Music Recommendation Tutorial

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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!
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

- Indifferents
- Casuals
- Enthusiasts
- Savants

- 40% Indifferents
- 32% Casuals
- 21% Enthusiasts
- 7% Savants

- Hype Machine
- Last.fm
- Pandora
- Clear Channel
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:: enthusiasm

- 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

- FM/AM Radio: 55% in 2007, 60% in 2006
- On music TV: 37% in 2007, 42% in 2006
- From friends: 24% in 2007, 22% in 2006
- In a shop/music store: 5% in 2007, 7% in 2006
- On community websites: 7% in 2007, 4% in 2006
- DAB radio: 6% in 2007, 5% in 2006
- Specialist music press: 8% in 2007, 6% in 2006
- Mainstream terrestrial TV channels: 3% in 2007, 6% in 2006
- Artist/fan websites: 6% in 2007, 5% in 2006
- Internet radio: 5% in 2007, 5% in 2006
- Legal download site: 3% in 2007, 4% in 2006
- In a club: 4% in 2007, 3% in 2006
- Advertisement: 4% in 2007, 3% in 2006
- General press: 4% in 2007, 3% in 2006
- File sharing service: 2% in 2007, 3% in 2006
- In a bar: 3% in 2007, 2% in 2006
- Mail order site like Amazon: 2% in 2007, 2% in 2006
- Music sites like Launch.com: 2% in 2007, 2% in 2006
- Message boards/chat rooms: 2% in 2007, 2% in 2006
- Movies: 2% in 2007, 2% in 2006
- From Podcasts / blogs: 2% in 2007, 1% in 2006
- News or recommendations using IM: 1% in 2007, 1% in 2006
- Other: 2% in 2007, 2% in 2006

Base: Q4, All respondents (1,721)
introduction:: sources of new music

- Hype Machine Survey

How do you Discover New Music?

User Survey, July 2007

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
- Musiccovery
- 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:
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
formalization:: describing users & items

<table>
<thead>
<tr>
<th>USERS</th>
<th>ITEMS</th>
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<tbody>
<tr>
<td>HUMAN KNOWLEDGE</td>
<td>CONTENT OBJECTS</td>
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<td>expectations</td>
<td>similarity</td>
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<td>content features</td>
<td>shot rhythm</td>
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<td>SIGNAL FEATURES</td>
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<td>duration</td>
<td>shapes</td>
</tr>
<tr>
<td>energy</td>
<td>colors</td>
</tr>
<tr>
<td>audio (music recordings)</td>
<td>text (lyrics, editorial data, press releases, ...)</td>
</tr>
<tr>
<td>video (video clips, CD covers, printed scores, ...)</td>
<td></td>
</tr>
</tbody>
</table>
formalization:: describing users & items

get a better understanding of the music assets!
formalization:: describing users & items

**USERS**
- get a better understanding of the users preferences!

**ITEMS**
- get a better understanding of the music assets!
formalization:: describing users

- get a better understanding of the users preferences!
formalization:: describing users (me)

- get a better understanding of the users preferences!
formalization:: describing users (me)

• me and myself (user profile) [Uitdenboger, 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!

<table>
<thead>
<tr>
<th>Ocelma's Music Charts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Show: overall charts for artists</td>
</tr>
</tbody>
</table>

**Top Artists**

1. The Dogs D'Amour 160
2. U2 76
3. The White Stripes 38
4. Spiritualized 32
5. Yann Tiersen 31
6. The Black Crowes 26
7. Lhasa 17
8. Ryan Adams 16
9. Martirio y Chano Domínguez 13
10. The Rolling Stones 10
11. Bob Dylan 9
12. Kraftwerk 9
13. Nirvana 7
14. Björk 7
15. Creedence Clearwater Revival 6
15. The Wildhearts 6
15. Pearl Jam 6
15. Franz Ferdinand 6
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:
formalization: describing users

- get a better understanding of the users preferences!
formalization:: describing users (us)

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/XML-Schema 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>
</user>
formalization:: describing users :: umirl

 téléchargement

 a complete example...

<user>
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  <musicbackground>
    <education>none</education>
    <instrument>guitar</instrument>
    <instrument>vocal</instrument>
  </musicbackground>
  <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>
</user>
formalization:: describing users :: umirl

(continue....)

