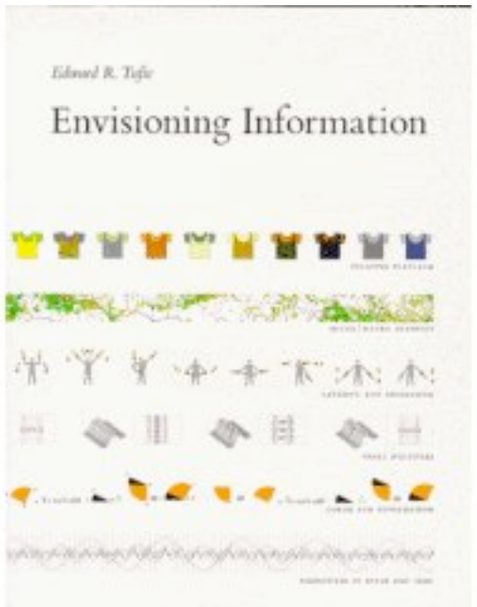
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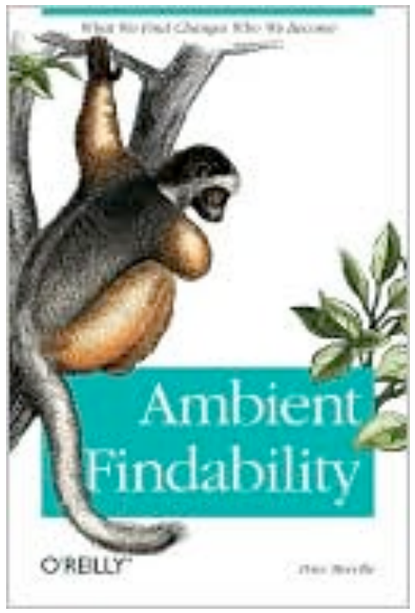
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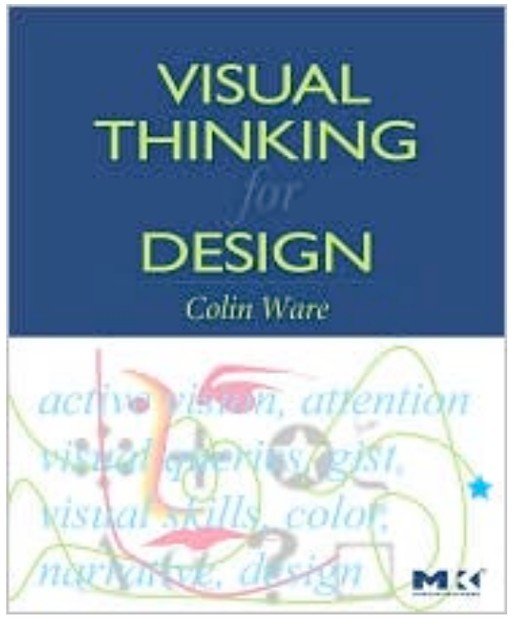
VISUAL
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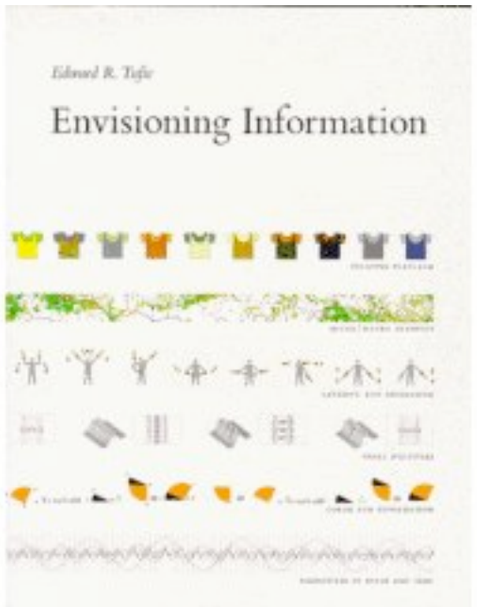
for
DESIGN
Colin Ware

