Department of Computational Perception

JKU JOHANNES KEPLER UNIVERSITY LINZ

Part IV: Personalization, Context-awareness, and Hybrid Methods

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Overview

1. Personalization and Context-awareness

2. Hybrid Methods

Computational Factors Influencing Music Perception and Similarity

(Schedl et al., JIIS 2013)

music content

Examples:
- rhythm
- timbre
- melody
- harmony
- loudness

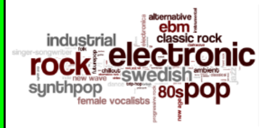
Examples:
- mood
- activities
- social context
- spatio-temporal context
- physiological aspects

user context

music perception and similarity

Examples:
- semantic labels
- song lyrics
- album cover artwork
- artist's background
- music video clips

music context



Examples:
- music preferences
- musical training
- musical experience
- demographics

user properties

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(Schedl et al., JIIS 2013)

Computational Factors Influencing Music Perception and Similarity

music content

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- rhythm
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Examples:
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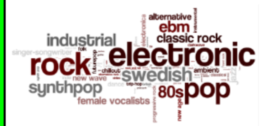
- activities
- social context
- spatio-temporal context
- physiological aspects

user context

personalized/context-aware methods: typically extend music content or music context with a user-category

Examples:
- semantic labels
- song lyrics
- album cover artwork
- artist's background
- music video clips

music context



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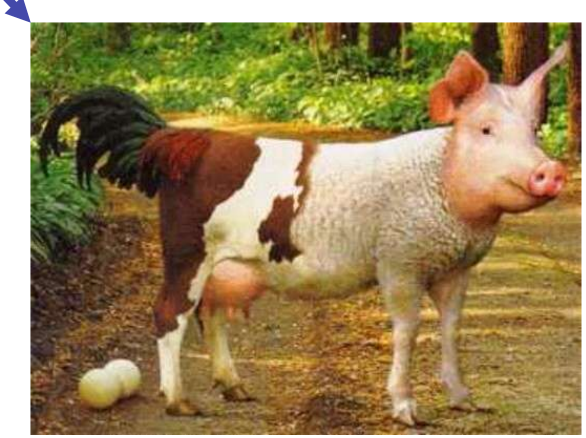


Computational Factors Influencing Music Perception and Similarity

(Schedl et al., JIIS 2013)

music content

Examples:
- rhythm
- timbre
- melody
- harmony
- loudness

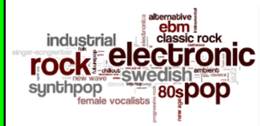
Examples:
- mood
- activities
- social context
- spatio-temporal context
- physiological aspects

user context

hybrid methods:
combine factors of at least two categories

Examples:
- semantic labels
- song lyrics
- album cover artwork
- artist's background
- music video clips

music context



Examples:
- music preferences
- musical training
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user properties

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Basic Categorization

- Personalized systems/methods
  - incorporate aspects of the *user properties*, i.e. static attributes
  - take into account music genre preference, music experience, age, etc.

- Context-aware systems/methods
  - incorporate aspects of the *user context*, i.e. dynamic aspects
    - **active user-awareness**: new user context is automatically incorporated into the system, adaptively changing its behavior
    - **passive user-awareness**: application presents the new context to the user for later retrieval/incorporation

Typical Features used in CA

- Temporal and spatial features
  - temporal: weekday, time of day, season, month, etc.
  - spatial: position (coordinates), location (country, city, district; home, office)

- Physiological features
  - heart rate, pace, body temperature, skin conductance, etc.
  - application scenarios: music therapy [Liu, Rautenberg; 2009], sport trainer [Elliot, Tomlinson; 2006] [Moens et al.; 2010]
    - achieving and maintaining a healthy heart rate in music therapy
    - adapting music to pace of runner
    - selecting music suited to stimulate a particular running behavior, reach a performance level, or fit a training program

Gathering the User Context

- Implicit
  - sensors: GPS, heart rate, accelerometer, pressure, light intensity, environmental noise level (now available in abundance through smart phones)
  - derived features: location + time → weather
  - learned features (via ML): accelerometer, speed → user activity
- Explicit
  - via user involvement/feedback
  - e.g., mood, activity, item ratings, skipping behavior [Pampalk et al.; 2005]

Overview

1. Personalization and Context-awareness

2. Hybrid Methods
   - Music playlist generation using music content and music context
   - *#nowplaying* approaches: music taste analysis, browsing the world of music on the microblogosphere
   - Geospatial music recommendation
   - User-Aware music recommendation on smart phones
   - Matching places of interest and music

Music playlist generation using music content and music context

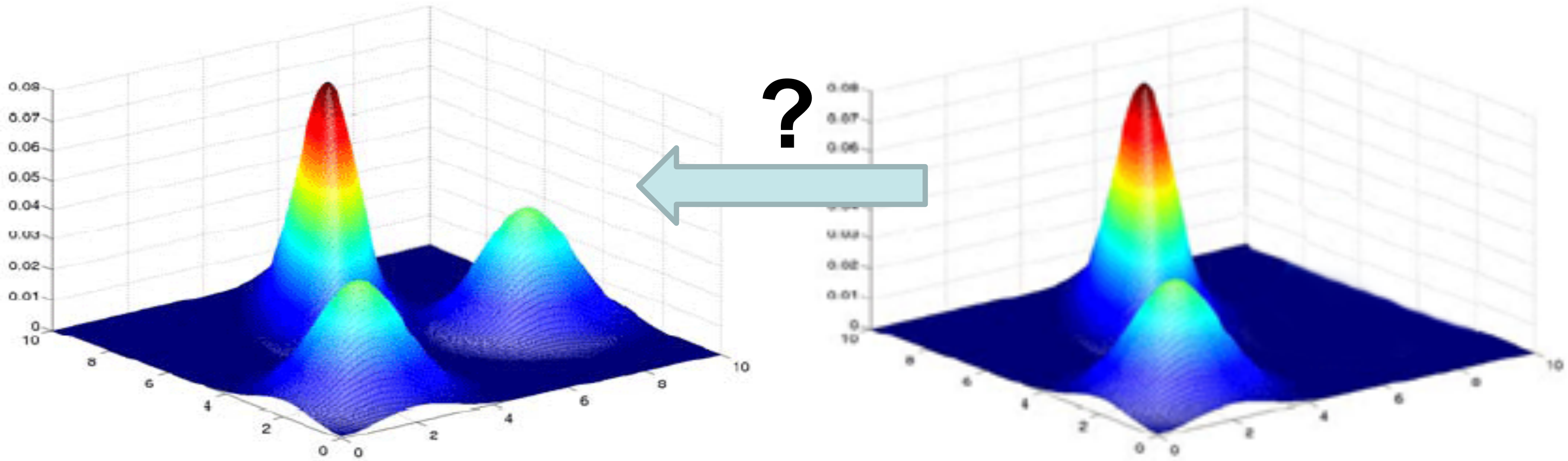
(Knees et al.; 2006)

- Idea: combine music content + music context features to improve and speed up playlist generation
- Application scenario: “The Wheel” – create a circular playlist containing all tracks in a user’s collection (consecutive tracks as similar as possible)
- Approach: use web features to confine search for similar songs (carried out on music content features)

Music playlist generation using music content and music context

(Knees et al.; 2006)

- Audio/content features:
  - compute Mel-Frequency Cepstral Coefficients (MFCC)
  - model song's distribution of MFCCs via Gaussian Mixture Models (GMM)
  - estimate similarity between two songs *A* and *B* by sampling points from *A*'s GMM and computing probability that points "belong to" GMM of *B*



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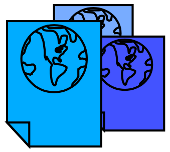
Music playlist generation using music content and music context

(Knees et al.; 2006)

- Web/music context features: 
  - query Google for `[artist "music"]`
  - fetch 50 top-ranked web pages
  - remove HTML, stop words, and infrequent terms
  - for each artist's virtual document, compute tf-idf vectors:

$$w_{ta} = \begin{cases} (1 + \log_2 tf_{ta}) \log_2 \frac{N}{df_t} & \text{if } tf_{ta} > 0 \\ 0 & \text{otherwise} \end{cases}$$

  - perform cosine normalization (different document length!)

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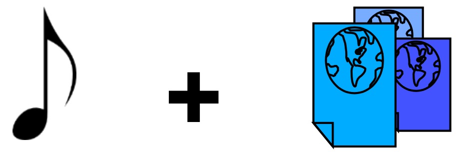
Music playlist generation using music content and music context

(Knees et al.; 2006)

We computed so far…

- *similarities* based on music content (song level)
- *feature vectors* (tf-idf) from web content (artist level)

How to combine the two?



- adapt the content similarities according to web similarity
- penalize transitions (decrease similarity) between songs whose artists are dissimilar in terms of web features

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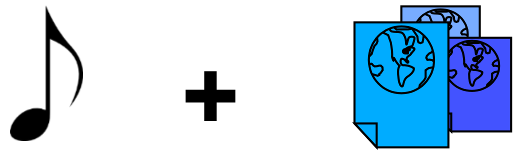
Music playlist generation using music content and music context

(Knees et al.; 2006)



To obtain the final, hybrid similarity measure:

Folk−Rock(4) Rap(4) Jazz(1) Punk−Rock(1)	Electronica(2)	Electronica(5)	Electronica(1)	Electronica(16) Acid Jazz(1)
Folk−Rock(1) Italian(1)	Electronica(1)	Acid Jazz(1)		Acid Jazz(1) Electronica(1)
Italian(3) Electronica(1)		Reggae(2) Italian(1)		Rap(2) A Cappella(1) Acid Jazz(1) Electronica(1)
Punk−Rock(4) Electronica(1)	Rap(4)		Blues(1)	Jazz(3)
Electronica(12) Punk−Rock(1)	Rap(1) Electronica(1)	Celtic(2) Reggae(1)	Celtic(3) A Cappella(1)	Jazz(5) Bossa Nova(4) Blues(3) A Cappella(2) Rap(1)

train Self-Organizing Map (SOM) on artist web features

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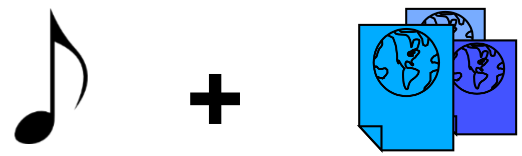
Music playlist generation using music content and music context

(Knees et al.; 2006)



To obtain the final, hybrid similarity measure:

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– set to zero content-based similarity of songs by dissimilar artists (according to position in SOM)
– i.e., when creating playlists, consider as potential next track only songs by artists close together on SOM

