

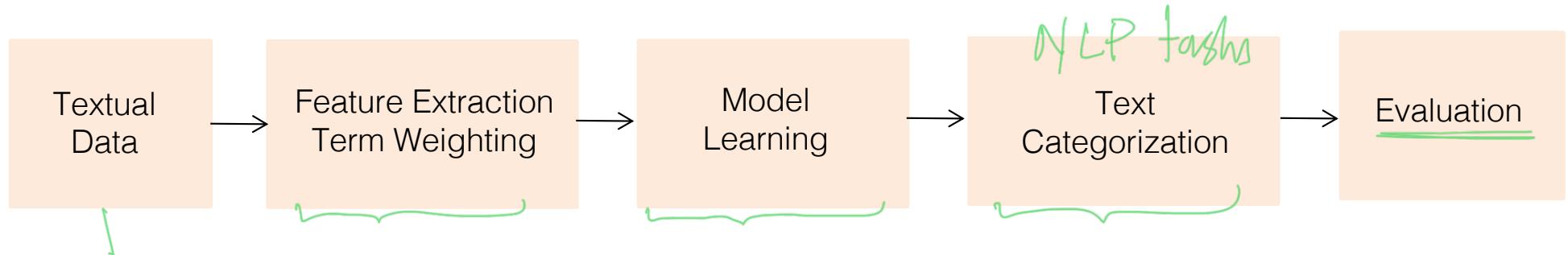
"Graph-Based Text Minings"

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Example: Text Categorization

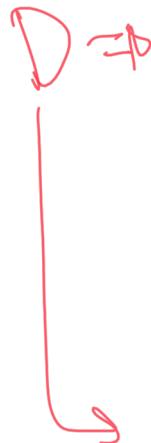


Applications:

- Opinion mining (sentiment analysis)
- Email spam classification
- Web-pages classification
- ...

Bag-of-Words (BoW) - Issues

Example text



information retrieval is the activity of obtaining
information resources relevant to an information need
from a collection of information resources

Bag of words: $\left[\begin{array}{l} (\text{activity}, 1), (\text{collection}, 1) \\ (\text{information}, 4), (\text{relevant}, 1), \\ (\text{resources}, 2), (\text{retrieval}, 1), \dots \end{array} \right]$

- Term independence assumption
- Term frequency weighting

*Assumptions made by
the BoW model*

BM25 Ranking Function

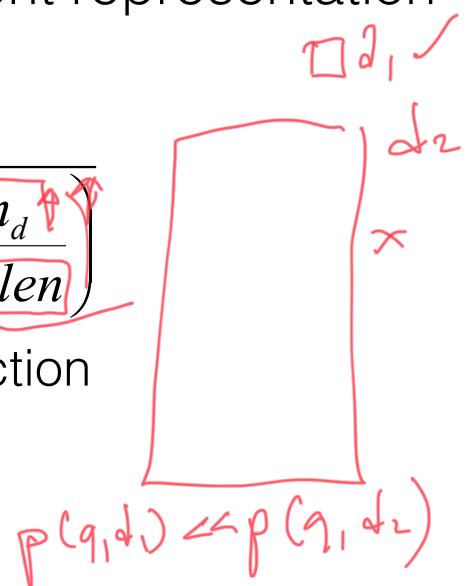
score(q, d_i)

- Ranking function assuming bag-of-words document representation

$$\text{score}(d, q) = \sum_{t \in d \cap q} idf_t \times \frac{tf_{t,d} \cdot (k_1 + 1)}{tf_{t,d} + k_1 \cdot \left(1 - b + b \frac{\text{len}_d}{\text{avglen}}\right)}$$

+ tf · idf + length of doc

- len_d is the length of document d
- avglen is the average document length in the collection



- Score depends only on query terms
- Values of parameters k_1 and b depend on collection/task
 - k_1 controls term frequency saturation
 - b controls length normalization
 - Default values: $k_1 = 1.2$ and $b = 0.75$

Graph-based Document Representation

- Challenge the term independence and term frequency weighting assumptions taking into account word dependence, order and distance
- Employ a graph-based document representation capturing the above
- Graphs have been successfully used in IR to encompass relations and propose meaningful weights (e.g., PageRank)

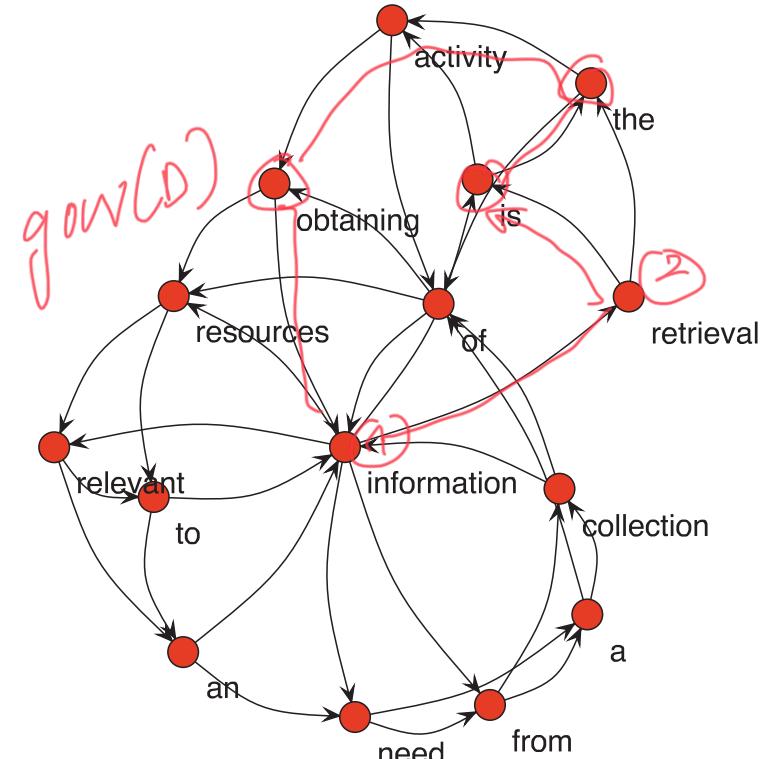
Graph-based Document Representation - Example

information retrieval is the activity of obtaining
information resources relevant to an information need
from a collection of information resources

Idea: Replace term frequency with node centrality

Captures: frequency, order and distance

CICM 2013 (Rousseau, V) best paper mention



Tutorial Outline

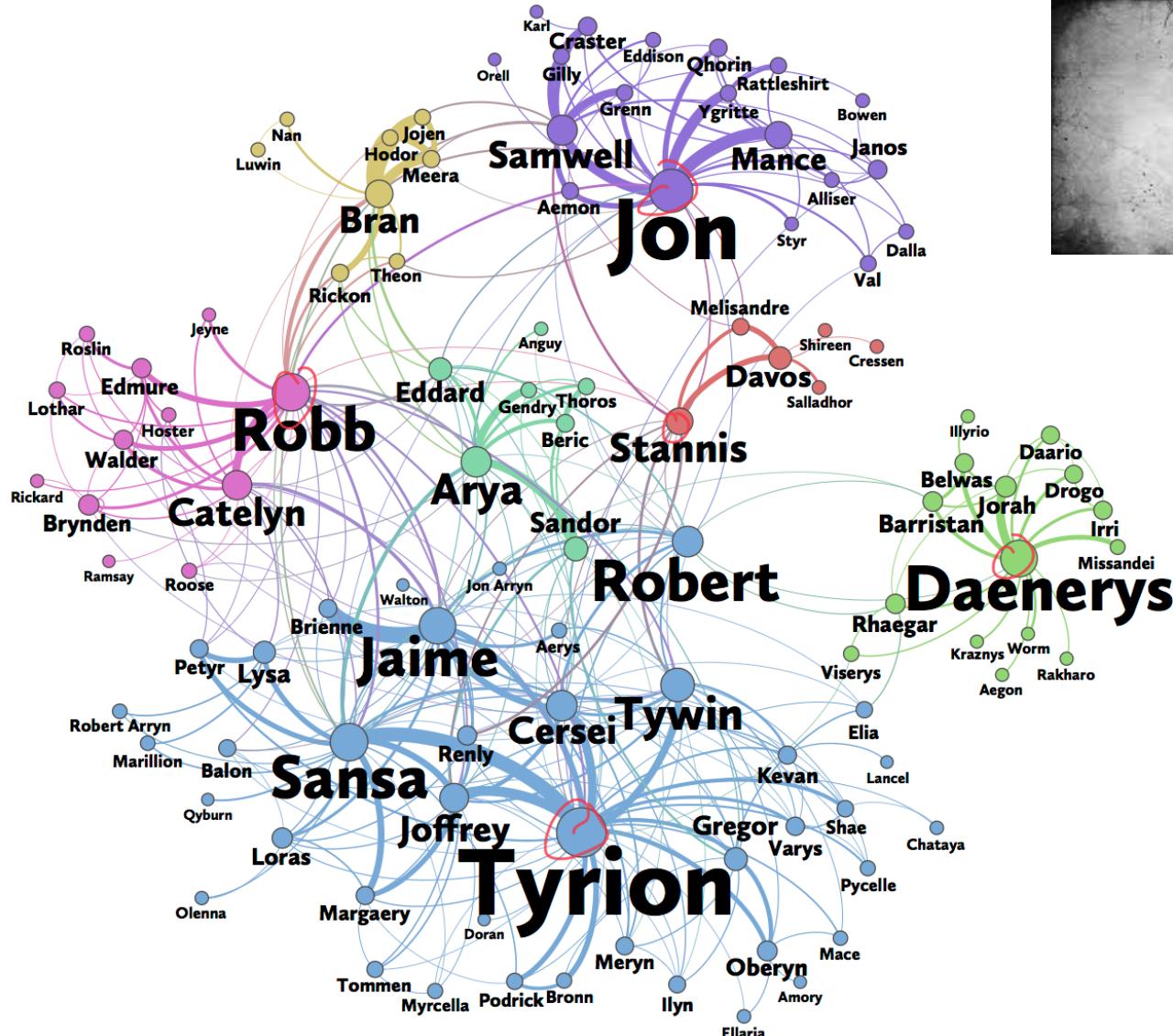
- Part I. Some useful concepts from Graph-theory
- Part II. Graph of Words - Information retrieval
- Part III. Graph based Event detection
- Part IV. Graph based text Categorization

Centrality criteria

Centrality in Networks (1/2)

- Determine the relative importance of a node in the network
 - Applications in Social Network Analysis, the Internet, Epidemiology, Urban informatics, ...
- What do we mean by **centrality**?
 - A central node is more important or powerful ...
 - Or, more influential ...
 - Or, is more critical due to its location in the graph
- Also, very closely related to the problem of **ranking** in the context of **Web search**
 - Each webpage can be considered as a ‘user’
 - Each hyperlink is an endorsement relationship
 - Centrality measures provide a query independent link-based score of importance of a web page

Centrality in Networks (2/2)

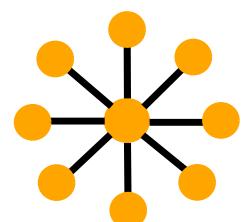


Types of Centrality

- Starting point: the central node of a **star** is the most important
- Why?
 - The node with the highest degree
 - The node that is closest to the rest nodes (e.g., has the smallest average distance to other nodes)
 - The node through which all shortest paths pass
 - The node that maximizes the dominant eigenvector (the one that corresponds to the largest eigenvalue) of the adjacency matrix
 - The node with highest probability in the stationary distribution of a random walk on the graph

⋮

Various competing views of centrality



Measures of Centrality

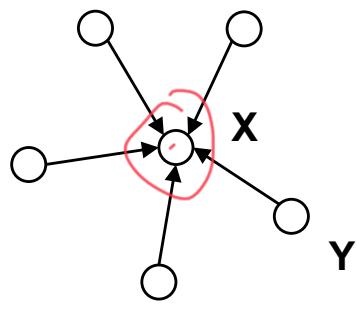
- This observation leads to the following classes of indices of centrality:
 - Measures based on **distances** (e.g., degree, closeness)
 - Measures based on **paths** (e.g., betweenness, Katz's index)
 - **Spectral** measures (eigenvector, PageRank, HITS, SALSA, random walks with restarts)
 - Measure based on **groups of nodes** (e.g., cliques, cores)
 - Related to the “clustering” structure
 - More on that in another lecture

$$A = V \Lambda V^T$$

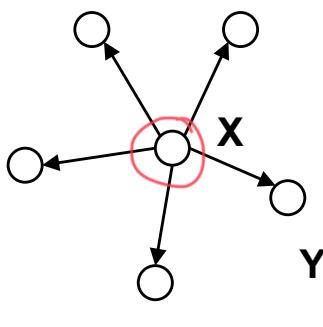
\Downarrow \rightarrow page rank

A First Example

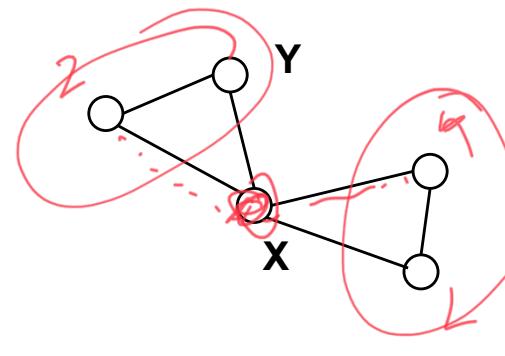
In each of the following networks, **X** has higher centrality than **Y** according to a particular measure



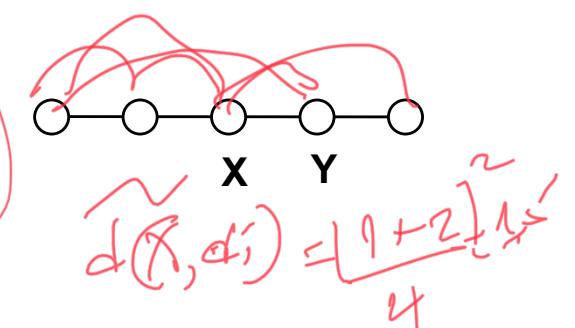
in-degree



out-degree



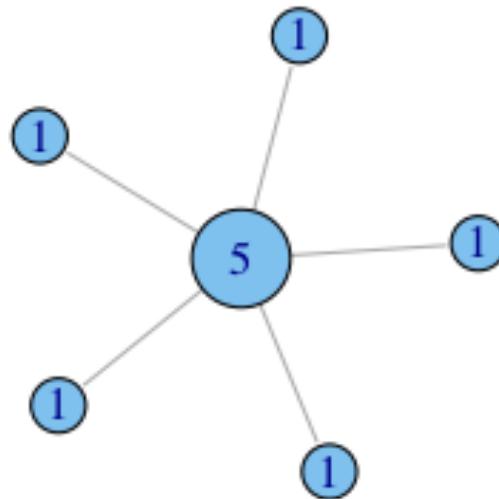
betweenness



closeness

Degree Centrality (1/2)

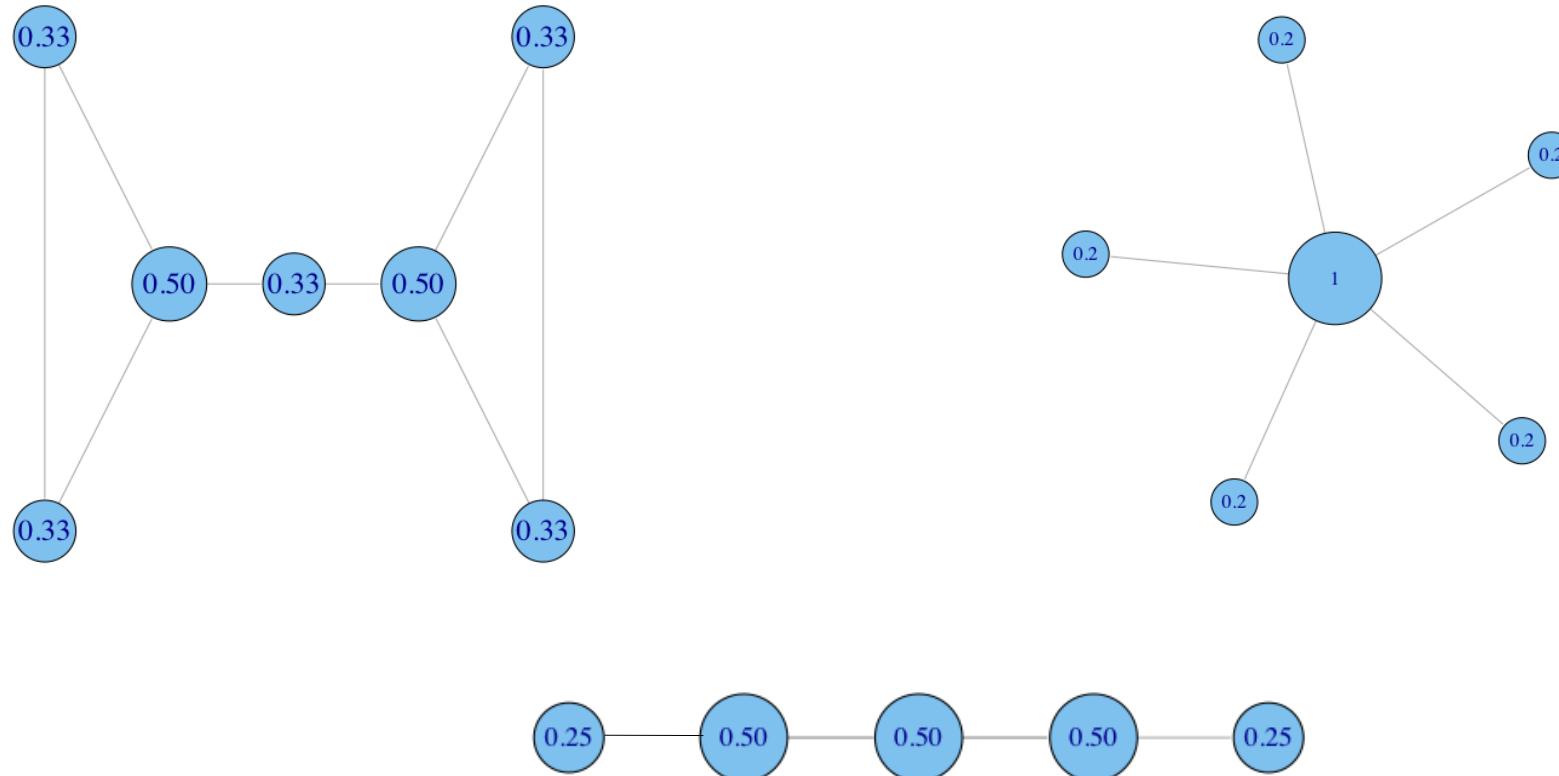
- **Idea:** A central node is one with many connections



- $C_d(i) = k(i)$, where $k(i)$ is the degree of node i

Degree Centrality (2/2)

- **Idea:** A central node is one with many connections



- Normalized degree centrality: divide by the max possible degree ($n-1$)

Closeness Centrality

- **Motivation:** it measures the ability to quickly access or pass information through the graph

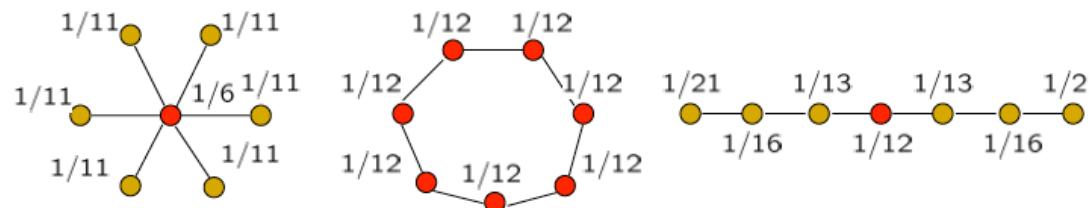
$$C_{cl}(i) = \frac{n - 1}{\sum_{j \neq i} d(i, j)}$$

values in the range [0,1]

Mean distance from a node to other nodes

$d(i, j)$ is the length of the shortest path between i and j (geodesic distance)

- The **closeness** of a node is defined as the **inverse** of the sum of the shortest path (SP) distances between the node and all other nodes in the graph



Be close to everybody else
(e.g., influence on other nodes)

Why inverse the distance?
• Nodes with **low mean distance** should get **high score**

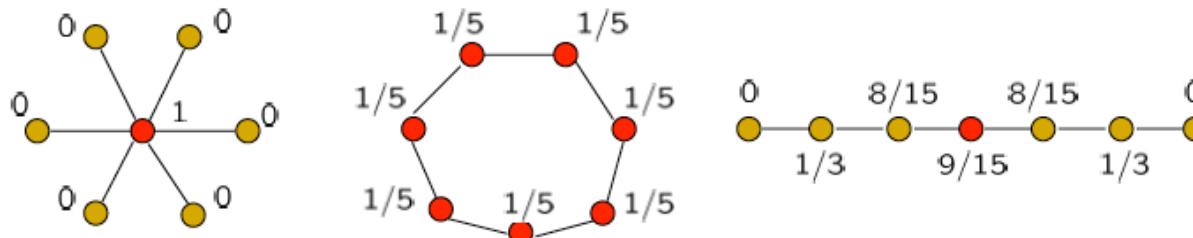
[Mateos, '17]

Betweenness Centrality

- **Motivation:** a node is important if it lies in many shortest paths

$$C_{bt}(i) = \sum_{s \neq i \neq t \in V} \frac{\sigma(s, t|i)}{\sigma(s, t)}$$

- $\sigma(s, t)$ is the total number of shortest paths from s to t
- $\sigma(s, t|v)$ is the number of shortest paths from s to t that pass through i



Essential nodes in passing information through the network

Oftentimes it is normalized: $\frac{C_{bt}(i)}{\binom{n-1}{2}}$

Core decomposition in networks

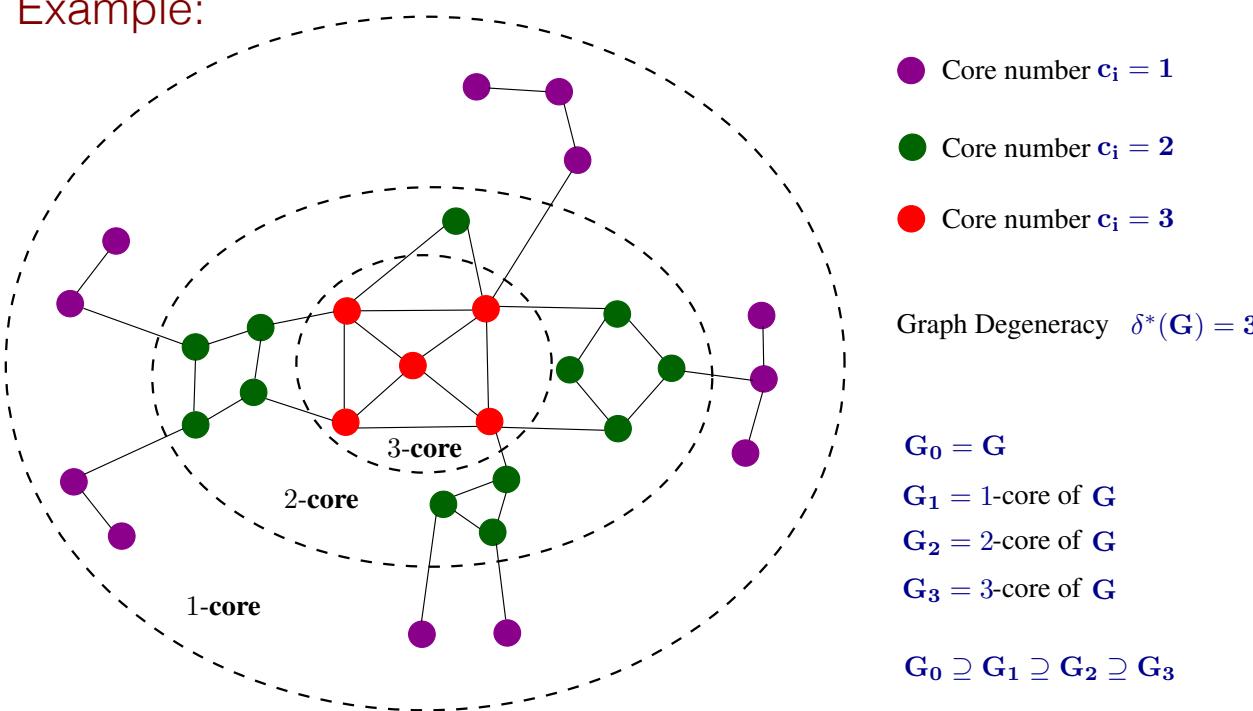
Core Decomposition

- Tool to analyze the structure of real networks
 - Quantify community and clustering structure
- Hierarchical representation of a graph into nested subgraphs of increased connectivity and coherence properties
- **Basic idea:**
 - Set a threshold on the node degree, say k
 - Nodes that do not satisfy the threshold are removed from the graph
- Extensions to other node properties (e.g., triangles)
- Plethora of applications
 - Dense subgraph discovery and community detection
 - Evaluation of collaboration in social networks
 - Identification of influential spreaders in social networks
 - **Text analytics**

k-Core Decomposition

- Degeneracy for an **undirected** graph \mathbf{G}
 - Also known as the **k**-core number
 - The **k**-core of \mathbf{G} is the largest subgraph in which every vertex has degree at least **k** within the subgraph