Resources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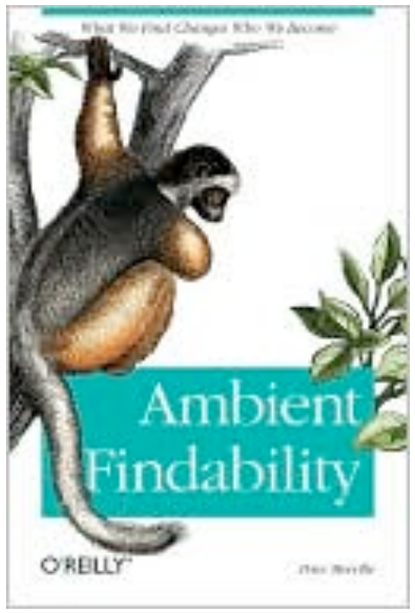
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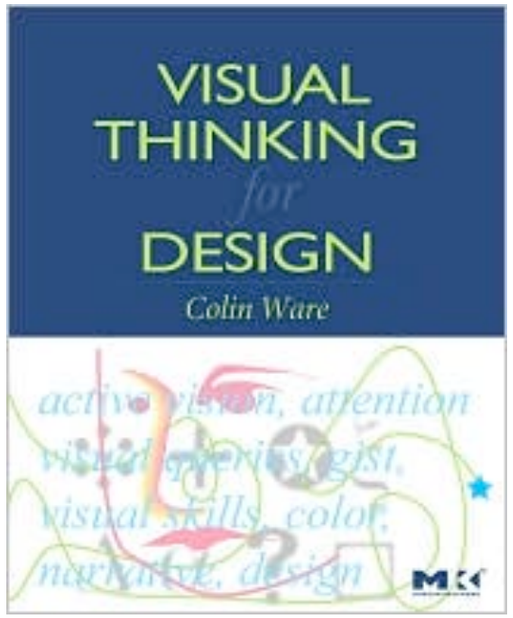
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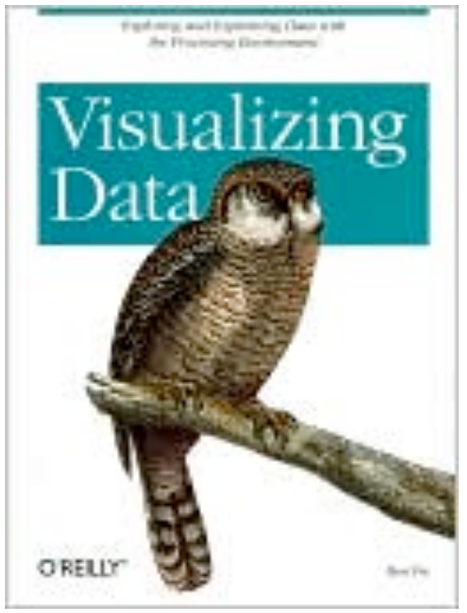
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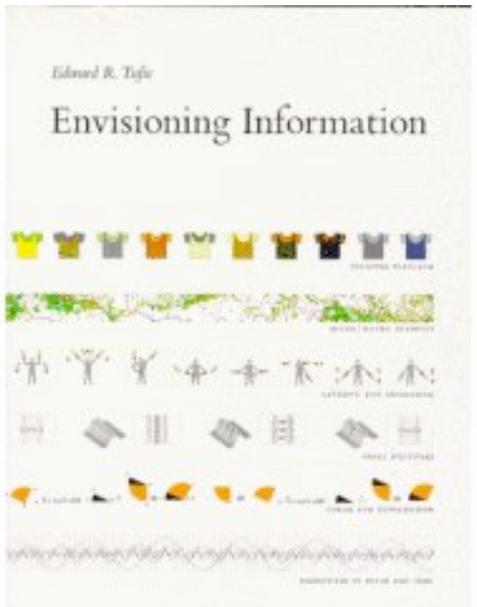
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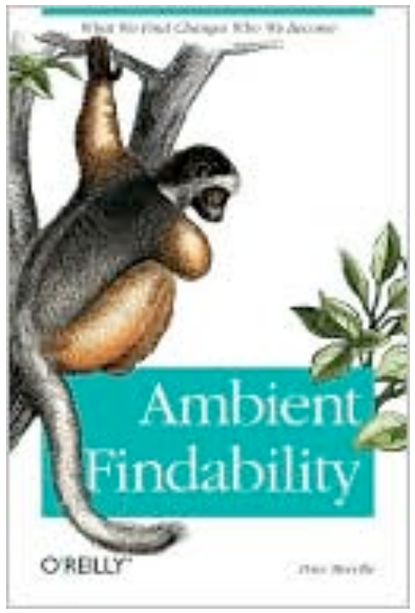
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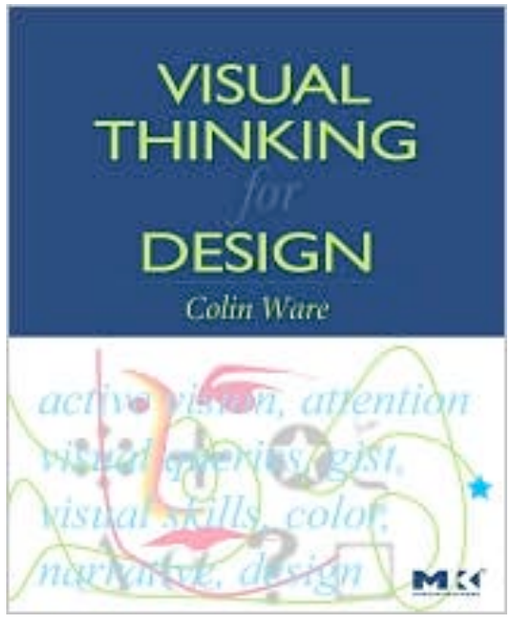
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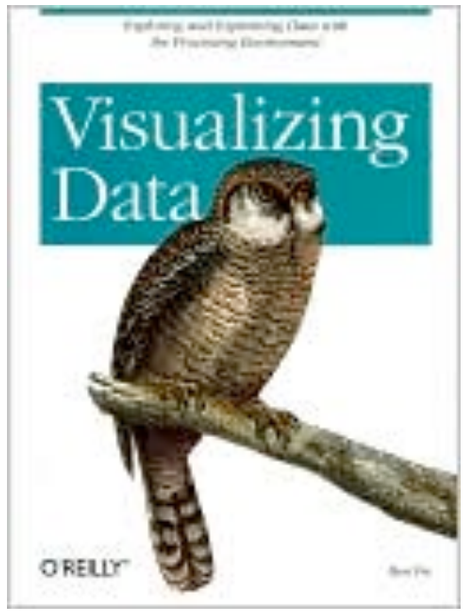
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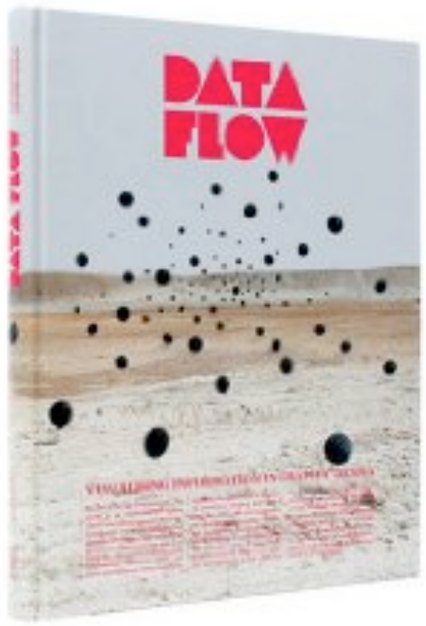
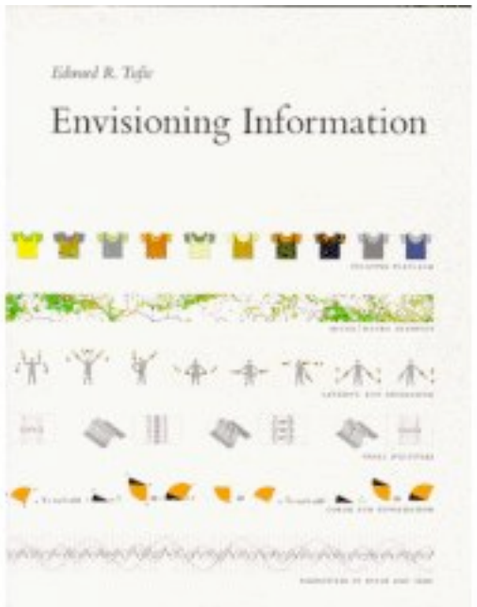