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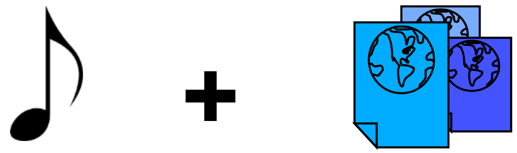
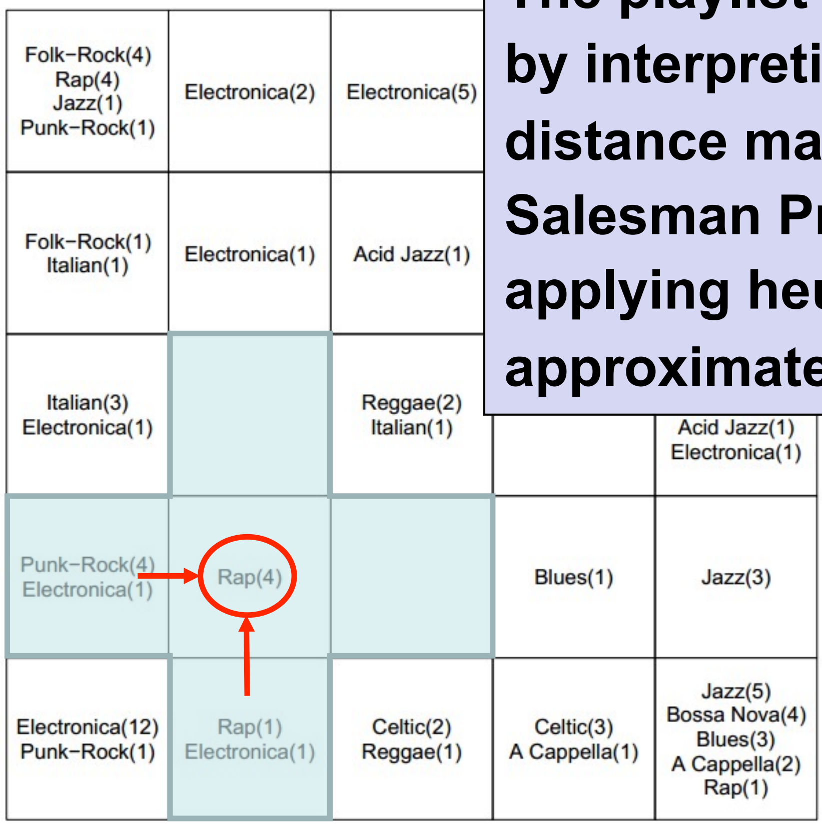
Music playlist generation using music content and music context

(Knees et al.; 2006)



To obtain the final, hy



The playlist is eventually created by interpreting the adapted distance matrix as Traveling Salesman Problem (TSP) and applying heuristics to approximate a solution.

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aylists,

consider as potential next track only songs by artists close together on SOM

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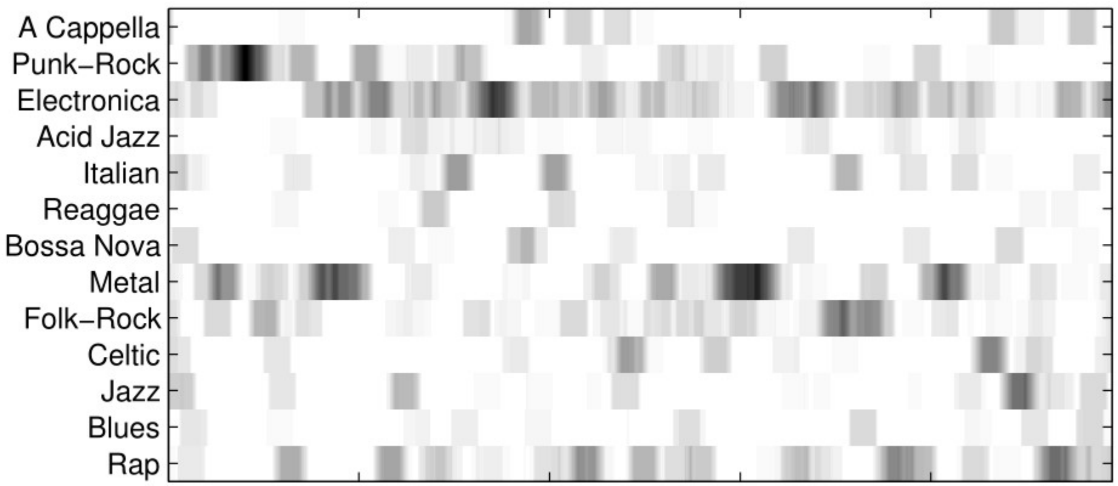
Music playlist generation using music content and music context

(Knees et al.; 2006)

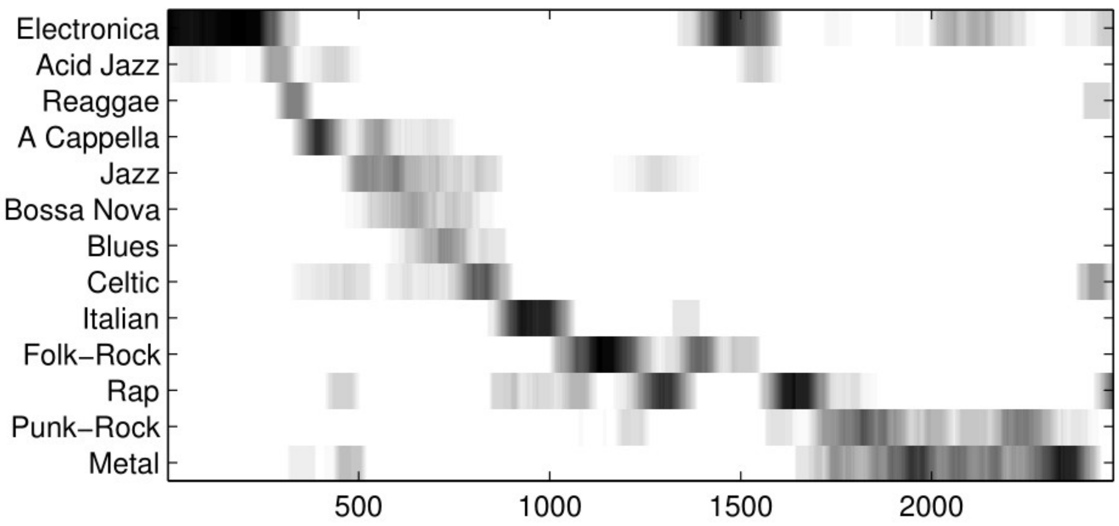
- Evaluation:
  - dataset: 2,545 tracks from 13 genres, 103 artists
  - performance measure: consistency of playlists (for each track, how many of its 75 consecutive tracks belong to a certain genre)

Music playlist generation using music content and music context

(Knees et al.; 2006)



music content similarity only



hybrid approach

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#nowplaying approaches: Basics

(Schedl, ECIR 2013)

- Extract listening events from microblogs

(a) Filter Twitter stream (#nowplaying, #itunes, #np, …)
(b) Multi-level, rule-based analysis (artists/songs) to find relevant tweets (MusicBrainz)
(c) Last.fm, Freebase, Allmusic, Yahoo! PlaceFinder to annotate tweets

„Alice Cooper“
„BB King“
„Prince“
„Metallica“
…


```
{"id_str":"142338125895696385","place":null,"text":"#NowPlaying Christmas Tree-Lady Gaga","in_reply_to_user_id":null,"favorited":false,"geo":null,"retweet_count":0,"in_reply_to_screen_name":null,"in_reply_to_status_id_str":null,"source":"web","retweeted":false,"in_reply_to_user_id_str":null,"coordinates":null,"created_at":"Thu Dec 01 20:23:48 +0000 2011","in_reply_to_status_id":null,"contributors":null,"user":{"id_str":"20209983","profile_link_color":"2caba5","screen_name":"tamse77","follow_request_sent":null,"geo_enabled":false,"favourites_count":26,"location":"Maryland ","following":null,"verified":false,"profile_background_color":"e80e0e","show_all_inline_media":true,"profile_background_tile":true,"followers_count":309,"profile_image_url":"http:\/\/a1.twimg.com\/profile_images\/1647613274\/392960_10150559294659517_793614516_11700077_1689597400_n_normal.jpg","description":"being awesome since 1990. ","is_translator":false,"profile_background_image_url_https":"https:\/\/si0.twimg.com\/profile_background_images\/359728130\/frames.gif","friends_count":148,"profile_sidebar_fill_color":"ffffff","default_profile":false,"listed_count":3,"time_zone":"Central Time (US & Canada)","contributors_enabled":false,"created_at":"Fri Feb 06 01:51:10 +0000 2009","profile_sidebar_border_color":"f5f8ff","protected":false,"notifications":null,"profile_use_background_image":true,"name":"Katie","default_profile_image":false,"statuses_count":22172,"profile_text_color":"615d61","url":null,"profile_image_url_https":"https:\/\/si0.twimg.com\/profile_images\/1647613274\/392960_10150559294659517_793614516_11700077_1689597400_n_normal.jpg","id":20209983,"lang":"en","profile_background_image_url":"http:\/\/a2.twimg.com\/profile_background_images\/359728130\/frames.gif","utc_offset":-21600},"truncated":false,"id":142338125895696385,"entities":{"hashtags":[{"text":"NowPlaying","indices":[0,11]}],"urls":[],"user_mentions":[]}}
```


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#nowplaying approaches: Basics

(Schedl, ECIR 2013)

