GoWvis:
a Web App for Graph-based Text Visualization & Summarization

https://safetyapp.shinyapps.io/GoWvis/

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Introduction

Graph-of-Words (GoW) fundamentals:

- statistical approach based on the **Distributional Hypothesis**
- edge between two terms if they **co-occur** within a **fixed-size sliding window**
- encodes **term dependence** strength (via edge weights) and **term order** (via edge direction)
- enables **graph theory** to be applied to text
- **linear** in time and space (resp. $O(nW)$, $O(n+m)$)

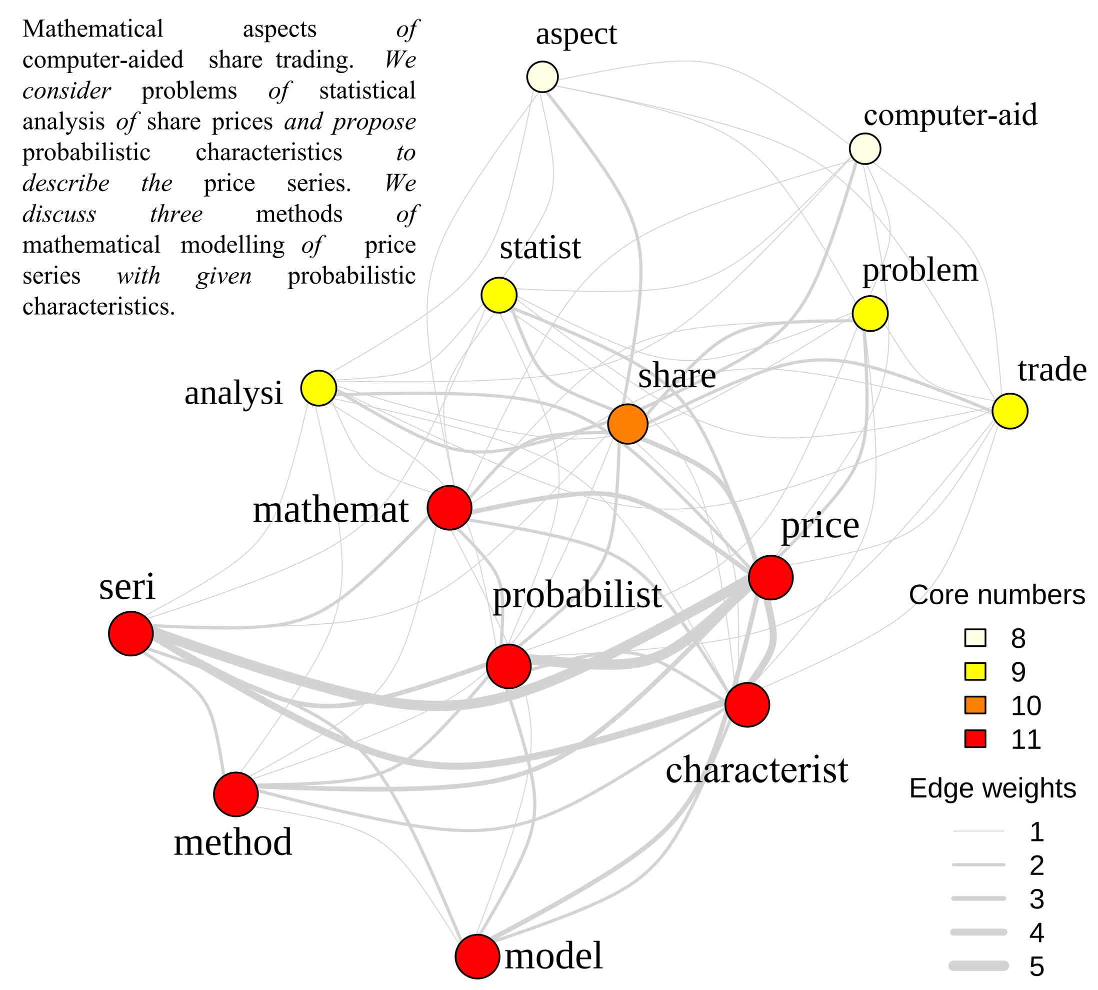
GoW proved highly successful:

- keyword extraction and summarization [Mihalcea & Tarau 2004, Rousseau & Vazirgiannis 2015]
- information retrieval [Rousseau & Vazirgiannis 2013]
- document classification [Malliaros & Skianis 2015, Rousseau et al. 2015]
- and more...

Motivation for GoWvis:

- GoW can be used to improve almost any NLP task...
- ... but it has many pre-processing, graph building, and graph mining parameters

↪ **there are needs to interactively explore the parameter space**



$W = 8$. Weighted, undirected edges. k-core. No community detection. POS-based screening.

I. Text pre-processing

- **Keep only nouns and adjectives?** Boolean, defaults to TRUE
- **Remove SMART stopwords?** Boolean, defaults to TRUE
- **Stemming?** Boolean, defaults to TRUE. If used, tends to yield smaller and denser graphs.