DATA FLOW

Resources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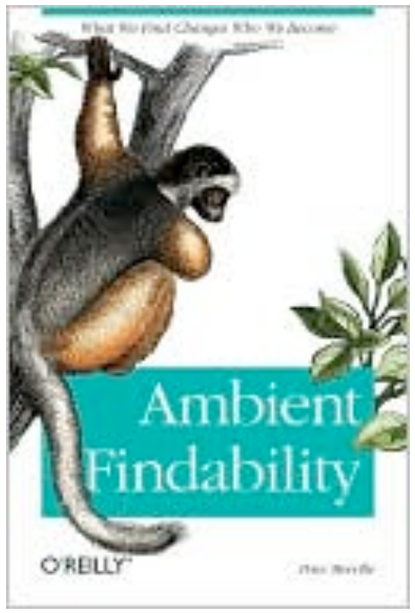
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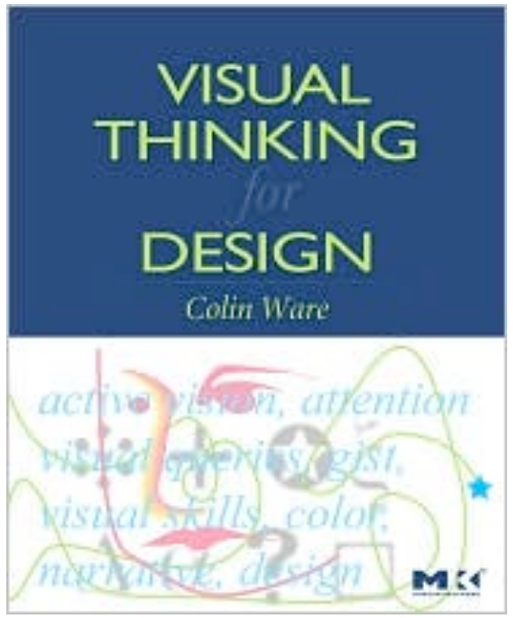
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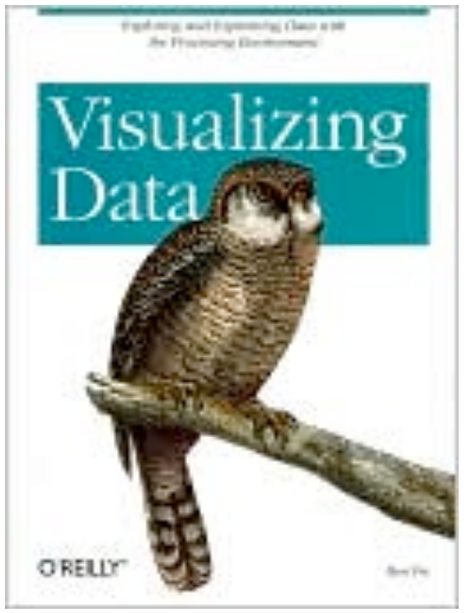
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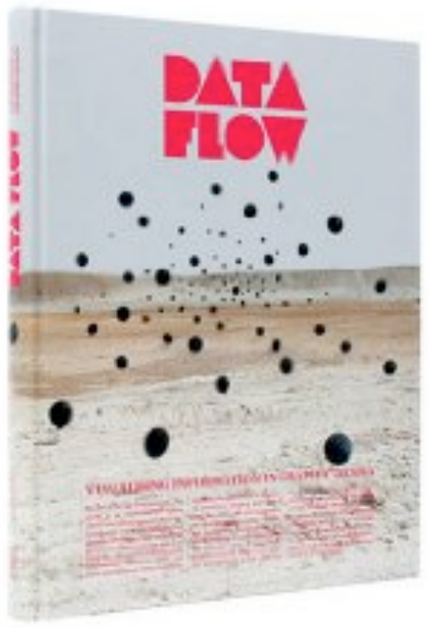
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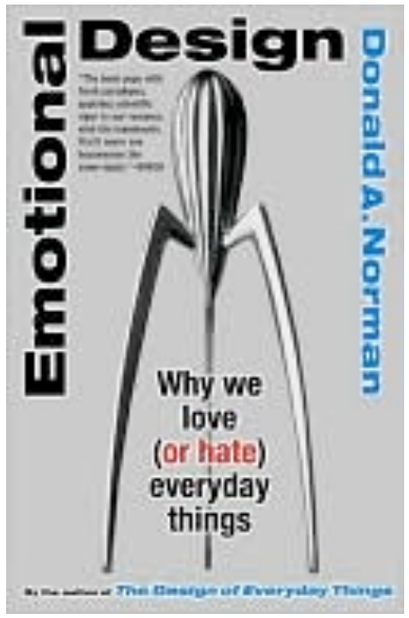
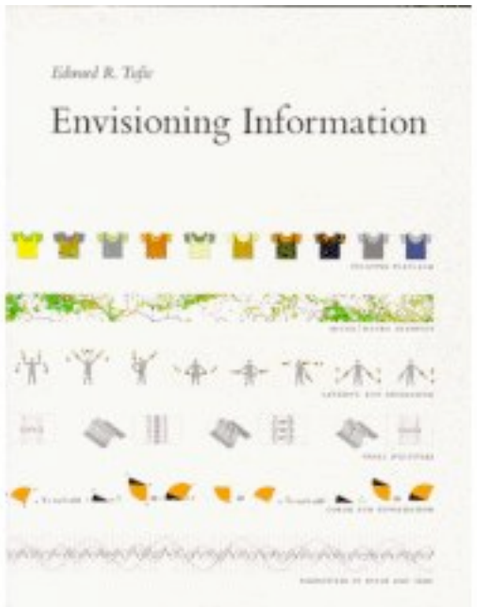

