



Music Recommendation Tutorial

**Òscar Celma
Paul Lamere**

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introduction

- Speaker Introductions
 - ❖ Òscar Celma – Music Technology Group
 - ❖ Paul Lamere – Sun Labs



- Goals for the tutorial

outline

- Introduction
- Formalization of the recommendation problem
- Recommendation algorithms
- Problems with recommenders
- Recommender examples
- Evaluation of recommenders
- Conclusions / Future

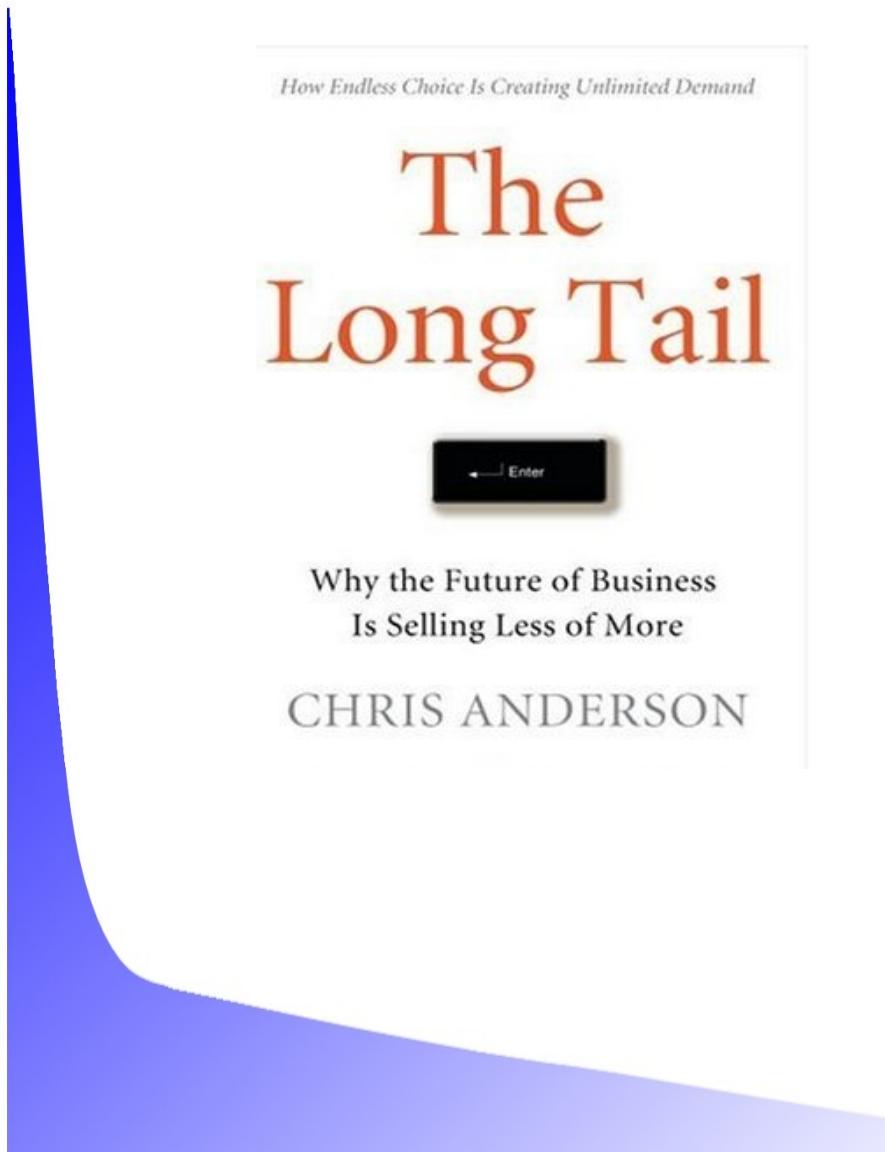
introduction:: what's the problem?

- Today
 - iTunes: 6M tracks
 - iTunes: 3B Sales
 - P2P: 15B tracks
 - 53% buy music on line
- Tomorrow
 - **All** music will be on line
 - Billions of tracks
 - Millions more arriving every week
- Finding new, relevant music is hard!



Photo by oh snap

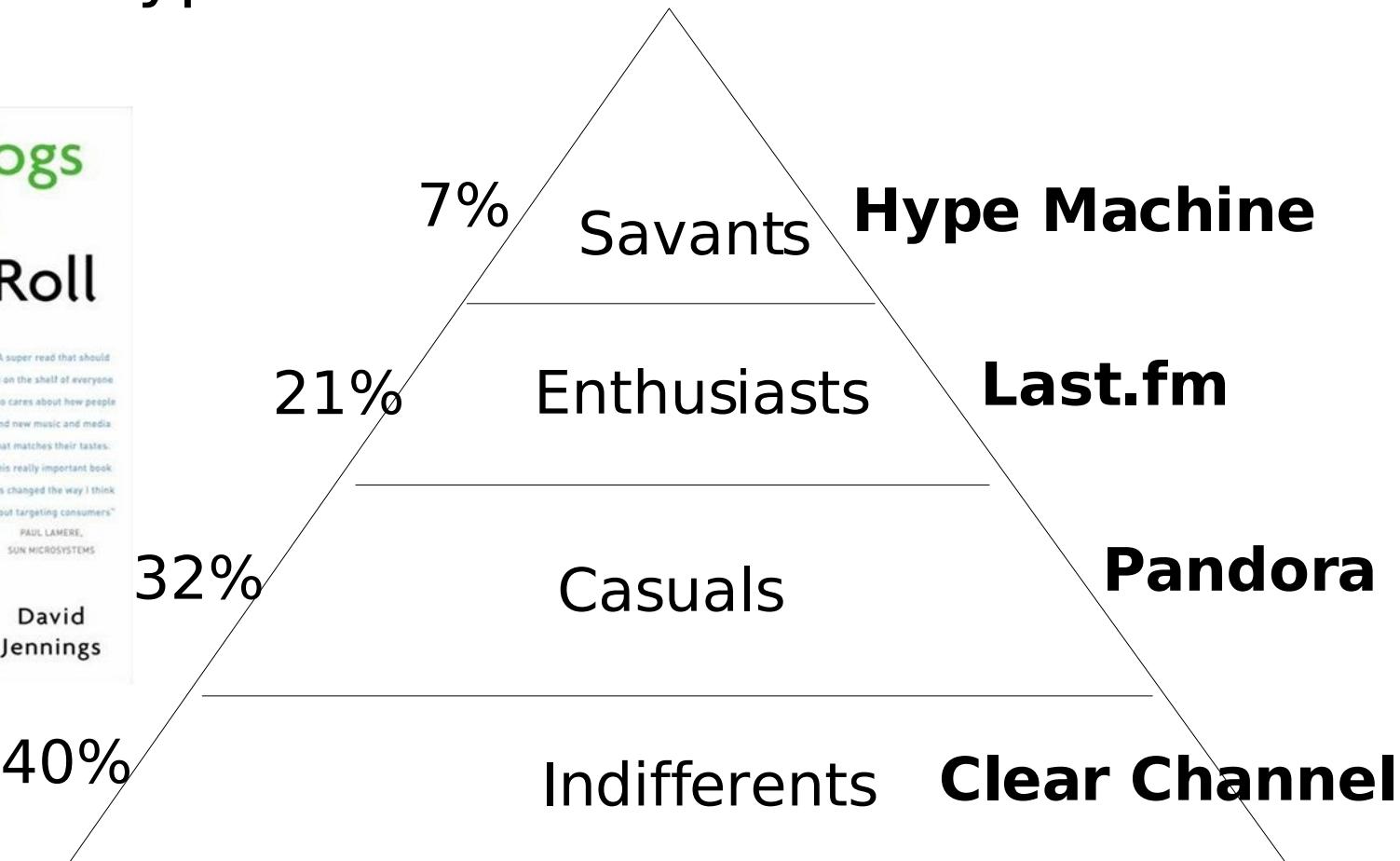
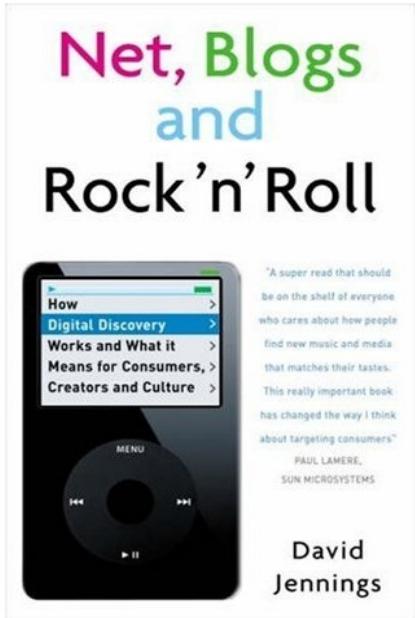
introduction:: why music rec is important?



- **Long Tail Rules**
 - Make everything available
 - Help me find it
- **How do we find it?**
 - Experts
 - Friends
 - Content

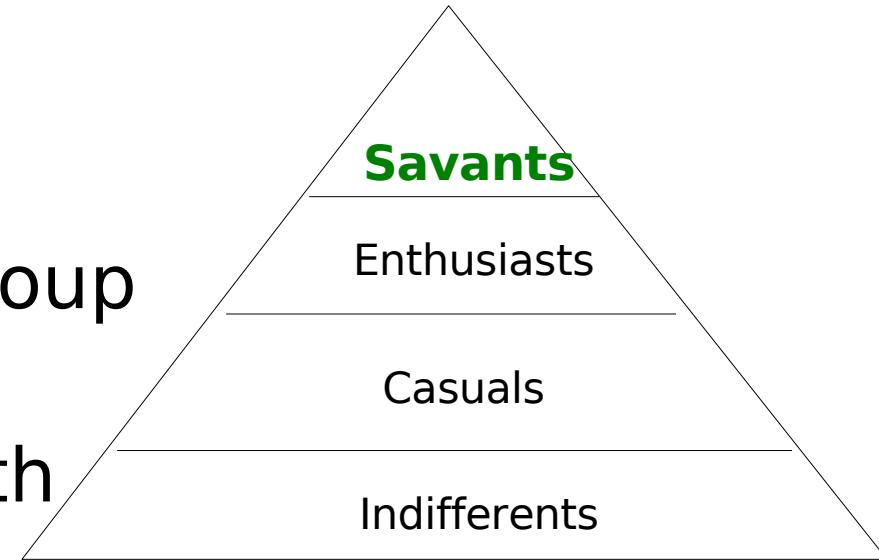
introduction:: who is recommendation for?

- Different types of users
- Different types of recommendation



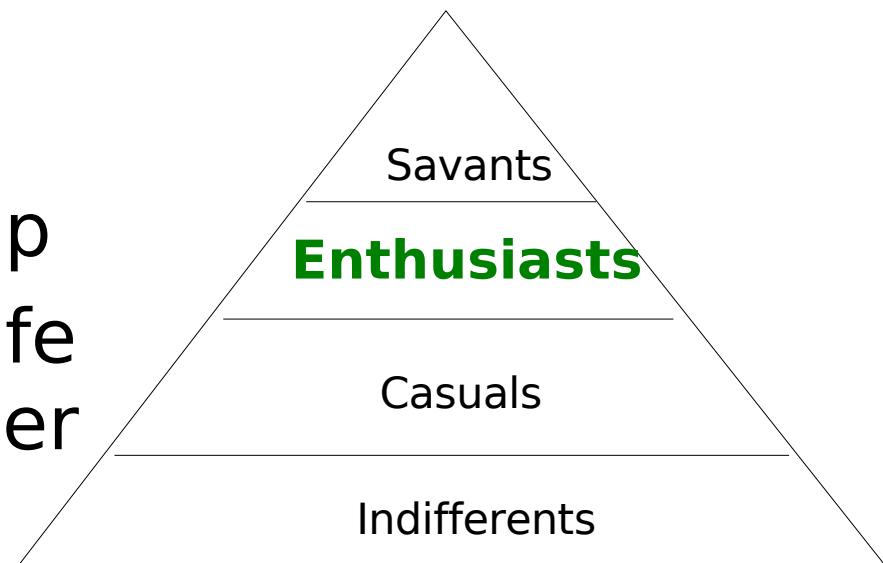
introduction:: Savants

- 7% of the 16-45 age group
- Everything in life seems to be tied up with music
- Example identifying characteristics
 - ❖ Being knowledgeable about music is central to “who I am”
 - ❖ You reckon you could write better questions for the local bar’s music quiz



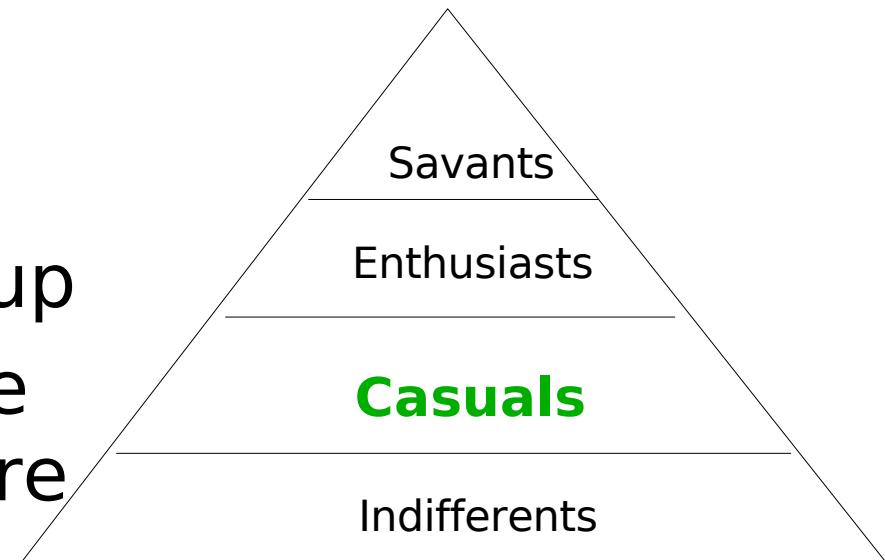
introduction:: **enthusiasts**

- 21% of 16-45 age group
- Music is a key part of life but is balanced by other interests
- Example identifying characteristics:
 - ❖ Believe that the iPod has made the world a better place
 - ❖ Get more of a kick from hearing a favorite song on CD than watching its video on television
 - ❖ Less “purist” in their musical tastes than savants



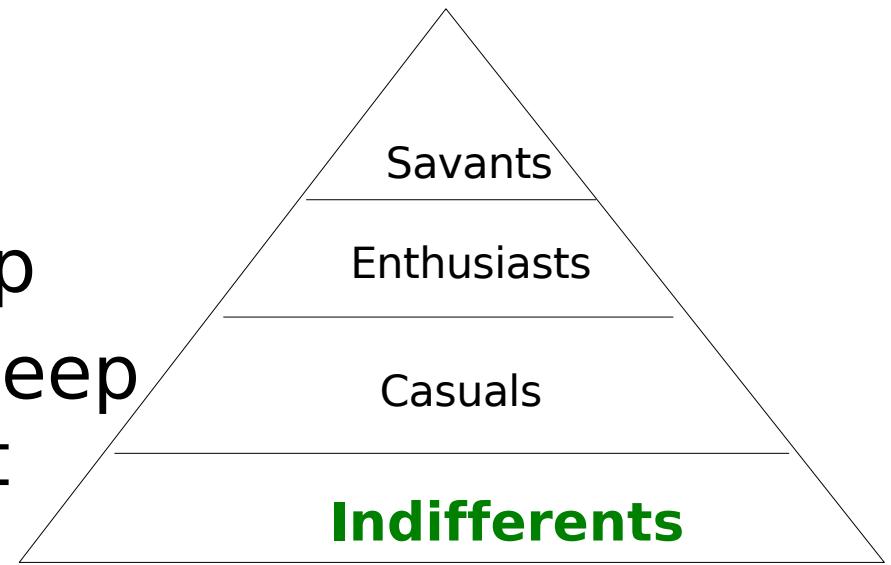
introduction:: **casuals**

- 32% of 16-45 age group
- Music plays a welcome role, but other things are far more important
- Example identifying characteristics:
 - ❖ Got into Coldplay about the same time that Gwyneth Paltrow did
 - ❖ Equally, or more, interested in the lifestyle and fashion trappings of the music world than the music itself



introduction:: indifferents

- 40% of 16-45 age group
- Would not lose much sleep if music ceased to exist
- Example identifying characteristics:
 - ❖ Most of the songs they hear at parties sound unfamiliar
 - ❖ Tend to listen to talk radio or sports rather than music



introduction:: music discovery in the small

- Personal music players:
 - ❖ No Experts to guide you
 - ❖ No Social network
 - ❖ Music discovery is **random**
 - ❖ Shuffle Play doesn't scale
 - ❖ Results:
 - iPod **whiplash**
 - The music graveyard
- Study of 5,000 iPod users:
 - ❖ 80% of plays in 23% of songs
 - ❖ 64% of songs **never** played



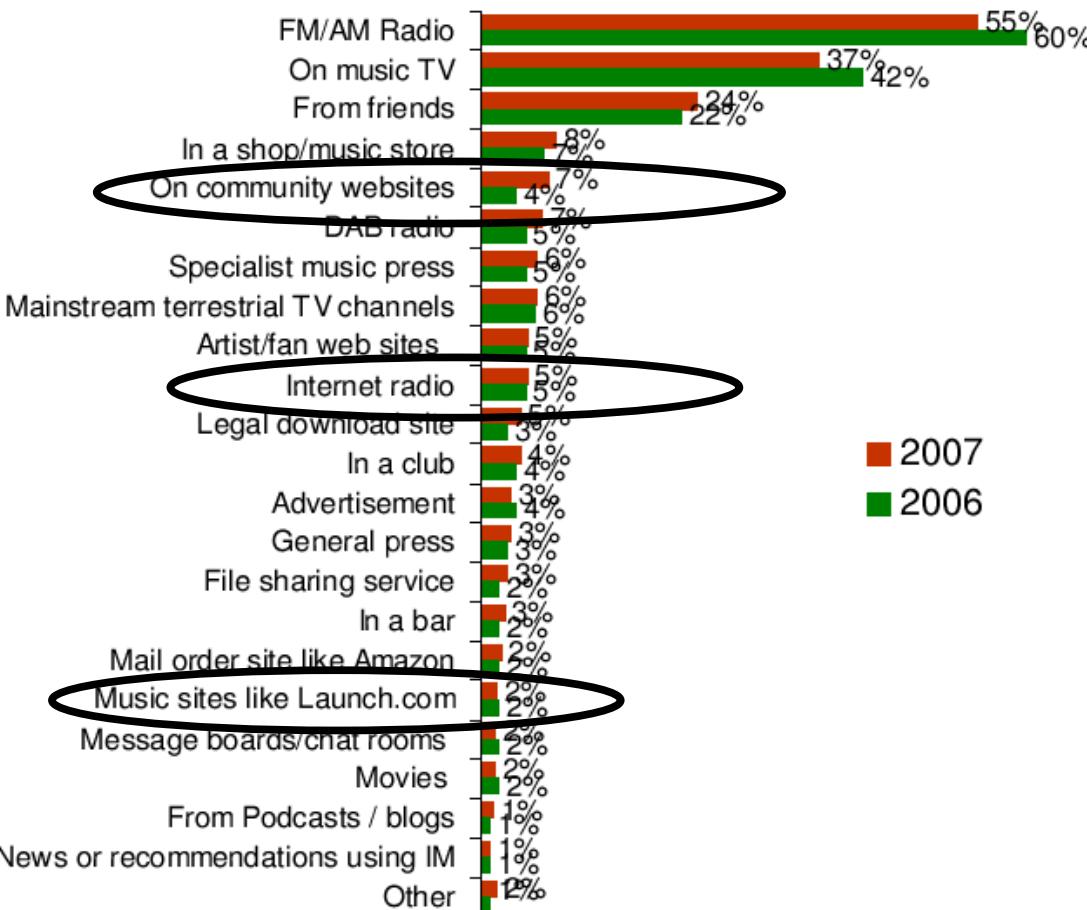
introduction:: the value of recommendation

- **Netflix:**
 - ❖ 2/3 of movies rented were recommended
 - ❖ recommendation is “absolutely critical to retaining users”
- **Google News:**
 - ❖ Recommendations generate 38% more click-throughs
- **Amazon:**
 - ❖ claims 35% of product sales result from recommendations

introduction:: the value of recommendation

- **Greg Linden (Findory, Amazon):**
 - ❖ “recommendations generated a couple orders of magnitude more sales than just showing top sellers”
- **ChoiceStream survey:**
 - ❖ 28% would buy more music if they could find more that they liked

introduction:: SOURCES OF NEW MUSIC

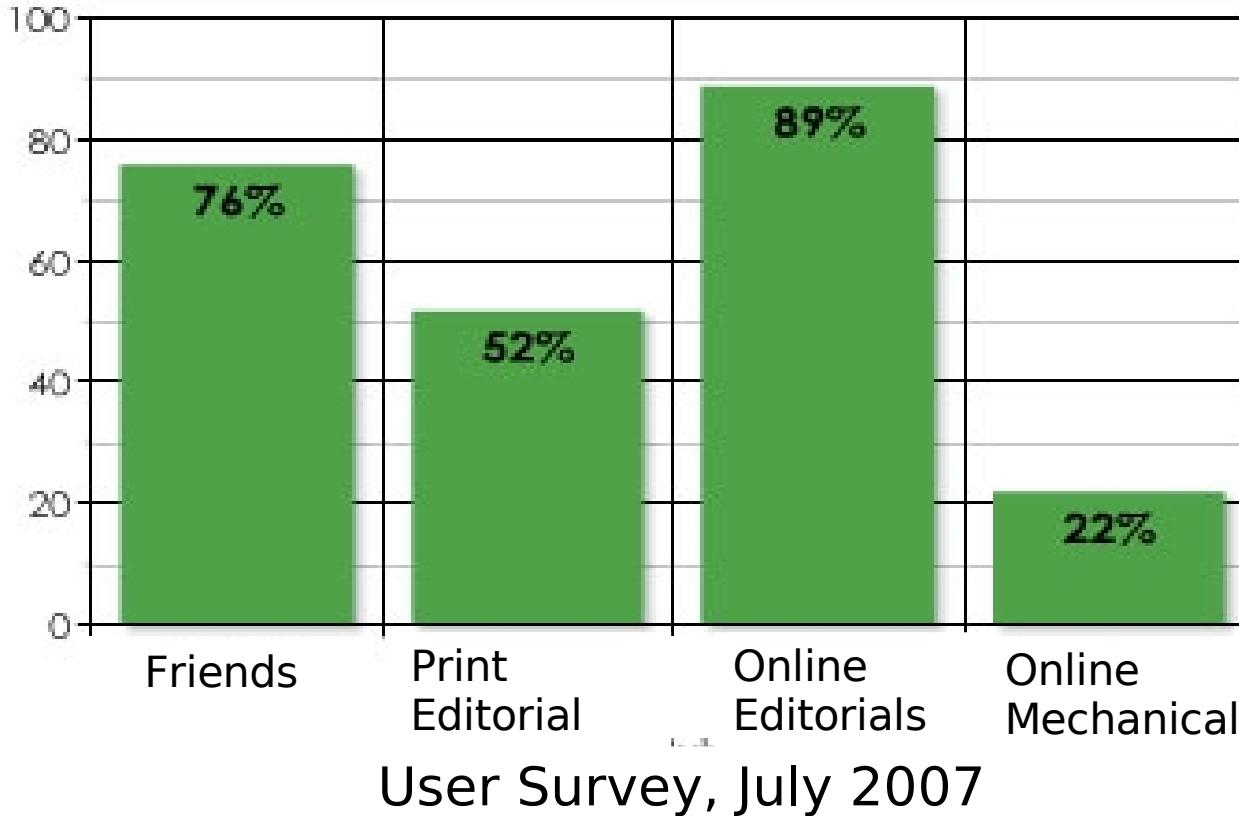


Base: Q4, All respondents (1,721)

introduction:: sources of new music

- Hype Machine Survey

How do you Discover New Music?



1430 responses

<http://non-standard.net/blog/?p=85>

introduction:: Commercial interest

- 9Vibe
- Aggrega
- All Music Guide
- AOL Music
- **AudioBaba**
- Audiri
- bandBuzz
- SoundsLikeNow
- Bandwagon
- Buzzwire
- **BMAT**
- Earfeeder
- Goombah
- Grepr
- Guruger
- HooQs
- Idio
- iLike
- inDiscover
- iTunes
- LaunchCast
- **Last.fm**
- Mercora
- MOG
- MusicCodex
- MusicIP
- Musicover
- Musicmobs
- Musio
- **MyStrands**
- **One Llama**
- **Owl Multimedia**
- Pandora
- QLoud
- RateYourMusic
- SeeqPod
- Slacker
- Soundflavor
- **Spotify**
- The Filter
- UpTo11.net
- ZuKool Music

introduction:: commercial interest



introduction:: recent investment

- Qloud – \$1 million
- MOG - \$1.4 million
- The Filter - \$5 million
- Social.fm - \$5 million
- Groove Mobile - \$6 million
- Pandora – \$6 million
- iLike – \$13.3 million
- MyStrands - \$25 million
- Slacker - \$40 million
- Last.fm - \$280 million

introduction:: **Summary**

- Massive Increase in volume of online music
 - ❖ Huge shift from physical media to digital media
 - ❖ Huge drop in cost to produce new music
- Long Tail Economics
 - ❖ Make everything available
 - ❖ Help me find it
- Strong commercial interest
- Related Topics
 - ❖ Exploration
 - ❖ Discovery
 - ❖ Playlisting

outline

- Introduction
- **Formalization of the recommendation problem**
- Recommendation algorithms
- Problems with recommenders
- Recommender examples
- Evaluation of recommenders
- Conclusions / Future

formalization:: definition

- Definition of a recommender system
 - ❖ Recommender systems are a specific type of **information filtering** technique that attempt to present to the user information **items** (movies, *music*, books, news, web pages) the **user is interested in**. To do this the **user's profile** is compared to some reference characteristics.
 - ❖ from:
 - http://en.wikipedia.org/wiki/Recommendation_system

formalization:: definition

- Recommendation as a prediction problem
 - ❖ attempt to predict items that a user might be interested in
 - ❖ compute *similarity* between objects
 - user-user
 - item-item
 - ❖ form *predictions* based on the computed similarities

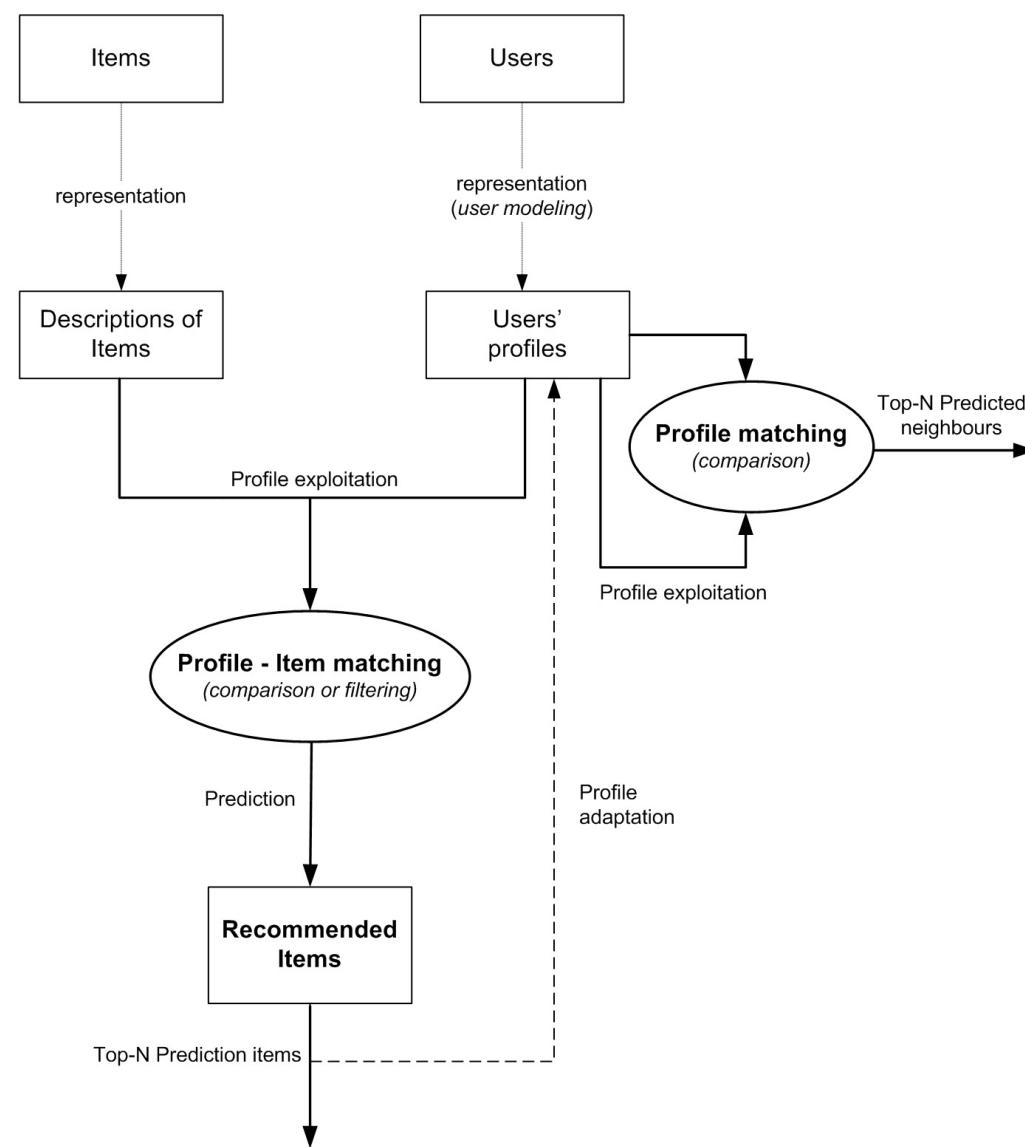
formalization: use cases

- Use cases of a recommender system [Herlocker, 2004]
 - ❖ Find good items
 - provide a ranked list of items
 - expect some novel items
 - ❖ Find all good items
 - coverage
 - low false positive rate
 - ❖ Recommend sequence
 - an ordered sequence of items that is pleasing as a whole (i.e playlist generation)
 - ❖ Just browsing
 - ❖ Find credible recommender

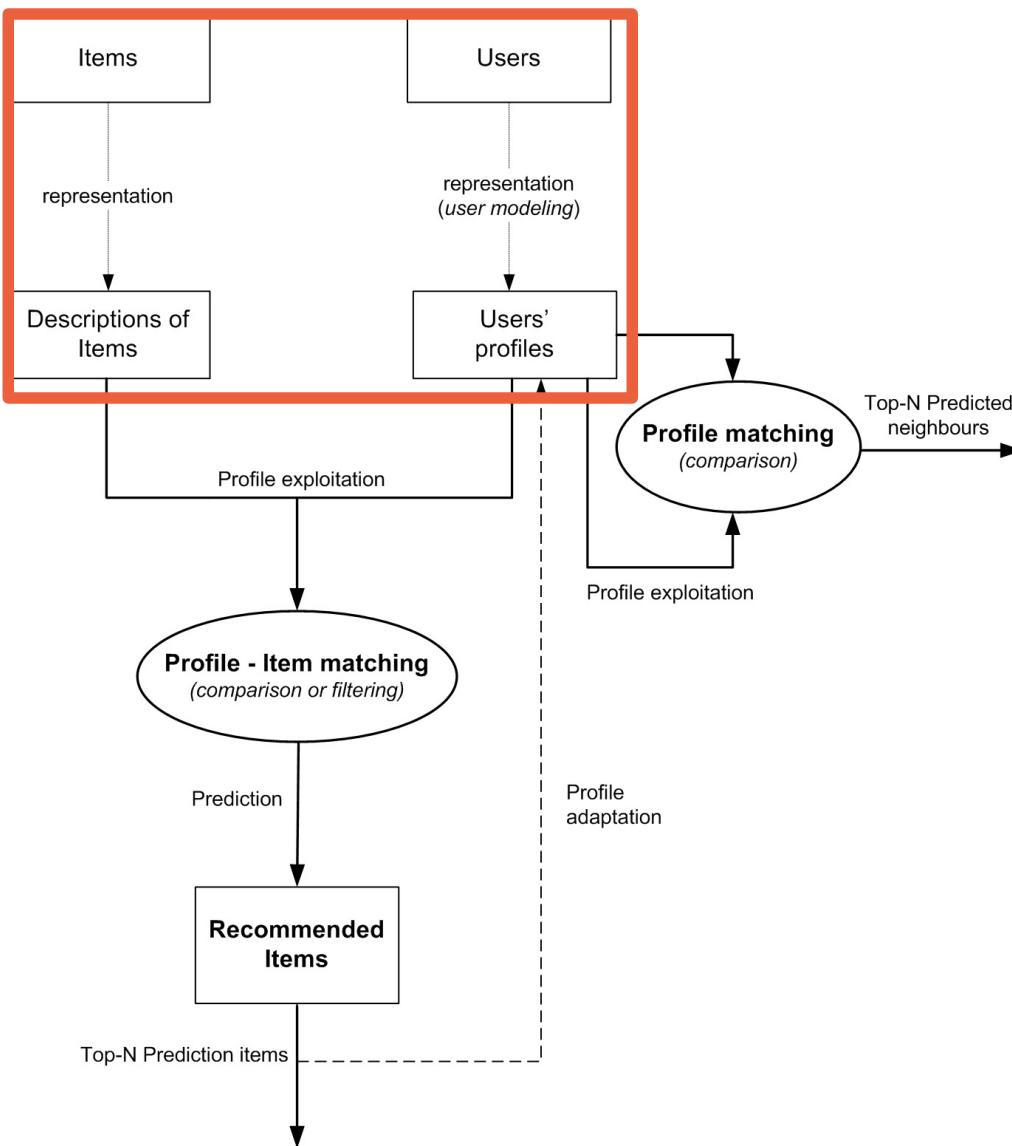
formalization: use cases

- Use cases of a recommender system [Herlocker, 2004]
 - ❖ Improve profile
 - important in recommenders that have a strong community component
 - ❖ Express self
 - communicate and interact with other users (messages, forums, weblogs, etc.)
 - ❖ Influence others
 - the most negative one
 - influence the community in viewing or purchasing a particular item (e.g labels trying to *promote* artists into the recommender)

formalization:: the whole picture

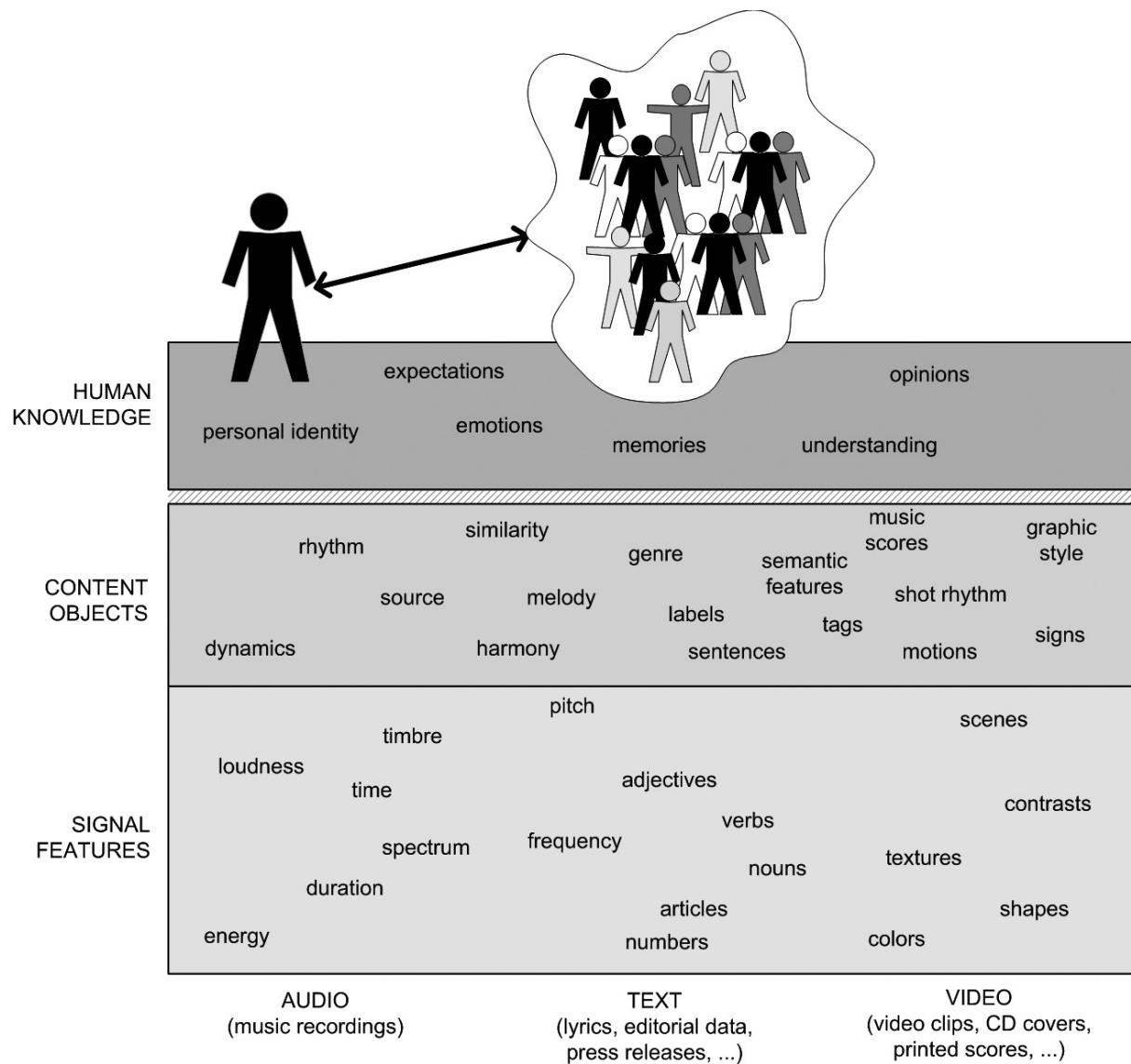


formalization:: describing users & items



formalization:: describing users & items

USERS

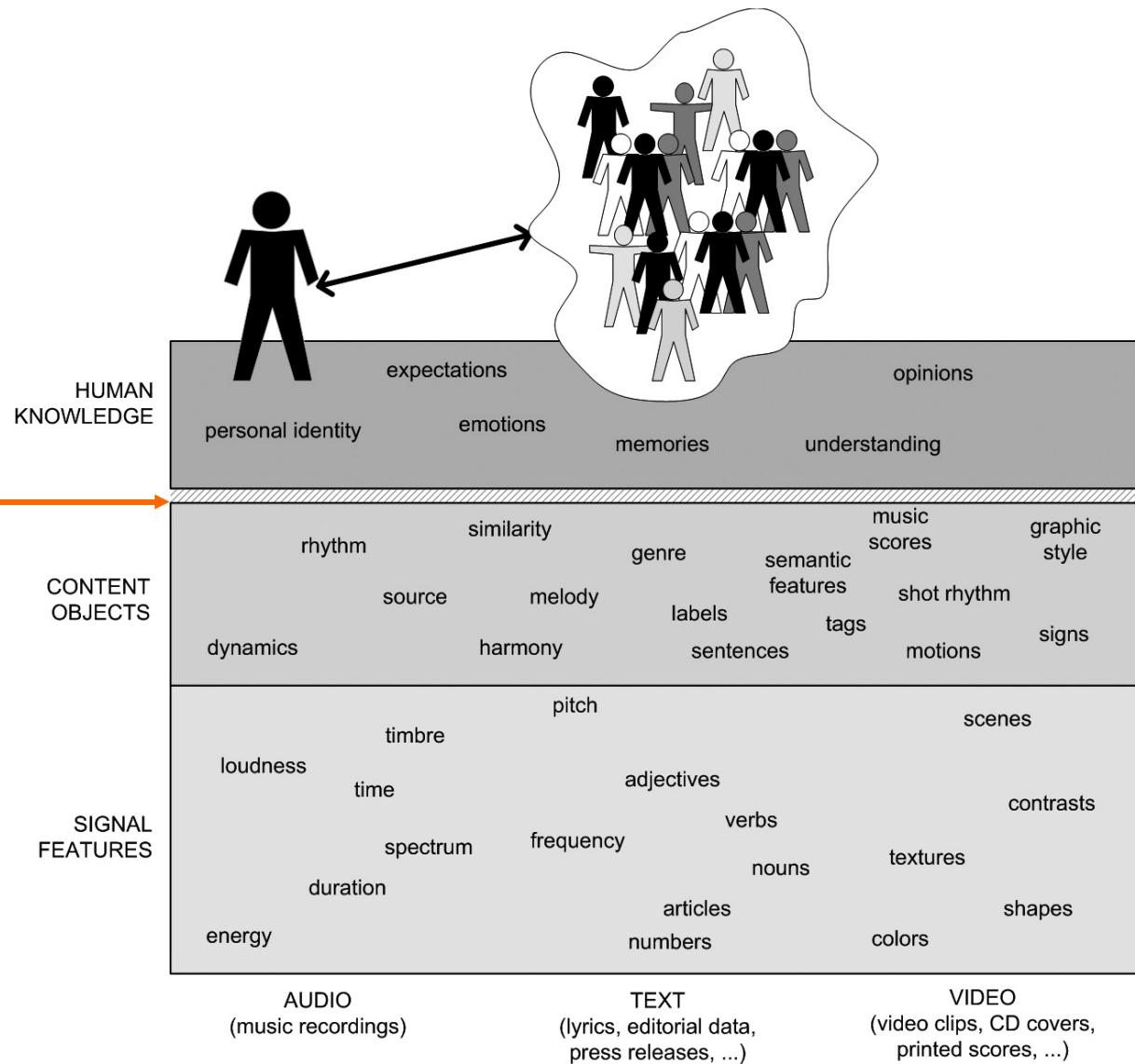


ITEMS

formalization:: describing users & items

USERS

semantic
gap



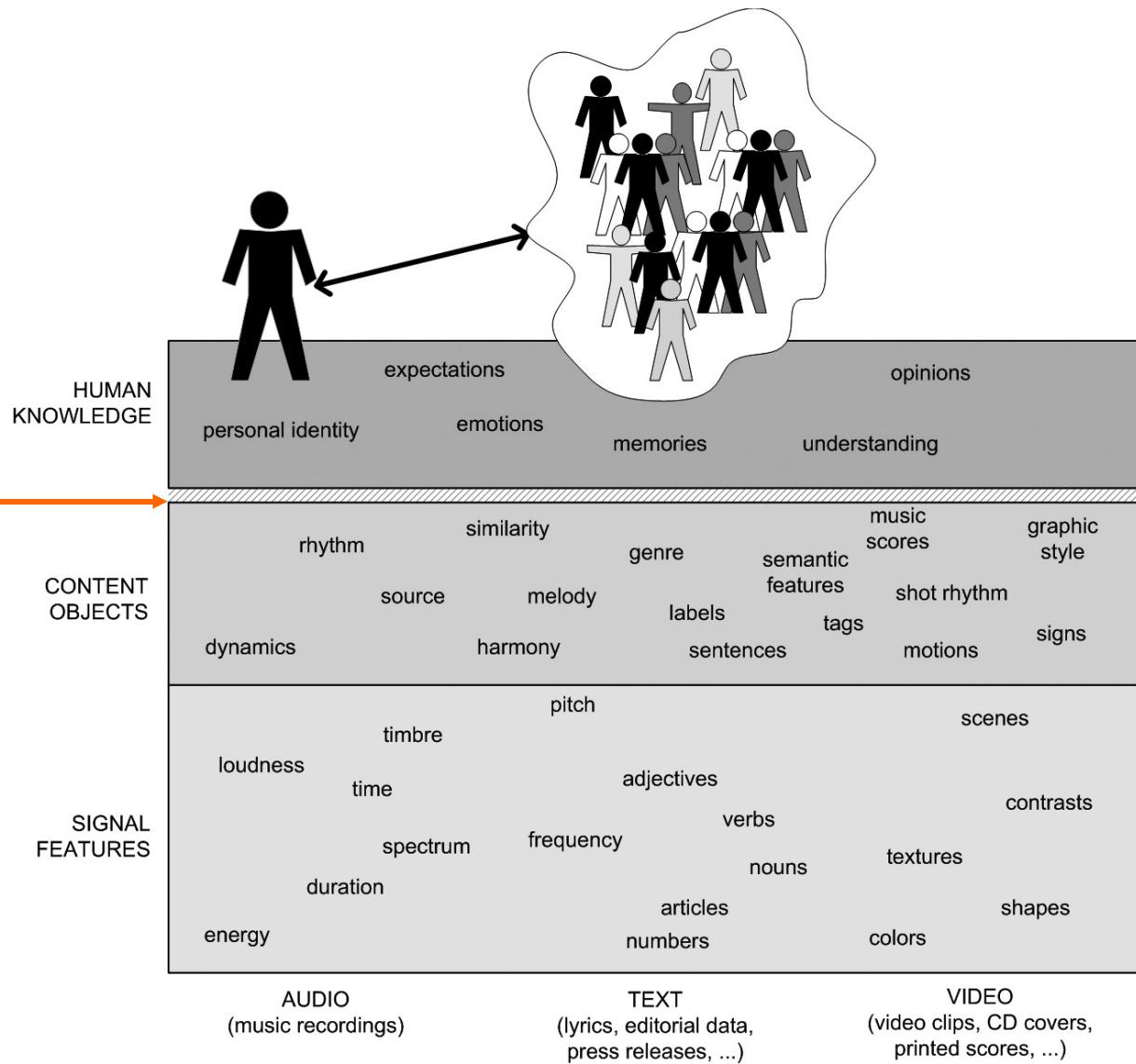
formalization:: describing users & items

USERS

semantic gap

✓ get a better understanding of the music assets!

ITEMS



formalization:: describing users & items

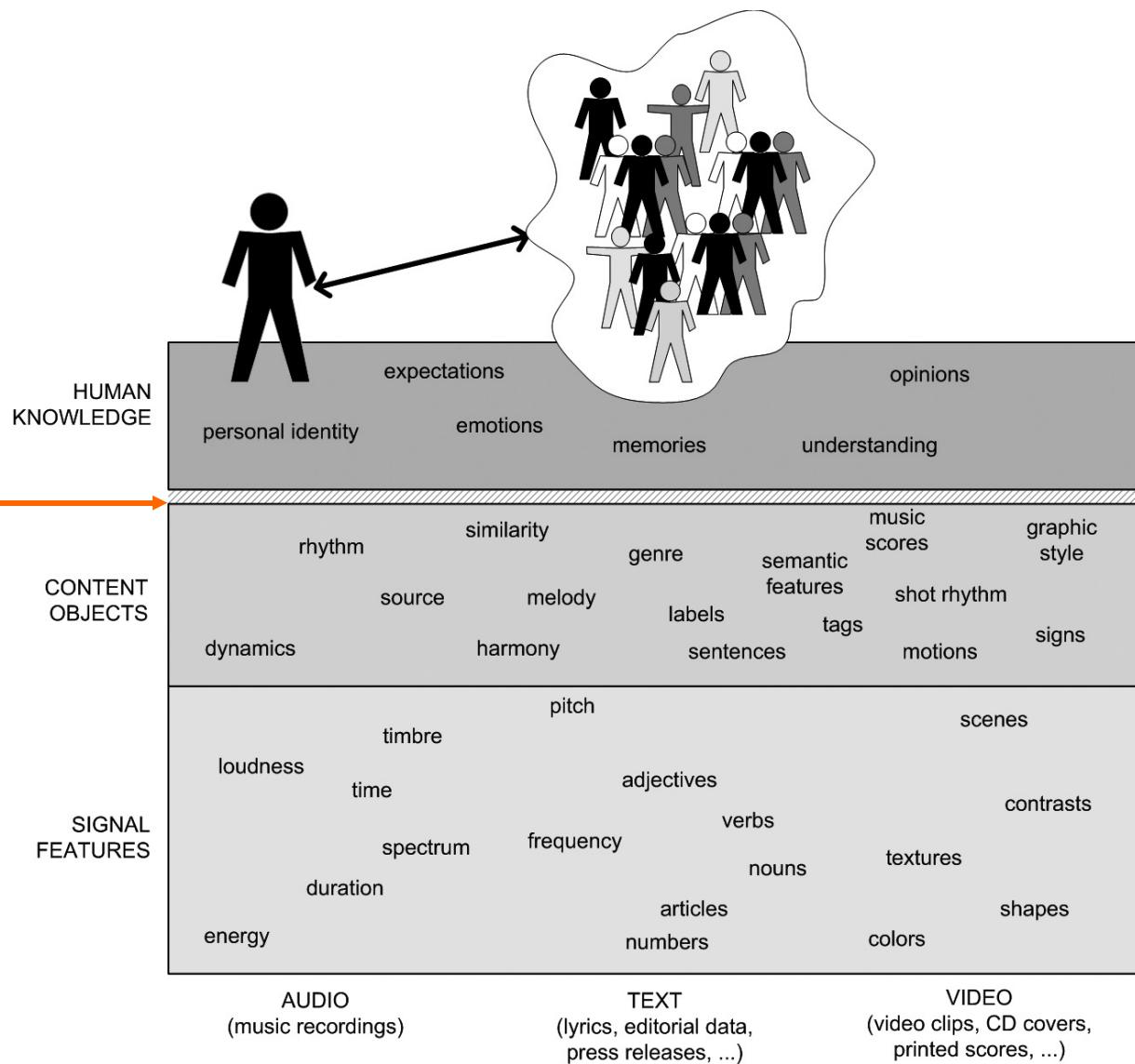
USERS

- get a better understanding of the users preferences!

semantic gap

- get a better understanding of the music assets!