- Annotate identified listening events and create a database

{"id_str":"142338125895696385","place":null,"text":"**#NowPlaying Christmas Tree-Lady Gaga**","in_reply_to_user_id":null,"favorited":false,"geo":null,"retweet_count":0,"in_reply_to_screen_name":null,"in_reply_to_status_id_str":null,"source":"web","retweeted":false,"in_reply_to_user_id_str":null,"coordinates":null,"created_at":"Thu Dec 01 20:23:48 +0000 2011","in_reply_to_status_id":null,"contributors":null,"user":{"id_str":"20209983","profile_link_color":"2caba5","screen_name":"tamse77","follow_request_sent":null,"geo_enabled":false,"favourites_count":26,"location":"Maryland ","following":null,"verified":false,"profile_background_color":"e80e0e","show_all_inline_media":true,"profile_background_tile":true,"followers_count":309,"profile_image_url":"http:\/\/a1.twimg.com\/profile_images\/1647613274\/392960_10150559294659517_793614516_11700077_1689597400_n_normal.jpg","description":"being awesome since 1990. ","is_translator":false,"profile_background_image_url_https":"https:\/\/si0.twimg.com\/profile_background_images\/359728130\/frames.gif","friends_count":148,"profile_sidebar_fill_color":"ffffff","default_profile":false,"listed_count":3,"time_zone":"Central Time (US & Canada)","contributors_enabled":false,"created_at":"Fri Feb 06 01:51:10 +0000 2009","profile_sidebar_border_color":"f5f8ff","protected":false,"notifications":null,"profile_use_background_image":true,"name":"Katie","default_profile_image":false,"statuses_count":22172,"profile_text_color":"615d61","url":null,"profile_image_url_https":"https:\/\/si0.twimg.com\/profile_images\/1647613274\/392960_10150559294659517_793614516_11700077_1689597400_n_normal.jpg","id":20209983,"lang":"en","profile_background_image_url":"http:\/\/a2.twimg.com\/profile_background_images\/359728130\/frames.gif","utc_offset":-21600},"truncated":false,"id":142338125895696385,"entities":{"hashtags":[{"text":"NowPlaying","indices":[0,11]}],"urls":[],"user_mentions":[]}}

```
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134243869201154048  174194590  11  2  -0.142  51.52  2  2  330061  5762915  1  0 ...
```

twitter-id user-id month weekday longitude latitude country-id city-id artist-id track-id <tag-ids>

"MusicMicro" dataset available:
http://www.cp.jku.at/datasets/musicmicro

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Some statistics on spatial distribution

#nowplaying		#itunes	
country	tweets	country	tweets
Brazil	725,389	USA	78,460
USA	673,839	Japan	30,932
Japan	458,558	Mexico	23,047
Mexico	419,584	Brazil	16,390
Indonesia	284,082	UK	15,134
South Korea	251,132	Canada	11,266
China	183,178	South Korea	8,652
UK	128,744	Australia	5,119
Netherlands	121,134	China	4,492
Venezuela	110,336	Germany	3,157

most active countries

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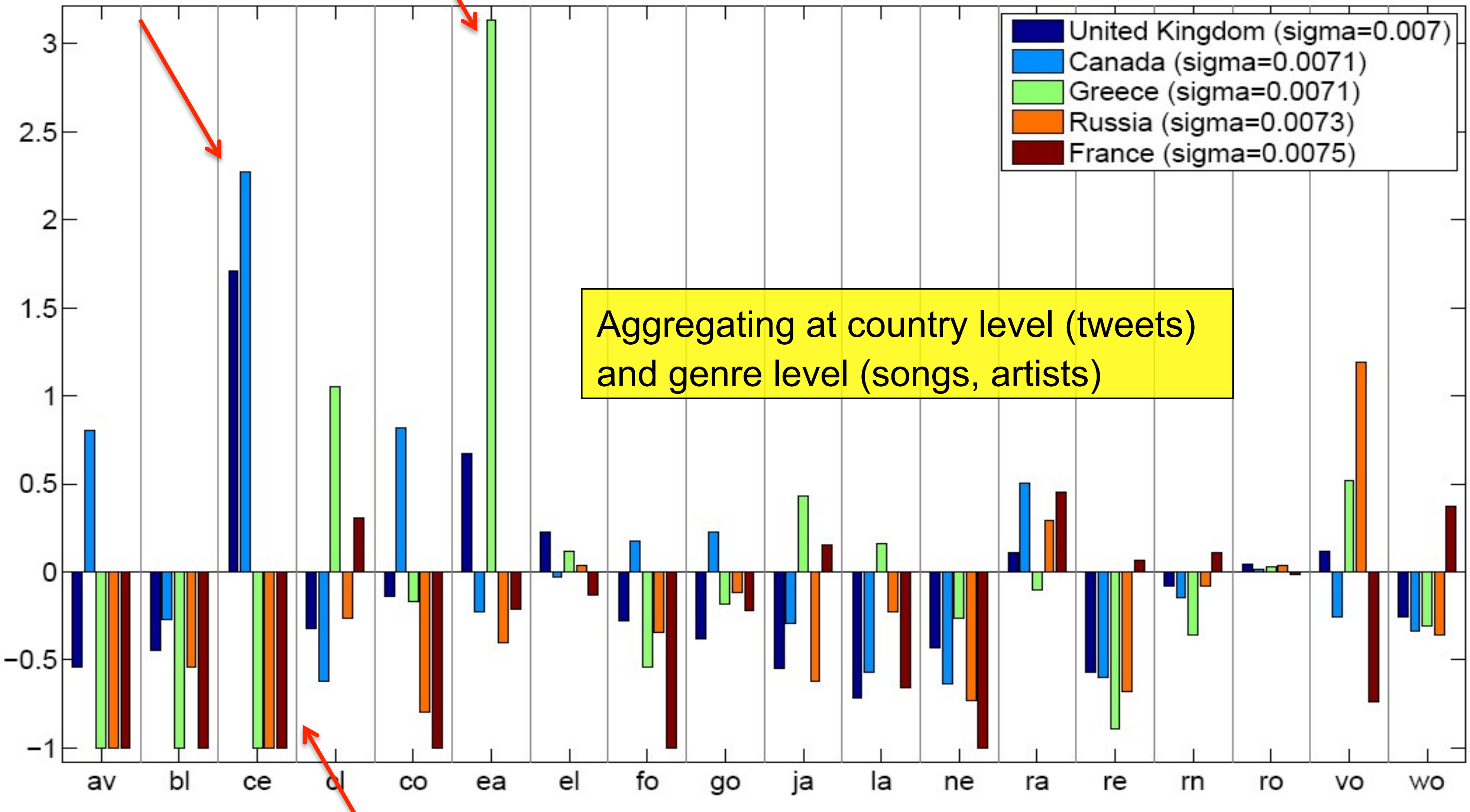
Some statistics on artist distribution

most frequently listened artists

#nowplaying		#itunes	
artist	tweets	artist	tweets
Paramore	9,066	The Beatles	939
Drake	7,697	Daft Punk	683
Katy Perry	6,998	Britney Spears	567
Bruno Mars	6,932	Adele	462
Lady Gaga	6,919	Coldplay	428
Coldplay	6,434	Bruno Mars	416
Eminem	6,352	Katy Perry	374
Rihanna	6,038	The Black Eyes Peas	373
Taylor Swift	5,844	Kanye West	367
Usher	5,445	Lady Gaga	358
Muse	5,383	Avril Lavigne	308
Justin Bieber	5,028	Arcade Fire	299
The Beatles	4,579	Radiohead	266
Michael Jackson	4,476	Kings of Leon	240
Linkin Park	4,285	Duran Duran	238
Oasis	4,190	Michael Jackson	229
Kanye West	4,013	Linkin Park	228
Chris Brown	3,943	Eminem	211
Avril Lavigne	3,780	Muse	209
Radiohead	3,756	The Black Keys	203

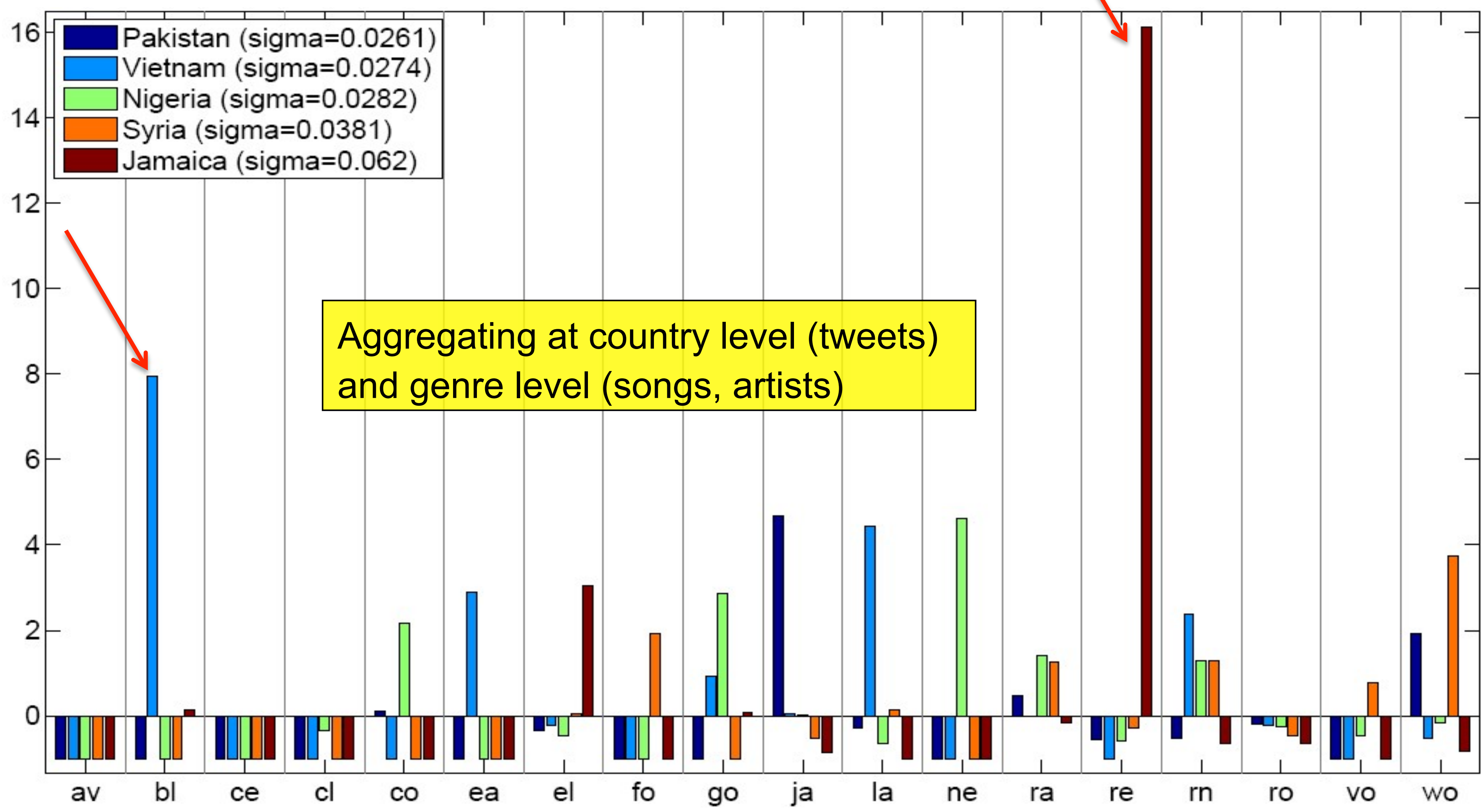
#nowplaying approaches: Music taste analysis
Most mainstreamy countries

