

# Visualizing the Knowledge Space of Music

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# Goal: Map the knowledge space of a given field

- ▶ How can the field be divided into subfields?
- ▶ What are the principle subfields?
- ▶ What are the emerging subfields?
- ▶ How do these subfields connect/interact?
  - ▶ Internally
  - ▶ externally

# Goal: Map the knowledge space of a given field

- ▶ Although Experts have deep insight into their specialty, they tend to be bias towards their own subfield. Also, expert surveys tend to be costly endeavors.

## Goal: Map the knowledge space of a given field

- ▶ **Co-Word Analysis** attempts to map the knowledge space of a given field by measuring and analyzing the strength of the associations between terms (keywords, indexed terms, or words from a corpus)
- ▶ The **strength** of the association between terms is based on how frequently they co-appear in documents.
- ▶ We use the results of co-word analysis to hierarchically cluster the terms.
- ▶ We visualize the clusters with **dendrograms**, **weighted graphs**, and **strategic diagrams**.

# Visualization techniques

- ▶ **Dendrograms:** detailed information on the relationship between terms and clustering.
- ▶ **Weighted graphs:** detailed of each cluster
- ▶ **Strategic Diagram:** Local and global view of the clusters

# What is music scholarship?

## Examples:

- ▶ **Musicology:** *Richard Wagners opposition to animal experimentation: A visionary social critic*
- ▶ **Ethnomusicology:** *A bird tradition in the west of the Balkan Peninsula*
- ▶ **Music pedagogy:** *From Mississippi hot dog to Arizona cactus*
- ▶ **Music therapy** *The use of music with chronic food refusal: A case study*
- ▶ **Popular music studies** *Crossing cinematic and sonic bar lines: T-Pains Cant believe it*

# What is RILM?

- ▶ A comprehensive music bibliography featuring
  - ▶ abstracts and citations
  - ▶ 143 languages
  - ▶ 1967 – present
  - ▶ 875,000 records
- ▶ RILM indexing represents hierarchical relationships with broader and narrower topics.

# The Data

	year	ac	class1	lvl1	cat1	lvl2	cat2	lvl3	cat3	lang	code
0	2013	6647	29	performing organizations	T	Germany	G	Berlin	G	Russian	2013-6647
1	2013	6648	29	Kopatchinskaja Patricia	N	interviews	M	NaN	NaN	Russian	2013-6648
2	2013	6648	29	performers--violin	T	Kopatchinskaja, Patricia	N	NaN	NaN	Russian	2013-6648
3	2013	6651	29	Gounod Charles	N	performances	M	<Faust>	W	Russian	2013-6651
4	2013	6651	29	performing organizations	T	Russia	G	Sankt-Peterburg	G	Russian	2013-6651

- ▶ Almost all academic music articles (2000-2015)
- ▶ 263,656 Rows
- ▶ 59,908 Articles
- ▶ 25,297 distinct terms (lvl1)



## 15 Most common terms

	count
<b>pedagogy</b>	5499
<b>China</b>	5084
<b>instruments--keyboard (organ family)</b>	3011
<b>popular music</b>	2388
<b>aesthetics</b>	2037
<b>singing</b>	2024
<b>song--popular and traditional</b>	1886
<b>pedagogues</b>	1844
<b>performing organizations</b>	1836
<b>religious institutions</b>	1788
<b>instrument builders--organ</b>	1773
<b>sound recordings</b>	1734
<b>academic institutions</b>	1657
<b>instruments--keyboard (piano family)</b>	1639
<b>psychology</b>	1608

# Co-occurrence

## Definition

For two terms,  $i$  and  $j$ , their co-occurrence is defined as

$C_{i,j}$  = How often  $i$  and  $j$  appear in the same article

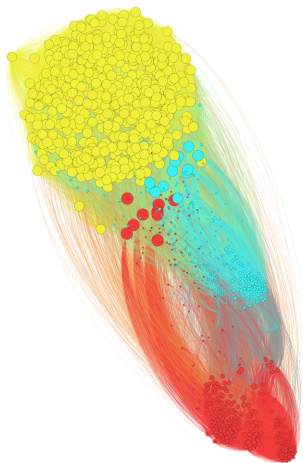
## Example

The terms 'aesthetics' and 'popular music' appear together in 123 articles.

