A Semantic Landscape of the Last.fm Music Folksonomy

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Motivation

• Domain

 How is the world of music and music experience organized?

What kinds of themes emerge in this domain and what is their structure?

Challenges

- Collect and prepare high-dimensional social data
- Create a model large enough to faithfully represent the domain
- Train a model of this substantial size
- Design a visualization that does justice to the richness of the model









Raw Data - Source

Last.fm is a social Internet radio site

 Users share information about songs they are listening to
 They can also tag songs
 With any strings of text they like



Need new music?

Last.fm lets you effortlessly keep a record of what you listen to* from any player. Based on your taste, Last.fm recommends you more music and concerts!

*We had to invent a word for this, it's called scrobbling.







Raw Data - Summary

- Gathered during the first half of 2009
- 99,405 registered users
 52,452 active
- 281,818 tags
- 1,393,559 songs
- 10,936,545 annotations

 An annotation is a (user, tag, song) triple, a tagging event

Data originally collected for:

Schifanella, R., Barrat, A., Cattuto, C., Markines, B., and Menczer, F. (2010). Folks in Folksonomies: Social Link Prediction from Shared Metadata. Proc. 3rd ACM International Conference on Web Search and Data Mining (WSDM).







Top Tags

rock electronic seen live indie alternative рор female vocalists jazz classic rock experimental ambient metal alternative rock

singer-songwriter 80s folk hard rock progressive rock indie rock electronica punk instrumental SOU black metal industrial death metal

heavy metal chillout dance british 90s psychedelic blues hip-hop post-rock new wave soundtrack classical 00s







Tags Are More Than Just Genres

- Intensional
 - From recognized genres to simple objective facts
 - rock (rank 1)
 - electronic (2)
 - **.**..
 - female vocalists (7)
 - female vocalist (64)
 - acoustic (51)
 - ..
 - *title is a full sentence* (101)
- Extensional
 - A mix of social signals, properties of the user-song experience, and aides to personal categorization
 - seen live (3)
 - beautiful (48)
 - favorites (54)
 - albums i own (97)
 - altar of the metal gods (58)
 - A case of graffiti?

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Raw Data - Thresholding

- The self-organizing map (SOM) method will not scale to 280,000+ tags/dimensions in raw form
 Not often used with more than hundreds of dimensions
- Consider only the 1,000 most frequently applied tags
 Keep only songs annotated by some user with any of these tags







Thresholded Data - Summary

	Raw	Thresholded
Tags	281,818	1,000
Songs	1,393,559	1,088,761 (78% of original)
Annotations per song (average)	7.8	6.8









- Characterize each song as a vector over each tag dimension
 - Each coordinate is the number of annotations
 Summed across users
- A song is a piece of tag relationship evidence







Method - Background

• Self-organizing maps

- Neural network training algorithm
- \circ Unsupervised
- High-dimensional data

Low-dimensional discrete geometric model

Goal:
 Proximity in the input space
 Proximity on the map







Self-Organizing Map Algorithm - Classical

- 1. Create a lattice of neurons
- 2. To each neuron assign an initial (often random) vector with as many dimensions as the training data
- 3. For each training vector:
 - 1. Identify the neuron of minimal distance according to the input space metric (the "best-matching unit")
 - 2. For each neuron:
 - 1. Pull this neuron's vector toward the training vector in proportion with this neuron's distance from the best-matching unit







Self-Organizing Map Algorithm -Parallelized Implementation

- A previous project trained on twice as many data and twice as many dimensions
 - Completely intractable using widely available software
 - Created our own implementation
 - Divide the training data among multiple processes
 Each process holds a complete copy of the map
 Deriodically experimentation process local conice of
 - Periodically synchronize process-local copies of the map to create a new process-global map
- Adapted with several project-specific optimizations from:
 - Lawrence, R.D., Almasi, G.S., Rushmeier, H.E. (1999). A Scalable Parallel Algorithm for Self-Organizing Maps with Applications to Sparse Data Mining Problems. Data Mining and Knowledge Discovery







Training the Map

2D hexagonal lattice of neurons
 180 on either side = 32,400 altogether

• Input space metric: **cosine similarity**

 Induced interpretation: Each training vector (and so consequently each neuron vector) represents a direction in the 1,000-dimensional tag space

similarity = $\cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2} \times \sqrt{\sum_{i=1}^{n} (B_i)^2}}$

• 50 complete passes over the training data







Computation

- 300 processes across 100 compute nodes of Big Red, a supercomputer at Indiana University
- Parallel runtime = 13 hours

o Serial equivalent runtime = 5 months







Legend









Visualization

- Recall there is a corresponding vector to each neuron which describes its position in the input space
- In other words, its position along each tag dimension
- Consider the nth strongest tag association of each neuron
- A contiguous swath of neurons sharing a common nth strongest tag association is termed a region
- As the map is trained over 1,000 tags, we have 1,000 distinct partitions of the map into such regions









Interpretation

- Interpreters report a mix of
 - Recognition
 - Patterns of hierarchical and neighborhood relationships among tags match expectations
 - \circ Discovery
 - Opportunities to find new musical categories
 Surprise
 - Relationship between *rock*, *blues*, and *jazz*















Potential Applications

- Interactive music navigator and playlist generator
- Mapping portfolios as fields of neuronal activation

 For the set of songs associated with any entity, we can see where in the world they belong
 - A user: Their favorite songs
 - A band: Their complete work
 - A group of users: What is their turf?
 - \circ .. or look at the difference of any of these fields
 - What is the difference between The Who and The Guess Who?
 - How has this entity moved through the world of music over time?
 - Where have listeners like me headed next?







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