Example:



Important property:

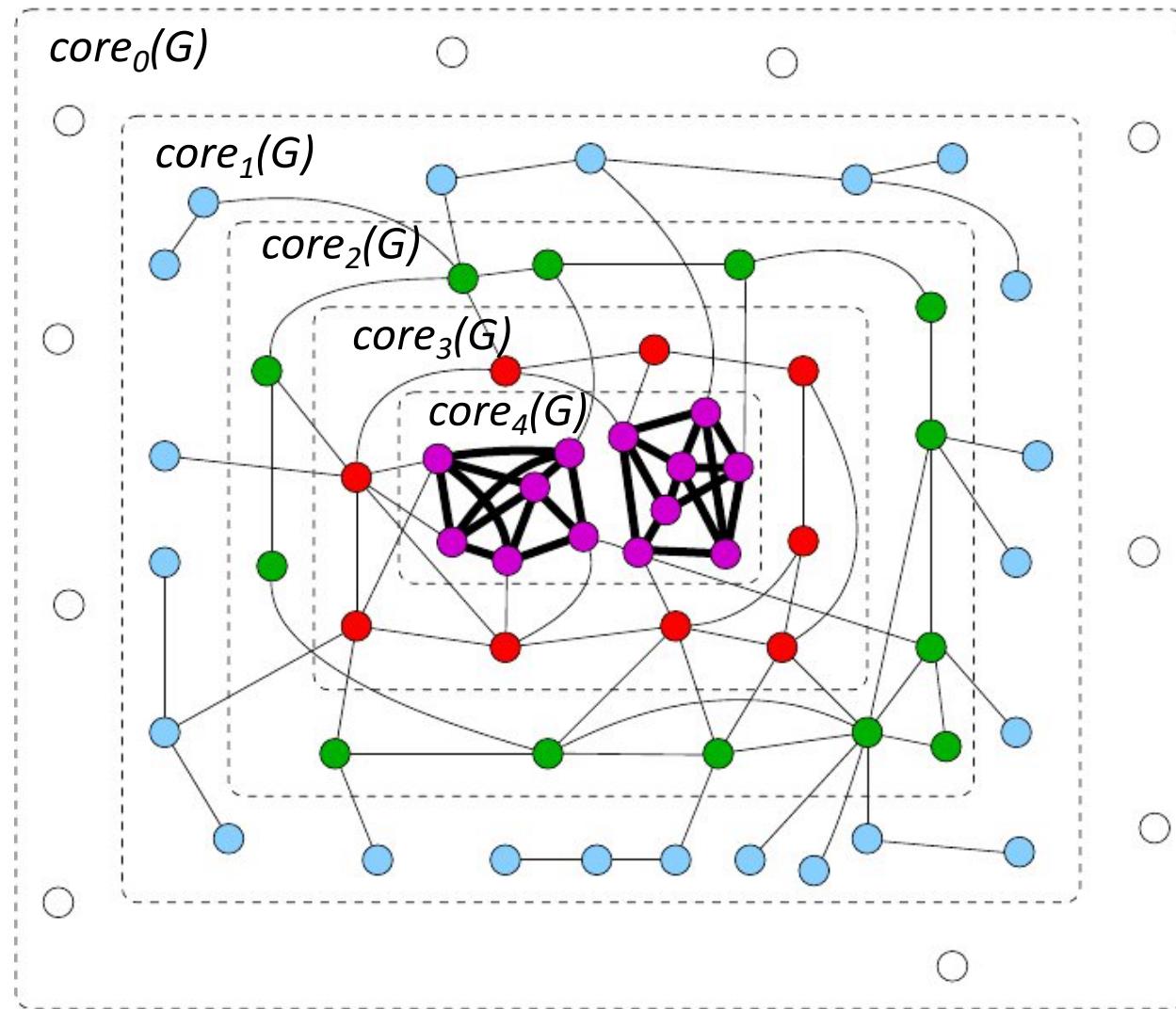
- Fast and easy to compute
- Linear to the size of the graph
- Scalable to large scale graphs

Note:

The degeneracy and the size of the **k**-core provide a good indication of the cohesiveness of the graph

Also known as **graph degeneracy**

Another Example



Algorithm for k-Core Decomposition

Algorithm $k\text{-core}(G, k)$

Input: An undirected graph G and positive integer k

Output: $k\text{-core}(G)$

1. let $F := G$

2. while there is a node x in F such that $\deg_F(x) < k$

delete node x from F

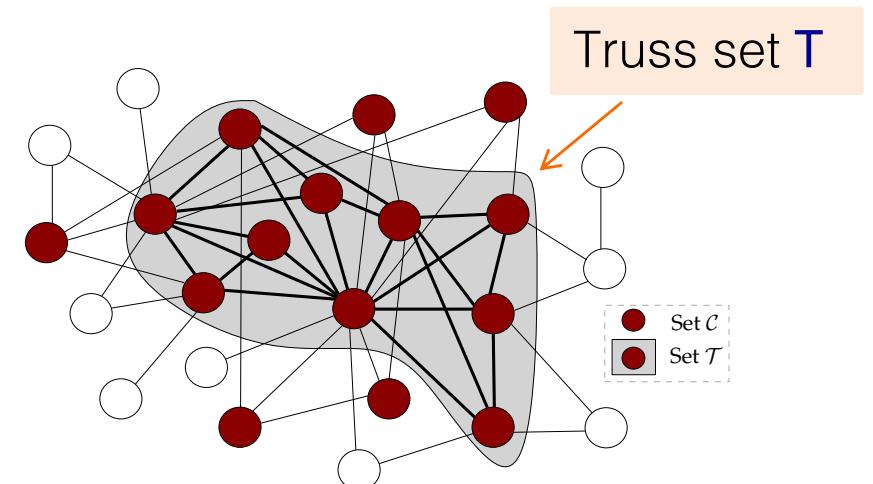
3. return F

- Many efficient algorithms have been proposed for the computation
 - Time complexity: $O(m)$

[Batagelj and Zaversnik, '03]

K-truss Decomposition (Triangles)

- K-truss decomposition [Cohen '08], [Wang and Cheng '12]
 - Triangle-based extension of the k -core decomposition
 - Each edge of the K -truss subgraph participates in at least $K-2$ triangles
 - Informally, the “core” of the maximal k -core subgraph
 - Subgraph of higher coherence compared to the k -core



Graph-based text representations

Graph Semantics

- Let $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ be the graph that corresponds to a document \mathbf{d}
- The **nodes** can correspond to:
 - Paragraphs
 - Sentences
 - Phrases
 - Words [Main focus of the tutorial]
 - Syllables
- The **edges** of the graph can capture various types of relationships between two nodes:
 - Co-occurrence within a window over the text [Main focus of the tutorial]
 - Syntactic relationship
 - Semantic relationship

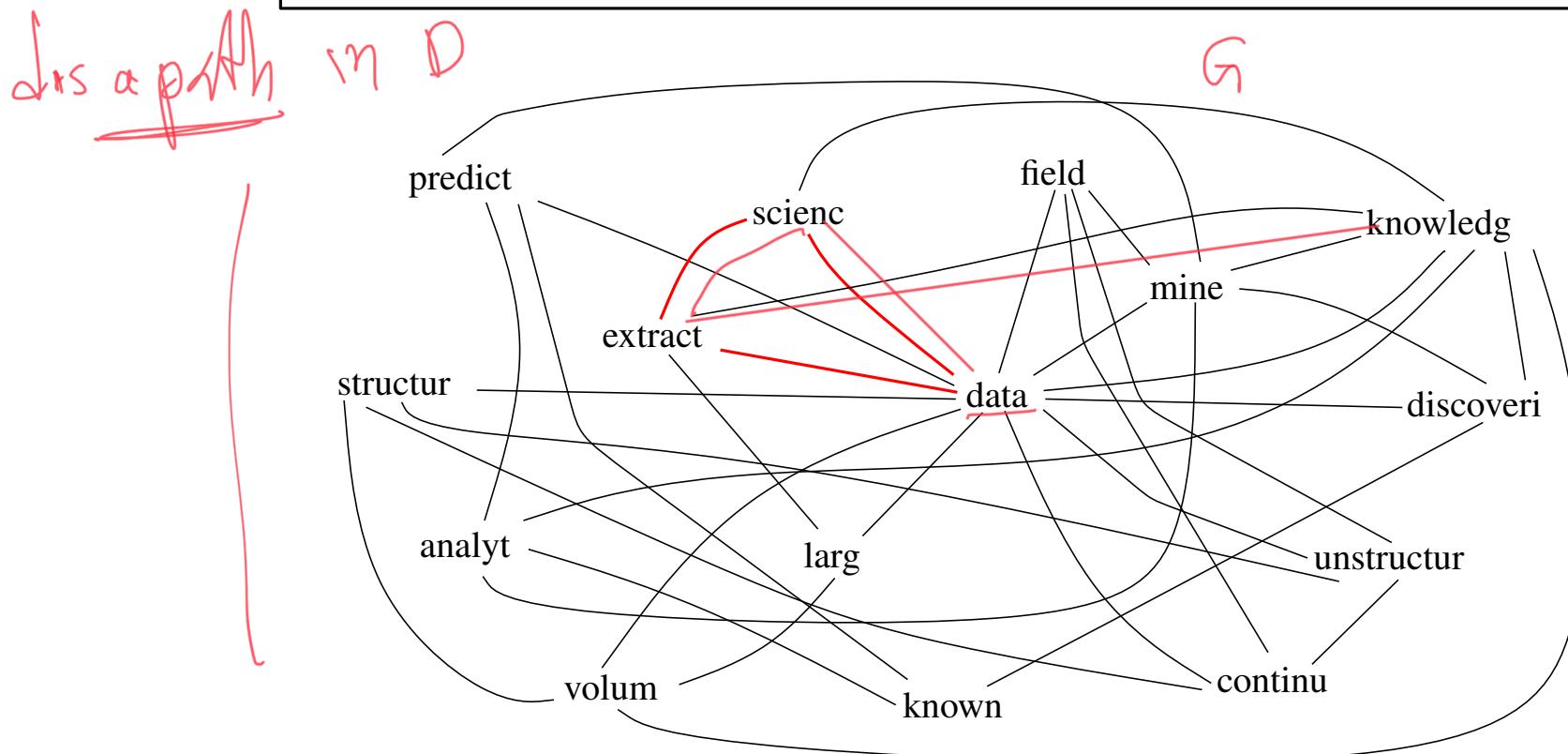
Graph-of-Words (GoW) Model

- Each document $d \in D$ is represented by a graph $G_d = (V_d, E_d)$, where the nodes correspond to the terms t of the document and the edges capture co-occurrence relationships between terms within a fixed-size sliding window of size w
- Directed vs. undirected graph
 - Directed graphs are able to preserve the actual flow of a text
 - In undirected graphs, an edge captures co-occurrence of two terms whatever the respective order between them is
- Weighted vs. unweighted graph
 - The higher the number of co-occurrences of two terms in the document, the higher the weight of the corresponding edge
- Size w of the sliding window
 - Add edges between the terms of the document that co-occur within a sliding window of size w
 - Larger window sizes produce graphs that are relatively dense

[Mihalcea and Tarau, EMNLP '04], [Blanco and Lioma, Inf. Retr. '12],
[Rousseau and Vazirgiannis, CIKM '13]

Example of Unweighted GoW

3
Data Science ~~is the~~ extraction of knowledge from large volumes of data that are structured or unstructured which is a continuation of the field of data mining and predictive analytics, also known as knowledge discovery and data mining.



w = 3

unweighted, undirected graph

dr gencordbo.

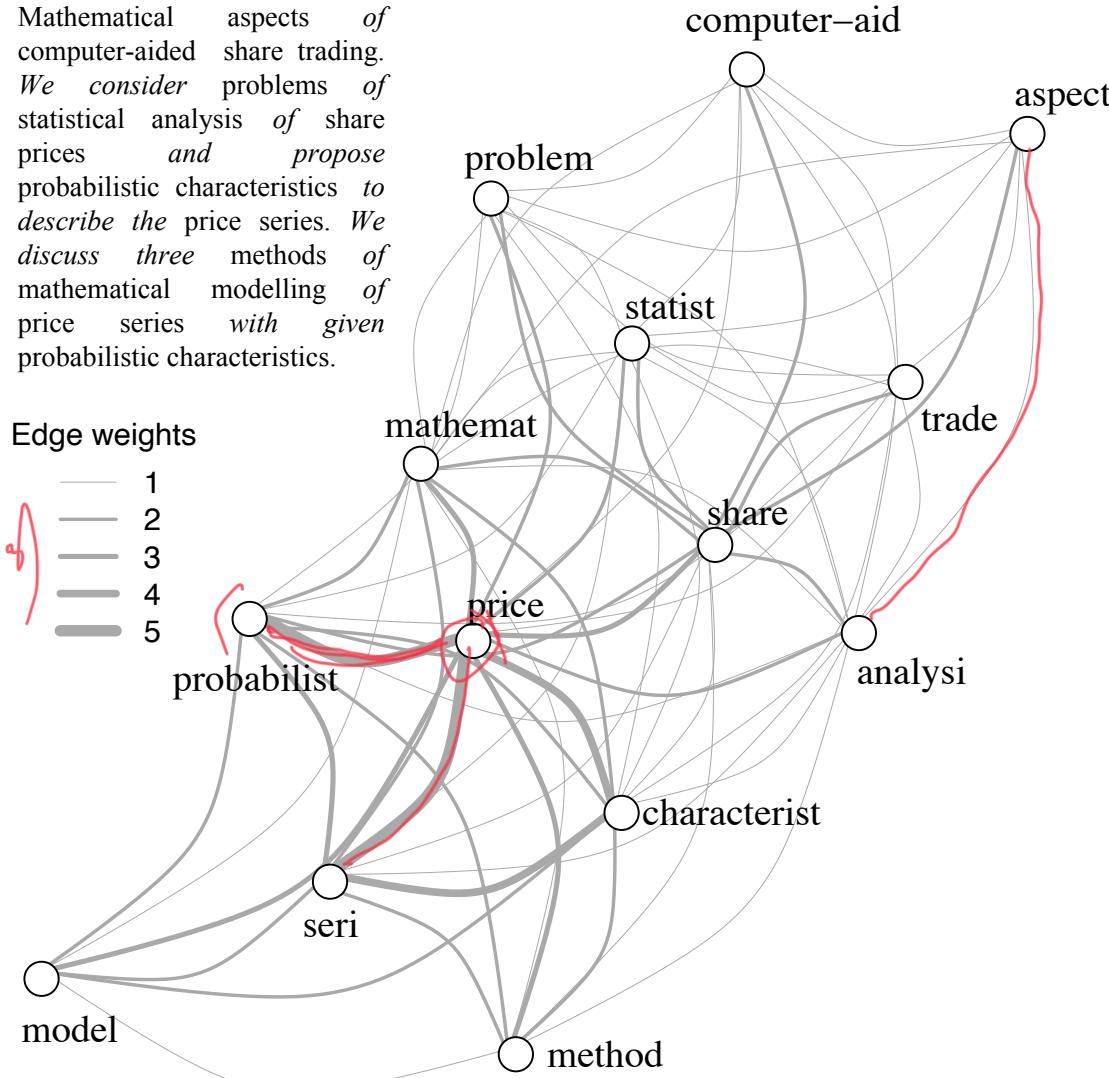
Example of Weighed Undirected GoW

Mathematical aspects of computer-aided share trading. We consider problems of statistical analysis of share prices and propose probabilistic characteristics to describe the price series. We discuss three methods of mathematical modelling of price series with given probabilistic characteristics.

Edge weights

- 1
- 2
- 3
- 4
- 5

$$t_w(v) = \text{indegree}(v)$$



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In-degree based TW

- The weight of a term in a document is its in-degree in the graph-of-words
 - It represents the number of distinct contexts of occurrence
 - We store the document as a vector of weights in the direct index and similarly in the inverted index
 - For example: $tw(t)$

For example:

information retrieval is the activity of obtaining resources relevant to an need from a collection

tw(t)

5

2

2

2

2

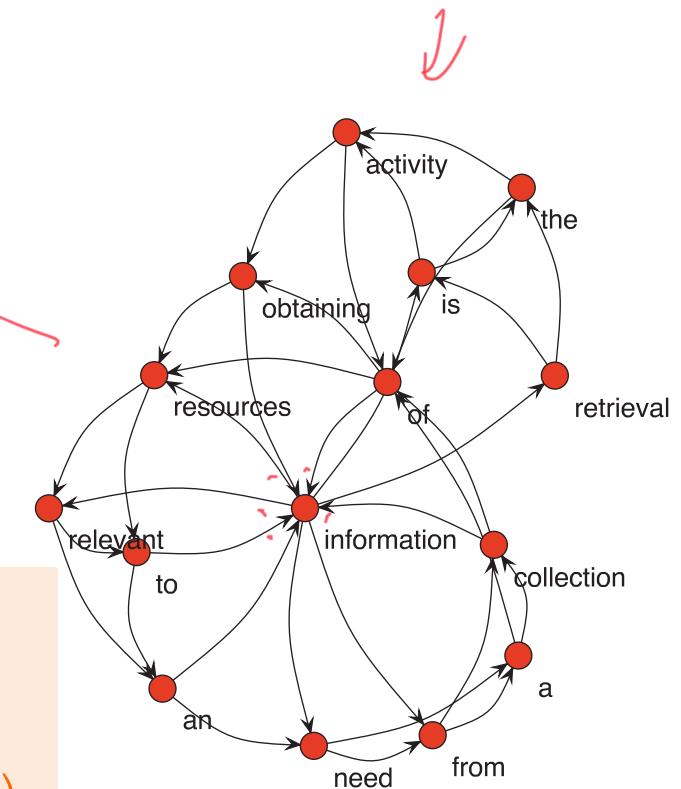
2

2

2

Bag of words:

((activity,1), (collection,1),
(information,4), (relevant,1),
(resources,2), (retrieval,1)...)



TF-IDF and BM25

- Term t , document d , collection of size N , term frequency $tf(t,d)$, document frequency $df(t)$, document length $|d|$, average document length $avdl$, asymptotical marginal gain k_1 (1.2), slope parameter b

- TF-IDF [Singhal et al., TREC-7]

$$\text{TF-IDF}(t, d) = \text{TF}_{\text{pol}}\text{-IDF}(t, d) = \text{TF}_{\text{po}}\text{TF}_{\text{l}}(t, d) \times \text{IDF}(t) = \left(\frac{1 + \log(1 + \log(tf(t, d)))}{1 - b + b \times \frac{|d|}{avdl}} \right) \times \log\left(\frac{N + 1}{df(t)}\right)$$

- BM25 [Lv and Zhai, CIKM '11]

$$\text{BM25}(t, d) = \left(\frac{(k_1 + 1) \times tf(t, d)}{k_1 \times \left(1 - b + b \times \frac{|d|}{avdl}\right) + tf(t, d)} \right) \times \log\left(\frac{N + 1}{df(t)}\right)$$

TW-IDF

- Term t , document d , collection of size N , term weight $tw(t, d)$, document frequency $df(t)$, document length $|d|$, average document length $avdl$, asymptotical marginal gain k_1 (1.2), slope parameter b

$$\text{TW-IDF}(t, d) = \underbrace{\left(\frac{tw(t, d)}{1 - b + b \times \frac{|d|}{avdl}} \right)}_{\text{TW-IDF}(t, d)} \times \log \left(\frac{N + 1}{df(t)} \right)$$

- In the **bag-of-word** representation, tw is usually defined as the term frequency or sometimes just the presence/absence of a term (binary tf)
- In the **graph-of-word** representation, tw is the **in-degree** of the vertex representing the term in the graph

[Rousseau and Vazirgiannis, CIKM '13]

Experimental Evaluation

- Datasets
- Platforms
- Evaluation
- Results

Datasets (1/2)

first retrieval conf. ≥ 30 years

- **Disks 1 & 2 (TREC)**
741,856 news articles from Wall Street Journal (1987-1992), Federal Register (1988-1989), Associated Press (1988-1989) and Information from the Computer Select disks (1989-1990)
- **Disks 4 & 5 (TREC, minus the Congressional Record)**
528,155 news releases from Federal Register (1994), Financial Times (1991-1994), Foreign Broadcast Information Service (1996) and Los Angeles Times (1989-1990)
- **WT10G (TREC)**
1,692,096 crawled pages from a snapshot of the Web in 1997
- **.GOV2 (TREC)**
25,205,179 crawled Web pages from .gov sites in early 2004

Datasets (2/2)

Statistic	Dataset	Disks 1 & 2	Disks 4 & 5	WT10G	.GOV2
# of documents		<u>741,856</u>	528,155	1,692,096	<u>25,205,179</u>
# of unique terms		535,001	520,423	3,135,780	<u>15,324,292</u>
average # of terms (avdl)		<u>237</u>	272	398	<u>645</u>
average # of vertices		<u>125</u>	<u>157</u>	165	<u>185</u> <i>for core</i>
average # of edges		<u>608</u>	<u>734</u>	<u>901</u>	<u>1,185</u> <i>for core</i>

Table: Statistics on the four TREC datasets used; Disks 4&5 excludes the Congressional Record. The average values are computed per document.