$$C_{\text{'aesthetics', 'popular music'}} = 123$$

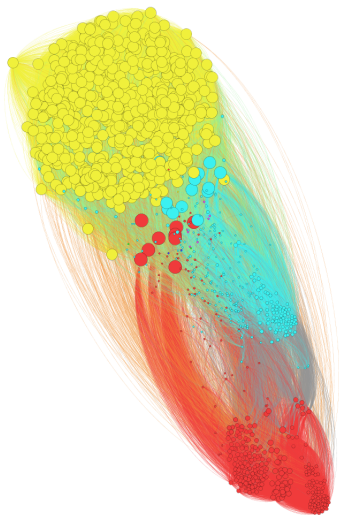
# From matrix to graph using the matrix $C$

- ▶ Dots (nodes) are terms.
- ▶ Lines between terms indicate that  $C > 4$ .
- ▶ Colors indicate terms that are highly interconnected (clusters).



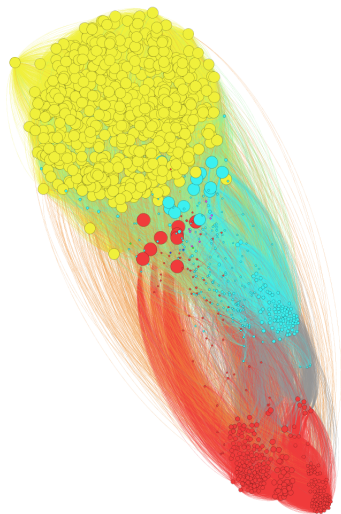
# From matrix to graph using the matrix C

- Despite its beauty, we could not obtain valuable information from this graph!



# From matrix to graph using the matrix $C$

- High frequency terms dominate the connections.



# Term-vectors and cosine similarity

## Definition

- ▶ Fix an arbitrary ordering on the 59,908 articles under study.
- ▶ Associate each term, with a 59,908 dimensional vector of 1s and 0s.
  - ▶ If the term indexes the  $i$ th article then the  $i$ th entry is a 1.
  - ▶ Otherwise the  $i$ th entry is 0.
- ▶ Two terms with vectors  $i, j$  have cosine-similarity (CS),

$$CS(i, j) = \frac{i \cdot j}{\sqrt{i \cdot i} \sqrt{j \cdot j}}. \quad (1)$$

# Term-vectors and cosine similarity

## Example

	<b>Terms</b>
Article 1	animal, food
Article 2	food, death and dying
Article 3	film and videos

'Animal' = (1, 0, 0)

'food' = (1, 1, 0)

'death and dying' = (0, 1, 0)

'film and videos' = (0, 0, 1)

# Term-vectors and cosine similarity

## Example

'animal' = (1, 0, 0)

'food' = (1, 1, 0)

'death and dying' = (0, 1, 0)

'film and videos' = (0, 0, 1)

$$\begin{aligned}\text{CS ('food', 'animal')} &= \frac{(1, 1, 0) \cdot (1, 0, 0)}{\sqrt{(1, 1, 0) \cdot (1, 1, 0)} \sqrt{(1, 0, 0) \cdot (1, 0, 0)}} \\ &= \frac{1 \cdot 1 + 1 \cdot 0 + 0 \cdot 0}{\sqrt{1 \cdot 1 + 1 \cdot 1 + 0 \cdot 0} \sqrt{1 \cdot 1 + 0 \cdot 0 + 0 \cdot 0}} \\ &= \frac{1}{\sqrt{2}}\end{aligned}$$



## Another way to calculate cosine similarity

$$\begin{aligned} \text{CS}(i, j) &= \frac{i \cdot j}{\sqrt{i \cdot i} \sqrt{j \cdot j}} \\ &= \sqrt{\frac{C_{ij}^2}{C_{ii} C_{jj}}} \\ &= \sqrt{\frac{C_{ij}}{C_{jj}} \frac{C_{ji}}{C_{ii}}} \\ &= \sqrt{P(i | j) P(j | i)} \end{aligned}$$

Where  $P(i | j)$  is the probability of finding term  $i$  in an article given that it had term  $j$ .