(Schedl, Hauger; 2012)



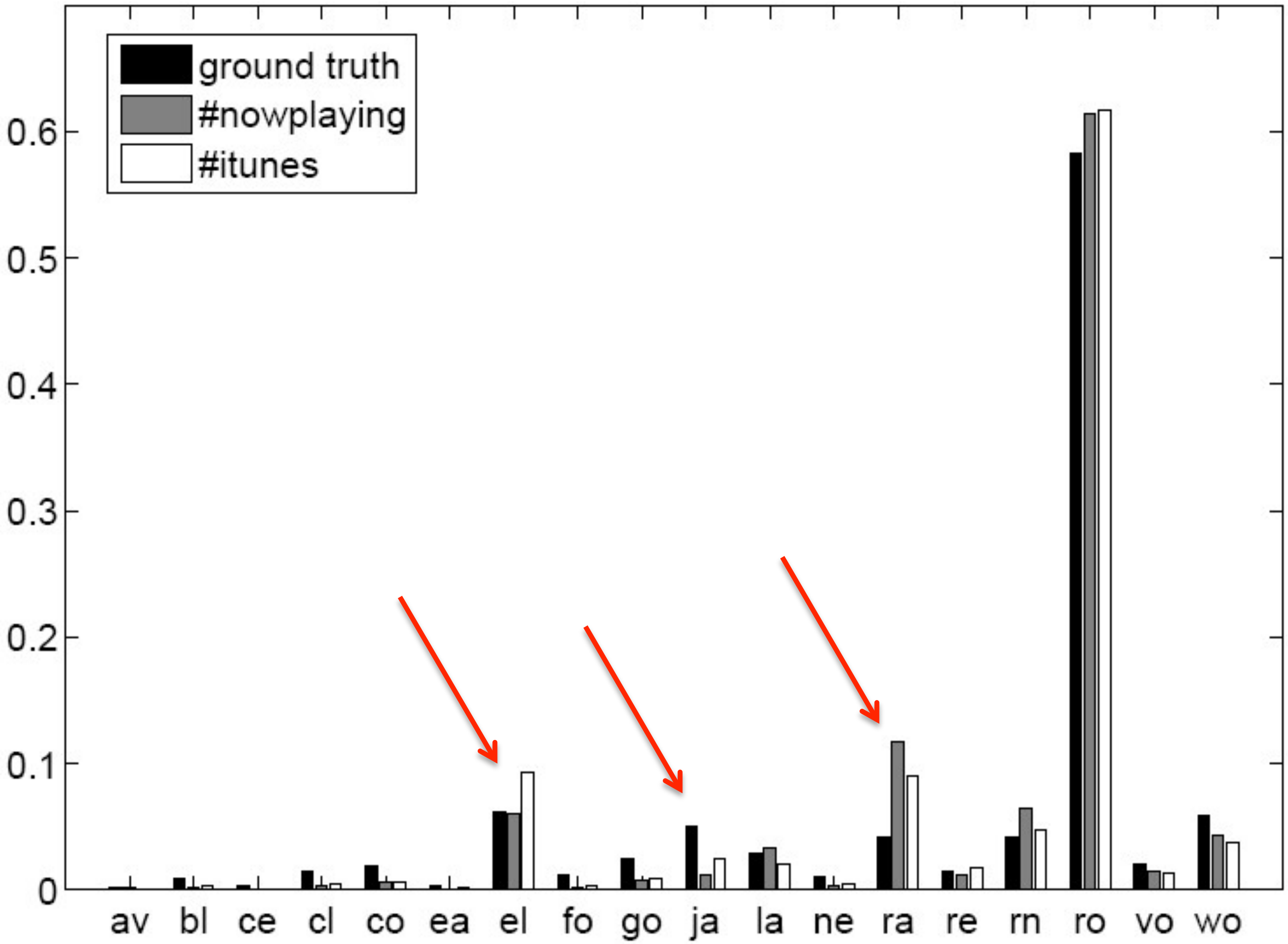
#nowplaying approaches: Music taste analysis
Least mainstreamy countries

(Schedl, Hauger; 2012)



#nowplaying approaches: Music taste analysis
Usage of specific products

(Schedl, Hauger; 2012)

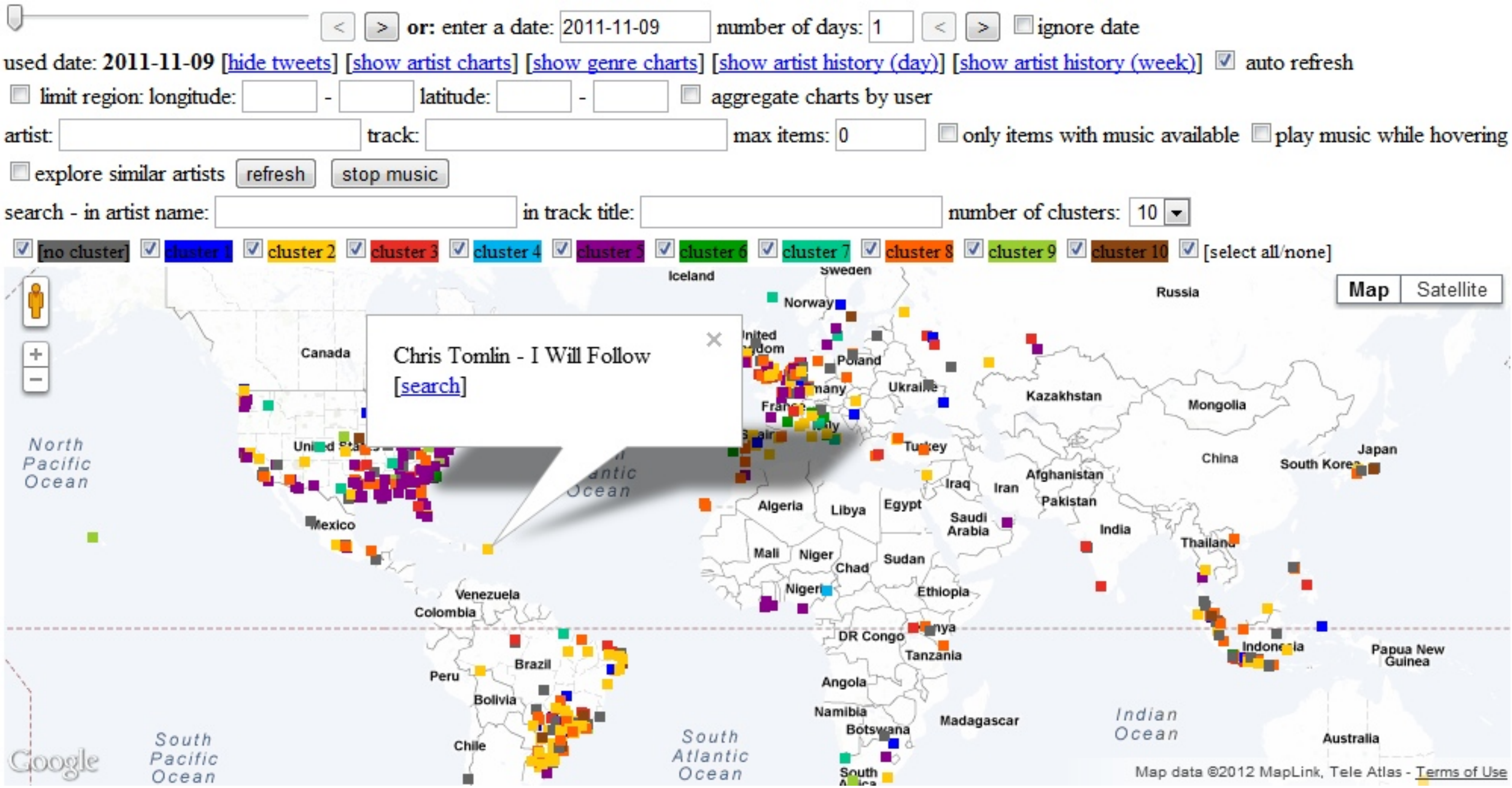


#nowplaying approaches: Browsing the world of music on the microblogosphere

- *"MusicTweetMap"*
  - Info: http://www.cp.jku.at/projects/MusicTweetMap
  - App: http://songwitch.cp.jku.at/cp/maps/tweetMapOverlay.php
  - Features:
    - browse by specific date/day or time range
    - show similar artists (based on co-occurrences in tweets)
    - restrict to country, state, city, and longitude/latitude coordinates
    - metadata-based search (artist, track)
    - clustering based on Non-negative Matrix Factorization (NMF) on Last.fm tags → genres
    - artist charts, genre charts
    - artist histories on plays

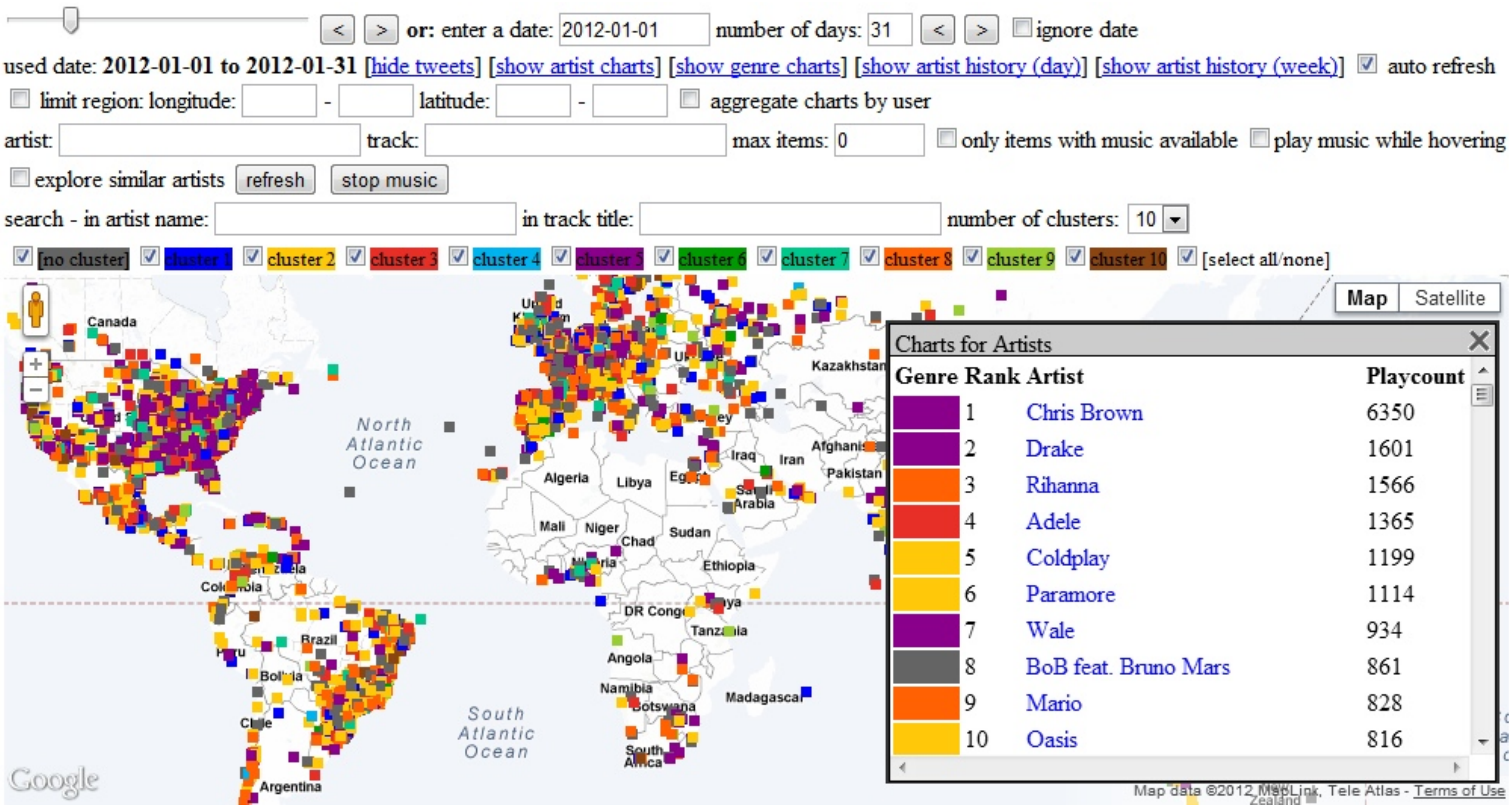
#nowplaying approaches: Browsing the world of music on the microblogosphere