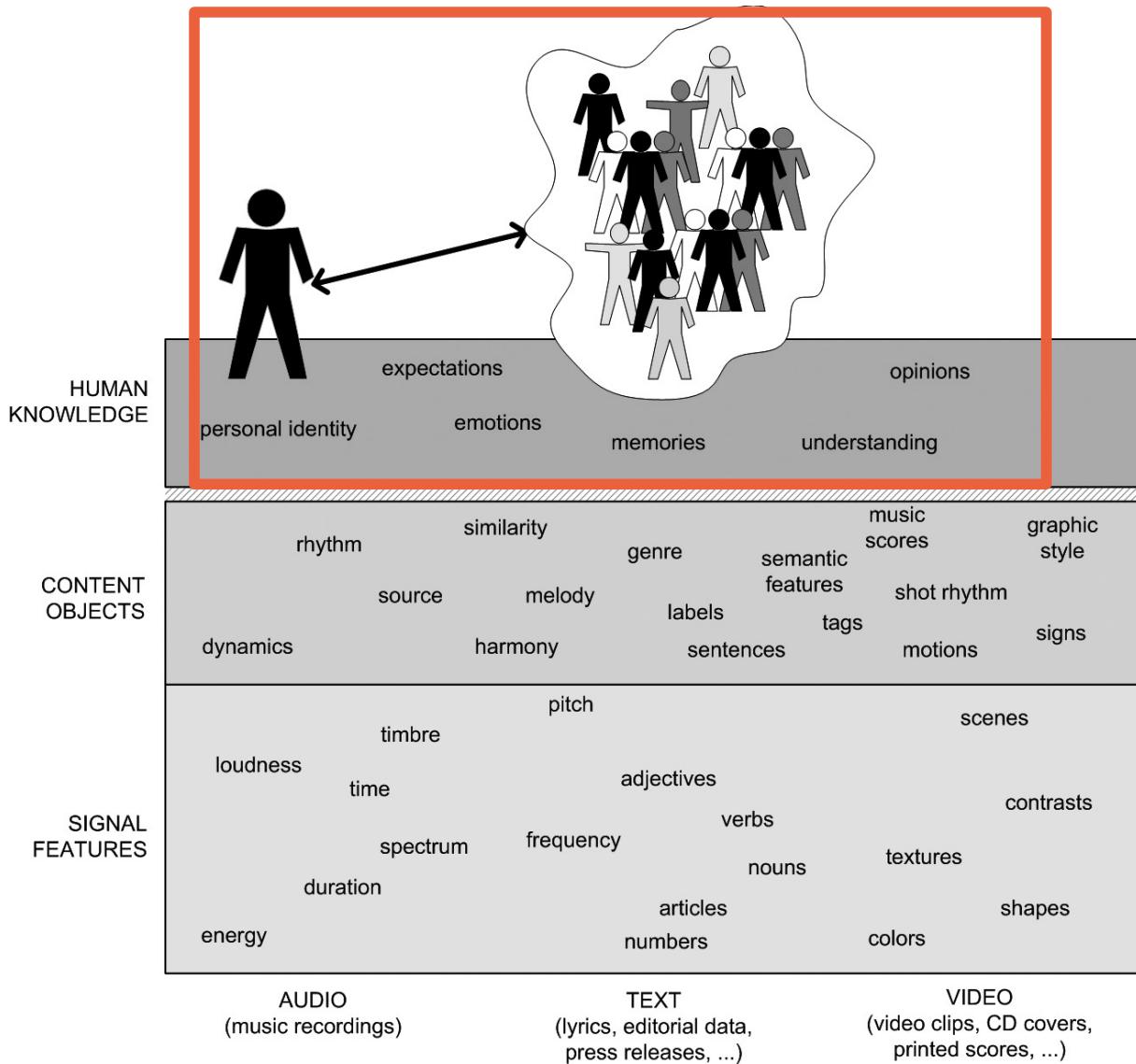
ITEMS



formalization:: describing users

USERS

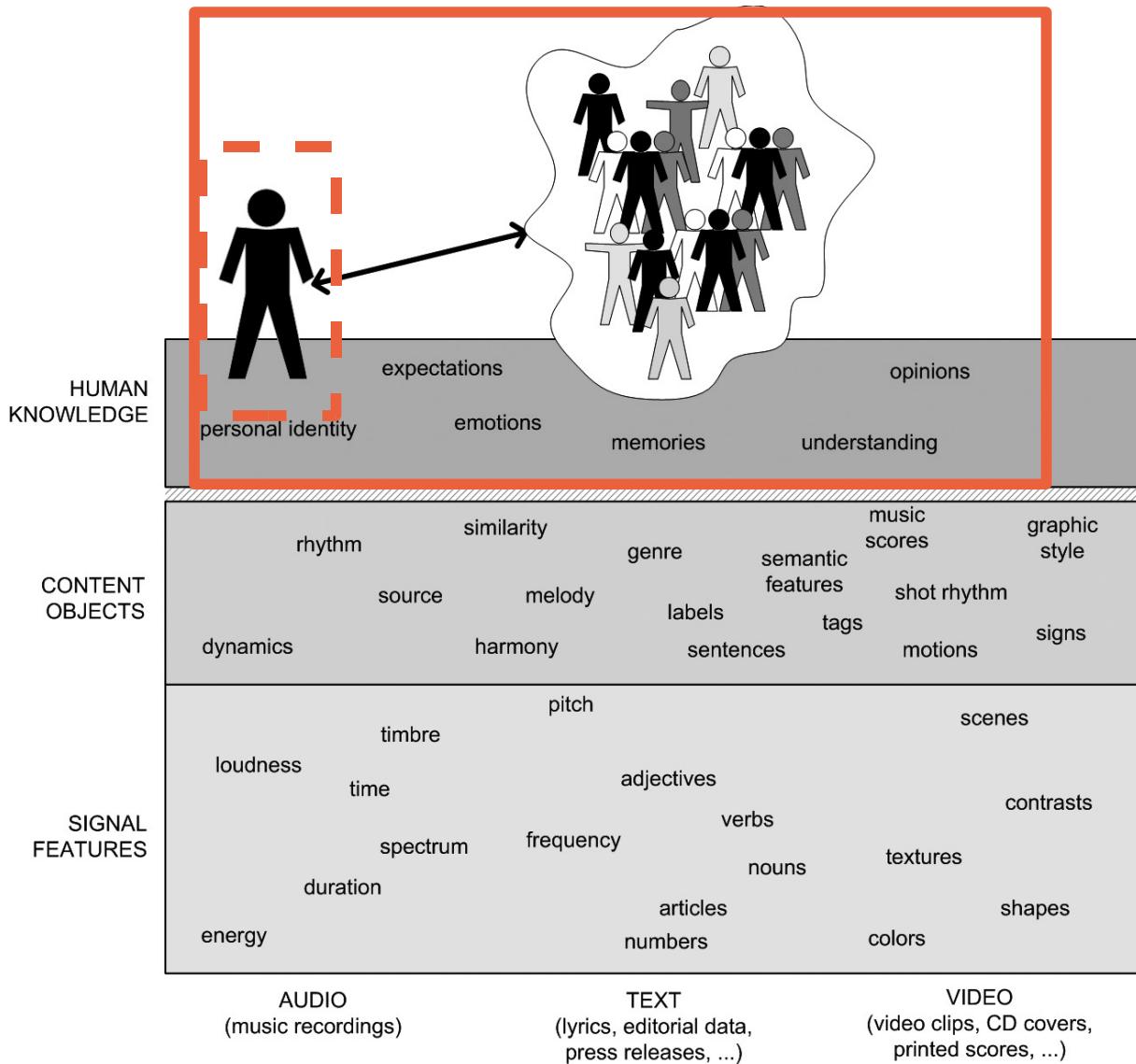
- get a better understanding of the users preferences!



formalization:: describing users (me)

USERS

- get a better understanding of the users preferences!



formalization:: describing users (me)

- me and myself (user profile) [Uitdenbogerd, 2002]
 - ❖ demographic
 - age, gender, languages, family status, income, education level, etc.
 - ❖ geographic
 - location
 - ❖ psychographic
 - general interests
 - hobbies
 - music preferences
 - ...

formalization: describing users (me)

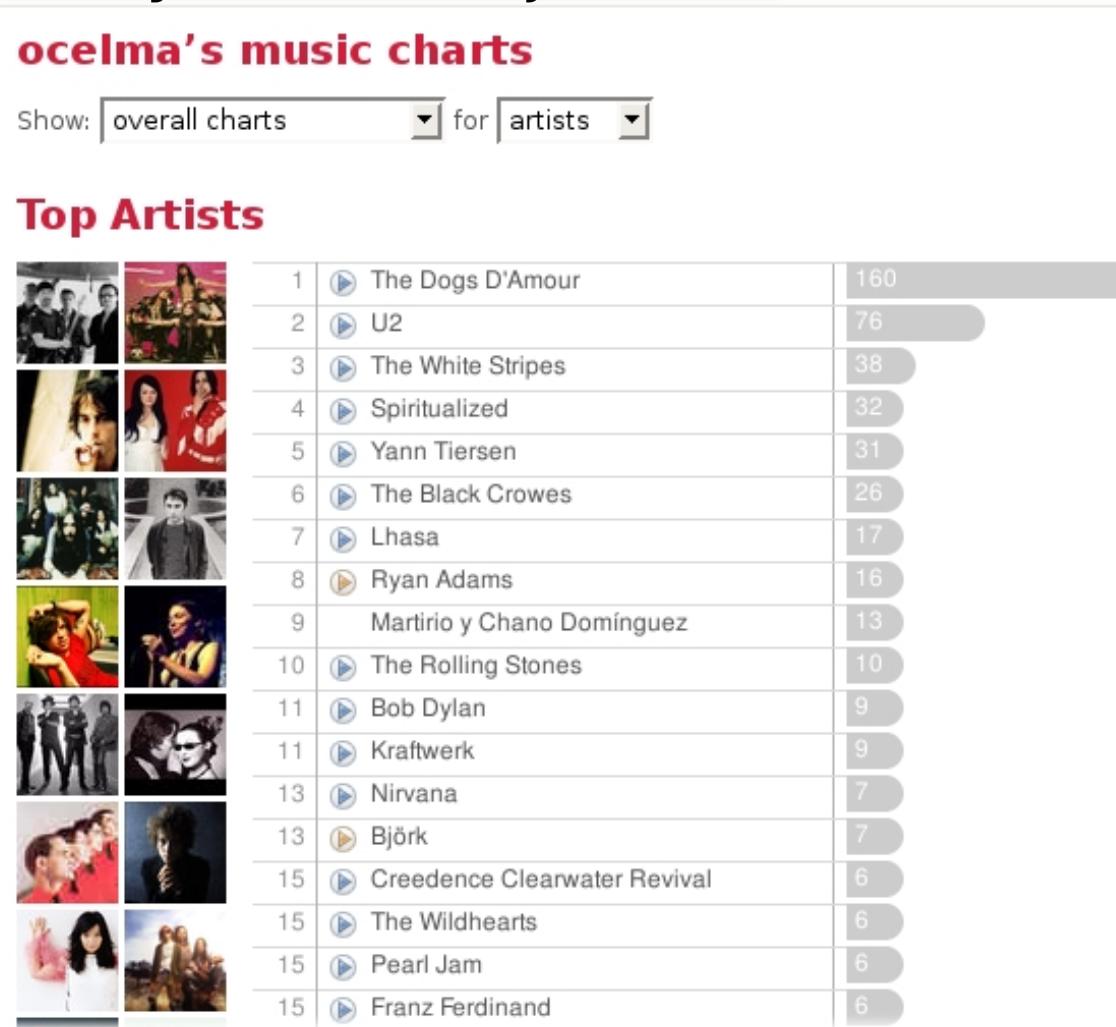
- ...me and myself (user profile)
 - ❖ music preferences
 - explicit
 - ❖ list of preferred / hated artists
 - ❖ list of preferred / hated songs
 - ❖ ratings / reviews / opinions (my blog)
 - ❖ (relevance feedback)
 - implicit
 - ❖ listening habits (play / stop / skip)
 - ❖ pages / blogs visited
 - ❖ ...

formalization:: describing users (me)

- ...me and myself (user profile)
 - ❖ a note about **implicit** and **explicit** data
 - Implicit data like purchases may be noisy, but it also can be more accurate
 - “I love *cool* Jazz (especially Chet Baker), as well as J.S.Bach fugues”

formalization:: describing users (me)

- ...me and myself (user profile)
 - ❖ Yeah, yeah... cool jazz and Bach!



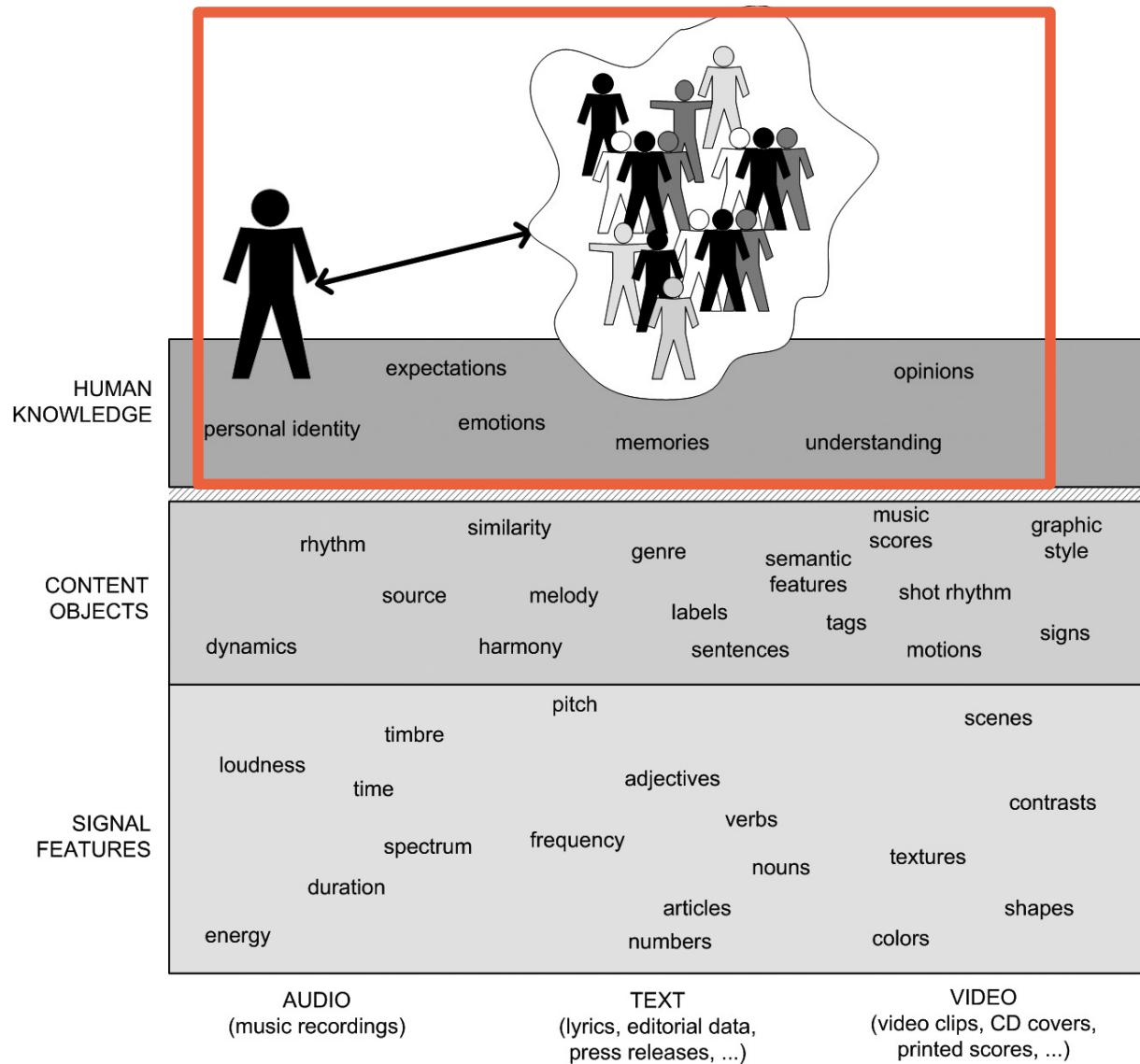
formalization:: describing users (me)

- ...me and myself (user profile)
 - ❖ Explicit data: People...
 - (1) usually **won't bother**,
 - (2) if they do bother, only provide **partial information** or even lie,
 - (3) even if they bother, tell the truth, and provide complete information, they usually **fail to update** their information over time."
 - ❖ From:
 - <http://glinden.blogspot.com/2007/05/explicit-vs-implicit-data-for-news.html>
 - <http://glinden.blogspot.com/2004/05/interview-with-craig-silverstein-from.html>

formalization:: describing users

USERS

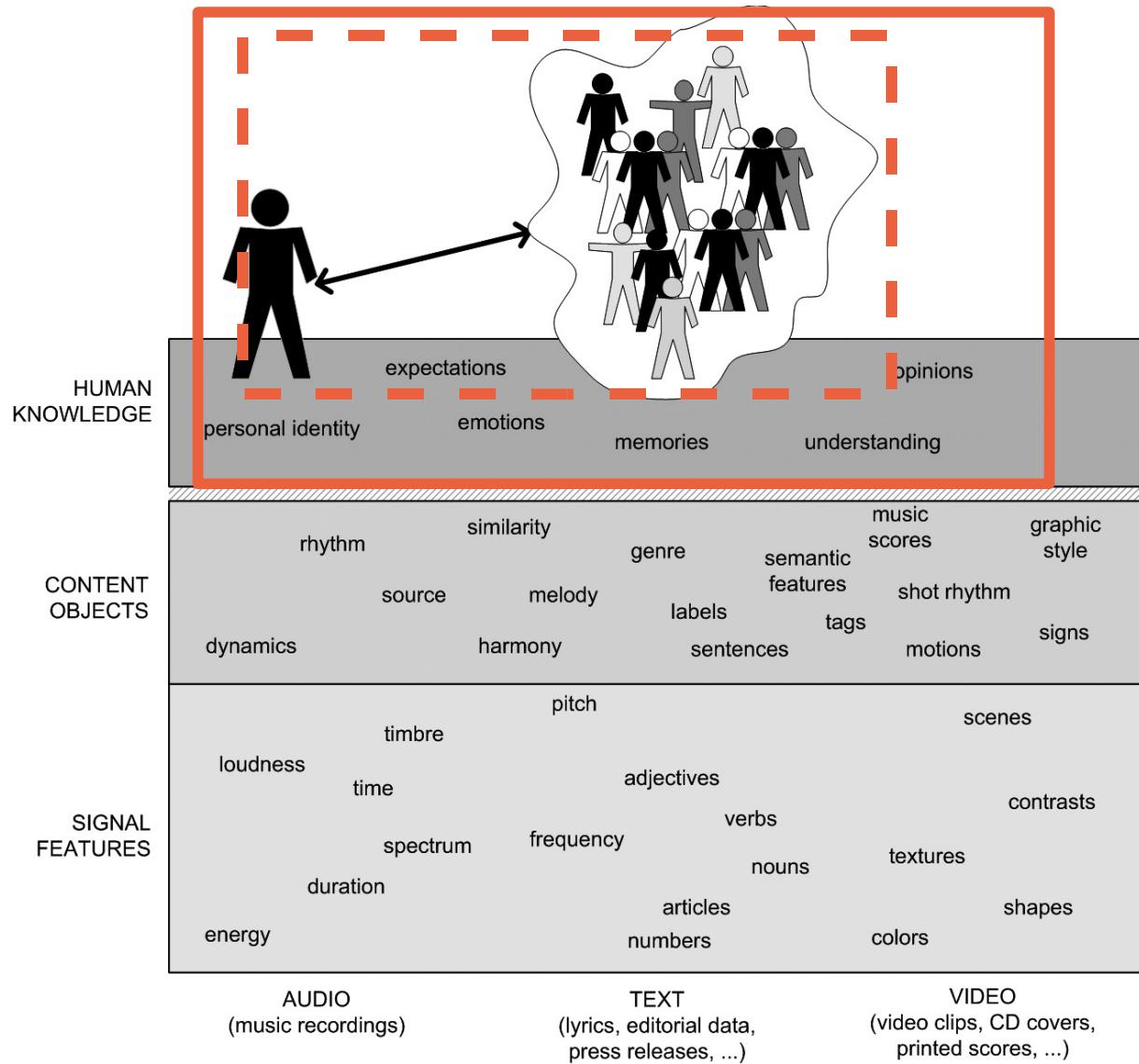
- get a better understanding of the users preferences!



formalization:: describing users (us)

USERS

- get a better understanding of the users preferences!



formalization:: describing users (us)

- me and the world (socializing) [Kazienko, 2006]
 - ❖ interaction with other users
 - ❖ relationships among users
 - duration
 - mutual watchings of blogs, artists pages, songs, etc.
 - common communications

formalization:: describing users (us)

- **BlueTuna** [Baumann, 2007]
 - ❖ a socializer: share your music tastes with people near by
 - ❖ meeting people who share the same music tastes
 - check with a mobile phone to see who in a close proximity has my tastes



formalization:: describing users :: languages

- Some representations
 - ❖ User Modelling for Information Retrieval Language (UMIRL)
 - ❖ MPEG-7
 - ❖ Friend of a Friend (FOAF)
 - ❖ General User Model Ontology (GUMO)
- ...based on XML/XMLSchema or RDF/OWL

formalization:: describing users :: umirl

- User Modelling for Information Retrieval Language (UMIRL) [Chai, 2000]
 - ❖ demographic & geographic information
 - ❖ music background and music preferences
 - ❖ create definition of a perceptual feature, and its context (usage)
 - perceptual feature: “a **romantic** piece has a **slow tempo, lyrics** are related with *love*, and has a **soft intensity**”
 - usage: while **having** a special **dinner** with **girlfriend**
 - ❖ Languages
 - XML
 - No XML Schema (!)

formalization:: describing users :: umirl

❖ a complete example...

```
<user>
  <generalbackground>
    <name>Joan Blanc</name>
    <education>MS</education>
    <citizen>Catalan</citizen>
    <sex>male</sex>
  </generalbackground>
  <musicbackground>
    <education>none</education>
    <instrument>guitar</instrument>
    <instrument>vocal</instrument>
  </musicbackground>
```

formalization:: describing users :: umirl

❖ a complete example...

```
<user>
  <generalbackground>
    <name>Joan Blanc</name>
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    <citizen>Catalan</citizen>
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  </generalbackground>
  <musicbackground>
    <education>none</education>
    <instrument>guitar</instrument>
    <instrument>vocal</instrument>
  </musicbackground>
  (continue...)
  <musicpreferences>
    <genre>blues</genre>
    <genre>rock</genre>
    <composer>Johann Sebastian Bach</composer>
    <artist>The Dogs d'Amour</artist>
    <sample>
      <title>Two hearts beat as one</title>
      <artist>U2</artist>
    </sample>
  </musicpreferences>
```

formalization:: describing users :: umirl

(continue....)

<**habit**>

<context>**Happy**

<tempo>very fast</tempo>

<genre>rock</genre>

</context>

<perceptualfeature>**Romantic**

<tempo>very slow</tempo>

<intensity>soft</intensity>

<lyrics>*love*</lyrics>

</perceptualfeature>

<context>**Dinner with fiance**

<perceptualfeature>**Romantic**</perceptualfeature>

</context>

</habit>

</user>

formalization:: describing users :: mpeg-7

- **MPEG-7**
 - ❖ “standard” for multimedia content description
 - ❖ Languages
 - XML
 - huge XML-Schema (!!!)
 - ❖ modeling user preferences
 - content filtering
 - searching and browsing
 - usage history
 - ❖ Example
 - “I like the album **To bring you my love**, from **P.J. Harvey**”

formalization:: describing users :: mpeg-7

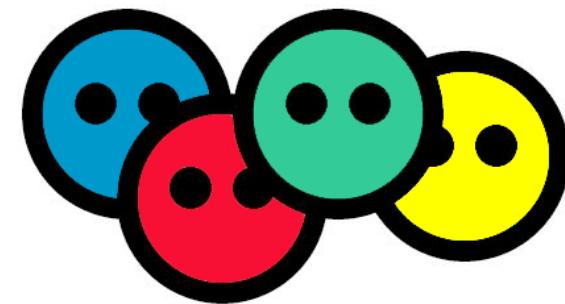
```
<UserPreferences>
  <UserIdentity protected="true">
    <Name xml:lang="ca">Joan Blanc</Name>
  </UserIdentity>
  <FilteringAndSearchPreferences>
    <CreationPreferences>
      <Title preferenceValue="8">To bring you my love</Title>
      <Creator>
        <Role>
          <Name>Singer</Name>
        </Role>
        <Agent xsi:type="PersonType">
          <Name>
            <GivenName>Polly Jean</GivenName>
            <FamilyName>Harvey</FamilyName>
          </Name>
        </Agent>
      </Creator>
```

(continue...)

```
        <Keyword>dramatic</Keyword>
        <Keyword>fiery</Keyword>
        <DatePeriod>
          <TimePoint>1995-01-01</TimePoint>
        </DatePeriod>
      </CreationPreferences>
    </FilteringAndSearchPreferences>
  </UserPreferences>
```

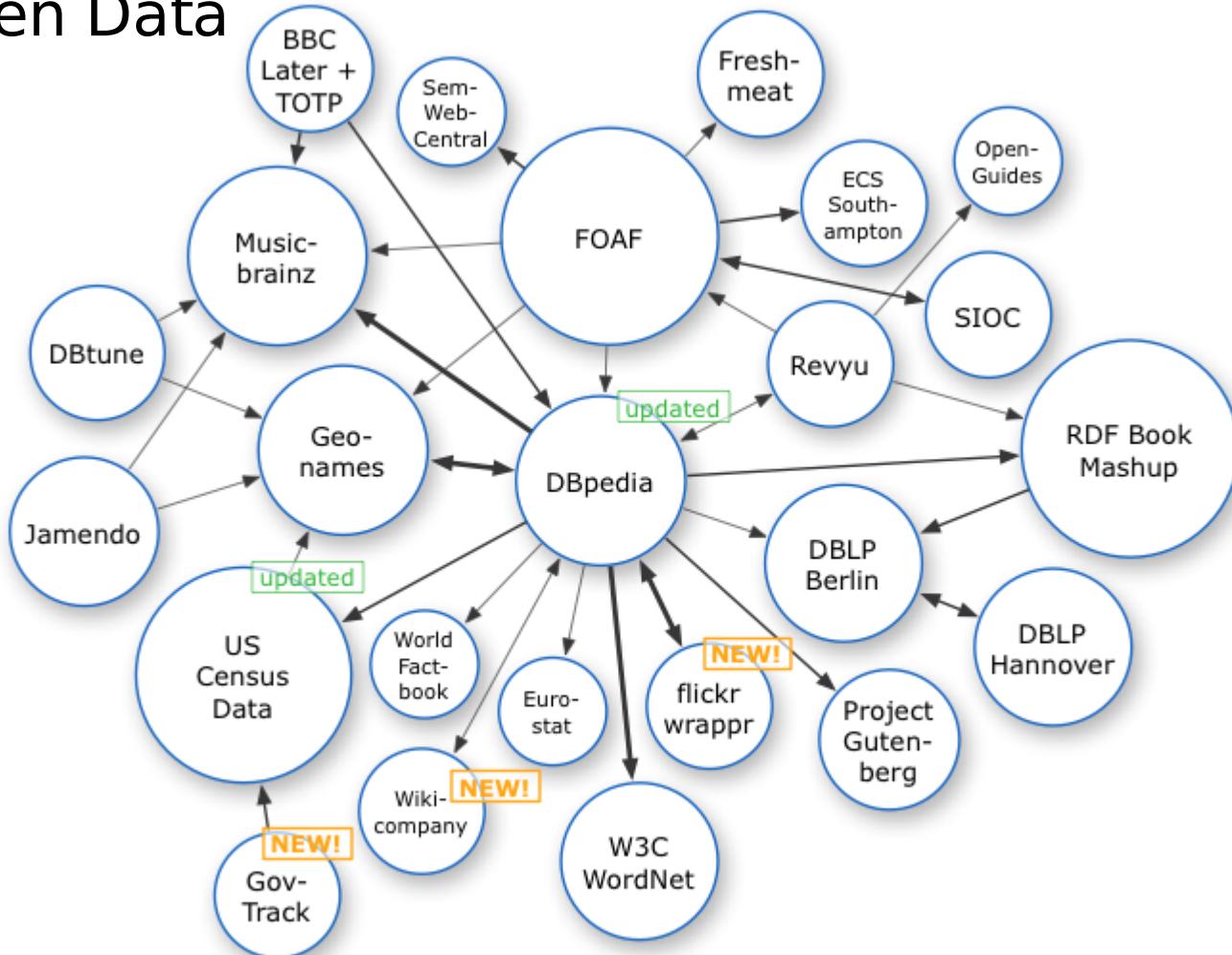
formalization:: describing users :: foaf

- Friend of a Friend (FOAF)
 - ❖ “a machine readable homepage”
 - ❖ semantic web flavour
 - add any available ontology
 - (in particular the Music Ontology)
 - ❖ Languages
 - OWL (the ontology)
 - RDF (the actual data)
 - ❖ Example
 - FOAFing the Music



formalization:: describing users :: foaf

- Friend of a Friend (FOAF)
 - ❖ Linking Open Data



formalization:: describing users :: foafexample

```
<foaf:Person rdf:ID="me">  
  <foaf:name>Oscar Celma</foaf:name>  
  <foaf:nick>ocelma</foaf:nick>  
  <foaf:gender>male</foaf:gender>  
  <foaf:depiction rdf:resource="http://www.iua.upf.edu/mtg/img/faces/ocelma.png" />  
  <foaf:homepage rdf:resource="http://www.iua.upf.edu/~ocelma"/>  
  <foaf:workplaceHomepage rdf:resource="http://mtg.upf.edu"/>  
  <foaf:mbox rdf:resource="mailto:oscar.celma@iua.upf.edu"/>  
  <foaf:based_near geo:lat='41.385' geo:long='2.186' />  
  <foaf:holdsAccount>  
    <foaf:OnlineAccount>  
      <foaf:accountName>ocelma</foaf:accountName>  
      <foaf:accountServiceHomepage rdf:resource="http://last.fm" />  
    </foaf:OnlineAccount>  
  </foaf:holdsAccount>  
  <foaf:interest dc:title="Gretsch Guitars" rdf:resource="http://en.wikipedia.org/wiki/Gretsch" />  
</foaf:Person>
```

formalization:: describing users :: foaf

- Add explicit music interests and preferences into a FOAF profile
 - ❖ using the Music Ontology [Raimond, 2007]
 - ❖ Example
 - “I like the album **To bring you my love**, from **P.J. Harvey**”

formalization:: describing users :: foafexample

```
<foaf:interest>

<mo:Record rdf:about="http://zitgist.com/music/record/24e5b7f5-14cd-4a65-b87f-91b5389a4e3a">

  <dc:title>To bring you my love</dc:title>
  <dcterms:created>1995-02-22T00:00:00Z</dcterms:created>
  <mo:releaseType rdf:resource="http://purl.org/ontology/mo/album"/>
  <mo:releaseStatus rdf:resource="http://purl.org/ontology/mo/official"/>
  <mo:discogs rdf:resource="http://www.discogs.com/release/379469"/>
  <foaf:img rdf:resource="http://g-ec2.images-amazon.com/images/I/21cwiSYVYkL.jpg"/>

  <foaf:made>

    <mo:MusicGroup rdf:about='http://zitgist.com/music/artist/e795e03d-b5d...fb308a2c'>
      <foaf:name>Polly Jean Harvey</foaf:name>
      <mo:discogs rdf:resource="http://www.discogs.com/artist/PJ+Harvey" />
      <mo:wikipedia rdf:resource="http://en.wikipedia.org/wiki/PJ_Harvey" />
    </mo:MusicGroup>
  </foaf:made>
</mo:Record>
</foaf:interest>
```

formalization:: describing users :: gumo

- General User Model Ontology (GUMO) [Heckmann, 2007]
 - ❖ top level ontology
 - ❖ Aim
 - exchange of user profile data between adaptive systems
 - ❖ includes the Big Five personality traits
 - Neuroticism, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience
 - ❖ Language
 - OWL

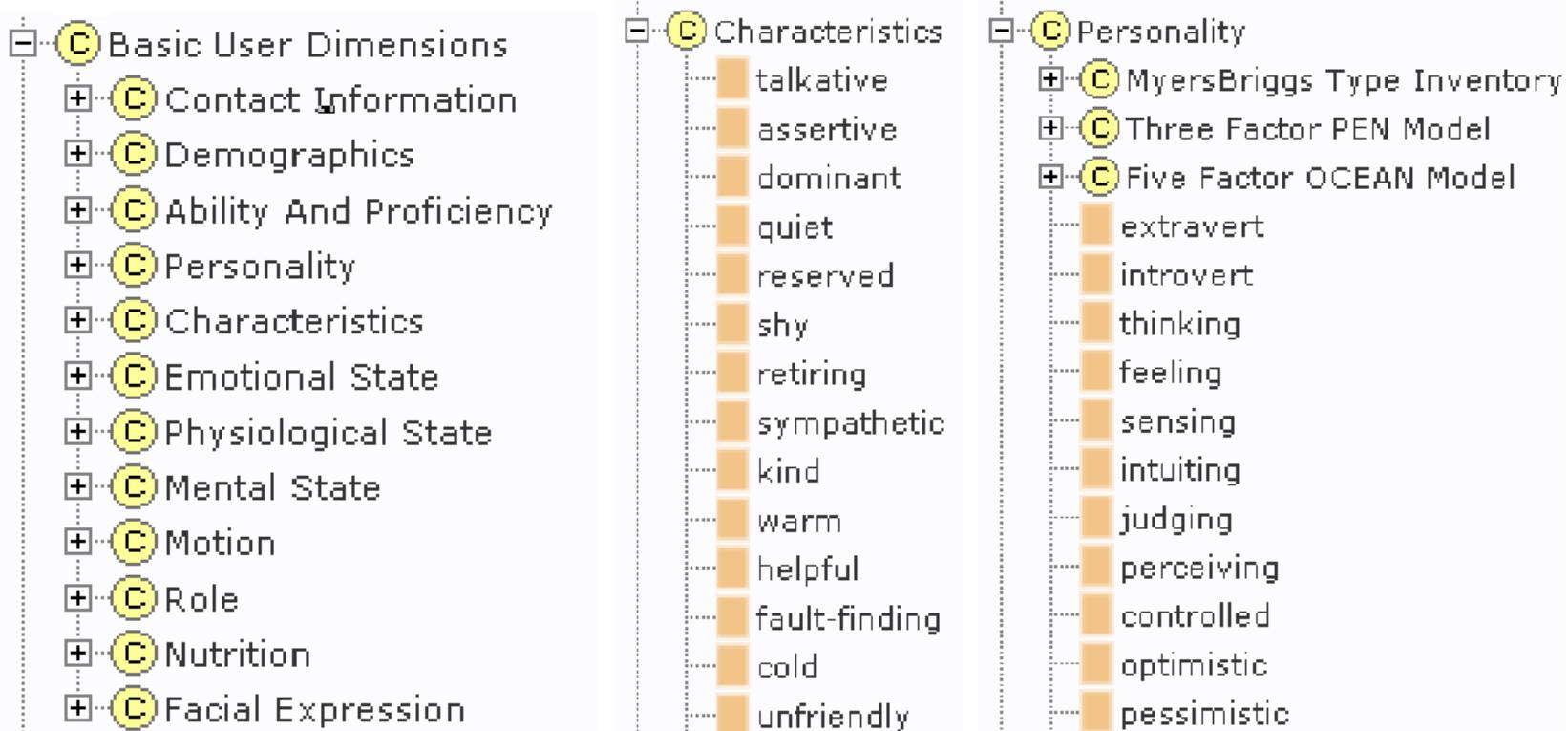
formalization:: describing users :: gumo

❖ main elements

- [C] Basic User Dimensions
 - + [C] Contact Information
 - + [C] Demographics
 - + [C] Ability And Proficiency
 - + [C] Personality
 - + [C] Characteristics
 - + [C] Emotional State
 - + [C] Physiological State
 - + [C] Mental State
 - + [C] Motion
 - + [C] Role
 - + [C] Nutrition
 - + [C] Facial Expression
- [C] Emotional State
 - + [C] Five Basic Emotions
 - happiness
 - anxiety
 - fear
 - love
 - hate
 - pride
 - shame
 - anger
 - disgust
 - sadness
 - satisfaction
 - confusion

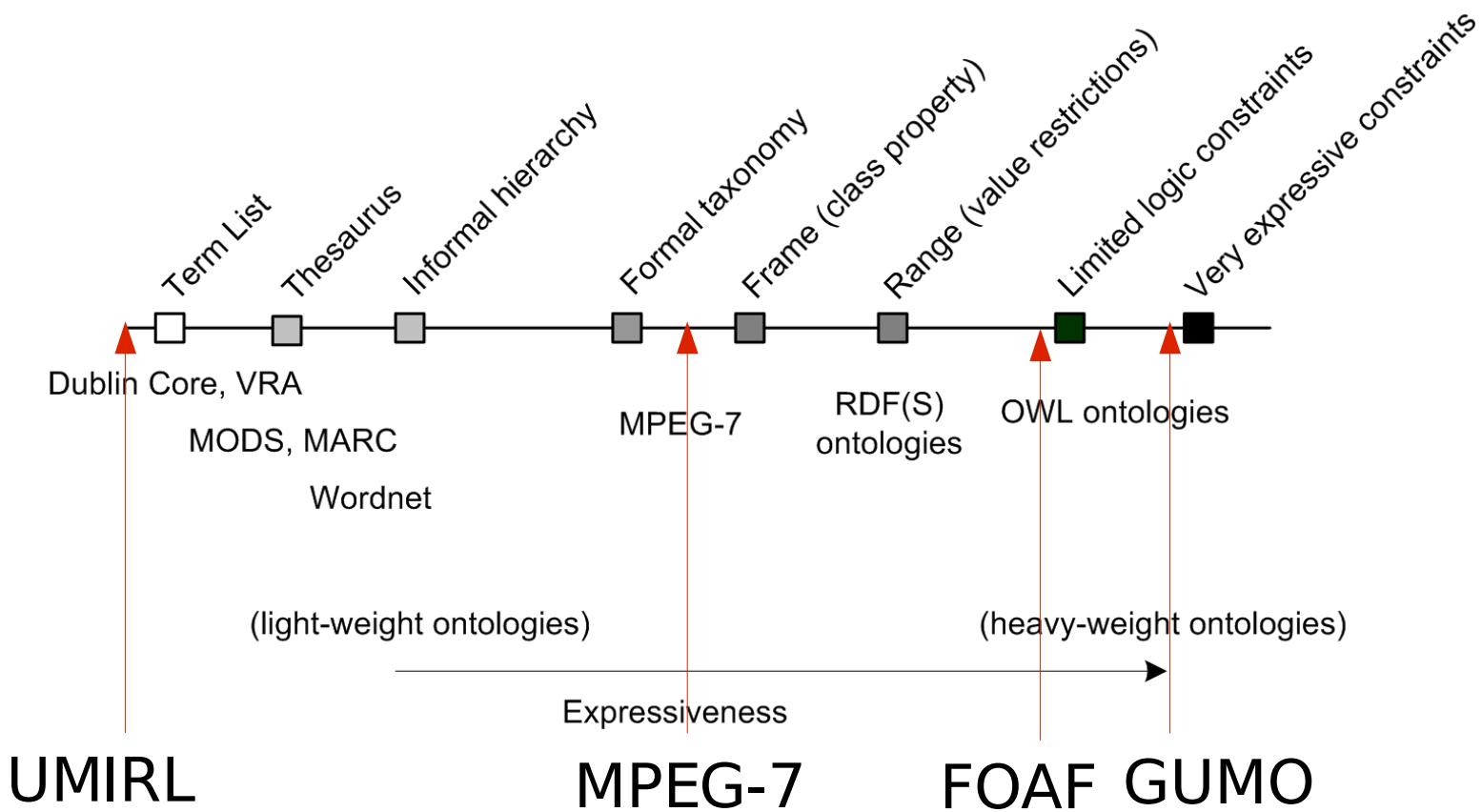
formalization:: describing users :: gumo

❖ main elements



formalization:: describing users

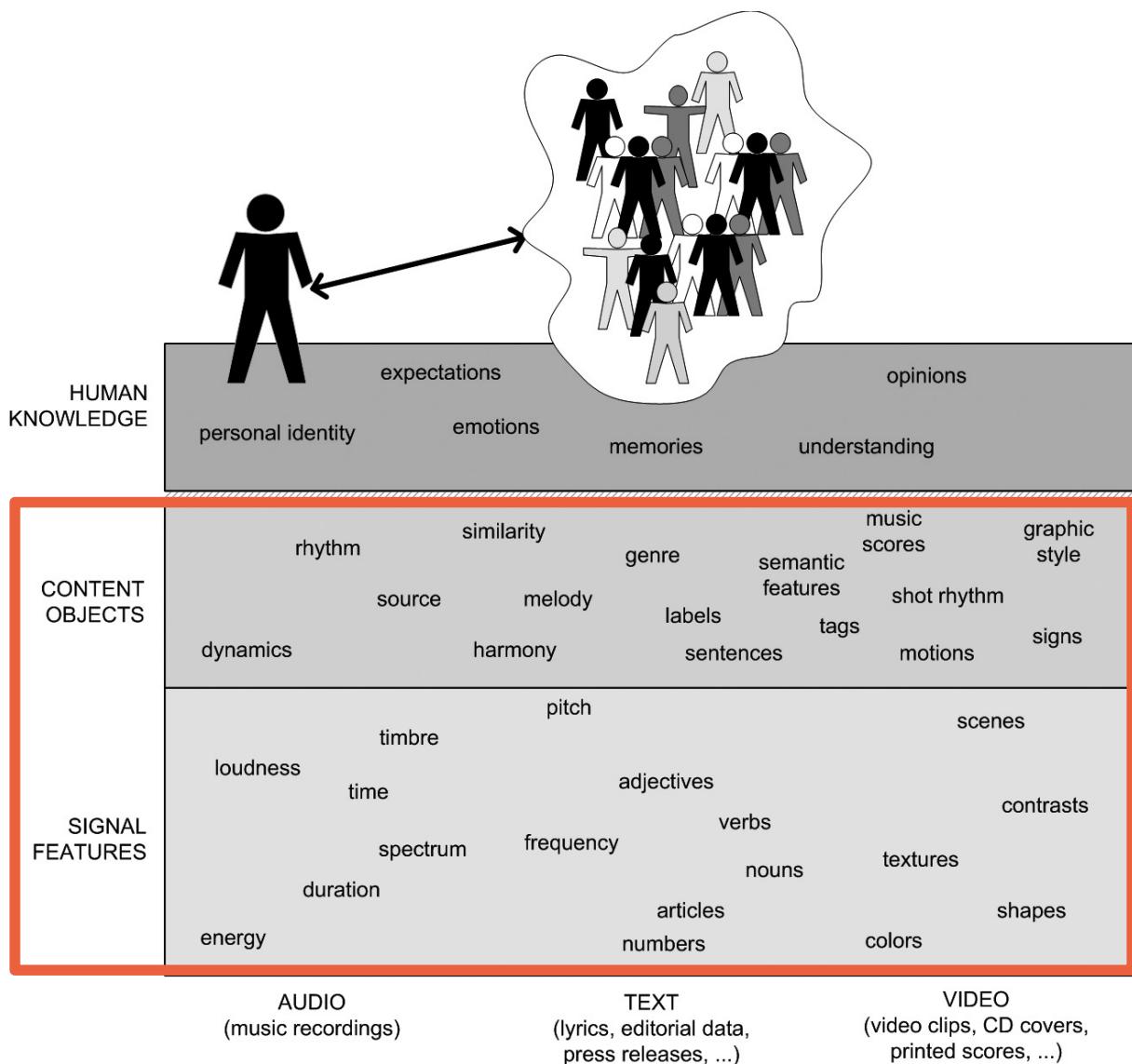
- Complexity and expressiveness of the representations



formalization:: describing users

- Issues
 - ❖ What about all the information that the user has on the "Web 2.0" (her blog, her *other* accounts, etc)? How to exploit them?
 - ❖ What about multiple-profiles?
 - me-at-work, me-at-home or me-on-weekends, etc.
 - ❖ Each system handles user information in their way
 - No interoperability between systems
 - Most information is not used

formalization:: describing items

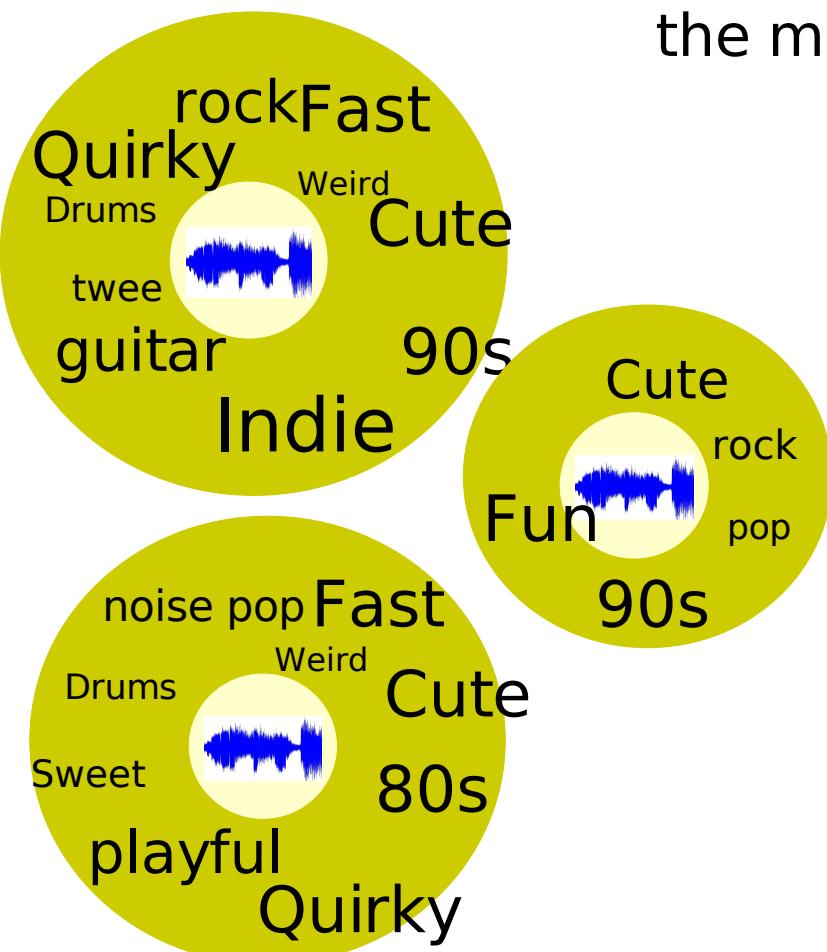


formalization:: describing items

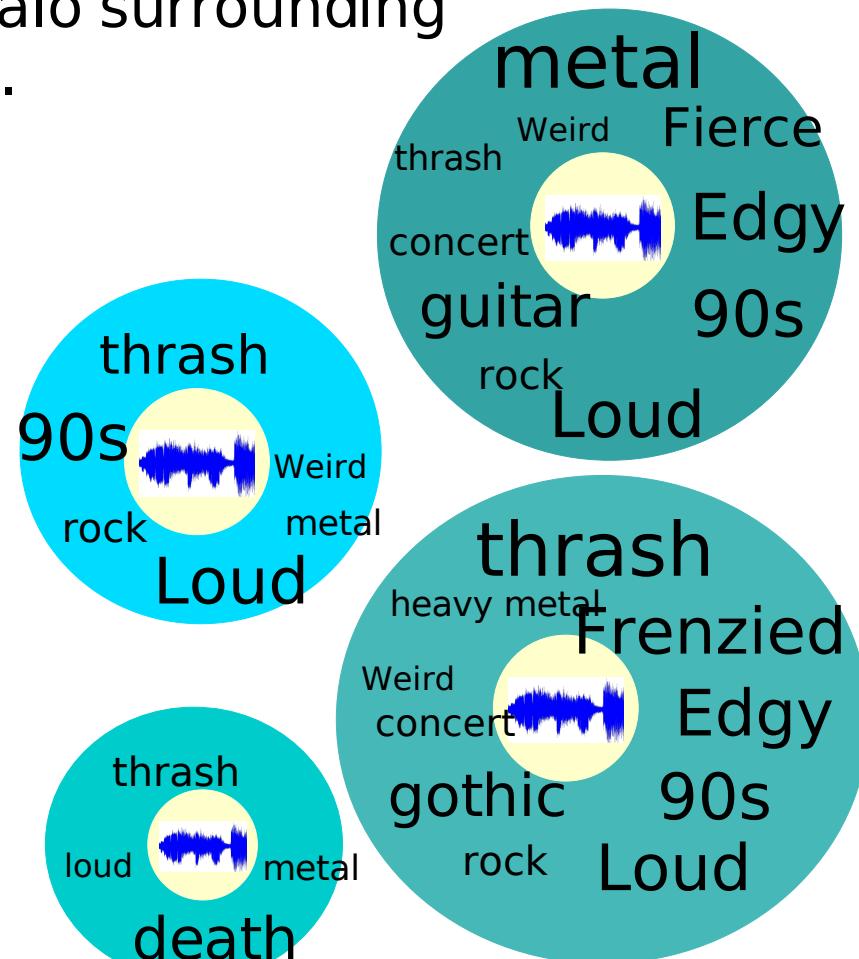
- Text description – using the halo of text surrounding music
 - ❖ Expert-applied metadata
 - ❖ Web Mining
 - Reviews, Playlists, Lyrics
 - ❖ Tagging
 - last.fm, qloud
- Audio description
 - ❖ instrumentation / tonality / rhythm / timbre
 - Manual – Pandora, SoundFlavor
 - Automatic – Owl MM, MusicIP, One Llama, SITM, BMAT

formalization:: describing items :: text

- the text halo



Similarity based upon the text halo surrounding the music.



formalization:: describing items :: text

- determining similarity of text

- ❖ Traditional text information retrieval technique: TF x IDF

- TF – Term Frequency – a measure of the frequency of a term (word) within a document
 - IDF – Inverse Document Frequency
 - ❖ Measure of a term's rarity across the set of documents
 - ❖ Could be: 1 / document frequency
 - ❖ But more typically: $\log(n / df)$

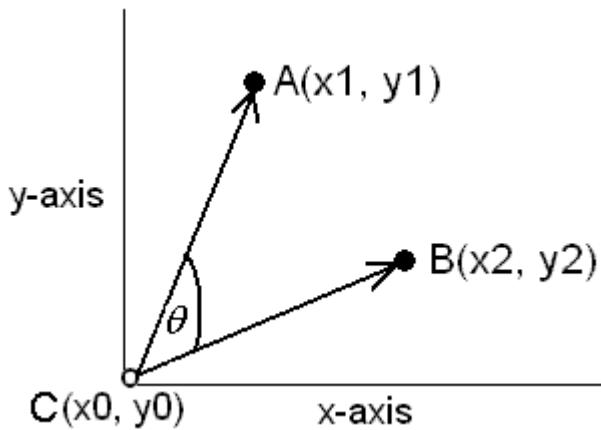
$$tf_i = \frac{n_i}{\sum_k n_k}$$

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

$$tfidf = tf \cdot idf$$

formalization:: describing items :: text

- determining similarity of text
 - ❖ cosine similarity



$$\text{Sim}(A, B) = \text{cosine } \theta = \frac{\mathbf{A} \bullet \mathbf{B}}{|\mathbf{A}| |\mathbf{B}|} = \frac{x_1 * x_2 + y_1 * y_2}{(x_1^2 + y_1^2)^{1/2} (x_2^2 + y_2^2)^{1/2}}$$

formalization:: describing items :: text

- Expert-applied metadata

- ❖ **Deerhoof:**

- **Genre:** rock

- **Styles:**

- Indie Rock, Noise Pop, Noise-Rock, Post-Rock, Experimental

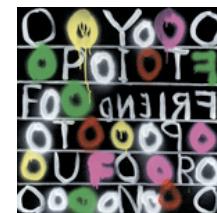
- **Moods:**

- Volatile, Freewheeling, Energetic, Whimsical, Playful, Rambunctious, Exuberant, Carefree, Irreverent, Springlike, Fun, Bittersweet, Cheerful, Cathartic, Innocent, Messy, Sweet, Precious, Naïve

- **Similar Artists:** Persephone's Bees, Black Dice ...

- **Influenced By:** Boredoms, Yoko Ono ...

- **Followers:** The Mae Shi ...



formalization:: describing items :: text

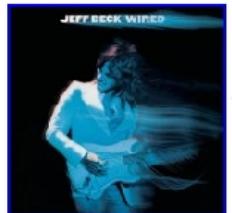
Six Degrees of Black Sabbath

Starting Artist: Jeff Beck

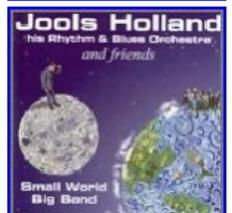
Ending Artist: Beck

[Find Path](#)

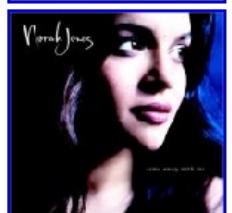
I can find a path from **Jeff Beck** to **Beck** in 3 steps.