Emotional Design
Donald A. Norman
Why we love (or hate) everyday things

Resources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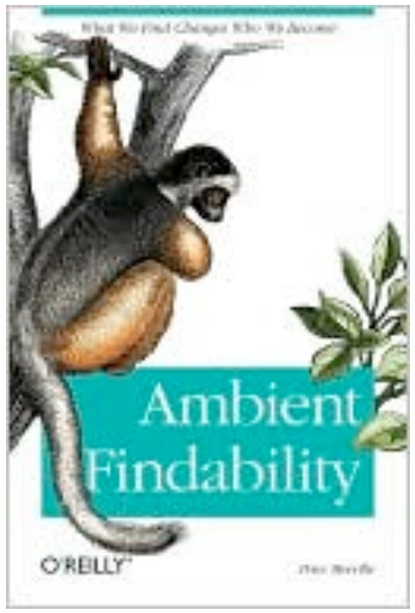
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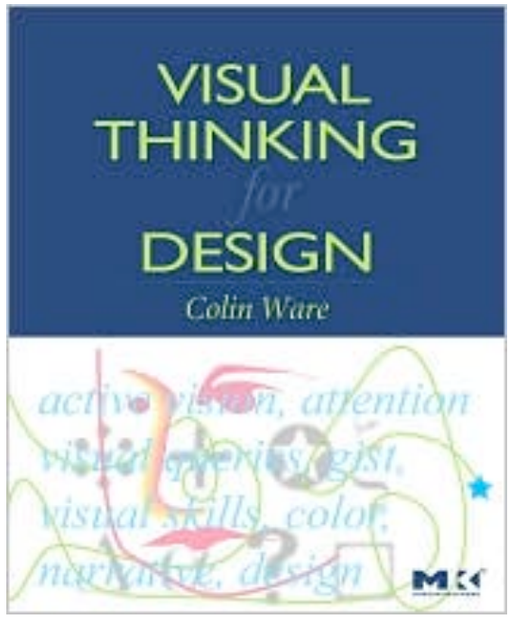
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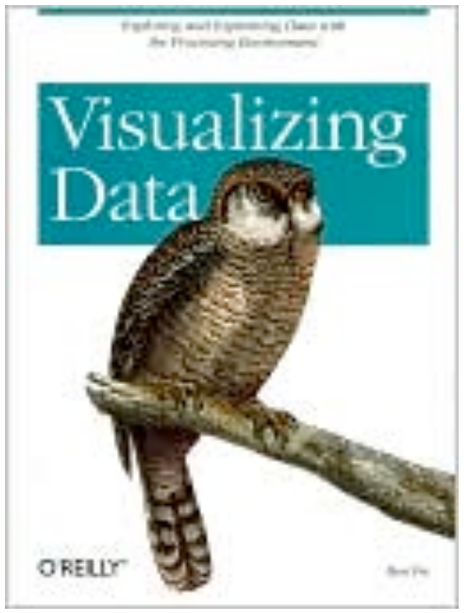
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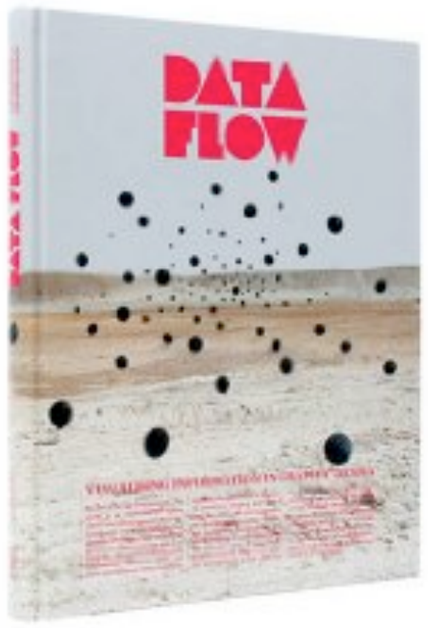
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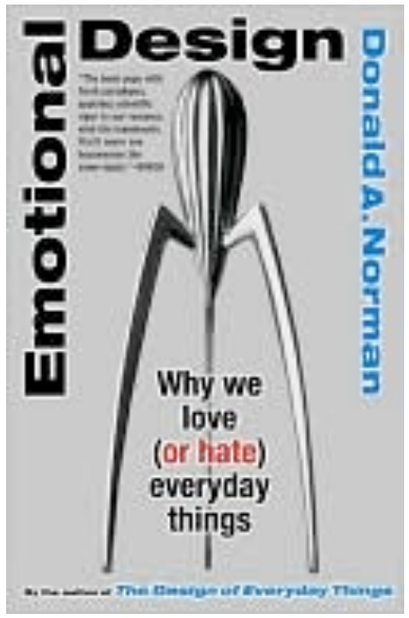
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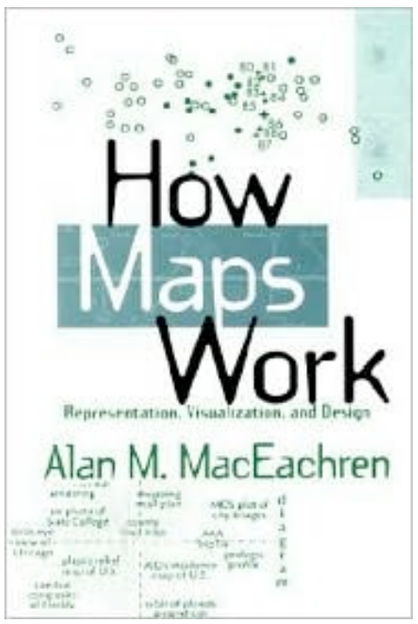
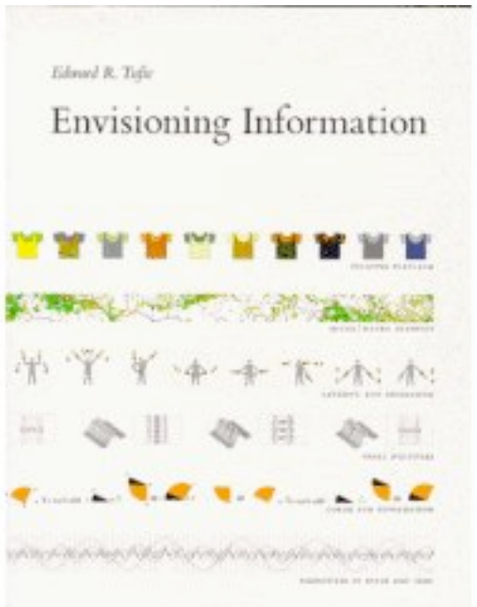

