

# Applying Ideas from Homogeneity Analysis to Visualize Similarity Data

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# Outline of the presentation

Homogeneity analysis

VOS

Empirical comparison between VOS, MDS, and DAM

Application to a large data set

Conclusions

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# Homogeneity analysis

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- ▶ A method for visualizing the relations between categories and objects

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## Objective

- ▶ To provide a low-dimensional visualization in which categories and objects are located in such a way that each category is the centroid of all objects that score on the category

# Constrained optimization problem

## Objective function

$$\sigma(\mathbf{X}, \mathbf{Y}; \mathbf{G}) = \sum_{i < j} g_{ij} \|\mathbf{x}_i - \mathbf{y}_j\|^2$$

where  $\mathbf{x}_i$  and  $\mathbf{y}_j$  denote, respectively, the location of object  $i$  and category  $j$  and  $g_{ij} \in \{0, 1\}$  denotes whether or not object  $i$  scores on category  $j$

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## Constraints

$$\mathbf{X}'\mathbf{X} = n\mathbf{I}$$

$$\mathbf{1}'\mathbf{X} = 0$$

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- ▶ An abbreviation for *visualization of similarities*
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## Objective

- ▶ To provide a low-dimensional visualization in which objects are located in such a way that the distance between any pair of objects reflects their similarity as accurately as possible

# Mathematical notation

## Input

- ▶  $n$ : number of objects
- ▶  $m$ : number of dimensions of the solution
- ▶  $\mathbf{S} = (s_{ij})$ :  $n \times n$  similarity matrix (measured on a ratio scale)

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## Output

- ▶  $\mathbf{X}$ :  $n \times m$  coordinate matrix  
 $\mathbf{x}_i = (x_{i1}, \dots, x_{im})$  contains the coordinates of object  $i$

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- ▶ VOS:

$$\sum_{i < j} \|\mathbf{x}_i - \mathbf{x}_j\| = n(n-1)$$

# Motivation for the objective function

- ▶ Ideal coordinates of object  $i$

$$c_i(\mathbf{X}, \mathbf{S}) = \frac{\sum_{j \neq i} s_{ij} \mathbf{x}_j}{\sum_{j \neq i} s_{ij}}$$

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- ▶ Objective function for object  $i$  when the coordinates of all other objects are fixed

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- ▶ VOS seems to have the tendency to locate objects close to their ideal coordinates

# Relationship between VOS and MDS

## Objective function of weighted ratio MDS

$$\sigma(\mathbf{X}; \mathbf{D}, \mathbf{W}) = \sum_{i < j} w_{ij} (d_{ij} - \|\mathbf{x}_i - \mathbf{x}_j\|)^2$$

where  $d_{ij}$  denotes the dissimilarity between objects  $i$  and  $j$  and  $w_{ij}$  denotes the weight of objects  $i$  and  $j$

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### Theorem

*Let  $s_{ij} > 0$  for all  $i$  and  $j$  ( $i \neq j$ ).*

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*Let  $s_{ij} > 0$  for all  $i$  and  $j$  ( $i \neq j$ ).*

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*VOS and weighted ratio MDS are then equivalent in the sense that solutions from these methods differ only by a multiplicative constant.*

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# Empirical comparison between VOS, MDS, and DAM (1)

## Real-world bibliometric data sets

- ▶ Cocitation data of 376 journals in the field of economics and management (obtained from CWTS, Leiden University)
- ▶ Co-occurrence data on 332 concepts from the field of computational intelligence (obtained from Elsevier Scopus)
- ▶ In each data set around 75% of the similarities equal zero

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## Methods

- ▶ VOS
- ▶ Unweighted ordinal MDS (SPSS PROXSCAL)
- ▶ Distance association model (DAM; De Rooij and Heijser, 2005)

# Empirical comparison between VOS, MDS, and DAM (2)

## VOS/MDS

- ▶ Co-occurrences/cocitations normalized using

$$s_{ij} = \frac{c_{ij}}{(\sum_k c_{kj})(\sum_k c_{ik})}$$

where  $c_{ij}$  denotes the co-occurrence/cocitation of objects  $i$  and  $j$   
( $c_{ii} = 0$ )