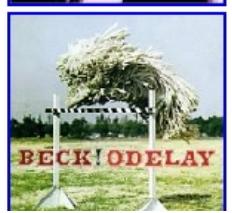
Jeff Beck who [performed with](#)
[neighbors](#) [start](#) [end](#)



Jools Holland & His Rhythm & Blues Orchestra who [performed with](#)
 ↳ bypass [neighbors](#) [start](#) [end](#)



Norah Jones who [performed with](#)
 ↳ bypass [neighbors](#) [start](#) [end](#)



Beck
[neighbors](#) [start](#) [end](#)

Fun with metadata



formalization:: describing items :: text

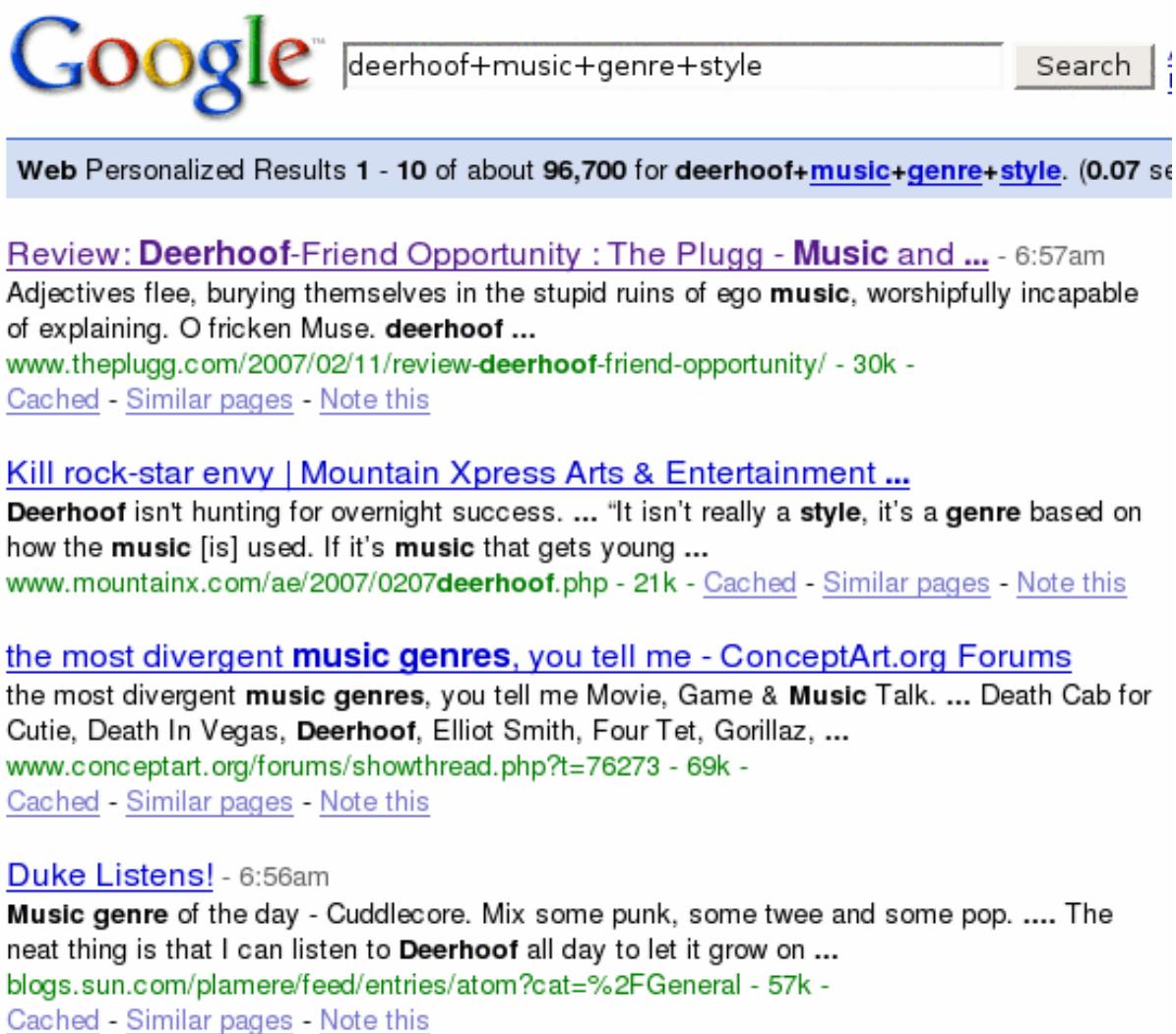
- deerhoof biography



By turns **cuddly** and **chaotic**, San Francisco's Deerhoof mixes **noise**, **sugary melodies**, and an **experimental** spirit into **sweetly challenging** and utterly **distinctive** music. The group began as the brainchild of guitarist Rob Fisk and drummer/keyboardist Greg Saunier in 1994; early releases, such as 1995's 7"s Return of the Woods M'Lady and For Those of Us on Foot, had a more traditionally **harsh**, **no wave-inspired** sound, though they also included the **quirky tendencies** that dominated their later efforts.

formalization:: describing items :: text

- Web mining



Google™ deerhoof+music+genre+style Search

Web Personalized Results 1 - 10 of about 96,700 for **deerhoof+music+genre+style**. (0.07 se

[Review: Deerhoof-Friend Opportunity : The Plugg - Music and ...](#) - 6:57am
Adjectives flee, burying themselves in the stupid ruins of ego **music**, worshipfully incapable of explaining. O fricken Muse. **deerhoof** ...
www.theplugg.com/2007/02/11/review-deerhoof-friend-opportunity/ - 30k -
[Cached](#) - [Similar pages](#) - [Note this](#)

[Kill rock-star envy | Mountain Xpress Arts & Entertainment ...](#)
Deerhoof isn't hunting for overnight success. ... "It isn't really a **style**, it's a **genre** based on how the **music** [is] used. If it's **music** that gets young ...
www.mountainx.com/ae/2007/0207deerhoof.php - 21k - [Cached](#) - [Similar pages](#) - [Note this](#)

[the most divergent music genres, you tell me - ConceptArt.org Forums](#)
the most divergent **music genres**, you tell me Movie, Game & **Music** Talk. ... Death Cab for Cutie, Death In Vegas, **Deerhoof**, Elliot Smith, Four Tet, Gorillaz, ...
www.conceptart.org/forums/showthread.php?t=76273 - 69k -
[Cached](#) - [Similar pages](#) - [Note this](#)

[Duke Listens! - 6:56am](#)
Music genre of the day - Cuddlecore. Mix some punk, some twee and some pop. The neat thing is that I can listen to **Deerhoof** all day to let it grow on ...
blogs.sun.com/plamere/feed/entries/atom?cat=%2FGeneral - 57k -
[Cached](#) - [Similar pages](#) - [Note this](#)

formalization:: describing items :: text

- Web mining
 - ❖ Music blogs



Deerhoof's new album, Friend Opportunity is **amazing**. I've never been a gung-ho **fan**, despite having numerous friends **rave** to me about how **awesome** these Bay Area **indie-rock** mainstays are. But this new full-length album strikes me immediately as their **finest to date**. **Not bad** for a group 12-years into its career. Its **radiant** yet skewed **beauty** and **surprising dynamics** set a towering example for how **indie** rock should sound and move in 2007. You can sense that they have intimate knowledge of **no wave**, **sunshine pop**, **astral jazz**, **Captain Beefheart**, **J pop**, **Raincoats**, **Polvo**, **Boredoms**, and many other exemplary touchstones. Yet they weave these styles and influences so adroitly that the resultant songs are instantly identifiable as only Deerhoof compositions.

formalization:: describing items :: text

- Web mining
 - ❖ Heavy metal terms

100	*sabbath	26	heavy	17	riff	12	butler
97	*pantera	26	ulrich	17	leaf	12	blackened
89	*metallica	26	vulgar	17	superjoint	12	bringin
72	*leppard	25	megadeth	17	maiden	12	purple
58	metal	25	pigs	17	armageddon	12	foolin
56	hetfield	24	halford	17	gillan	12	headless
55	hysteria	24	dio	17	ozzfest	12	intensity
53	ozzy	23	reinventing	17	leps	12	mob
52	iommi	23	lange	16	slayer	12	excitable
42	puppets	23	newsted	15	purify	12	ward
40	dimebag	21	leppards	15	judas	11	zeppelin
40	anselmo	21	adrenalize	15	hell	11	sandman
40	pyromania	21	mutt	15	fairies	11	demolition
40	paranoid	20	kirk	15	bands	11	sanitarium
39	osbourne	20	riffs	15	iron	11	*black
37	*def	20	s&m	14	band	11	appice
34	euphoria	20	trendkill	14	reload	11	jovi
32	geezer	20	snowblind	14	bassist	11	anger
29	vinnie	19	cowboys	14	slang	11	rocked
28	collen	18	darrell	13	wizard	10	drummer
28	hammett	18	screams	13	vivian	10	bass
27	bloody	18	bites	13	elektra	9	rocket
27	thrash	18	unforgiven	13	shreds	9	evil
27	phil	18	lars	13	aggression	9	loud
26	lep	17	trujillo	13	scar	9	hard

formalization:: describing items :: text

- Web mining
 - ❖ playlists: Mine music playlist sites for song and artist co-occurrence

» Living Room	Basement Jaxx
» Wonderland (The S-Mans Dark Tribe	The Psychedelic Walto
» Lisbon Acid	AFX
» Flashdance (Club Mix)	Deep Dish
» Love And Imitation	Infusion
» Do It Now (Extended Disco Version)	Dubtribe Sound System
» Wir Sind Die Anderen (Boris Dl	2raumwohnung
» Steppin Out	Kaskade
» Black Water (Vocal Mix)	Octave One
» Pornography	Client
» Du What Ya Du (Trentemoller Mix)	Yoshimoto



formalization:: describing items :: text

- Lyric similarity
 - ❖ Recommend music based upon similarity of the lyrics:
 - ❖ Seed song: Led Zeppelin's Gallows Pole
 - Peter, Paul & Mary: Hangman
 - Robert Plant: Hey Joe
 - Dust for life: The End
 - The Walkabouts: Hang Man
 - Smog: Hangman blue
 - Bay Laurel: We Lost
 - Samael: Worship him



LyricWiki.org

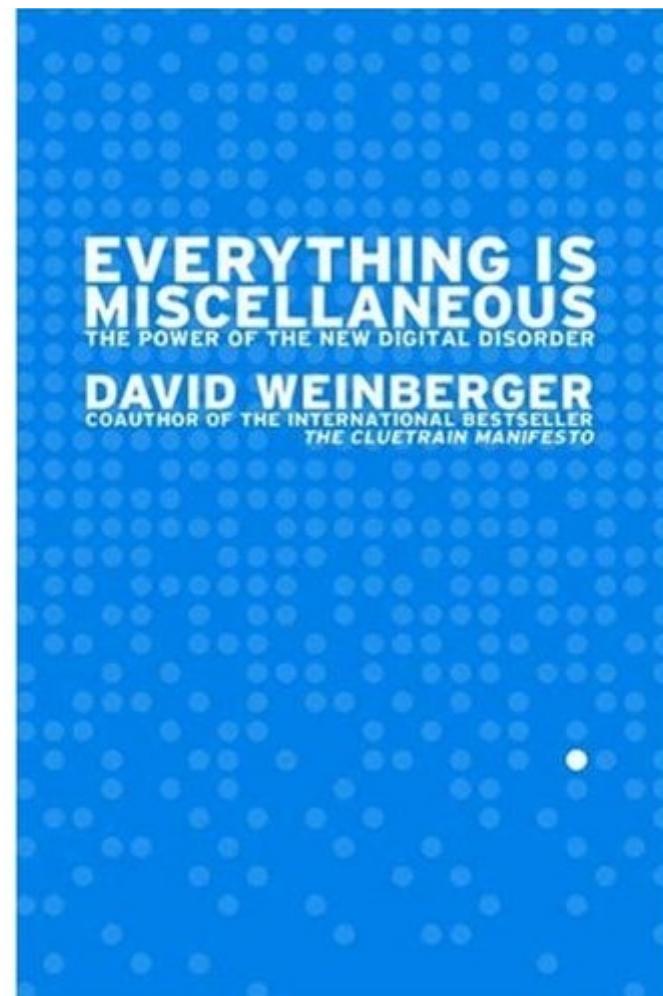
formalization:: describing items :: text

- Lyric similarity
- **Led Zeppelin: Gallows Pole:** Hangman, hangman, hold it a little while, Think I see my friends coming, Riding a many mile.
- **Peter, Paul & Mary: Hangman:** Slack your rope hangman, slack it for a while think I see my father comin' ridin' many a mile Father have you brought me hope or have you paid my fee Or have you come to see me hangin' from the gallows tree?
- **The Walkabouts: Hang Man:** Hangman take these heads from me And swing 'em from your money tree Hear me laughing in my steps These heads are yours, they're yours to keep
- **Bay Laurel: We Lost:** Our hangman will wait until the end Our hangman will smile he knows you can There is no need to let me slip by Make me feel closer... my grave
- **Samael:Worship Him:** He is the fire of vengeance He is the blade of revenge He is the executioner's axe He is the hangman's rope

formalization:: describing items :: text :: tags

ISMIR – Isn't Social Music Incredibly Relevant?

- Social tags
 - ❖ Collaborative Categorization
 - ❖ 'Folksonomy'
 - ❖ Some examples:
 - Del.icio.us, Flickr, LibraryThing
 - Last.fm, Qloud, MusicMobs
 - ❖ Why do people tag?
 - Personal organization



formalization:: describing items :: text :: tags

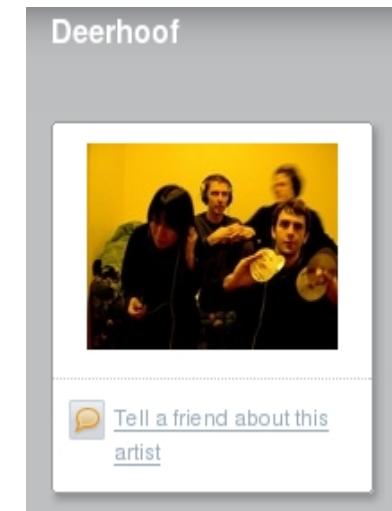
- Social tags

Browse by Tags

drums experimental instrumental **punk** sickdrums

Popular Tags for This Artist

00s alternative alternative rock ambient american americana art punk art rock avant-garde california canadian
classic rock downtempo drone electronic electronica energetic **experimental** experimental
rock female vocalists folk fun funk fusion happy hip-hop **indie** indie pop **indie**
rock industrial japanese jazz kill rock stars lo-fi math rock metal new wave **noise** noise pop **noise**
rock noise-rock pop post rock post-punk post-rock power pop psychedelic rock punk rap **rock** san francisco
seen live shoegaze singer-songwriter smooth soul stoner rock sweet trumpet weird



formalization:: describing items :: text :: tags

- Social tags
 - ❖ Tags – The Shins

Tag	Freq	Tag	Freq	Tag	Freq
Indie	2375	The Shins	190	Punk	49
Indie rock	1138	Favorites	138	Chill	45
Indie pop	841	Emo	113	Singer-songwriter	41
Alternative	653	Mellow	85	Garden State	39
Rock	512	Folk	85	Favorite	37
Seen Live	298	Alternative rock	83	Electronic	36
Pop	231	Acoustic	54	Love	35

Table 1: Top 21 tags applied to *The Shins*

The Shins



The Shins performing in London, March 2007

Background information

Origin  Albuquerque, New Mexico

Genre(s) Indie rock
Indie pop

Years active 1997–present

Label(s)  Sub Pop
 Transgressive (distributing label)
 Cargo Records (distributing label)

Website www.theshins.com 

Members

James Mercer
Martin Crandall
Dave Hernandez
Jesse Sandoval
Eric Johnson

Former members

Neal Langford

formalization:: describing items :: text :: tags

- Social tags

- ❖ Artist similarity based on tags for The Beatles

Top Tags

- ❖ classic rock
- ❖ rock
- ❖ pop
- ❖ british
- ❖ 60s
- ❖ oldies
- ❖ psychedelic
- ❖ alternative
- ❖ indie
- ❖ britpop

Distinctive Tags

- ❖ The Beatles
- ❖ 60s
- ❖ liverpool
- ❖ british
- ❖ british psychedelia
- ❖ oldies
- ❖ britrock
- ❖ psychedelic
- ❖ classic rock
- ❖ Rock and Roll

Similar Artists via Tags

- ❖ John Lennon
- ❖ Rolling Stones
- ❖ Paul McCartney
- ❖ The Kinks
- ❖ The Who
- ❖ Pink Floyd
- ❖ Queen
- ❖ The Police
- ❖ Led Zeppelin
- ❖ David Bowie

5628 unique tags have been applied to the Beatles

formalization:: describing items :: text :: tags

- Social tags

- ❖ Tag similarity based on artists

Metal

- ❖ Metallica
- ❖ System of a down
- ❖ Iron Maiden
- ❖ Rammstein
- ❖ Slipknot
- ❖ In Flames
- ❖ Korn
- ❖ Pantera
- ❖ Judas Priest

Heavy Metal

- ❖ Iron Maiden
- ❖ Judas Priest
- ❖ Black Sabbath
- ❖ Manowar
- ❖ Motorhead
- ❖ Pantera
- ❖ Megadeth
- ❖ Ozzy Osbourne
- ❖ Dio

Pop

- ❖ Madonna
- ❖ The Beatles
- ❖ Black Eyed Peas
- ❖ Beach Boys
- ❖ Kelly Clarkson
- ❖ Michael Jackson
- ❖ Gwen Stefani
- ❖ Coldplay
- ❖ U2

formalization:: describing items :: text :: tags

- Social tags

- ❖ Tag similarity based on artists

Metal

- ❖ Heavy Metal
- ❖ Death metal
- ❖ Hard Rock
- ❖ Thrash Metal
- ❖ Progressive Metal
- ❖ Rock
- ❖ Metalcore
- ❖ Seen live
- ❖ Melodic Death Metal
- ❖ Power Metal
- ❖ Gothic Metal

Pop

- ❖ Rock
- ❖ Alternative
- ❖ Female vocalists
- ❖ Indie
- ❖ Singer-Songwriter
- ❖ Classic Rock
- ❖ Favorites
- ❖ 80s
- ❖ Seen Live
- ❖ Dance
- ❖ Pop Rock

Classical

- ❖ Composers
- ❖ Clasica
- ❖ Eurite Music
- ❖ Baroque
- ❖ Classic
- ❖ Opera
- ❖ Instrumental
- ❖ Orchestral
- ❖ Piano
- ❖ Romantic
- ❖ Vivaldi

formalization:: describing items :: text :: tags

- Social tags
 - ❖ Tag clustering example

Explore / Tags / apple / clusters

Jump to:



[mac](#), [macintosh](#), [ipod](#),
[powerbook](#), [computer](#), [laptop](#), [ibook](#),
[imac](#), [g4](#), [macbook](#)

→ [See more in this cluster...](#)



[fruit](#), [red](#), [food](#), [apples](#), [green](#),
[macro](#), [orange](#), [tree](#), [banana](#)

→ [See more in this cluster...](#)



[osx](#), [screenshot](#), [desktop](#), [tiger](#)

→ [See more in this cluster...](#)

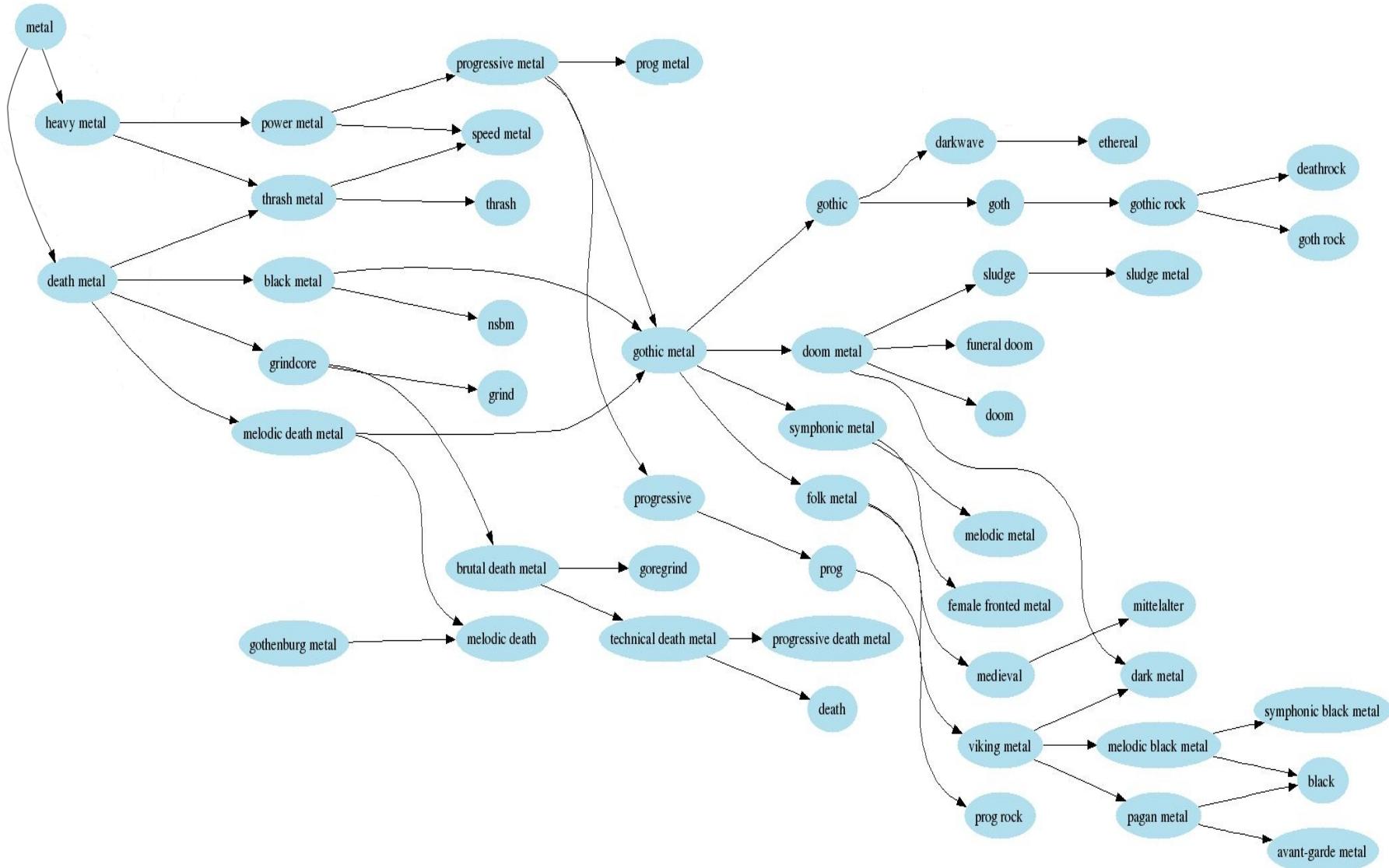


[nyc](#), [newyork](#), [applestore](#),
[newyorkcity](#), [manhattan](#)

→ [See more in this cluster...](#)

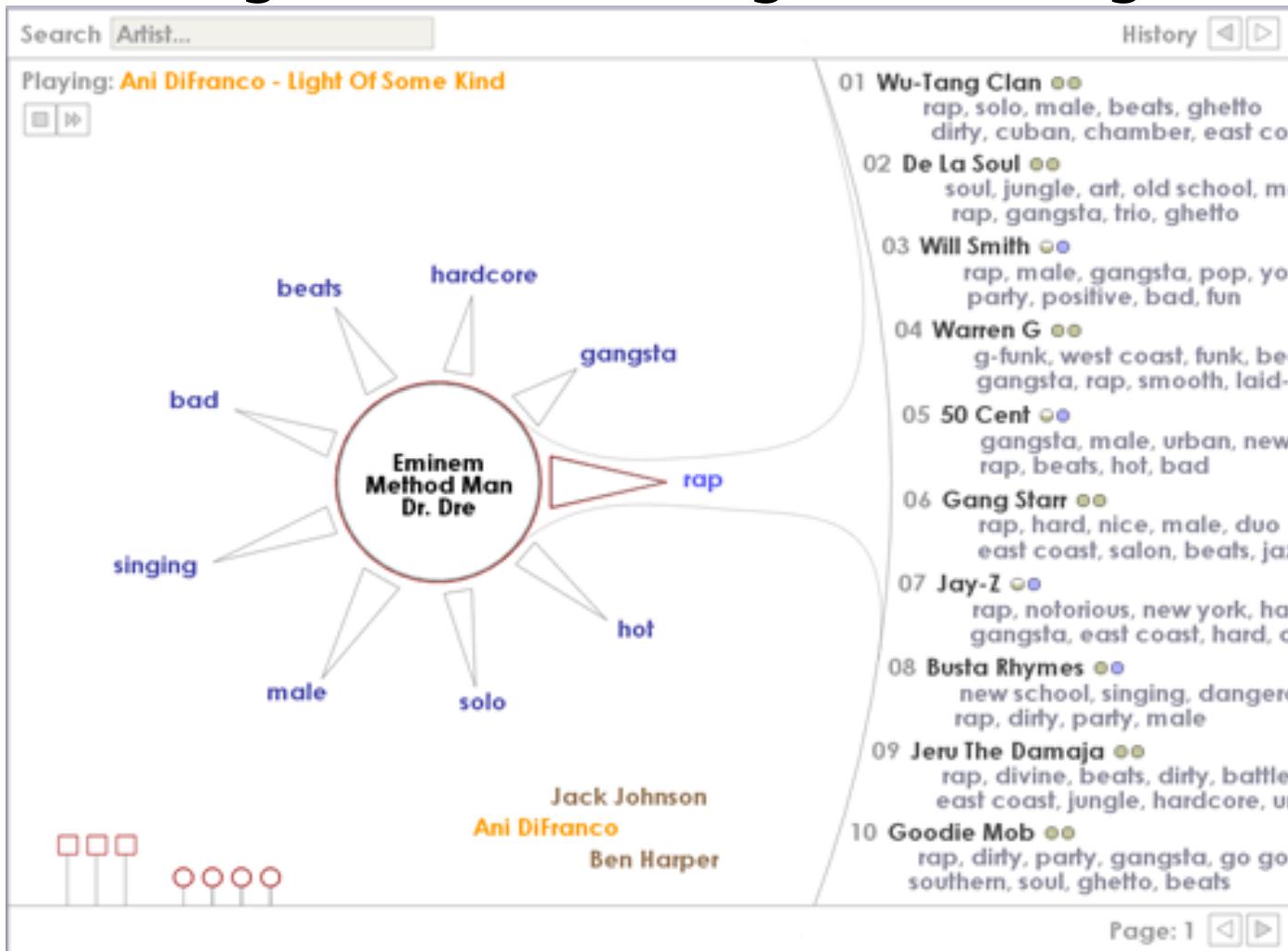
formalization:: describing items :: text :: tags

Social tags -Tag browsing: the world of metal



formalization:: describing items :: text :: tags

- Social tags -Faceted Tag browsing



formalization:: describing items :: text :: tags

- Social tags
 - ❖ Distribution of Tags

Type	Freq	Examples
Genre	68%	Heavy metal, punk
Locale	12%	French, Seattle
Mood	5%	Chill, party
Opinion	4%	Love, favorite
Instrumentation	4%	Piano, female vocal
Style	3%	Political, humor
Misc	3%	Coldplay, composers
Personal	1%	Seen live, I own it

formalization:: describing items :: text :: tags

- Social tags: Issues

- ❖ Polysemy

- progressive
 - love

- ❖ Synonymy

- hip hop, hip-hop, hiphop, rap

- ❖ Personal tags:

- Seen live, I own it, Favorite

- ❖ Noise

- stuff a donut would like, woot, Lazy-eye

formalization:: describing items :: text :: tags

- Issues - Population bias: last.fm tags

All Music	Genre	Rank	Volume	Metal Tags	Rank
Rock		1	1	Metal	4
Electronica		5	0.36	Death Metal	16
Rap		9	0.21	Black Metal	26
Jazz		18	0.15	Metal Core	34
Classical		52	0.06	Power Metal	35
Blues		55	0.06	Thrash Metal	36
R&B		66	0.05	Progressive Metal	37
Country		68	0.04	Melodic Death Metal	42
World		121	0.02	Gothic Metal	54
				Doom Metal	59
				Folk Metal	75
				Nu Metal	83
				Symphonic Metal	88
				Industrial Metal	89
				Viking Metal	103

Gothic Metal more popular than Country

formalization:: describing items :: text :: tags

- Social tags: Issues
 - ❖ Sparsity of data

Browse by Tags

drums experimental instrumental **punk** sickdrums

- Not enough tags for new bands
- Not enough tags at the track level
- MIR Techniques can help:
 - ❖ Learn to predict social tags
 - ❖ Apply social tags to new music
 - ❖ Related work at ISMIR2007:
 - ☠ Poster: *Autotagging Music Using Supervised Machine Learning - Douglas Eck, Thierry Bertin-Mahieux, Paul Lamere*
 - ☠ Short paper: *Annotating music collections: How content-based Similarity helps to propagate labels* – Mohamed Sordo, Cyril Laurier, Oscar Celma

Deerhoof

Tell a friend about this artist

formalization:: describing items :: text :: tags

- Social tags: Issues
 - ❖ Sources of tags

A Web-Based Game for Collecting Music Metadata
Michael I Mandel and Daniel P W Ellis

The Listen Game interface features a yellow header with the text "listen game" and a speaker icon. Below it, a black square icon with a white cross is visible. The main area has a title "Use of the Song" and a score "Score: 0". A list of activities is presented from "best" to "worst": Exercising, At a Party, Studying, Sleeping, At Work, and Romancing. Each activity is enclosed in a rectangular box with a green dot on the left and an orange dot on the right.

	best	worst
Exercising	green dot	orange dot
At a Party	green dot	orange dot
Studying	green dot	orange dot
Sleeping	green dot	orange dot
At Work	green dot	orange dot
Romancing	green dot	orange dot



Describe this clip

Your tags: metal fast

New clip Game summary

Tag colors: 2 points, 1 point, no points yet (but could be 2), 0 points.

new! [Blog](#) | [Intro](#) | [FAQ](#) | [Contact](#) | [Privacy Policy](#)

11 diggs [digg it](#)

© 2007 Major Miner, Inc.

Avg 4.5 tags per clip

Identifying words that are musically meaningful

David Torres, Douglas Turnbull, Luke Barrington, and Gert Lanckriet

formalization:: describing items :: text :: tags

- Social tags: Issues
 - ❖ Hacking and Vandalism

Top Artists tagged “brutal death metal”

1	▶ Paris Hilton	718
2	▶ Nile	528
3	▶ Cannibal Corpse	474
4	▶ Suffocation	281
5	▶ Aborted	259
6	▶ Cryptopsy	241
7	▶ Dying Fetus	181
8	▶ Deicide	170
9	▶ Devourment	166
10	▶ Behemoth	142



CC by Metal Chris

formalization:: describing items :: text :: tags

- Social tags: Issues

- ❖ Hacking: Paris Hilton – Raw tag counts

- Brutal Death Metal 1145
 - atainwptiosb*: 508
 - Crap 290
 - Pop: 287
 - Officially Sh*t 248
 - Sh*t 143
 - Your ears will bleed: 140
 - emo 120
 - whore 103
 - in prison 98
 - female vocalist 80
 - whore untalented: 79
 - Best Singer in the World: 72
 - sexy 50
 - the worst thing ever to happen to music: 47
 - b*tch: 42
 - dance: 41
 - Guilty Pleasures: 40
 - Death Metal: 30
 - Female: 29
 - Slut: 29

*all things annoying in the world put together into one stupid b*tch

formalization: describing items :: text :: tags

- Social tags: Issues

- ❖ Hacking: Dealing with vandals

- Reduce influence of untrusted taggers
 - ❖ Does the tagger listen to the music they are tagging?
 - ❖ Does the tagger use the tags that they are applying?
 - ❖ Does anyone use the tags?
 - Tag Clustering
 - ❖ pop, female, sexy, guilty pleasure not often clustered with Brutal Death metal
 - ❖ Artists tagged with Brutal Death Metal are also tagged with:
 - ☠ *brutal, grind, death,*
 - ☠ *death metal, extreme metal,*
 - ☠ *gore metal, goregrind, grind, grindcore*
 - ☠ *tech technical death, technical death metal*

formalization:: describing items :: text :: tags

- Social tags: Issues

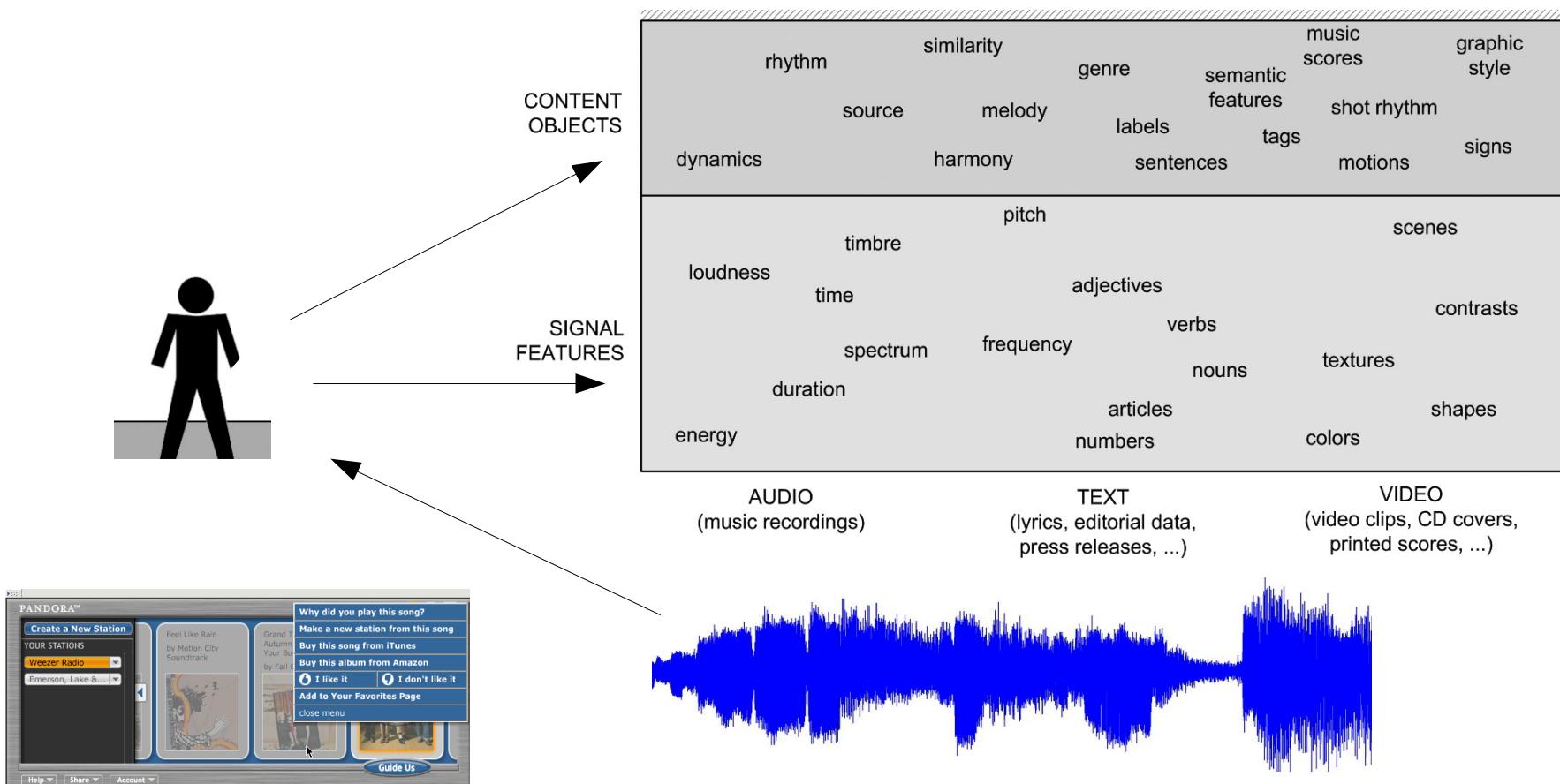
- ❖ Hacking: last.fm strikes back!
- ❖ Paris Hilton – Normalized Tag Counts

- Pop: 100
- Female Vocalists: 28
- Dance: 18
- American: 14
- Sexy: 13
- Brutal Death Metal: 11
- rnb: 8
- female vocalist: 8
- female: 7
- 00s: 6
- Guilty Pleasure: 6
- guilty pleasure: 6
- California: 5
- emo: 4
- Crap: 3
- Reggae: 3
- awful: 3
- party: 3
- underrated: 2
- Best Singer in the world: 2
- ataitwptiosb*: 2
- hot: 2

**all things annoying in the world put together into one stupid b*tch*

formalization:: describing items :: audio

- Manual annotation



formalization:: describing items :: audio

- Manual annotation

- ❖ Human-analysis of music:

- Pandora

- ❖ 50+ Musicians, 45 minutes per song

- ❖ 400 Parameters per song, 500,000 song Catalog

- SoundFlavor

- ❖ '100s of parameters', 5 minutes per song

- ❖ **But ... this doesn't scale to all music:**

- Takes 5 years to analyze 1 year of new releases

- Music editor becomes the **Gatekeeper**

- Variability across 40 musician analysts

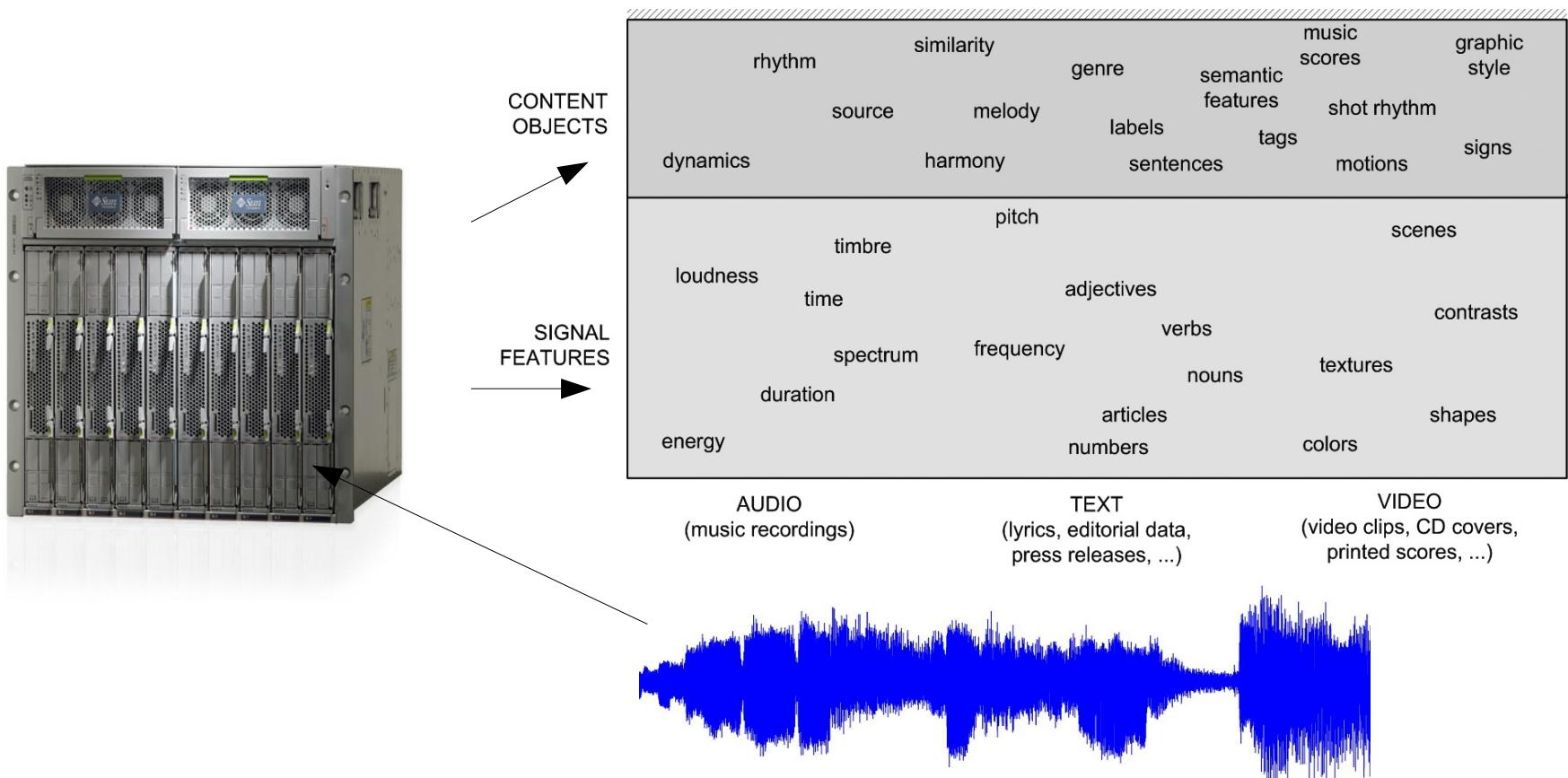
- Ignore certain types of music (no 'Classical')

- ❖ **Perhaps machines can do the job!**

The logo for Pandora, featuring the word "PANDORA" in a blue serif font with a registered trademark symbol.The logo for Soundflavor, featuring the word "Soundflavor" in a black sans-serif font next to a red cherry icon, with the word "beta" in small blue text to the right.

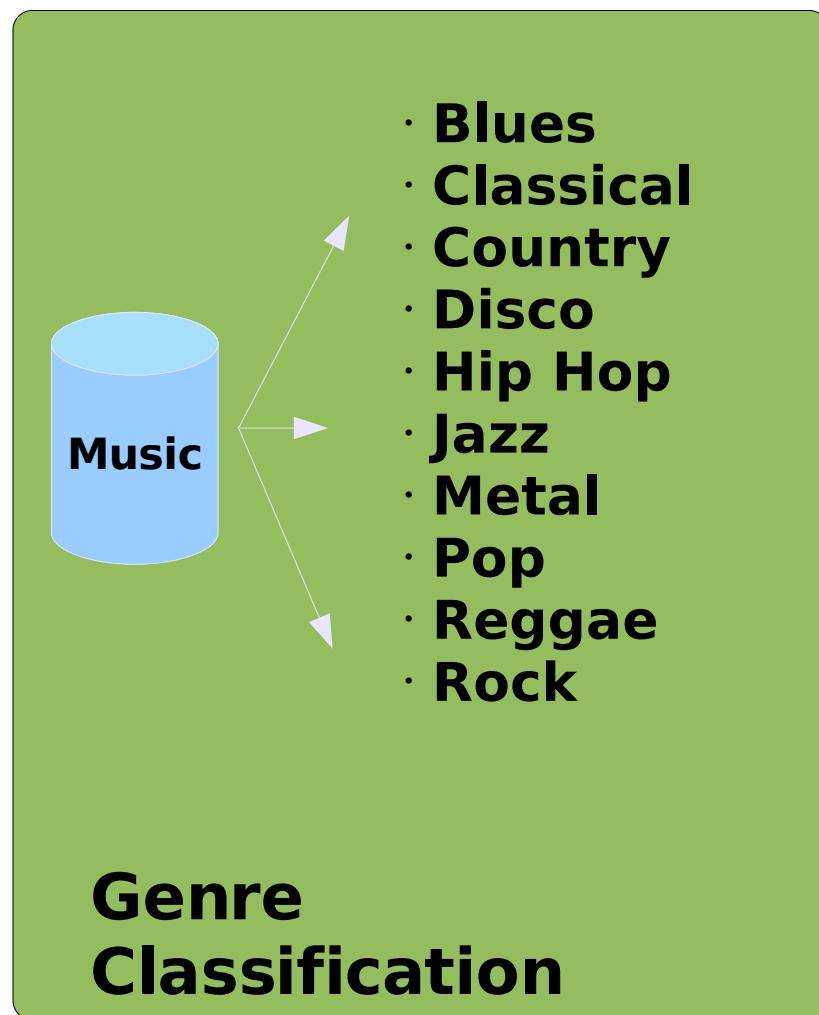
formalization:: describing items :: audio

- Automatic annotation



formalization:: describing items :: audio

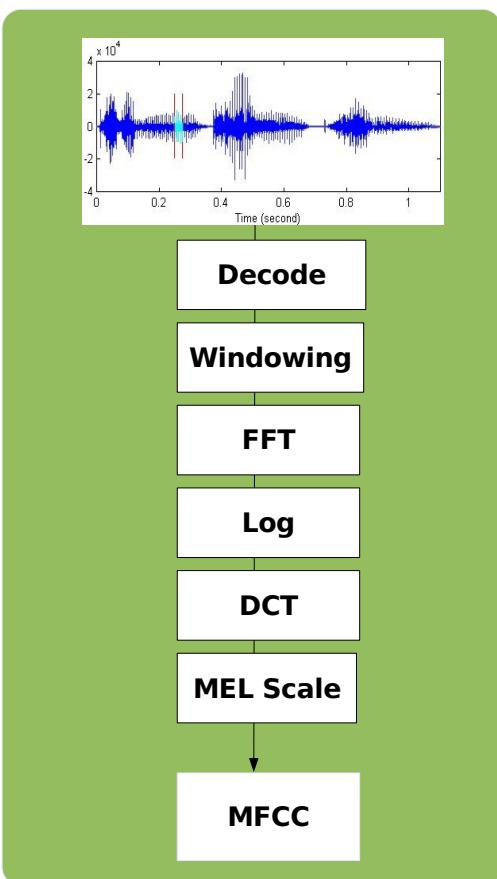
- Automatic annotation
 - ❖ Can machines understand music?
 - **Music Similarity is hard:**
 - Hard to decide what is similar
 - Hard to evaluate
 - Start with something easier...
 - **Genre Classification:**
 - Manual : 72%
(Perrot/Gjerdigen)
 - Automated (2002) 60%
(Tzanetakis)
 - Automated (2005) 82%
(Bergstra/Casagrande/Eck)
 - Automated (2007) 76%



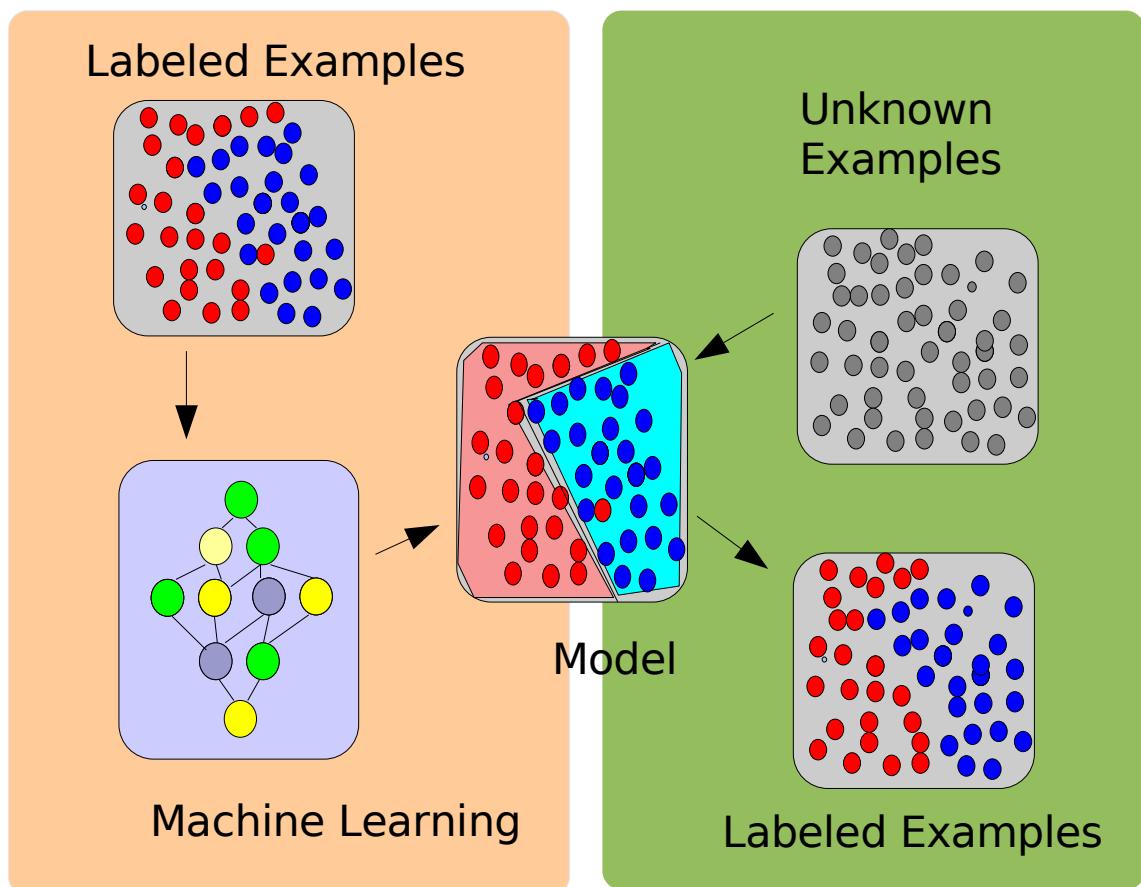
formalization:: describing items :: audio

- Automatic annotation
 - ❖ How does classification work?

Feature Extraction



Training



formalization:: describing items :: audio

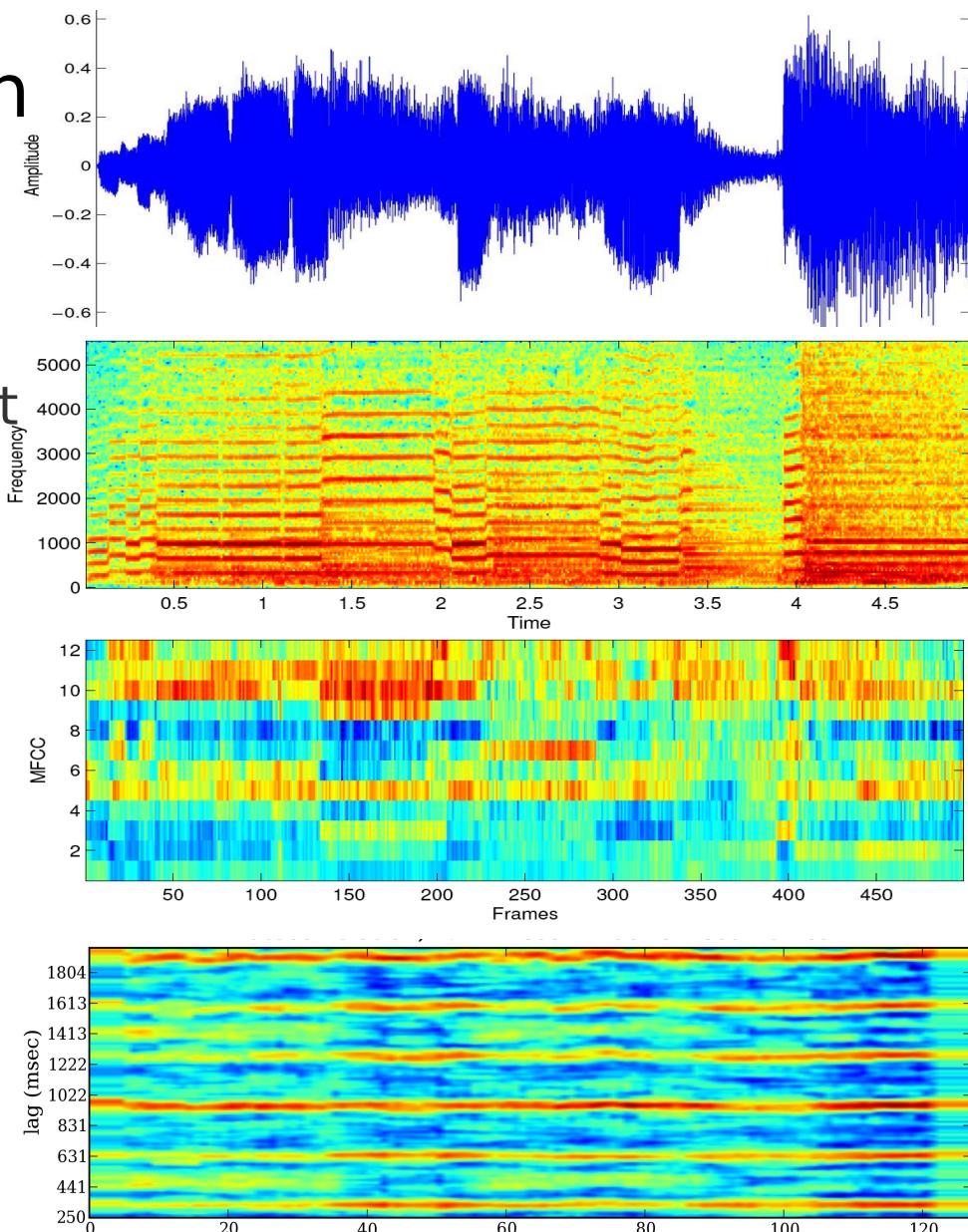
- Automatic annotation

- ❖ Feature extraction

- Challenge: Too much audio data

- Reduce audio to extract information about:

- ❖ Pitch
 - ❖ Timbre
 - ❖ Rhythm



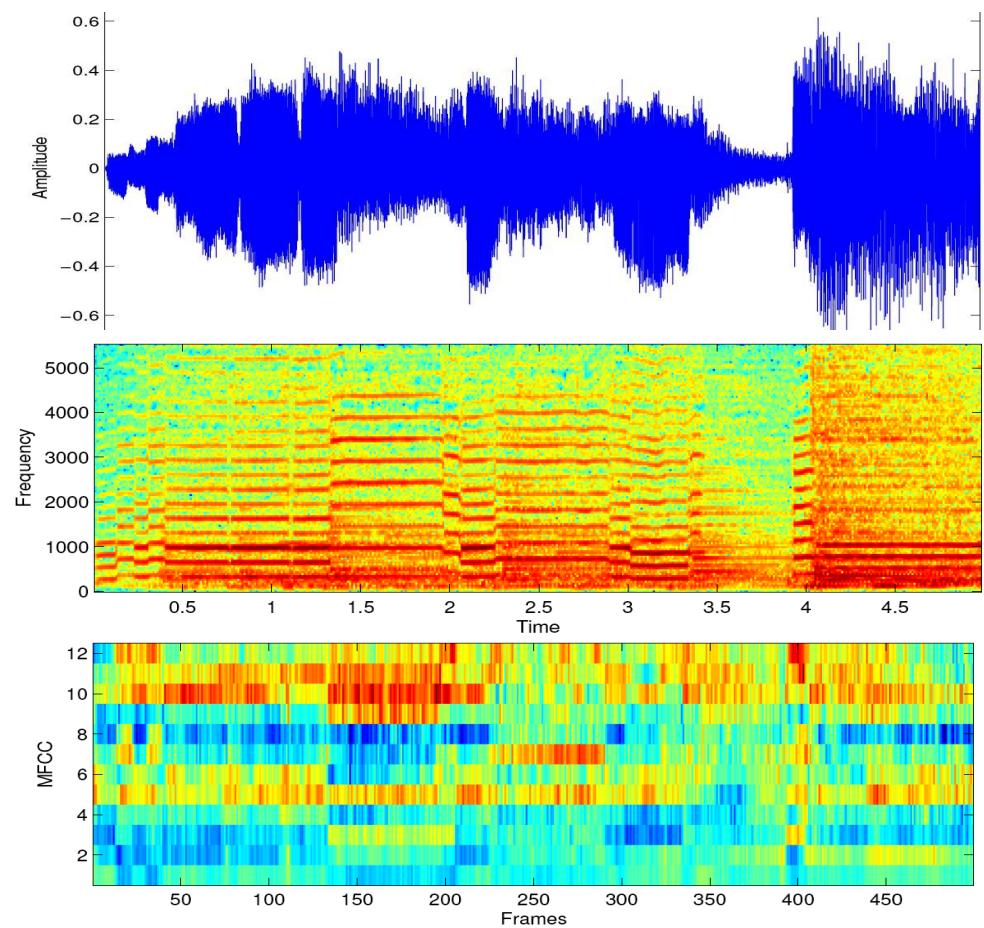
formalization:: describing items :: audio

- Automatic annotation

- ❖ Feature extraction

- MFCC

- ❖ Used in speech recognition
 - ❖ Model human auditory response
 - ❖ Show rate of change in the different spectrum bands
 - ❖ Good for **Timbre**



formalization:: describing items :: audio

- Automatic annotation

- ❖ Feature extraction

- Log Spectrogram

- ❖ Retains pitch info

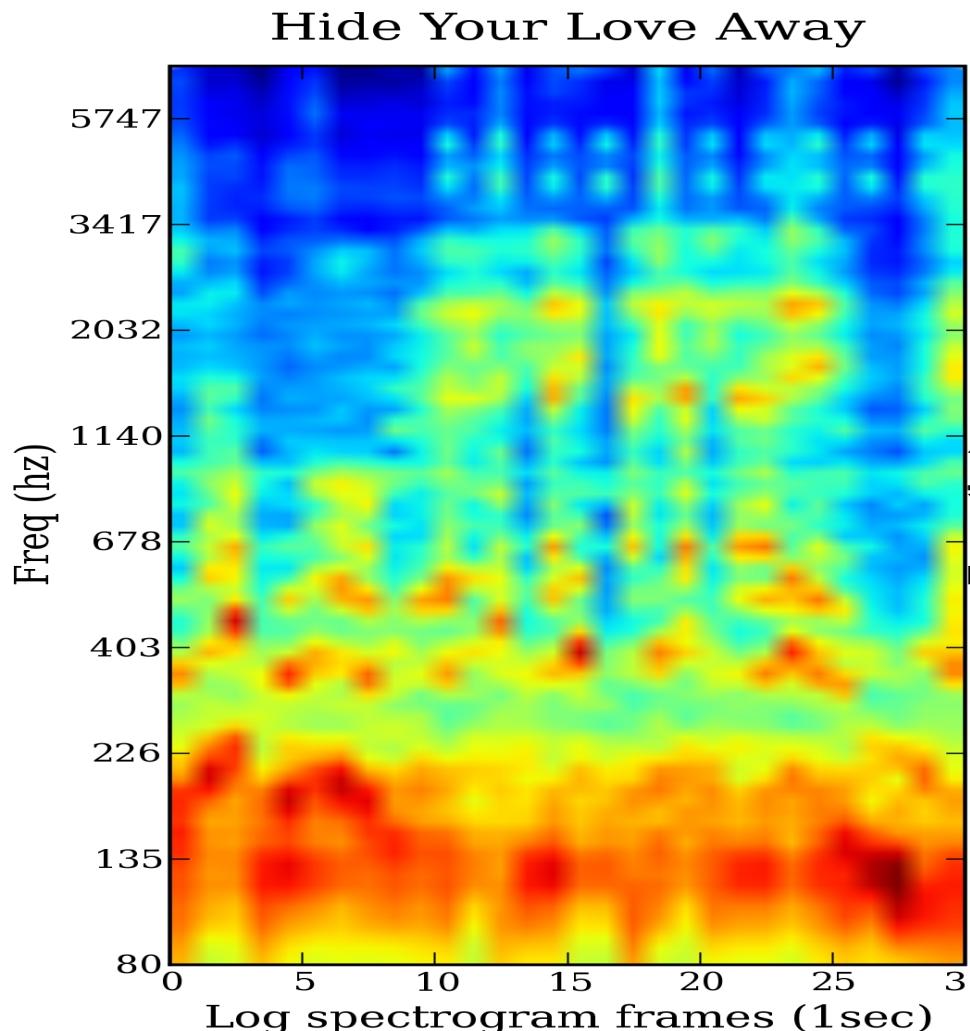
- Useful for:

- ❖ Key identification

- ❖ Mode identification

- ❖ Mood classification

- ❖ Style identification

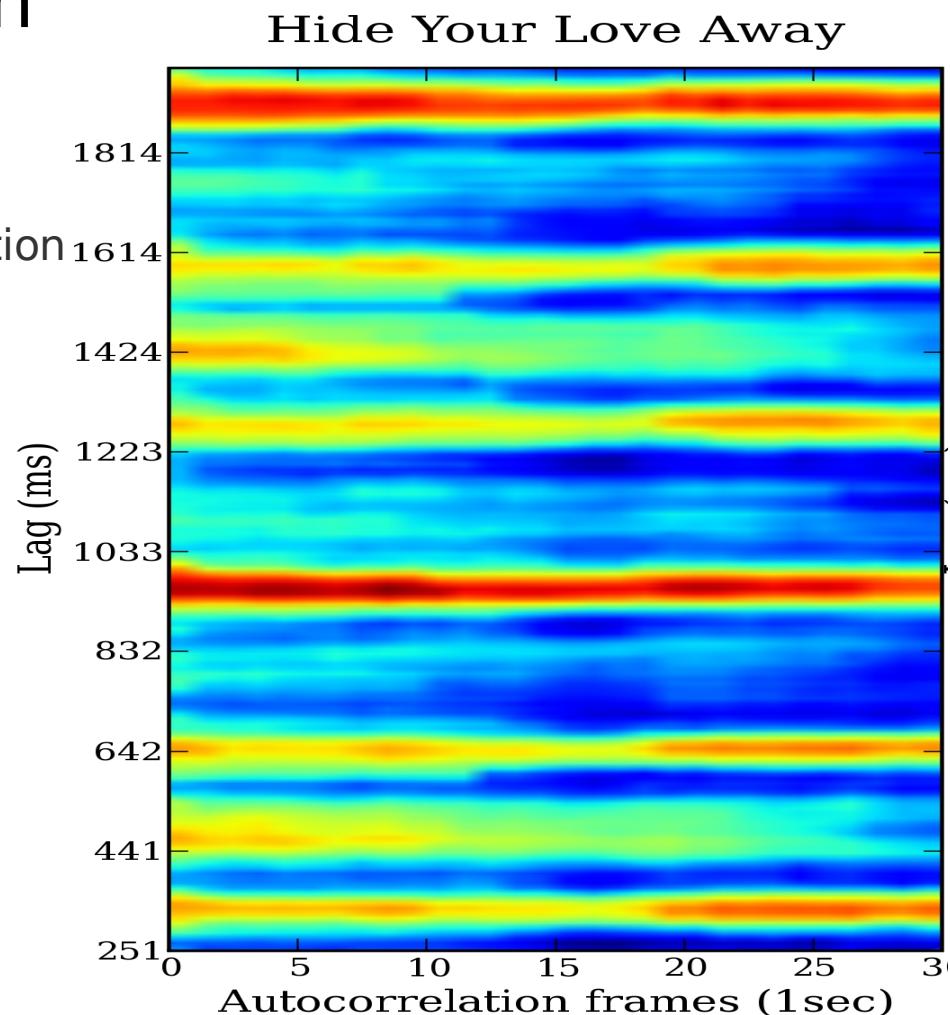


formalization:: describing items :: audio

- Automatic annotation

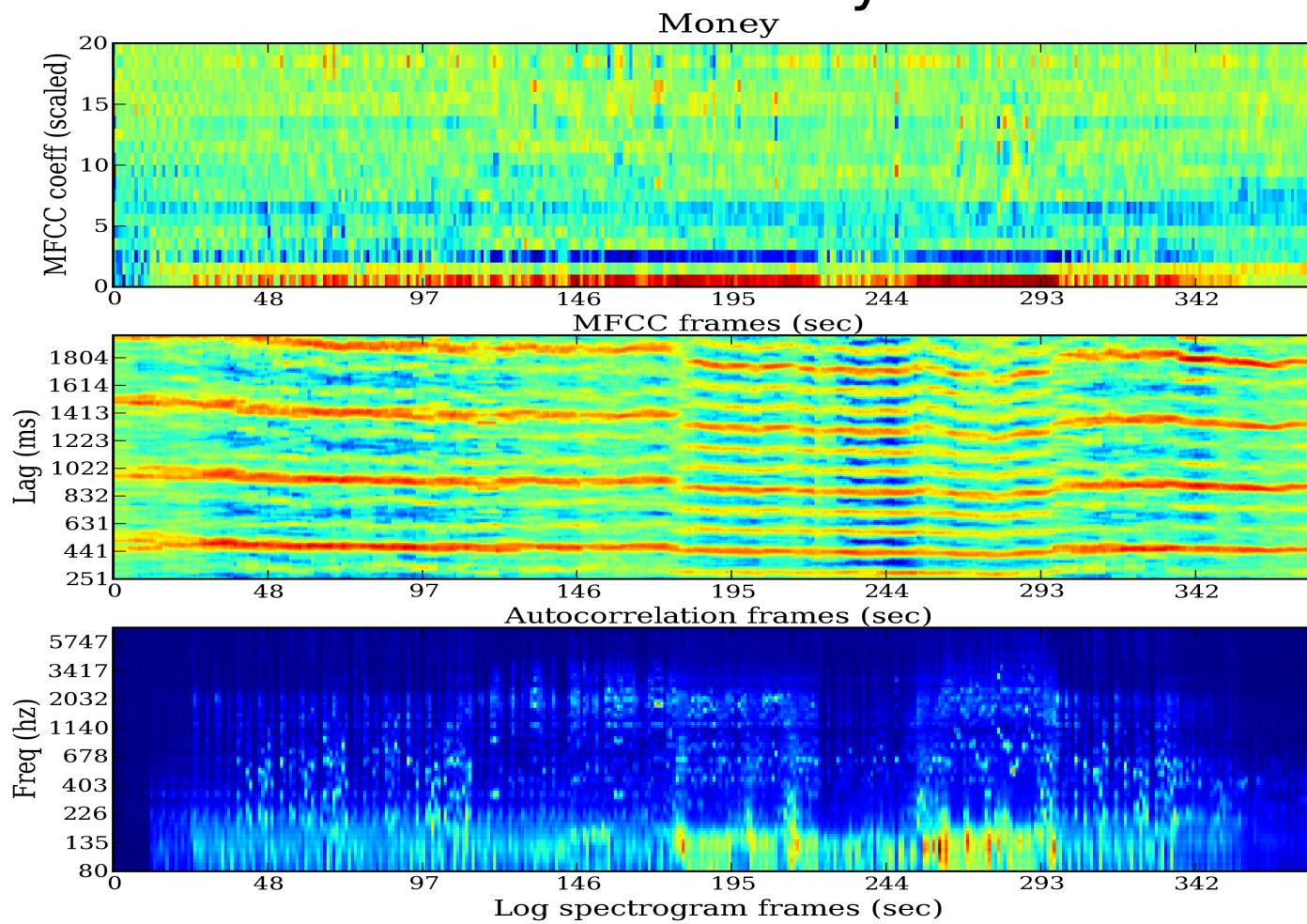
- ❖ Feature extraction

- Autocorrelation
 - ❖ Represents Timing information
 - Useful for:
 - ❖ Rhythm
 - ❖ Time signature
 - ❖ Tempo
 - ❖ Tempo drift



formalization:: describing items :: audio

- Automatic annotation
 - ❖ Feature extraction: Summary

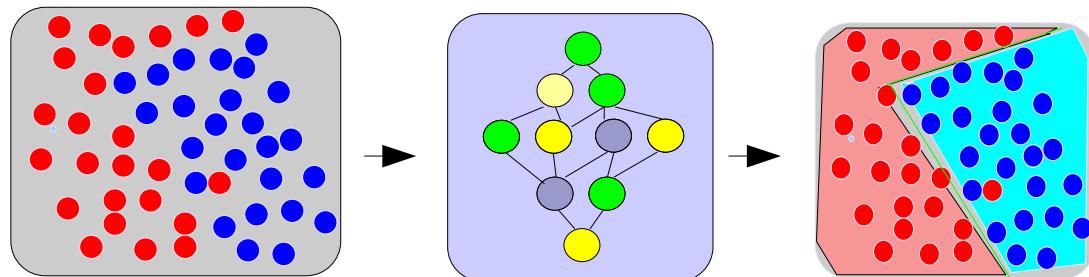


formalization:: describing items :: audio

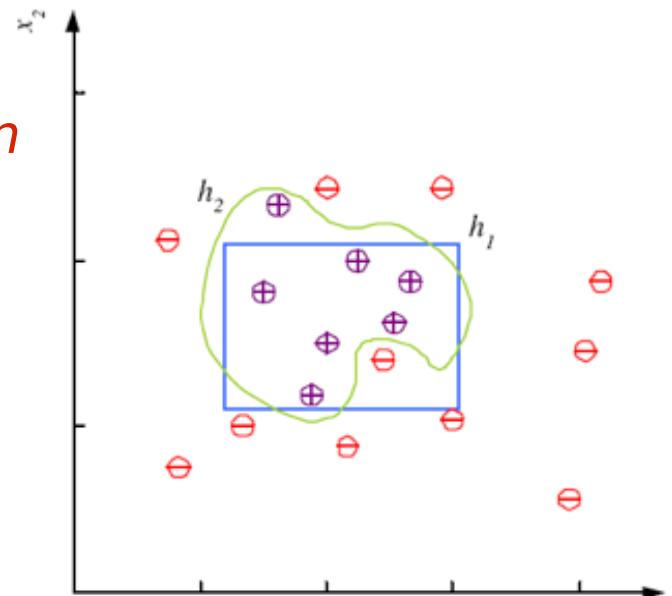
- Automatic annotation

- ❖ Machine learning

- Statistical modeling
 - Exploit regularities in the data
 - Generalize to previously *unseen* examples
 - Predict without overfitting



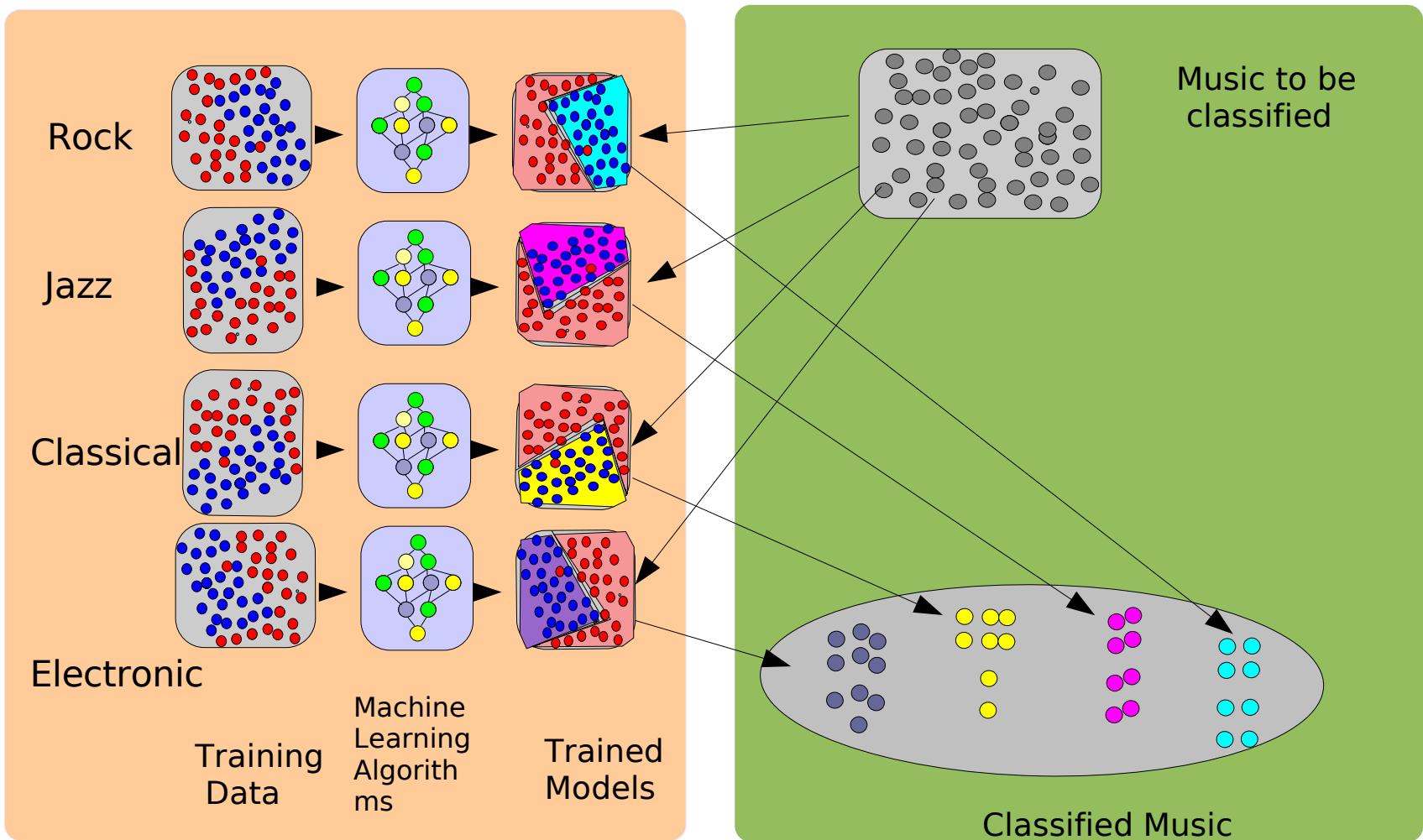
Supervised learning example



From Alpaydin (2004)

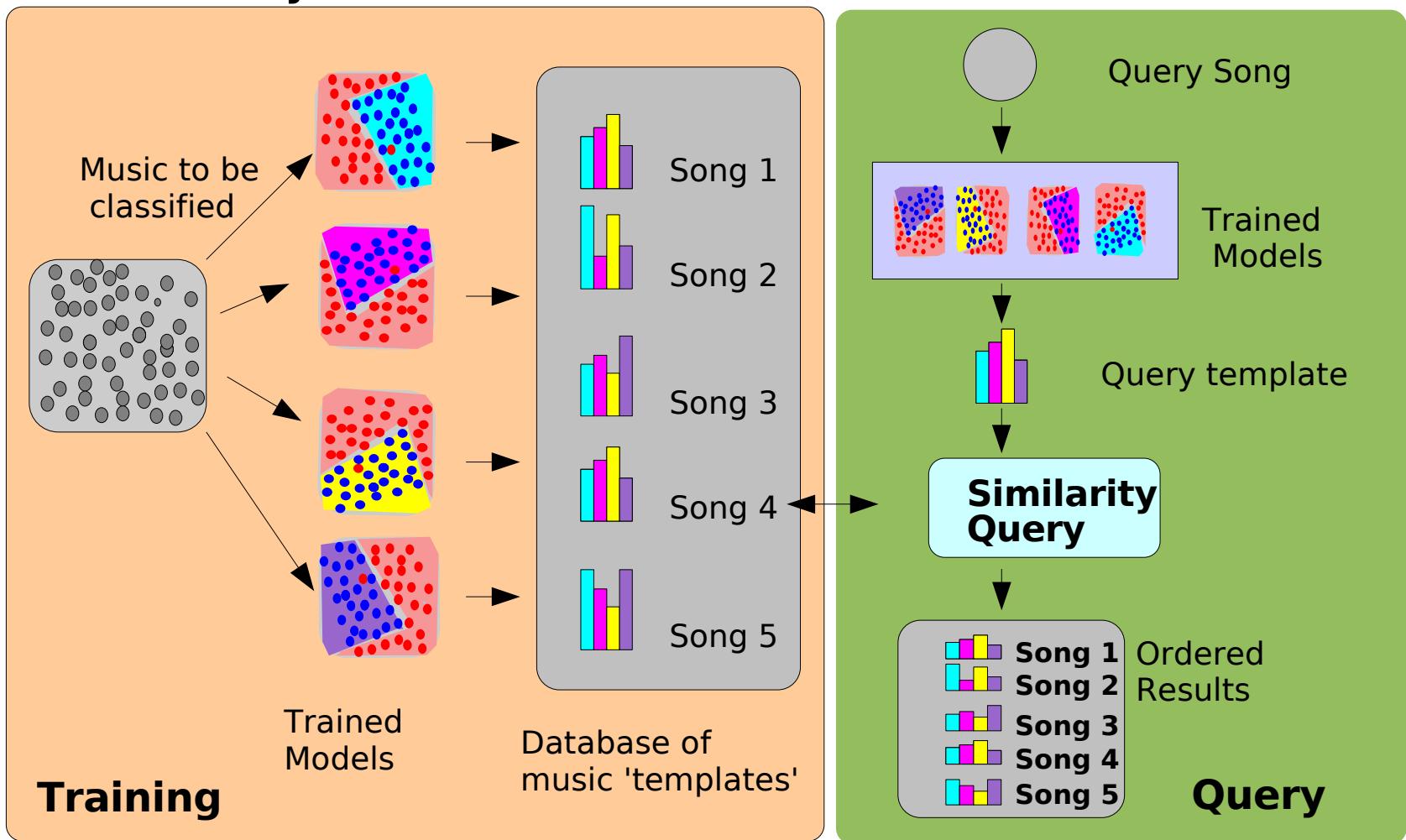
formalization:: describing items :: audio

- Automatic annotation
 - ❖ Multiple class machine classification



formalization:: describing items :: audio

- Automatic annotation
 - ❖ Similarity based on classification



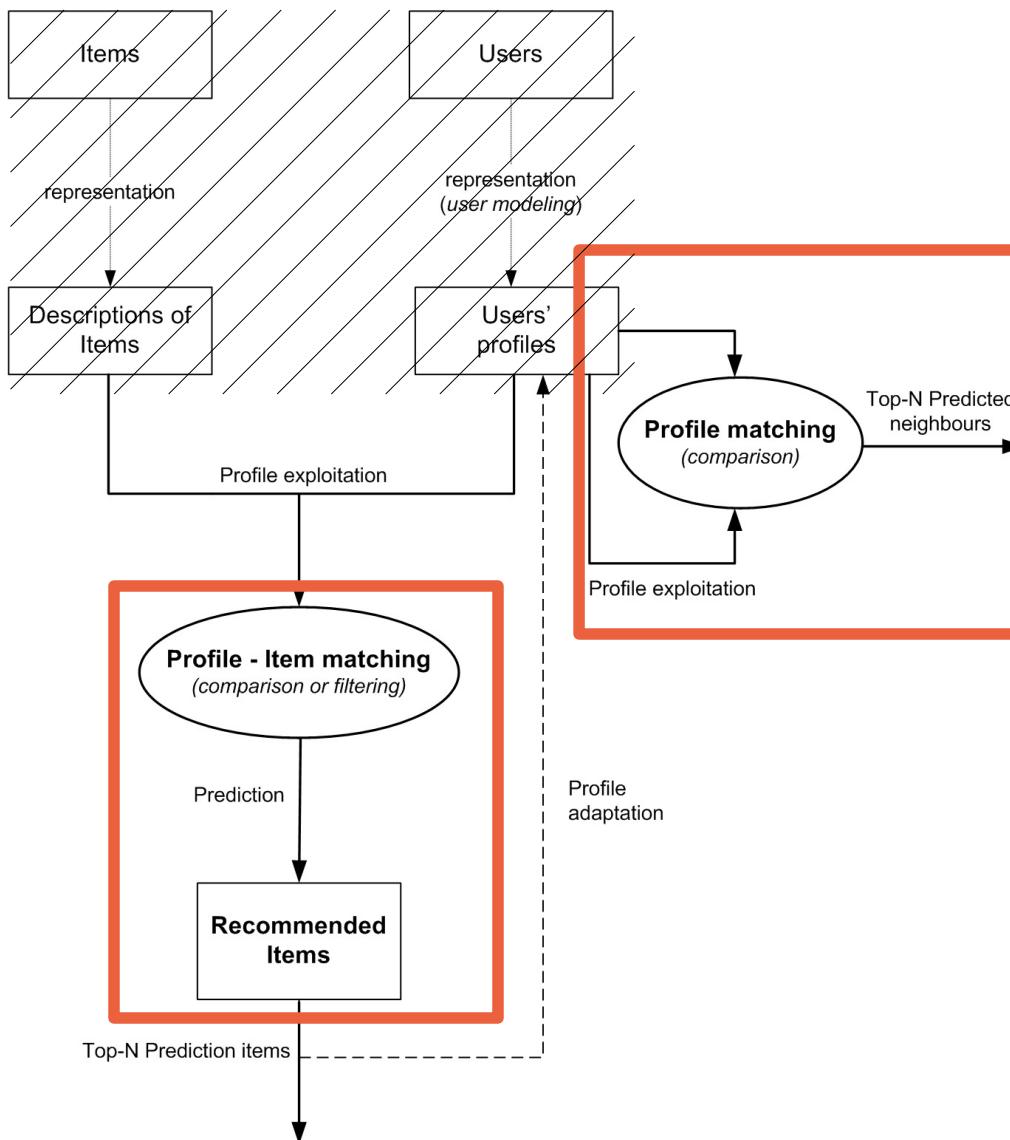
formalization:: describing items :: audio

- Automatic annotation
 - ❖ Content analysis: State of the art
 - Machines more accurate for simple tasks
 - Still early days for automated music similarity
 - **Time per million songs:**
 - ❖ Manual: with 100 people = 3 Years
 - ❖ Automatic: with 100 CPUs = 8 Hours
 - **Cost per million songs**
 - ❖ Manual: ~ \$10,000,000
 - ❖ Automatic: ~ \$1,000

outline

- Introduction
- Formalization of the recommendation problem
- **Recommendation algorithms**
- Problems with recommenders
- Recommender examples
- Evaluation of recommenders
- Conclusions / Future

music recommendation:: algorithms



music recommendation:: algorithms

- elements
 - ❖ transactional dataset
 - ❖ user-item interaction
 - explicit data
 - ❖ rating
 - ❖ purchase
 - ❖ relevance feedback (e.g love & ban this song/artist)
 - ❖ etc.
 - implicit data
 - ❖ listen to (play / stop / skip)
 - ❖ time spent in a webpage
 - ❖ etc.

music recommendation:: algorithms

- general approaches

- ❖ user-based

- compute top-N neighbours for a given user
 - ❖ similarity measure
 - ❖ clustering
 - recommend items from the user's neighbourhood

- ❖ item-based

- compute item similarity
 - ❖ ratings / num. plays: linear regression, cosine, pearson correlation, adjusted cosine
 - ❖ content based: EMD, Manhattan distance, MFCC/GMM, etc.
 - recommend items to a user, based on her profile

music recommendation:: algorithms

- general approaches

- ❖ model-based

- create a model based on the user profile
 - ❖ probabilistic models (three way aspect model) [Yoshii, 2006], [Yoshii, 2007]
 - ❖ decision trees
 - ❖ neural networks
 - ❖ etc.
 - recommend items based on the user's model
 - ❖ Usually, recommendation seen as a classification problem

music recommendation:: algorithms

- Expert
- Demographic Filtering
- Collaborative Filtering
- Content-based Filtering
- Hybrid methods

music recommendation:: algorithms :: expert

- Expert
 - ❖ AMG editors
 - Genre
 - Styles
 - Moods
 - Themes
 - Similar artists

The screenshot shows an AllMusic artist profile for 'The Crybabys'. The top navigation bar includes links for Overview, Biography, Discography, Songs, Credits, and Charts & Awards. The main title 'The Crybabys' is displayed above a red-bordered box containing genre and mood information. To the right of this box are two album covers: 'What Kind of Baby's That?' and 'Cry Baby'. Below the red box, there are sections for 'Similar Artists' (listing Rock City Angels, Dogs D'Amour, The Black Crowes, and Cinderella) and 'See Also' (listing The Boys). The AllMusic logo and links for allmusic, allmovie, and allgame are visible at the bottom.

Years Active	
1910	20
30	40
50	60
70	80
90	2000

Genre	Styles
Rock	Hard Rock
	American
	Trad Rock

Moods
Rambunctious
Rowdy
Reckless
Energetic
Rebellious

AMG Artist ID: P 395897

Corrections to this Entry?

Similar Artists

- Rock City Angels
- Dogs D'Amour
- The Black Crowes
- Cinderella

See Also

- The Boys

- eMusic in 2005-2006
 - expands its editors staff to 120
 - 2nd licensed music download service, on a specialized market



music recommendation:: algorithms :: expert

- Expert

- ❖ AMG Tapestry, a playlist generator based on
 - Styles,
 - Moods,
 - Themes, and
 - tempo, dynamics, instrumentation, etc.

http://tapestry.allmusic.com - Playlist - Swiftweasel

CRITERIA FOR CUSTOM PLAYLIST:	TITLE	PERFORMER	TIME
• Vocal Jazz	[100%] Girl Talk	Betty Carter	04:25
• Late Night	[100%] That Lucky Old Sun (Just Rolls Around Heave...	Louis Armstrong	03:07
• Melancholy	[100%] It's Always You	Chet Baker	03:35
	[100%] Loverman	Billie Holiday	04:23
	[85%] Humpty Dumpty Heart	Bing Crosby	02:59
	[100%] Lonely House	June Christy	04:07
	[85%] I Thought About You	Frank Sinatra	02:31
	[100%] Lover Man (Oh, Where Can You Be)	Billie Holiday	03:18
	[85%] Miss Otis Regrets	Ethel Waters	03:02
	[100%] When Your Lover Has Gone	Johnny Hartman	03:10
	[84%] It's Been a Long, Long Time	Les Paul Trio	02:58
	[84%] The Christmas Song	Louis Armstrong	03:06
	[84%] Who's Minding the Store?	Dianne Reeves	04:31
	[84%] Tight	Betty Carter	03:44
	[100%] Not I	June Christy	02:45
	[84%] So...	Betty Carter	07:02
	[100%] Stormy Weather	Ella Fitzgerald	05:16
	[85%] I Got It Bad (And That Ain't Good)	Frank Sinatra	03:25
	[84%] Pick Yourself Up	Dianne Reeves	02:38
	[84%] Blues Is My Middle Name	Ray Charles	03:08

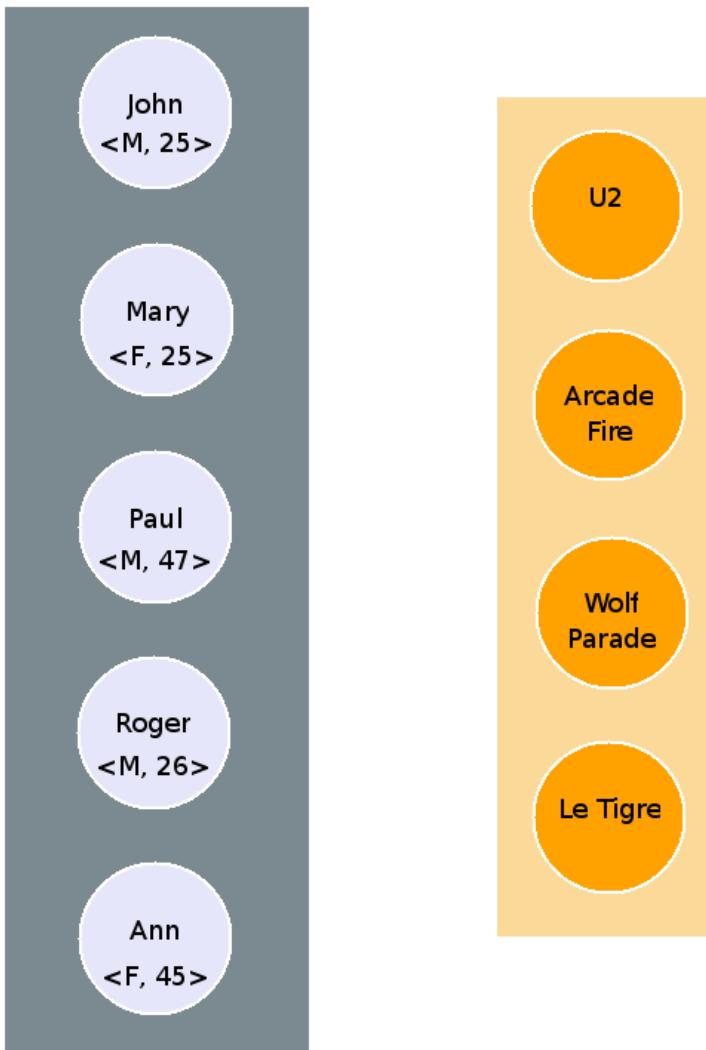
music recommendation:: algorithms :: expert

- Expert

- ❖ rely on *experts* to recommend music
 - metadata by editors (Allmusic, eMusic, etc.)
 - expert reviews (pitchforkmedia, rollingstone, etc.)
 - mp3 blogs (hypem.com)
- ❖ Pros
 - transparency of the recommendations
 - can differentiate between “good and bad” music, according to the expert
- ❖ Cons
 - not personalized
 - limited coverage
 - no scaling

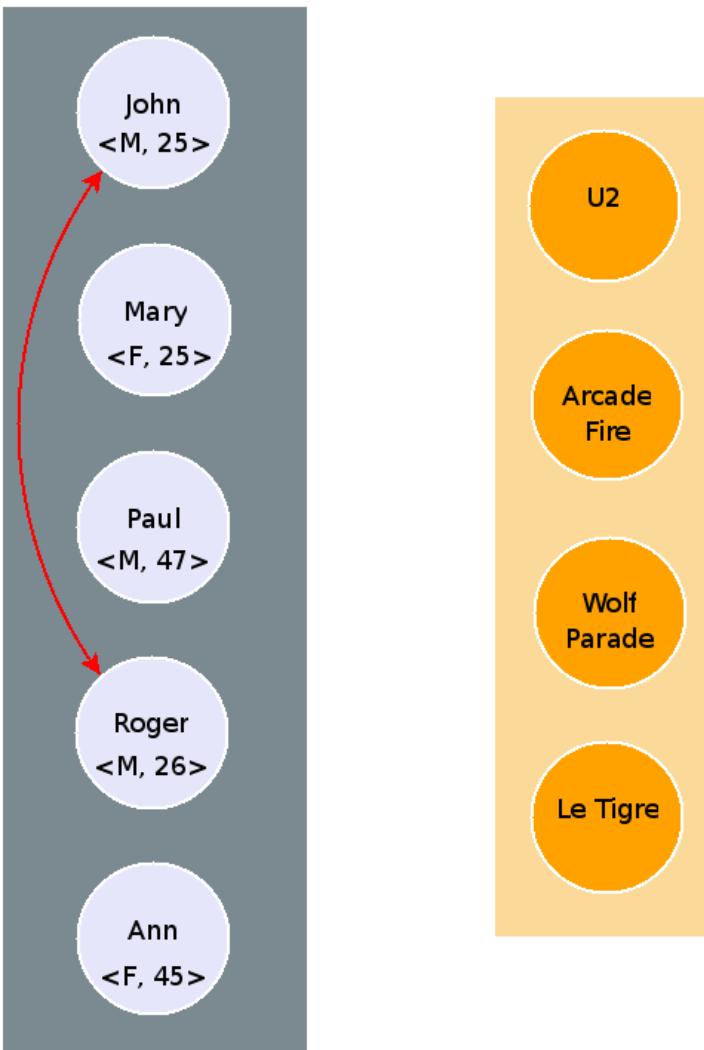
music recommendation:: algorithms :: demogr

- Demographic Filtering



music recommendation:: algorithms :: demogr

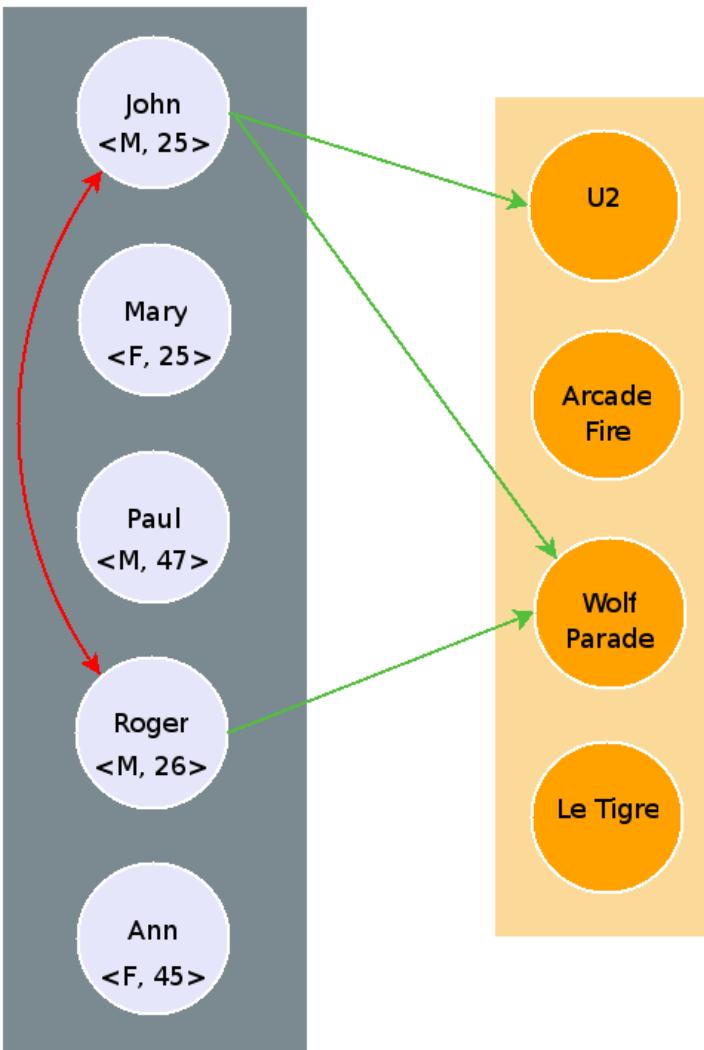
- Demographic Filtering



- **John** and **Roger** have similar profiles (gender, age)

music recommendation:: algorithms :: demogr

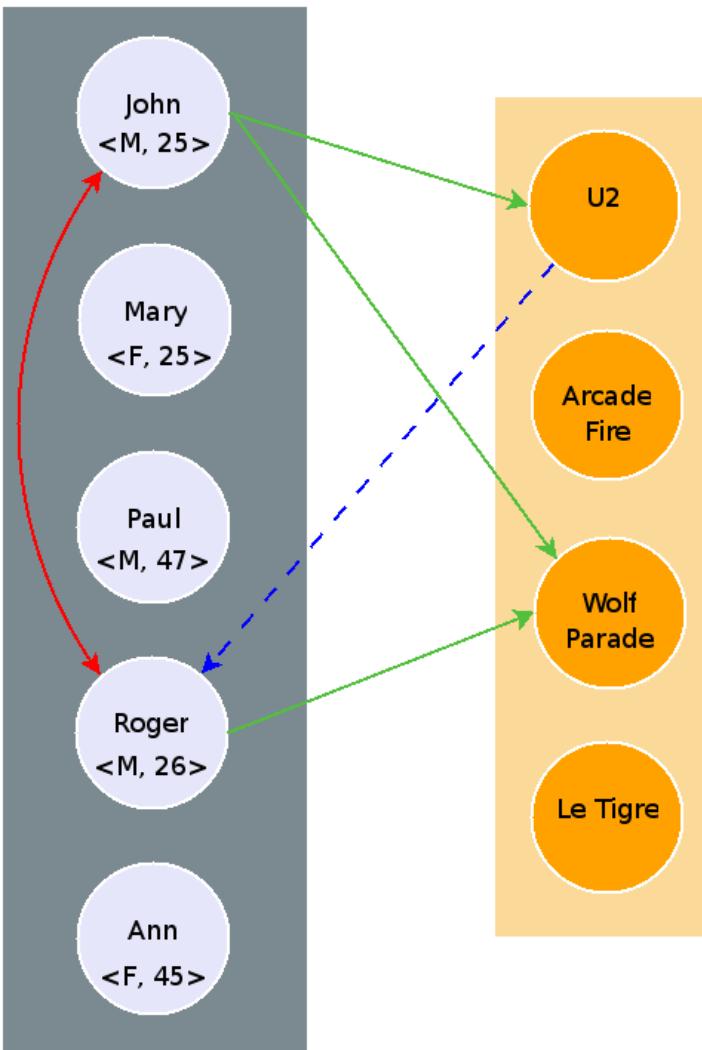
- Demographic Filtering



- Analyse **John** and **Roger** preferences for the artists

music recommendation:: algorithms :: demogr

- Demographic Filtering



- Recommend **U2** to **Roger**

music recommendation:: algorithms :: demogr

- Demographic Filtering

- ❖ Process

- 1) find users with similar features
 - ❖ define similarity function among users
 - ❖ clustering based on the similarity distance
 - 2) recommend items preferred by similar users
 - ❖ prediction based on weighted average

- ❖ Pros

- avoids user cold-start problem (more later on...)

- ❖ Cons

- totally dependant on user's features (sometimes unknown / private / ...)
 - not personalized recommendations

music recommendation:: algorithms :: colfilter

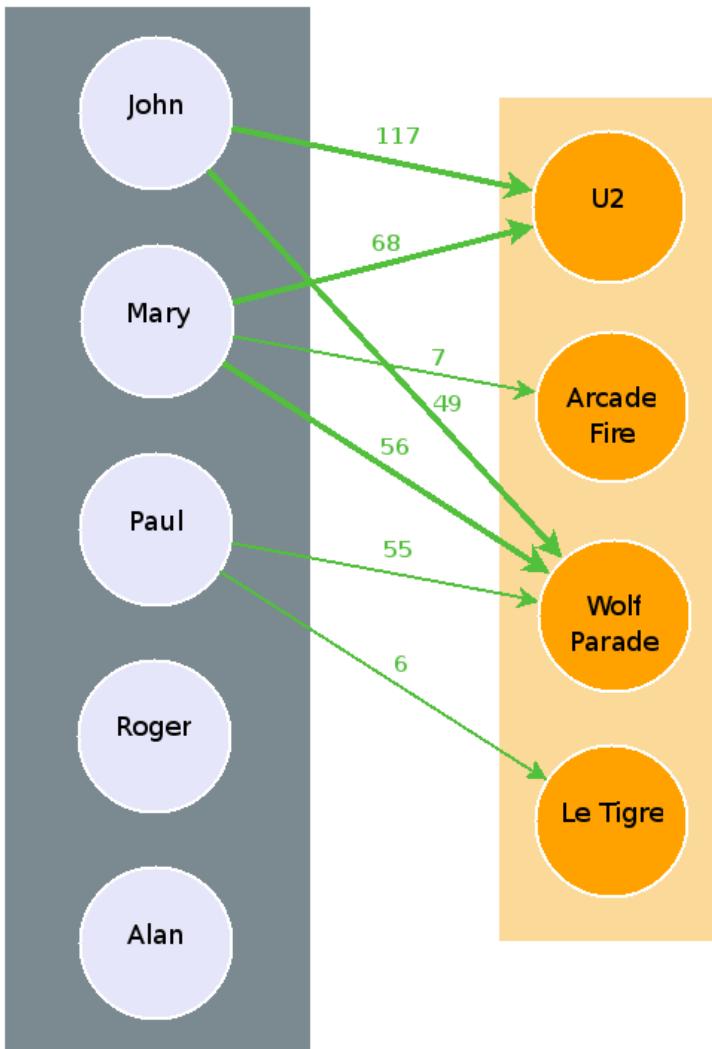
- Collaborative Filtering

- ❖ approaches

- user-based
 - ❖ “recommend items from like-minded people”
 - item-based
 - ❖ Amazon example “people who buy this also bought that”
 - model-based
 - ❖ model the user behavior using bayesian network, clustering, association rules, neural networks, etc.

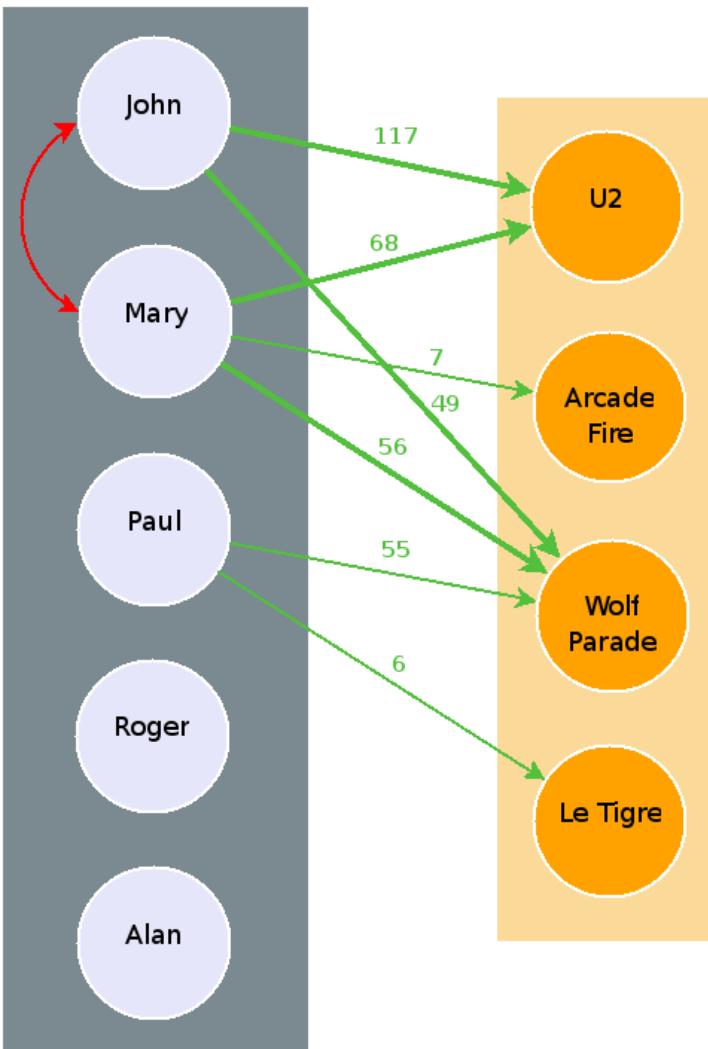
music recommendation:: algorithms :: colfilter

- Collaborative Filtering: User-based [Shardanand, 1995]



music recommendation:: algorithms :: colfilter

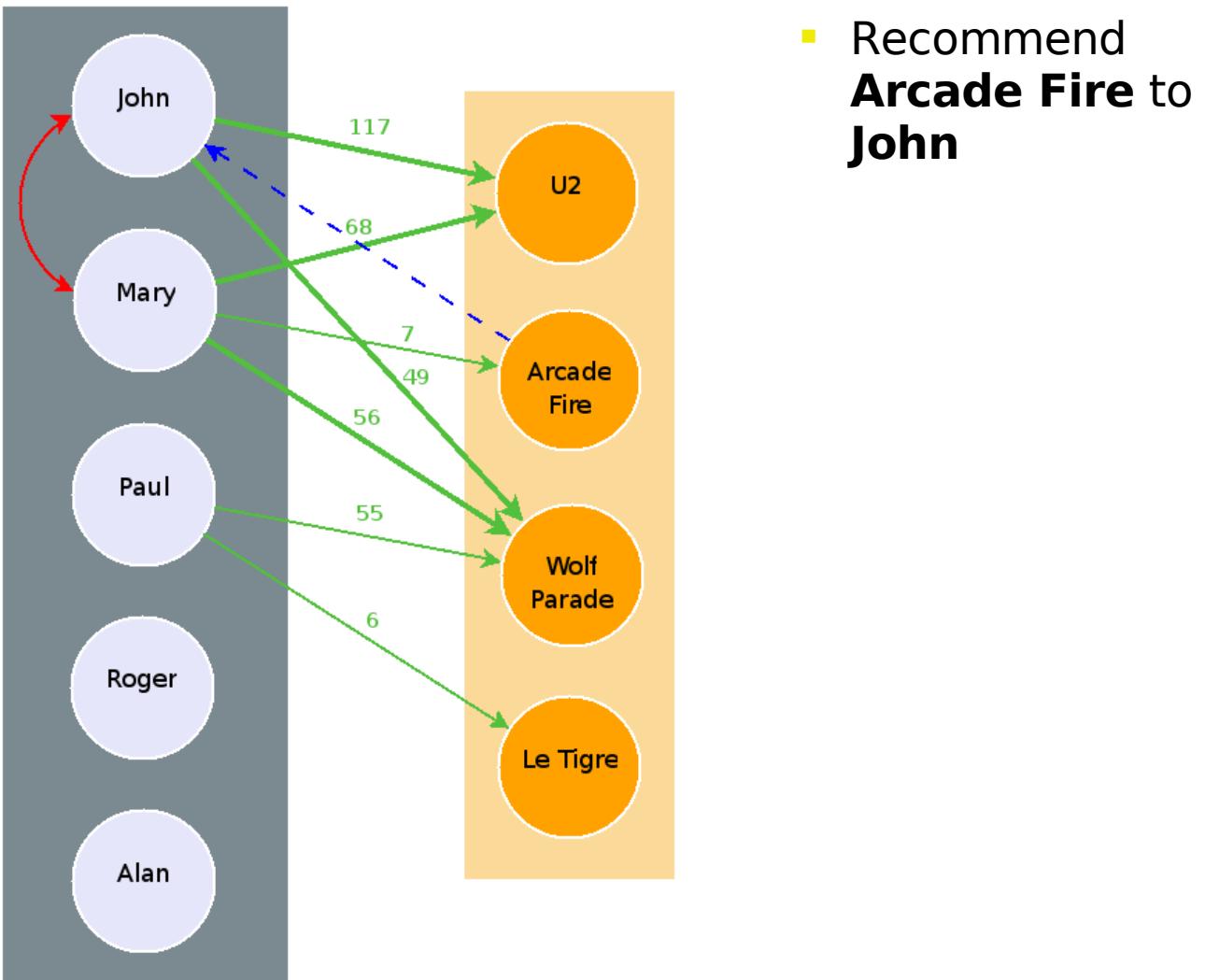
- Collaborative Filtering: User-based



- **John** and **Mary** have similar listening habits

music recommendation:: algorithms :: colfilter

- Collaborative Filtering: User-based



music recommendation:: algorithms :: colfilter

- Collaborative Filtering: User-based
 - ❖ user-item matrix

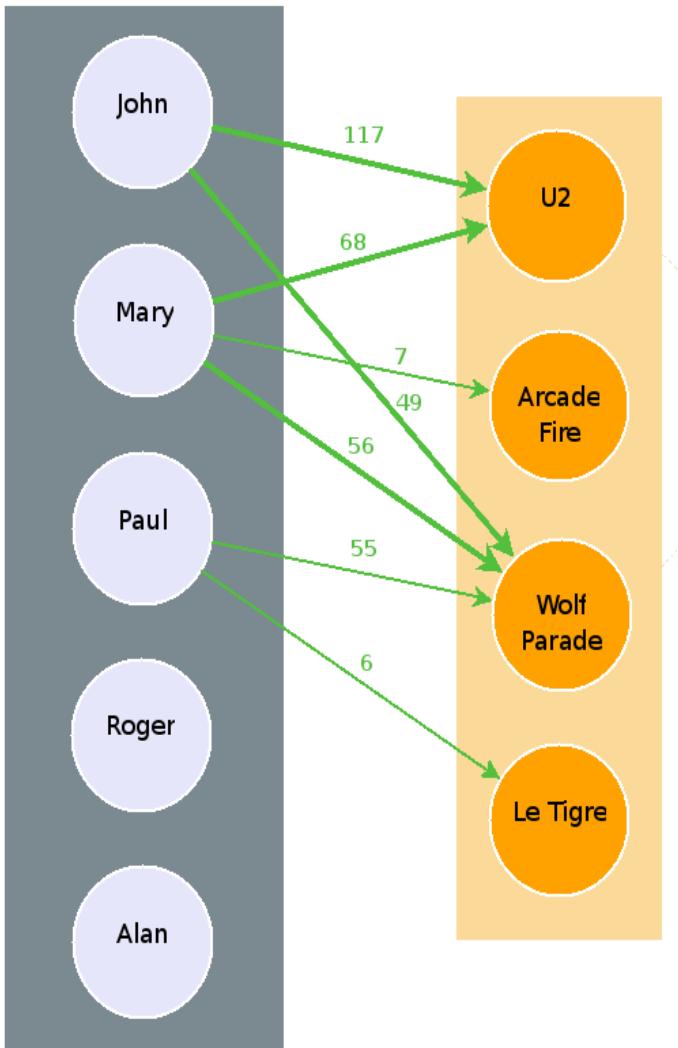
	i ₁	i ₂		i _j		i _n
u ₁				4		
u ₂				Φ		
				4		
u _a				?		
				2		
				1		
u _m				Φ		

- ❖ prediction (user U_a, item i_j): adjusted weighted sum

$$P_{a,j} = \bar{R}_a + \sum_{u \in Neighbours(u_a)} sim(u_a, u)(R_{u,j} - \bar{R}_u)$$

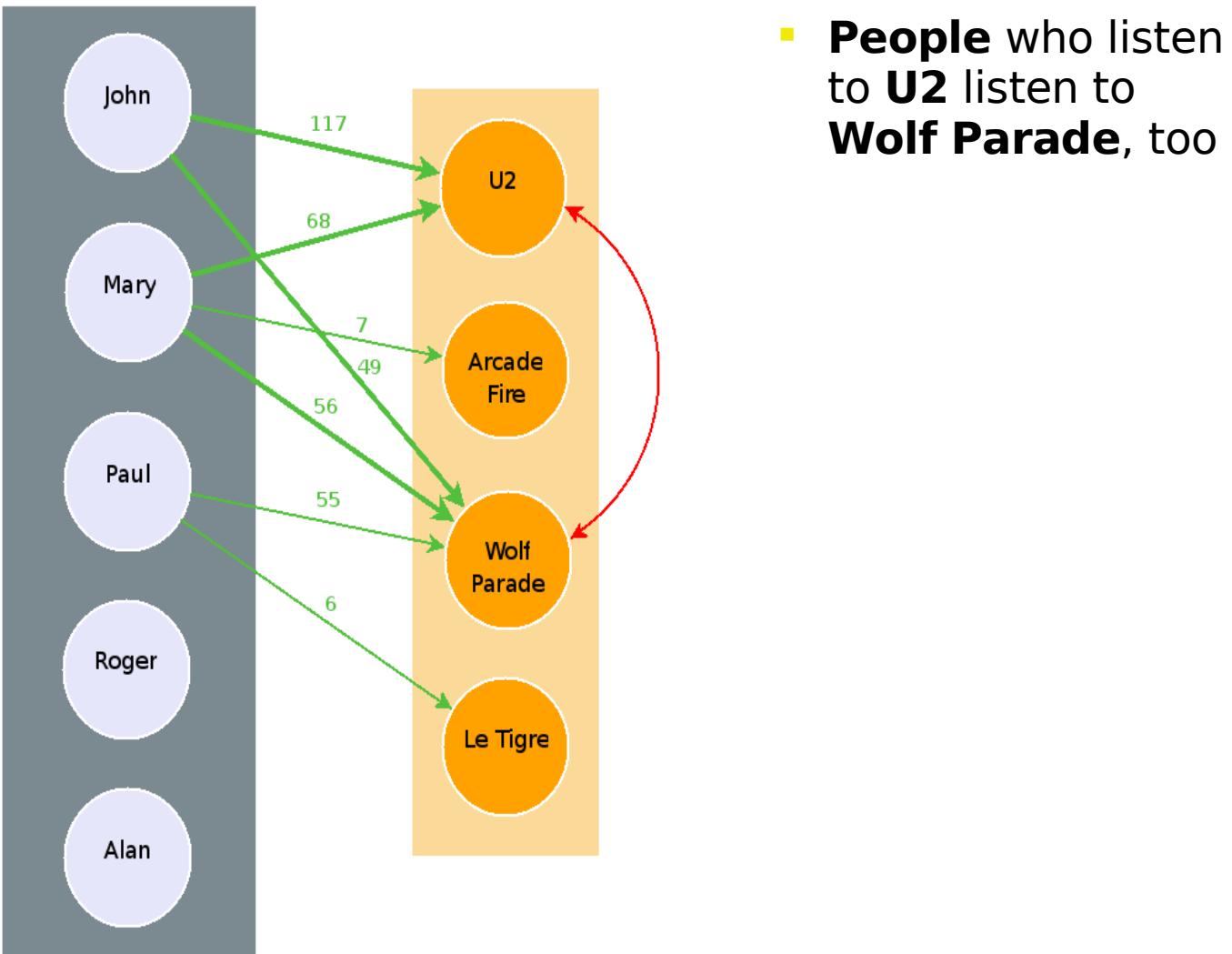
music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based [Sarwar, 2001]