How Maps Work
Representation, Visualization, and Design
Alan M. MacEachren

Resources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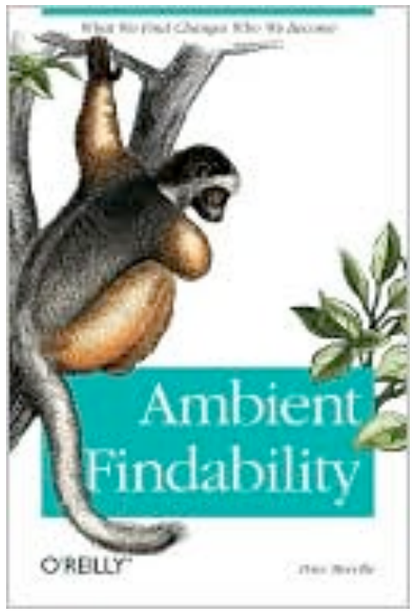
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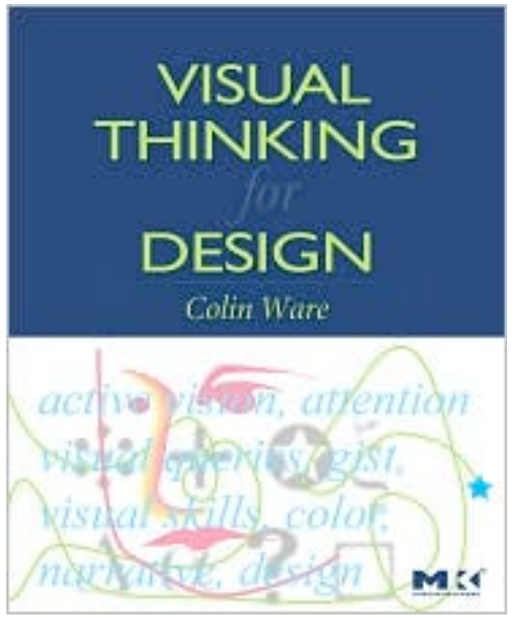
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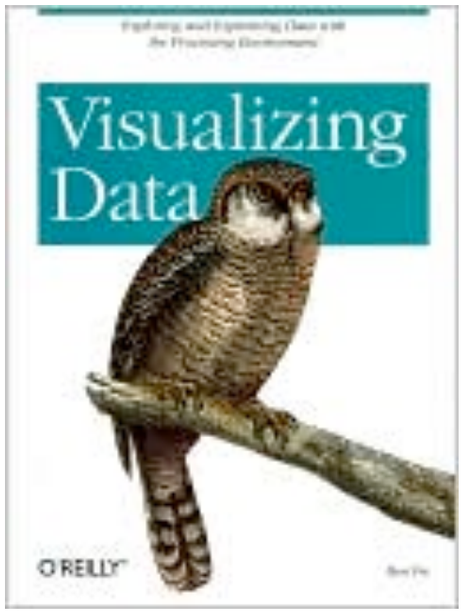
Visualizing Data