## Example

Let

$$\begin{aligned}i &= \text{'China'} & j &= \text{'popular music'} \\k &= \text{'mathematics'} & l &= \text{'scales'}.\end{aligned}$$

Then,

$$\begin{aligned}C_{ij} &= 151 & CS(i, j) &= \sqrt{151^2 / (5084 \cdot 2388)} &= .04 \\C_{kl} &= 15 & CS(k, l) &= \sqrt{15^2 / (309 \cdot 303)} &= .05.\end{aligned}$$

# Hierarchical Clustering (a rough sketch)

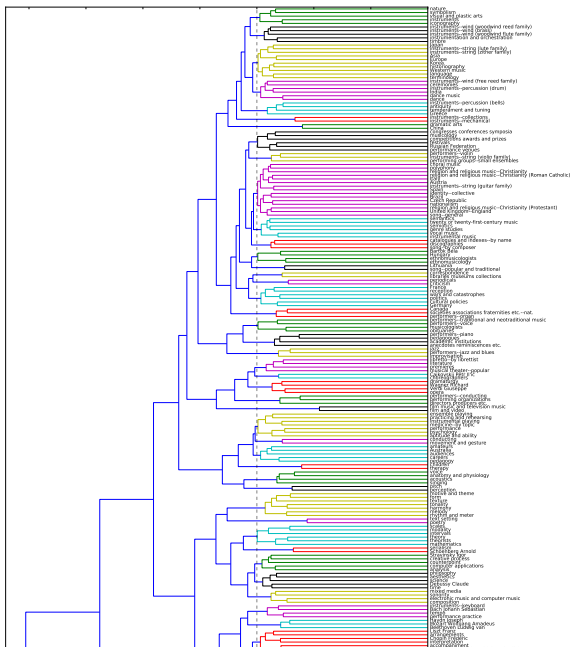
- ▶ Distance between individual terms:  $d(i, j) = 1 - CS(i, j)$ .
- ▶ At the start, each term,  $t_i$ , is contained in its own cluster  $c_i = \{t_i\}$ .
- ▶ Define distance between clusters  $D(c_i, c_j)$ .
  - ▶ Many ways to do this

Repeat until there is only one cluster:

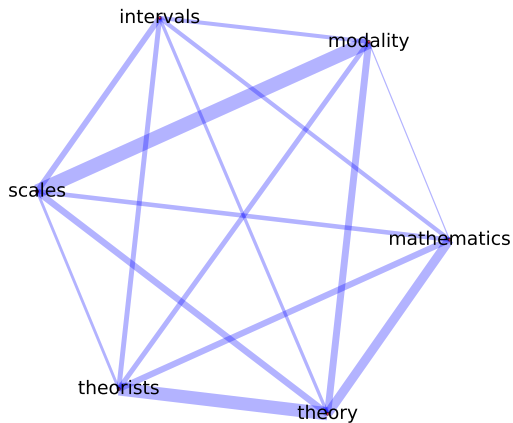
- ▶ Find two clusters of minimal distance, i.e.  $\min D(c_i, c_j)$ .
- ▶ Merge the clusters  $c_i$  and  $c_j$  into a cluster  $c_{i \& j}$ .
- ▶ Delete the clusters  $c_i$  and  $c_j$ .

We visualize Hierarchical clustering with a dendrogram.