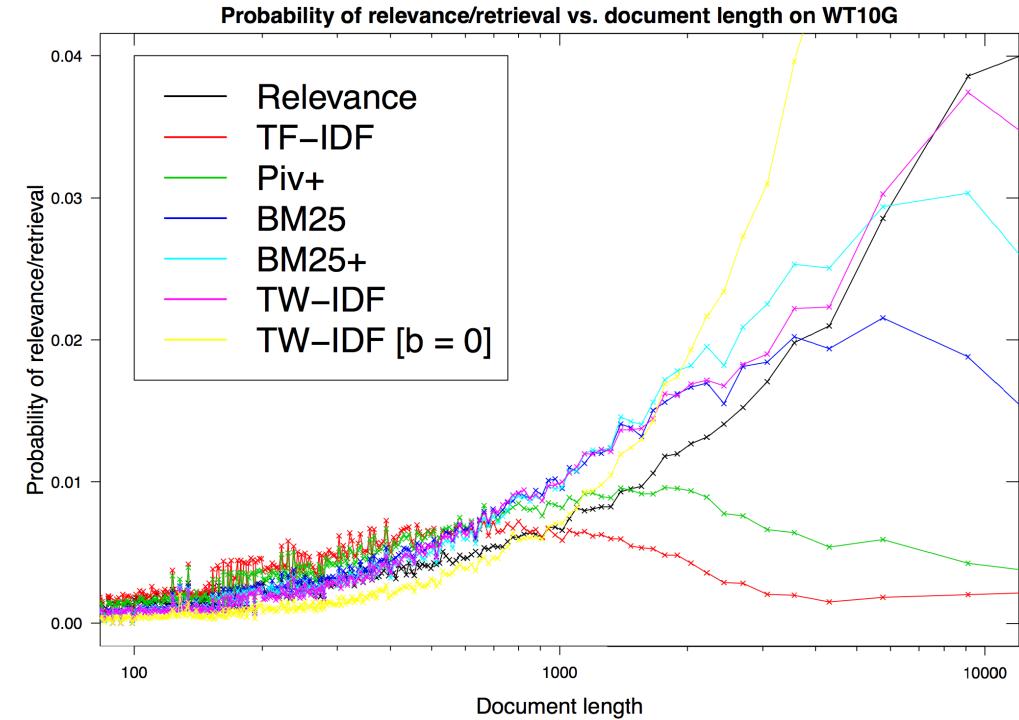
Evaluation

- Mean Average Precision (MAP) and Precision at 10 (P@10)
 - Considering only the top-ranked 1000 documents for each run
- Statistical significance of improvement was assessed using the Student's paired t-test
 - R implementation (`t.test {stats}` package), `trec_eval` output as input
 - Two-sided p-values less than 0.05 and 0.01 to reject the null hypothesis
- Likelihood of relevance vs. likelihood of retrieval [Singhal et al., SIGIR '96]
- 4 baseline models: TF-IDF, BM25, Piv+ and BM25+
 - Tuned slope parameter b for pivoted document length normalization (2-fold cross-validation, odd vs. even topic ids, MAP maximization)
 - Default (1.0) lower-bounding gap [Lv and Zhai, CIKM '11]

$$Q = \{(q_1, \underbrace{\{d_1, \dots, d_m\}}_{\text{ground truth}}), (q_2, \underbrace{\{d_1, \dots, d_m\}}_{\text{MAP}}), \dots\}$$

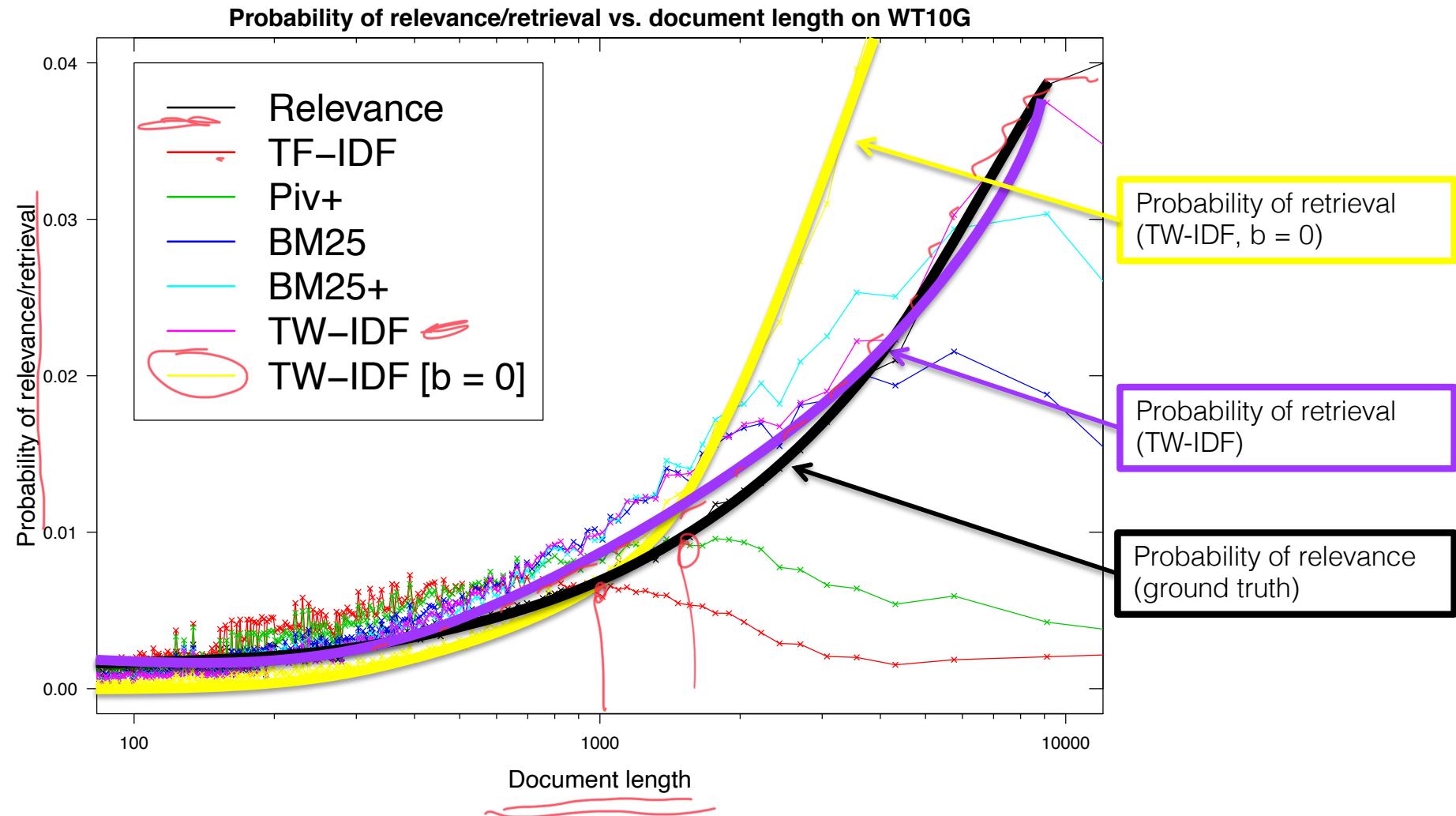
Graph-based Ad Hoc IR

- Evaluation in terms of:
 - Mean Average Precision
 - Precision@10
 - Probability of relevance vs. probability of retrieval



Model	b	TREC1-3 Ad Hoc		TREC 2004 Robust		TREC9-10 Web		TREC 2004-2006 Terabyte	
		MAP	P@10	MAP	P@10	MAP	P@10	MAP	P@10
corpus {gr}	0.20	0.1471	0.3960	0.1797	0.3647	0.1260	0.1875	0.1853	0.4913
	0.75	0.1346	0.3533	0.2045	0.3863	0.1702	0.2208	0.2527	0.5342
	none	0.1502	0.3662	0.1809	0.3273	0.1430	0.1979	0.2081	0.5021
	0.003	0.1576**	0.4040**	0.2190**	0.4133**	0.1946**	0.2479**	0.2828**	0.5407**
TF-IDF	0.20	0.1832	0.4107	0.2132	0.4064	0.1430	0.2271	0.2068	0.4973
BM25	0.75	0.1660	0.3700	0.2368	0.4161	0.1870	0.2479	0.2738	0.5383
TW-IDF	0.003	0.1973**	0.4148*	0.2403**	0.4180*	0.2125**	0.2917**	0.3063**	0.5633**

Likelihood of Relevance vs. Likelihood of Retrieval



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Single Document Keyword Extraction

Keywords are used everywhere

- Looking up information on the Web (e.g., via a search engine bar)
- Finding similar posts on a blog (e.g., tag cloud)
- For ads matching (e.g., AdWords' keyword planner)
- For research paper indexing and retrieval (e.g., SpringerLink)
- For research paper reviewer assignment

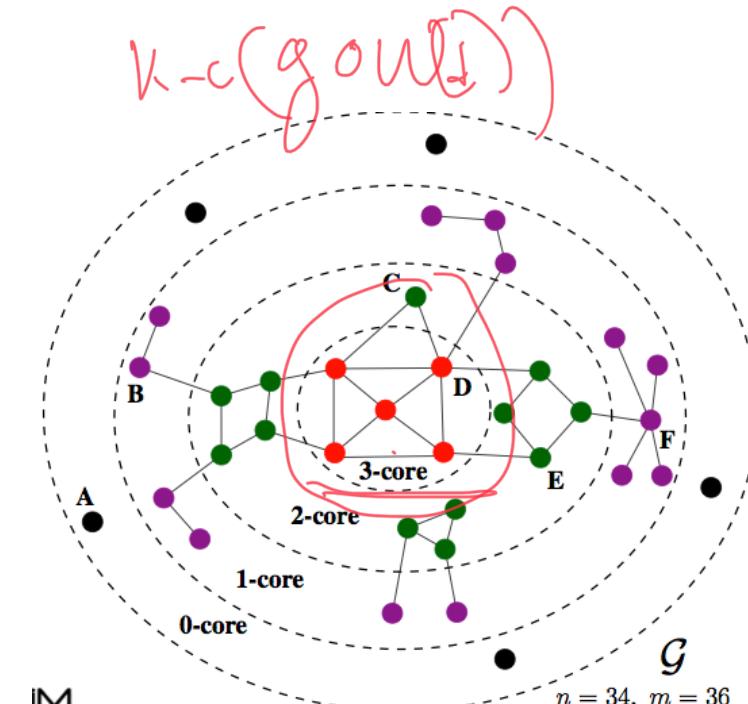
Applications are numerous

- Summarization (to get a gist of the content of a document)
- Information filtering (to select specific documents of interest)
- Indexing (to answer keyword-based queries)
- Query expansion (using additional keywords from top results)

Graph-based Keyword Extraction (1/2)

Existing graph-based keyword extractors:

- Assign a **centrality** based score to a node
- Top ranked ones will correspond to the most representative
- **TextRank (PageRank)** [Mihalcea and Tarau, EMNLP '04]
- **HITS** [Litvak and Last, MMIES '08]
- **Node centrality (degree, betweenness, eigenvector)** [Boudin, IJNLP '13]

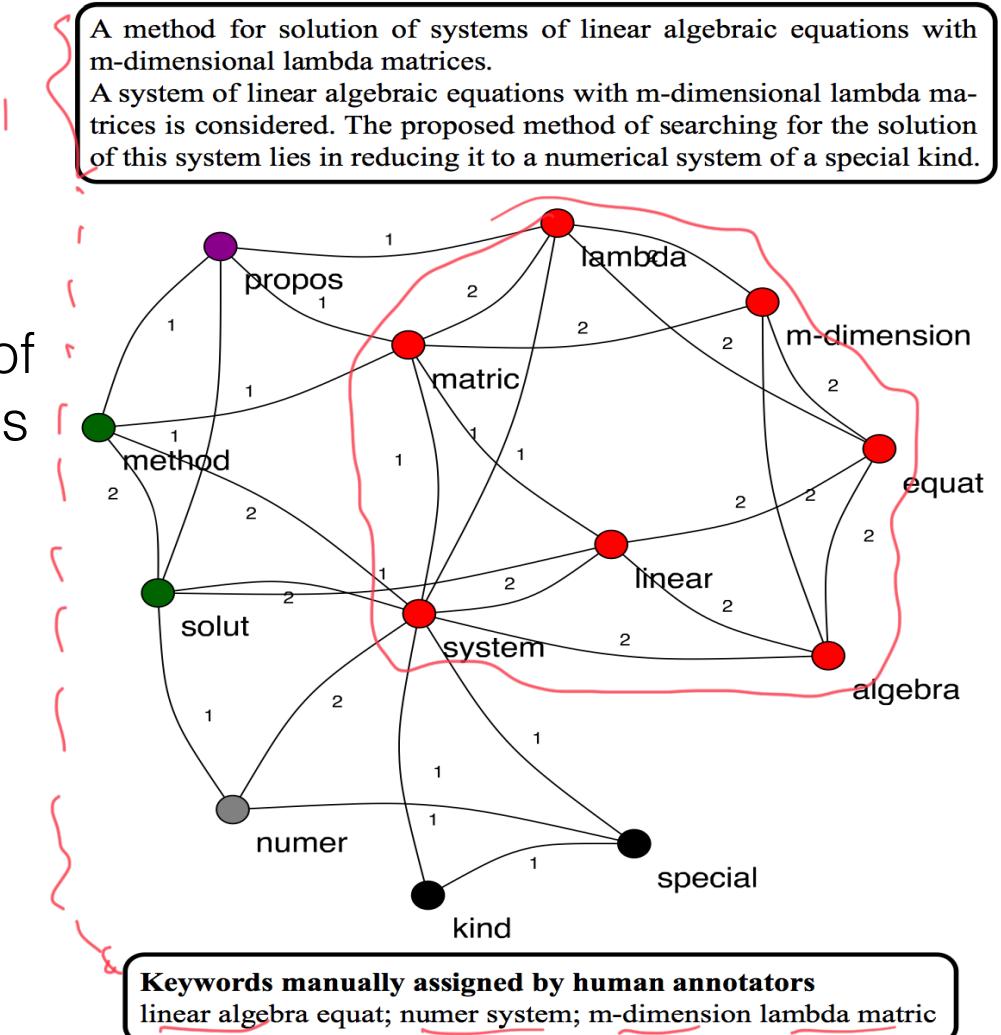


k-core decomposition of the graph

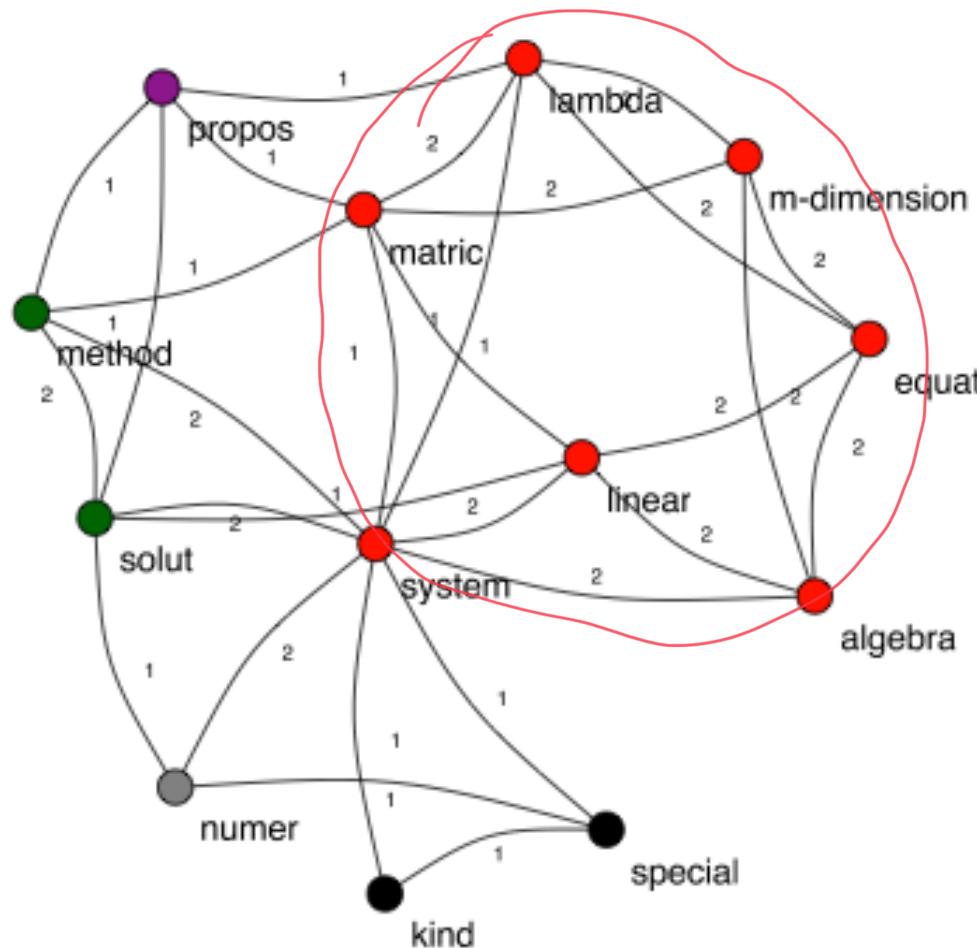
Idea: retain the **k-core subgraph** of the graph to extract the nodes based on their centrality and cohesiveness

Graph-based Keyword Extraction (2/2)

- Single-document keyword extraction
 - Select the most cohesive sets of words in the graph as keywords
 - Use k-core decomposition to extract the main core of the graph
 - Weighted edges



PageRank vs. k-core



WK-core	PageRank
system	1.93
matric	1.27
lambda	1.10
linear	1.08
equat	1.08
algebra	0.90
m-dim...	0.90
method	0.90
solut	0.89
propos	0.88
numer	0.78
specia	0.74
kind	0.55

Keywords are not Unigrams

- 500 abstracts from the *Inspec* database used in our experiments,
- 4,913 keywords manually assigned by human annotators
- only 662 are unigrams (13%).
- Bigrams (2,587 – 52%) ... 7-grams (5).
 - ⇒ keywords are bigrams, if not higher order n-grams.
 - ⇒ the interactions within keywords need to be captured in the first place – i.e. in the graph.
 - ⇒ we can consider a k-core to form a “long-distance (k+1)-gram” [Bassiou and Kotropoulos, 2010]

How Many Keywords?

- Most techniques in keyword extraction assign a score to each feature and then take the top ones
- But how many?
 - Absolute number (top X) or relative number (top $X\%$)?
- Besides, at fixed document length, humans may assign more keywords for a document than for another one

X is decided at document level (size of the k -core subgraph)

k -cores are adaptive

Datasets

- Hulth2003 – 500 abstracts from the *Inspec* database [Hulth, 2003]
- Krapi2009 – 2,304 ACM full papers in Computer Science (references and captions excluded) [Krapivin et al., 2009]

All approaches are unsupervised and single-document

Models and Baseline Methods

Graph-of-words:

- 1) Undirected edges
- 2) Forward edges
 - Natural flow of the text
 - An edge $\text{term1} \rightarrow \text{term2}$ meaning that term1 precedes term2 in a sliding window
- 3) Backward edges

Keyword extractors:

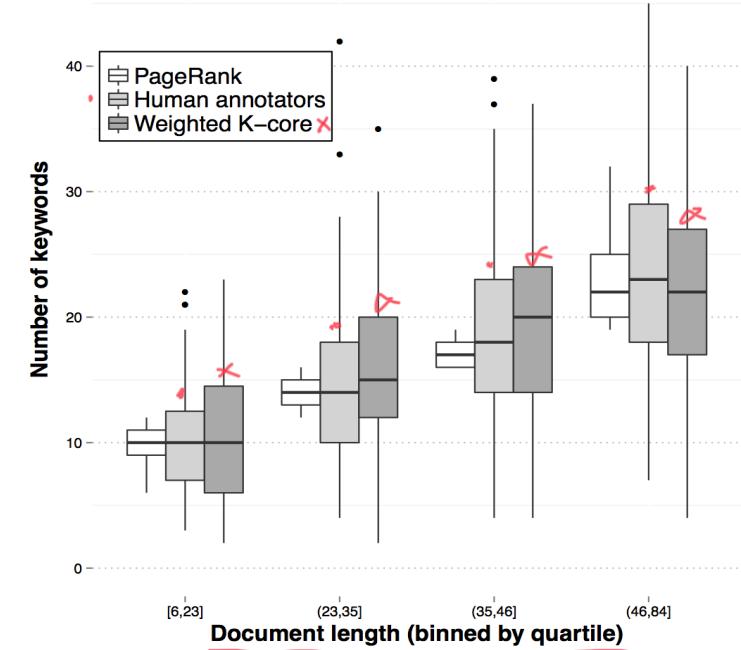
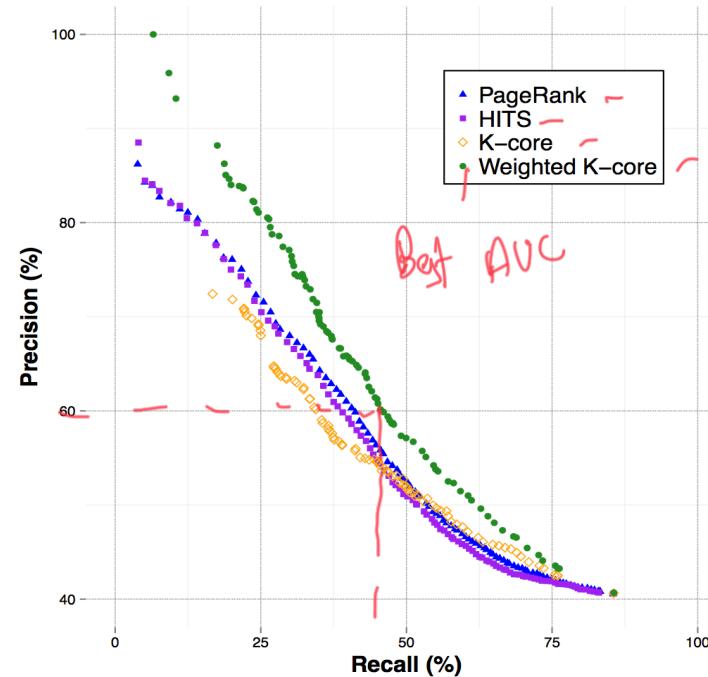
- { PageRank
 - { HITS (authority scores only)
 - { k-core
 - { Weighted k-core
-
- The diagram shows four items from the list grouped into two categories. The first two items are grouped by a brace on the left and another brace on the right, labeled "Top 33% or top 15% keywords". The last two items are grouped by a single brace on the left and another brace on the right, labeled "Main core".