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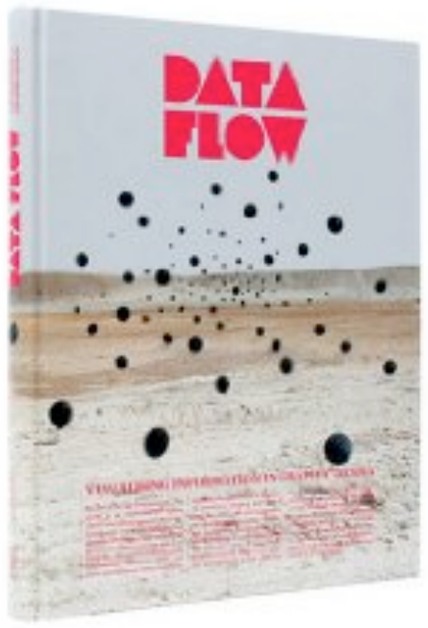
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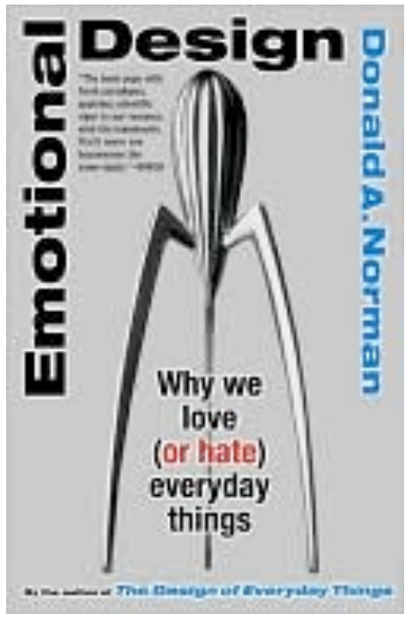
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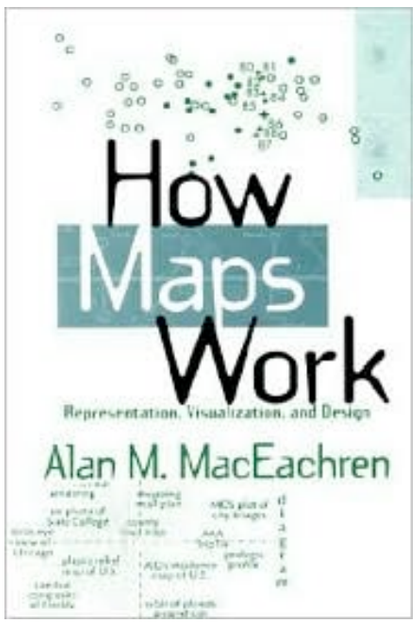
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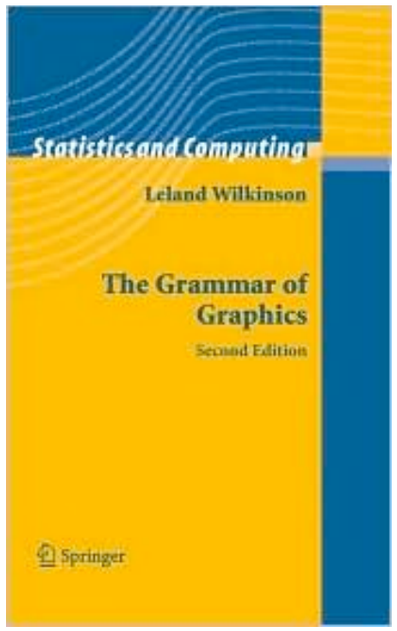
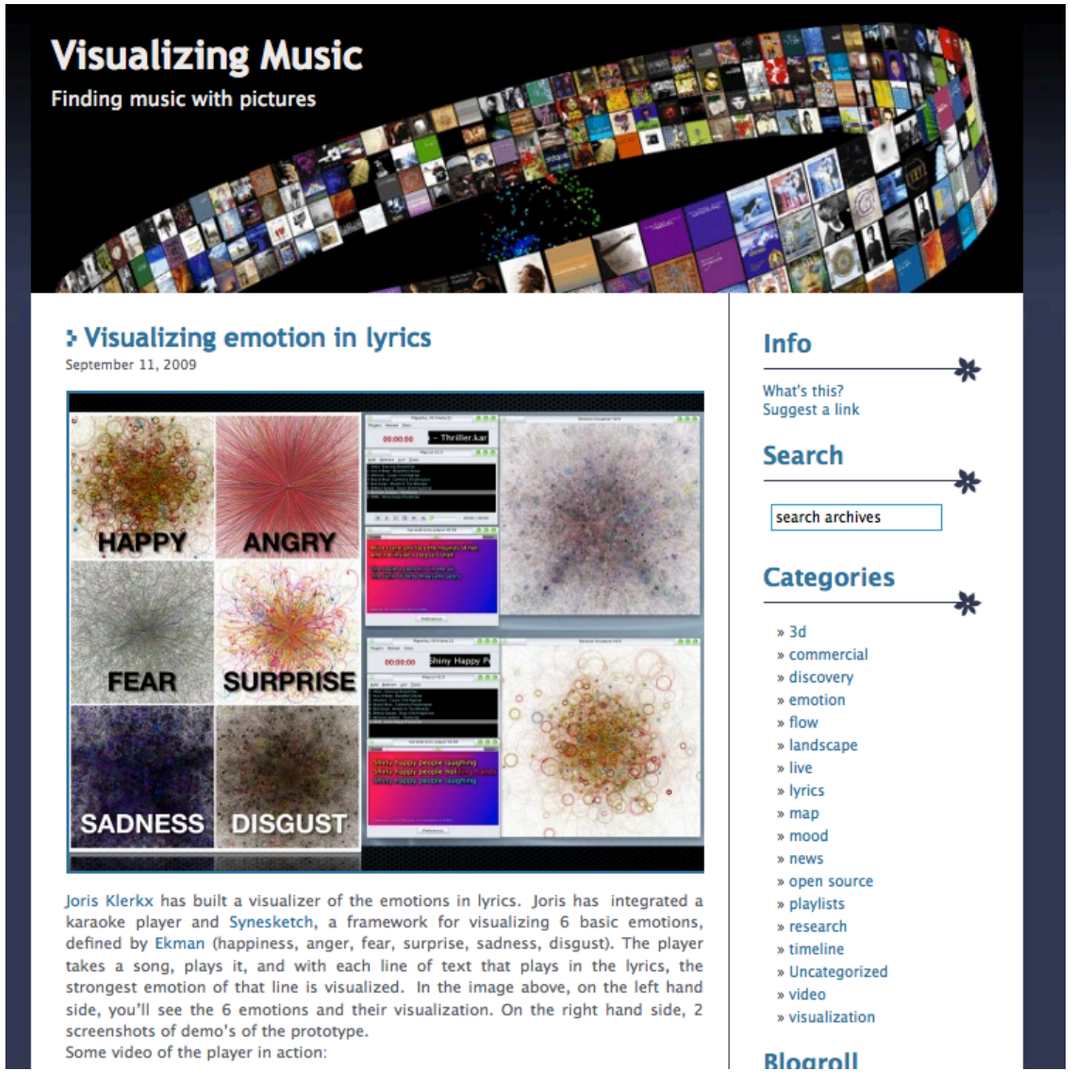
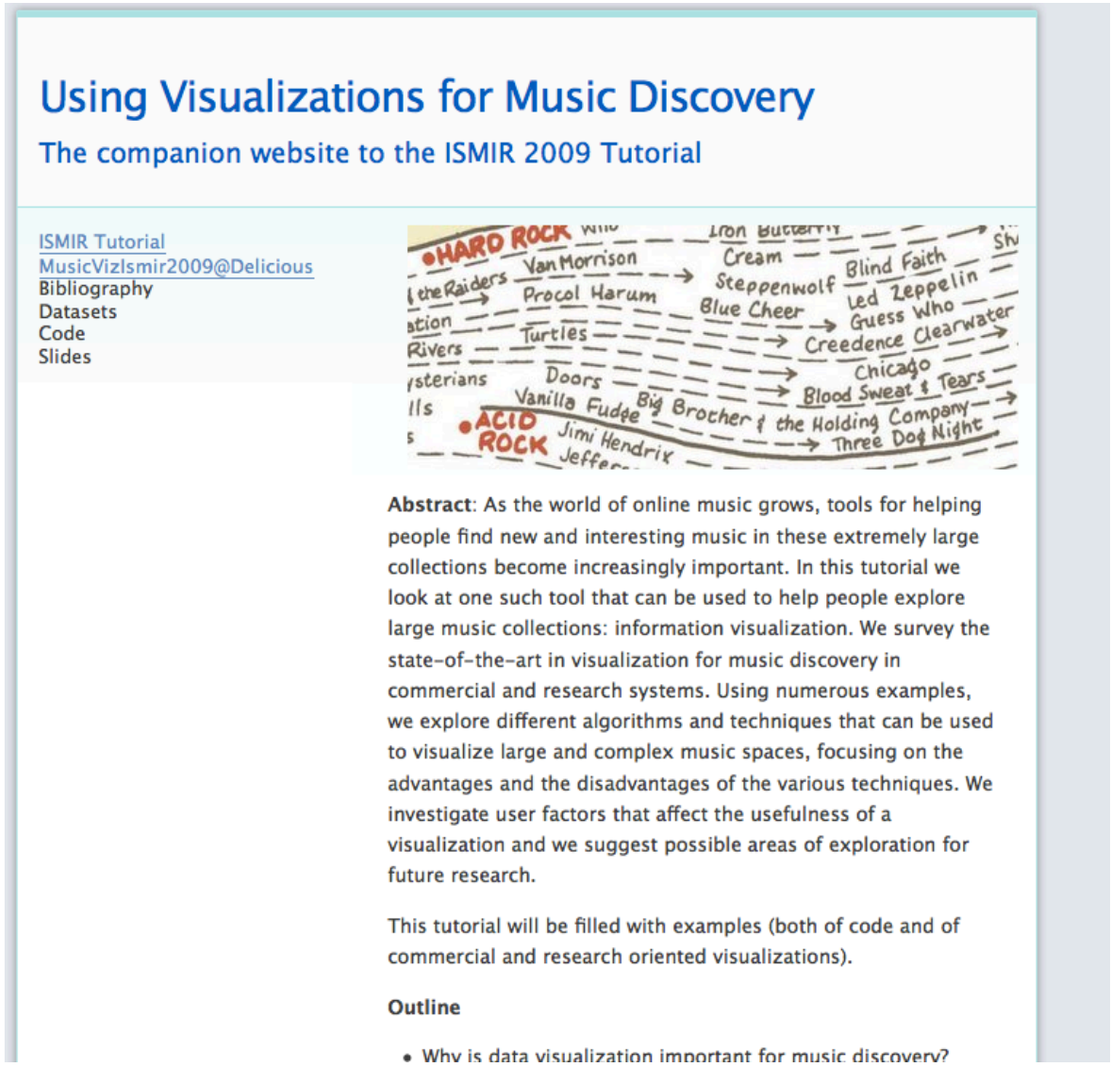