<habit>
  <context><tempo>Happy</tempo>
  <tempo>very fast</tempo>
  <genre>rock</genre>
</context>

<perceptualfeature>Romantic</perceptualfeature>
  <tempo>very slow</tempo>
  <intensity>soft</intensity>
  <lyrics>*love*</lyrics>
</perceptualfeature>

<context><tempo>Dinner with fiance</tempo>
  <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>
  <UserIdentifier protected="true">
    <Name xml:lang="ca">Joan Blanc</Name>
  </UserIdentifier>
  <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>
      </CreationPreferences>
    </FilteringAndSearchPreferences>
  </UserPreferences>

(continue...)

  <Keyword>dramatic</Keyword>
  <Keyword>fiery</Keyword>
  <DatePeriod>
    <TimePoint>1995-01-01</TimePoint>
  </DatePeriod>
</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: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: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"/>
    <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: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

- Basic User Dimensions
  - Contact Information
  - Demographics
  - Ability And Proficiency
  - Personality
  - Characteristics
  - Emotional State
  - Physiological State
  - Mental State
  - Motion
  - Role
  - Nutrition
  - Facial Expression

- Emotional State
  - Five Basic Emotions
    - happiness
    - anxiety
    - fear
    - love
    - hate
    - pride
    - shame
    - anger
    - disgust
    - sadness
    - satisfaction
    - confusion
formalization:: describing users :: gumo

- main elements

- Basic User Dimensions
  - Contact Information
  - Demographics
  - Ability And Proficiency
  - Personality
  - Characteristics
  - Emotional State
  - Physiological State
  - Mental State
  - Motion
  - Role
  - Nutrition
  - Facial Expression

- Characteristics
  - talkative
  - assertive
  - dominant
  - quiet
  - reserved
  - shy
  - retiring
  - sympathetic
  - kind
  - warm
  - helpful
  - fault-finding
  - cold
  - unfriendly

- Personality
  - MyersBriggs Type Inventory
  - Three Factor PEN Model
  - Five Factor OCEAN Model
  - extravert
  - introvert
  - thinking
  - feeling
  - sensing
  - intuiting
  - judging
  - perceiving
  - controlled
  - optimistic
  - pessimistic
formalization:: describing users

- Complexity and expressiveness of the representations

Diagram:
- Term List
- Thesaurus
- Informal hierarchy
- Formal taxonomy
- Frame (class property)
- Range (value restrictions)
- Limited logic constraints
- Very expressive constraints

Ontologies:
- Dublin Core, VRA
- MODS, MARC
- Wordnet
- (light-weight ontologies)
- MPEG-7
- RDF(S) ontologies
- OWL ontologies
- (heavy-weight ontologies)
- UMIRL
- MPEG-7
- FOAF
- GUMO
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

get a better understanding of the music assets!
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)

\[
tf_i = \frac{n_i}{\sum_k n_k}
\]
\[
idf_i = \log \frac{|D|}{|\{d : t_i \in d\}|}
\]
\[
tfidf = tf \cdot idf
\]
formalization: describing items :: text

- determining similarity of text
  - cosine similarity

\[
\text{Sim}(A, B) = \cos \theta = \frac{A \cdot B}{|A||B|} = \frac{x_1^*x_2 + y_1^*y_2}{(x_1^2 + y_1^2)^{1/2} (x_2^2 + y_2^2)^{1/2}}
\]
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

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

Fun with metadata
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
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