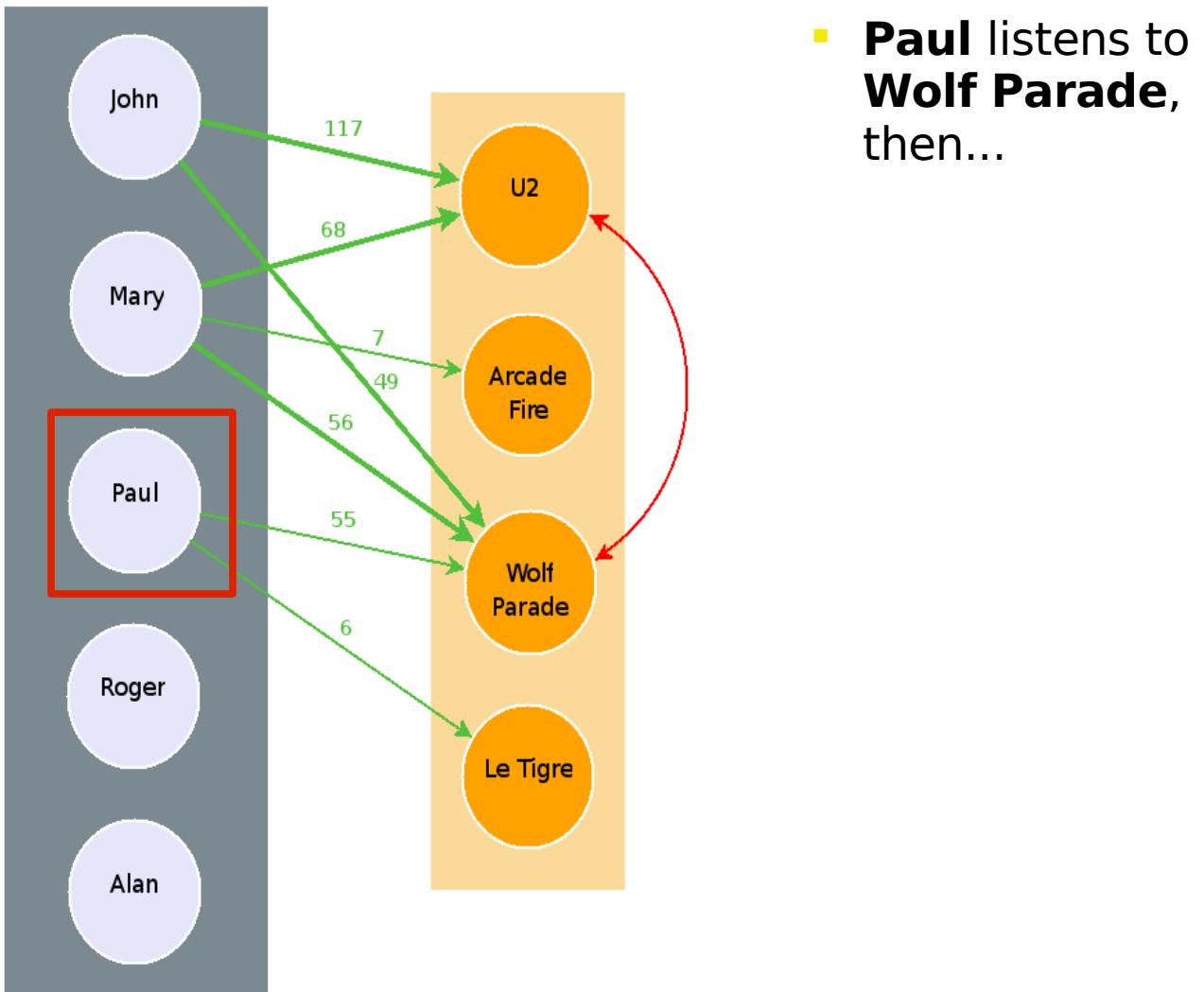
music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based



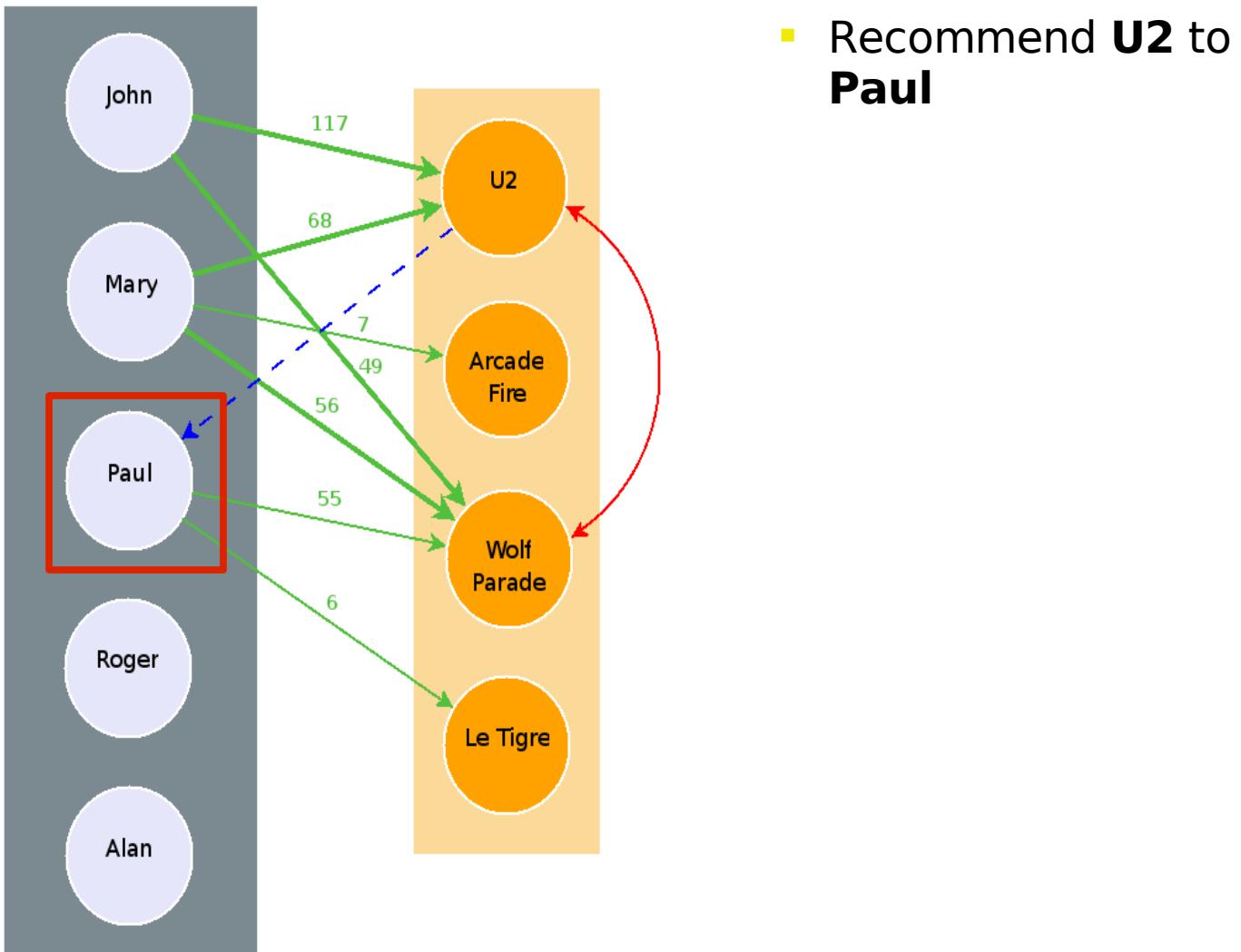
music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based



music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based



music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based
 - ❖ user-item matrix

	i_1	i_2		i_j		i_k		i_n
u_1								
u_2				R		R		
u_i				R		R		
u_{m-1}				R		Φ		
u_m								

music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based
 - ❖ item similarity measures

- cosine

$$\text{sim}(i, j) = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\| * \|\vec{j}\|} = \frac{\sum_{u \in U} R_{u,i} R_{u,j}}{\sqrt{\sum_{u \in U} R_{u,i}^2} \sqrt{\sum_{u \in U} R_{u,j}^2}}$$

- adjusted cosine

$$\text{sim}(i, j) = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_u)(R_{u,j} - \bar{R}_u)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_u)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_u)^2}}$$

- pearson correlation

$$\text{sim}(i, j) = \frac{\text{Cov}(i, j)}{\sigma_i \sigma_j} = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_i)(R_{u,j} - \bar{R}_j)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_i)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_j)^2}}$$

music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based
 - ❖ item similarity measures

- cosine

$$\text{sim}(i, j) = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\| * \|\vec{j}\|} = \frac{\sum_{u \in U} R_{u,i} R_{u,j}}{\sqrt{\sum_{u \in U} R_{u,i}^2} \sqrt{\sum_{u \in U} R_{u,j}^2}}$$

- adjusted cosine

$$\text{sim}(i, j) = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_u)(R_{u,j} - \bar{R}_u)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_u)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_u)^2}}$$

- pearson correlation

$$\text{sim}(i, j) = \frac{\text{Cov}(i, j)}{\sigma_i \sigma_j} = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_i)(R_{u,j} - \bar{R}_j)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_i)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_j)^2}}$$

music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based
 - ❖ Prediction
 - user u , item i
 - Weighted sum

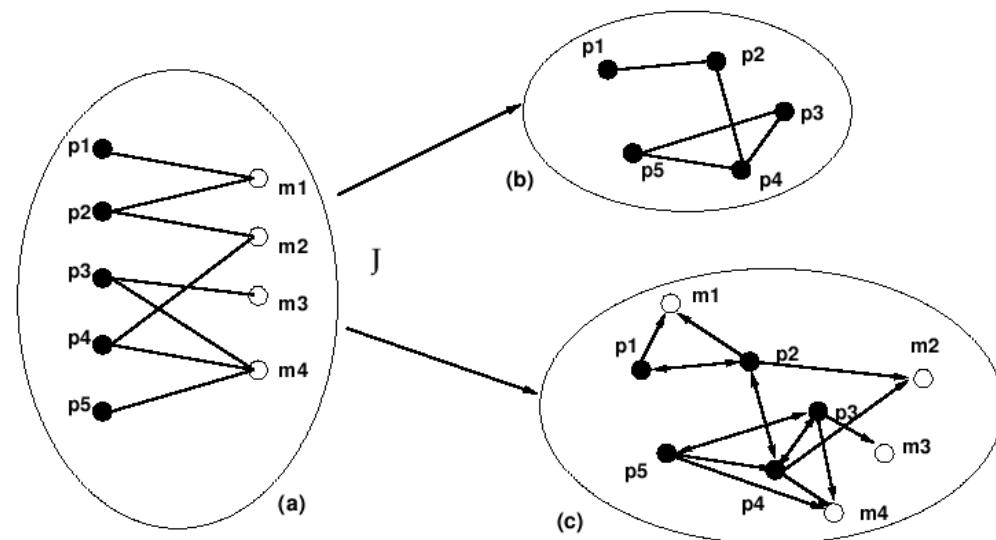
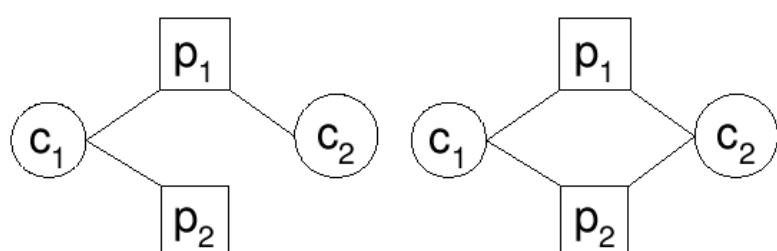
$$P_{u,i} = \frac{\sum_j s(i,j) R_{u,j}}{\sum_j s(i,j)}$$

music recommendation:: algorithms :: colfilter

- Collaborative Filtering

- ❖ other approaches

- Dimensionality reduction of the user-item matrix
 - ❖ SVD (LSA) [Hofmann, 2004]
 - ❖ Multidimensional Scaling [Platt, 2004]
 - graph based, with link prediction
 - ❖ consumer – product bipartite graphs [Huang, 2005], [Huang, 2007], [Mirza, 2003]



music recommendation:: algorithms :: content

- Content-based filtering

- based on item similarity
- usually at song level
- similarity can be
 - content-based
 - editorial
 - tag-based
 - etc.

for I'm So Glad - Skip James - Blues from the Delta

Restrict to genre: All Genres

Play all Songs

Searched 1.3 M songs in 0.17 s

Ofrenda Guadalupana
Lola Beltrán
Canciones a la Virge...
Latin

Crow Jane
Skip James
Blues from the Delta
Blues

Macédoine
Lynda Lemay
Les lettres rouges
French Pop

It's Better With A Band
Barbara Cook
It's Better with a B...
Vocal

I'll Marry The Very Next Man
Barbara Cook
Barbara Cook's Broad...

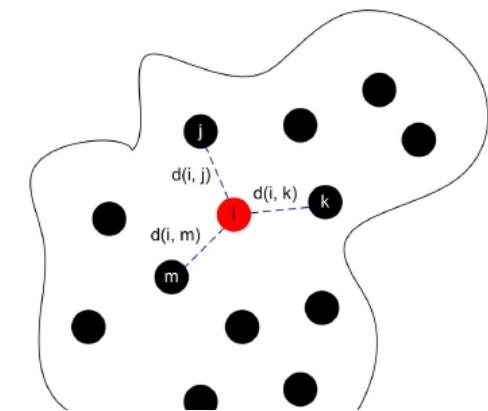
I'm So Glad
Skip James
Blues from the Delta
Blues

Tempo
Energy
Danceability

Now's the Time (Original Take 4)
Charlie Parker
The Charlie Parker S...
Jazz

What's Your Story Morning Glory?
Ella Fitzgerald
Ella Swings Lightly
Vocal

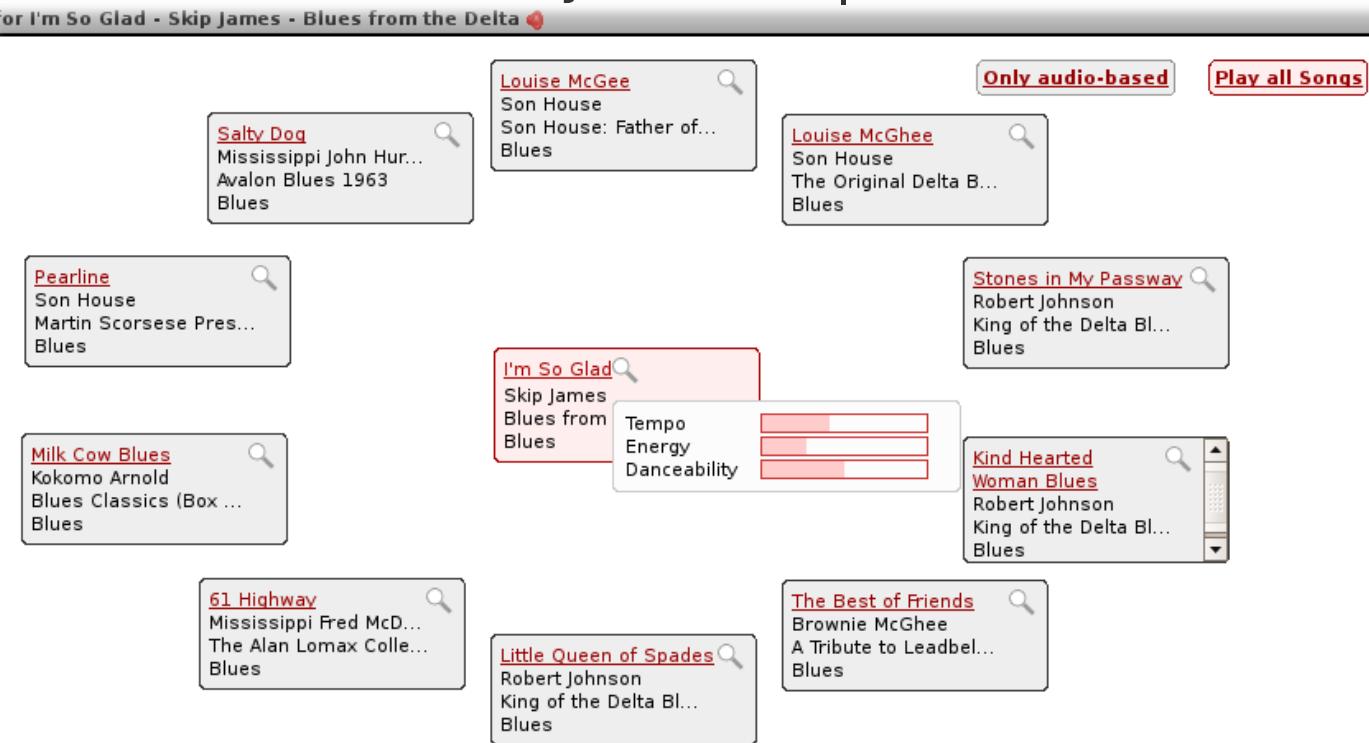
Yesterdays
Pucci Amanda
Jhones
Wild Is the Wind
Jazz



music recommendation:: algorithms :: hybrid

- Hybrid methods

- ❖ combine previous approaches (mainly CF and CB)
 - combining both outputs (e.g linear combination)
 - cascade: CF -> CB, or CB -> CF
 - select the best method at anytime (CF | CB)
 - etc.



outline

- Introduction
- Formalization of the recommendation problem
- Recommendation algorithms
- **Problems with recommenders**
- Recommender examples
- Evaluation of recommenders
- Conclusions / Future

problems:: Social recommenders :: Cold Start

- Sparse Data can lead to poor recommendations
 - ❖ Postal Service - “Such Great Heights”
 - 2.4 million scrobbles
 - 1000s of tags
 - ❖ Mike Shupps's - “All Over Town”
 - 3 scrobbles
 - 0 Tags
- A problem for:
 - ❖ New artists/Tracks
 - ❖ New users
 - ❖ New recommenders

problems:: Social recommenders:: Cold Start



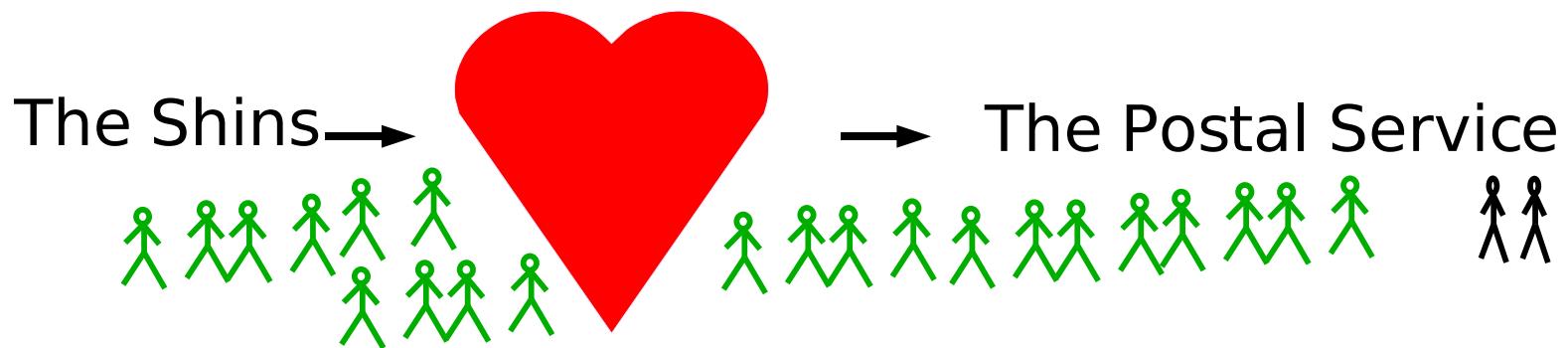
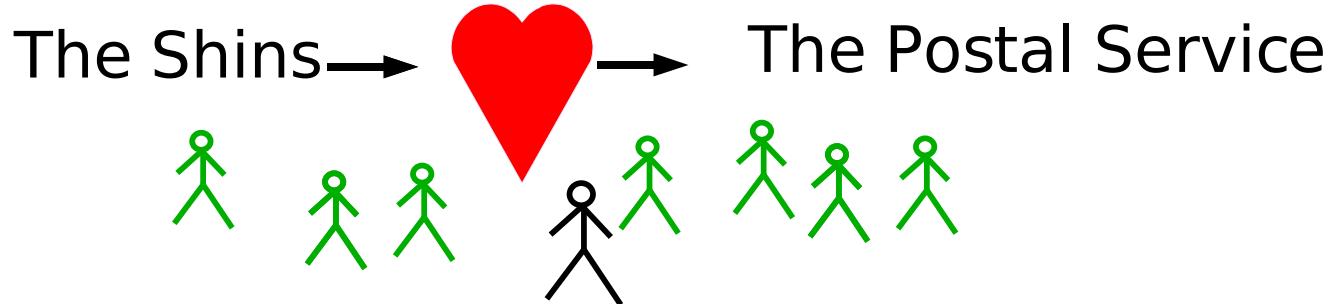
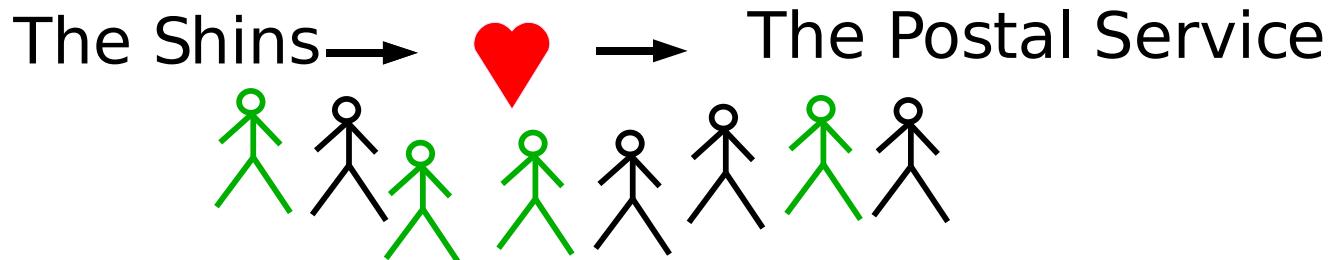
Emerson, Lake & Palmer
Played the most by: [David M](#) (1,370 plays)
Most recently played by: [Casey N](#) (about 1 hour ago)

Related artists

Elmo & Patsy 	Jose Feliciano 
Vince Guaraldi Trio 	Brenda Lee 
Holiday Express 	Bing Crosby 
Burl Ives 	Trans-Siberian Orchestra 

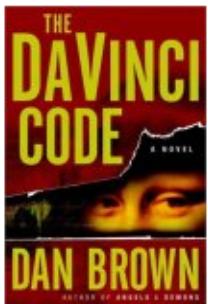
iLike^{Beta}

problems:: Social recommenders:: Feedback Loops



problems:: Social recommenders:: Popularity Bias

Customers who bought this item...



[The Da Vinci Code \(Hardcover\)](#)

by [Dan Brown](#)

Average Customer Review: (3376)

Usually ships in 24 hours

Eligible for **FREE Super Saver Shipping** on orders over \$25. [See details](#)

[Amazon.com](#)

With The Da Vinci Code, Dan Brown masterfully concocts an intelligent and lucid thriller that marries the gusto of an international murder mystery with a collection of fascinating esoteria culled from 2,000 years of Western history. A murder in the silent after-hour halls of the Louvre museum... [Read More](#)

\$24.95 **\$14.97**

[Add to cart](#)

[Add to Wish List](#)

761 used & new from \$2.96

Available for in-store pickup now from \$24.95

Price may vary based on availability

Enter your ZIP Code:

[Choose a store](#)

Also bought these items...

Show items in:

[All Categories](#)

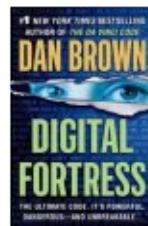
► [Books](#)

[DVD](#)

Show items that:

► [Customers also bought](#)

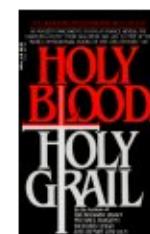
[Customers also viewed](#)



[Digital Fortress : A Thriller](#)

Mass Market Paperback by
Dan Brown

[More like this](#)



[Holy Blood, Holy Grail](#)

Mass Market Paperback by
Michael Baigent

[More like this](#)



[Harry Potter and the](#)

[Half-Blood Prince \(Book 6\)](#)
Hardcover by J.K. Rowling

[More like this](#)

problems:: Social recommenders:: Scale

❖ Netflix:

- 5 million customers
- 50,000 items
- 1.4B ratings
- 2M ratings per day
- 1B predictions per day
- 2 days to retrain

❖ Amazon:

- 30 million customers
- 1 million items

❖ Yahoo! Music:

- 25 million Users
- 600 million minutes/month
- 7 billion Ratings
- 30 million user-customized radio stations

❖ Last.fm

- 500 million 'scrobbles' per month
- 20 million unique users
- 100 million tracks
- 2 million tags applied per month

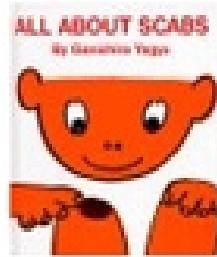
problems:: Social recommenders

- Lack of transparency



Recommended for You

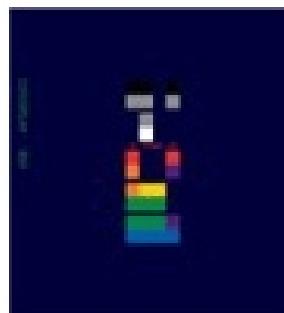
Charlie Love, Amazon.com has new recommendations for you based on [10 items](#) you purchased or told us you own.



[All About Scabs \(My Body Science Series\)](#)



[Breasts \(My Body Science\)](#)



[X&Y](#)



[The Historian](#)

► [Rate These Items](#)

► [See More Recommendations](#)

problems:: Social recommenders:: Early Rater Bias

- Early rater bias
 - ❖ Rich get Richer (Cumulative Advantage)
 - ❖ **Social Influence** as important as **quality**
 - ❖ Success of a song depends on the decisions of a few early-arriving individuals
 - ❖ The particular songs that became hits were different in different worlds

Is Justin Timberlake a Product of Cumulative Advantage?
Duncan Watts



problems:: Social recommenders

- Gray sheep
 - ❖ Common tastes mixed with uncommon tastes



Top Artists for the week

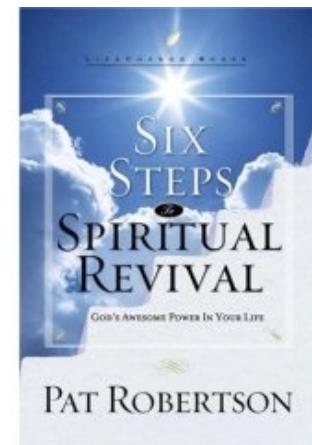


1	▶	Vanessa Hudgens
2	▶	Team Sleep
2	▶	Kanye West
2	▶	Bone Thugs-N-Harmony
2	▶	Britney Spears
2	▶	Sol Invictus
2	▶	Jason Collett
2	▶	Ryan and Sharpay
2		Jasmine France and Dona
2	▶	troy
2	▶	Cookie Monster
2	▶	Young Galaxy
2	▶	Jay-Z and Linkin Park
2	▶	Gabriella
2	▶	Fort Minor
2	▶	Tokyo Police Club
2	▶	Islands
2	▶	The Go! Team
2	▶	Jimmy Eat World
2	▶	High School Musical

problems:: Social recommenders

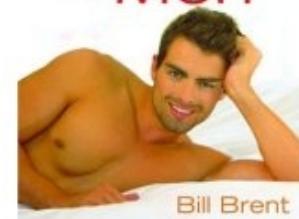
- Hacking the recommender
 - ❖ Profile Injection Attack

The screenshot shows a product page for 'Six Steps to Spiritual Revival' by Pat Robertson on a website with a green header bar. The header includes links for Welcome, OpalCat's Store, Books, Apparel & Accessories, Electronics, Toys & Games, Magazine Subscriptions, Browse Subjects, Bestsellers, Magazines, Corporate Accounts, and E-Books & Docs. A promotional banner at the top says 'Get \$30 to spend at Amazon! Just spend \$50 in Apparel & Accessories'. The main product image is a blue book cover with the title 'Six Steps to Spiritual Revival' and the author's name. Below the image, the price is listed as \$9.99, with a note about free shipping. Availability information, used and new options from \$7.00, and a hardcover edition are also provided. A link to see more product details is available. At the bottom, a section titled 'Customers who shopped for this item also shopped for these items:' lists three other books: 'The End of the Age' by Pat Robertson, 'The Ultimate Guide to Anal Sex for Men' by Bill Brent, and 'Esther's Gift' by Jan Karon.



PAT ROBERTSON

The
Ultimate
Guide to
Anal Sex
for Men

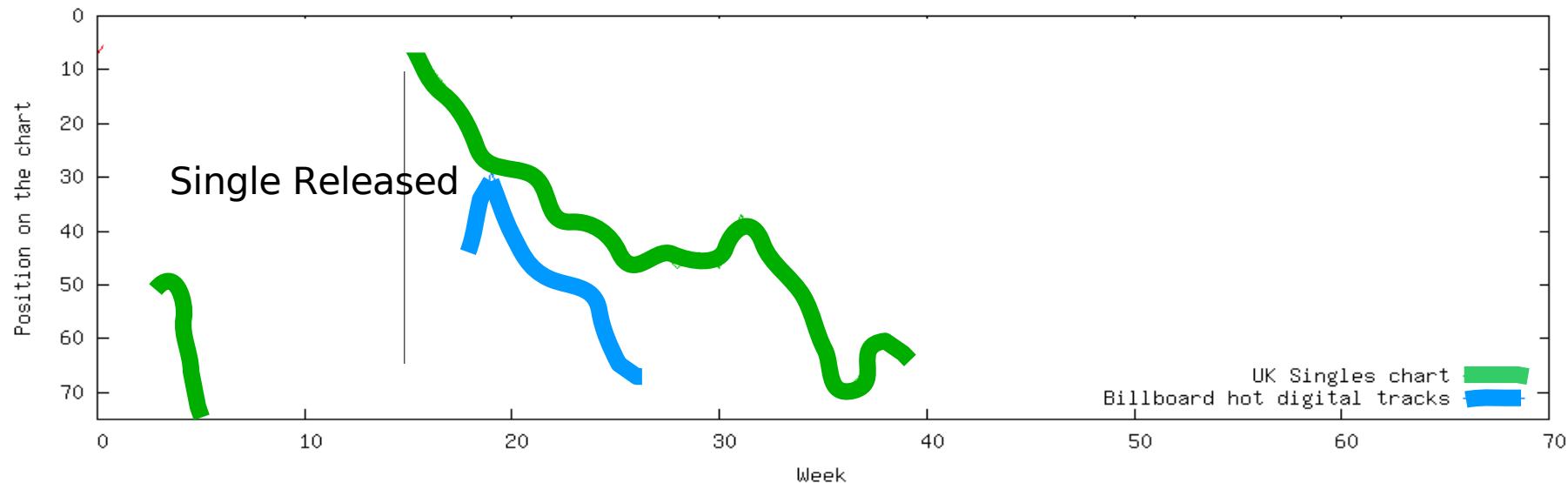


Bill Brent

problems:: Social recommenders

- Inertia / Aging

Coldplay's '**Fix You**' on the charts

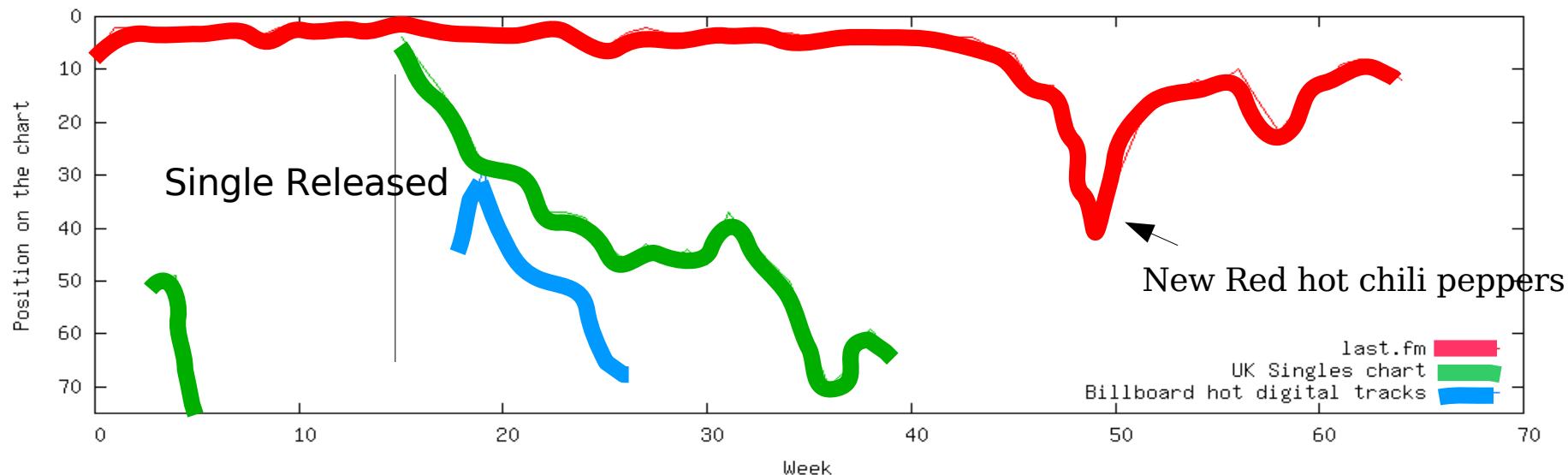


- ❖ Traditional sales charts have built-in decay

problems:: Social recommenders

- Inertia / Aging

Coldplay's '**Fix You**' on the charts

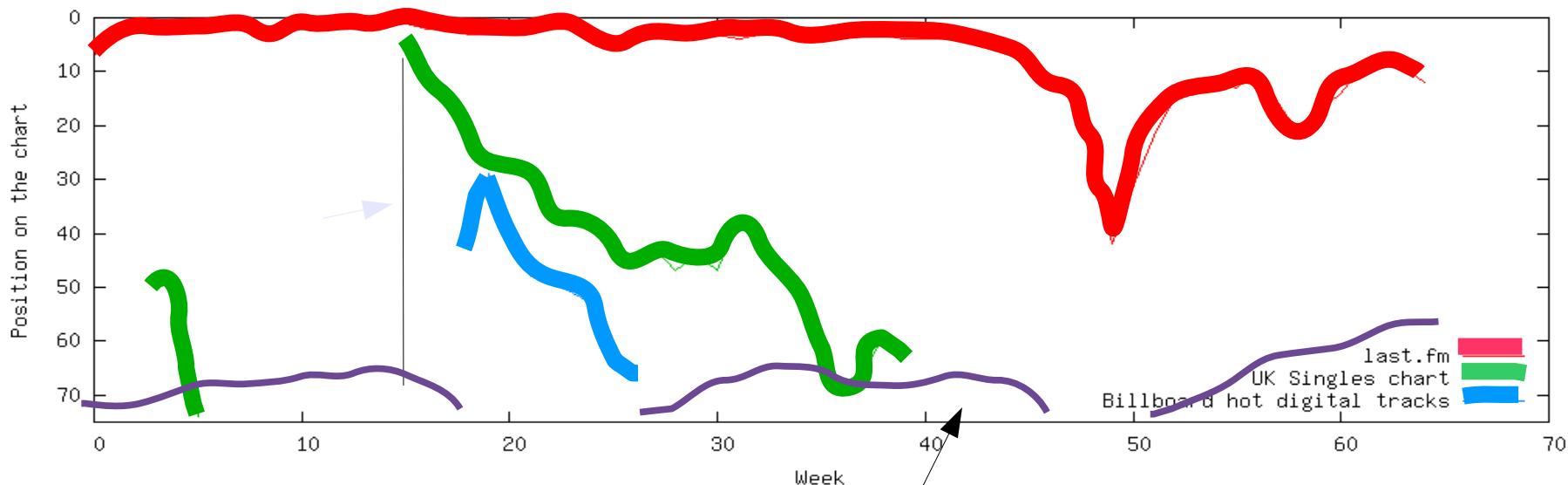


- ❖ Traditional charts have built-in decay
- ❖ New 'play' charts resist decay

problems:: Social recommenders

- Inertia / Aging

Coldplay's '**Fix You**' on the charts

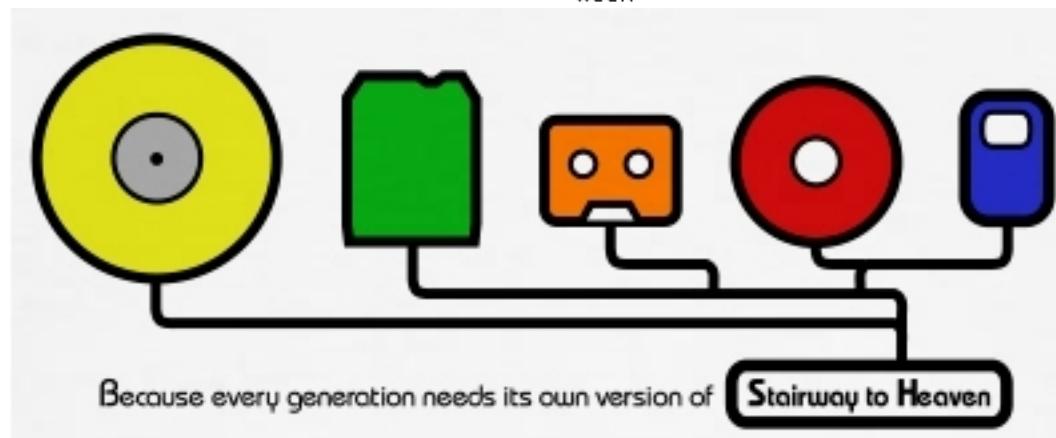
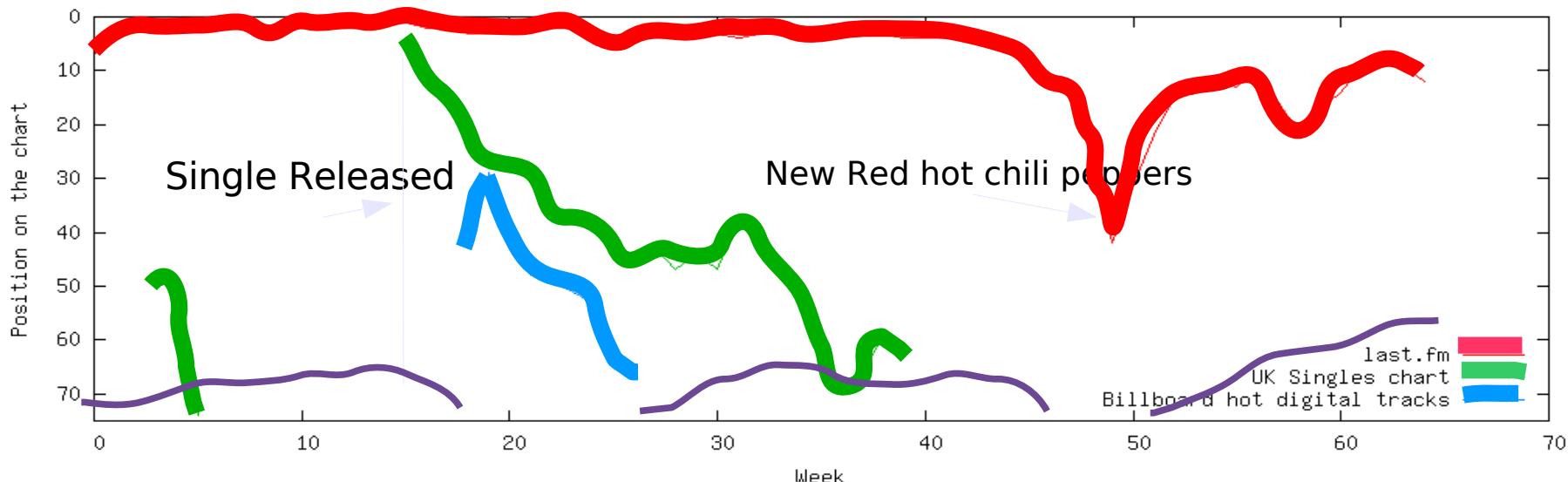


- #1 with a lead weight
 - ❖ “**Such Great Heights**” – 150 weeks in the top 10
 - ❖ “**Stairway to Heaven**” – #58 after 35 years

problems:: Social recommenders

- Inertia / Aging

Coldplay's '**Fix You**' on the charts



problems:: Social recommenders

- Novelty / Serendipity

↳ Songs like "Hey Jude" by Elvis Presley

Discover Share Export to iTunes Save Advanced Controls New Search				
Preview	Play	Song		Artist
		Hey Jude		Elvis Presley
		Hey Jude		Arthur Fiedler
		Hey Jude		Luca Colombo
		Hey Jude		Espitia, J. Lennon/P. McCartney
		Hey Jude		Wilson Pickett
		Hey Jude		Chokocheeky
		Hey Jude		Dale Miller
		Hey Jude		Tiny Tim
		Mother Nature's Son		John Denver
		Strawberry Fields Forever		The Real Group

problems:: Social recommenders

- Trust
 - ❖ How can you trust a recommendation?
 - ❖ Payola
 - ❖ Amazon “Reviewer Scandal”
 - ❖ Pay-per-post
 - ❖ Pay-per-digg
- Coming soon:
 - ❖ Pay per Scrobble?



problems:: Social recommenders:: trust

- PayPerPost

He wants to create a buzz for his new product.

She wants to make money.

Advertisers

PayPerPost™ is an automated system that allows you to promote your Web site, product, service or company through the PayPerPost network of bloggers. [Advertise on blogs](#) to create buzz, build traffic, gain link backs for search engine ranking, syndicate content and much more. You provide the topic to our [blog advertising](#) network and our bloggers create stories and post them on their individual blogs.

[how it works](#)

[get started](#)

Bloggers

[Get Paid for Blogging.](#) You've been writing about Web sites, products, services and companies you love for years and you have yet to benefit from all the sales and traffic you have helped generate. That's about to change. With PayPerPost™ advertisers are willing to pay you to post on topics. Search through a list of topics, make a blog posting, get your content approved, and get paid. It's that simple.

[how it works](#)

[get started](#)

problems:: Social recommenders

- Gallery of bad recommendations

Better Together

Buy this DVD with World Trade Center (Two-Disc Speci



+

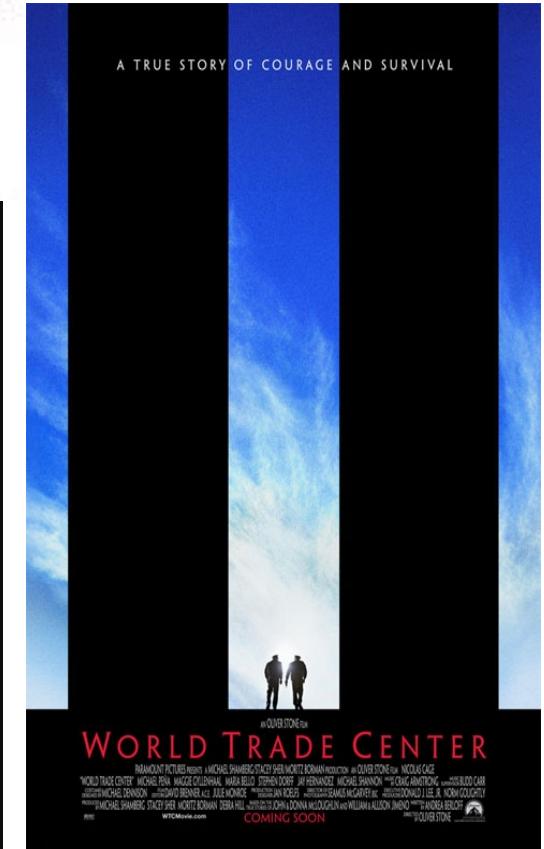
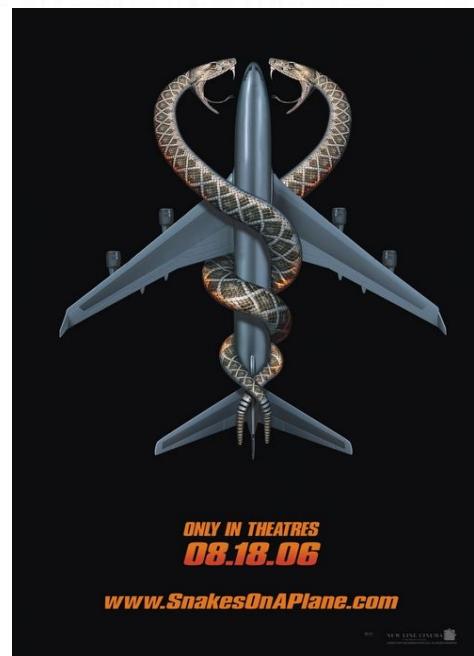


Total List Price: \$63.97

Buy Together Today: \$40.47

 Buy both now!

Are these really
Better Together?



problems:: Social recommenders

- Strange connections

amazon.com.

Rate this item



[Durex Avanti Polyurethane Condoms, 6 Condoms](#)

Durex

Price: \$8.99

Add to Cart

Add to Wish List

...because you were interested in:

[Netgear WG511 Wireless 802.11g PC Card](#)

by Netgear

You purchased or rated this item



problems:: Social recommenders

Strange
Connections



Panasonic ER411NC Nose and Ear Hair Groomer

Average Customer Review: 4.5 stars

Release Date: May 16, 2002

Our Price: \$14.88 Used & new from \$14.88

Own It



Not Interested

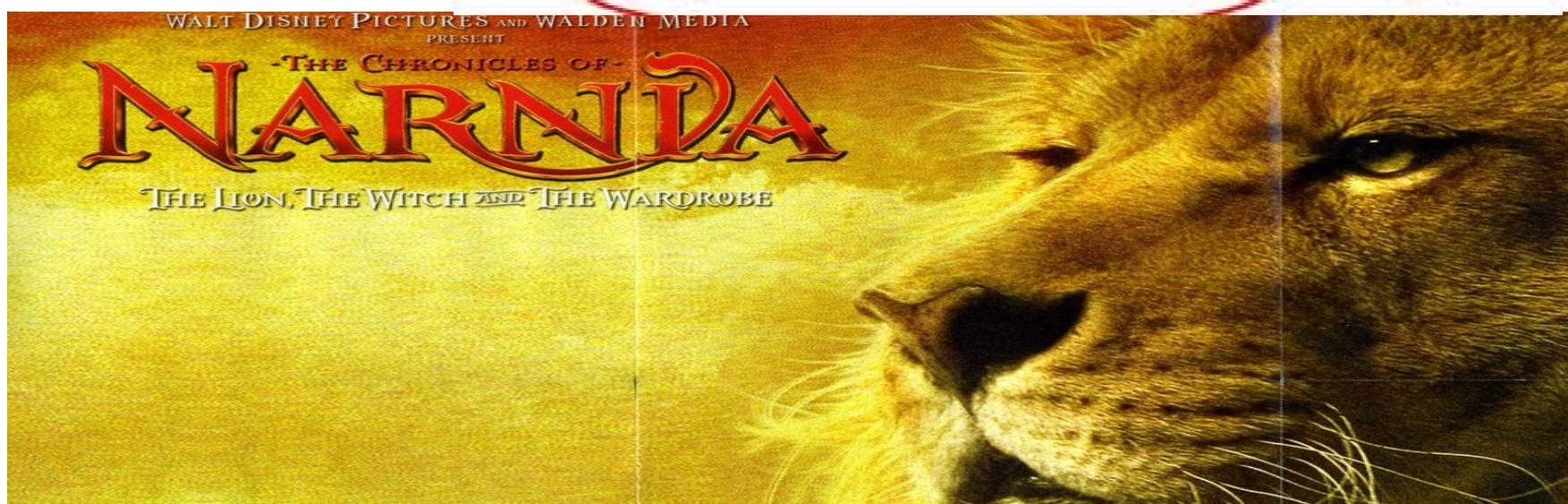


Want it



Saved

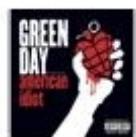
Recommended because you rated The Chronicles of Narnia Boxed Set and more ([edit](#))



problems:: Social recommenders

If you like Gregorian Chants you might like Green Day

Recommendations based on the items in your cart



American Idiot EXPLICIT

Green Day

Genre: Alternative

£28.99

[ADD ALBUM](#)



Antics

Interpol

Genre: Alternative

£27.90

[ADD ALBUM](#)



Contraband EXPLICIT

Velvet Revolver

Genre: Rock

£27.99

[ADD ALBUM](#)



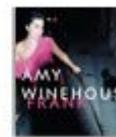
Deloused In the Comatorium

The Mars Volta

Genre: Rock

£27.99

[ADD ALBUM](#)



Frank EXPLICIT

Amy Winehouse

Genre: Pop

£27.99

[ADD ALBUM](#)



Blue

Joni Mitchell

Genre: Rock

£27.90

[ADD ALBUM](#)

Song Name	Time	Artist	Album	Genre	Price
▶ Selected Chants of the Russian Orthodox Church			2 cds in1-Monks and Metropolitan...	Selected Chants ...	Classical £11.95
▶ Gregorian Chant			Benedictine Monks of the Abbey...	Gregorian Chant	Classical £7.99

If you like Britney Spears
you might like...

You own *Baby One More Time*.
We recommend:

Report On Pre-War Intelligence

[Report On Pre-War Intelligence...](#)

Senate Intelligence Committee ...

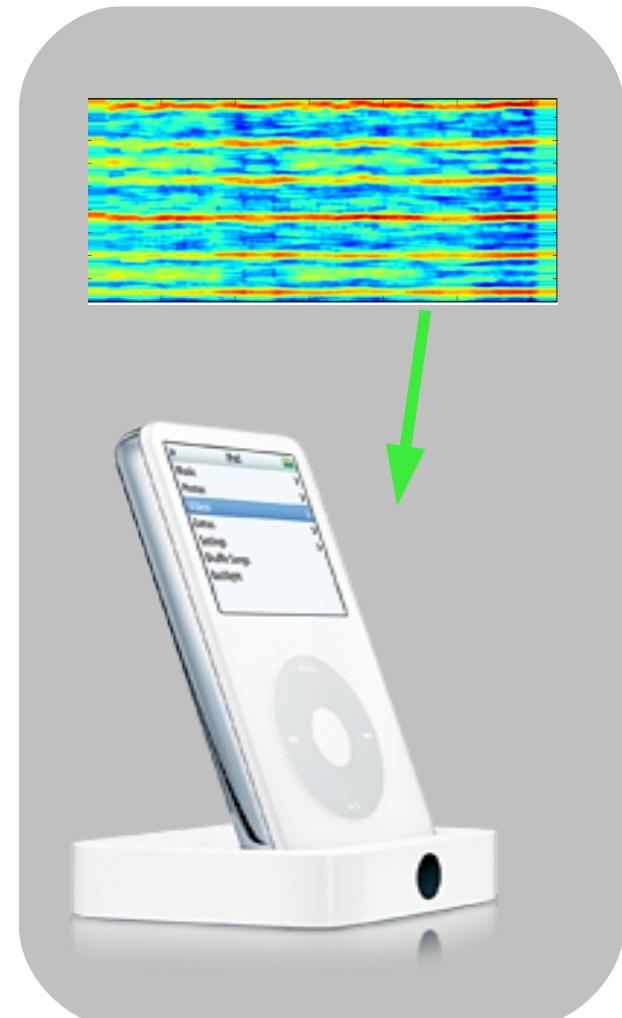
Released 2005

\$0.95 [ADD BOOK](#)

[Already Own It](#)
[Don't Like It](#)

problems:: Content based recommenders

- Social effects are extremely important
- Early days:
 - ❖ Poor quality recommendations
 - ❖ Can't tell 'good' music from 'bad'
 - ❖ Can make mistakes no human would make:
 - harpsichord <-> distorted electric guitar
 - ❖ “Pandora isn’t broken. The listener is.”
 - ❖ DRM – listen only music



problems:: Content based recommenders

- Analysis is hard

Your search (by selection):

The Beatles - Revolution 9

[iTunes] [Back] [Forward]

Recommendations :

[83%] Beatles - Let It Be

[iTunes] [Back] [Forward]

[80%] Ike & Tina Turner - It's Gonna Work Out Fine

[iTunes] [Back] [Forward]

[79%] Lonnie Mack - Stop

[iTunes] [Back] [Forward]

[79%] Bo Diddley - Go For Broke

[iTunes] [Back] [Forward]

[78%] Tom McRae - A Day Like Today

[iTunes] [Back] [Forward]

XXX's technology analyses the music content to extract information about rhythm, tempo, timbre, instruments, vocals, and musical surface of a song.