Statistics and Computing
Leland Wilkinson
The Grammar of Graphics
Second Edition
Springer

Visualizing Music



VisualizingMusic.com

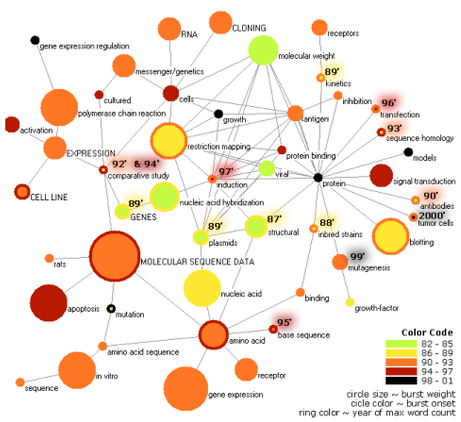


musicviz.googlepages.com/home

Other Tools

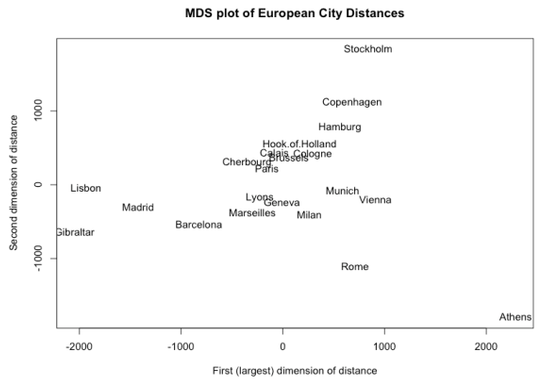
Other Analytic* Tools

- Matlab
  - Dimensionality Reduction Toolbox
  - (missing good network viz/analysis option)
  - Extensive Interactive Pub-quality plotting environment



- Pajek (standalone Network Visualization/Analysis Platform)

- IVC Software Framework (research platform for analysis and viz).
- R
  - Excellent network viz/analysis package "network"
  - PCA/MDS (base library), ISOMap {vegan}
    (no LLE, T-SNE yet)
  - Pub quality plotting environments (default, ggplot2, iplots)

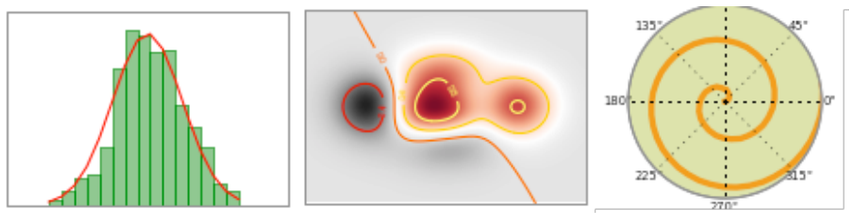


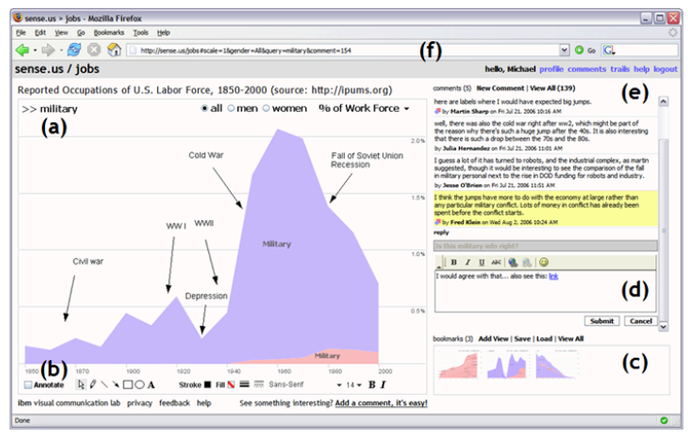
http://ict.ewi.tudelft.nl/~lvandermaaten/Matlab_Toolbox_for_Dimensionality_Reduction.html
http://cran.r-project.org/web/packages/network/index.html
http://cran.r-project.org/web/packages/vegan/index.html
http://vlado.fmf.uni-lj.si/pub/networks/pajek/
http://iv.slis.indiana.edu/sw/index.html

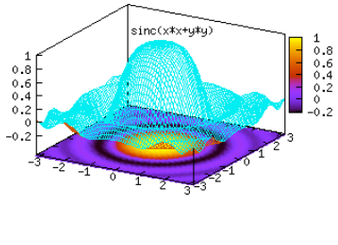
*for publications

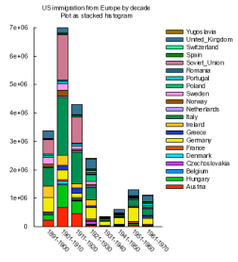
Other "Generic" Viz Tools

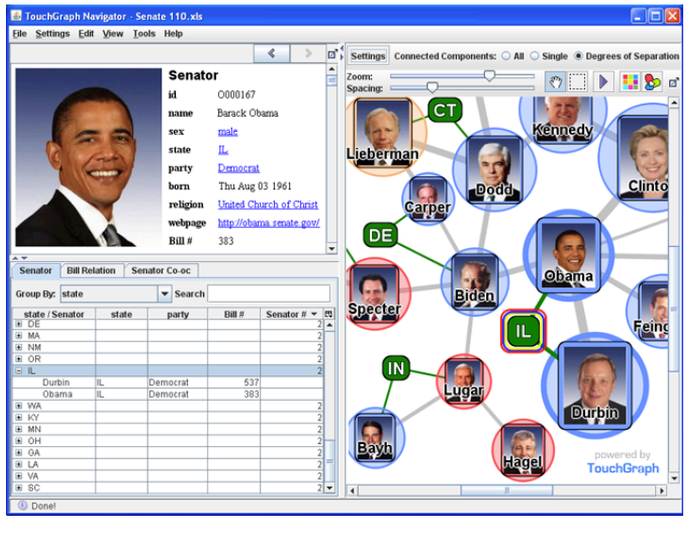
- Prefuse (java/as3)
- Processing*
- Gephi
- TouchGraph
- Gnuplot
- matplotlib (python)