<table>
<thead>
<tr>
<th>100</th>
<th>*sabbath</th>
<th>26</th>
<th>heavy</th>
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</thead>
<tbody>
<tr>
<td>97</td>
<td>*panthera</td>
<td>26</td>
<td>ulrich</td>
</tr>
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<td>53</td>
<td>ozzy</td>
<td>23</td>
<td>reinventing</td>
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<td>52</td>
<td>iommi</td>
<td>23</td>
<td>lange</td>
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<td>42</td>
<td>puppets</td>
<td>23</td>
<td>newsted</td>
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<tr>
<td>40</td>
<td>dimebag</td>
<td>21</td>
<td>leppards</td>
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<td>40</td>
<td>anselmo</td>
<td>21</td>
<td>adrenalize</td>
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<tr>
<td>40</td>
<td>pyromania</td>
<td>21</td>
<td>mutt</td>
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<td>40</td>
<td>paranoid</td>
<td>20</td>
<td>kirk</td>
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<td>39</td>
<td>osbourne</td>
<td>20</td>
<td>riffs</td>
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<td>37</td>
<td>*def</td>
<td>20</td>
<td>s&amp;m</td>
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<tr>
<td>34</td>
<td>euphoria</td>
<td>20</td>
<td>trendkill</td>
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<tr>
<td>32</td>
<td>geezer</td>
<td>20</td>
<td>snowblind</td>
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<tr>
<td>29</td>
<td>vinnie</td>
<td>19</td>
<td>cowboys</td>
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<tr>
<td>28</td>
<td>collen</td>
<td>18</td>
<td>darrell</td>
</tr>
<tr>
<td>28</td>
<td>hammett</td>
<td>18</td>
<td>screams</td>
</tr>
<tr>
<td>27</td>
<td>bloody</td>
<td>18</td>
<td>bites</td>
</tr>
<tr>
<td>27</td>
<td>thrash</td>
<td>18</td>
<td>unforgiven</td>
</tr>
<tr>
<td>27</td>
<td>phil</td>
<td>18</td>
<td>lars</td>
</tr>
<tr>
<td>26</td>
<td>lep</td>
<td>17</td>
<td>trujillo</td>
</tr>
</tbody>
</table>

Knees; Pampalk ; Widmer  Artist Classification with Web-Based Data
formalization:: describing items :: text

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

<table>
<thead>
<tr>
<th>Song 1</th>
<th>Song 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Living Room</td>
<td>Basement Jaxx</td>
</tr>
<tr>
<td>Wonderland (The S-Mans Dark Tribe)</td>
<td>The Psychedelic Waltos</td>
</tr>
<tr>
<td>Lisbon Acid</td>
<td>AFX</td>
</tr>
<tr>
<td>Flashdance (Club Mix)</td>
<td>Deep Dish</td>
</tr>
<tr>
<td>Love And Imitation</td>
<td>Infusion</td>
</tr>
<tr>
<td>Do It Now (Extended Disco Version)</td>
<td>Dubtribe Sound System</td>
</tr>
<tr>
<td>Wir Sind Die Anderen (Boris Di)</td>
<td>2raumwohnung</td>
</tr>
<tr>
<td>Steppin Out</td>
<td>Kaskade</td>
</tr>
<tr>
<td>Black Water (Vocal Mix)</td>
<td>Octave One</td>
</tr>
<tr>
<td>Pornography</td>
<td>Client</td>
</tr>
<tr>
<td>Du What Ya Du (Trentemoller Mix)</td>
<td>Yoshimoto</td>
</tr>
</tbody>
</table>
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
formalization:: describing items :: text :: tags

- Social tags
  - Tags – The Shins

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

Table 1: Top 21 tags applied to The Shins
formalization: describing items :: text :: tags

• Social tags
  - Artist similarity based on tags for The Beatles

<table>
<thead>
<tr>
<th>Top Tags</th>
<th>Distinctive Tags</th>
<th>Similar Artists via Tags</th>
</tr>
</thead>
<tbody>
<tr>
<td>classic rock</td>
<td>The Beatles</td>
<td>John Lennon</td>
</tr>
<tr>
<td>rock</td>
<td>60s</td>
<td>Rolling Stones</td>
</tr>
<tr>
<td>pop</td>
<td>liverpool</td>
<td>Paul McCartney</td>
</tr>
<tr>
<td>british</td>
<td>british</td>
<td>The Kinks</td>
</tr>
<tr>
<td>60s</td>
<td>british psychedelia</td>
<td>The Who</td>
</tr>
<tr>
<td>oldies</td>
<td>oldies</td>
<td>Pink Floyd</td>
</tr>
<tr>
<td>psychedelic</td>
<td>britrock</td>
<td>Queen</td>
</tr>
<tr>
<td>alternative</td>
<td>psychedelic</td>
<td>The Police</td>
</tr>
<tr>
<td>indie</td>
<td>classic rock</td>
<td>Led Zeppelin</td>
</tr>
<tr>
<td>britpop</td>
<td>Rock and Roll</td>
<td>David Bowie</td>
</tr>
</tbody>
</table>

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

mac, macintosh, ipod, powerbook, computer, laptop, ibook, imac, gd, 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

Elias Pampalk & Masataka Goto, "MusicSun: A New Approach to Artist Recommendation"
formalization:: describing items :: text :: tags

• Social tags
  ❖ Distribution of Tags

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

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

Gothic Metal more popular than Country
formalization:: describing items :: text :: tags