Top 33% or top 15% keywords

Main core

Performance Evaluation

Precision
Recall
F1-score
Precision/recall



Graph	Dataset	Macro-averaged precision (%)				Macro-averaged recall (%)				Macro-averaged F1-score (%)			
		PageRank	HITS	K-core	WK-core	PageRank	HITS	K-core	WK-core	PageRank	HITS	K-core	WK-core
undirected edges	Hulth2003	58.94	57.86	46.52	61.24*	42.19	41.80	62.51*	50.32*	47.32	46.62	49.06*	51.92*
	Kapi2009	50.23	49.47	40.46	53.47*	48.78	47.85	78.36*	50.21	49.59	47.96	46.61	50.77*
forward edges	Hulth2003	55.80	54.75	42.45	56.99*	41.98	40.43	72.87*	46.93*	45.70	45.03	51.65*	50.59*
	Kapi2009	47.78	47.03	39.82	52.19*	44.91	44.19	79.06*	45.67	45.72	44.95	46.03	47.01*
backward edges	Hulth2003	59.27	56.41	40.89	60.24*	42.67	40.66	70.57*	49.91*	47.57	45.37	45.20	50.03*
	Kapi2009	51.43	49.11	39.17	52.14*	49.96	47.00	77.60*	50.16	50.51	47.38	46.93	50.42

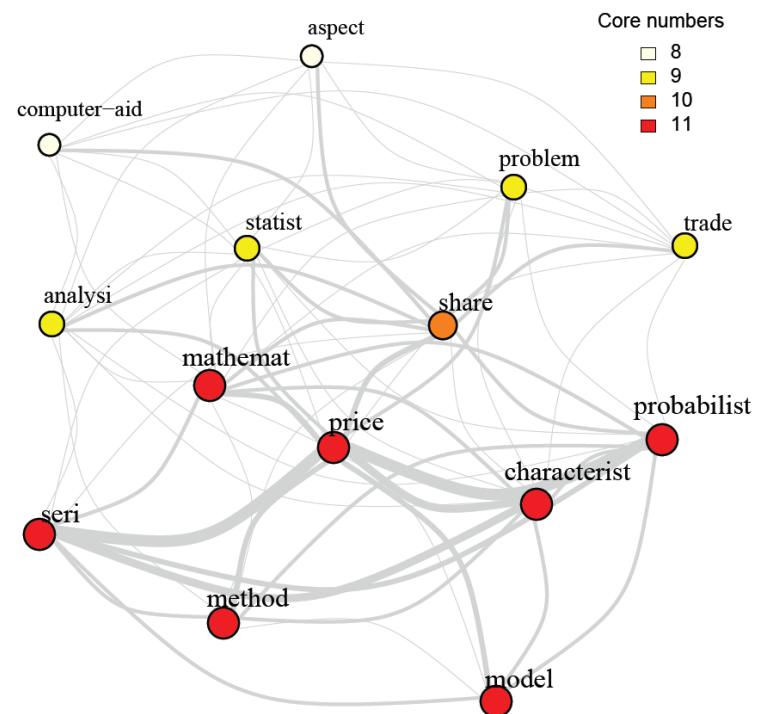
Example – ECIR'15 Paper

- Stemmed unigrams of the main core of the graph- of-words of the paper document: {keyword, extract, graph, represent, text, weight, graph-of-word, k-core, degeneraci, edg, vertic, number, document}
- Using PageRank, “work” appears in the top 5, “term” and “pagerank” in the top 10, and “case” and “order” in the top 15. Central words but not in cohesion with the rest and probably not relevant

A Different Point of View

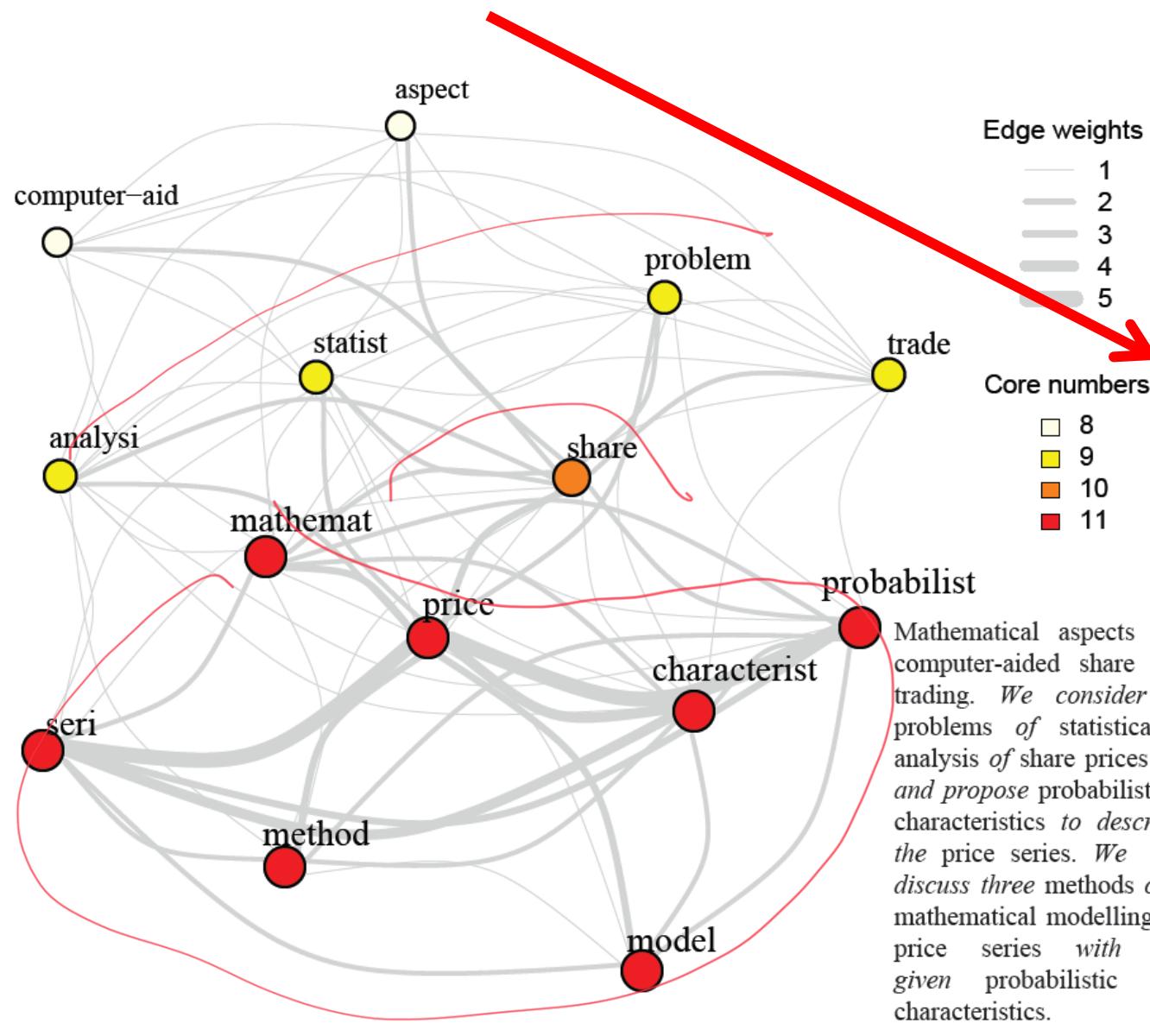
Graph degeneracy:

- In social networks, nodes part of the highest levels of the hierarchy are **better spreaders** than nodes high on **PageRank**
- Nodes with **high truss numbers** are **even more influential** than nodes with high core numbers
- **Spreading influence** may be a better “keywordness” metric than **prestige** (captured by PageRank)



Drawbacks of Graph Degeneracy (1/4)

Retaining the **top level** like in may be an appealing initial idea



	Core numbers		
	P	R	F1
MAIN	0.86	0.55	0.67
INF	0.83	0.91	0.87
DENS	0.88	0.64	0.74

	mathemat	price	probabilist	characterist	seri	method	model	MAIN
mathemat	11							
price	11							
probabilist	11							
characterist	11							
seri	11							
method	11							
model	11							
share								DENS
trade								9
problem								9
statist								9
analysi								INF
aspect								8
computer-aid								8

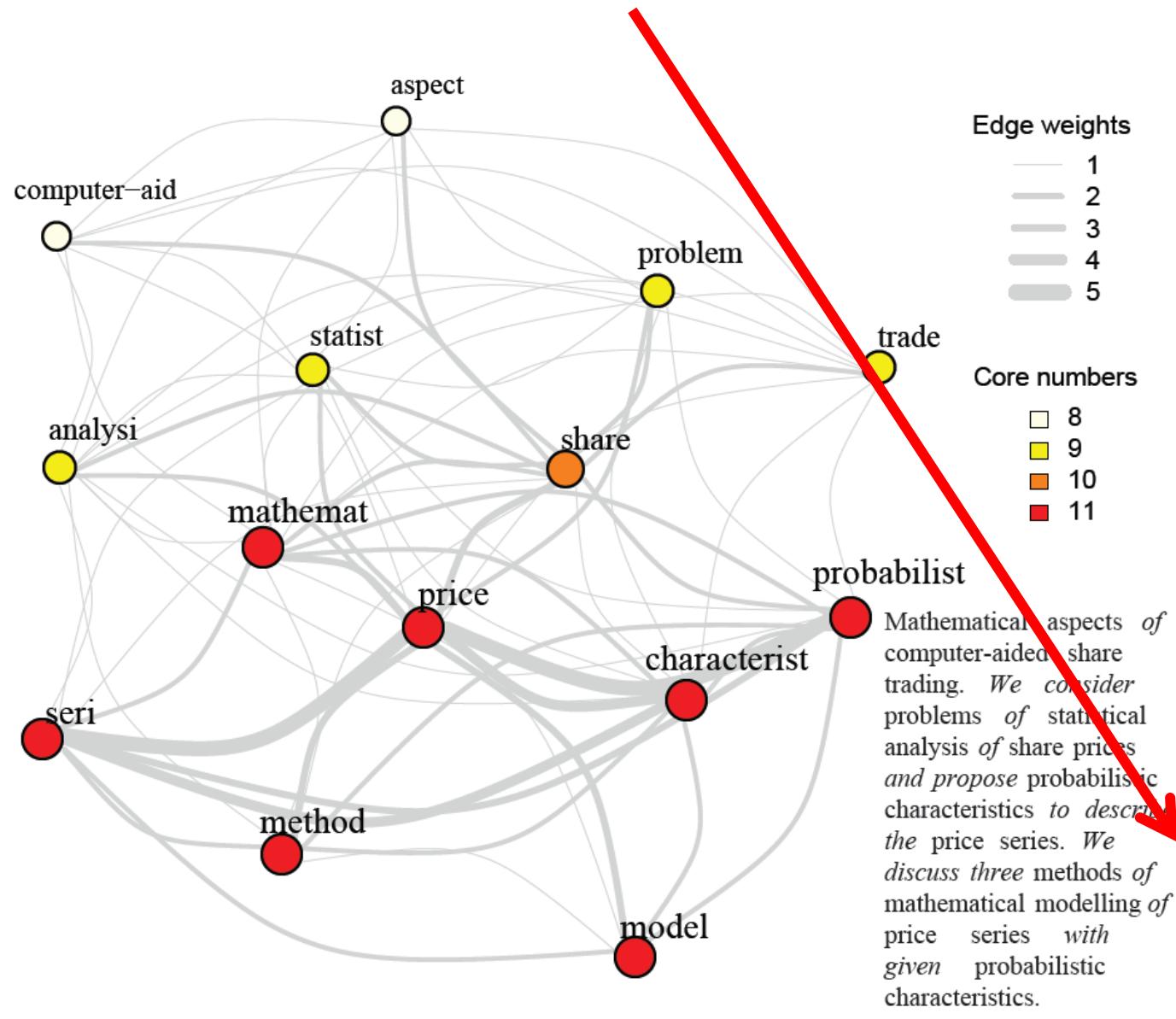
K-FDP

K

K

Drawbacks of Graph Degeneracy (2/4)

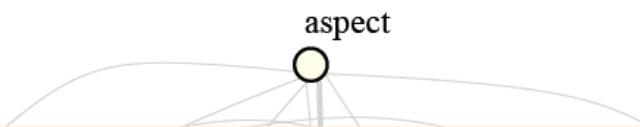
But many keywords live **below the top** level -> good precision, poor recall



Core numbers			
	P	R	F1
MAIN	0.86	0.55	0.67
INF	0.83	0.91	0.87
DENS	0.88	0.64	0.74

mathemat	11
price	11
probabilist	11
characterist	11
seri	11
method	11
model	11
MAIN	11
share	DENS 10
trade	9
problem	9
statist	9
analysi	INF 9
aspect	8
computer-aid	8

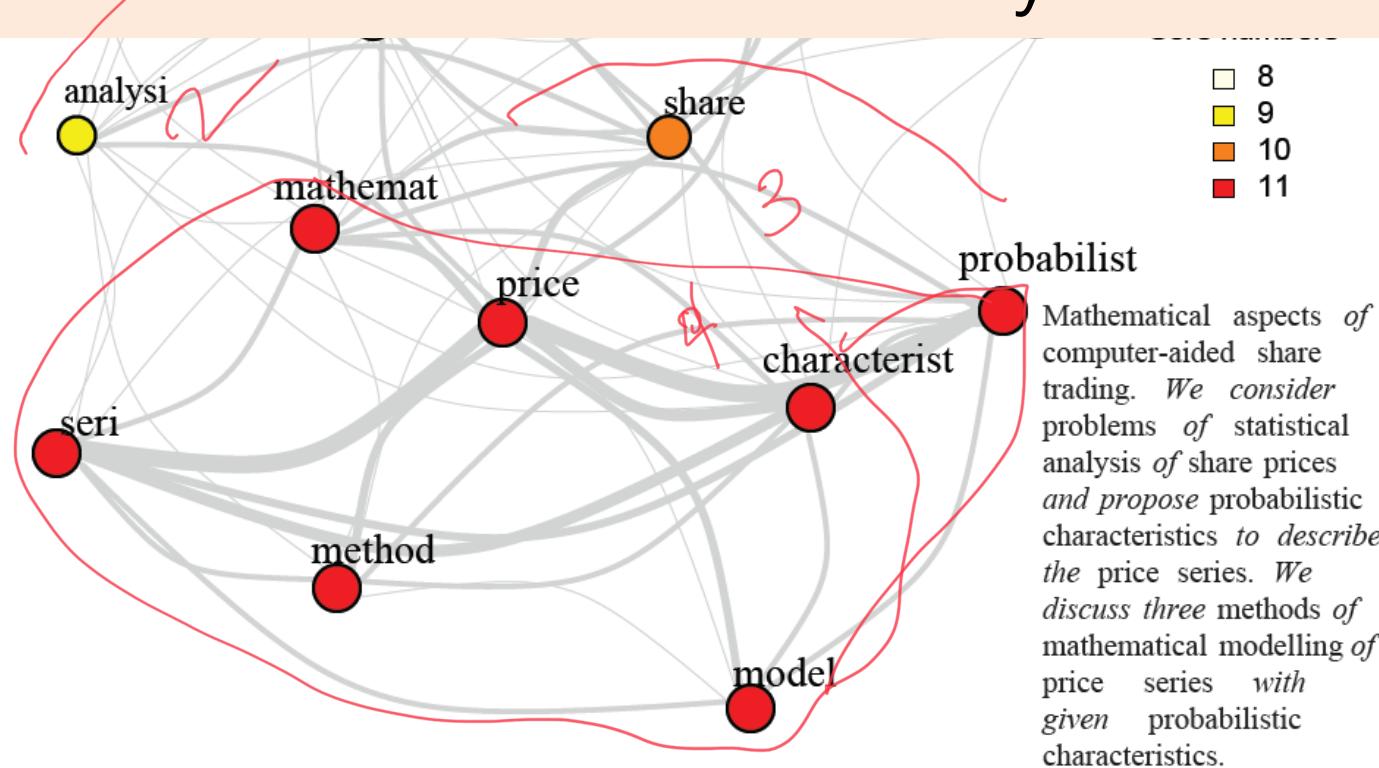
Drawbacks of Graph Degeneracy (3/4)



Edge weights
— 1

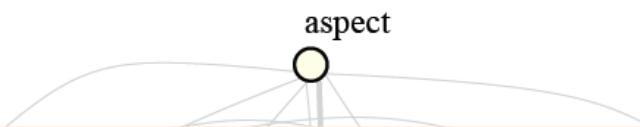
Core numbers			
	P	R	F1

How to automatically select the best level in the hierarchy?



probabilist	11	
characterist	11	
seri	11	
method	11	
model	MAIN 11	
share	DENS 10	
trade	9	
problem	9	
statist	9	
analysi	INF 9	
aspect	8	
computer-aid	8	

Drawbacks of Graph Degeneracy (4/4)



Edge weights
— 1

Core numbers			
	P	R	F1

How to automatically select the best level in the hierarchy?



■ 8
■ 9
■ 10
■ 11

probabilist	11
characterist	11
seri	11

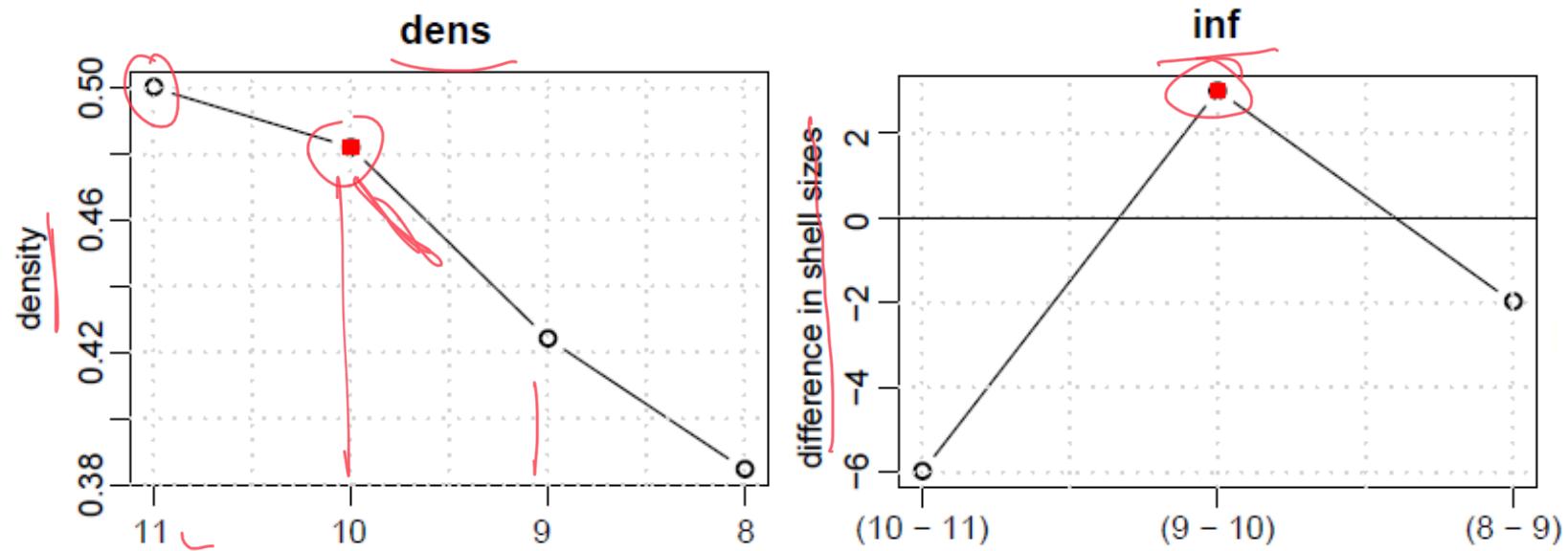
In order to improve recall while not losing too much in precision?



the price series. We discuss three methods of mathematical modelling of price series with given probabilistic characteristics.

statist	9
analysi	INF
aspect	8
computer-aid	8

Graph Degeneracy for Keyword Extraction

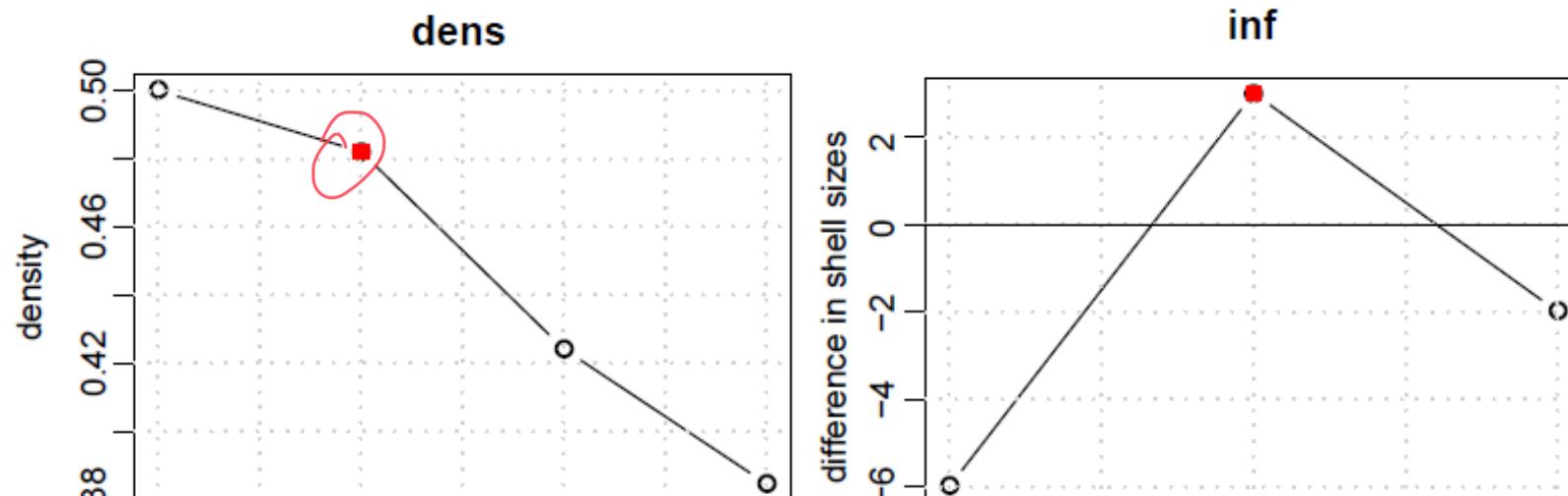


Heuristics: *k*-Core

- dens: go down the hierarchy until a drop in k -core (or truss) density is observed, i.e., as long as the desirable cohesiveness properties are kept
- inf: go down the hierarchy as long as the shells increase in size (starting at the main – 1 level)

Problem: both methods work at the subgraph level -> lack flexibility for large graphs (adding an entire group of nodes or not)

Graph Degeneracy for Keyword Extraction

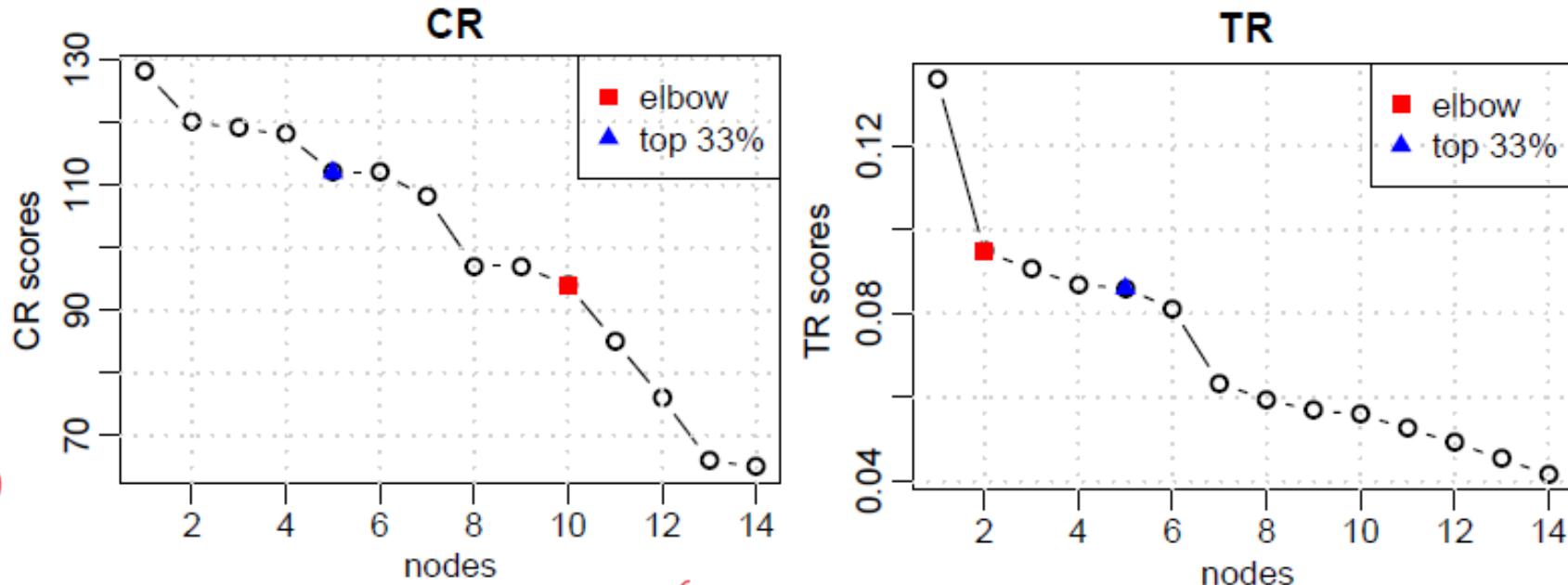
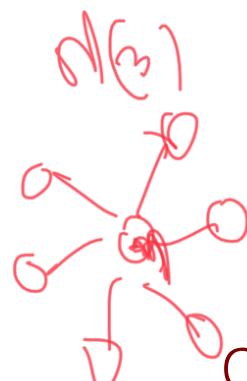


How to work at the node level while still retaining the valuable cohesiveness information captured by degeneracy?