Visualization and browsing of geospatial music taste



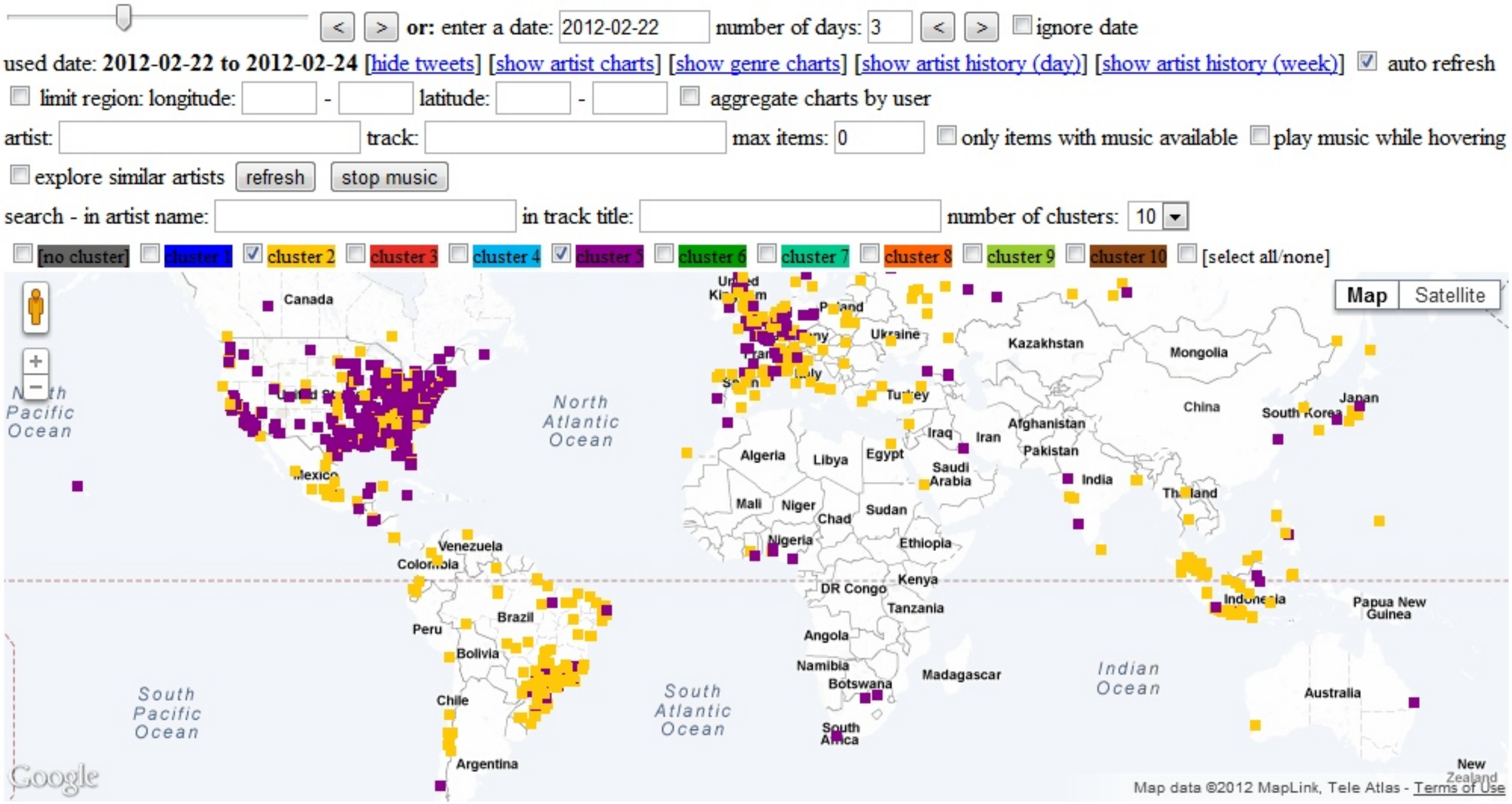
#nowplaying approaches: Browsing the world of music on the microblogosphere

Investigating geospatial music taste: 1 month



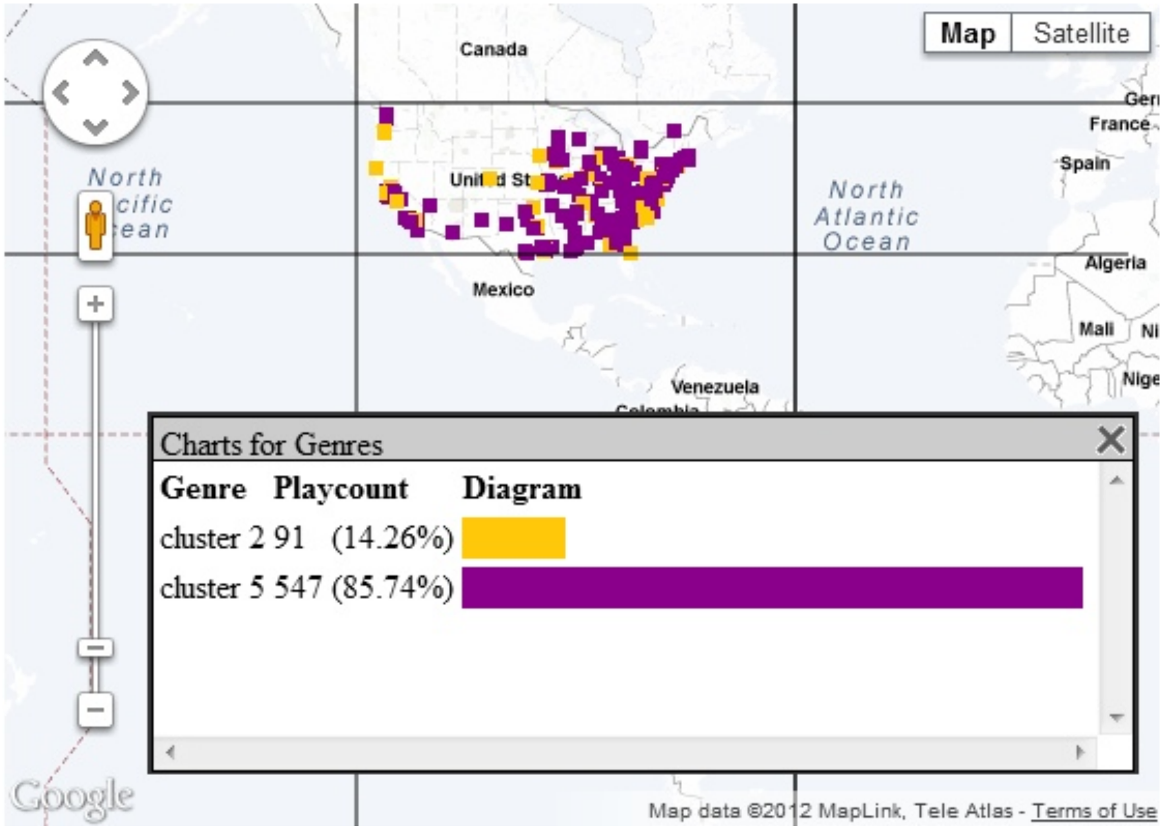
#nowplaying approaches: Browsing the world of music on the microblogosphere

Geospatial music taste: “hip-hop” vs. “rock”



#nowplaying approaches: Browsing the world of music on the microblogosphere

Geospatial music taste: “hip-hop” vs. “rock” (USA)