• Social tags: Issues
  ❖ Sparsity of data
  ▪ 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
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

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”

<table>
<thead>
<tr>
<th></th>
<th>Artist</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Paris Hilton</td>
<td>718</td>
</tr>
<tr>
<td>2</td>
<td>Nile</td>
<td>528</td>
</tr>
<tr>
<td>3</td>
<td>Cannibal Corpse</td>
<td>474</td>
</tr>
<tr>
<td>4</td>
<td>Suffocation</td>
<td>281</td>
</tr>
<tr>
<td>5</td>
<td>Aborted</td>
<td>259</td>
</tr>
<tr>
<td>6</td>
<td>Cryptopsy</td>
<td>241</td>
</tr>
<tr>
<td>7</td>
<td>Dying Fetus</td>
<td>181</td>
</tr>
<tr>
<td>8</td>
<td>Deicide</td>
<td>170</td>
</tr>
<tr>
<td>9</td>
<td>Devourment</td>
<td>166</td>
</tr>
<tr>
<td>10</td>
<td>Behemoth</td>
<td>142</td>
</tr>
</tbody>
</table>

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!
formalization:: describing items :: audio

- Automatic annotation

<table>
<thead>
<tr>
<th>CONTENT OBJECTS</th>
<th>SIGNAL FEATURES</th>
</tr>
</thead>
<tbody>
<tr>
<td>rhythm</td>
<td>pitch</td>
</tr>
<tr>
<td>source</td>
<td>timbre</td>
</tr>
<tr>
<td>melody</td>
<td>loudness</td>
</tr>
<tr>
<td>genre</td>
<td>time</td>
</tr>
<tr>
<td>similarity</td>
<td>spectrum</td>
</tr>
<tr>
<td>labels</td>
<td>frequency</td>
</tr>
<tr>
<td>tags</td>
<td>articles</td>
</tr>
<tr>
<td>music scores</td>
<td>numbers</td>
</tr>
<tr>
<td>shot rhythm</td>
<td>colors</td>
</tr>
<tr>
<td>motions</td>
<td>shapes</td>
</tr>
<tr>
<td>signs</td>
<td>contrasts</td>
</tr>
<tr>
<td>scenes</td>
<td>textures</td>
</tr>
<tr>
<td>graphic style</td>
<td>nouns</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>AUDIO (music recordings)</th>
<th>TEXT (lyrics, editorial data, press releases, ...)</th>
<th>VIDEO (video clips, CD covers, printed scores, ...)</th>
</tr>
</thead>
<tbody>
<tr>
<td>content objects</td>
<td>signal features</td>
<td>content objects</td>
</tr>
</tbody>
</table>
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% (IMIRSEL)
formalization:: describing items :: audio

• Automatic annotation
  ❖ How does classification work?

Feature Extraction

- Decode
- Windowing
- FFT
- Log
- DCT
- MEL Scale
- MFCC

Training

- Labeled Examples
- Machine Learning
- Model

Classifying

- Unknown Examples
- Labeled Examples
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 Spectogram
      - 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

From Alpaydin (2004)
formalization:: describing items :: audio

- Automatic annotation
  - Multiple class machine classification
formalization:: describing items :: audio

- Automatic annotation
  - Similarity based on classification

Training

Music to be classified

Trained Models

Database of music 'templates'

Query

Query Song

Query template

Ordered Results

Similarity Query

Song 1
Song 2
Song 3
Song 4
Song 5
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

![Diagram showing the process of music recommendation algorithms]

- **Items** and **Descriptions of Items**
- **Users** and **Users' profiles**
- **Profile matching (comparison)**
- **Profile - Item matching (comparison or filtering)**
- **Recommended Items**
- **Prediction**
- **Profile exploitation**
- **Top-N Predicted neighbours**
- **Profile adaptation**
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

- 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.
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 :: demogrp

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

  ❖ Cons
    1) totally dependant on user's features (sometimes unknown / private / ...)
    2) 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]
**Collaborative Filtering: User-based**

- **John** and **Mary** have similar listening habits.
**Collaborative Filtering: User-based**

- Recommend **Arcade Fire** to John
music recommendation:: algorithms :: colfilter