In fact, they rely mostly (or entirely on metadata for recommendations).

outline

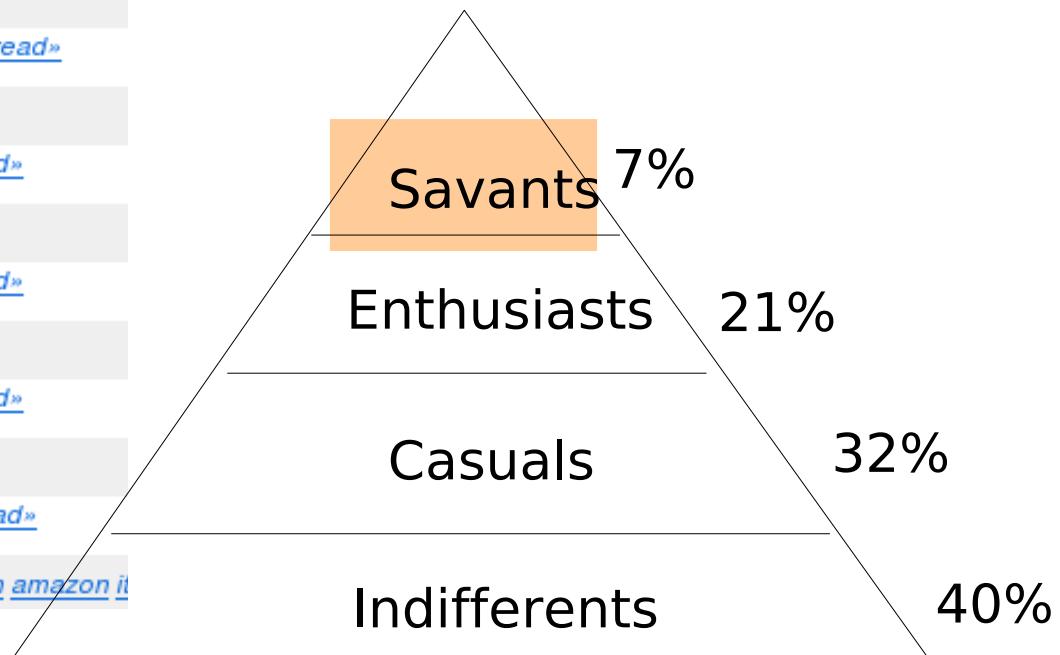
- Introduction
- Formalization of the recommendation problem
- Recommendation algorithms
- Problems with recommenders
- **Recommender examples**
- Evaluation of recommenders
- Conclusions / Future

examples:: Hard core music discovery

September 7, 2007

- 11am tez - head attack [listen](#) [amazon](#) [itunes](#)
posted by Streetkiss music in "We Kiss Fantasy" [read»](#)
- 11am Bitchee Bitchee Ya Ya Ya - Fuck Friend [listen](#)
posted by Streetkiss music in "We Kiss Fantasy" [read»](#)
- 11am Bitchee Bitchee Ya Ya Ya - Fuck Friend [listen](#)
posted by Streetkiss music in "We Kiss Fantasy" [read»](#)
- 9am beirut - nantes [listen](#) [itunes](#)
posted by Ugly Talented in "For Yesterday..." [read»](#)
- 9am Bonobo - Walk In The Sky [listen](#) [itunes](#)
posted by Ugly Talented in "For Yesterday..." [read»](#)
- 9am Kazi - A.V.E.R.A.G.E. [listen](#) [itunes](#)
posted by Ugly Talented in "For Yesterday..." [read»](#)
- 9am Positive K - It's All Over [listen](#) [amazon](#) [itunes](#)
posted by HeroBlog in "News:: Football...Bah" [read»](#)
- 9am Method Man - Somebody Done Fucked Up [listen](#) [amazon](#) [itunes](#)

- No filter - High Risk listening
- Long tail - without the “help me find it”



examples:: Hard core music discovery

- Primary discovery tool is “What's Hot” charts

What's hot

Most Blogged

[Beirut](#)
[Kanye West](#)
[Band Of Horses](#)
[animal collective](#)
[Klaxons](#)
[Rilo Kiley](#)
[Bruce Springsteen](#)
[Radiohead](#)
[Bat For Lashes](#)
[Caribou](#)
[Jens Lekman](#)
[Le Loup](#)
[Spoon](#)
[Elliott Smith](#)
[Feist](#)

Popular Searches

[Kanye West](#)
[Beirut](#)
[Band Of Horses](#)
[Mia](#)
[Feist](#)
[Justice](#)
[Rilo Kiley](#)
[Britney Spears](#)
[Daft Punk](#)
[Bat For Lashes](#)
[Amy Winehouse](#)
[Klaxons](#)
[Jens Lekman](#)
[Kate Nash](#)
[Radiohead](#)

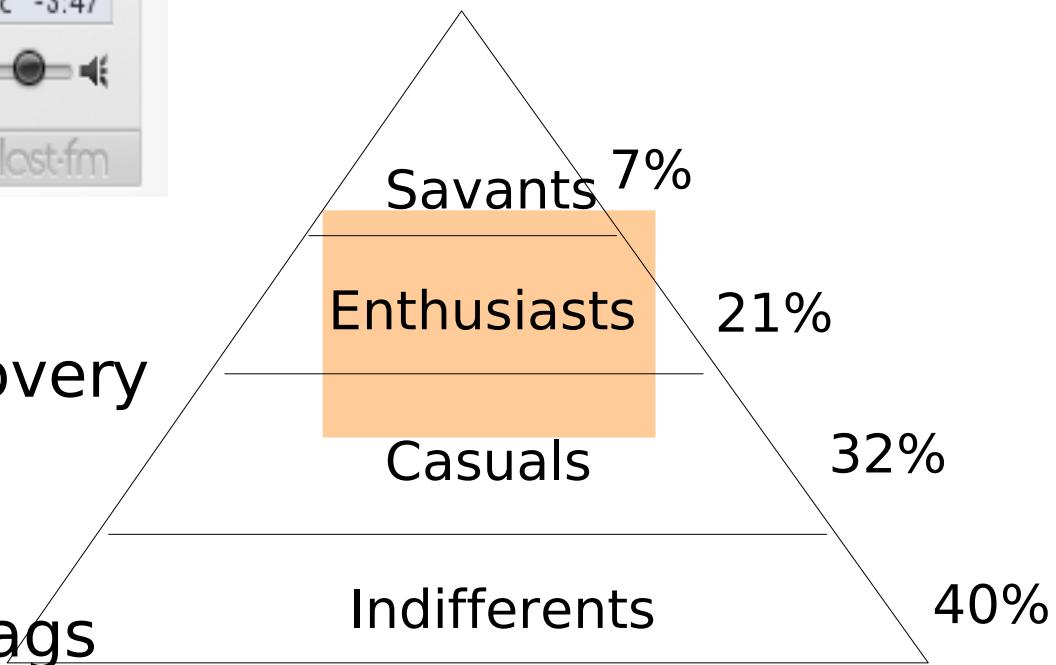
Popular Blogs

[The Music Slut >>](#)
[This Recording >>](#)
[Berkeley Place >>](#)
[get weird turn pro >>](#)
[The Yellow Stereo >>](#)
[Rock Sellout >>](#)
[jefitoblog >>](#)
[brugo >>](#)
[Cause=Time >>](#)
[Fabulist! >>](#)
[Missingtoof >>](#)
[wongie's music world >>](#)
[Neiles Life >>](#)
[BadmintonStamps >>](#)
[Palms Out Sounds >>](#)

examples:: Social music



- Kitchen Sink Interface
- Focus is on music discovery
- Many tools for music discovery
 - ❖ recommendations, tags
 - ❖ friends, videos, charts ...



examples:: Social music

- Last.fm Features
 - ❖ Scrobbler
 - ❖ Artist, Album and Track tagging
 - ❖ Internet Radio
 - ❖ Recommendations
 - Similar artists,
 - Similar Listeners
 - ❖ Charts
 - Tracks, Artists, Albums, Videos, Movers, Tags
 - ❖ Videos, Events
 - ❖ Social Features
 - Friends, messages, shoutouts

Your stations

- Play lamere's Neighbourhood
- Play lamere's Recommendations

Related Stations

- Play Music tagged tried to eat kermit the frog once
- Play Music like Kurtis Blow
- Play Music like Treacherous Three
- Play Music like Funky 4+1
- Play Music like DJ Kent
- Play Music like EWF

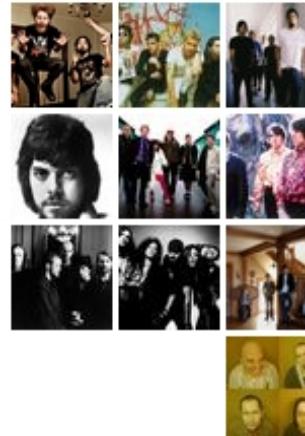


examples:: Social music

Last.fm recommendations

- Recommendations:
 - ❖ Primarily Collaborative Filtering
 - ❖ Item-Item (artist recommendations)
 - ❖ User-User (Neighbors)
 - ❖ Could use:
tags, audio, metadata
- Evaluating (rel. feedback)
 - ❖ Tracking Love/Ban behavior

Recommended Artists (see all)



- ▶ Team Sleep
- ▶ Manic Street Preachers
- ▶ CKY
- ▶ Procol Harum
- ▶ The Sugarcubes
- ▶ Alan Parsons
- ▶ Grizzly Bear
- ▶ The 69 Eyes
- ▶ Blind Melon
- ▶ Halloween, Alaska



examples:: Social music

Internet radio

- Neighbor radio
- Recommender Radio
- “My Radio”
- Tag Radio
- User Radio
- While listening:
 - ❖ Artist Bio
 - ❖ Related Stations
 - ❖ Top Listeners

Lazy Eye Tag Radio



[Play in pop up](#) | [Embed](#)

Cookie Monster

9,240 plays scrobbled on Last.fm



Cookie Monster is a popular Muppet character on the children's television show Sesame Street. He is covered with blue fur and has "googly eyes", but he is most known for his voracious appetite. He can (and often does) eat anything and everything, but his favorite choice of food above everything else is cookies. The character has been performed by [Frank Oz](#) and David Rudman. ([read more](#))



examples:: Social music Last.fm Charts

Artist Hype List

Top artist movers for the week of 26 Aug 2007:

Sharpay	Up 336%	
Chad & Ryan	Up 282%	
High School Musical 2 Cast	Up 265%	
High School Musical 2	Up 258%	
Baroness	Up 240%	

Music Video Charts

26 Aug 2007 – 2 Sep 2007



Hypnotized
by Aquarian Age



Perfect Day
by Aquarian Age



Do It Again
by The Chemical Brothers



Honey, This Mirror Isn't
Big Enough for the
Two of Us
by Feist



1234
by Feist



Stranger
by Hilary Duff

Top Artists for the week ending 2 Sep 2007

1		The Beatles	65,236 listeners	
2		Red Hot Chili Peppers	61,956 listeners	
3		Radiohead	57,507 listeners	
4		Muse	51,363 listeners	
5		Linkin Park	50,875 listeners	



examples:: Social music

Last.fm - Scale

- 20 Million unique visitors per month
- 100 million unique tracks (including misspellings)
- 500 million 'scrobbles' per month
- 2 million tags applied per month
- Streamable tracks – 'millions'
- 100,000 independent artists
- 20,000 labels



examples:: Social music

Last.fm – web services

- Much of last.fm data is available via web services (Creative Commons License)
 - ❖ User Profile Data
 - ❖ Artist Data
 - ❖ Album Data
 - ❖ Track Data
 - ❖ Tag Data
 - ❖ Group Data
 - ❖ Forum Data
- <http://www.audioscrobbler.net/data/webservices/>



Powered by
Audioscrobbler™



examples:: Social music

Last.fm – web services

<http://ws.audioscrobbler.com/1.0/artist/Deerhoof/toptags.xml>

```
<toptags artist="Deerhoof">
  <tag>
    <name>indie</name>
    <count>100</count>
    <url>http://www.last.fm/tag/indie</url>
  </tag>
  <tag>
    <name>experimental</name>
    <count>94</count>
    <url>http://www.last.fm/tag/experimental</url>
  </tag>
  <tag>
    <name>indie rock</name>
    <count>60</count>
    <url>http://www.last.fm/tag/indie%20rock</url>
  </tag>
  <tag> ... </tag>
</toptags>
```

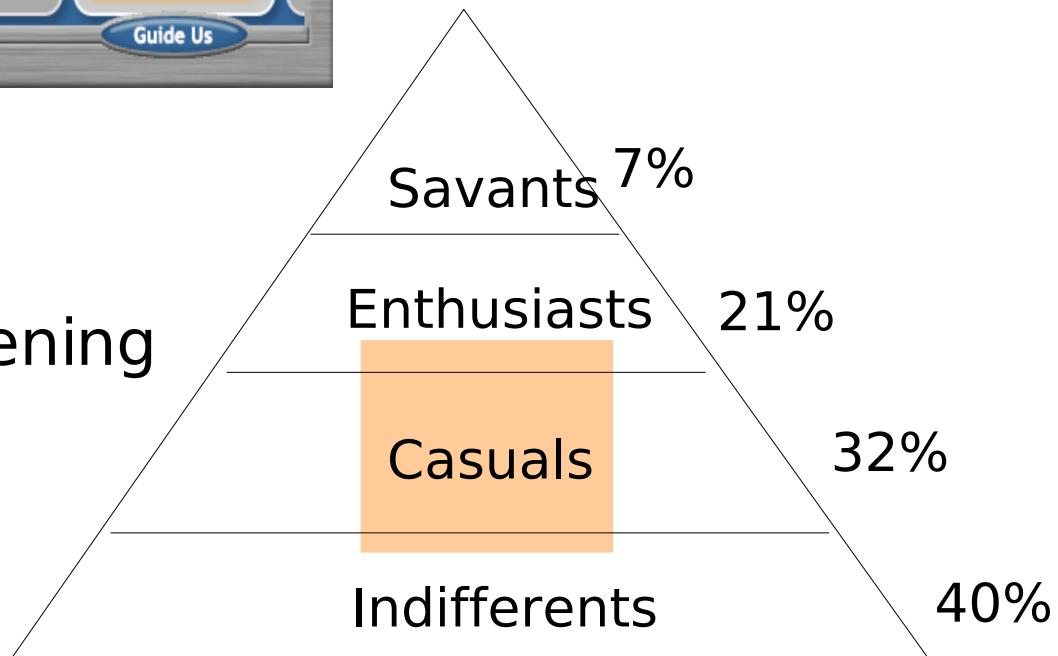


examples:: Content-based:: Pandora



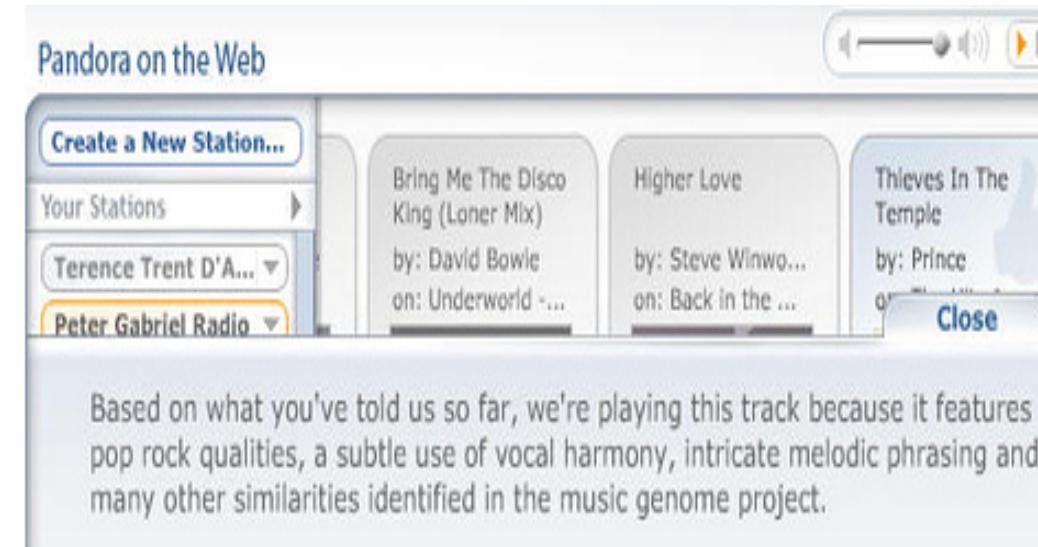
PANDORA™

- Low touch interface
- Focus is on music listening
- Transparent recommendations



examples:: Content-based:: Pandora

- Transparency
- Technology losing its "cold"



Pandora feels like a smart friend to me. This friend can articulate the reasons I love some of the things I love most (songs) better than I can, but only because I have told it what I like. This is one of my very favorite Prince songs and Pandora knows just why I like it so much. And I didn't know how to say it so well. Makes the technology seem very warm and reflective of my feelings and identity. It's an extension of the user, not a cold, isolating technology. I feel a part of Pandora some times. I'll bet they LOVE this.

<http://flickr.com/photos/libraryman/1225285863/>

examples:: Content-based:: Pandora

- Pandora: Scale
 - ❖ 35,000 artists
 - ❖ 500,000 songs
 - ❖ 15,000 songs analyzed per month
 - ❖ 8 Million registered users

examples:: Content-based:: Pandora

- Pandora: How does it work?
 - ❖ Curators select music to add to the catalog
 - ❖ Curators attach metadata (from AMG)
 - ❖ Music analysts characterize tracks across 400 features
 - ❖ Simple weighed Euclidean distance used to find similar songs
 - ❖ Playlists generated from seed songs/artists conforming to sets of rules

examples:: Content-based:: Pandora

- Enrolling a new CD
 - ❖ Phase 1: Curator
 - Curator Selects CD based on
 - Proof of audience
 - Curator judgment
 - “Does a song make listening better or worse?”
 - Curator rips CD, attaches metadata
 - ❖ Phase 2: Analysis
 - 160 Hours of training
 - Use double analysis to verify consistency of analysis
 - Analysis can be a collaborative process



examples:: Content-based:: Pandora

- Pandora analysis
 - ❖ Typically analyze 4 songs per album -
 - Choose songs that are representative of an artist's career
 - ❖ Include music outliers
 - ❖ Data Entry – 400 attributes with a 10 point scale:
 - [0-1-2-3-4-5-6-7-8-9-10] – Back beat prominence
 - [0-1-2-3-4-5-6-7-8-9-10] – Electric Guitar Wah-Wah
 - [0-1-2-3-4-5-6-7-8-9-10] – light or breathy vocals
 - ❖ 400 Attributes are a trade secret

examples:: Content-based:: Pandora

- Pandora analysis

- ❖ Dolly Parton – Stairway to heaven

- country influences
 - bluegrass influences
 - folk influences
 - a subtle use of vocal harmony
 - mild rhythmic syncopation
 - acoustic sonority
 - demanding instrumental part writing
 - intricate melodic phrasing
 - thru composed melodic style
 - a clear focus on recording studio production
 - minor key tonality
 - melodic songwriting
 - a heavy twang in the vocals
 - acoustic rhythm guitars

Curiously, no Pandora attributes are given for Led Zeppelin's version

examples:: Content-based:: Pandora

- Pandora recommendation
 - ❖ 400 song parameters form euclidean space
 - ❖ Genre specific weights
 - Problems with cross-genre recommendations
 - ❖ Simple nearest neighbors for song selection – filtered for:
 - licensing compliance
 - mix of familiarity, variety, discovery
 - ❖ For artist similarity use specific songs – not an average of all songs.

examples:: Content-based:: Pandora

- Pandora goes social
 - ❖ Crowd understands things that the genome doesn't
 - ❖ CF used initially as a safety net
 - ❖ Started using 'thumbs-down' data to filter out songs
 - ❖ 'Thumbs-up' data correlates with 'familiarity'
 - ❖ Use 'familiarity' to select songs
 - ❖ Result: "Playlists are massively improved"

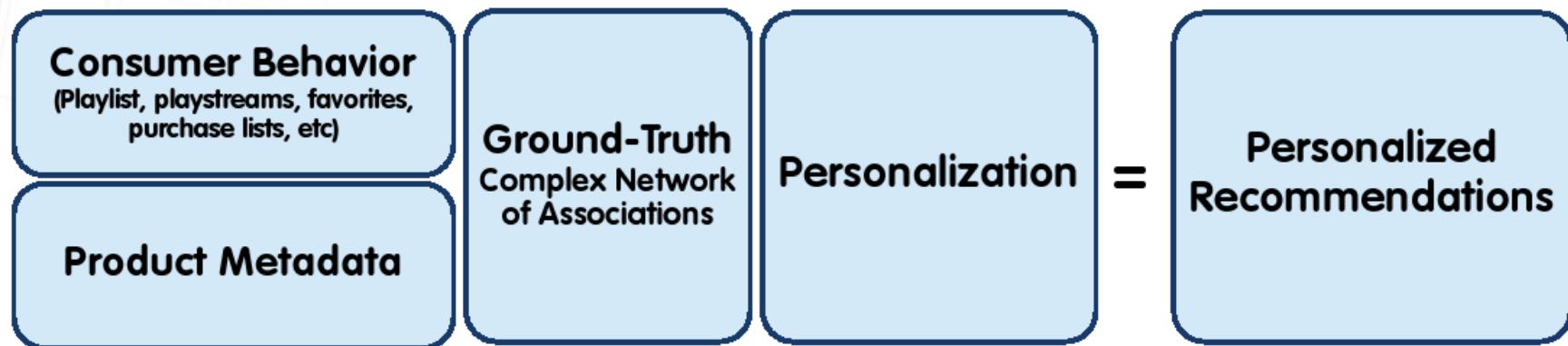
examples:: Content-based:: Pandora

- The New Pandora
 - ❖ Bigger is not always better
 - ❖ A Radio Station not a Recommender
 - Precision important, recall not.
 - ❖ All forms of song selection are good
 - ❖ New Hybrid approach:
 - Much happier listeners
 - Avoid some of the CF problems – coldstart and 'early rater' feedback loops
 - No longer strictly a Content-based recommender

examples:: Content-based:: Pandora

- The New Pandora
 - ❖ Pandora futures
 - Machine listening to add dimensions to their data
 - Social tags
 - ❖ Pandora issues
 - Adding new genres
 - Cross genre artists (the 'shakira' problem)
 - New music features – 'scratching'

examples:: Hybrid:: Mystrands



- Use
 - ❖ Precomputed top item-item correlations
 - ❖ Metadata – genre, year, popularity, tags, etc
 - ❖ User History – plays, skips, put on a playlist
 - ❖ User libraries

examples:: Hybrid:: One Llama

- ❖ Creating a Hybrid recommender

- Content-based similarity:

- ❖ Features = spectral, psycho-acoustic, MFCCs
 - ❖ Genetic algorithms for feature selection
 - ❖ Similarity metric – akin to VQ or hamming
 - ❖ Training similarity on production music
 - ❖ Fast similarity search – 200ms for 500K catalog

- Social-based similarity:

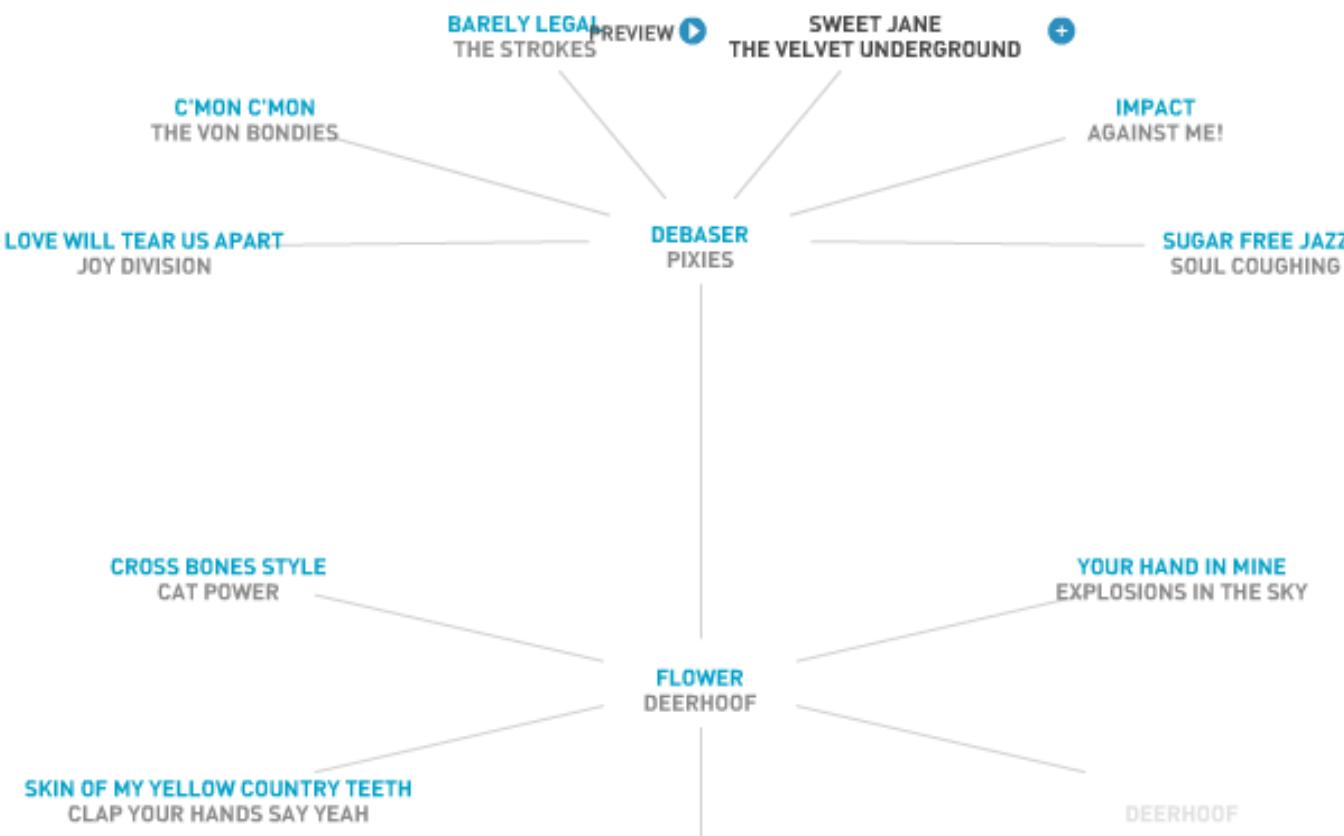
- ❖ Crawling web for playlists for co-occurrence similarity

- ❖ Still early days

- ❖ Strong ties to the MIR community (IMIRSEL)

examples:: Hybrid:: One Llama

- One Llama – playlist generator



examples:: Hybrid:: BMAT

- spin-off of the MTG, started in 2006

The screenshot shows the BODiBEAT software interface. At the top left is the Yamaha logo. To the right is the BODiBEAT logo with the text "COMING FALL 2007". Below the logo is a navigation bar with tabs: OVERVIEW, OPERATING MODES, BODiBEAT STATION (which is highlighted in blue), and SETTINGS. The main content area is titled "BODiBEAT STATION - MUSIC/WORKOUT MANAGING SOFTWARE". It features two sections: "Manage your music" and "Manage your workouts". The "Manage your music" section includes a description and a screenshot of the software's music library interface. The "Manage your workouts" section includes a description and a screenshot of the software's workout tracking interface. A green circle highlights the "bmat POWERED BY" logo at the bottom of the software interface.

 **bmat** barcelona music & audio technologies

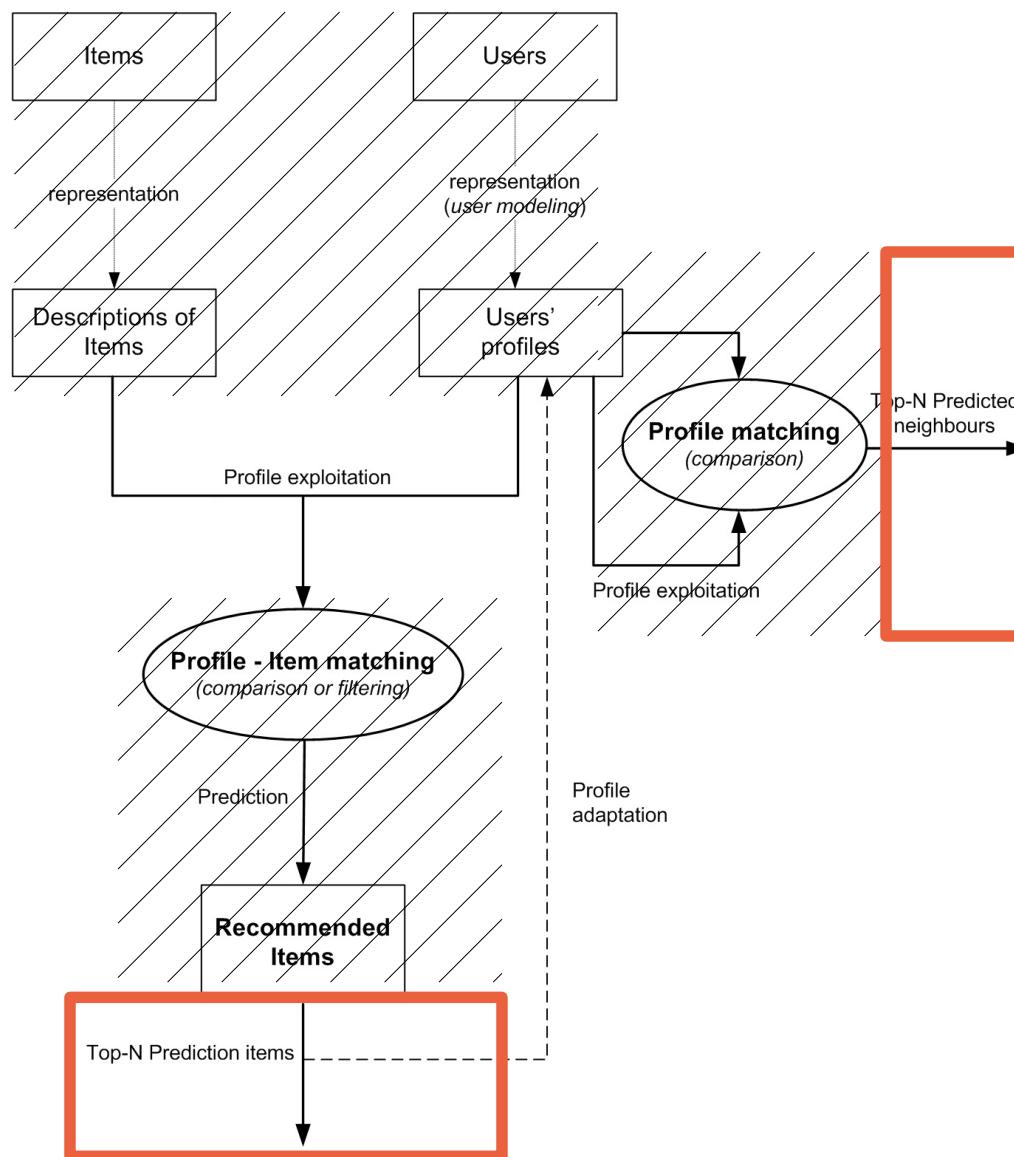


Company

outline

- Introduction
- Formalization of the recommendation problem
- Recommendation algorithms
- Problems with recommenders
- Recommender examples
- **Evaluation of recommenders**
- Conclusions / Future

evaluation



evaluation

- Is it possible to create a *standard* ground truth?
- Need of a music dataset
 - ❖ such as Netflix for movies (ask last.fm :-)
 - ❖ split dataset (train / test set)?
- Goals
 - 1) measuring the quality of the items recommended to a given user
 - 2) measuring *how good* is the music collection
- Constraints
 - 1) do not recommend an item if the user has previously *purchased / listened to / etc.* that item

evaluation

- Outline
 - ❖ common metrics
 - ❖ new metrics to exploit the long tail (popularity)
 - ❖ complex network analysis
 - ❖ informal survey of different recommenders

evaluation:: common metrics

- Accuracy metrics

- ❖ Statistical

- measure deviation between prediction and the actual *rating*
- Examples
 - ❖ Mean Absolute Error (MAE)
 - ❖ Root Mean Squared Error (RMSE) **Netflix Prize**
 - ❖ Correlation

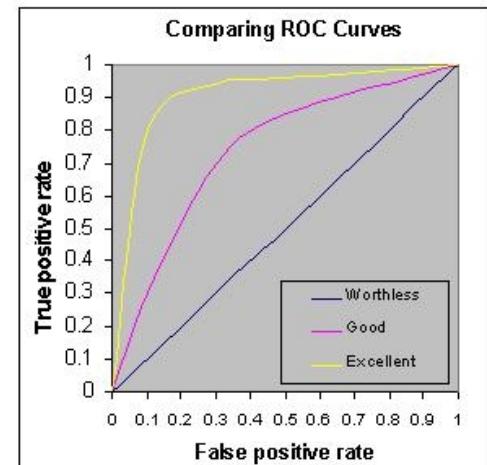
- ❖ Decision support

- measure the selection of high-quality items from the whole list
- Examples
 - ❖ (area of the) ROC curve
 - ☠ trade-off between True Positives and False Positives
 - ❖ Customer ROC curve
 - ☠ constrained to recommend the same number of items to each user

$$|E_{MAE}| = \frac{1}{N} \sum_{i=1}^N |x_i - \hat{x}_i|$$

$$\text{MSE}(\hat{\theta}) = \text{E}((\hat{\theta} - \theta)^2).$$

$$\text{RMSE}(\hat{\theta}) = \sqrt{\text{MSE}(\hat{\theta})}.$$



evaluation:: common metrics

- Relevance metric
 - ❖ Precision = $TP / TP + FN$
- Coverage metric
 - ❖ Recall = $TP / TP + FP$
- ...and both
 - ❖ F-measure
- Ranking quality of the recommendation list
 - ❖ Rank score
 - combine the hits and their position
 - ❖ if the training dataset contains ordered lists:
 - kendall tau
 - spearman rho

evaluation:: limitations

- Limitations of the current metrics
 - ❖ skewness
 - performed on test data that users *chose* to rate
 - ❖ do not take into account
 - usefulness
 - novelty / serendipity
 - *goodness* of the collection
 - ❖ analysis of the items' relationships

evaluation:: limitations

- Limitations of the current metrics
 - ❖ other components (user-dependent)

How eclectic is the musical preference of ocelma?

ocelma's eclectic score is

87/100

If your score is small (lower than 70) your musical preferences are very limited, and if it is large (larger than 80), then you have an eclectic musical preference.

<http://anthony.liekens.net/pub/scripts/last.fm/eclectic.php>

http://mainstream.vincentahrend.com/
Mainstream-O-Meter

Username:



ocelma

Powered by
Audioscrobbler™

Artist	Mainstreamness	Listeners	Weight
1. The Dogs D'Amour	0.32 %	2,597	100 %
2. U2	81.49 %	669,199	48 %
3. The White Stripes	86.10 %	707,040	24 %
4. Spiritualized	7.89 %	64,812	20 %
5. Yann Tiersen	21.21 %	174,175	19 %
6. The Black Crowes	9.55 %	78,438	16 %
7. Lhasa	3.40 %	27,950	11 %
8. Ryan Adams	22.22 %	182,505	10 %
9. Martirio y Chano Domínguez	0.01 %	94	8 %
10. The Rolling Stones	64.58 %	530,305	6 %
11. Bob Dylan	59.02 %	484,687	6 %
12. Kraftwerk	23.20 %	190,529	6 %
13. Nirvana	85.65 %	703,330	4 %
14. Björk	56.32 %	462,460	4 %
15. Radiohead	103.00 %	845,815	4 %

30.82 % mainstream

Number of users



evaluation:: limitations

- New proposed metric: “novelty+relevance”
 - ❖ novelty (serendipity “Oh!”)
 - How? exploit the long-tail of the collection (popularity)
 - ❖ ...but still *relevant* to the user

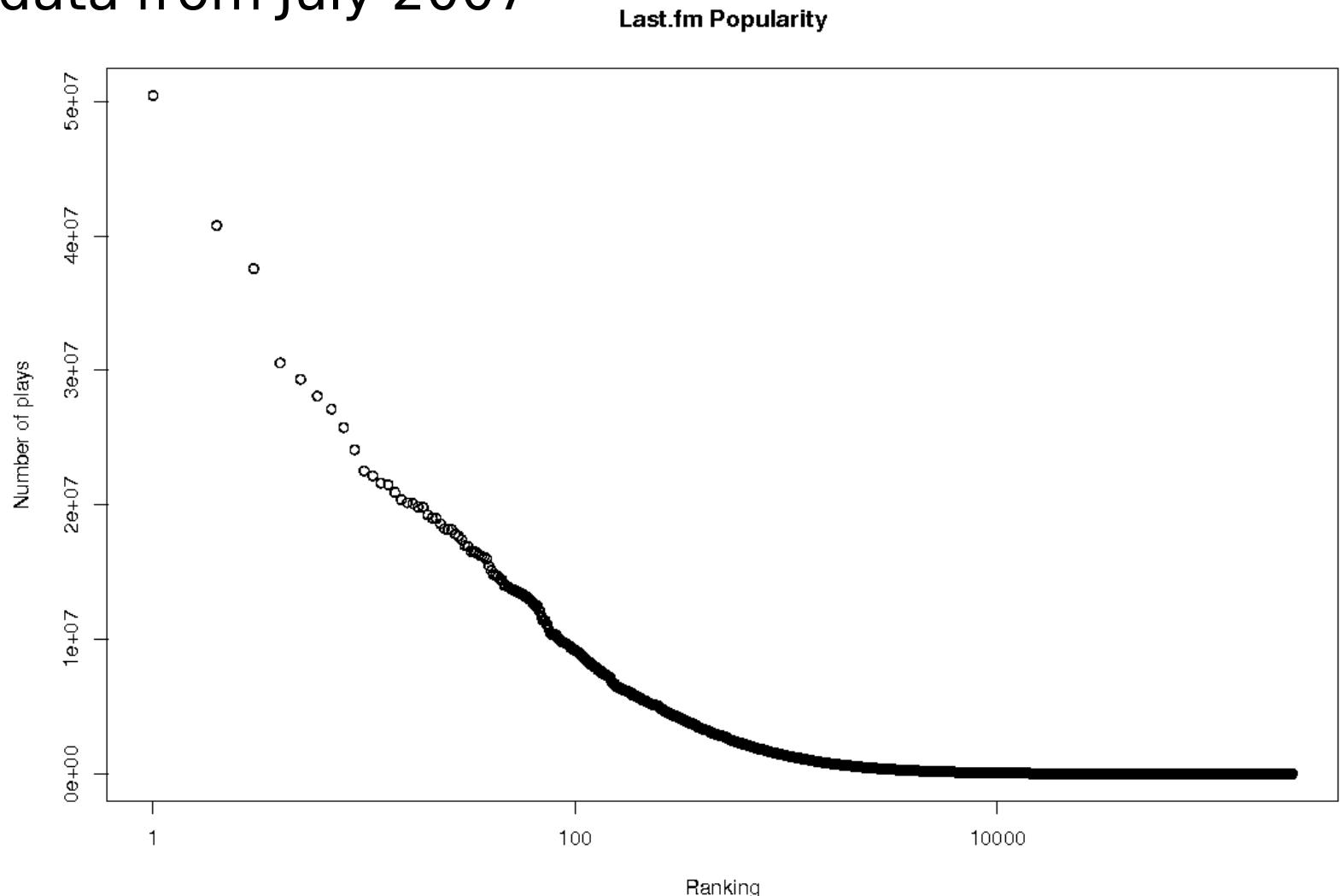
evaluation:: novelty & relevance

- Dealing with novelty
 - ❖ Experiment with **last.fm** data
 - 249,753 artists
 - for each artist, get
 - ❖ total number of plays, and
 - ❖ similar artists (3,846,262 of relationships)



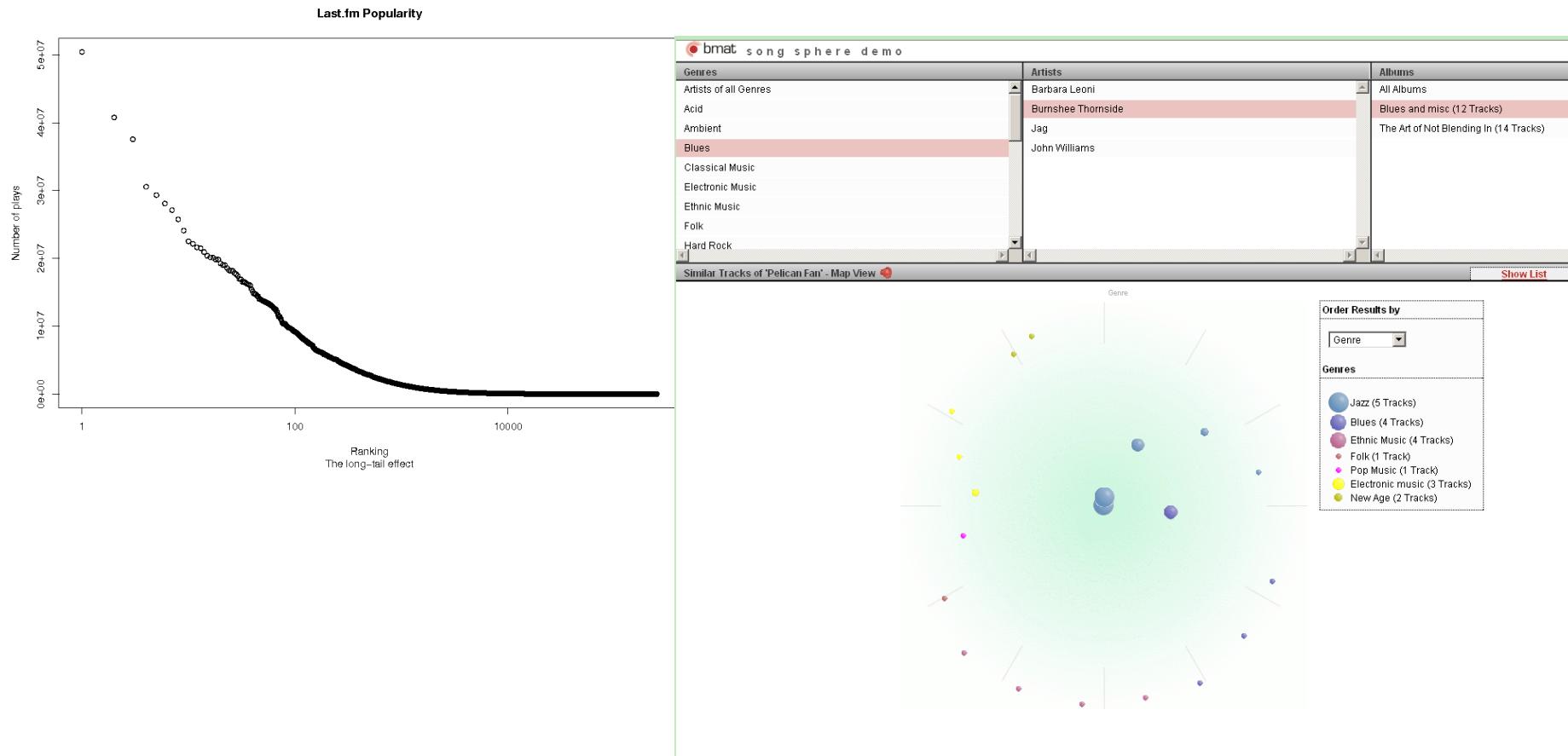
evaluation:: novelty & relevance

- **Last.fm** long-tail analysis (#artists plays)
 - ❖ data from July 2007



evaluation:: novelty & relevance

- **Last.fm** long-tail analysis (#artists plays)
 - ❖ 1st Example: explore the **long tail**, by means of content-based audio similarity

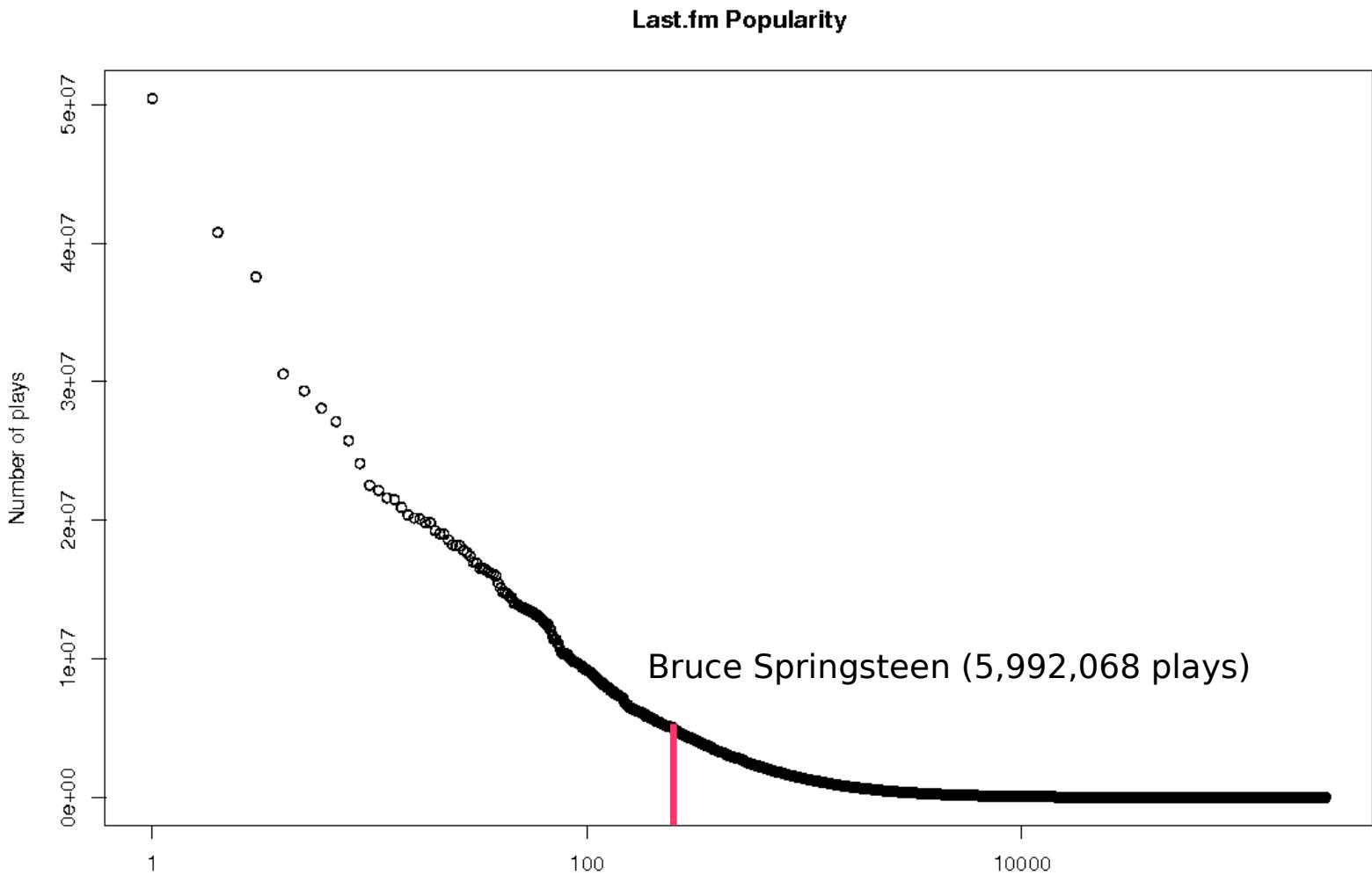


evaluation:: novelty & relevance

- Bruce Springsteen
 - ❖ total # plays in last.fm = 5,992,068
 - ❖ # plays for “Better days” (seed song) = 33,995
 - ❖ data from July 2007

evaluation:: novelty & relevance

- **Last.fm** long-tail analysis (#artists plays)
 - ❖ Bruce Springsteen

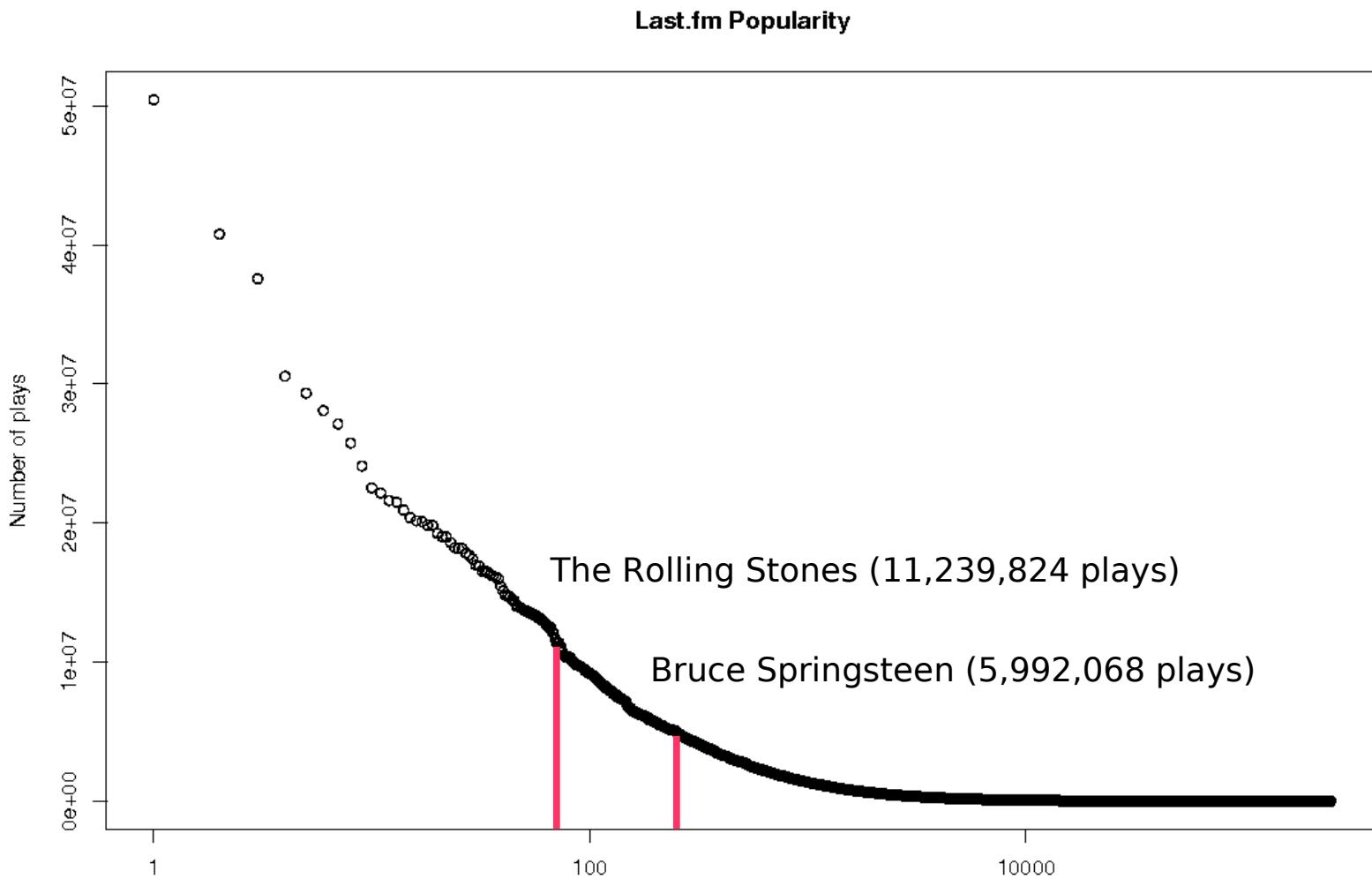


evaluation:: novelty & relevance

- The Rolling Stones
 - ❖ total # plays in last.fm = 11,239,824
 - ❖ # plays for “Mixed emotions” = 50,778
 - ❖ data from July 2007

evaluation:: novelty & relevance

- **Last.fm** long-tail analysis (#artists plays)
 - ❖ The Rolling Stones

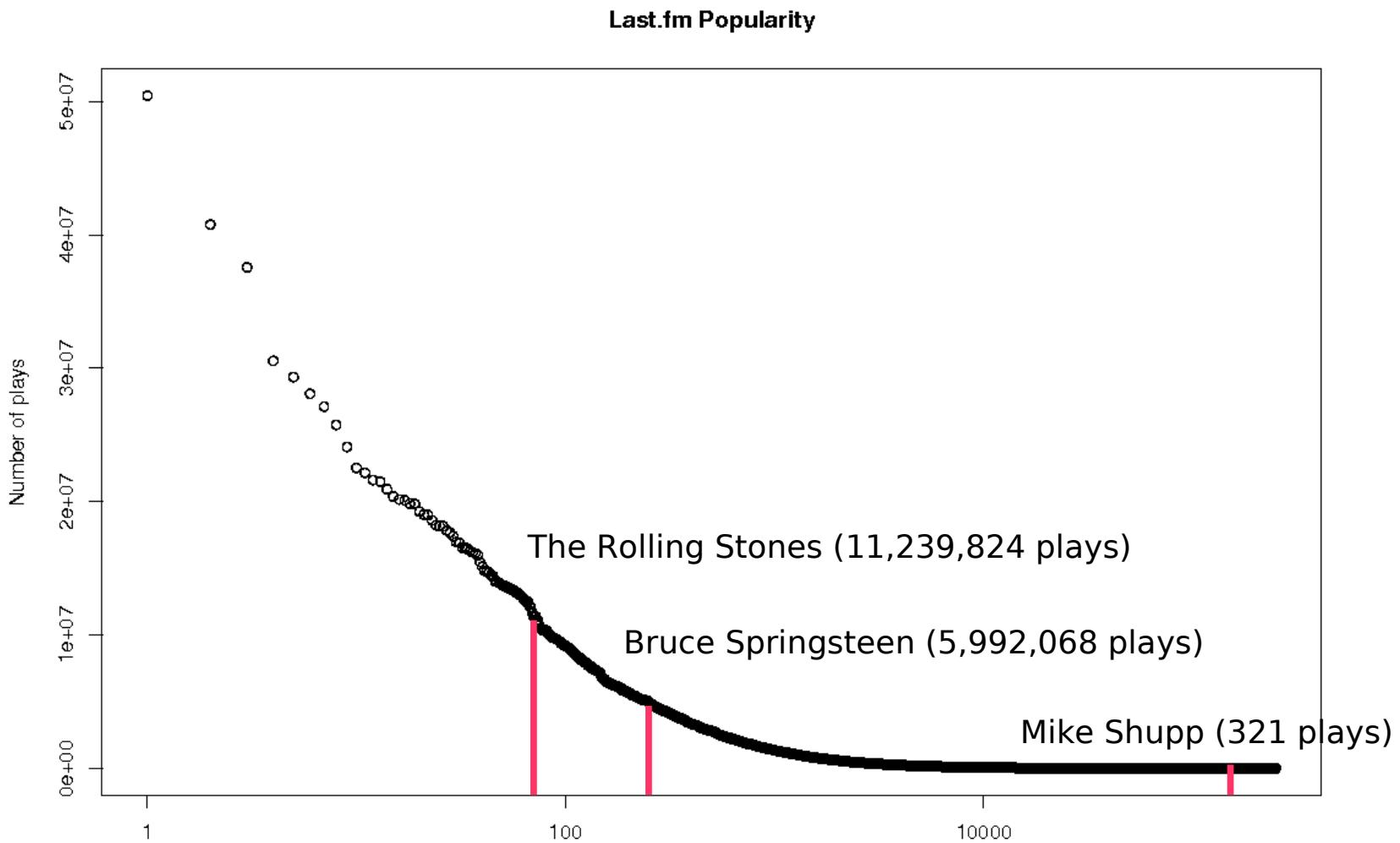


evaluation:: novelty & relevance

- Mike Shupp
 - ❖ total # plays in last.fm = 321
 - ❖ # plays for “Letter to Annette” = 0
 - ❖ data from July 2007

evaluation:: novelty & relevance

- **Last.fm** long-tail analysis (#artists plays)
 - ❖ Mike Shupp

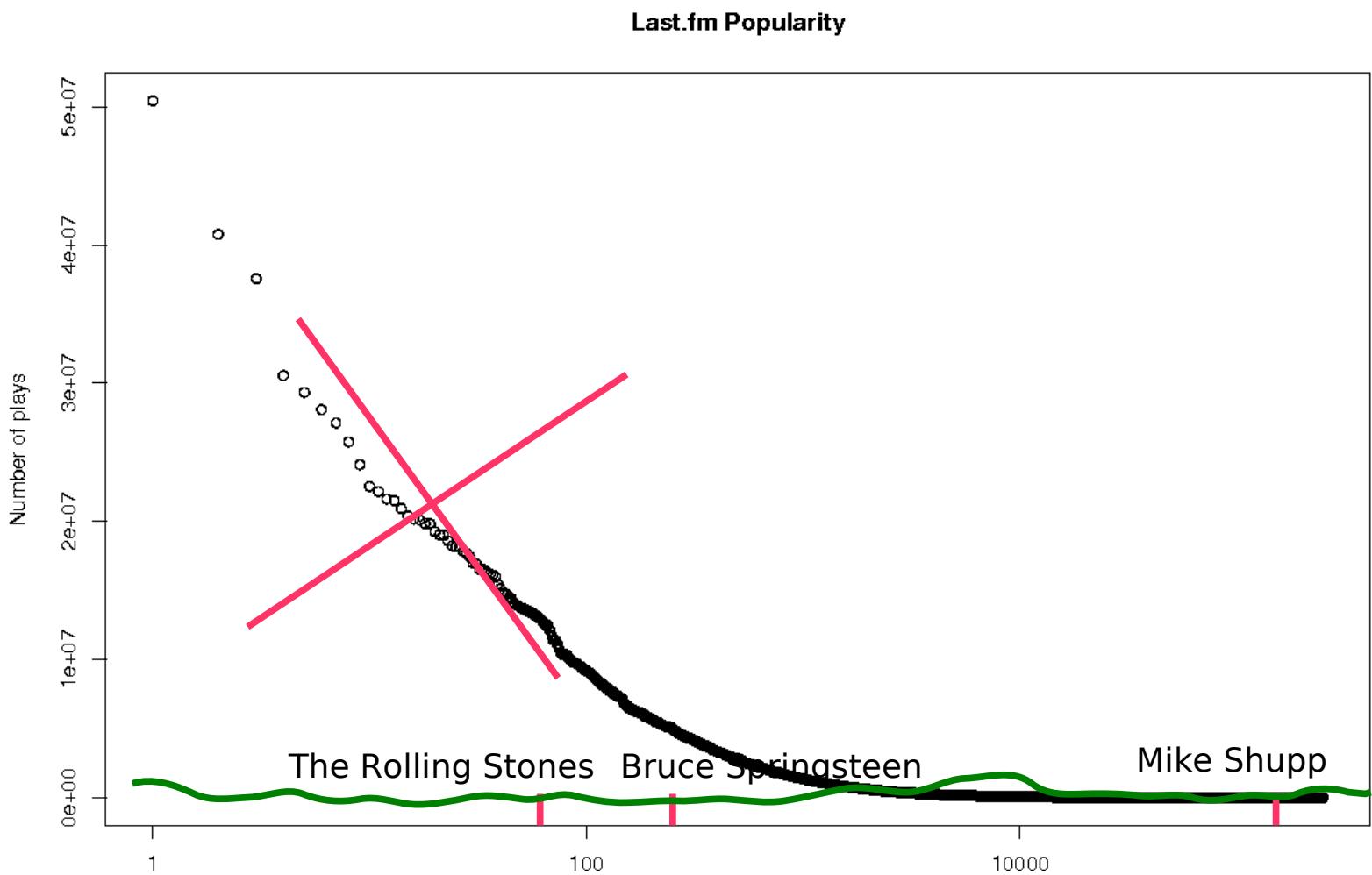


evaluation:: novelty & relevance

- Using CB similarity
 - ❖ Bruce Springsteen -> The Rolling Stones -> Mike Shupp
- ⇒ with collaborative filtering we would *never* reach Mike Shupp:
- Shortest path in the **last.fm** graph
 - ❖ Directed graph
 - Infinite! (in different graph components)
 - ❖ Undirected graph
 - Bruce Springsteen<->Steve Kilbey<->Mike Shupp

evaluation:: novelty & relevance

- CB democratizes the music, but who's voting?