- **inf**: go down the hierarchy as long as the shells increase in size (starting at the main – 1 level)

Problem: both methods work at the subgraph level -> lack flexibility for large graphs (adding an entire group of nodes or not)

CoreRank



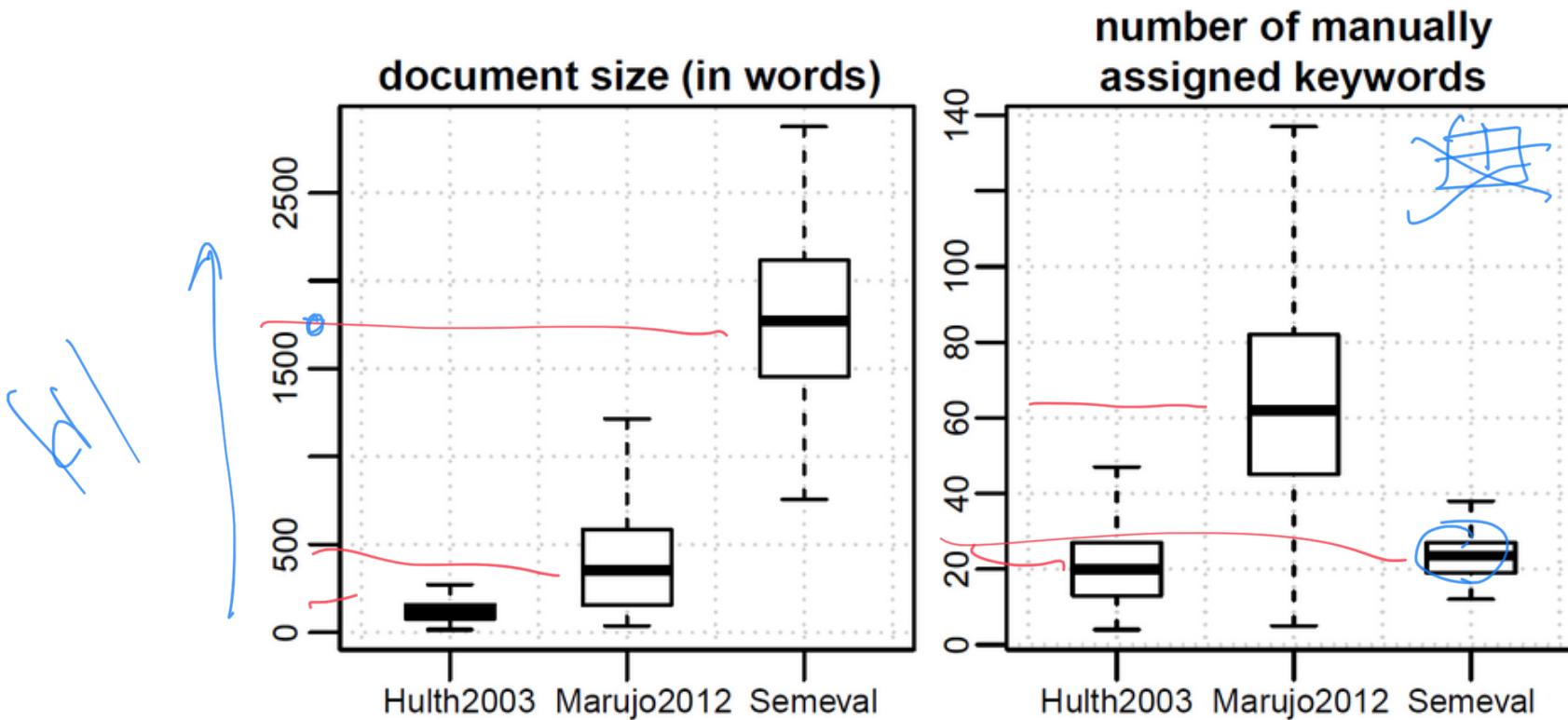
CoreRank (CR):

$$CR(n_i) = \sum_{j \in N(i)} K(n_j)$$

- Assign to each node the sum of the core (or truss) numbers of its neighbors
- Granularity is much finer and allows for much flexible selection
- Comparable to applying PageRank to the graph-of-words (aka TextRank) but taking into account cohesiveness concerns rather than individual prestige only

Heuristics: nodes can be selected based on the elbow or top p% method

CoreRank – Experimental Evaluation (1/2)



Datasets

- Hulth2003: 500 abstracts from the Inspec physics & engineering database
- Marujo2012: 450 web news stories covering 10 different topics
- Semeval: 100 scientific papers from the ACM

CoreRank – Experimental Evaluation (2/2)



	precision	recall	F1-score
dens	48.79	72.78	56.09*
inf	48.96	72.19	55.98*
CRP	61.53	38.73	45.75
CRE	65.33	37.90	44.11
main [†]	51.95	54.99	50.49
TRP [†]	65.43	41.37	48.79
TRE [†]	71.34	36.44	45.77

Hulth2003, K-truss, $W = 11$. *stat. sign.
($p < 0.001$) w.r.t. all baselines[†]

	precision	recall	F1-score
dens	47.62	71.46	52.94*
inf	53.88	57.54	49.10*
CRP	54.88	36.01	40.75
CRE	63.17	25.77	34.41
main [†]	64.05	34.02	36.44
TRP [†]	55.96	36.48	41.44
TRE [†]	65.50	21.32	30.68

Marujo2012, k-core, $W = 13$. *stat. sign.
($p < 0.001$) w.r.t. all baselines[†]

	precision	recall	F1-score
dens	8.44	79.45	15.06
inf	17.70	65.53	26.68
CRP	49.67	32.88	38.98*
CRE	25.82	58.80	34.86
main [†]	25.73	49.61	32.83
TRP [†]	47.93	31.74	37.64
TRE [†]	33.87	46.08	37.55

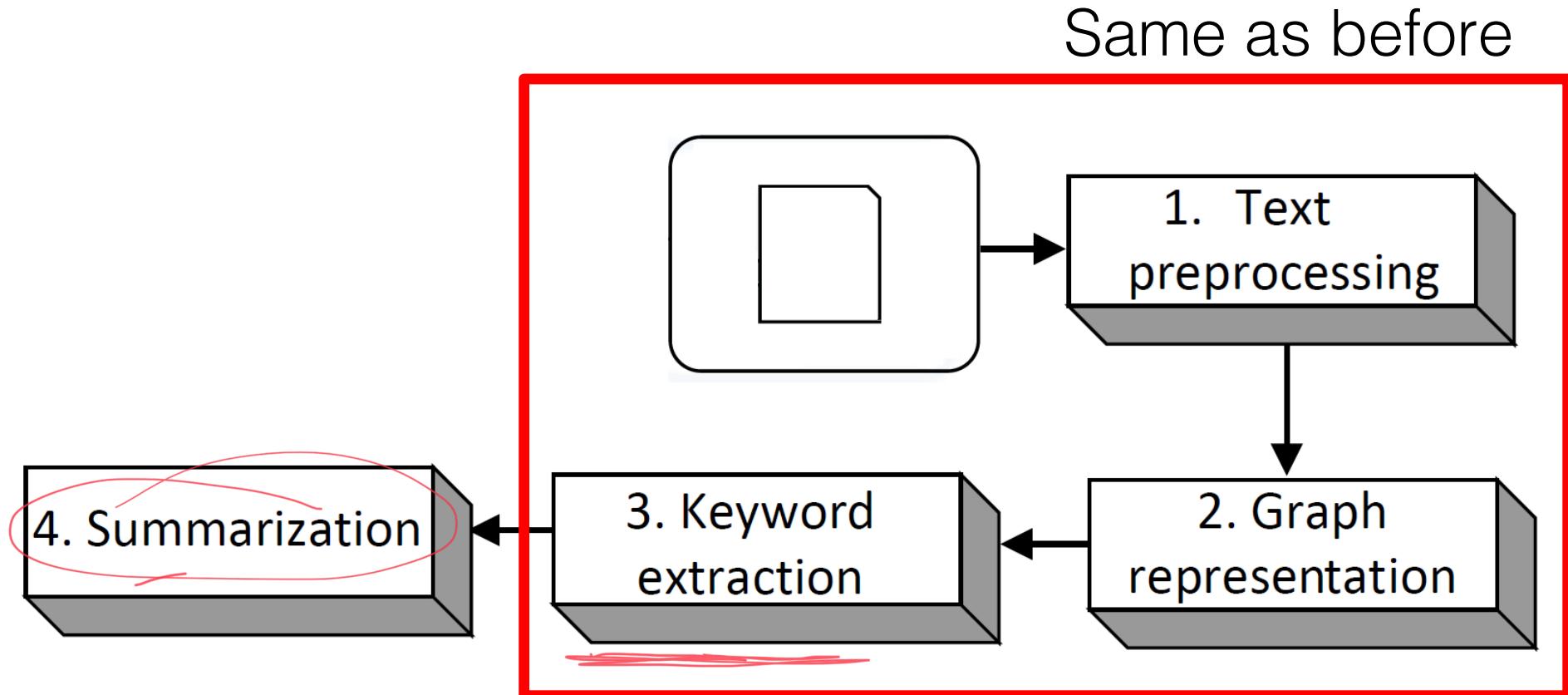
Semeval, K-truss, $W = 20$. *stat. sign.
($p < 0.001$) w.r.t. main

- For small documents (i.e., small graphs), the subgraph-level heuristics significantly outperform main core retention (main) and TextRank (TRP, TRE)
- Recall is drastically improved, precision is maintained (especially with inf)
- For long documents (Semeval), the node-level heuristics are better
- CoreRank with top p% retention (CRP) reaches best performance

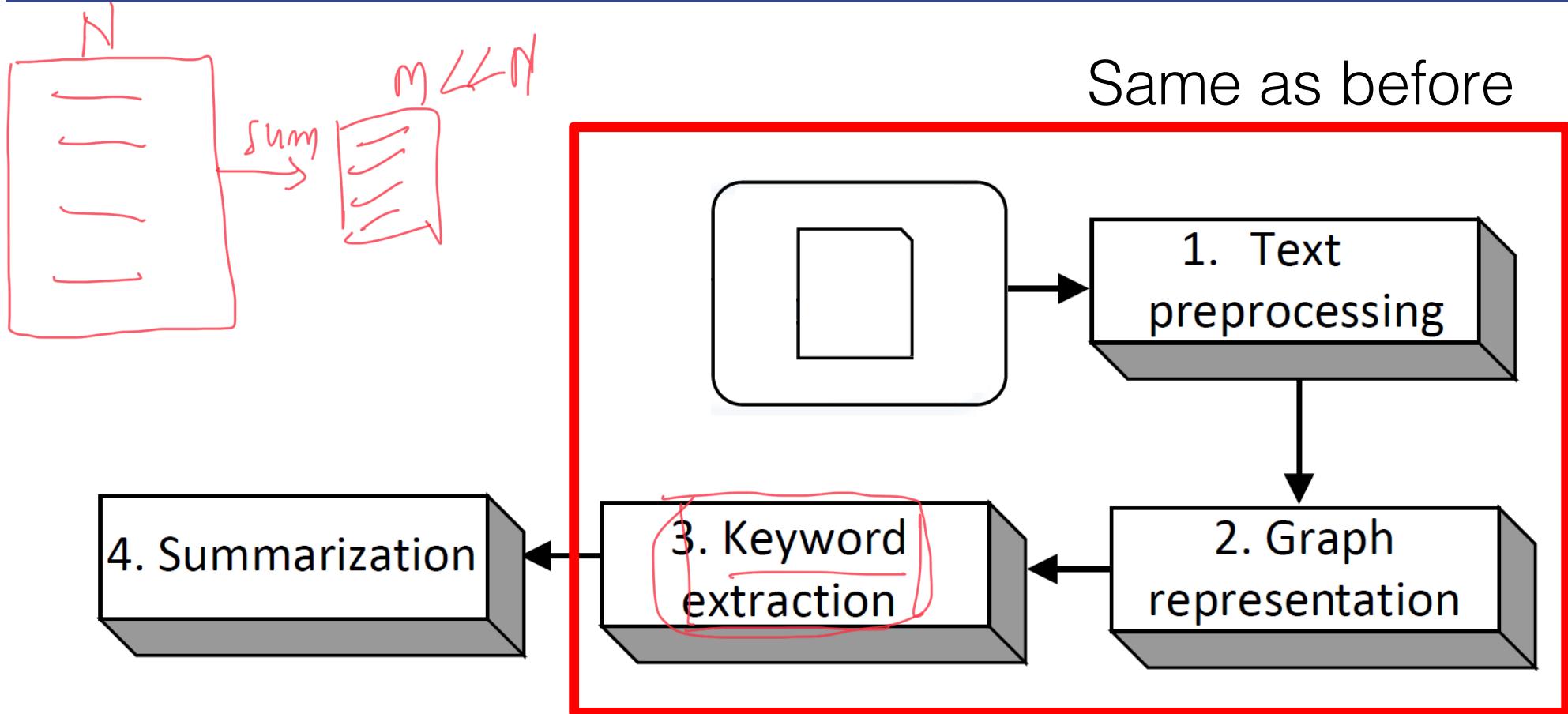
Extractive summarization



Extension to Extractive Document Summarization



Extension to Extractive Document Summarization



How to use keywords (and their scores) to select the best sentences in a document?

Extractive Document Summarization (1/4)

- Generating a summary in an extractive way is akin to selecting the best sentences in the document under a budget constraint (max number of words allowed)
- Combinatorial optimization task:

$$\overbrace{\arg \max_{S \subseteq V} F(S)} \mid \sum_{v \in S} c_v \leq \overbrace{B}$$

- S is a given summary (a subset of the set of sentences V)
- F is the objective function to maximize (measuring summary quality)
- c_v is the cost of sentence v (number of words it contains)
- B is the budget (in words)

Extractive Document Summarization (2/4)

$$\arg \max_{S \subseteq V} \underline{F(S)} \mid \sum_{v \in S} c_v \leq B$$

- Solving this task is NP-complete
- It has been shown that if F is non-decreasing and submodular, a greedy algorithm can approach the best solution with factor $(e - 1)/e$
- At each step, the algorithm selects the sentence v that maximizes:

objective function gain



$$\frac{F(G \cup v) - F(G)}{c_v^r}$$

scaled cost



$$c_v^r$$

- r is a tuning parameter

Extractive Document Summarization (3/4)

$$\arg \max_{S \subseteq V} F(S) \mid \sum_{v \in S} c_v \leq B$$

- The choice of F , the **summary quality objective function**, is what matters
- A good summary should cover all the important topics in the document, while not repeating itself
 - Maximize **coverage**
 - Penalize **redundancy** (reward diversity to ensure monotonicity)

$$F(S) = L(S) + \lambda R(S)$$

$$L(S) = \sum_{i \in S} n_i w_i$$

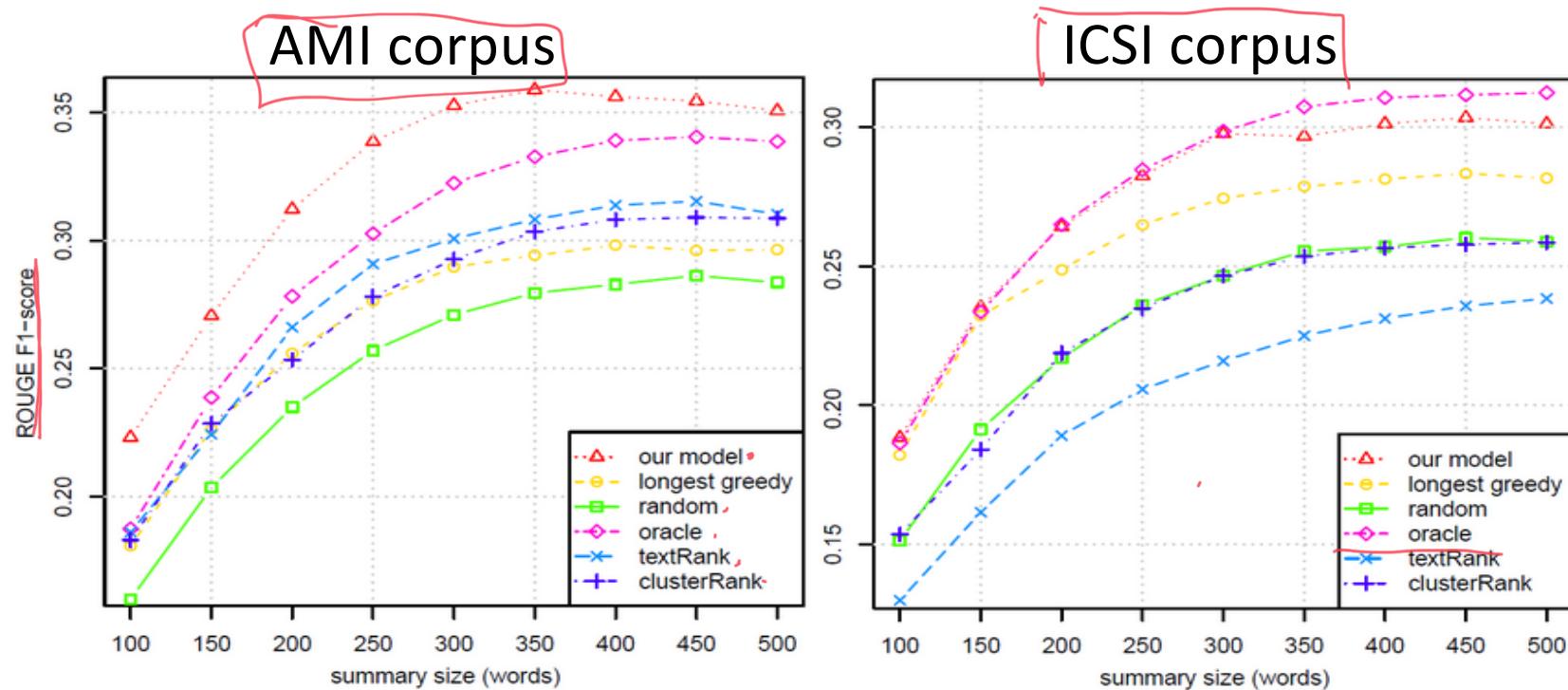
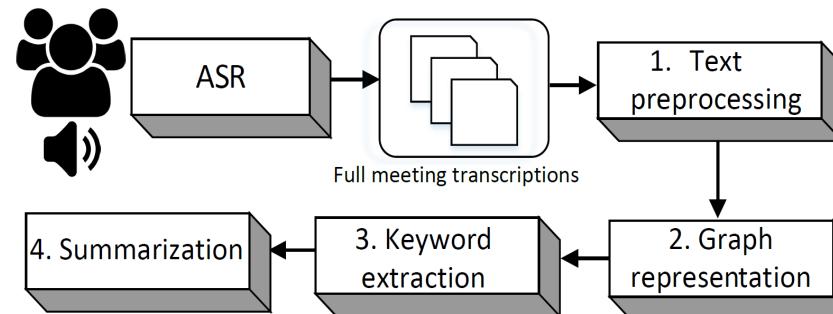
weighted sum of the keywords
contained in the summary

$$R(S) = \underbrace{N_{\text{keywords} \in S}} / \underbrace{N_{\text{keywords}}}$$

proportion of unique keywords
contained

Extractive Document Summarization (4/4)

Tested for multiparty virtual meetings summarization:



Event detection in text streams

1: Threshold based approach

Introduction - Twitter

- Very popular microblogging service
 - 330 million active users
- Real time messages known as tweets
 - Instantaneous nature
 - Major communication medium
- Why Twitter
 - Large variety of usages: communication, news, politics, celebrities
 - Huge volume of data
 - Transmission in real time

Introduction - Event Detection

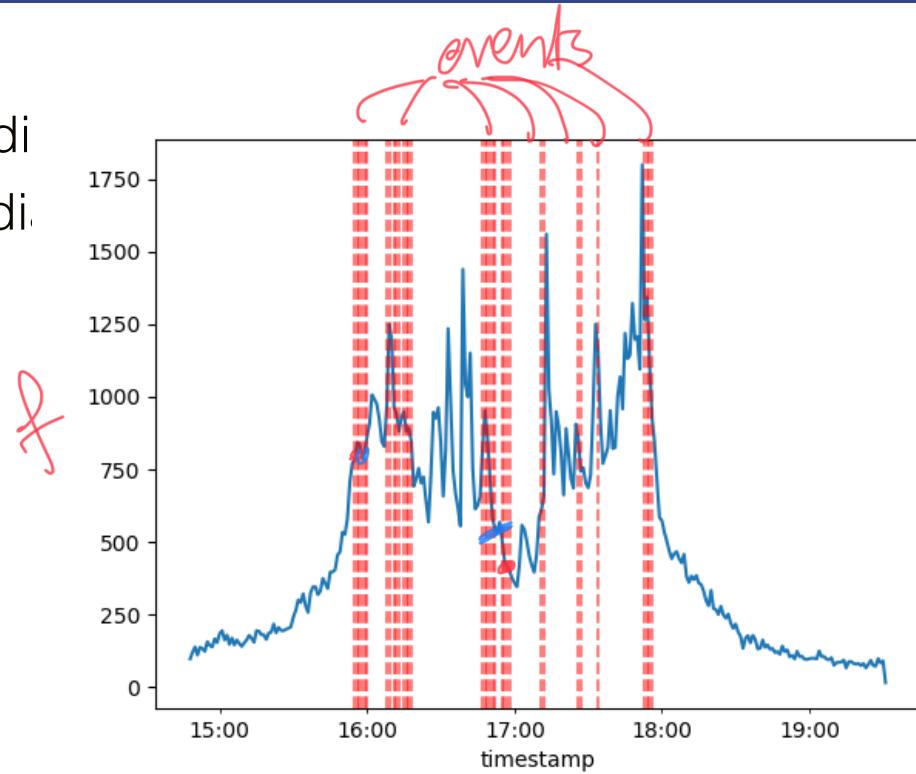
- Users report latest news or comment about real-world events
 - Events consisting of a sequence of important moments
 - Events not covered systematically by traditional media
 - Interest in tracking the evolution of an event
- Challenges:
 - Huge volume of tweets - Noisy content
 - Heterogeneous users
 - Multiple hashtags per event
 - Generating short summary

Sub-event Detection in Twitter Streams

1. Large volume of documents in social medi
2. Events are not covered by traditional medi
3. News appear fast in Twitter
4. Is Tweet rate suited for sub-event
Detection?