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

<table>
<thead>
<tr>
<th></th>
<th>i₁</th>
<th>i₂</th>
<th>i₃</th>
<th>...</th>
<th>iₙ</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
<td>4</td>
<td></td>
<td></td>
</tr>
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<td>uₐ</td>
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<td>?</td>
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<td></td>
<td></td>
<td></td>
<td>φ</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- prediction (user $uₐ$, item $iₗ$): adjusted weighted sum

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

- Collaborative Filtering: Item-based [Sarwar, 2001]
music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based

People who listen to U2 listen to Wolf Parade, too
music recommendation:: algorithms :: colfilter

• Collaborative Filtering: Item-based

- Paul listens to Wolf Parade, then...
music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based

- Recommend **U2** to **Paul**
music recommendation:: algorithms :: colfilter

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

<table>
<thead>
<tr>
<th></th>
<th>U1</th>
<th>U2</th>
<th>U_i</th>
<th>U_{m-1}</th>
<th>U_m</th>
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<tbody>
<tr>
<td>i1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_j</td>
<td></td>
<td>R</td>
<td>R</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_k</td>
<td></td>
<td>R</td>
<td>R</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i_n</td>
<td></td>
<td></td>
<td></td>
<td>R</td>
<td>R</td>
</tr>
</tbody>
</table>
music recommendation:: algorithms :: colfilter

- Collaborative Filtering: Item-based
  - item similarity measures
    - cosine
      \[
      \text{sim}(i, j) = \cos(\vec{i}, \vec{j}) = \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\| \ast \|\vec{j}\|} = \frac{\sum_{u \in U} R_{u,i} R_{u,j}}{\sqrt{\sum_{u \in U} R_{u,i}^2} \sqrt{\sum_{u \in U} R_{u,j}^2}}
      \]
    - 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
      \[
      sim(i, j) = \cos(i, j) = \frac{\vec{i} \cdot \vec{j}}{\|i\| \times \|j\|} = \frac{\sum_{u \in U} R_{u,i} R_{u,j}}{\sqrt{\sum_{u \in U} R_{u,i}^2} \sqrt{\sum_{u \in U} R_{u,j}^2}}
      \]
    - adjusted cosine
      \[
      sim(i, j) = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_u)(R_{u,j} - \bar{R}_u)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_u)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_u)^2}}
      \]
    - pearson correlation
      \[
      sim(i, j) = \frac{Cov(i, j)}{\sigma_i \sigma_j} = \frac{\sum_{u \in U} (R_{u,i} - \bar{R}_i)(R_{u,j} - \bar{R}_j)}{\sqrt{\sum_{u \in U} (R_{u,i} - \bar{R}_i)^2} \sqrt{\sum_{u \in U} (R_{u,j} - \bar{R}_j)^2}}
      \]
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.
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
problems:: Social recommenders:: Feedback Loops

The Shins → ❤ → The Postal Service

The Shins → ❤ → The Postal Service

The Shins → ❤ → The Postal Service
problems:: Social recommenders:: Popularity Bias
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
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
problems:: Social recommenders

- Hacking the recommender
  - Profile Injection Attack

Courtesy of Bamshad Mobasher
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

<table>
<thead>
<tr>
<th>Preview</th>
<th>Play</th>
<th>Song</th>
<th>Artist</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hey Jude</td>
<td>Elvis Presley</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hey Jude</td>
<td>Arthur Fiedler</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hey Jude</td>
<td>Luca Colombo</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hey Jude</td>
<td>Espitia, J. Lennon/P. McCartney</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hey Jude</td>
<td>Wilson Pickett</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hey Jude</td>
<td>Chokocheeky</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hey Jude</td>
<td>Dale Miller</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hey Jude</td>
<td>Tiny Tim</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mother Nature's Son</td>
<td>John Denver</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Strawberry Fields Forever</td>
<td>The Real Group</td>
</tr>
</tbody>
</table>
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
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
problems:: Social recommenders

Strange Connections
problems:: Social recommender

If you like Gregorian Chants you might like Green Day

If you like Britney Spears you might like...
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

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

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examples:: Hard core music discovery