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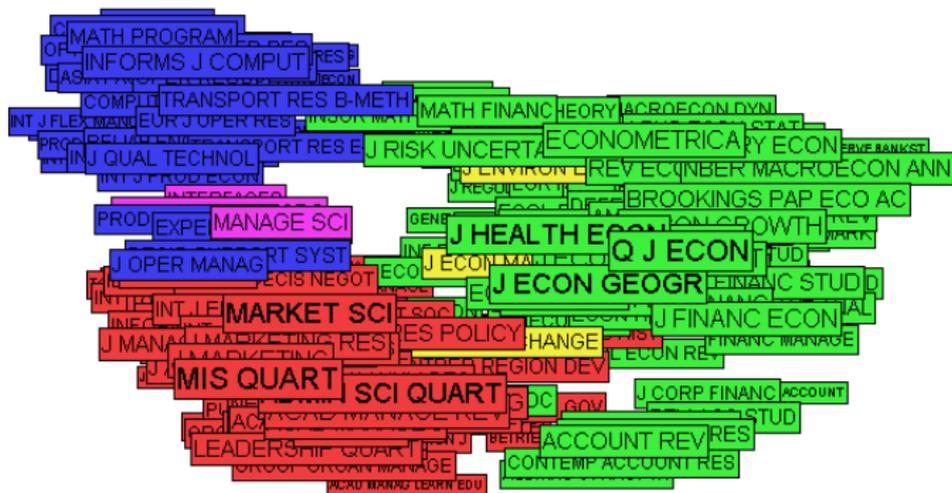
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## DAM

- ▶ One-mode DAM with symmetric associations is used
- ▶ Row and column margins are assumed equal
- ▶ Distances are transformed into associations using the Gaussian function
- ▶ Likelihood under independent Poisson sampling is maximized