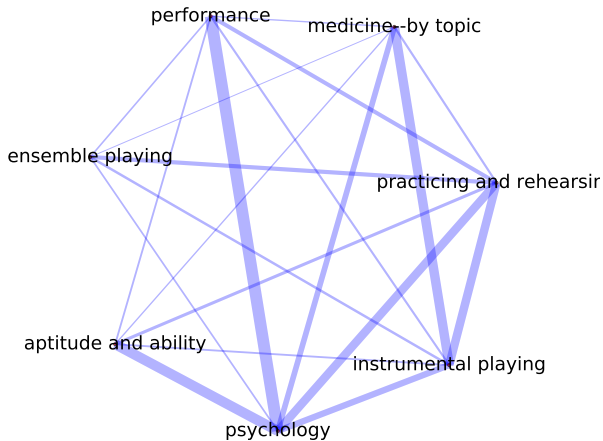
## Dendrogram



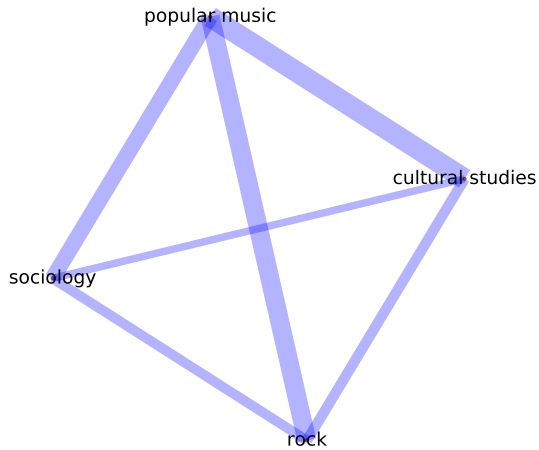
# Clusters: Theory



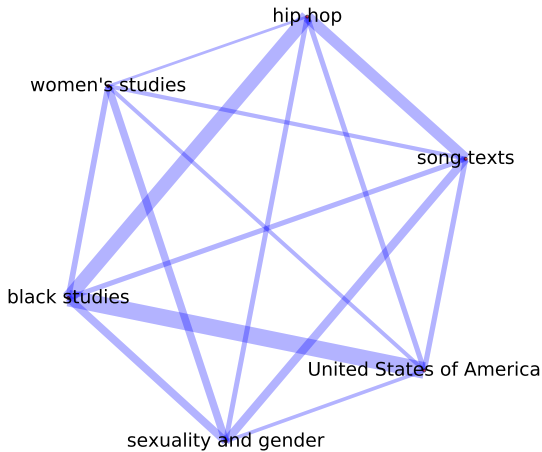
# Clusters: Performance



# Clusters: Rock

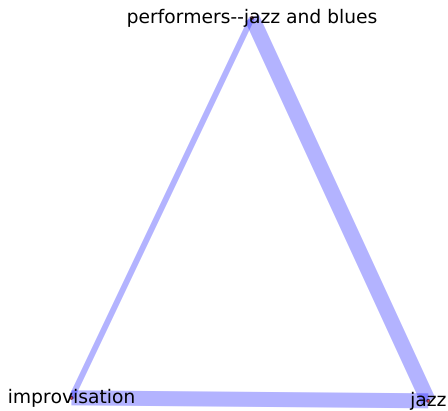


# Clusters: Black Studies and United States

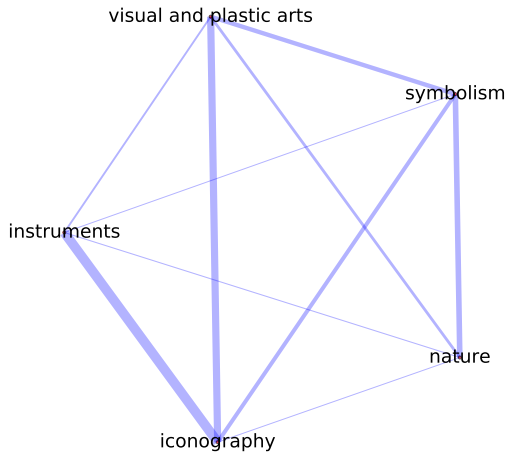




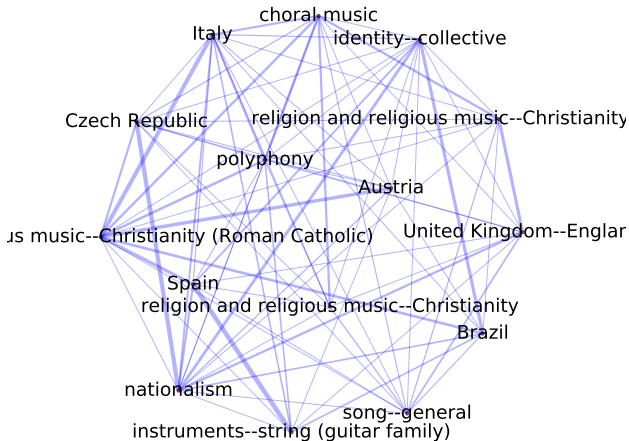
# Clusters: Jazz



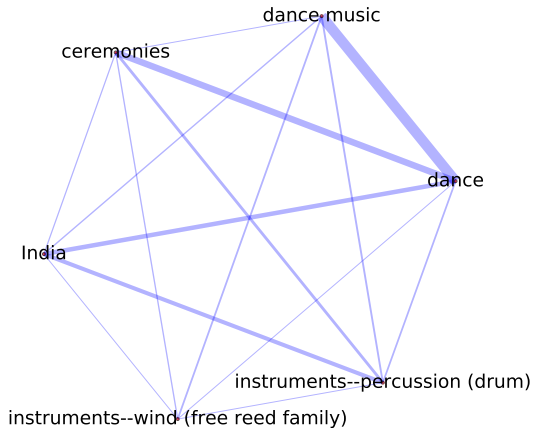