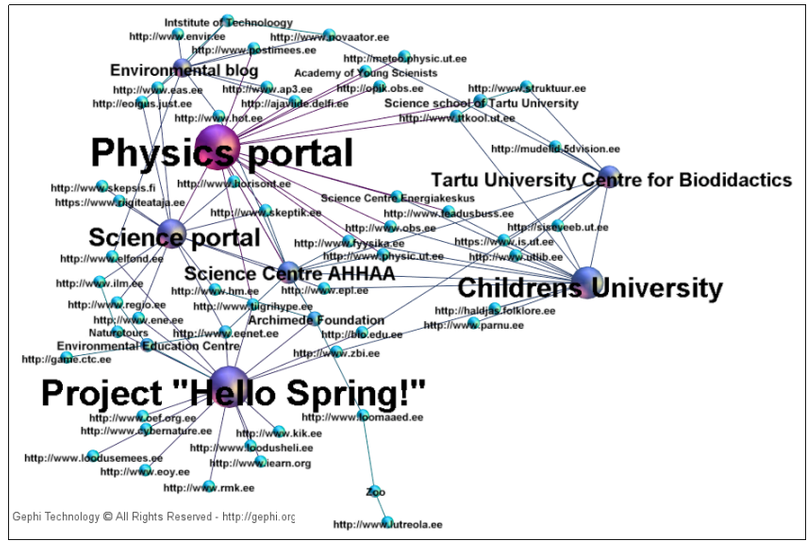










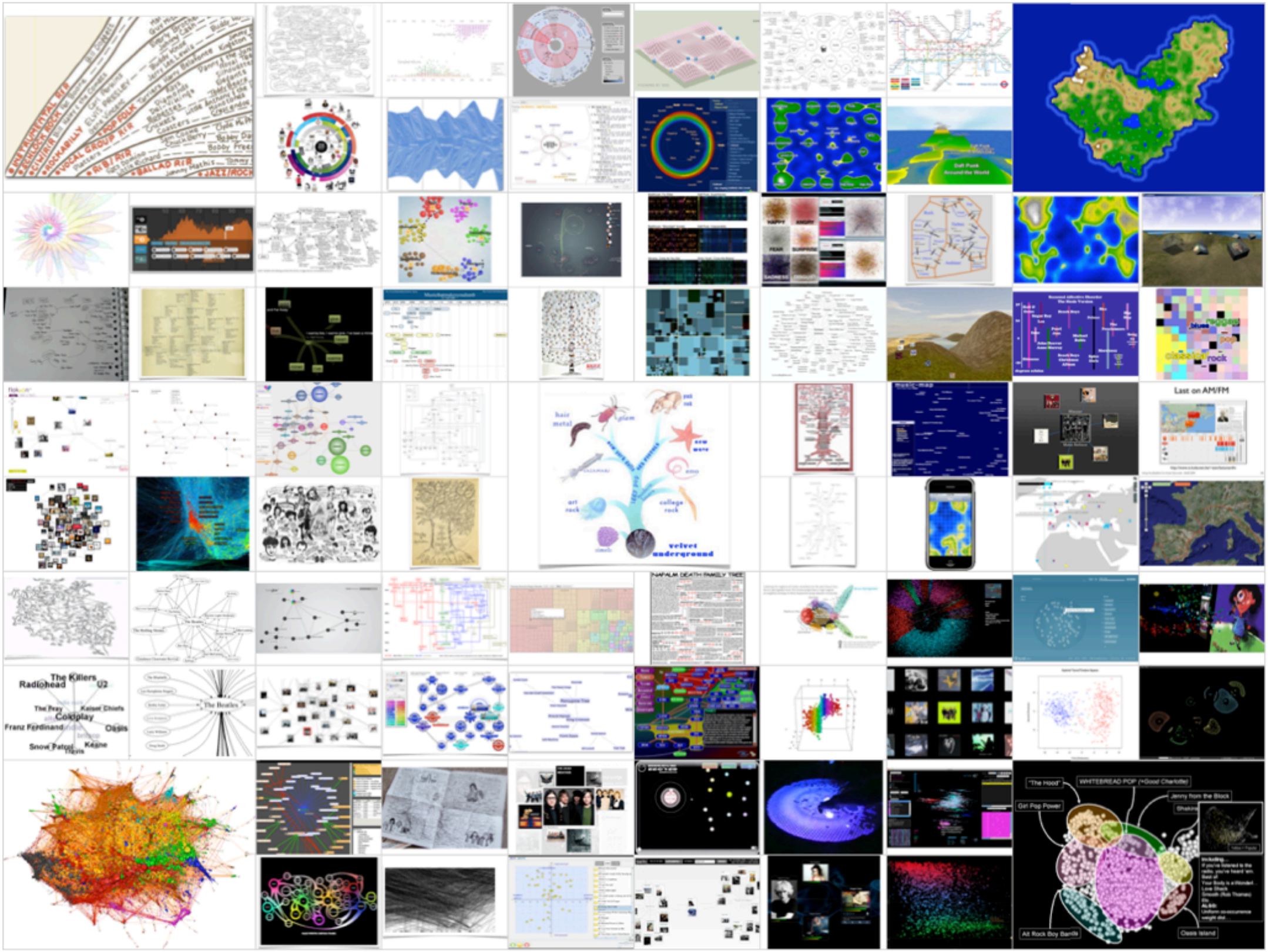


http://www.prefuse.org/
http://processing.org/
http://gephi.org/
http://www.touchgraph.com/navigator.html
http://www.gnuplot.info/
http://matplotlib.sourceforge.net/

Conclusions

- Music visualizations reflect *ways of understanding music*.
- Music understanding draws from many different *type*s of information (musicological, acoustic, social, bibliographic, etc.)
- Music visualizations can help to express this understanding in a way that can help aid navigation and discovery.

Questions?


hair metal
art rock
college rock
velvet underground
The Killers
Radiohead
U2
Coldplay
Oasis
Franz Ferdinand
Snow Patrol
Keane
The Beatles
"The Hood"
WHITEBREAD POP' (+Good Charlotte)
Girl Pop Power
Jenny from the Block
Alt Rock Boy Bands
Oasis Island