# Journal cocitation map constructed using VOS



# Journal cocitation map constructed using MDS

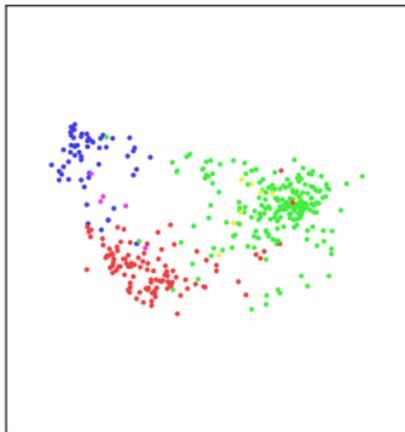


# Journal cocitation map constructed using DAM

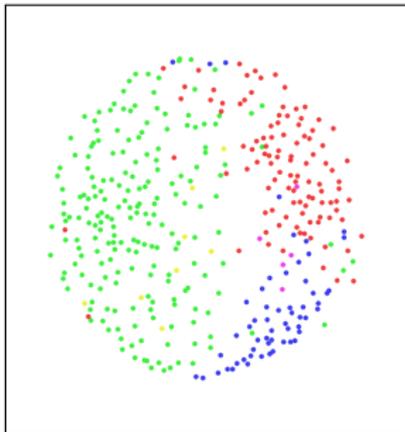


# Comparison of journal cocitation maps

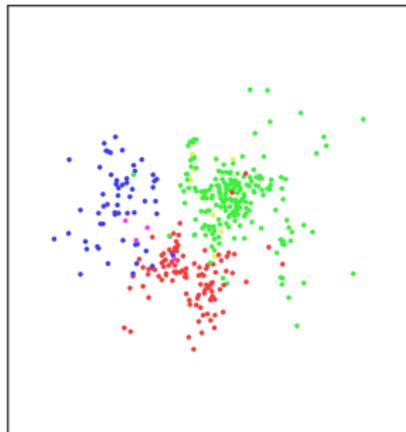
VOS



MDS

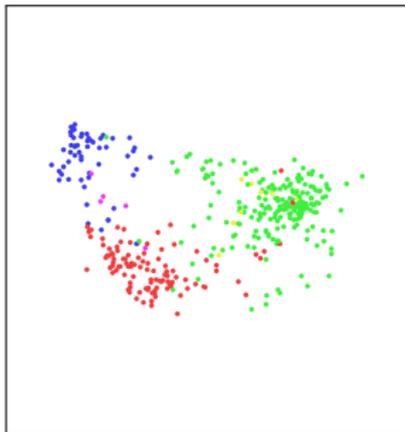


DAM

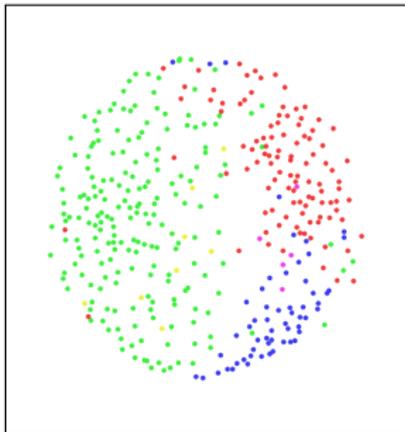


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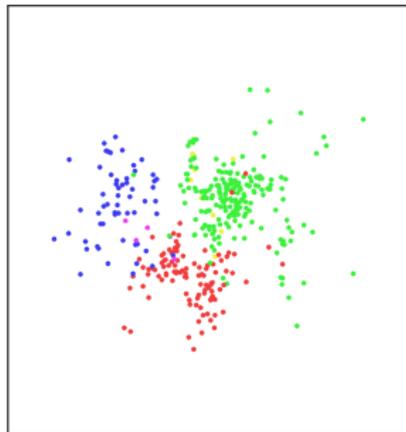
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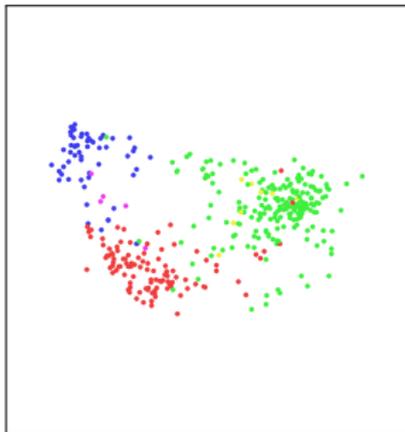
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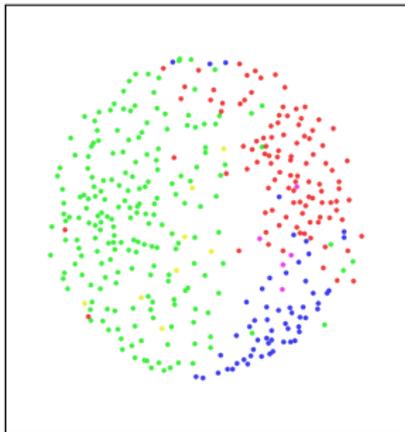
- ▶ MDS locates all objects roughly uniformly distributed within a circle

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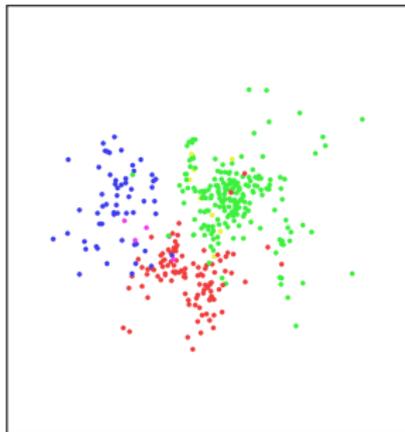
VOS



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- ▶ MDS locates all objects roughly uniformly distributed within a circle
- ▶ VOS better separates the fields of economics, management, and operations research from each other than MDS and DAM

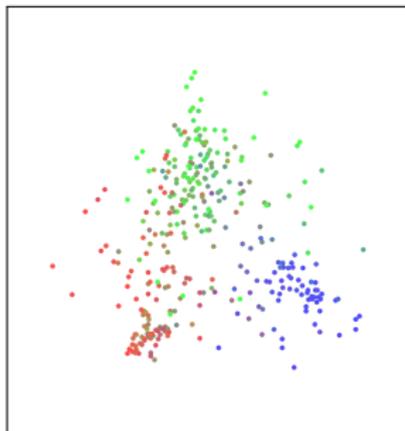




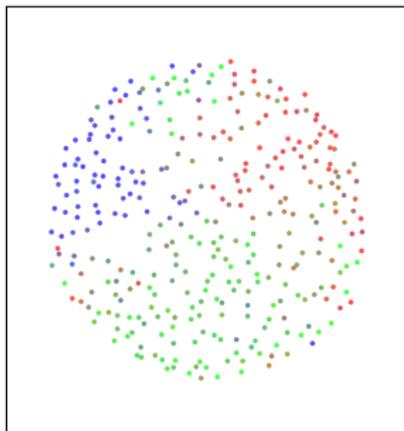


# Comparison of concept co-occurrence maps

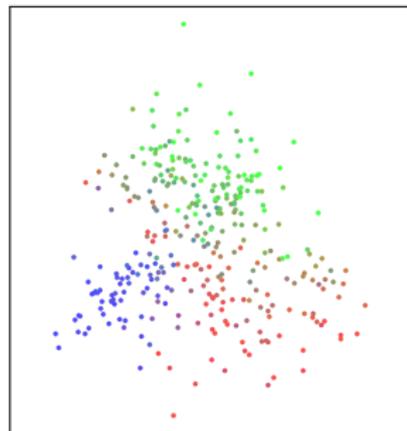
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MDS



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- ▶ Unweighted ordinal MDS locates objects roughly uniformly distributed within a circle
- ▶ Solutions from VOS show better separated clusters than solutions from MDS and DAM

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## Future research

- ▶ The effect on homogeneity analysis of using the VOS constraint

## More information on VOS

References to our papers and a computer implementation of VOS are available at:

<http://www.neesjanvaneck.nl/vos/>