# Clusters: Iconography



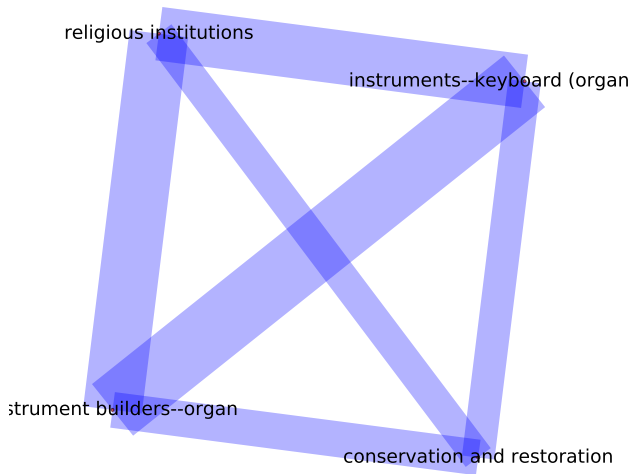
# Clusters: Religious Music



# Clusters: Dance



# Clusters: Organ Music and Restoration

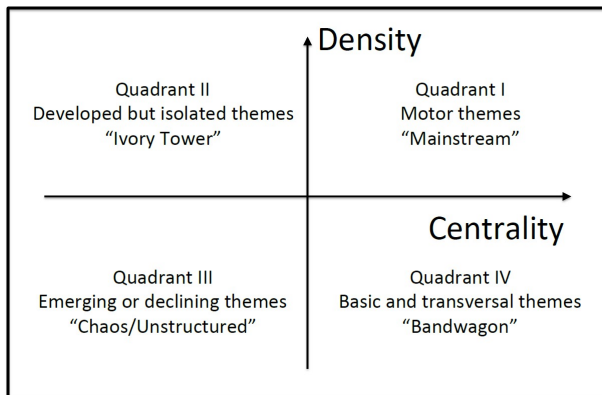


# Density and Centrality

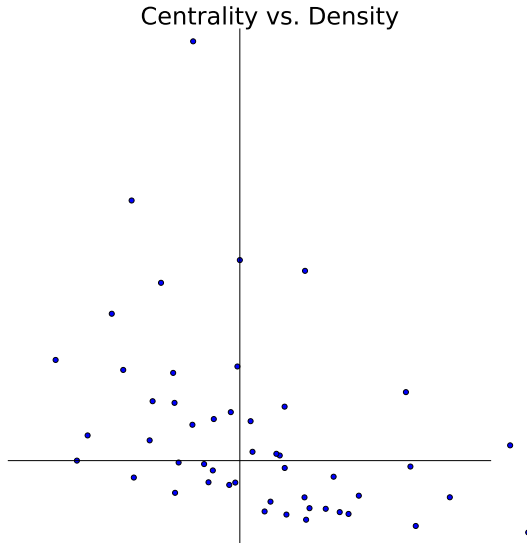
For each cluster we calculate:

- ▶ **Density** - Average strength of all the connections within a cluster
- ▶ **Centrality** - The square root of the sum of the squares of all connections to outside clusters