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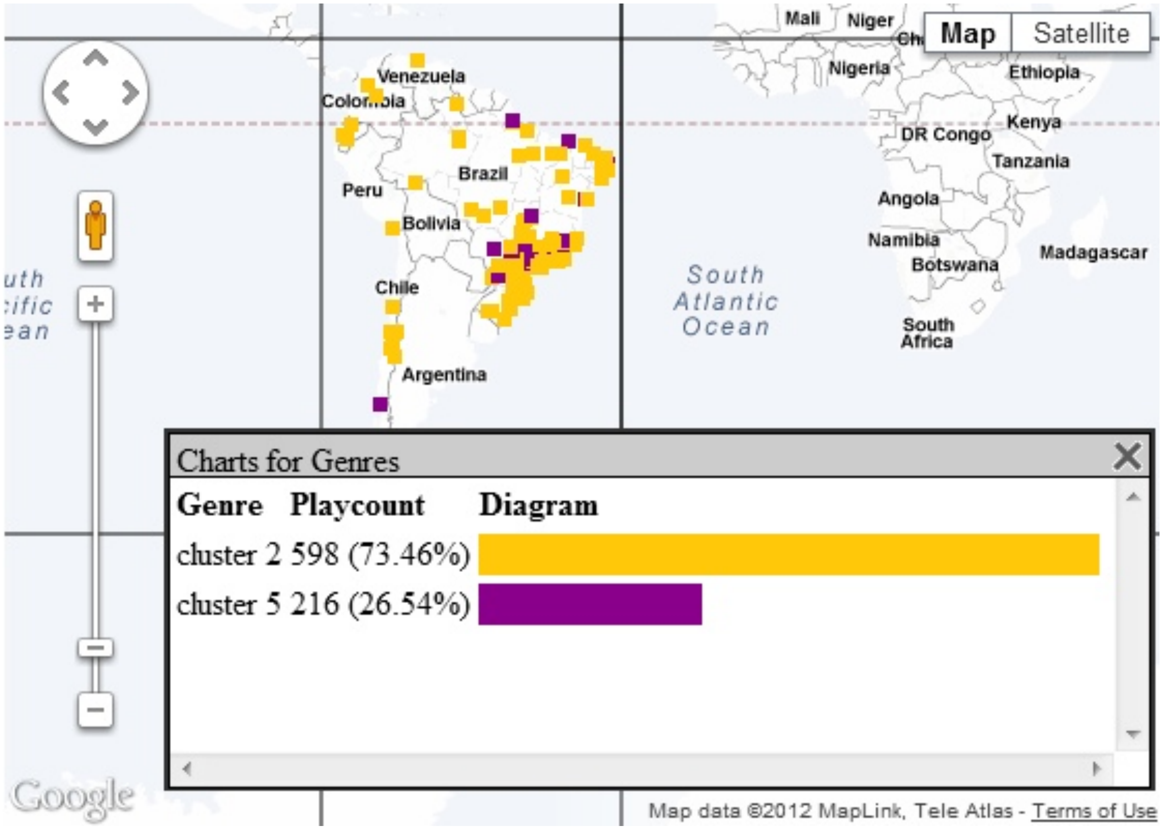
Geospatial music taste: “hip-hop” vs. “rock” (South America)



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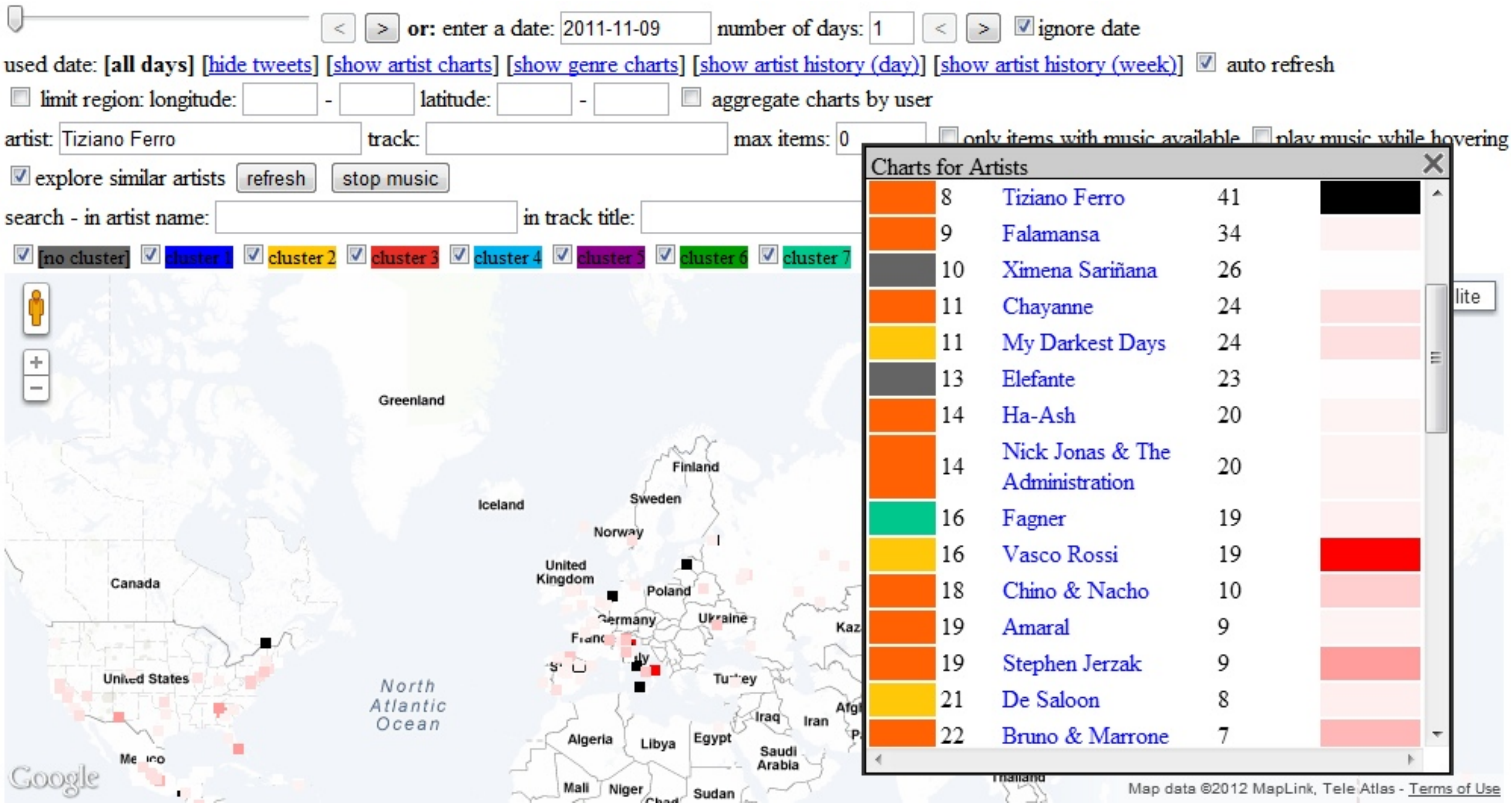
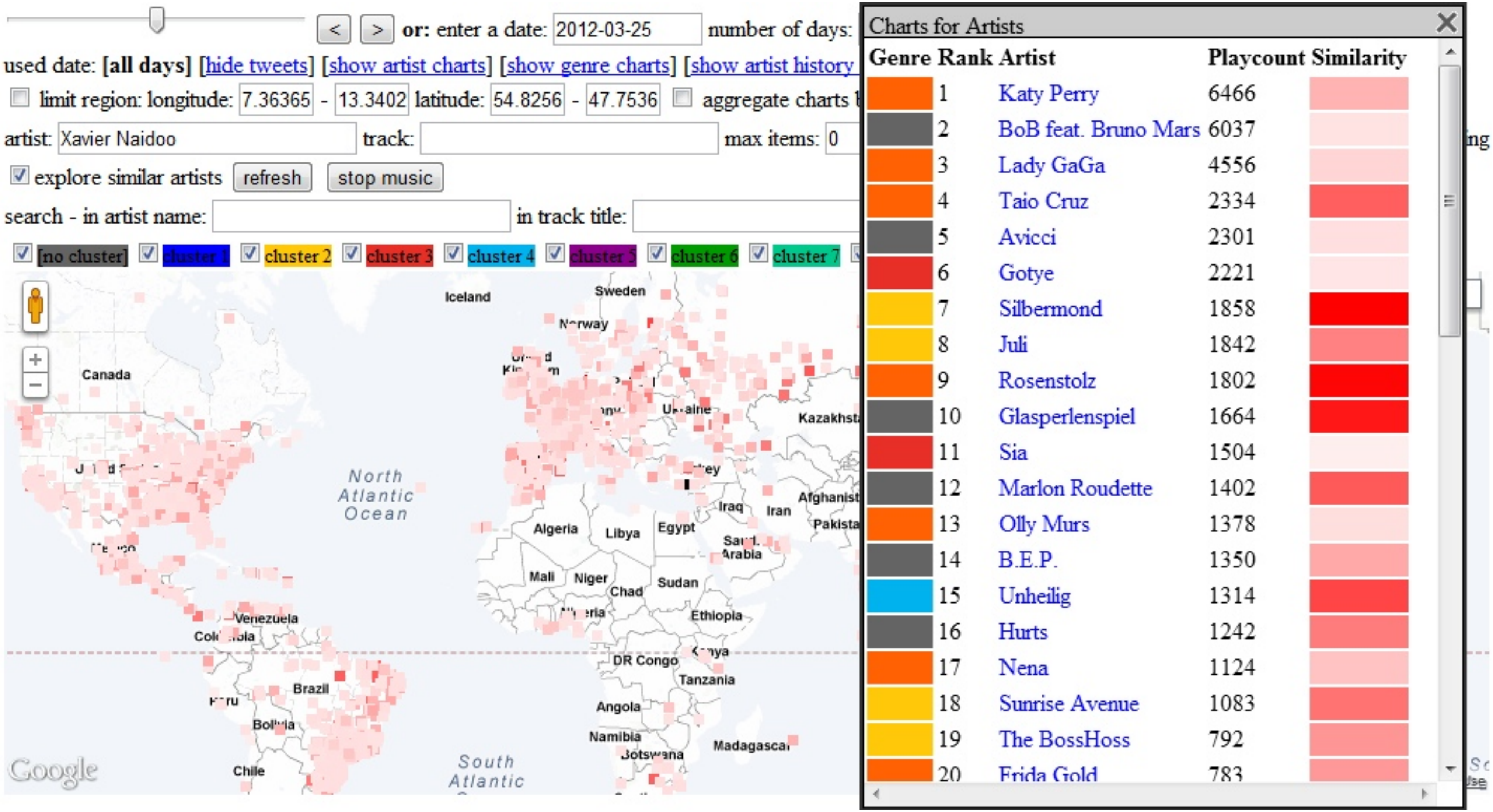
#nowplaying approaches: Browsing the world of music on the microblogosphere

Exploring similar artists: Example “Tiziano Ferro”