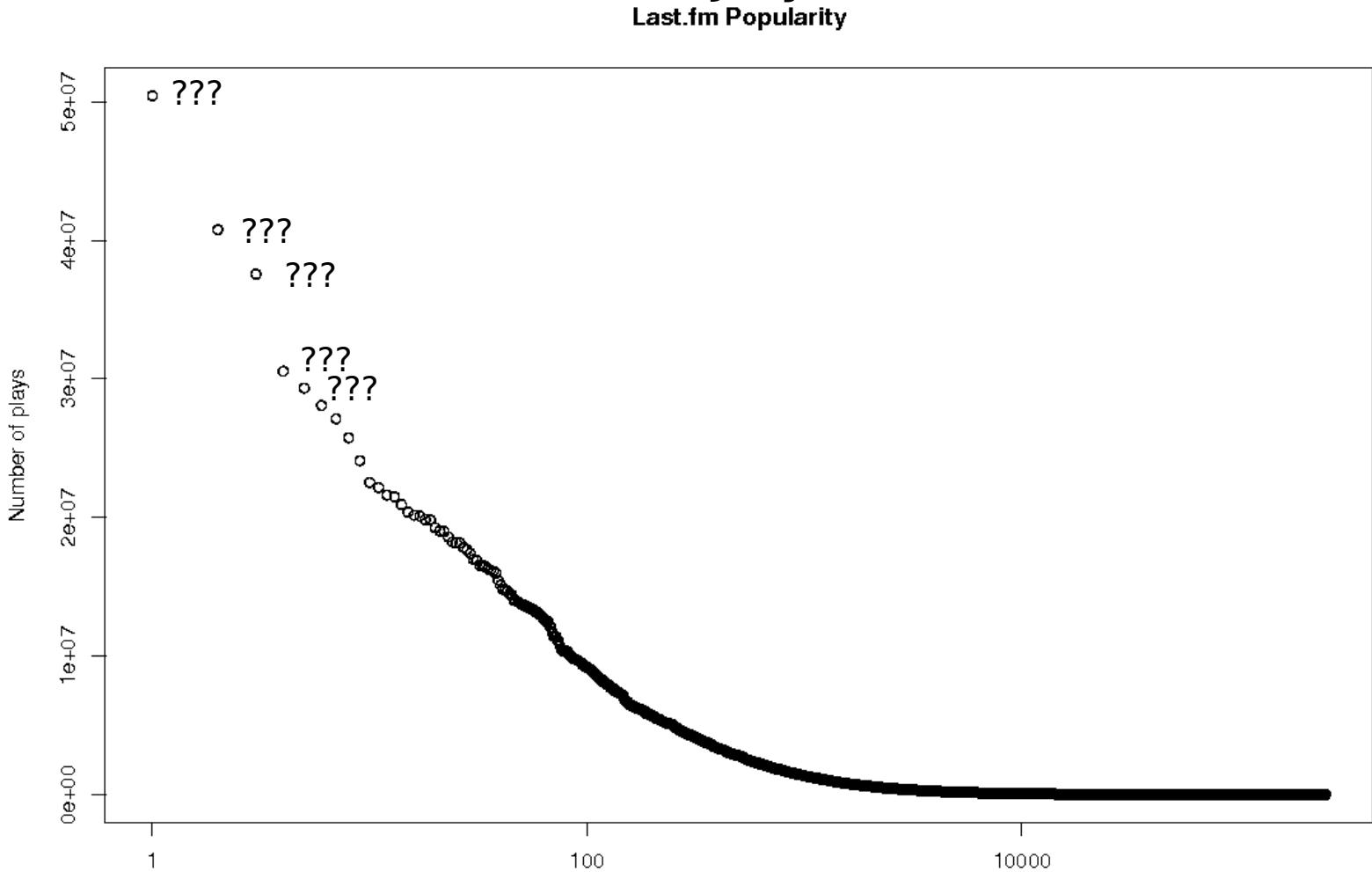


evaluation:: novelty & relevance

- And it seems that CB was not that wrong...
 - ❖ Mike Shupp review
 - “Letter to Annette”, “Right For You” and eight more (...). It's comforting to know that melodic rock and roll is still alive and kicking in the US (...) guitarist/songwriter Mike Shupp is deft with the straightahead country-inflected pop-rock that the likes of Paul Westerberg, **Bruce Springsteen**, Steve Forbert and Neil Young are renowned for. (...) -- *Kevin Mathews*
- Now, let's analyze the relationships between the long tail and the similar artists...

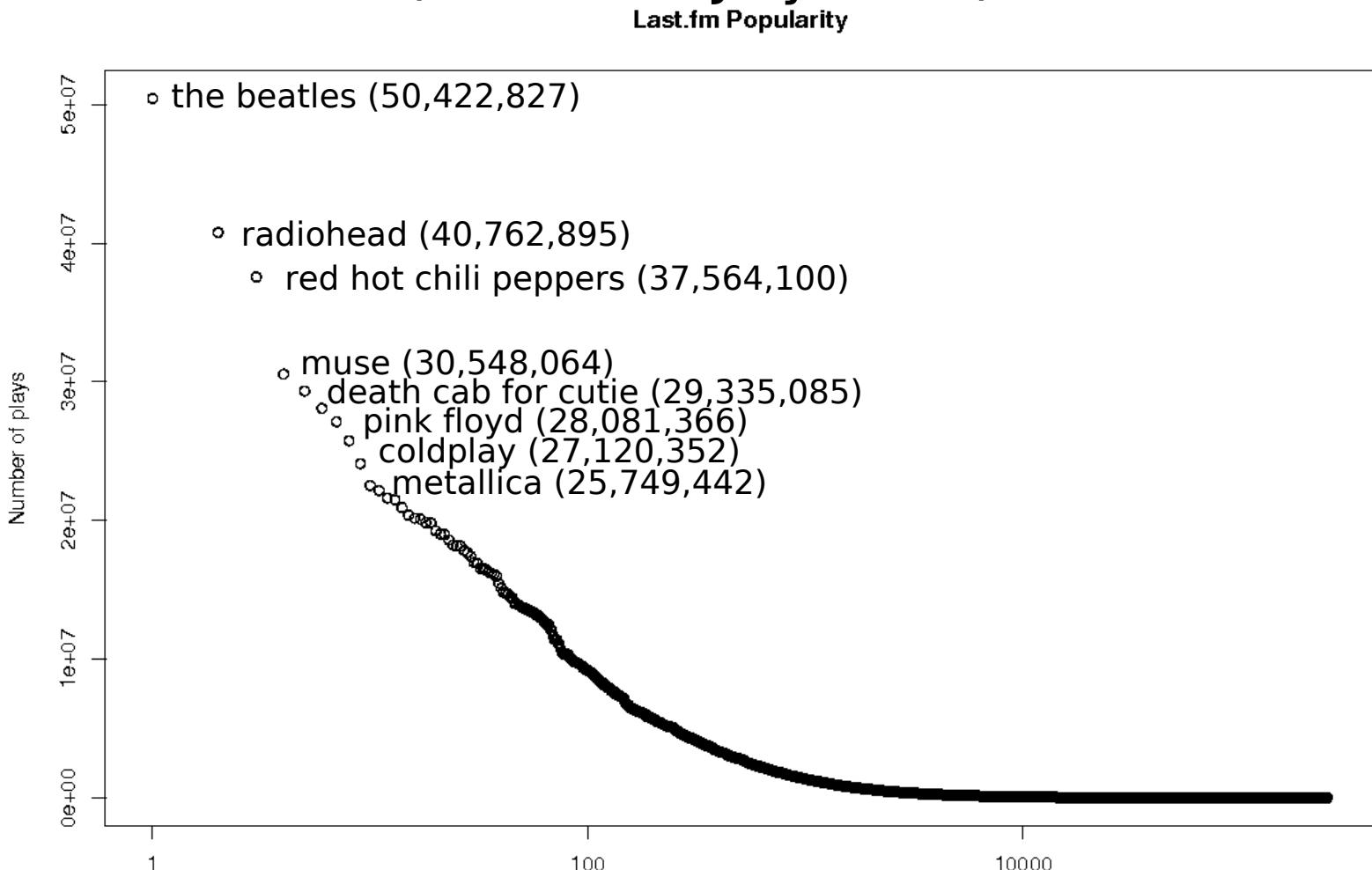
evaluation:: novelty & relevance

- **Last.fm** long-tail analysis (#artists plays)
 - ❖ 249,753 artists (data from July 2007)



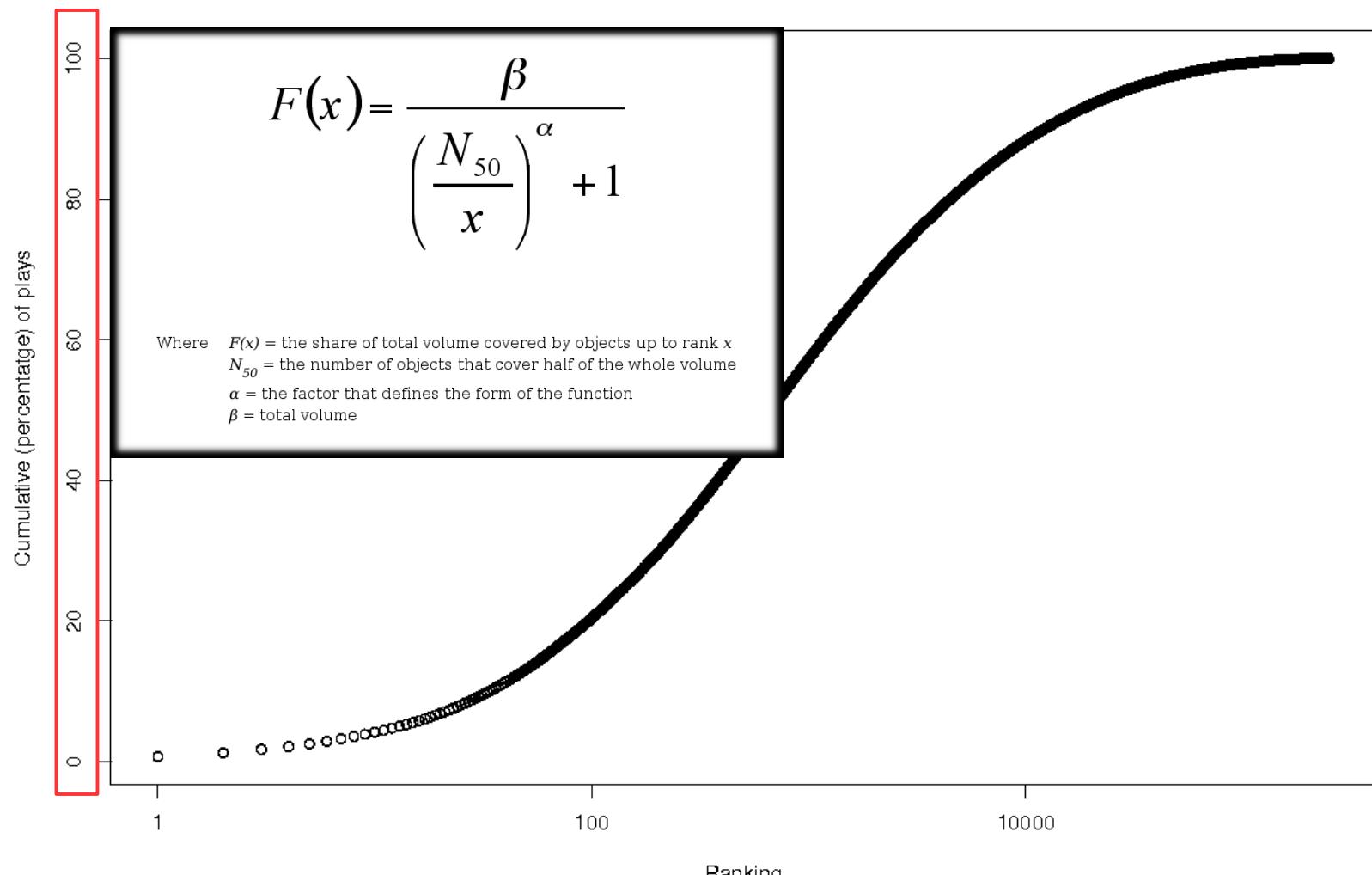
evaluation:: novelty & relevance

- **Last.fm** long-tail analysis (#artists plays)
 - ❖ 249,753 artists (data from July 2007)



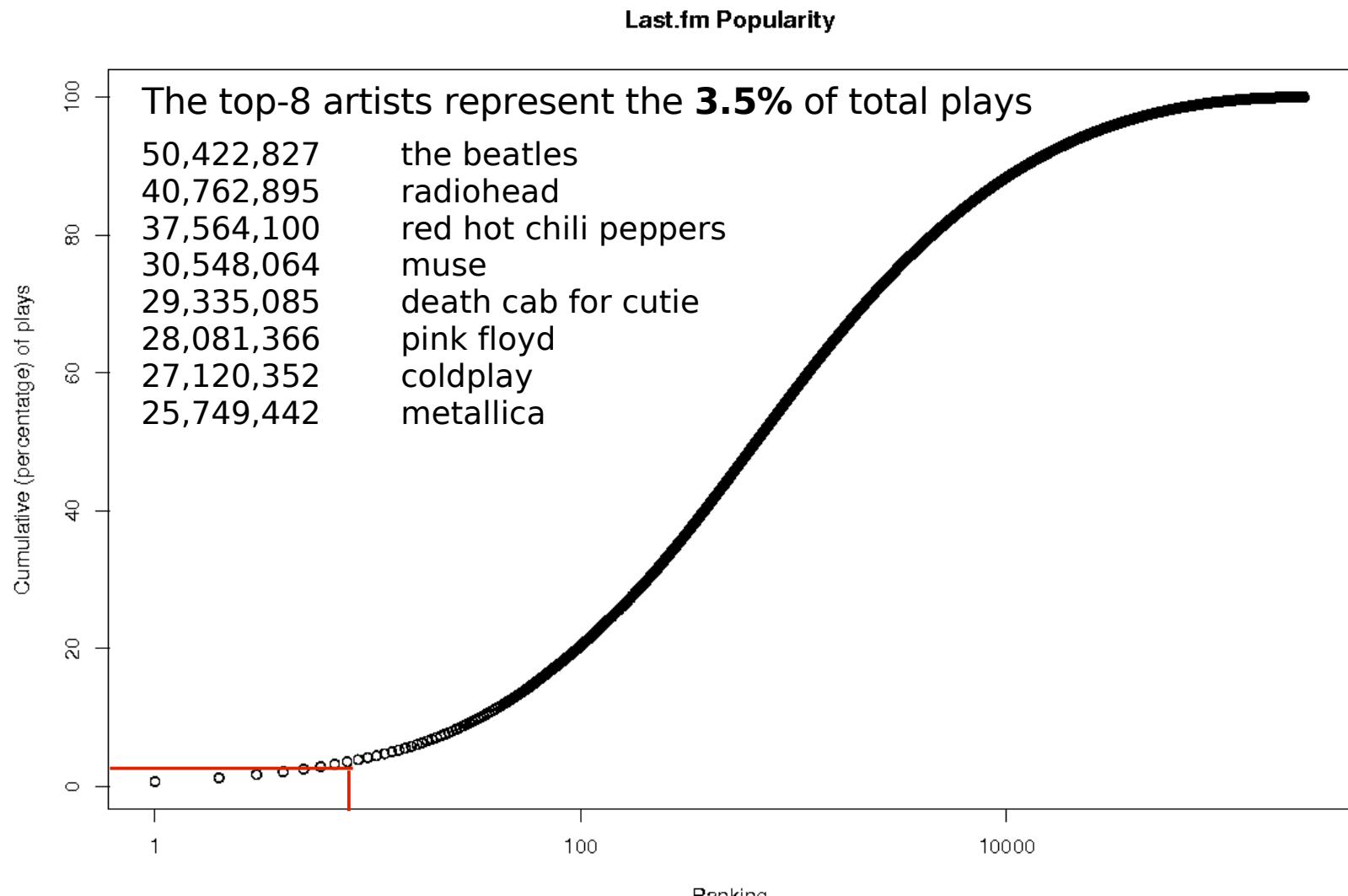
evaluation:: novelty & relevance

- **Last.fm long-tail model** [Kilkki, K., 2007]
 - ❖ cumulative percentage Last.fm Popularity



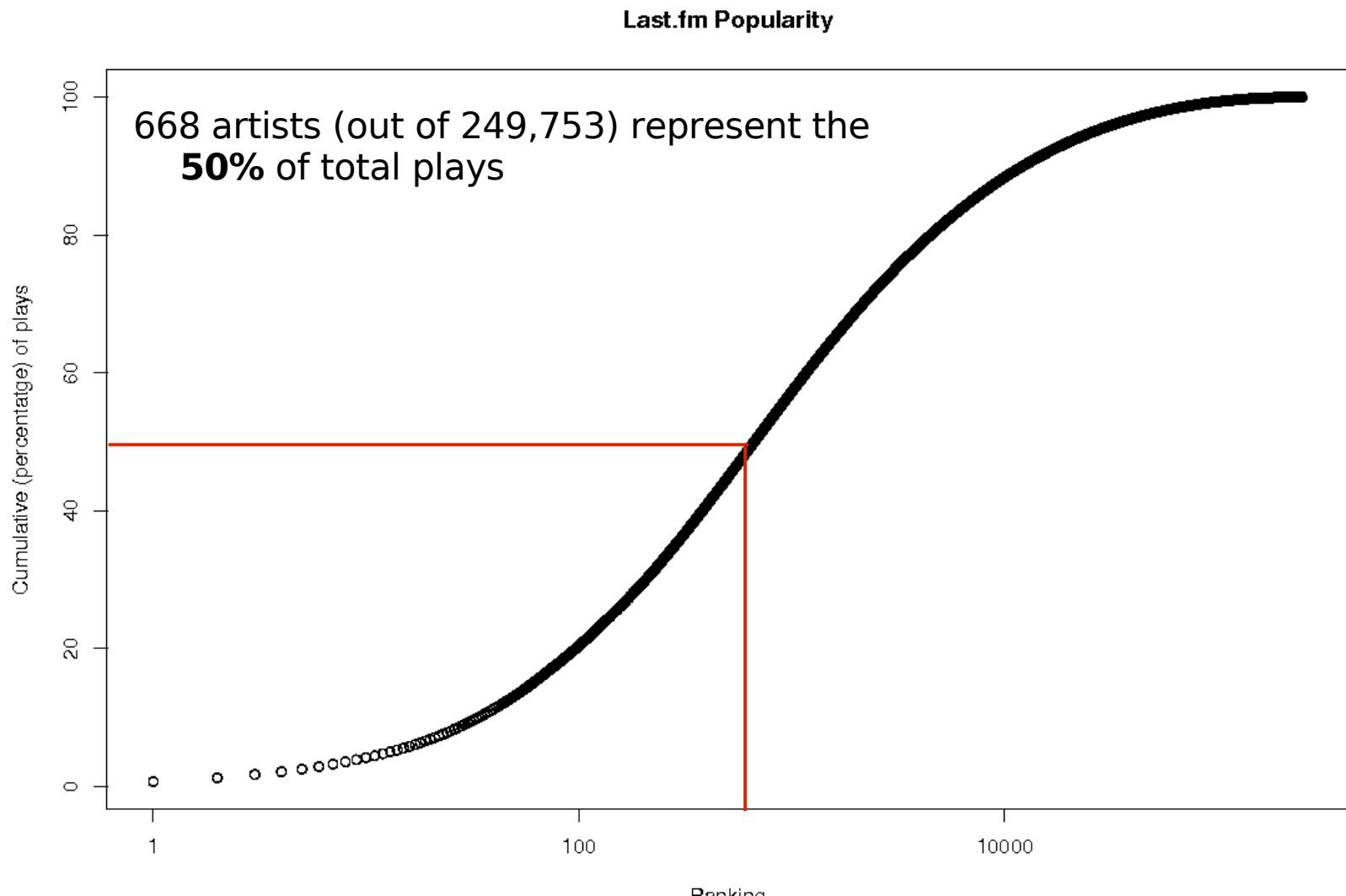
evaluation:: novelty & relevance

- **Last.fm** long-tail model



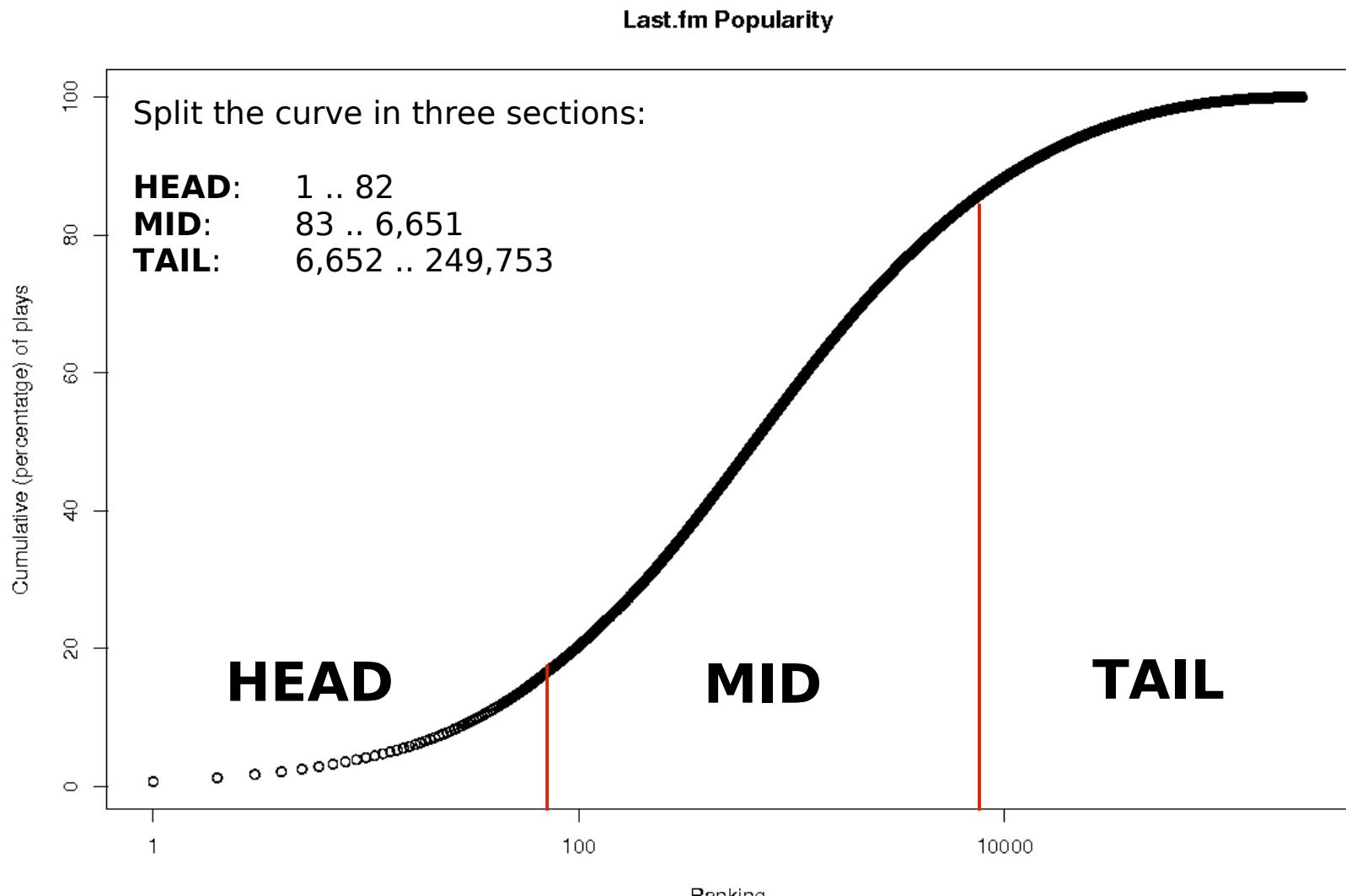
evaluation:: novelty & relevance

- **Last.fm** long-tail model



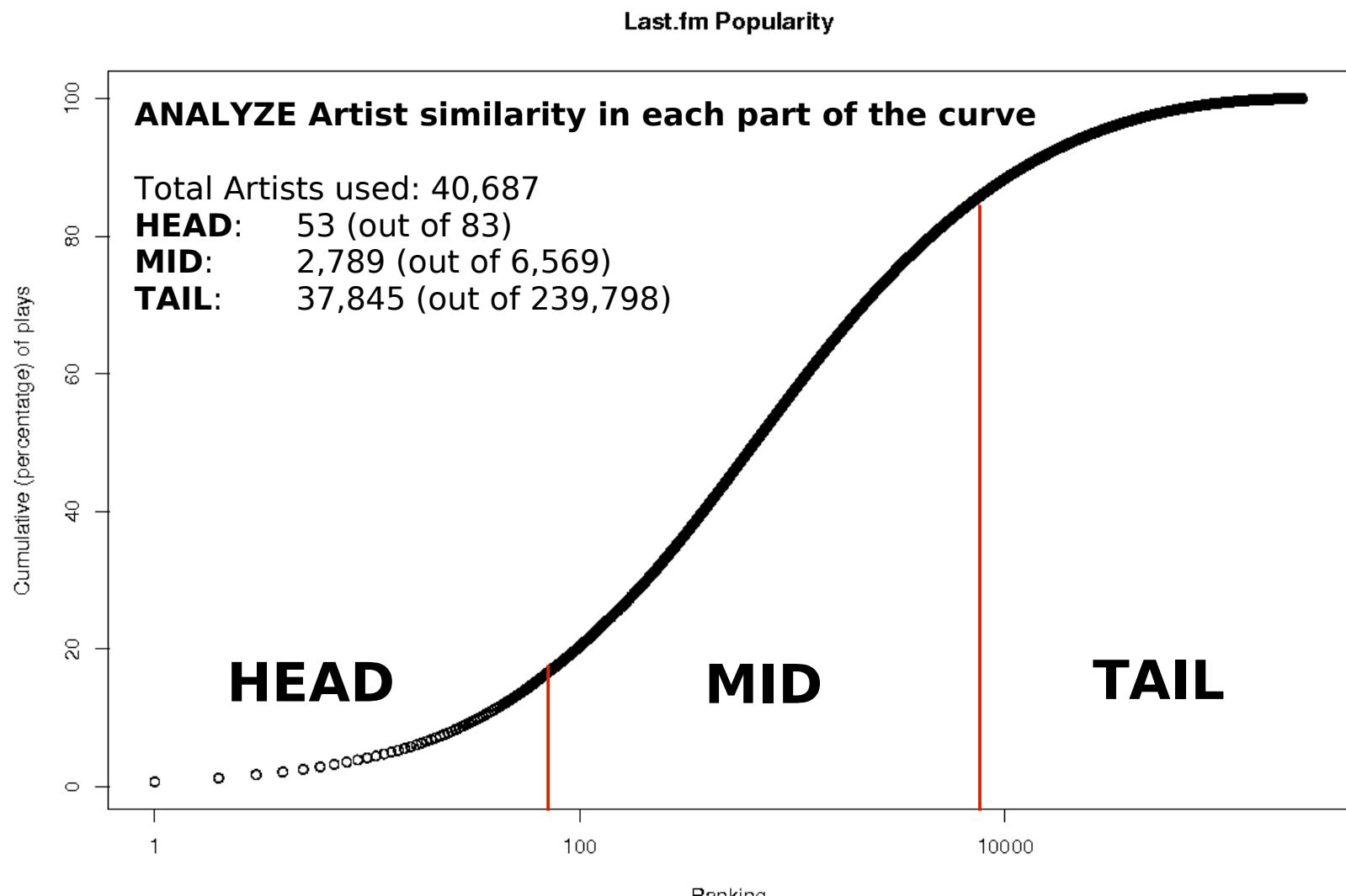
evaluation:: novelty & relevance

- **Last.fm long-tail & artist similarity**



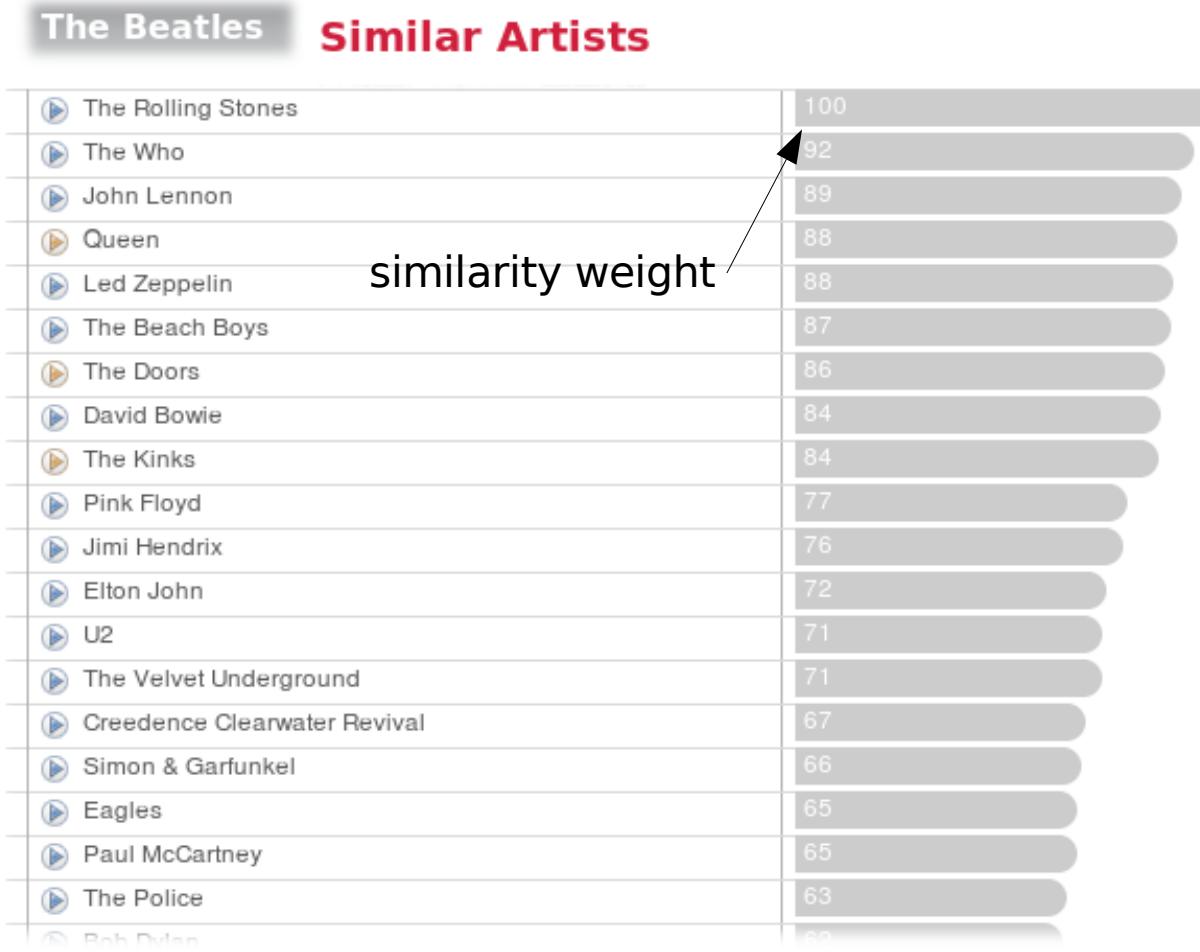
evaluation:: novelty & relevance

- **Last.fm** long-tail & artist similarity



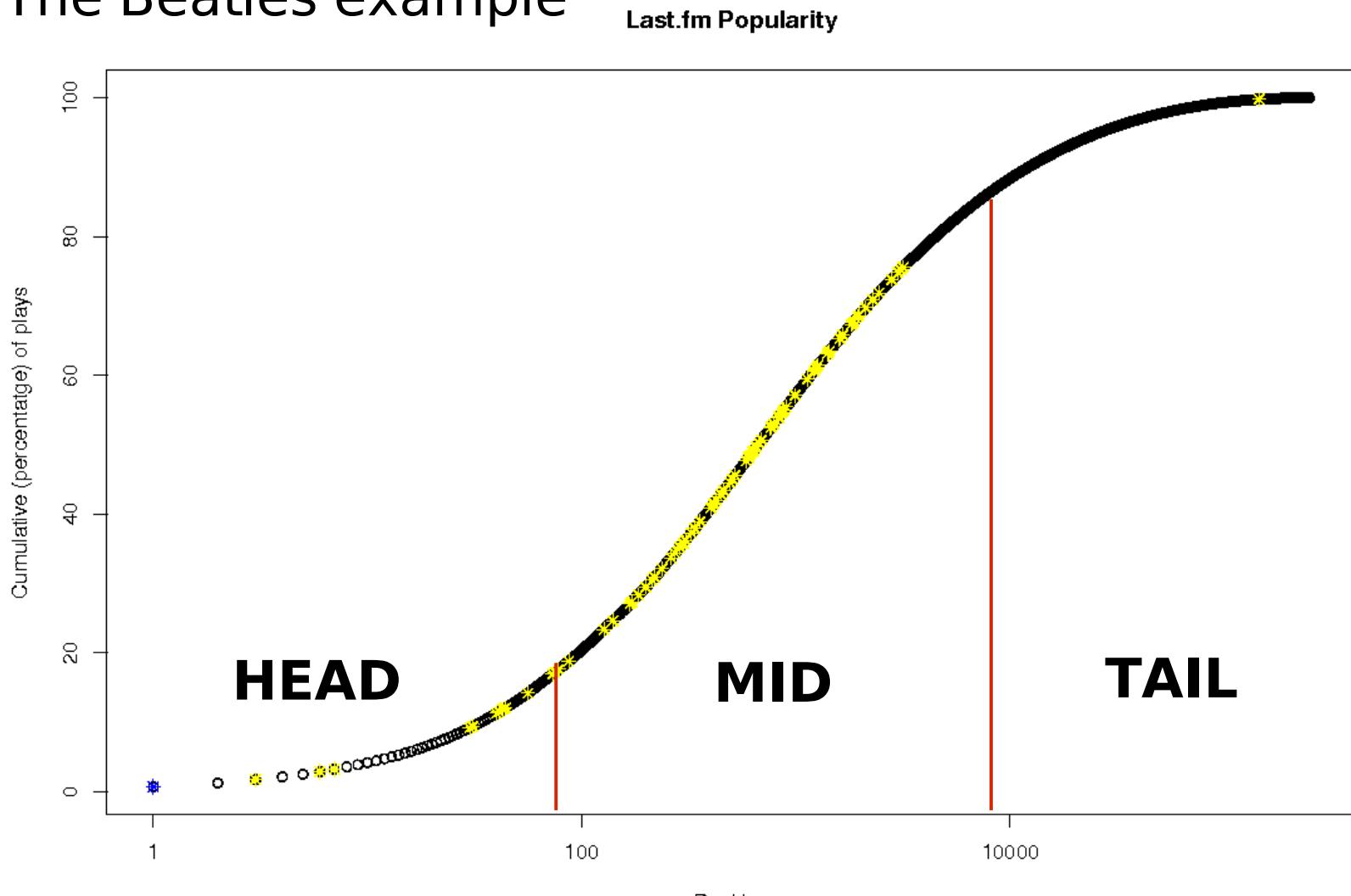
evaluation:: novelty & relevance

- **Last.fm** long-tail & artist similarity
 - ❖ The Beatles example



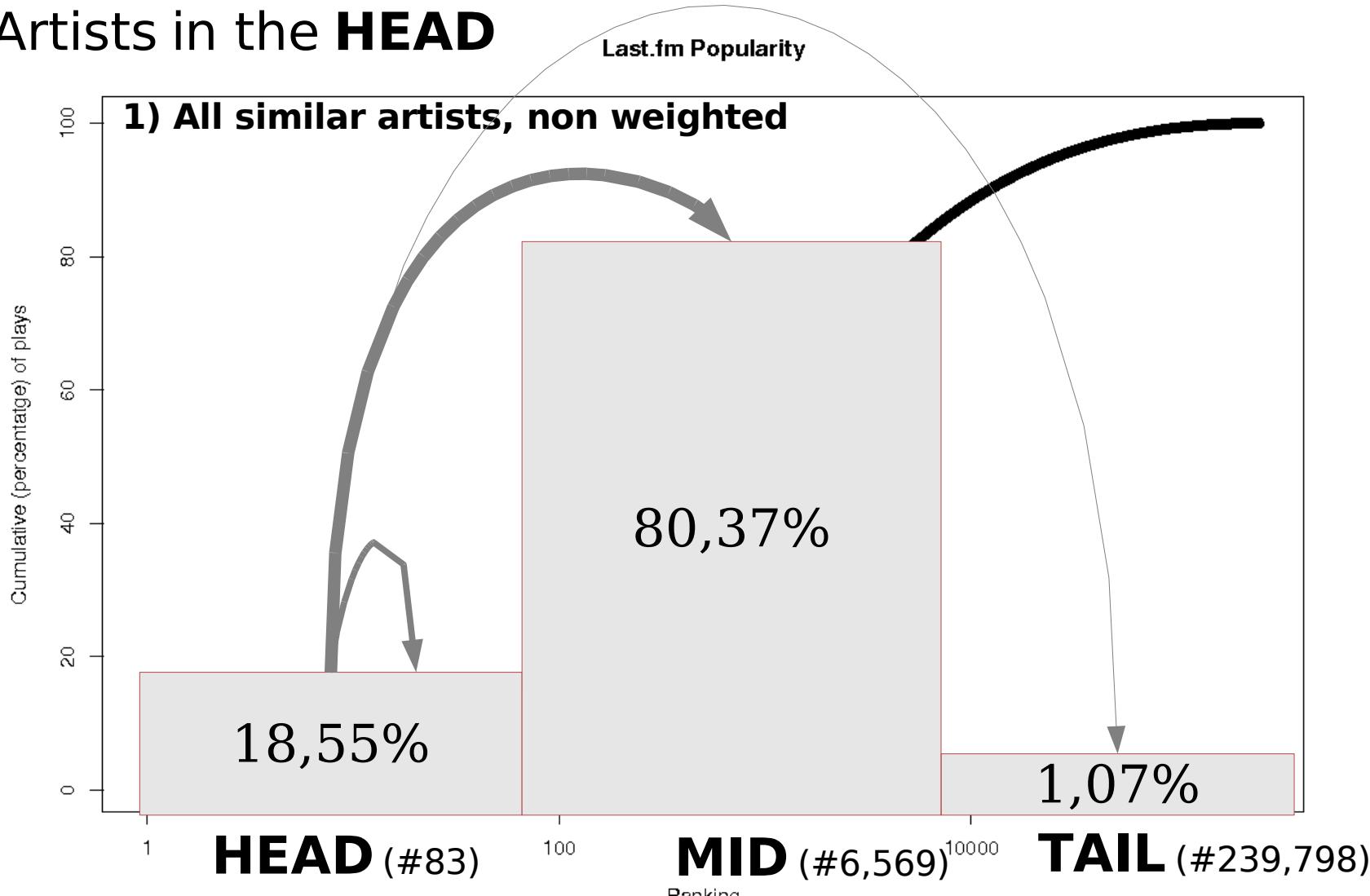
evaluation:: novelty & relevance

- **Last.fm** long-tail & artist similarity
 - ❖ The Beatles example



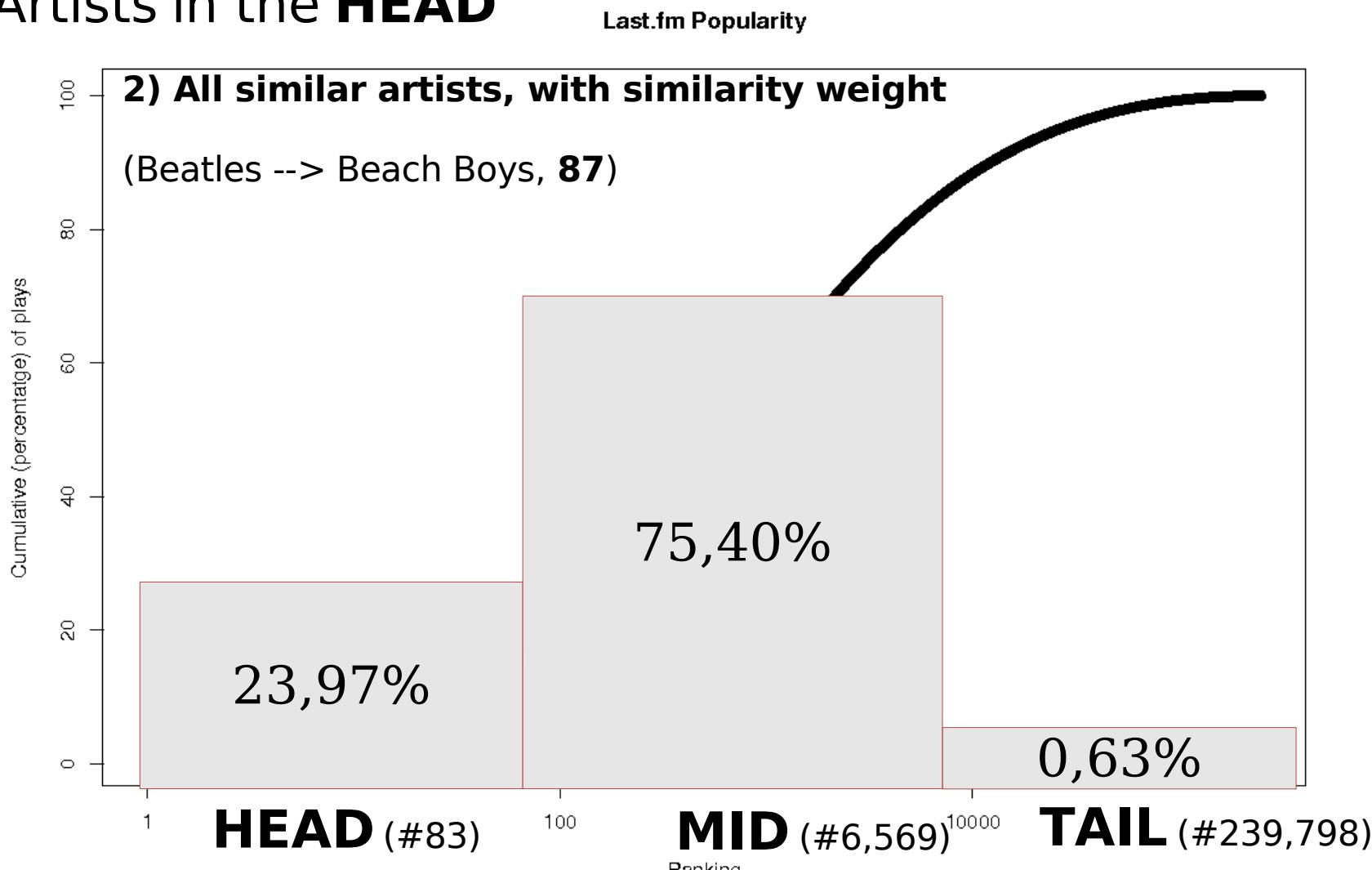
evaluation:: novelty & relevance

- **Last.fm** long-tail & artist similarity
 - ❖ Artists in the **HEAD**



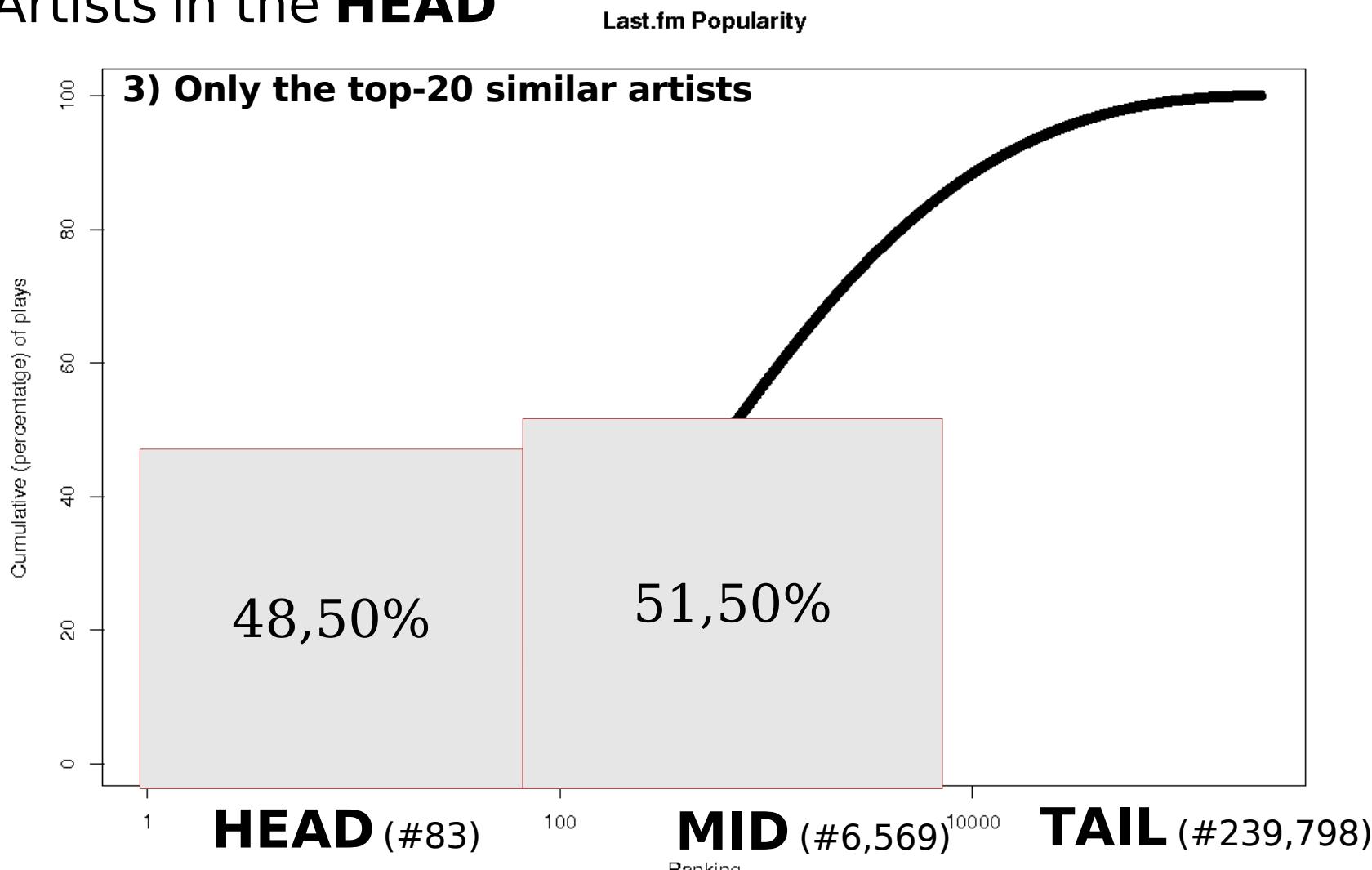
evaluation:: novelty & relevance

- **Last.fm** long-tail & artist similarity
 - ❖ Artists in the **HEAD**



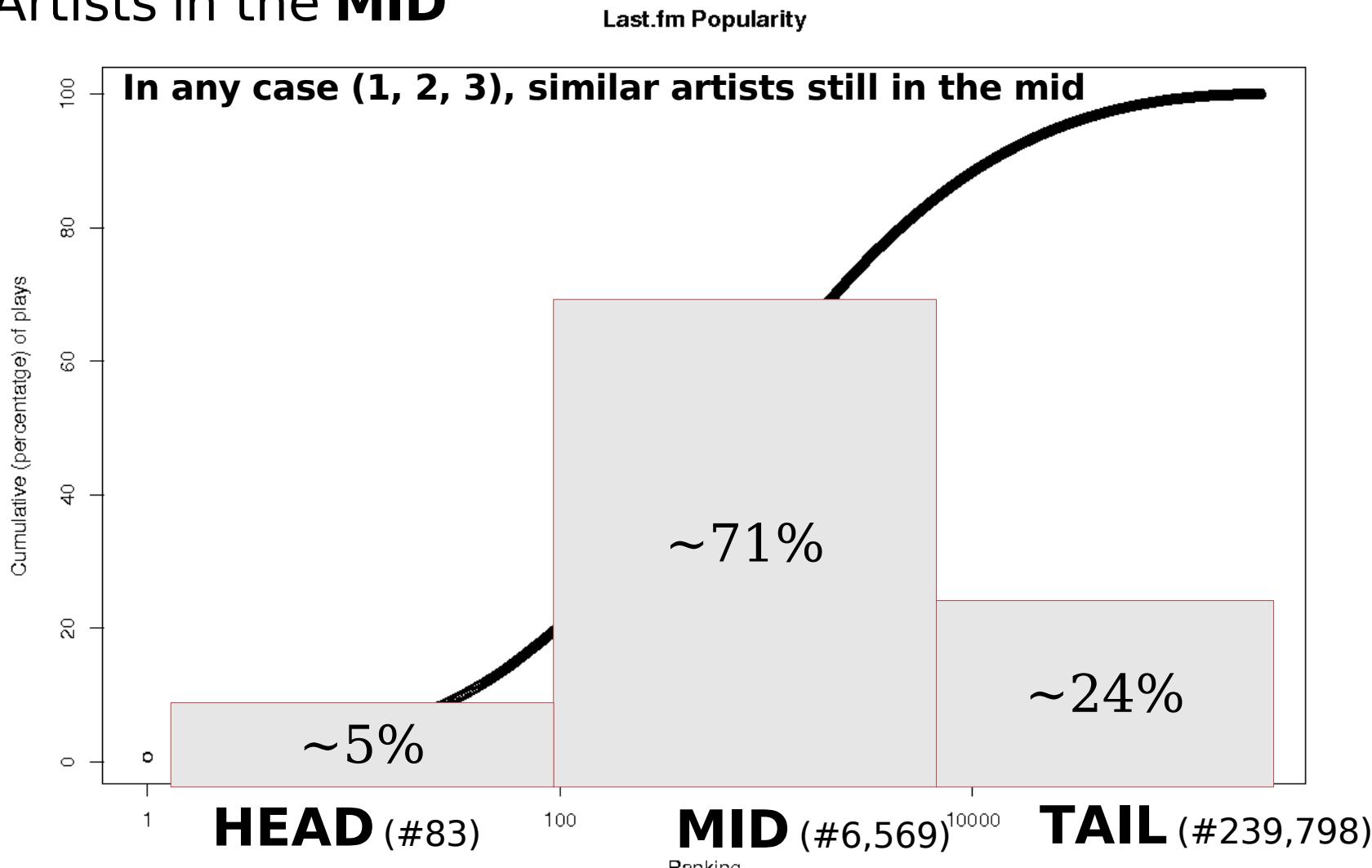
evaluation:: novelty & relevance

- **Last.fm** long-tail & artist similarity
 - ❖ Artists in the **HEAD**



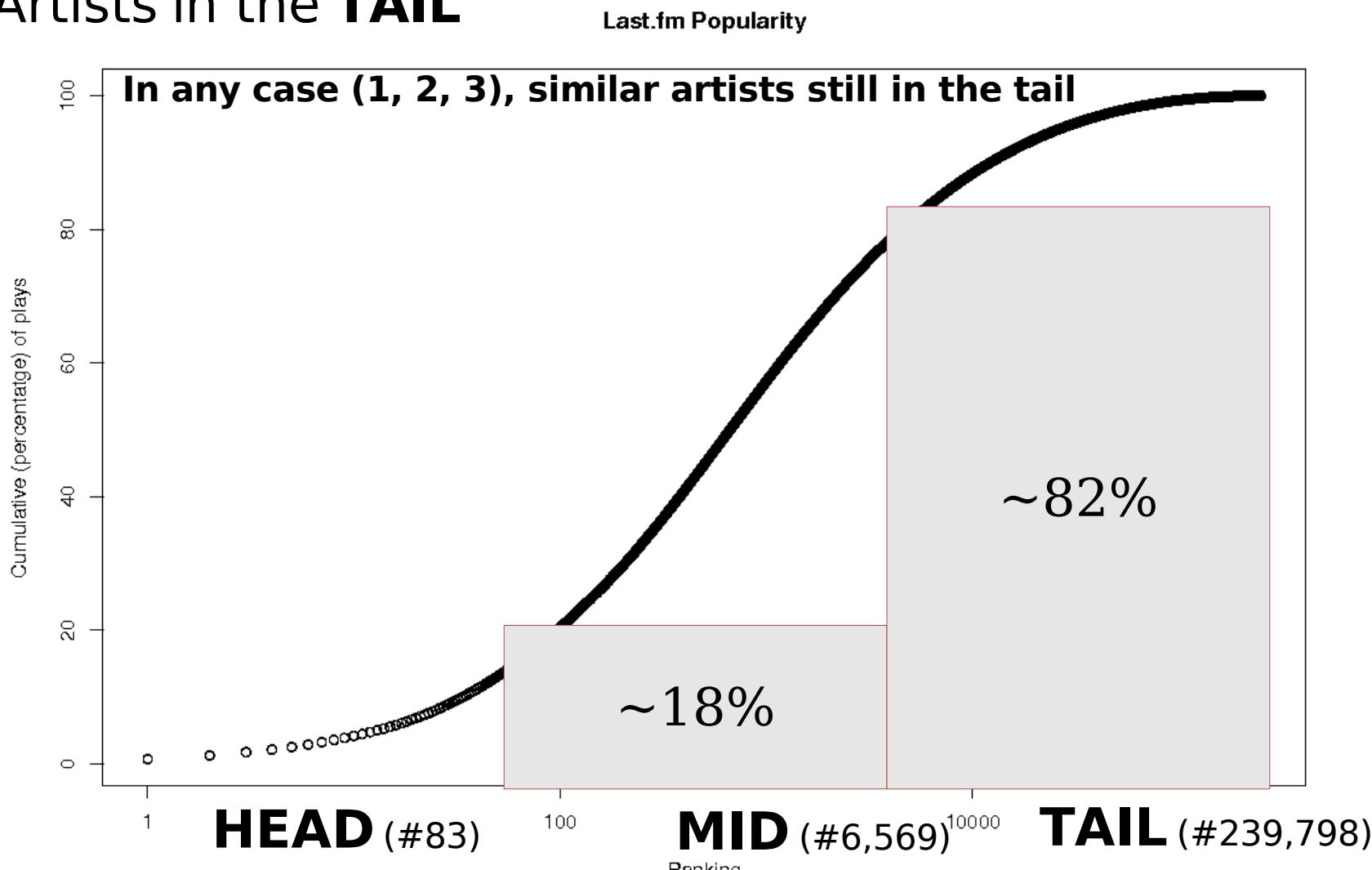
evaluation:: novelty & relevance

- **Last.fm** long-tail & artist similarity
 - ❖ Artists in the **MID**



evaluation:: novelty & relevance

- **Last.fm** long-tail & artist similarity
 - ❖ Artists in the **TAIL**



evaluation:: *novelty & relevance*

- **Last.fm** long-tail & artist similarity
 - ❖ implications on the navigation & discovery
 - From Bruce Springsteen to Mike Shupp, or the other way around?
 - ❖ implications on the recommendation algorithm itself
 - How to deal with the long-tail?