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

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 listened amazon itunes


Savants    7%

Enthusiasts  21%

Casuals     32%

Indifferents 40%
examples:: Hard core music discovery

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

## What's hot

<table>
<thead>
<tr>
<th>Most Blogged</th>
<th>Popular Searches</th>
<th>Popular Blogs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beirut</td>
<td>Kanye West</td>
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<td>Kanye West</td>
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<td>This Recording</td>
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<td>Beirut</td>
<td>Berkeley Place</td>
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<tr>
<td>animal collective</td>
<td>Band Of Horses</td>
<td>get weird turn pro</td>
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<td>Klaxons</td>
<td>Mia</td>
<td>The Yellow Stereo</td>
</tr>
<tr>
<td>Rilo Kiley</td>
<td>Feist</td>
<td>Rock Sellout</td>
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<tr>
<td>Bruce Springsteen</td>
<td>Justice</td>
<td>jefitoblog</td>
</tr>
<tr>
<td>Radiohead</td>
<td>Rilo Kiley</td>
<td>brugo</td>
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<tr>
<td>Bat For Lashes</td>
<td>Britney Spears</td>
<td>Cause=Time</td>
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<tr>
<td>Caribou</td>
<td>Daft Punk</td>
<td>Fabulist!</td>
</tr>
<tr>
<td>Jens Lekman</td>
<td>Bat For Lashes</td>
<td>Missingtoof</td>
</tr>
<tr>
<td>Le Loup</td>
<td>Amy Winehouse</td>
<td>wongie's music world</td>
</tr>
<tr>
<td>Spoon</td>
<td>Klaxons</td>
<td>Neiles Life</td>
</tr>
<tr>
<td>Elliott Smith</td>
<td>Jens Lekman</td>
<td>BadmintonStamps</td>
</tr>
<tr>
<td>Feist</td>
<td>Kate Nash</td>
<td>Palms Out Sounds</td>
</tr>
</tbody>
</table>
examples:: Social music

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

[Diagram showing different music listeners: Savants (7%), Enthusiasts (21%), Casuaries (32%), Indifferent (40%).]
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
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

Examples: Social music
examples:: Social music

Internet radio

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

Last.fm Charts
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)
  v User Profile Data
  v Artist Data
  v Album Data
  v Track Data
  v Tag Data
  v Group Data
  v Forum Data

• http://www.audioscrobbler.net/data/webservices/
examples:: Social music

Last.fm – web services

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

<toptags artist="Deerhoof">
  <tag>
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    <name>indie rock</name>
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    <url>http://www.last.fm/tag/indie%20rock</url>
  </tag>
  ... </tag>
</toptags>
examples:: Content-based:: 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 -
    ▪ Chose songs that are representative of an artists 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
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
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
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)

<table>
<thead>
<tr>
<th>How eclectic is the musical preference of ocelma?</th>
</tr>
</thead>
<tbody>
<tr>
<td>ocelma's eclectic score is</td>
</tr>
<tr>
<td>87/100</td>
</tr>
</tbody>
</table>

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
### Mainstream-O-Meter

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

30.82 % mainstream
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

![Last.fm Popularity](image-url)
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
  - Bruce Springsteen (5,992,068 plays)
  - The Rolling Stones (11,239,824 plays)
evaluation:: novelty & relevance

- Mike Shupp
  - total # plays in last.fm = 321
  - # plays for “Letter to Annete” = 0
  - data from July 2007
evaluation:: novelty & relevance

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

![Last.fm Popularity](image-url)

- The Rolling Stones (11,239,824 plays)
- Bruce Springsteen (5,992,068 plays)
- Mike Shupp (321 plays)
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)

```
    the beatles (50,422,827)
    radiohead (40,762,895)
    red hot chili peppers (37,564,100)
    muse (30,548,064)
    death cab for cutie (29,335,085)
    pink floyd (28,081,366)
    coldplay (27,120,352)
    metallica (25,749,442)
```
evaluation:: novelty & relevance

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

\[
F(x) = \frac{\beta}{\left( \frac{N_{50}}{x} \right)^\alpha + 1}
\]

Where
- \( F(x) \) = the share of total volume covered by objects up to rank \( x \)
- \( N_{50} \) = the number of objects that cover half of the whole volume
- \( \alpha \) = the factor that defines the form of the function
- \( \beta \) = total volume
evaluation:: novelty & relevance

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

![Last.fm Popularity](image)

The top-8 artists represent the **3.5%** of total plays:

- **50,422,827** the beatles
- **40,762,895** radiohead
- **37,564,100** red hot chili peppers
- **30,548,064** muse
- **29,335,085** death cab for cutie
- **28,081,366** pink floyd
- **27,120,352** coldplay
- **25,749,442** metallica
evaluation: novelty & relevance