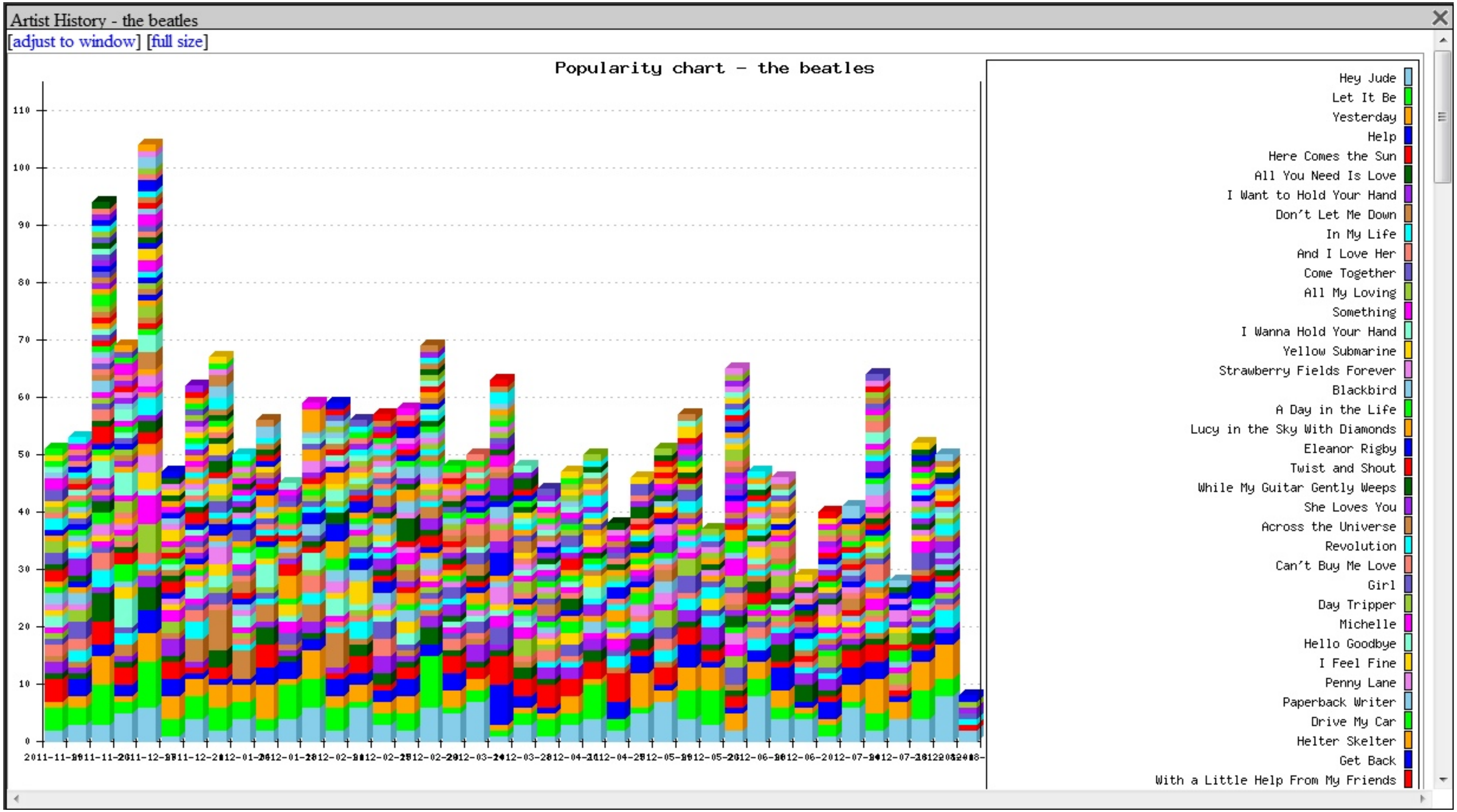
#nowplaying approaches: Browsing the world of music on the microblogosphere

Exploring similar artists: Example “Xavier Naidoo”



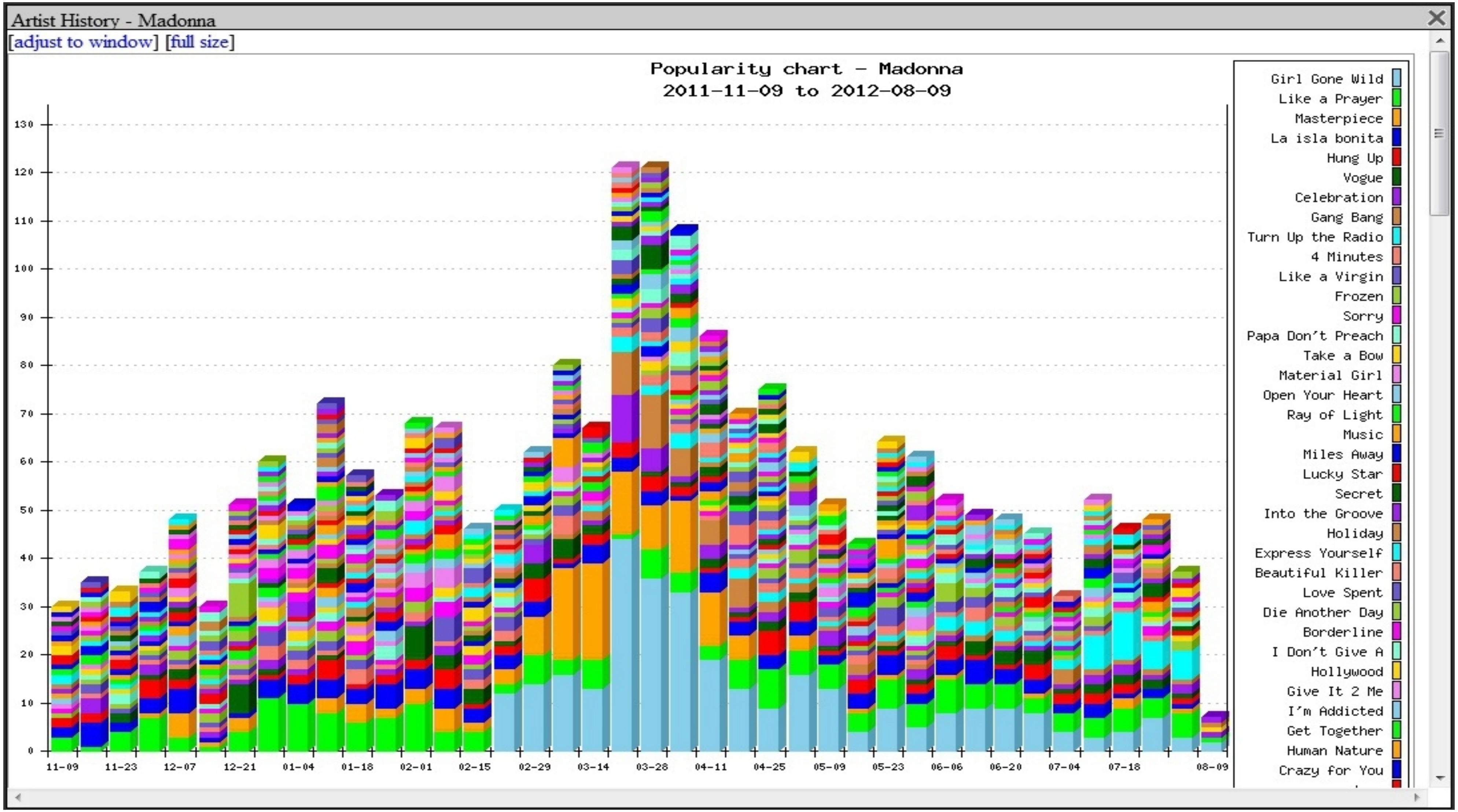
#nowplaying approaches: Browsing the world of music on the microblogosphere

Exploring music trends: Example “The Beatles”



#nowplaying approaches: Browsing the world of music on the microblogosphere

Exploring music trends: Example “Madonna”



Geospatial Music Recommendation

(Schedl, Schnitzer; SIGIR 2013)

- Combining music content + music context features
  - audio features: PS09 award-winning feature extractors (rhythm and timbre)
  - text/web: TFIDF-weighted artist profiles from artist-related web pages
- Using collection of geo-located music tweets (cf. (Schedl; ECIR 2013))
- Aims:

  (i) determining ideal combination of music content and –context

  (ii) ameliorate music recommendation by user's location information

Ideal combination of music content and context

(Schedl, Schnitzer; SIGIR 2013)

ξ	$K=1$	$K=3$	$K=5$
web only – 0.00	**.5829**	**.5753**	**.5774**
.05	.6421	.6280	.6257
.15	.6432	**.6286**	**.6261**
.25	**.6433**	.6275	.6258
.35	.6430	.6275	.6257
.45	.6408	.6266	.6252
.55	.6394	.6259	.6244
.65	.6379	.6255	.6232
.75	.6368	.6234	.6221
.85	.6330	.6202	.6188
.95	.6215	.6083	.6059
audio only – 1.00	**.5436**	**.5302**	**.5247**

Adding user context (different approaches)

(Schedl, Schnitzer; SIGIR 2013)

Abbreviation	Description
BL	random baseline
MU	hybrid music model
CF	collaborative filtering model
CF-GEO-Lin	CF model: geospatial user weighting using linear spatial distances
CF-GEO-Gauss	CF model: geospatial user weighting weighting using a Gauss kernel

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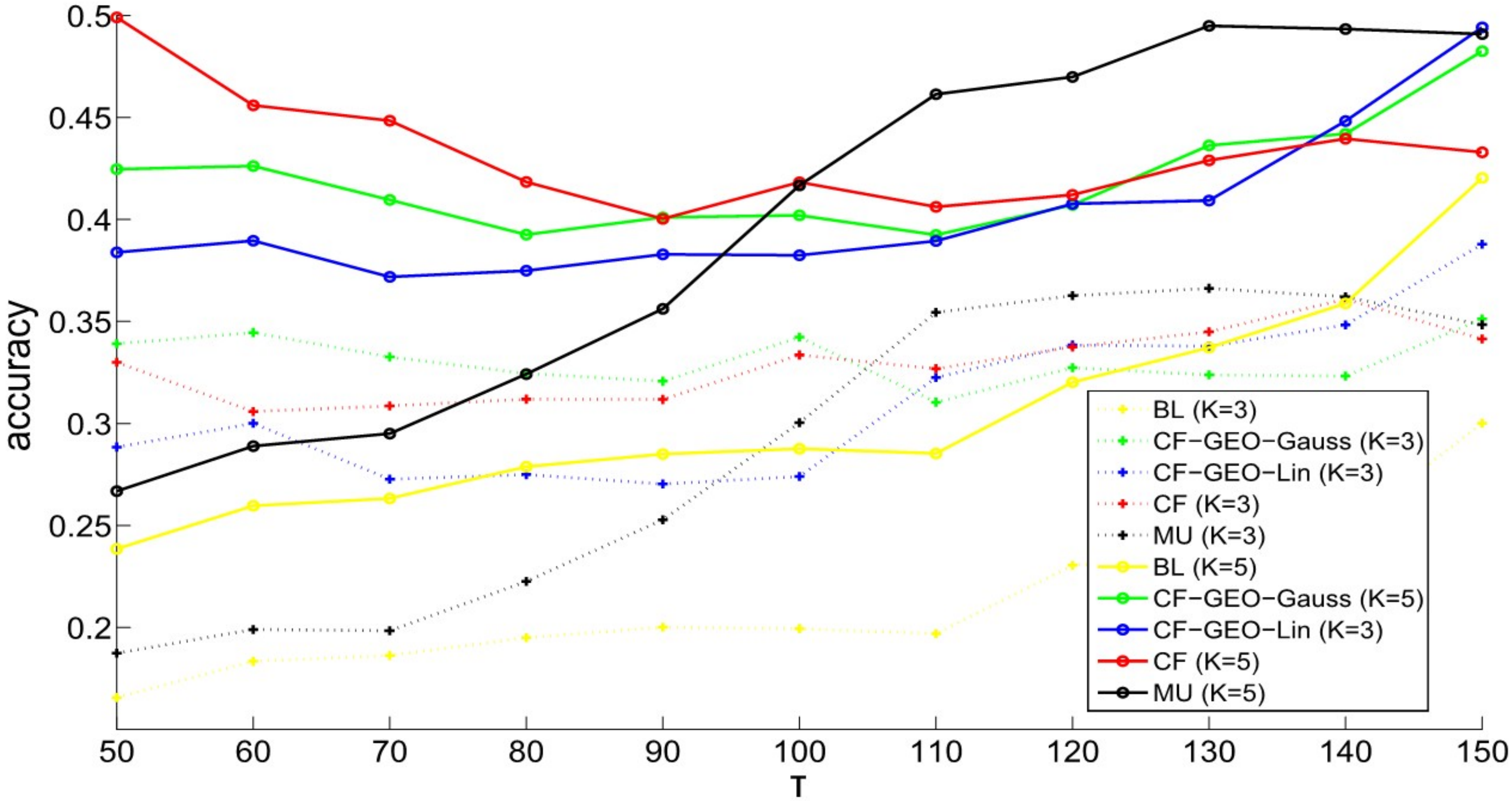
(Schedl, Schnitzer; SIGIR 2013)