Events in FB match

- goal
- red/yellow card
- begin/end match
- penalty
- beg/end of match

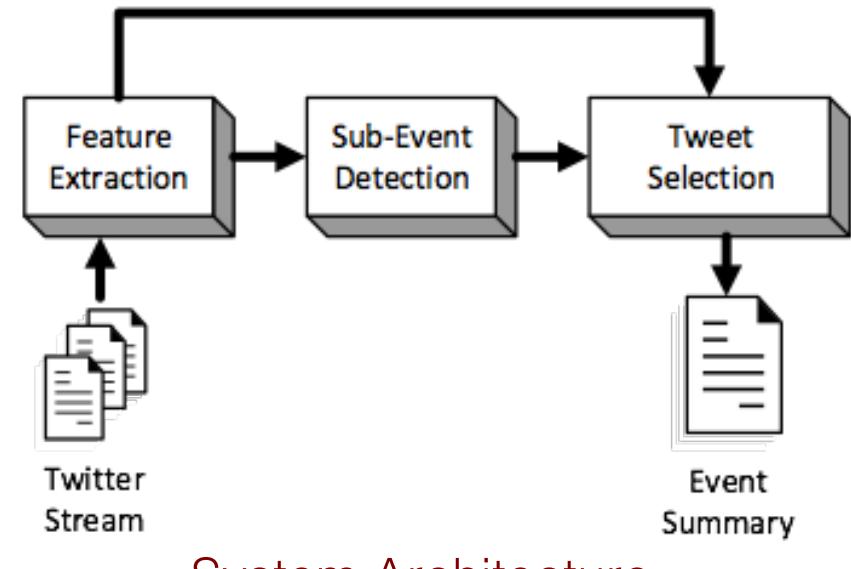


- Tweet Rate of a football Match
- Red lines: True Events
- Very noisy during the event!

Sub-event Detection in Twitter Streams

Real time event summarization

1. **Feature extraction:** extracts the terms that best describe the current state of the event
1. **Sub-event detection:** decides whether a sub-event has occurred
1. **Tweet selection:** ranks all the tweets and selects the first one



- Steps are repeated every 60 seconds
- The summary of the whole event is constructed by aggregating the individual sub-event descriptions

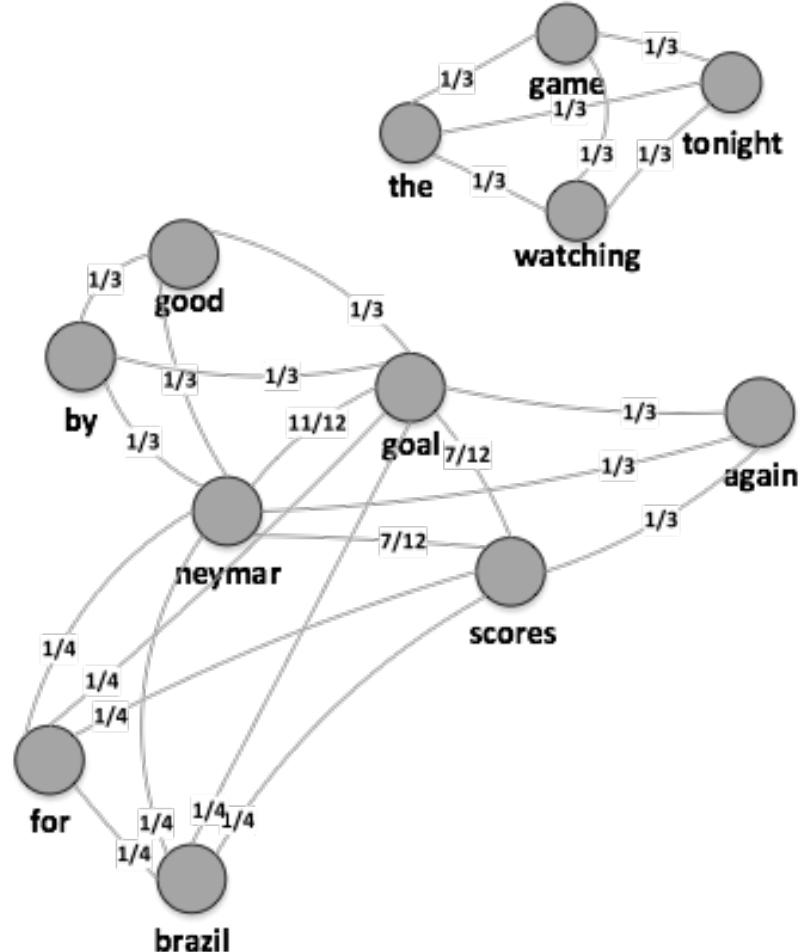
Graph-based Representation of Tweets

- Represents all the input tweets
- Nodes: unique terms
- Edges: #co-occurrences within a tweet

Example graph

1. Good goal by Neymar
2. Goal! Neymar scores for brazil
3. Goal!! Neymar scores again
4. Watching the game tonight

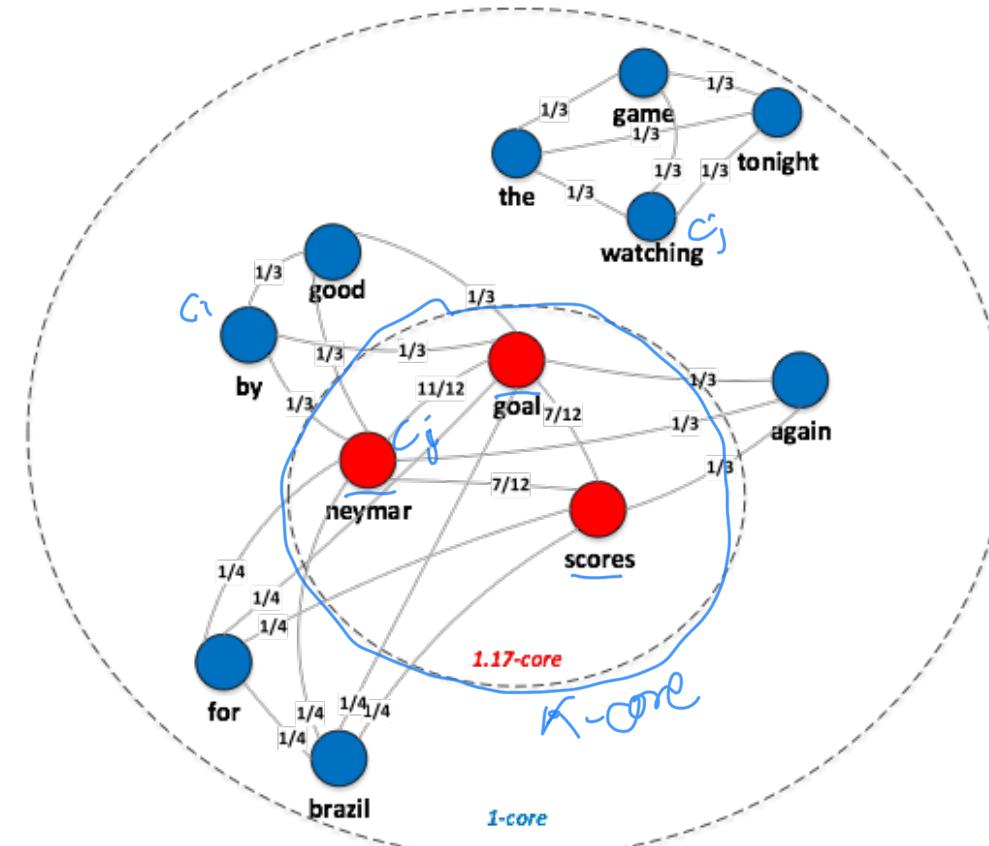
ML 2014 {
Dataset: tweets from the 2014 FIFA
World Cup in Brazil



The graph that was built from 4 tweets

k-core Decomposition for Feature Extraction

- Each term is given a score corresponding to its core number
 - Extract the k-core subgraph
 - Detect sub-events by considering how the sum of the core numbers extracted from the graph at time **t** has changed from a previous time point **t-1**

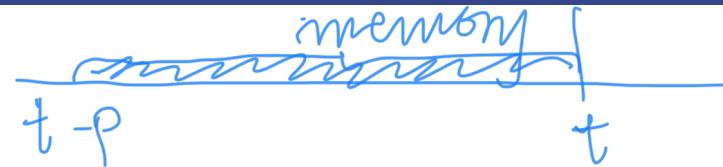


k-core decomposition of the Graph-of-Words

Sub-event Detection

$$\sum_{i=1}^d c_i^t > \theta \times \frac{1}{p} \sum_{j=t-p}^{t-1} \sum_{i=1}^d c_i^j$$

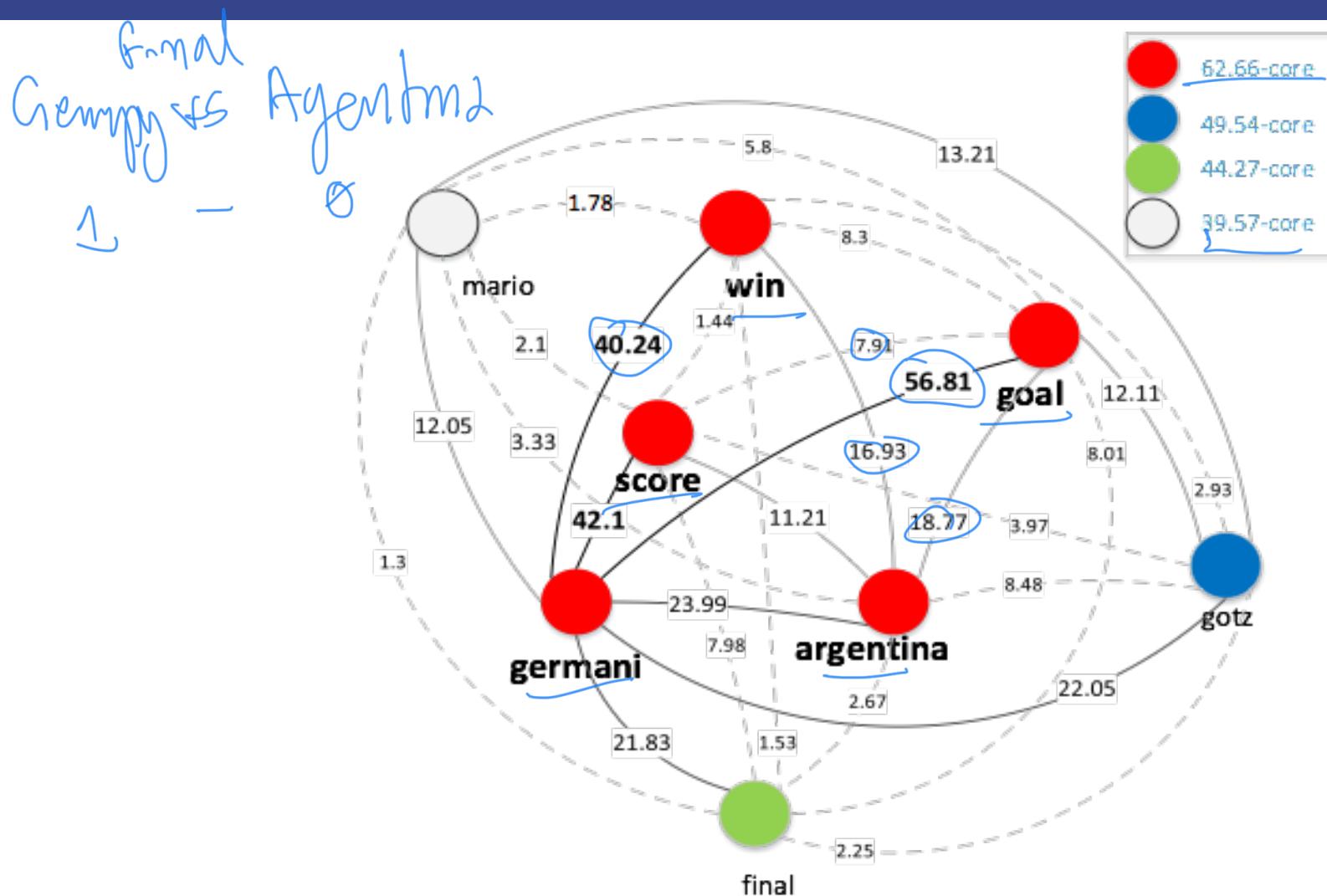
c_i^t Core number of term at time slot
 d Number of terms selected
 θ Decision Threshold
 p Number of previous time slots



Sub-event Detection steps:
(every 60 seconds)

1. Extract the top d terms with highest weights
2. Sum the term weights
3. If it exceeds the threshold a sub-event is detected

Germany's Goal - 2014 World Cup



Snapshot of the four highest cores of the graph generated after
Germany's goal in the 2014 FIFA World Cup final

Tweet Selection as Sub-event Summarization

- Activated only if a sub-event has been detected
- Tweets are scored based on the **sum of their term weights**
- Selects the most informative tweet of the sub-event
 - The tweet with the highest score is chosen

Experimental Setup



Dataset

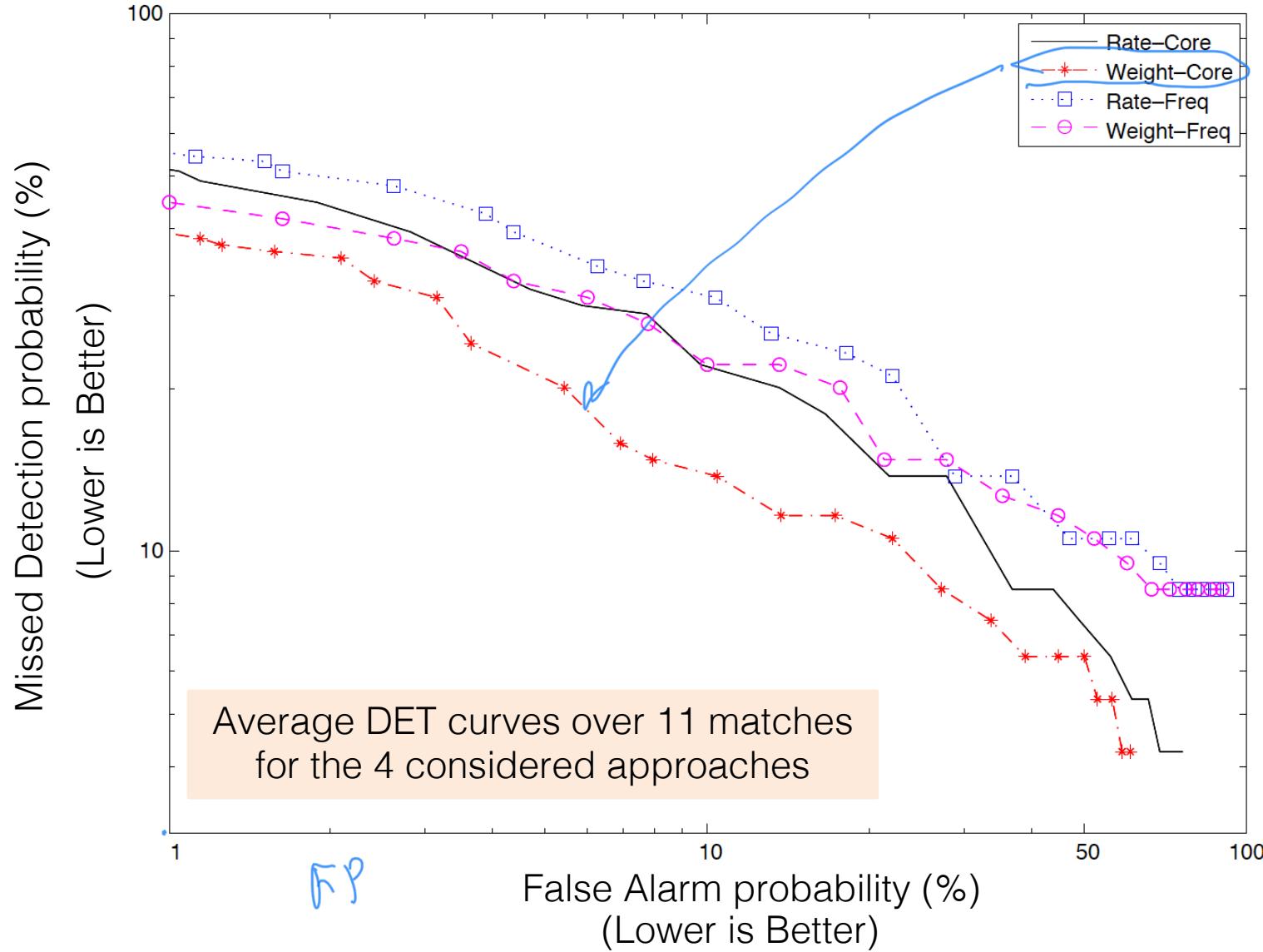


Match	#sub-events	#tweets
Germany - Argentina	8	1,907,999
Argentina - Belgium	7	1,355,472
France - Germany	6	1,321,781
Honduras-Switzerland	7	168,519
Greece - Ivory Coast	10	251,420
Croatia - Mexico	11	600,776
Cameroon - Brazil	11	532,756
Netherlands - Chile	7	301,067
Australia - Spain	9	252,086
Germany - Ghana	8	718,709
Australia - Netherlands	11	126,971
All Matches	95	7,537,556

FIFA 2014 World Cup Dataset

Evaluation (1/2)

FP



Evaluation (2/2)

Method	Micro F1-score	Macro F1-score
Weight-Core	0.68	0.72
Rate-Core	0.61	0.63
Weight-Freq	0.61	0.64
Rate-Freq	0.54	0.60

Average micro and macro F1-score over 11 matches for the 4 considered approaches

Event type	#actual Events	#detected Events
Goal	32	30
Penalty	2	2
Red Card	1	0
Yellow Card	27	14
Match Start	11	8
Match End	11	11
Half Time	11	10

Number of sub-events detected

Tweet Summarization Performance

Time	Summary	ESPN FC
8'	Goal!!!!Argentina!! After eight minutes Argentina lead Belgium by 1-0 scored by Higuain	Goal! Argentina 1, Belgium 0. Gonzalo Higuain (Argentina) right footed shot from the centre of the box to the bottom left corner.
45'+2'	HT: Argentina 1-0 Belgium. Fantastic goal by Higuain gives Argentina the slight lead over the red devils.	First Half ends, Argentina 1, Belgium 0.
52'	52m - Belgium's Eden Hazard with the first yellow card of the game	Eden Hazard (Belgium) is shown the yellow card for a bad foul.
75'	Argentina 1 - 0 Belgium Biglia booked a yellow card. Meanwhile, Chadli on for Eden Hazard.	Lucas Biglia (Argentina) is shown the yellow card for a bad foul.
90+5'	Well at least that goal makes them advance to the semi finals. Argentina gets the ticket to advance and Belgium goes home.	Match ends, Argentina 1, Belgium 0.

Summary of the Argentina vs. Belgium match generated automatically using Weight–Core and manually by ESPN

Summary

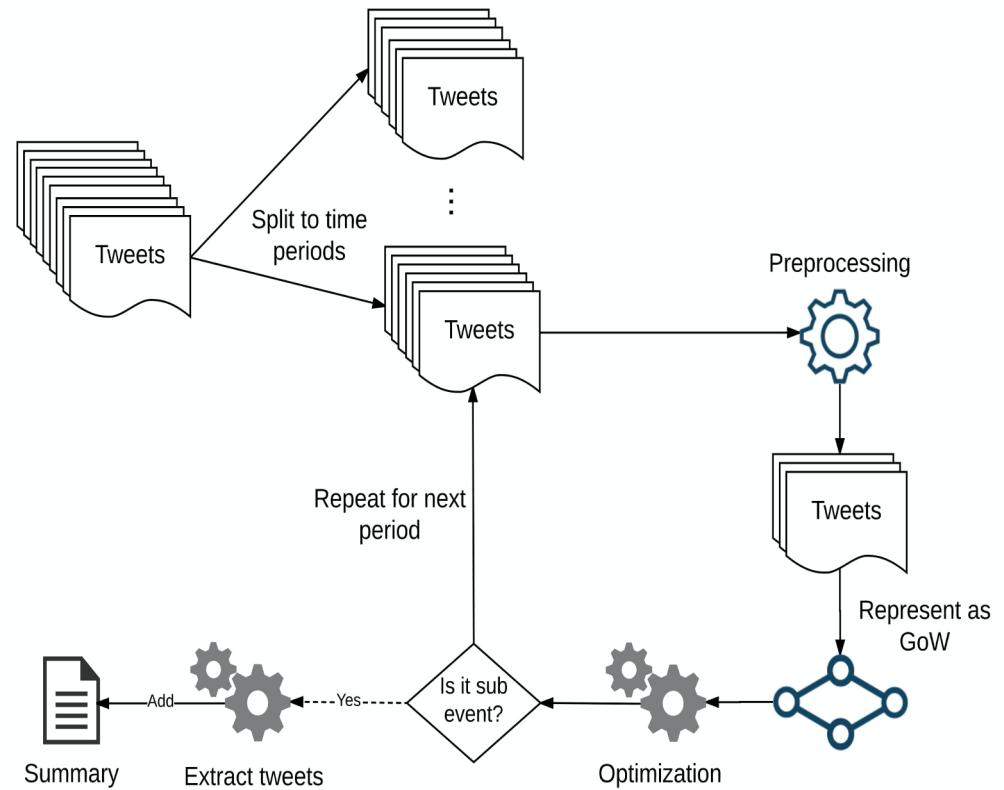
- Sub-event detection approach based on the k-core decomposition on graph-of-words
- The algorithm exploits the fact that the vocabulary of tweets gets more specific when a sub-event occurs
- The detection mechanism is able to accurately detect important moments as they occur
- The tweets selected by our system give an overview of the event

Event detection in text streams

**2: An Optimization Approach for
Sub-event Detection and Summarization in
Twitter**

Introduction - System Architecture

- Tweets decomposition into time intervals
- Graph of Words representation
- Convex optimization formulation
- Summarization



Methodology - Data Preprocessing

Given a set of raw tweets:

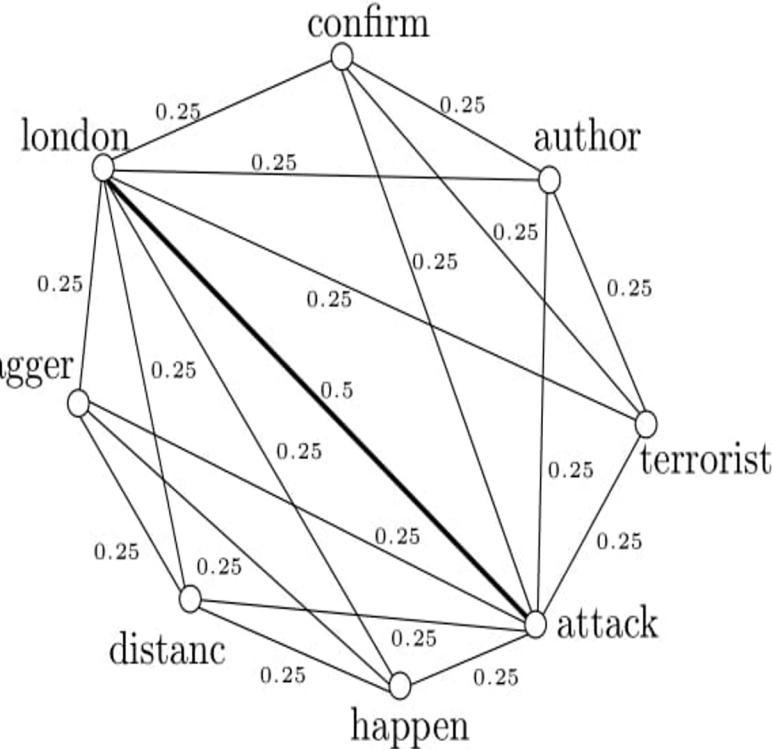
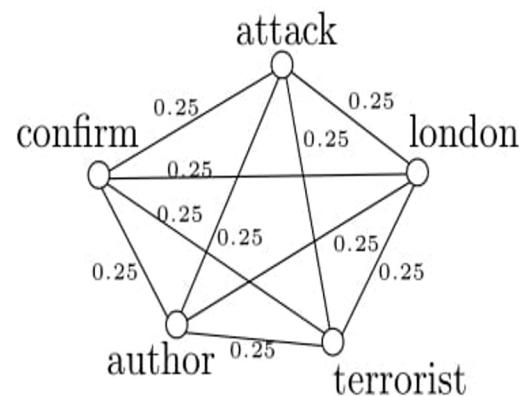
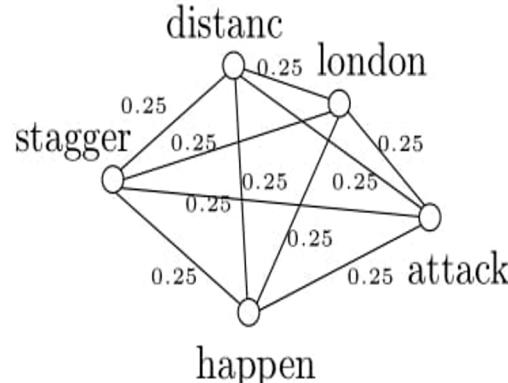
- Remove not relevant tweets
 - Retweets
 - Duplicates
 - Mentions
- Text preprocessing:
 - Tokenization
 - Stopword removal
 - Punctuation, special character and URL removal
 - Stemming using Porter's algorithm