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

668 artists (out of 249,753) represent the **50%** of total plays
evaluation:: novelty & relevance

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

Split the curve in three sections:

- **HEAD**: 1 .. 82
- **MID**: 83 .. 6,651
- **TAIL**: 6,652 .. 249,753
evaluation:: novelty & relevance

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

  **ANALYZE** Artist similarity in each part of the curve

  Total Artists used: 40,687
  - **HEAD:** 53 (out of 83)
  - **MID:** 2,789 (out of 6,569)
  - **TAIL:** 37,845 (out of 239,798)
evaluation:: novelty & relevance

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

<table>
<thead>
<tr>
<th>The Beatles</th>
<th>Similar Artists</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>The Rolling Stones</td>
</tr>
<tr>
<td></td>
<td>The Who</td>
</tr>
<tr>
<td></td>
<td>John Lennon</td>
</tr>
<tr>
<td></td>
<td>Queen</td>
</tr>
<tr>
<td></td>
<td>Led Zeppelin</td>
</tr>
<tr>
<td></td>
<td>The Beach Boys</td>
</tr>
<tr>
<td></td>
<td>The Doors</td>
</tr>
<tr>
<td></td>
<td>David Bowie</td>
</tr>
<tr>
<td></td>
<td>The Kinks</td>
</tr>
<tr>
<td></td>
<td>Pink Floyd</td>
</tr>
<tr>
<td></td>
<td>Jimi Hendrix</td>
</tr>
<tr>
<td></td>
<td>Elton John</td>
</tr>
<tr>
<td></td>
<td>U2</td>
</tr>
<tr>
<td></td>
<td>The Velvet Underground</td>
</tr>
<tr>
<td></td>
<td>Creedence Clearwater Revival</td>
</tr>
<tr>
<td></td>
<td>Simon &amp; Garfunkel</td>
</tr>
<tr>
<td></td>
<td>Eagles</td>
</tr>
<tr>
<td></td>
<td>Paul McCartney</td>
</tr>
<tr>
<td></td>
<td>The Police</td>
</tr>
</tbody>
</table>
evaluation:: novelty & relevance

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

![Last.fm Popularity Graph]

Cumulative (percentage) of plays

HEAD | MID | TAIL

1 | 100 | 10000
evaluation:: novelty & relevance

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

1) All similar artists, non weighted

- **HEAD** (#83) 18.55%
- **MID** (#6,569) 80.37%
- **TAIL** (#239,798) 1.07%
evaluation:: novelty & relevance

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

2) All similar artists, with similarity weight

(Beatles --> Beach Boys, **87**)

```
<table>
<thead>
<tr>
<th>Category</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>HEAD</td>
<td>23.97%</td>
</tr>
<tr>
<td>MID</td>
<td>75.40%</td>
</tr>
<tr>
<td>TAIL</td>
<td>0.63%</td>
</tr>
</tbody>
</table>
```
evaluation:: novelty & relevance

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

![Graph showing percentage of plays by artist popularity]

- **HEAD (#83)**: 48.50%
- **MID (#6,569)**: 51.50%
- **TAIL (#239,798)**
evaluation:: novelty & relevance

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

In any case (1, 2, 3), similar artists still in the mid

![Chart showing distribution of plays across different categories.

- **Head** (~5%): ~83
- **Mid** (~71%): ~6,569
- **Tail** (~24%): ~239,798

Cumulative (percentage) of plays vs. Ranking.
evaluation:: novelty & relevance

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

In any case (1, 2, 3), similar artists still in the tail

```
In the HEAD (~83), MID (~6,569), ~18% in the TAIL (~239,798), ~82%
```

Cumulative (percentage) of plays
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, $<k> = 15.4$
  - Diameter = 20
  - Small world effect
    - Avg. shortest path, $d = 6.24$ (dr = 4.6)
    - Clustering Coefficient, $C = 0.23$ (Cr = 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

  ![Graph showing top-100 artists with higher in-degree](image)

  - #78: r.e.m. (737)
  - #30: u2 (718)
  - #45: weezer (611)
  - #47: beck (592)
  - #41: foo fighters (582)
  - #64: pixies (568)
  - #73: the rolling stones (567)
  - #40: queen (544)
  - #2: radiohead (539)
  - #22: the white stripes (528)
  - #1: the beatles (500)
  - #56: david bowie (488)