# Strategic Diagram

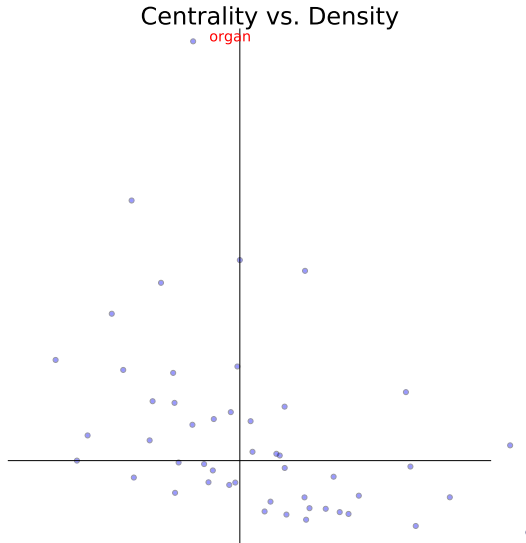


# Strategic Diagram

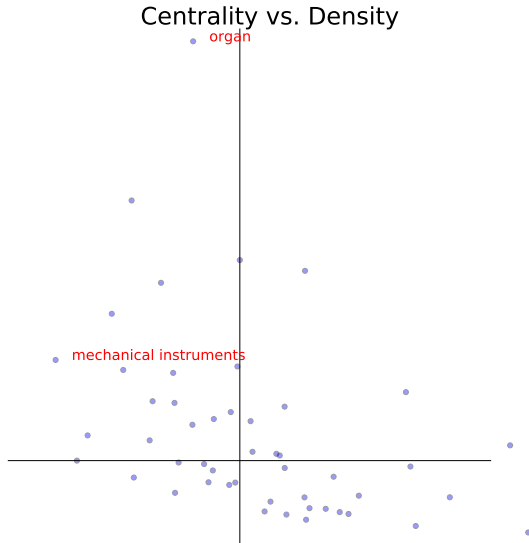




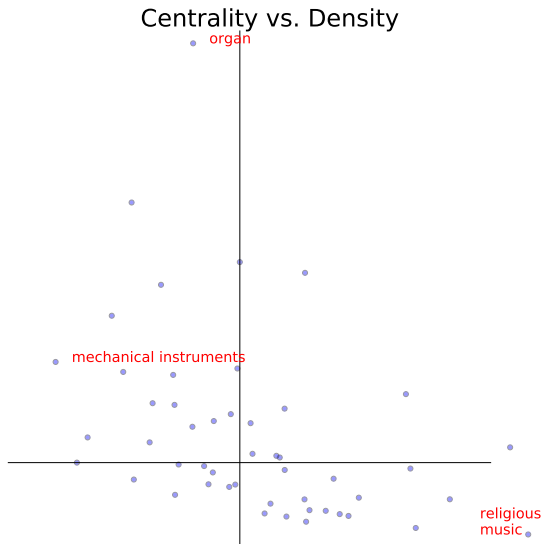
# Strategic Diagram



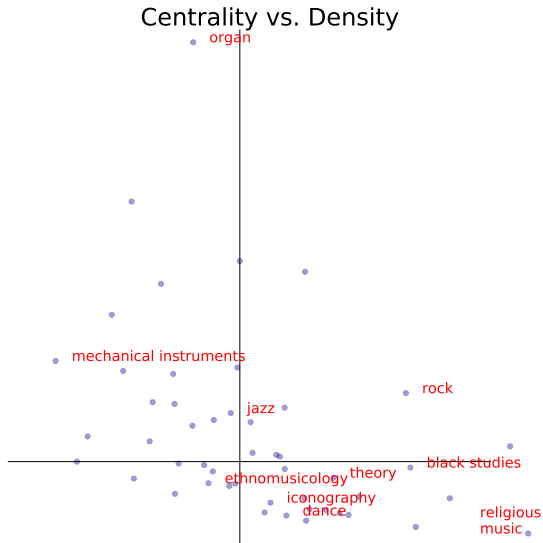
# Strategic Diagram



# Strategic Diagram



# Strategic Diagram



Thank You!