↪ The surviving terms are used as the nodes of the graph-of-words

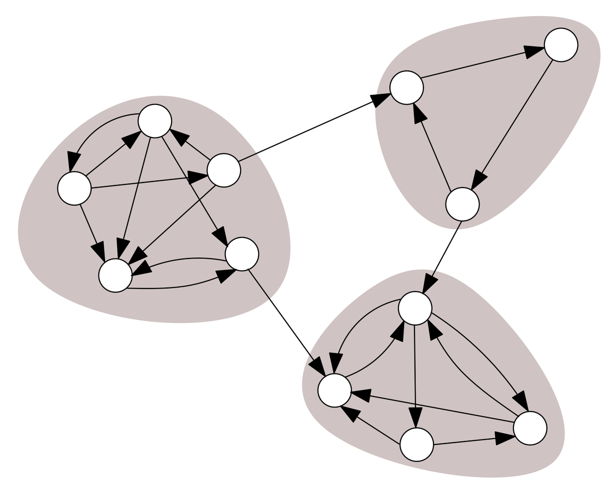
II. Graph building

- **Window size**. Integer between 2 and 12, defaults to 3. The larger the window, the denser the graph.
- **Build on processed text?** Boolean, defaults to TRUE. If used, tends to link more distant words and produce denser graphs.
- **Overspan sentences?** Boolean, defaults to TRUE. If FALSE, two words can only co-occur if they belong to the same sentence.

III. Graph mining: community detection

Goal: cluster the graph-of-words into groups within which connections are dense and between which they are sparse
↪ The clusters match the **topics** and **sub-topics** within the document
In practice: retaining only the **main communities** improves **coverage** and removes **noise**

- **Algorithm?** List, defaults to "none". Choices are "fast greedy", "louvain", "walktrap", "infomap", "label prop" and "none"
- **Size threshold?** Numeric (from 0.4 to 1.0, by 0.1), defaults to 0.8. Percentile size threshold used to determine which communities should be considered to be **main** ones.
- **Weighted?** Boolean, defaults to FALSE. Whether edge weights should be used.
- **Directed?** Boolean, defaults to FALSE. Whether edge direction should be used (only available for "infomap").

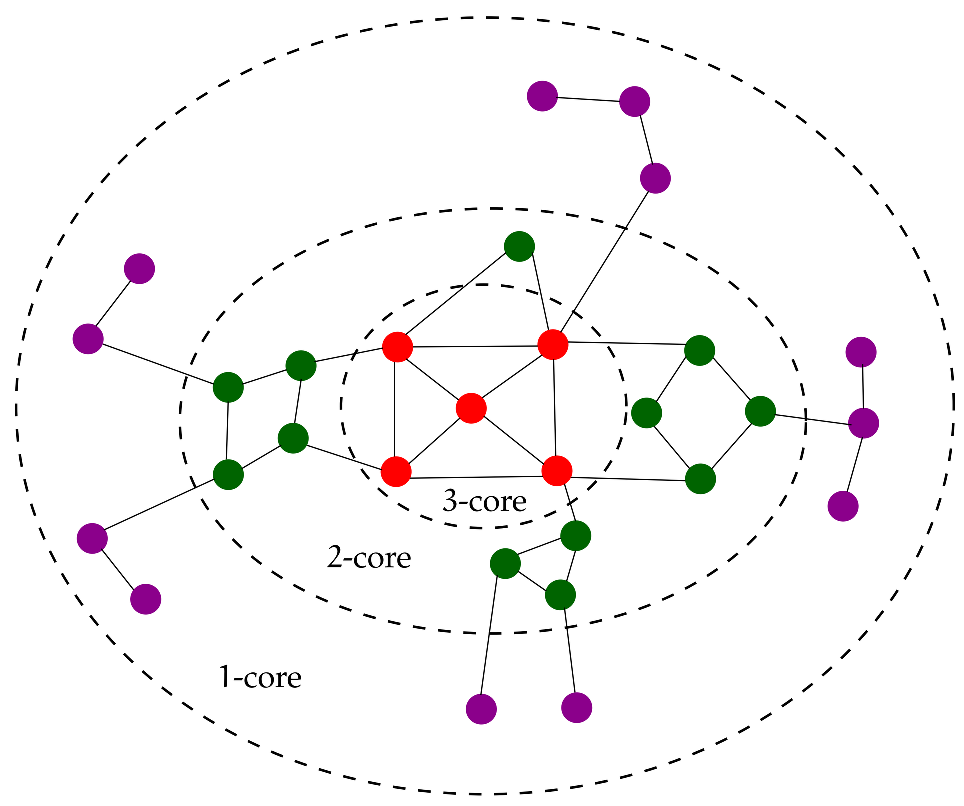


Graph communities

IV. Graph mining: degeneracy

K-CORE DECOMPOSITION

- a k-core of $G = (V, E)$ is a maximal connected subgraph of G in which every **vertex** v has at least degree k [Seidman 1983]
- v has **core number** k if it belongs to the k-core but not to the $(k+1)$-core
- the k-core decomposition of G is the set of all its cores from 0 (G itself) to k_{max} (its main core)
- **complexity**: $O(n+m)$ resp. $O(m\log(n))$ in time in the (un)weighted cases, $O(n)$ in space [Batagelj & Zaveršnik 2002]