  **Top-100 artist with higher in-degree**

  - #17956: little milton (774)
  - #13174: rufus thomas (758)
  - #8280: joe henderson (744)
  - #7281: mccoy tyner (739)
  - #7170: freddie hubbard (698)
  - #7304: lee morgan (660)
  - #26711: the bar-kays (639)
  - #312073: 34% rodgers (619)
  - #34198: maxine brown (594)
  - #16510: kenny dorham (579)
  - #10500: irma thomas (561)
  - #8121: coleman hawkins (556)
  - #314316: andrew hill (544)
  - #18373: johnnie taylor (558)
  - #16495: jackie mclean (544)
  - #22882: blue mitchell (536)
  - #10482: fred frith (525)
  ...

  **Distribution of plays**

  - **Head**: 52%
  - **Mid**: 12%
  - **Tail**: 36%
evaluation:: complex network analysis

• **Last.fm** artist similarity network
  
  ‣ assortative mixing
    
    ‣ degree correlation between adjacent nodes

\[
\text{in\_degree}(\text{Robert Palmer}) = 430 \Rightarrow \text{avg}(\text{in\_degree}(\text{sim}(\text{Robert Palmer}))) = 342
\]

\[
\text{in\_degree}(\text{Ed Alton}) = 11 \Rightarrow \text{avg}(\text{in\_degree}(\text{sim}(\text{Ed Alton}))) = 18
\]
evaluation:: novelty & relevance

• **Last.fm** summary
  ✤ Not (highly) influenced by the popularity effect
  ✤ But...not exploiting the long-tail for discovery!

![Graphs showing Last.fm Popularity](image)
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
- ...

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

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

- 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)

![Graphs showing in-degree and out-degree distributions for MSN and Amazon networks.](image)
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

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

**Human**

- 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

• 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?

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**  **Seed Artist: Arcade Fire**  **Human**

- 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

- Rankings

<table>
<thead>
<tr>
<th>Agreement with Experts</th>
<th>Agreement with Machines</th>
<th>Overall Agreement</th>
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</thead>
<tbody>
<tr>
<td><strong>System</strong></td>
<td><strong>Score</strong></td>
<td><strong>System</strong></td>
</tr>
<tr>
<td>Sun tags</td>
<td>0.88</td>
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<tr>
<td>Sun users</td>
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<td>Musicmatch</td>
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<td>Mystrands</td>
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</tr>
<tr>
<td>Musicmatch</td>
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<td>PC Dom</td>
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<tr>
<td>PC Brian</td>
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<td>PC Brian</td>
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<tr>
<td>iLike</td>
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<td>up to 11</td>
</tr>
<tr>
<td>up to 11</td>
<td>0.53</td>
<td>PC Chris</td>
</tr>
<tr>
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<td>MusicMobs</td>
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<tr>
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<td>Pandora*</td>
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<tr>
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</table>


Music Recommendation Survey

Thanks for agreeing to participate in the music recommendation survey. The survey is 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.

200 Responses

>10,000 datapoints
evaluation:: informal survey

• Results: systems ranked by survey

<table>
<thead>
<tr>
<th>System</th>
<th>Average Rating</th>
<th>System</th>
<th>Novelty</th>
<th>System</th>
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</table>
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
Acknowledgments

- Stephan Baumann – DFKI
- Thierry Bertin-Mahieux - UdeM
- Jim Bennet – Netflix
- Norman Casagrande – last.fm
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- Tom Conrad – Pandora
- Chris Dahlen – Pitchfork Media
- Justin Donaldson – Mystrands
- Douglas Eck – UdeM
- Dan Ellis - Columbia
- Bill Goldsmith – Radio Paradise
- Steve Green – Sun
- Brian Howe – Pitchfork Media
- David Jennings – NBRR Author
- Zac Johnson – All Music
- Richard Jones – last.fm
- Greg Linden – Amazon / Findory
- Alex Loscos – BMAT
- Dominique Leon – Pitchfork Media
- Franciso Martin – Mystrands
- Michael Mandel – Columbia
- Bamshad Mobasher – DePaul University
- Elias Pampalk – last.fm
- Jeremy Pickens – FXPAL
- David Raposa – Pitchfork Media
- Joe Tangari – Pitchfork Media
- David Tchang – One Llama
- Kris West – One Llama
- Ian Wilson – Zukool
- Mark Young – Itunes Registry
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
  ❖ 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.