Methodology - Graph of Words

Given a set of pre-processed tweets:

- Each tweet represented as a weighted graph
 - Vertices correspond to unique terms
 - Edges are drawn between all pairs of vertices (clique)
 - Weight set equal to $1/(n-1)$ n : number of unique terms in the tweet
 - The degree of all vertices is equal to 1
- Creating a graph G_i corresponding to the time period i
 - Add tweet-graphs sequentially
 - Increase weight of edges occurring in multiple tweets

Methodology - Graph of Words



Methodology - Sub-Event Detection

Sub-Event detection:

- Change rate among tweets posted currently compared to previous time periods
- Pairs of words with high co-occurrence frequency.
- Detection handled as *optimization problem*
 - For time period i , graph G_i
 - Adjacency Matrix $\mathbf{A}_i \in \mathbb{R}^{n \times n}$
 - Represents co-occurrence among words in tweets
- b is the n^2 rows matrix representing as well the co-occurrence of words in the tweets in the periods $1-p$

$$\mathbf{A}_i = \begin{bmatrix} | & | & & | \\ \mathbf{a}_1 & \mathbf{a}_2 & \dots & \mathbf{a}_n \\ | & | & & | \end{bmatrix}$$

$$\mathbf{b} = \text{vec}(\mathbf{A}_i) = \begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \\ \vdots \\ \mathbf{a}_n \end{bmatrix}$$

Methodology - Sub-Event Detection

- Construct matrix \mathbf{W} with weights from previous p periods
- each \mathbf{w}_i represents the co-occurrence weights of all terms in the graph time i (summarizing previous tweets)

$$\mathbf{W} = \begin{bmatrix} & & \\ | & & | \\ \mathbf{w}_{i-p} & \dots & \mathbf{w}_{i-1} \\ | & & | \end{bmatrix} \quad \mathbf{W} \in \mathbb{R}^{n^2 \times p}$$

- Optimization problem formulated as:
- \mathbf{x} represents the vector that matches best the current to the previous p time
- Event: large values of objective function
 - when $OF > \theta$ event

$$\begin{aligned} & \min_{\mathbf{x}} \frac{1}{2} \|\mathbf{W}\mathbf{x} - \mathbf{b}\|_2^2 \\ \text{s.t. } & \mathbf{1}^\top \mathbf{x} = 1 \\ & x_i \geq 0, \quad \forall i = 1, \dots, p \end{aligned}$$

Methodology - Summarization (1/2)

Extractive summarization algorithm → Select a subset of tweets

These tweets will serve as the summary of the sub-event

Goal: Selected tweets containing most significant terms of the detected sub-event

- Define a monotone sub modular function f that rewards both the **coverage** and the **diversity** of the set
- proposed function f can identify multiple sub-events in a single time period

Methodology - Summarization (2/2)

A sub-event is best described by tweets whose graph-of-words contains multiple “important” edges

G_i : graph-of-words representation of tweets posted during time period i

$\mathcal{S} \subseteq D_i$: a set of tweets extracted from time period i

$f(\mathcal{S})$: the sum of weights of the edges of $G_i^{\mathcal{S}}$ that are “covered” by tweets belonging to \mathcal{S}

f is monotone non-decreasing and submodular \rightarrow use greedy approximation algorithm

- guaranteed to be within $(1 - 1/e) \approx 0.63$ of the optimal solution

Evaluation - Experiments

Baseline method

- Tweeting rate (Burst)
 - Number of tweets in period
 - Ignores previous periods

Evaluation settings:

- Threshold: Training process
- Period duration: 1 min
- Number of previous periods: 10 periods

Evaluation - Dataset

- 18 FIFA World Cup 2014 and 2 FIFA World Cup 2010 matches
 - 3 used for tuning and the rest for testing
- Only some sub-event types considered
 - goals, penalties, cards, match start, match end and half time
 - injuries, substitutions, free kicks etc. ignored
- Groundtruth
 - Manual annotation of events

Match	Actual Events	Collected Tweets	Preprocessed Tweets
ARG - BEL	7	313,803	108,250
ARG - GER	9	824,241	262,112
AUS - NED	12	96,834	25,997
AUS - ESP	9	86,843	13,608
BEL - KOR	7	99,192	32,053
CMR - BRA	11	148,298	35,085
FRA - GER	6	525,725	160,727
FRA - NGA	6	367,899	128,718
GER - ALG	8	712,525	276,227
GER - BRA	12	973,985	295,875
GER - GHA	8	285,804	77,449
GER - USA	7	256,445	86,040
GRE - CIV	10	113,402	51,101
HON - SUI	8	41,539	10,082
MEX - CRO	11	155,549	36,981
NED - CHI	8	95,108	25,819
NED - MEX	10	628,698	217,472
POR - GHA	10	272,389	91,110
GER - SRB	14	45,024	29,062
USA - SVN	12	85,675	53,292
Total	185	6,128,978	2,017,060

Parameter Tuning

- Relationship between the optimal value of θ and the number of tweets
- Randomly selected 3 matches as training examples
 - 17 matches were placed into the test set
- Exhaustive grid search, $\theta \in [1, 100]$
- Minimize the least-squares-error

$$\hat{\theta} = w_1x^2 + w_2x + w_3$$

Evaluation - Results

Method \ Metric	Macro-average			Micro-average		
	precision	recall	f1-score	precision	recall	f1-score
OptSumm	0.76	0.75	0.75	0.73	0.74	0.73
Burst	0.78	0.54	0.64	0.72	0.54	0.62

- Evaluate the proposed system (OptSumm) on the task of sub-event detection
- Standard measures in information retrieval
 - 1) Precision
 - 2) Recall
 - 3) F1-score
- OptSumm detected sub-events that could not be detected by Burst,

Evaluation - Sub-events Detected

- Key sub-event types, their actual numbers and detected numbers over the 17 matches of the test set
- Successfully detected all goals, own goals, penalties and red cards
- Successfully detected all match ends and half times, and almost all match starts
- failed to detect the yellow cards consistently

Event type	# actual events	# detected events
Goal	42	42
Own Goal	2	2
Penalty	3	3
Red Card	3	3
Yellow Card	51	15
Match Start	17	14
Match End	17	17
Half Time	17	17

Evaluation - Summary

- System produces informative and reasonable textual descriptions of the important moments.

Our Summary	FIFA
Underdog Nigeria vs. European giants France. Going to be a great match!	The match kicks off.
Nigeria awarded a free kick in a good position after Matuidi collides with Odemwingie. Nigeria looking decent on the break so far. #fra #nga	Matuidi (France) concedes a free-kick following a challenge on Odemwingie (Nigeria).
France #fra 0-0 Nigeria #nig - Nigeria with Emenike score, but ruled out for offside, good decision 18mins	Emenike (Nigeria) is adjudged to be in an offside position.
Pogbaaaaa!!! excellent skill! made that entire move and ended it with a superb volley but keeper made a good save	Pogba (France) sees his effort hit the target.
Half time: France 0-0 Nigeria. Goalless in brasília. tight game.	The referee brings the first half to an end.
54: Blaise Matuidi gets the first yellow card of the game after a nasty challenge.	Matuidi (France) is booked by the referee.
Nigeria the best team by far. That usually means France will scrape a lucky win.	-
Omg! #Benzema so close to scoring, just 2? inches short. Still 0-0 (Nigeria-France) in a suddenly very exciting match!	Benzema (France) sees his effort hit the target.
If the French don't score in this game, it would be a miracle for Nigeria. France has been inches away from about 3 goals at this point.	-
Goal France! Who else, but the future, Paul Pogba, heading into an open net. Finally les blues score. 1-0, 80th min.	Pogba (France) scores!!
Gooool! France scores in the 91st minute! Partial score, France 2-0 Nigeria. #worldcup goal count - 147.	Yobo (Nigeria) scores an own goal!!
Full-time: #fra 2-0 #nga. France book their spot in the quarter-final while Nigeria crash out of the 2014 Fifa world cup	The final whistle sounds.

Evaluation - Other events

- Westminster bridge (London)
 - Terrorist attack on 22 March 2017
 - 5 people died, at least 50 were injured
- Collected 153, 485 tweets
 - Time period equal to 15 minutes
 - Taking into consideration only the previous period



Evaluation - Other events

Timestamp	Description
22 Mar 14:56	#BREAKING London Terror Attack - Parliament lockdown, man with knife shot by security. Many people ran down by car on Westminster Bridge. ◇ REPORTS AT LEAST 12 INJURED IN A CAR RAMMING/STABBING ATTACK OUTSIDE PARLIAMENT IN LONDON, UK. ASSAILANT SHOT BY POLICE.
22 Mar 15:26	#DEVELOPING: London police are treating the attack at Westminster near British Parliament "as a terrorist incident until we know otherwise.". ◇ #BREAKING Met confirm terror attack. Officer stabbed, shots heard at Parliament London. Many injured on Westminster Bridge hit by vehicle.
22 Mar 17:56	4 people dead, including police officer, and at least 20 injured in Parliament attack #Parliament London#terrorism. ◇ Thoughts with the victims of today's terrorist attack, their families & all those caught up at #Westminster. London will #KeepCalmAndCarryOn.
22 Mar 22:26	Metropolitan Police say 5 people have died and around 40 have been injured in the Westminster terror attack in London today #londonattack. ◇ 4 people including a terrorist and a police officer have been killed and 20 others injured in an terror attack in London.
23 Mar 10:26	Seven arrested as police raid addresses in Birmingham and London linked to Westminster terror attack #York. ◇ Mashable "Donald Trump Jr. tweeted about the London attack and got instantly dragged" #News.
23 Mar 11:56	BREAKING: Islamic State claims responsibility for terror attack outside Parliament in London #Westminster #londonattack. ◇ News agency linked to ISIS is out with a claim of responsibility from the terrorist organization for yesterday's deadly attack in #London.
23 Mar 15:26	Breaking: London police identify man behind UK terror attack as 52-year Khalid Masood, a Briton with a criminal history. ◇ London attack: Westminster terrorist named as Khalid Masood by Scotland Yard after Isil claims responsibility.

Summary

- Graphs have been widely used as modeling tools in
 - NLP
 - Text Mining
 - Information Retrieval
- Goal of the tutorial
 - Presentation of recent methods that rely on graph-based text representations to deal with various tasks in NLP and IR
 - Focus on the graph-of-words model
 - Borrow ideas from the graph mining and network analysis field

Graph based text Categorization

- Text Categorization as a Graph Classification ProblemMV Francois Rousseau, Emmanouil Kiagias **ACL 2015** 1, 1702-1712
- Shortest-path graph kernels for document similarityG Nikolentzos, P Meladianos, F Rousseau, Y Stavrakas, M Vazirgiannis, **EMNLP 2017**

Text Categorization as a Graph Classification Problem [ACL2015]

- Single-label multi-class text categorization
- **Graph-of-words** representation of textual documents
- Mining of frequent **subgraphs as features** for classification
- Main core retention to reduce the graph's sizes
- **Long-distance n-grams** more discriminative than standard n-grams

Applications of text classification are numerous:

- news filtering
- document organization
- spam detection
- opinion mining

Text documents classification compared to other domains:

- high number of features
- sparse feature vectors
- multi-class scenario
- skewed class distribution

Background

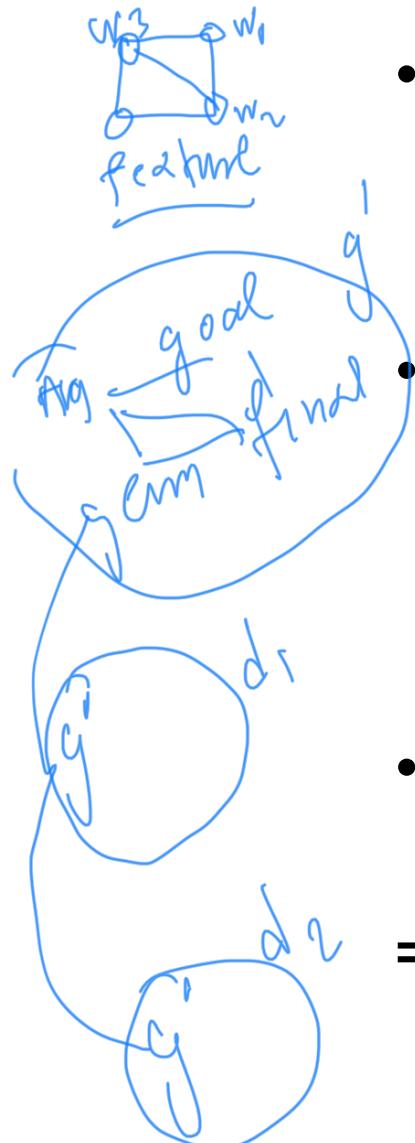
Text categorization [Sebastiani, 2002, Aggarwal and Zhai, 2012]

- Standard baseline: unsupervised n-gram feature mining + supervised linear SVM learning
 - Common approach for spam detection: same with Naive Bayes
- ⇒ n-grams to take into account some **word order** and some **word dependence** as opposed to unigrams
- ⇒ word inversion? subset matching?

Background

- Graph classification
 - subgraphs as features
 - graph kernels [Vishwanathan et al., 2010]
- Frequent subgraph feature mining
 - gSpan [Yan and Han, 2002]
 - FFSM [Huan et al., 2003]
 - Gaston [Nijssen and Kok, 2004]
- expensive to mine all subgraphs, especially for “large” collections of “large” graphs
⇒ unsupervised discriminative feature selection?

(Frequent itemsets, Association rules
Aggarwal 1994)



Subgraph-of-words

- A subgraph of size n corresponds to a long-distance n-gram \Rightarrow takes into account **word inversion** and **subset matching**
- For instance, on the R8 dataset, {bank, base, rate} was a discriminative (top 5% SVM features) long-distance 3-gram for the category “interest”
 - - “barclays bank cut its base lending rate”
 - - “midland bank matches its base rate”
 - - “base rate of natwest bank dropped”

!! patterns hard to capture with traditional n-gram bag-of-words.

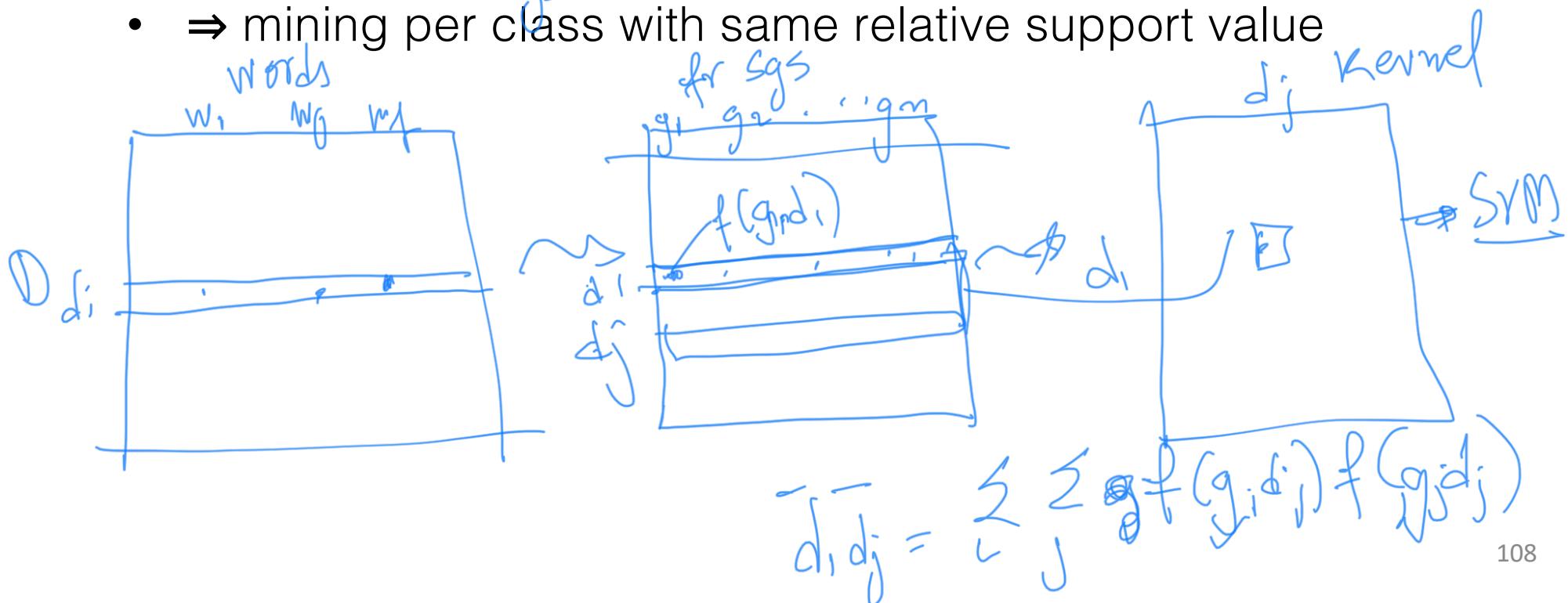
Graph of Words Classification

Unsupervised feature mining and support selection

- gSpan mines the most frequent “subgraph-of-words” in the collection of graph-of-words
- subgraph frequency == long-distance n-gram document frequency
- minimum document frequency controlled via a **support** parameter
- the lower the support, the more features but the longer the mining, the feature vector generation and the learning
- ⇒ unsupervised support selection using the **elbow method** (inspired from selecting the number of clusters in k-means)

Multiclass Scenario

- Text categorization ==
multiple classes + skewed class distribution + single overall support value (local frequency)
- 100k features for majority classes vs. 100 features for minority ones *Sgs*
- ⇒ mining per class with same relative support value



Main core mining and n-gram feature selection

- Complexity to extract all features! \Rightarrow reduce the size of the graphs
- Maintain word dependence and subset matching \Rightarrow keep the densest subgraphs
 - \Rightarrow retain the main core of each graph-of-words
 - use gSpan to mine frequent subgraphs in main cores
 - \Rightarrow extract n-gram features on remaining text (terms in main cores)

Experimental evaluation

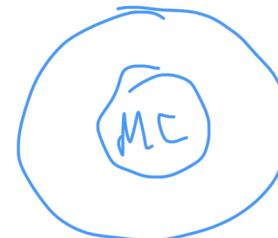
Standard datasets:

- WebKB: 4 most frequent categories among labeled webpages from various CS departments – split into 2,803 for training and 1,396 for test [Cardoso-Cachopo, 2007].
- R8: 8 most frequent categories of Reuters-21578, a set of labeled news articles from the 1987 Reuters newswire – split into 5,485 for training and 2,189 for test [Debole and Sebastiani, 2005].
- LingSpam: 2,893 emails classified as spam or legitimate messages – split into 10 sets for 10-fold cross validation [Androultsopoulos et al., 2000].
- Amazon: 8,000 product reviews over four different sub-collections (books, DVDs, electronics and kitchen appliances) classified as positive or negative – split into 1,600 for training and 400 for test each [Blitzer et al., 2007].

s(A)

Models

- 3 baseline models (n-gram features)
 - kNN (k=5)
 - Multinomial Naive Bayes (similar results with Bernoulli)
 - linear SVM
- 3 proposed approaches
 - gSpan + SVM (long-distance n-gram features)
 - MC + gSpan + SVM (long-distance n-gram features)
 - MC + SVM (n-gram features)



Evaluation metrics

- Micro-averaged F1-score (accuracy, overall effectiveness)
- Macro-averaged F1-score (weight each class uniformly)
- Statistical significance of improvement in accuracy over the n-gram SVM baseline assessed using the micro sign test ($p < 0.05$)
- For the Amazon dataset, we report the average of each metric over the four sub-collections

Effectiveness results (1/2)

Method	Dataset		WebKB		R8	
	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
kNN (k=5)	0.679	0.617	0.894	0.705		
NB (Multinomial)	0.866	0.861	0.934	0.839		
linear SVM	0.889	0.871	0.947	0.858		
gSpan + SVM	0.912*	0.882	0.955*	0.864		
MC + gSpan + SVM	0.901*	0.871	0.949*	0.858		
MC + SVM	0.872	0.863	0.937	0.849		

Table: Test accuracy and macro-average F1-score. Bold font marks the best performance in a column. * indicates statistical significance at $p < 0.05$ using micro sign test with regards to the SVM baseline of the same column. gSpan mining support values are 1.6% (WebKB) and 7% (R8).

Effectiveness results (2/2)

Method	Dataset		LingSpam		Amazon	
	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
kNN (k=5)	0.910	0.774	0.512	0.644		
NB (Multinomial)	0.990	0.971	0.768	0.767		
linear SVM	0.991	0.973	0.792	0.790		
gSpan + SVM	0.991	0.972	0.798*	0.795		
MC + gSpan + SVM	0.990	0.973	0.800*	0.798		
MC + SVM	0.990	0.972	0.786	0.774		

Table: Test accuracy and macro-average F1-score. Bold font marks the best performance in a column. * indicates statistical significance at $p < 0.05$ using micro sign test with regards to the SVM baseline of the same column. gSpan mining support values are 4% (LingSpam) and 0.5% (Amazon).

Dimension reduction – main core

full MC

Dataset	# n-grams before	# n-grams after	reduction
WebKB	1,849,848	735,447	60 %
R8	1,604,280	788,465	51 %
LingSpam	2,733,043	1,016,061	63 %
Amazon	583,457	376,664	35 %

Table: Total number of n-gram features vs. number of n-gram features present only in main cores along with the reduction of the dimension of the feature space on all four datasets.