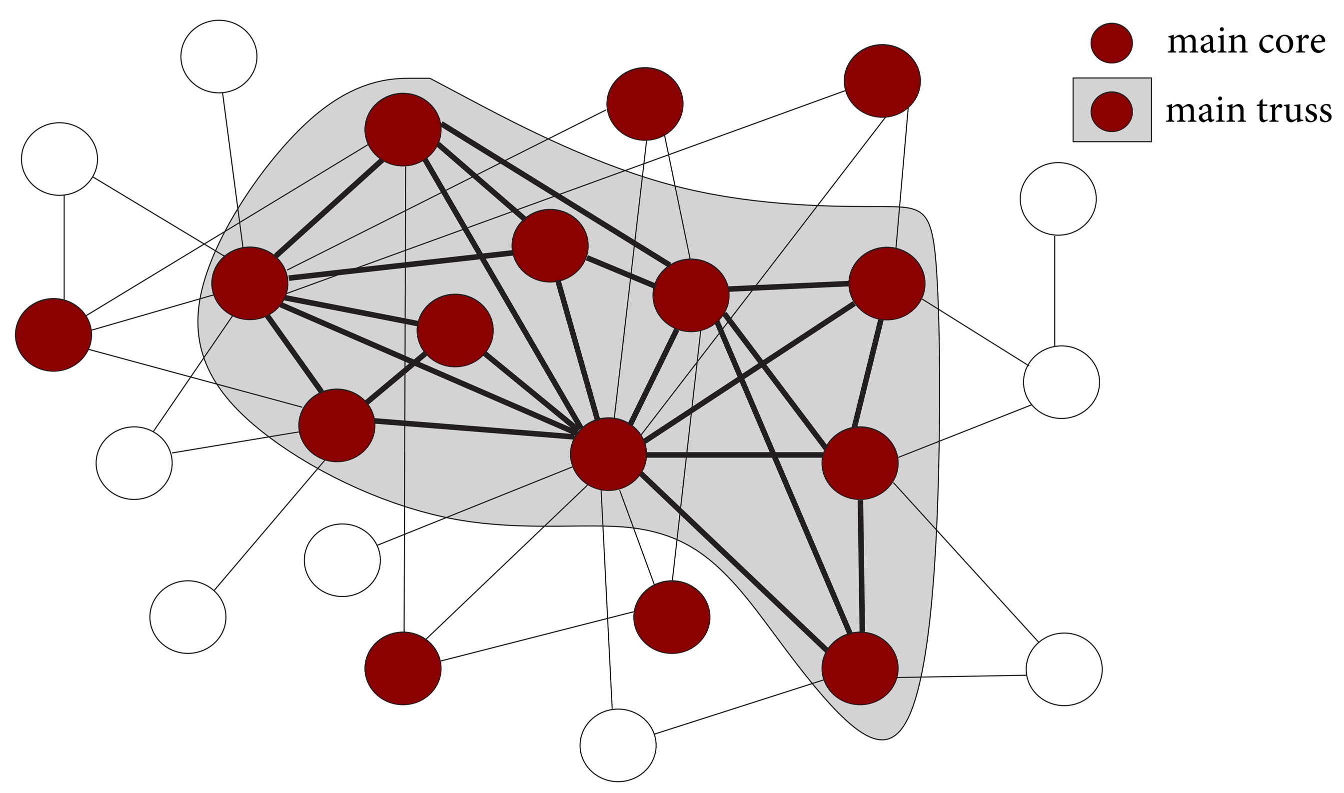


k-core decomposition

- hierarchy of nested subgraphs whose cohesiveness and size respectively ↗ and ↘ with k
- nodes with high core numbers are not only **central** but form **cohesive subgraphs** with other central nodes
  ↪ they make influential spreaders [Kitsak 2010] and good keywords [Rousseau 2015]

K-TRUSS DECOMPOSITION

- a k-truss of $G = (V, E)$ is the largest subgraph of G in which every **edge** e belongs to at least $k-2$ triangles [Cohen 2008]
- e has **truss number** k if it belongs to the k-truss but not to the $(k+1)$-truss
- the **truss number** of v is the maximum truss number of its adjacent edges
- the k-truss decomposition of G is the set of all its k-trusses from $k-2$ to k_{max}
- **complexity**: $O(m^{1.5})$ in time and $O(m+n)$ in space [Wang & Cheng 2012]



k-core versus k-truss

- compared to k-core, k-truss imposes constraints not only on the number of **direct links** but also on the number of **common neighbors**
- the k-trusses can be viewed as the cores of the k-cores that filter out the less cohesive elements [Wang and Cheng 2012]
- ↪ nodes with high truss numbers are **more influential** (compared to k-core) [Malliaros et al. 2016]

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