evaluation:: complex network analysis

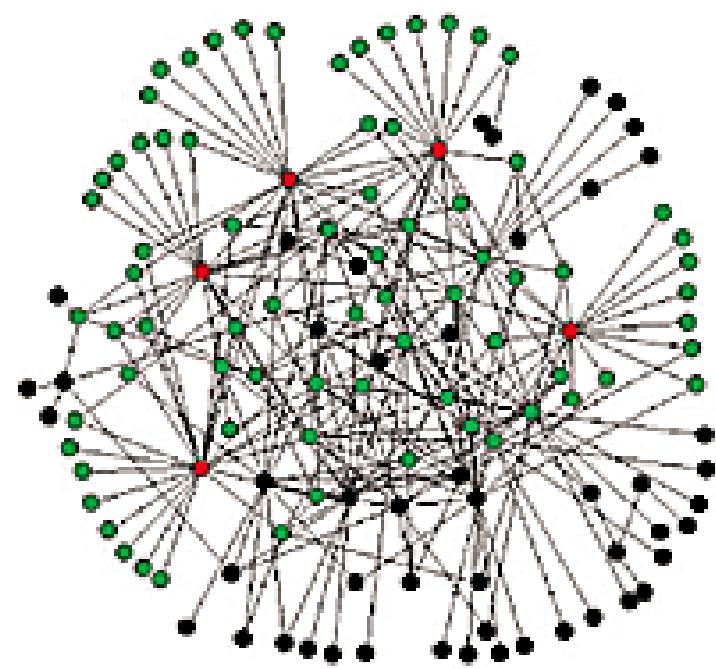
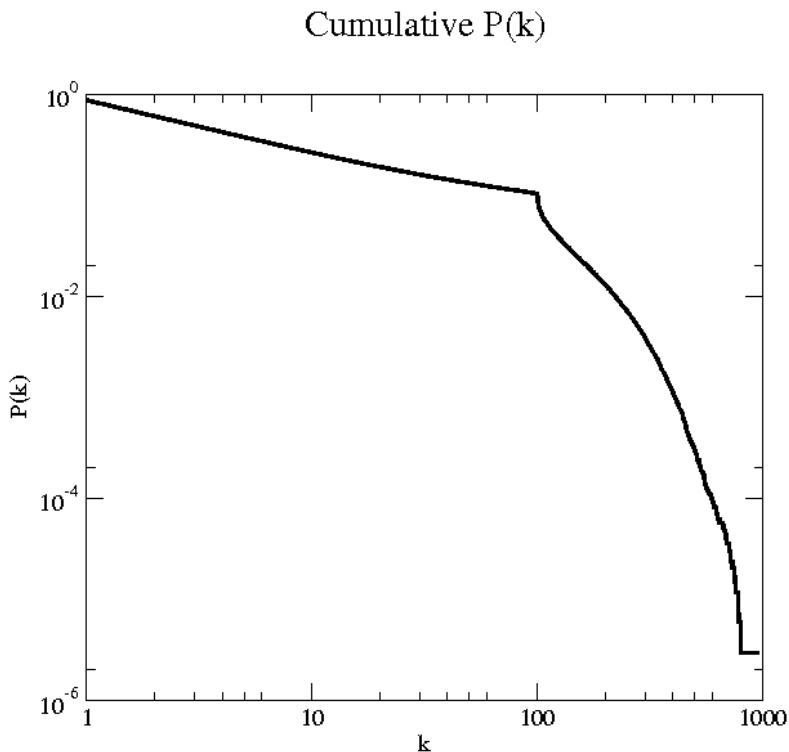
- Complex network analysis
 - ❖ get hints about the *inherent* structure of the artist similarities
 - ❖ characterize the network
 - Small world effect? ("6 degrees of Black Sabbath")
- Case Study 1: Last.fm artist similarity network
 - ❖ directed graph
 - ❖ 249,753 nodes
 - ❖ 3,846,262 edges
 - ❖ weighted graph (beatles --> the doors , *weight*=86)

evaluation:: complex network analysis

- **Last.fm** artist similarity network
 - ❖ Avg. degree, $\langle k \rangle = 15.4$
 - ❖ Diameter = 20
 - ❖ Small world effect
 - Avg. shortest path, $d = 6,24$ ($d_r = 4,6$)
 - Clustering Coefficient, $C = 0.23$ ($C_r = 0,0053$)

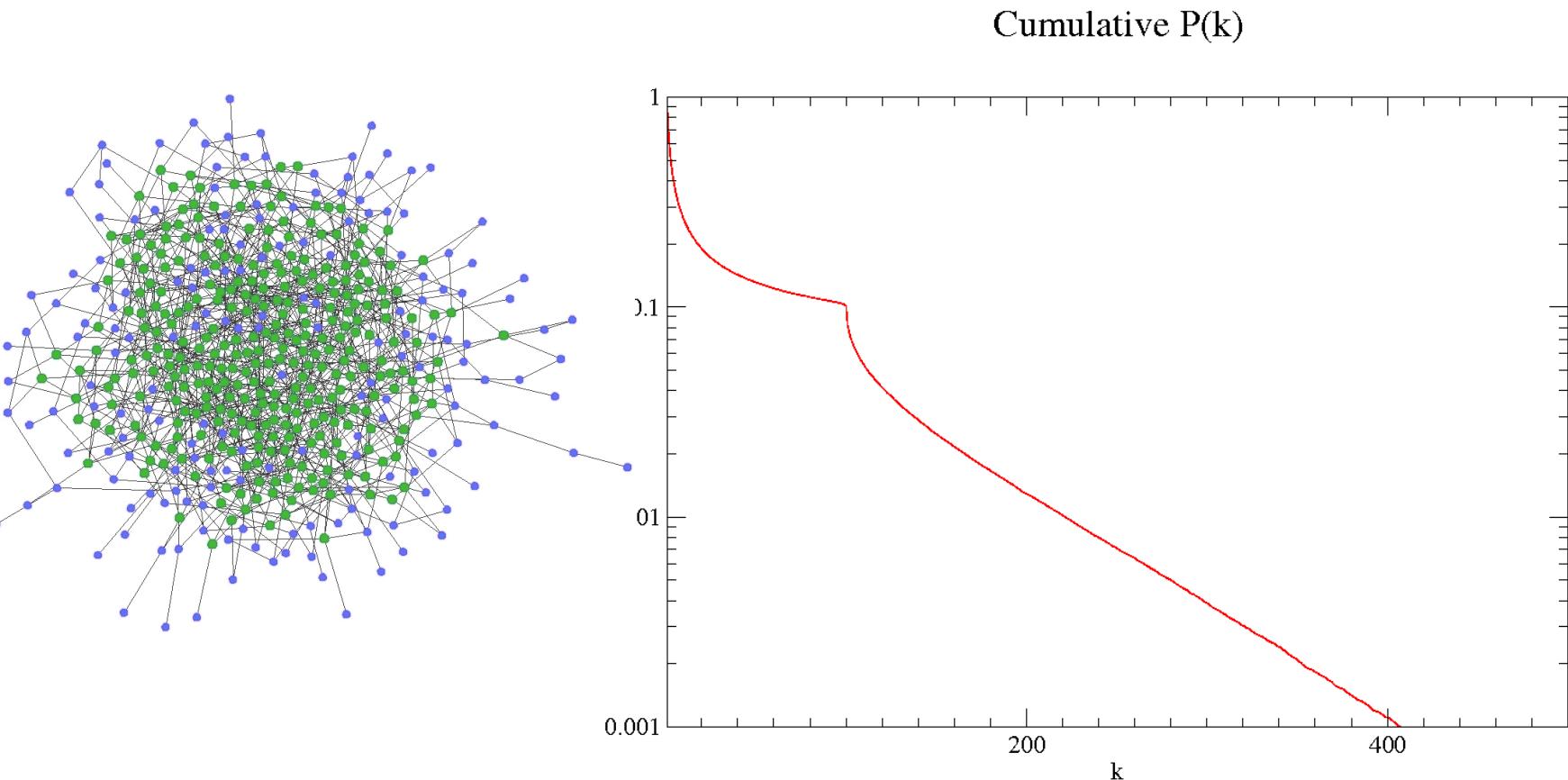
evaluation:: complex network analysis

- **Last.fm** artist similarity network
 - ❖ Cumulative indegree $P(K>k)$
 - **no** Power law distribution (log-log) => is not a scale-free network ("*highly connected hubs*")



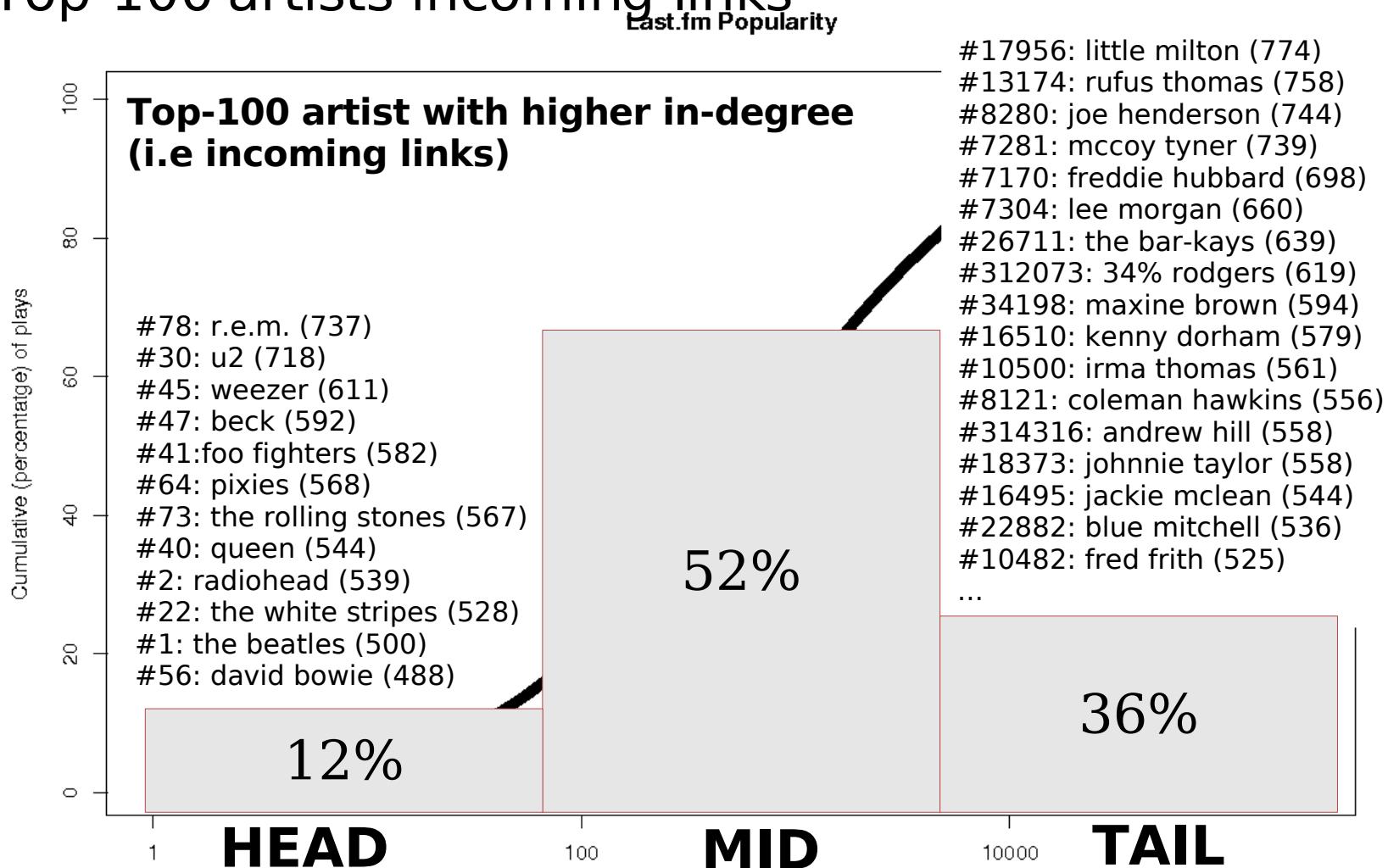
evaluation:: complex network analysis

- **Last.fm** artist similarity network
 - ❖ Cumulative indegree $P(K>k)$
 - follows an exponential decay (linear-log)



evaluation:: complex network analysis

- **Last.fm** long-tail & artist network
 - ❖ Top-100 artists incoming links



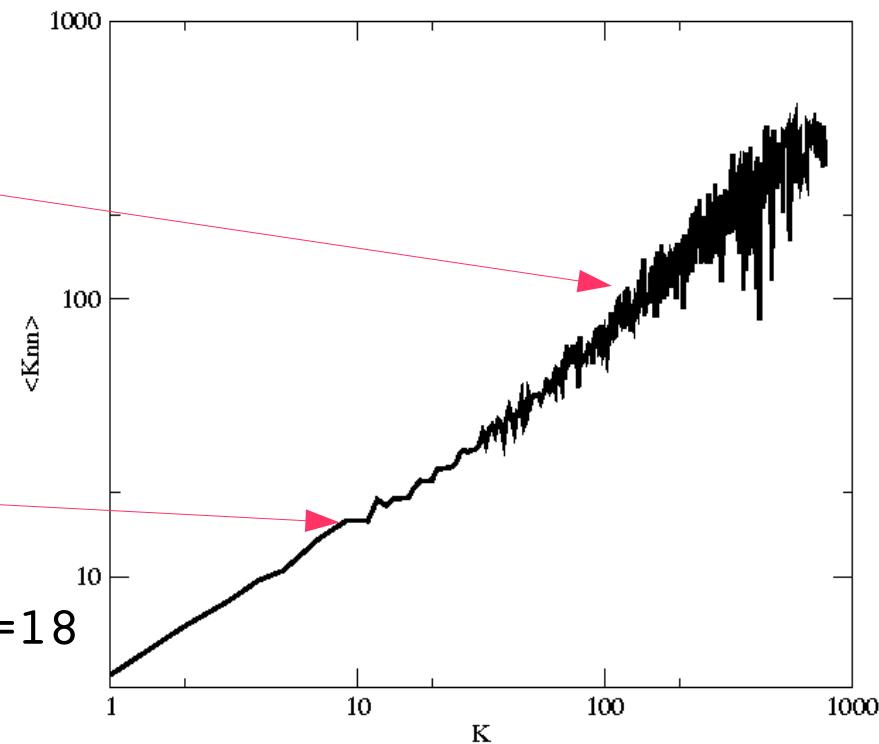
evaluation:: complex network analysis

- **Last.fm** artist similarity network
 - ❖ assortative mixing
 - degree correlation between adjacent nodes

Assortative mixing in Last.fm :: $K_{nn,in}(k_{in})$

in_degree(Robert Palmer)=430
=>
avg(in_degree(sim(Robert
Palmer)))=342

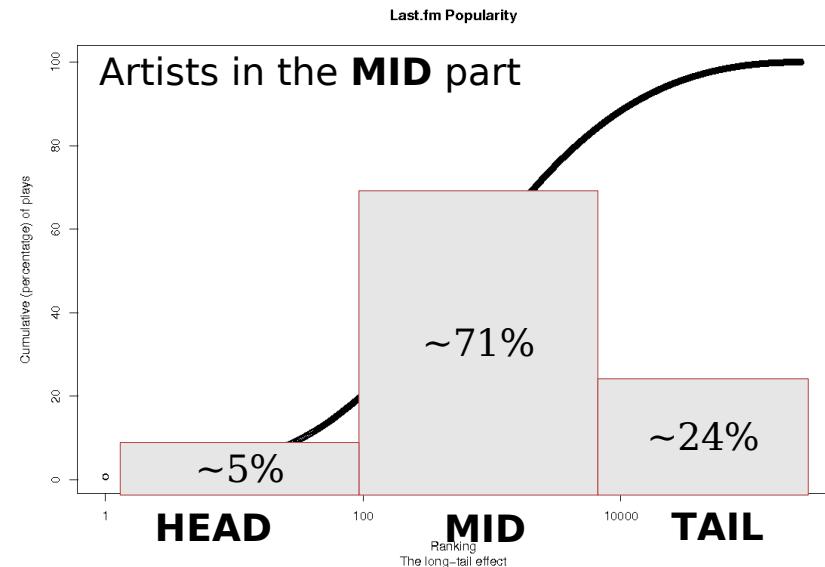
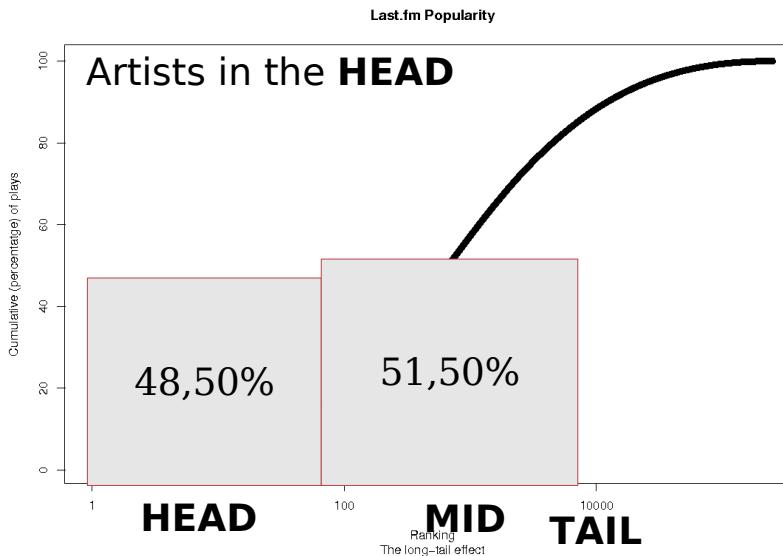
in_degree(Ed Alton)=11
=>
avg(in_degree(sim(Ed Alton)))=18



evaluation:: novelty & relevance

- **Last.fm summary**

- ❖ Not (highly) influenced by the popularity effect
- ❖ But...not exploiting the long-tail for discovery!



evaluation:: novelty & relevance

- **Last.fm** summary: exploit the long-tail
 - ❖ R.E.M “related” artists...

List #1

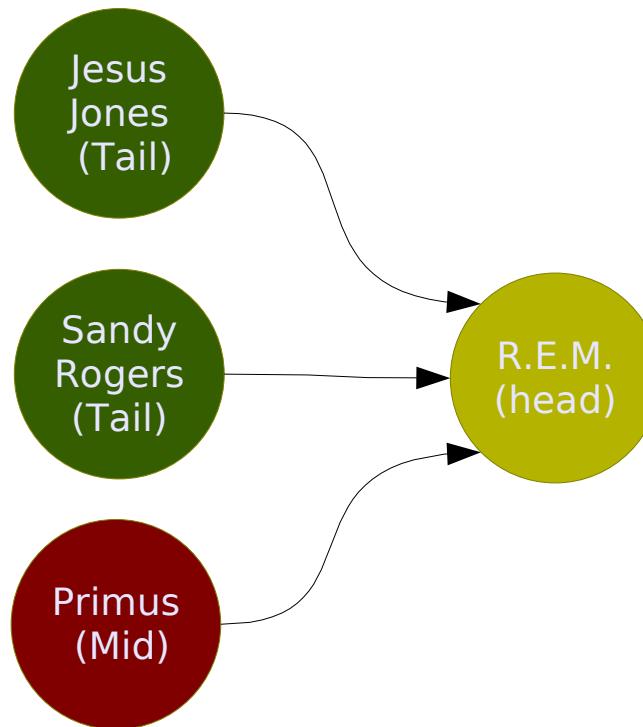
- U2
- Radiohead
- Coldplay
- Red Hot Chili Peppers
- The Smashing Pumpkins
- The White Stripes
- Foo Fighters
- Weezer
- Counting Crows
- Oasis
- Pixies
- ...

List #2

- Jesus Jones
- Primitive Radio Gods
- Love Spit Love
- Sprung Monkey
- Jeff Ament
- Flickerstic
- Lustre
- Loud Lucy
- The Primitives
- Mike Watt
- Weed
- ...

evaluation:: novelty & relevance

- **Last.fm** summary: exploit the long-tail
 - ❖ R.E.M “related” artists...
 - promoting the artists in the Long Tail
 - ❖ Jesus Jones, Sandy Rogers, (Primus is out!)

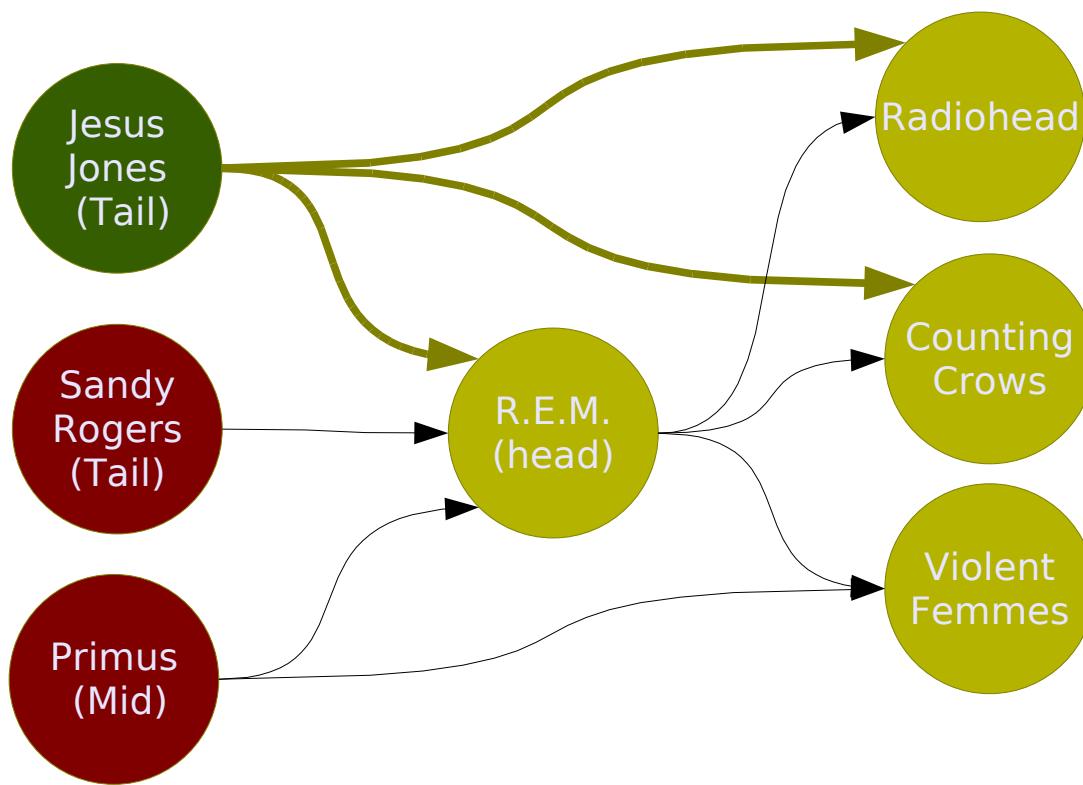


evaluation:: novelty & relevance

- **Last.fm** summary: exploit the long-tail

- ❖ R.E.M “related” artists...

- promoting the artists in the Long Tail
 - ❖ Jesus Jones, Sandy Rogers, (Primus is out!)
 - ...that are related, too, with R.E.M similar artists:
 - ❖ Jesus Jones



evaluation:: complex network analysis

- Case Study 2: CF vs. Expert recommenders [Cano, 2006]

- ❖ Networks

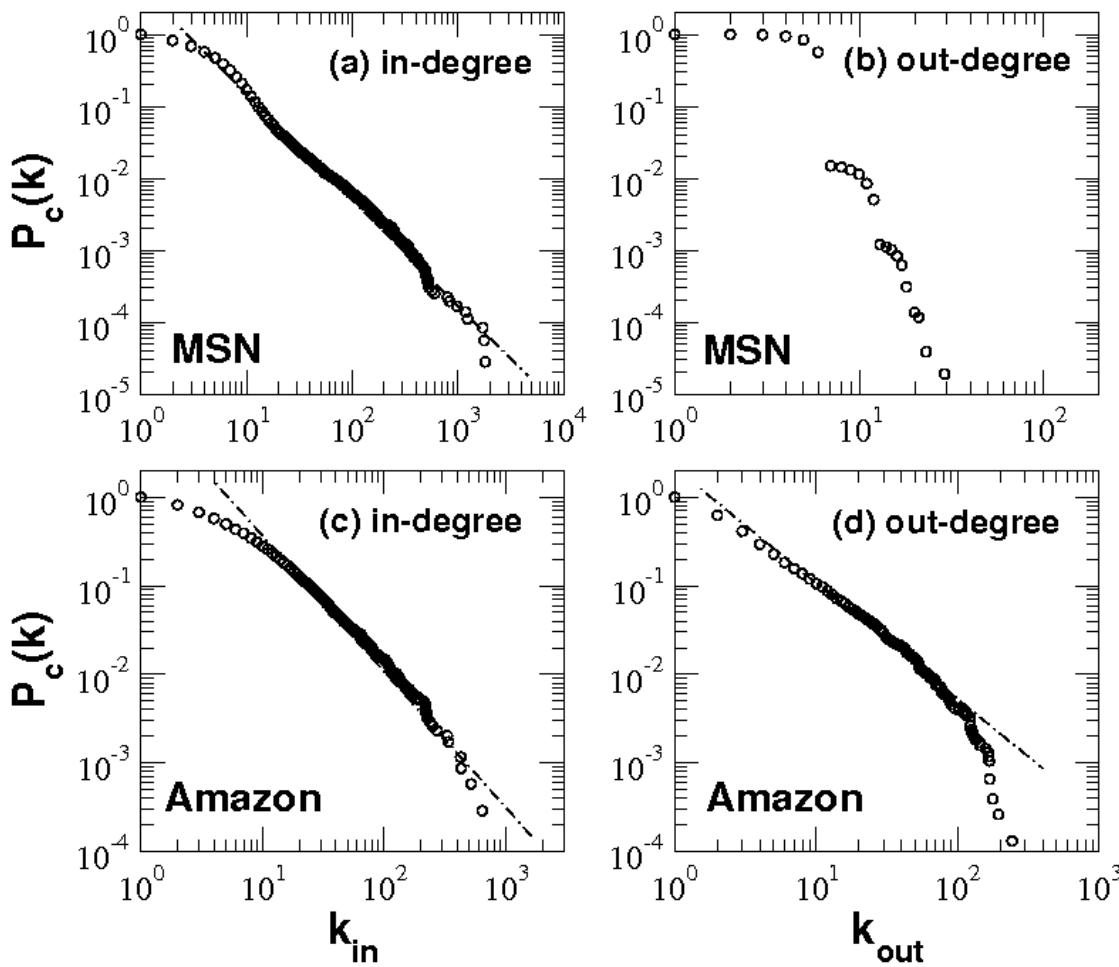
- Amazon and MSN: Collaborative filtering
- AMG: Expert
- Launch-Yahoo!: ???

	type	n	m	$\langle k \rangle$	C	C_r	d	d_r	γ_{in}	γ_{out}
MSN	directed	51,616	279,240	5.5	0.54	$1.0 \cdot 10^{-4}$	7.7	6.4	2.4 ± 0.01	-
Amazon	directed	23,566	158,866	13.4	0.14	$5.7 \cdot 10^{-4}$	4.2	3.9	2.3 ± 0.02	2.4 ± 0.04
AMG	directed	29,206	146,882	8.15	0.20	$2.8 \cdot 10^{-4}$	6.2	4.9	-	-
Yahoo	directed	16,302	511,539	62.8	0.38	$3.8 \cdot 10^{-3}$	2.7	2.3	-	-

- ❖ All the networks present the Small World effect
 - low avg. shortest path
 - high clustering coefficient

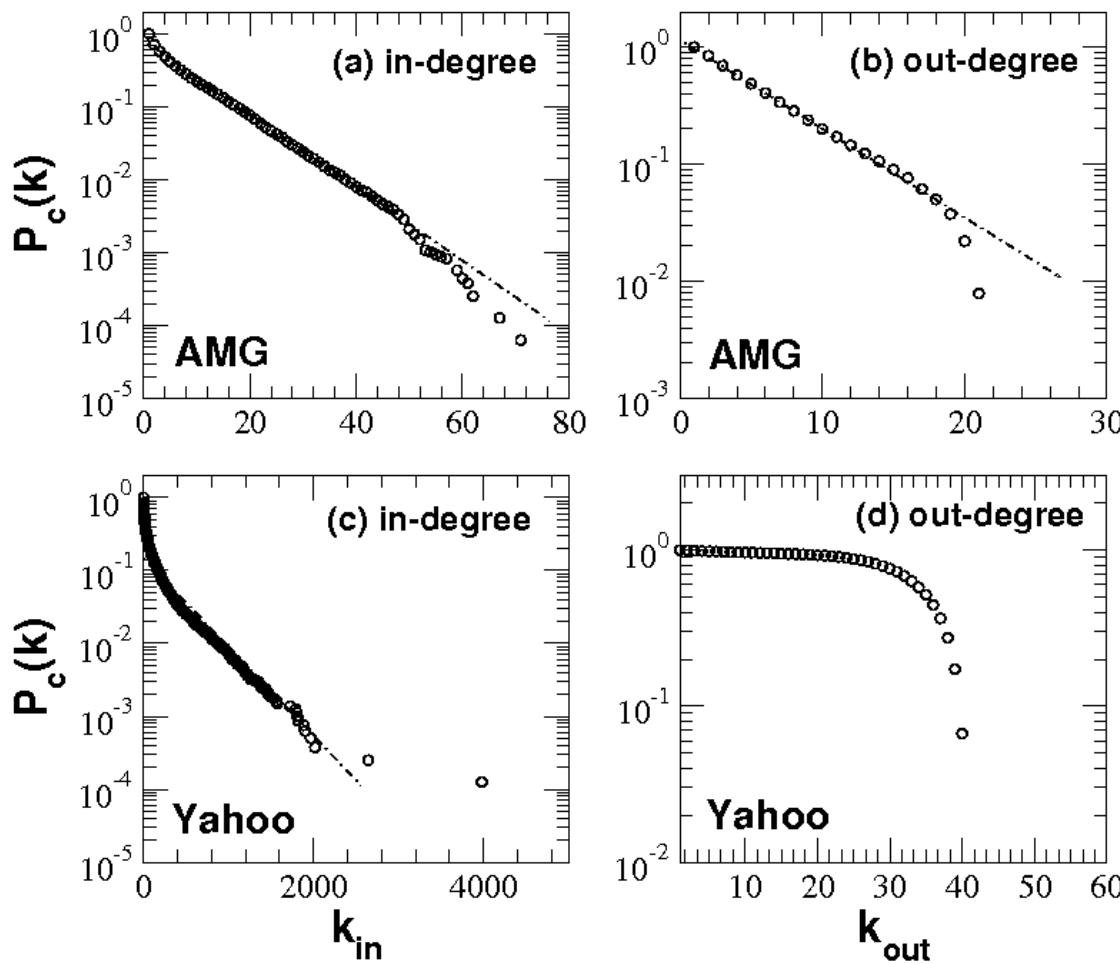
evaluation:: complex network analysis

- Collaborative filtering networks
 - ❖ scale-free networks (power law distribution, log-log)



evaluation:: complex network analysis

- Expert network (AMG) ...and Yahoo!
 - ❖ exponential decay (linear-log)



evaluation:: complex network analysis

- Summary
 - ❖ network structure clearly affects the recommendations, (as well as the navigation, and discovery)
 - predecessors (R.E.M.) could give more interesting information than successors (R.E.M.) !
 - ❖ Related work at ISMIR2007
 - Complex networks & clustering of users
 - ❖ Amélie Anglade, Marco Tiemann, Fabio Vignoli. '*Virtual Communities for Creating Shared Music Channels*'

evaluation:: informal survey

- Method:
 - ❖ Generate list of recommended artist based on seed artist
 - ❖ Compare lists to expert generated lists
 - ❖ Rank lists via survey
- Seed Artists:
 - ❖ The Beatles
 - ❖ Miles Davis
 - ❖ Emerson Lake and Palmer
 - ❖ Deerhoof
 - ❖ Arcade Fire
- Caveats

evaluation:: informal survey

- The recommenders

- ❖ Commercial

- All Music
 - iLike
 - last.fm
 - musicmobs
 - MusicMatch
 - MyStrands
 - Pandora
 - Unnamed Beta
 - Up To 11

- ❖ Research

- Sun tag-based
 - Sun user-based

- ❖ Expert

- Professional Critic
 - Brian
 - Chris
 - David
 - Dom
 - Joe

evaluation:: informal survey

- The Musical Turing Test

Which recommendation is from a human, which is from a machine?

Seed Artist: The Beatles

- Bob Dylan
- Beach Boys
- Billy Joel
- Rolling Stones
- Animals
- Aerosmith
- The Doors
- Simon & Garfunkel
- Crosby, Stills Nash & Young
- Paul Simon
- Chuck Berry
- Harry Nilsson
- XTC
- Marshall Crenshaw
- Super Furry Animals
- Badfinger
- The Raspberries
- The Flaming Lips
- Jason Faulkner
- Michael Penn

evaluation:: informal survey

- The Musical Turing Test

Which recommendation is from a human, which is from a machine?

Machine: Up to 11 Seed Artist: The Beatles **Human**

- Bob Dylan
- Beach Boys
- Billy Joel
- Rolling Stones
- Animals
- Aerosmith
- The Doors
- Simon & Garfunkel
- Crosby, Stills Nash & Young
- Paul Simon

- Chuck Berry
- Harry Nilsson
- XTC
- Marshall Crenshaw
- Super Furry Animals
- Badfinger
- The Raspberries
- The Flaming Lips
- Jason Faulkner
- Michael Penn

evaluation:: informal survey

- The Musical Turing Test

Which recommendation is from a human, which is from a machine?

Seed Artist: Miles Davis

- John Coltrane
- Thelonious Monk
- Charlie Parker
- Herbie Hancock
- Chet Baker
- Bill Evans
- Charles Mingus
- Lee Morgan
- Sonny Rollins
- John Coltrane
- Ken Vandermark
- Talk Talk
- James Brown
- Ornette Coleman
- Norah Jones
- Dizzy Gillespie
- Duke Ellington
- Steely Dan
- Sea & Cake

evaluation:: informal survey

- The Musical Turing Test

Which recommendation is from a human, which is from a machine?

Machine: Sun Tags	Seed Artist: Miles Davis	Human
<ul style="list-style-type: none">• John Coltrane• Thelonious Monk• Charlie Parker• Herbie Hancock• Chet Baker• Bill Evans• Charles Mingus• Lee Morgan• Sonny Rollins	<ul style="list-style-type: none">• John Coltrane• Ken Vandermark• Talk Talk• James Brown• Ornette Coleman• Norah Jones• Dizzy Gillespie• Duke Ellington• Steely Dan• Sea & Cake	

evaluation:: informal survey

- The Musical Turing Test

Which recommendation is from a human, which is from a machine?

Seed Artist: Arcade Fire

- Interpol
- Bloc Party
- Modest Mouse
- The Shins
- Clap Your Hands Say Yeah
- Arctic Monkeys
- Editors
- The Strokes
- The Decemberists
- Kings of Leon
- Echo & the Bunnymen
- the Sound
- Comsat Angels
- The Church
- House of Love
- Stone Roses
- The Smiths
- Gene
- Interpol
- U2

evaluation:: informal survey

- The Musical Turing Test

Which recommendation is from a human, which is from a machine?

Machine: last.fm

- Interpol
- Bloc Party
- Modest Mouse
- The Shins
- Clap Your Hands Say Yeah
- Arctic Monkeys
- Editors
- The Strokes
- The Decemberists
- Kings of Leon

Seed Artist: Arcade Fire

Human

- Echo & the Bunnymen
- the Sound
- Comsat Angels
- The Church
- House of Love
- Stone Roses
- The Smiths
- Gene
- Interpol
- U2

evaluation:: informal survey

- Rankings

Agreement with Experts		Agreement with Machines		Overall Agreement	
System	Score	System	Score	System	Score
Sun tags	0.88	last.fm	3.20	last.fm	3.98
Sun users	0.82	Sun users	3.11	Sun users	3.94
last.fm	0.78	Musicmatch	2.66	Sun tags	3.46
PC Dominique	0.78	Sun tags	2.60	Musicmatch	3.30
PC Chris	0.74	Mystrands	2.58	Mystrands	3.30
Mystrands	0.70	iLike	2.49	iLike	3.02
Musicmatch	0.64	PC Dom	1.92	PC Dom	2.70
PC Brian	0.64	PC Brian	1.80	PC Brian	2.44
iLike	0.54	up to 11	1.55	up to 11	2.08
up to 11	0.53	PC Chris	1.14	PC Chris	1.88
All Music	0.47	MusicMobs	0.88	PC Joe	1.22
PC Joe	0.46	Pandora*	0.88	MusicMobs	1.18
PC David	0.38	PC Joe	0.76	All Music	1.16
MusicMobs	0.30	All Music	0.69	Pandora*	1.08
Pandora*	0.20	PC David	0.66	PC David	1.04
Unnamed beta	0.13	Unnamed beta	0.27	Unnamed beta	0.39

evaluation:: informal survey

Music Recommendation Survey

Thanks for agreeing to participate in the music recommendation survey. The survey is very simple: you are asked to rate the quality of recommendations that are of the form "If you like XXX you might like YYY". The survey will take about 10 minutes per artist to complete. You don't have to complete the survey for all artists. If you don't know anything about a particular seed artist, you can skip that artist.

The Survey

- If you like The Beatles you might like ...
- If you like Miles Davis you might like ...
- If you like Emerson Lake and Palmer you might like ...
- If you like Deerhoof you might like ...
- If you like The Arcade Fire you might like ...

Your answers will be used to evaluate and compare a set of music recommenders. Send any questions or comments to Paul.Lamere@sun.com.

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200 Responses
>10,000 datapoints

Music Recommendation Survey

Instructions: Indicate how well the given artist answers the question:

If you like **The Beatles** you might like **XXX**?

Artist	Recommendation Rating				
	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
The Turtles	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
October Cherries	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
Chills	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
Counting Crows	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
The Zombies	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
Hoobastank	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
War	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
Aerosmith	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
Dave Clark Five	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
Michael Penn	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>
Donovan	Excellent: <input type="radio"/>	Good: <input type="radio"/>	Don't Know: <input checked="" type="radio"/>	Fair: <input type="radio"/>	Poor: <input type="radio"/>

evaluation:: informal survey

- Results: systems ranked by survey

System	Average Rating	System	Novelty	System	Rel. Precision
Sun Tags	4.02	PC Joe	0.64	Sun Tags	0.49
Music Match	3.68	All Music	0.58	last.fm	-0.02
last.fm	3.50	PC David	0.57	All Music	-0.16
Sun Users	3.48	Pandora*	0.57	Sun Users	-0.38
Mystrands	3.26	Unnamed beta	0.48	PC Joe	-0.47
PC Brian	2.89	PC Chris	0.47	MusicMatch	-0.49
PC Dom	2.76	MusicMobs	0.47	PC Brian	-0.70
Up to 11	2.59	PC Dom	0.45	PC Dom	-1.01
All Music	2.06	iLike	0.38	Mystrands	-1.17
iLike	1.82	PC Brian	0.33	Up to 11	-1.18
PC Chris	1.64	Up to 11	0.32	PC David	-1.56
PC Joe	1.59	Sun Tags	0.31	Pandora*	-1.95
PC David	1.14	last.fm	0.28	PC Chris	-2.00
Pandora*	0.89	Sun Users	0.26	iLike	-3.31
Musicmobs	0.82	Musicmatch	0.24	MusicMobs	-4.32
Unnamed Beta	-2.39	Mystrands	0.23	Unnamed beta	-13.18

outline

- Introduction
- Formalization of the recommendation problem
- Recommendation algorithms
- Problems with recommenders
- Recommender examples
- Evaluation of recommenders
- **Conclusions / Future**

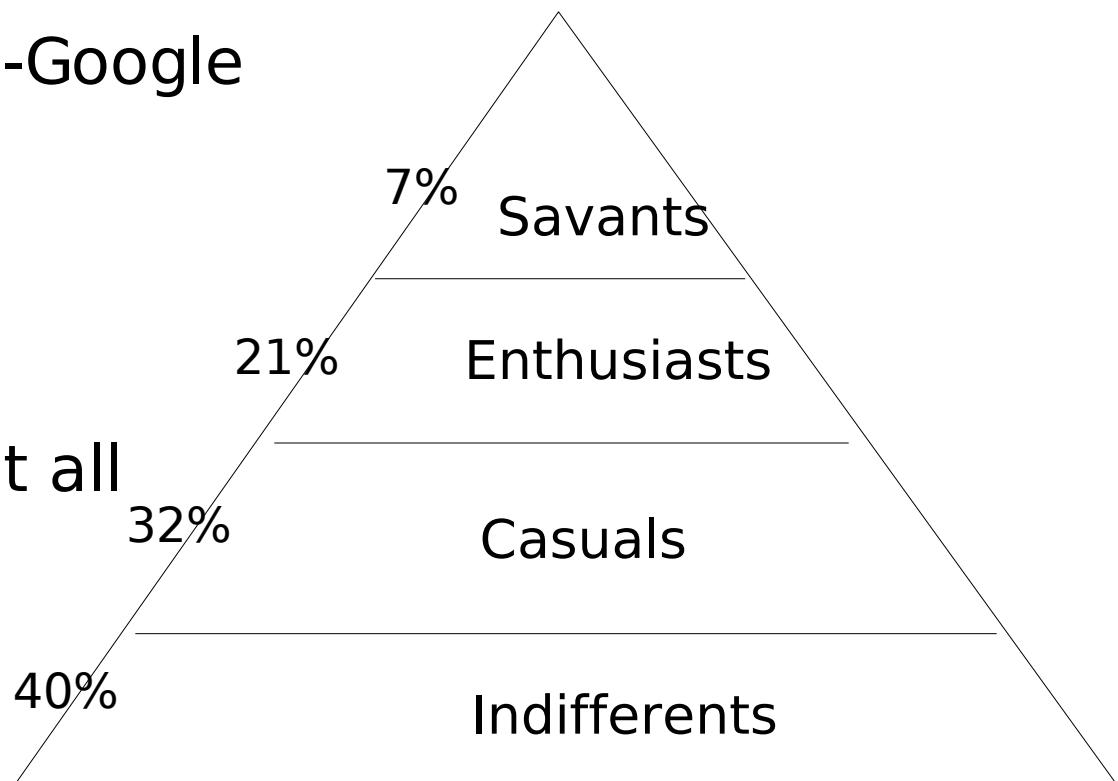
Conclusions / Future

- Coming soon: The Celestial Jukebox
 - ❖ All music in the world will be online
 - ❖ Millions of new tracks will be added every day
 - ❖ Lots of commercial interest
- Music tools will be essential
 - ❖ Exploration
 - ❖ Discovery
 - ❖ Recommendation
 - ❖ Organization
 - ❖ Playlisting



Conclusions / Future

- Current tools for finding music are inadequate
 - ❖ Like the web – pre-Google
 - ❖ Lots of problems:
 - scale, coldstart,
 - transparency
 - feedback loops
 - ❖ One size doesn't fit all
- Problems are opportunities for researchers



conclusions:: MIR Wishlist

- Big Problems
 - ❖ Coldstart
 - ❖ Feedback loops
 - ❖ Transparency
 - ❖ Scaling
 - ❖ Evaluation
 - Not just predicting ratings
 - Capture novelty / serendipity

conclusions:: MIR Wishlist

- Determining audio-based music similarity
- Extracting semantic descriptors from audio
- Recommendation for devices
- Recommendations for groups
- Combining different data sources
- Segmenting songs
- Creating intelligent playlists
- Creating user interfaces to browse music
- Learning from skipping behavior

conclusions:: MIR Wishlist

- Detecting cover songs
- Aligning lyrics with audio
- Separating audio sources
- Detecting and exploiting 'trendsetters'
- Extracting and aligning beat
- Supporting users in remixing/modifying their favorite songs
- Dealing with dirty, inconsistent metadata
 - ❖ As RJ from last.fm asks: "Just how many ways to write "Guns N' Roses – Knockin' on Heaven's Door" are there?"

And finally...

This is a very exciting time to be in a very fun field



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- Justin Donaldson – Mystrands
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- Dan Ellis - Columbia
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- Zac Johnson – All Music
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- Greg Linden – Amazon / Findory
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- Dominique Leon – Pitchfork Media
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- Kris West – One Llama
- Ian Wilson – Zukool
- Mark Young – Itunes Registry



Music Recommendation Tutorial

**Òscar Celma
Paul Lamere**

ISMIR 2007

September 23, 2007



misc:: patents

- MusicIP
- Polyphonic HMI
- Philips
- MyStrands
- Microsoft

misc:: patents

- Music Recommendation system and method
 - ❖ Filing Date: 08/13/2004 – Publication: 02/17/2005
 - ❖ Authors (MusicIP, formerly Predixis)
 - Hicken, Wendell T. (La Verne, CA, US)
 - Holm, Frode (Santa Barbara, CA, US)
 - Clune, James Edmond III (Glendora, CA, US)
 - Campbell, Marc Elroy (Monrovia, CA, US)
 - ❖ Keywords
 - audio fingerprint, song similarity, playlist generation
 - ❖ United States Patent 20050038819

misc:: patents

- Method and system for music recommendation
 - ❖ Filing Date: 10/03/2003 – Publication: 06/10/2004
 - ❖ Authors (Polyphonic HMI)
 - Alcalde, Vicenc Gaitan (Castella del Valles, ES)
 - Ullod, Carlos Maria Lopez (Zaragoza, ES)
 - Bonet, Antonio Trias (Sant Cugat del Valles, ES)
 - Llopis, Antonio Trias (Sant Cugat del Valles, ES)
 - Marcos, Jesus Sanz (Barcelona, ES)
 - Ysern, Daniel Caldentey (Barcelona, ES)
 - Arkwright, Dominic (Barcelona, ES)
 - ❖ Keywords
 - song similarity (FFT, chunks, avg. values), vector similarity, user's taste vector, relevance feedback
 - ❖ United States Patent 20040107821

misc:: patents

- Sharing music essence in a recommendation system
 - ❖ Filing Date: 05/23/2006 – Publication: 11/23/2006
 - ❖ Author (MusicIP)
 - Hicken, Wendell T. (La Verne, CA, US)
 - ❖ Keywords
 - playlist characterization, playlist sharing, fill-in the gap, modify playlist
 - ❖ United States Patent 20060265349

misc:: patents

- Introducing new content items in a community-based recommendation system
 - ❖ Filing Date: 10/27/2003 - Publication: 04/20/2006
 - ❖ Authors (Philips)
 - Bodlaender, Maarten Peter (Eindhoven, NL)
 - Hollemans, Gerrit (Eindhoven, NL)
 - Vignoli, Fabio (Eindhoven, NL)
 - ❖ Keywords
 - user community, comparing user profiles, generating a recommended user set for the user
 - ❖ United States Patent 20060085818

misc:: patents

- Client-based generation of music playlists from a server-provided subset of music similarity vectors
 - ❖ Filing Date: 01/27/2005 - Publication: 05/25/2006
 - ❖ Authors (Microsoft)
 - Platt, John (Redmond, WA, US)
 - Renshaw, Erin (Kirkland, WA, US)
 - ❖ Keywords
 - music similarity, hybrid graph, MDS embedding, euclidean space
 - ❖ United States Patent 20060112082

misc:: patents

- MyStrands
 - ❖ <http://labs.mystrands.com/patents.html>
 - ❖ 16 pending patents (from 2004-2006)
 - ❖ Examples
 - “Personal music recommendation mapping applet overview”
 - “Sharing tags between individual user media libraries”
 - “User to user recommender”
 - “Freeing space for new media items on a mobile media playback device based on inferred user taste”
 - “Building and sharing a composite playlist from collective group tastes on multiple media playback devices”
 - ...and a long etc.