Evaluation Results



T: minimum number of distinct artists a users must have listened to to be included

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User-Aware Music Recommendation on Smart Phones

(Breitschopf; 2013)

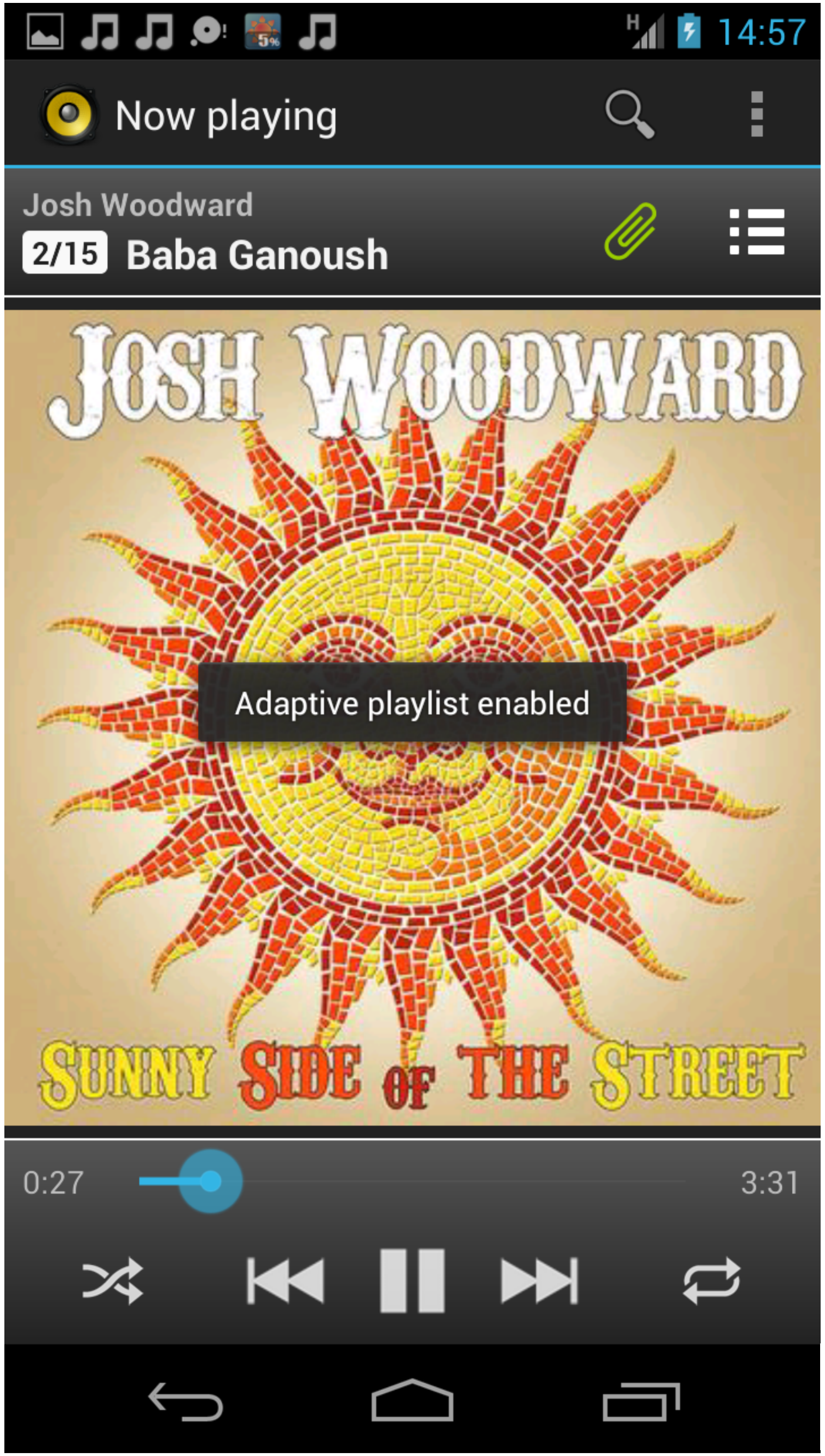
"Mobile Music Genius": music player for the Android platform

- collecting user context data while playing
- adaptive system that learns user taste/preferences from implicit feedback (player interaction: play, skip, duration played, playlists, etc.)
- ultimate aim: dynamically and seamlessly update the user's playlist according to his/her current context

Mobile Music Genius: Approach

"Mobile Music Genius": music player for the Android platform

- standard, non-context-aware playlists are created using Last.fm tag features (weighted tag vectors on artists and tracks); cosine similarity between linear combination (of artist and track features) used for playlist generation
- learning and adapting a user model via relations
  {user context – music preference}
  on the level of genre, mood, artist, and song
- playlist is adapted when change in similarity between current user context and earlier user context is above threshold



Mobile Music Genius

Music player in adaptive playlist generation mode

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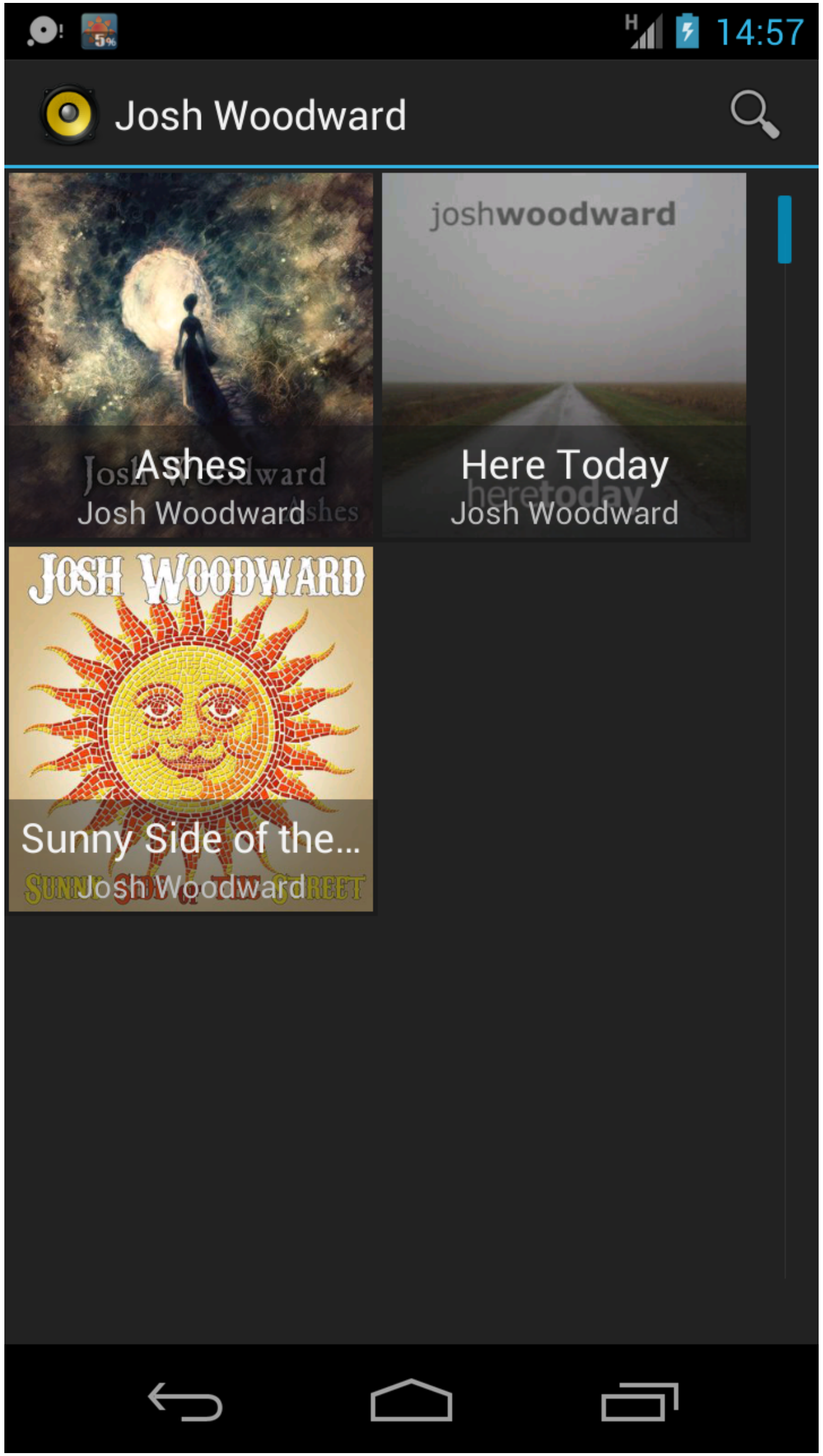

Mobile Music Genius

Album browser
in cover view

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