Unsupervised support selection

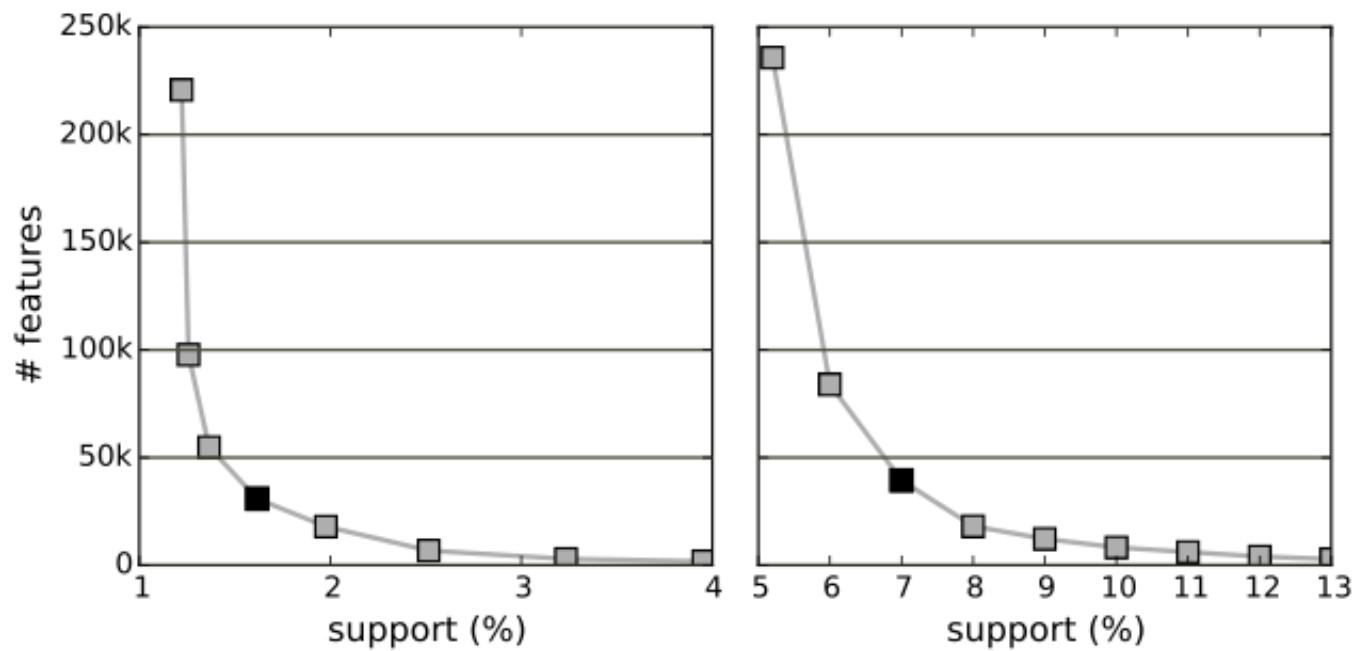


Figure: Number of subgraph features per support (%) on WebKB (left) and R8 (right) datasets. In black, the selected support chosen via the elbow method.

Distribution of mined n-grams

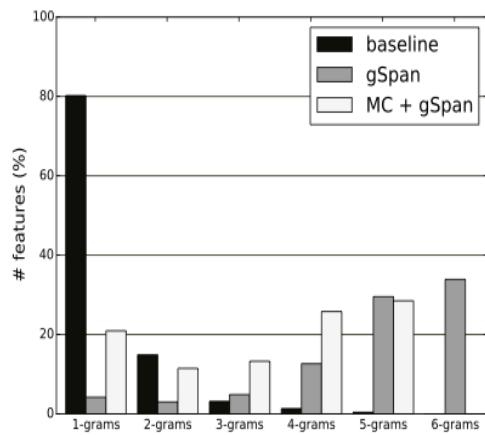


Figure: Distribution of n-grams (standard and long-distance ones) among all the features on WebKB dataset.

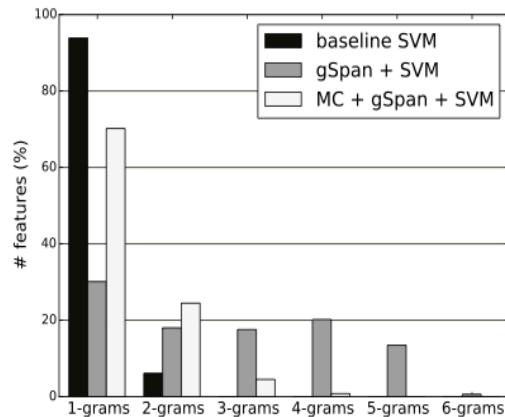


Figure: Distribution of n-grams (standard and long-distance ones) among the top 5% most discriminative features for SVM on WebKB dataset.

Contribution

- we explored a graph-of-words, to challenge the traditional bag-of-words for text classification.
- first trained a classifier using frequent sub- graphs as features for increased effectiveness.
- reduced each graph-of-words to its main core before mining the features for increased efficiency.
- reduced the total number of n-gram features considered in the baselines for little to no loss in prediction performances.

Shortest-Path Graph Kernels for Document Similarity (EMNLP 2017)

Bag Of Words

Traditionally, documents are represented as bag of words (BOW) vectors

- 1 entries correspond to terms
- 1 non-zero for terms appearing in the document

Example

- corpus vocabulary: {the, quick, brown, cat, fox, jumped, went, over, lazy, lion, dog}
- BOW representation of sentence: “the quick brown fox jumped over the lazy dog”

1	1	1	0	1	1	0	1	1	0	1
---	---	---	---	---	---	---	---	---	---	---

- However, BOW representation disregards word order!!!

Bag of n-grams

n-gram: a contiguous sequence of n words

For example, the previous sentence: “the quick brown fox jumped over the lazy dog“ contains the following tri-grams:

- | | |
|---------------------|--------------------|
| 1. the quick brown | 5. jumped over the |
| 2. quick brown fox | 6. over the lazy |
| 3. brown fox jumped | 7. the lazy dog |
| 4. fox jumped over | |

n-grams distinguish word order, however, they are *too strict*

- I unlikely that the same sequence of n word appears in independent documents

Graph of Words [Rousseau, 2013]

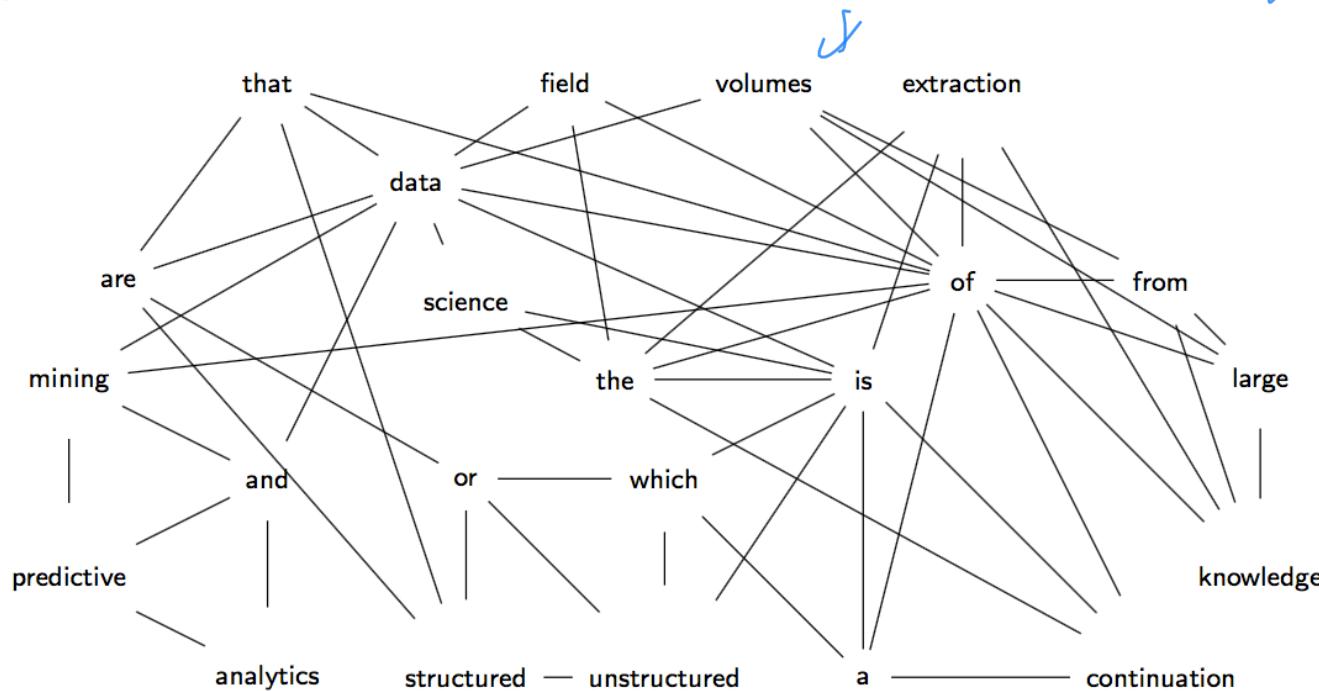
- Each document represented as a graph $G = (V, E)$ consisting of a set V of vertices and a set E of edges between them
- vertices → unique terms (i.e. pre-preprocessed words)
- edges → co-occurrences within a fixed-size sliding window no edge weight
- no edge direction

Graph representation more flexible than n-grams. It takes into account

- word inversion
- subset matching

Graph of Words Example

Data Science is the extraction of knowledge from large volumes of data that are structured or unstructured which is a continuation of the field of data mining and predictive analytics

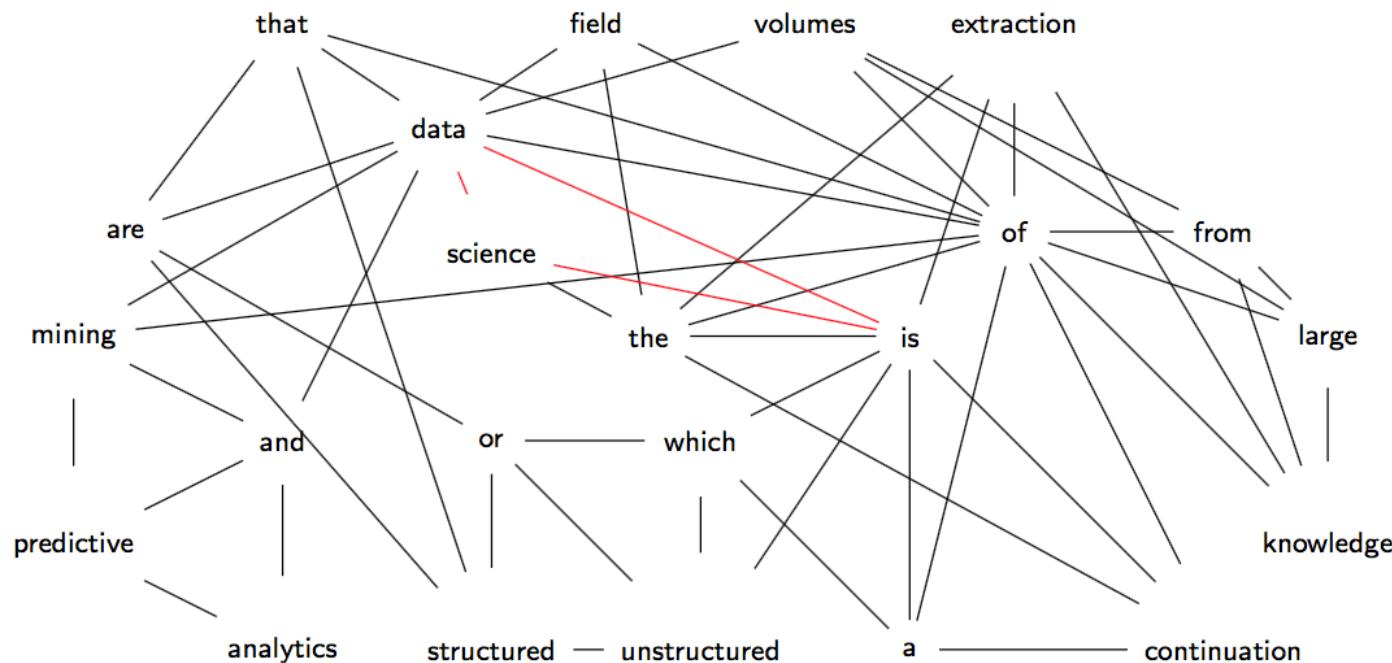


123

graph generator

Graph of Words Example

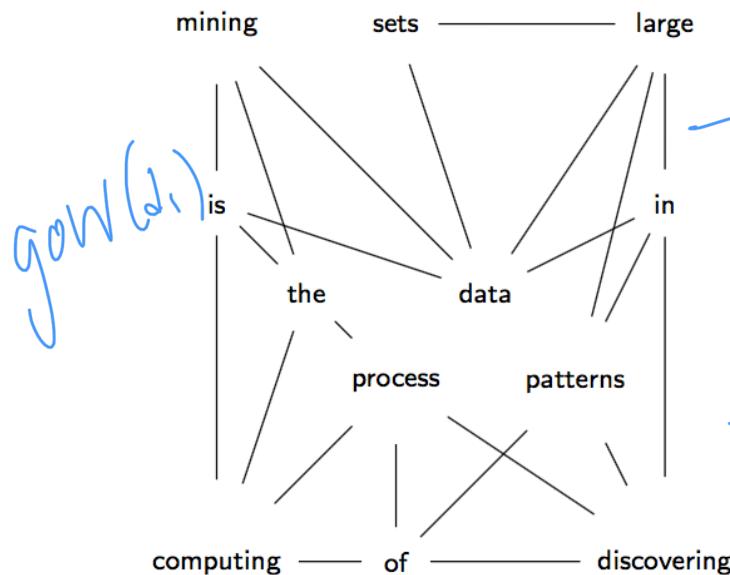
Data Science is the extraction of knowledge from large volumes of data that are structured or unstructured which is a continuation of the field of data mining and predictive analytics



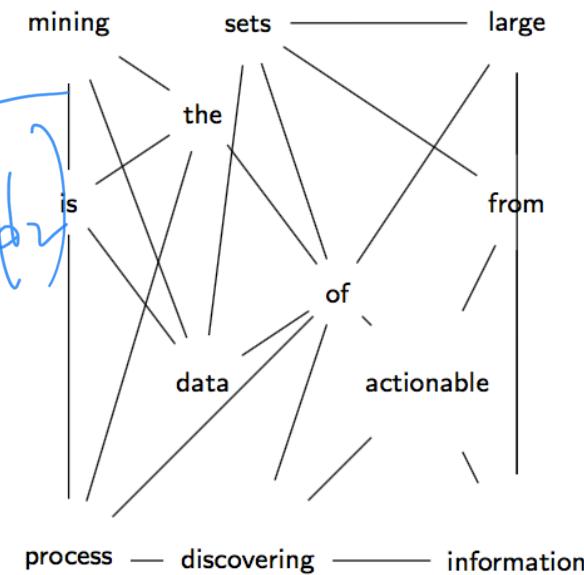
Document Similarity as Graph Comparison

$$\text{sim}(d_1, d_2) \leftarrow \text{tf-idf sm}$$

d₁ { Data mining is the computing process of discovering patterns in large data sets }



d₂ { Data mining is the process of discovering actionable information from large sets of data }



Hence, **document** similarity problem → **graph** comparison problem

Applications of Graph Comparison

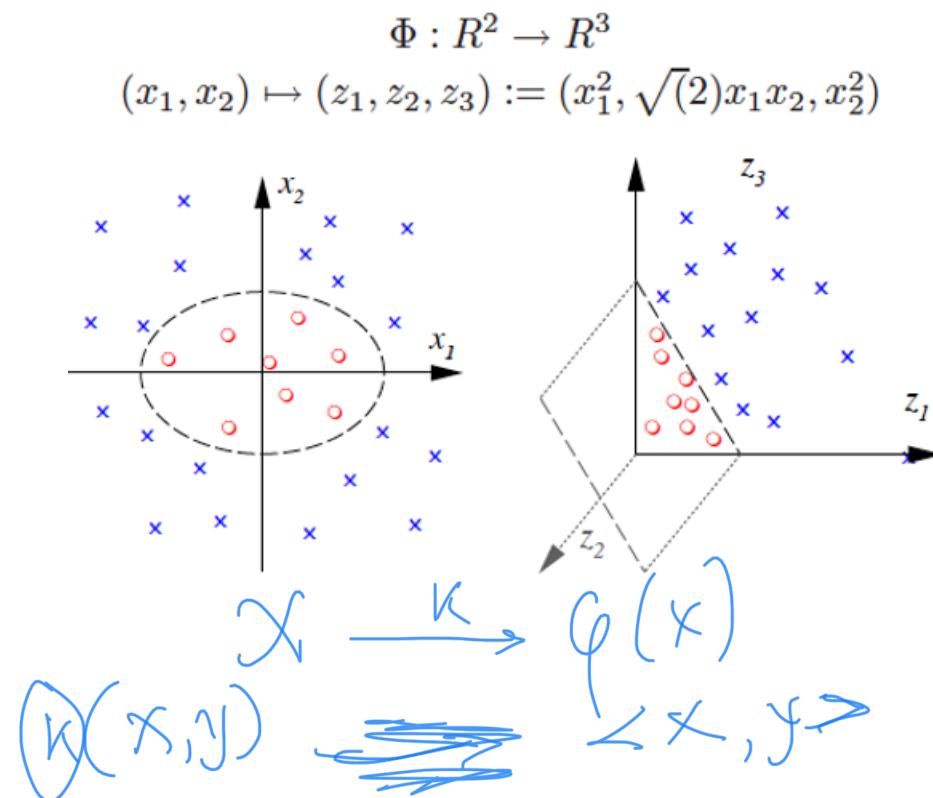
- Function prediction of chemical compounds
- Structural comparison and function prediction of protein structures
- Comparison of social networks
- Comparison of UML diagrams
- Document similarity

Approaches for Comparing Graphs

1. Graph isomorphism: find a mapping of the vertices of G_1 to the vertices of G_2 s.t. G_1 and G_2 are identical
 - No polynomial-time algorithm is known
 - Neither is it known to be NP-complete
2. Subgraph isomorphism: find if any subgraph of G_1 is isomorphic to a smaller graph G_2
 - NP-complete
3. Graph edit distance: count necessary operations to transform G_1 into G_2
 - Contains subgraph isomorphism check as one intermediate step
4. Graph kernels: compare substructures of graphs
 - Computable in polynomial time

Kernel Trick

The kernel trick avoids the explicit mapping that is needed to get linear learning algorithms to learn a nonlinear function or decision boundary



Kernels for Graphs

Graph representation of objects is advantageous compared to vectorial approaches :

- able to model relations between different parts of an object as well as the values of object properties
- The dimensionality of graphs is not fixed

Problem: How to compute kernels for structured data:

- Sequences
- Graphs

Custom Shortest Path Kernel

Based on the Shortest Path Kernel proposed by [Borgwardt and Kriegel, 2005]

Compares the length of shortest paths having the same source and sink labels in two graphs-of-words

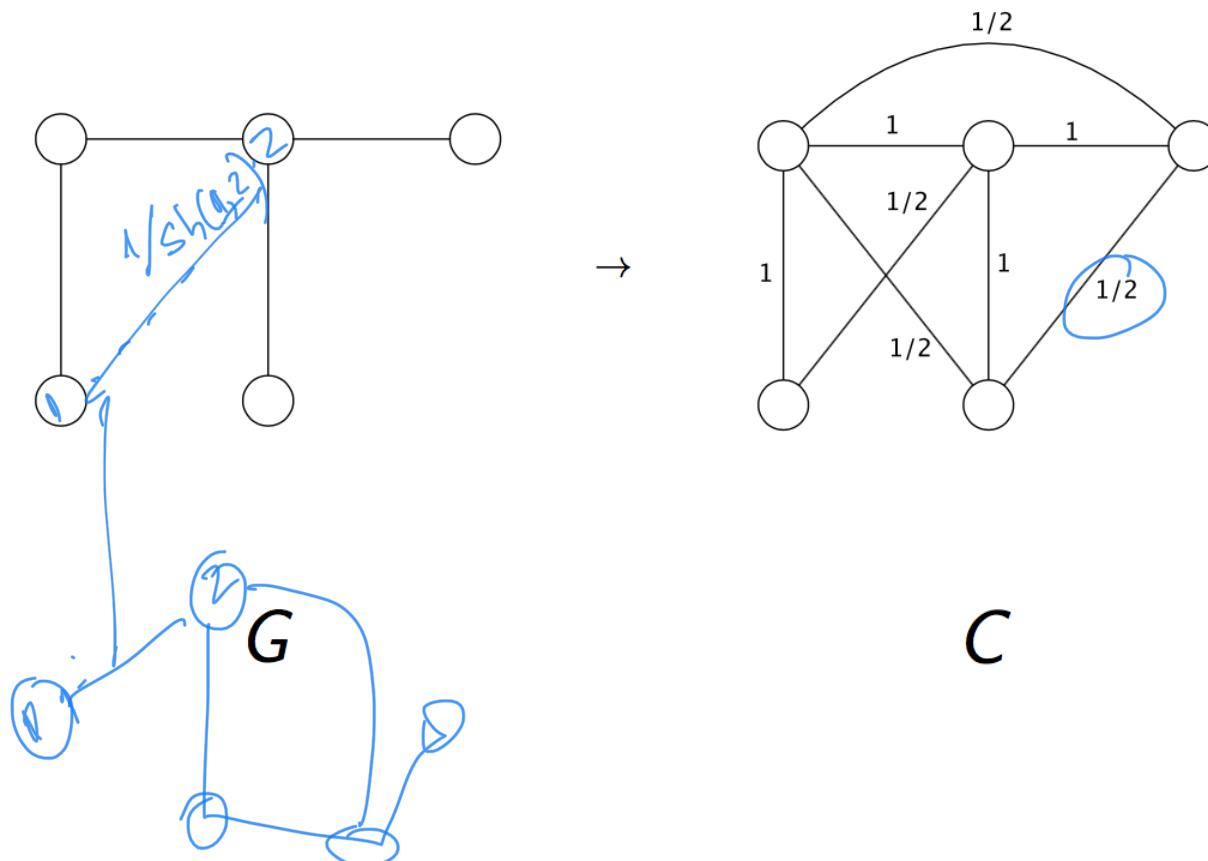
SP-transformation

Transforms the original graphs into shortest-paths graphs

- Compute the shortest-paths that are not greater than a variable d between all pairs of vertices of the input graph G using some algorithm (i. e. depth-first search)
- Create a shortest-path graph C which contains the same set of nodes as the input graph G
- All nodes which are connected by a path of length at most d in G are linked with an edge in C
- The label of an edge in C is set equal to $1/p$ where p is the length of the shortest path between its endpoints in G

Example

SP-transformation ($d = 2$)



Custom Shortest Path Kernel

Given the Floyd-transformed graphs $C_1 = (V_1, E_1)$ and $C_2 = (V_2, E_2)$ of G_1 and G_2 , the shortest path kernel is defined as:

$$k(G_1, G_2) = \frac{\sum_{v_1 \in V_1, v_2 \in V_2} k_{node}(v_1, v_2) + \sum_{e_1 \in E_1, e_2 \in E_2} k_{walk}^{(1)}(e_1, e_2)}{norm}$$

where k_{node} is a kernel for comparing two vertices, $k_{walk}^{(1)}$ a kernel on edge walks of length 1 and $norm$ a normalization factor. Specifically:

$$k_{node}(v_1, v_2) = \begin{cases} 1 & \text{if } \ell(v_1) = \ell(v_2), \\ 0 & \text{otherwise} \end{cases}$$

$$k_{walk}^{(1)}(e_1, e_2) = k_{node}(u_1, u_2) \times k_{edge}(e_1, e_2) \times k_{node}(v_1, v_2)$$

$$k_{edge}(e_1, e_2) = \begin{cases} \ell(e_1) \times \ell(e_2) & \text{if } e_1 \in E_1 \wedge e_2 \in E_2, \\ 0 & \text{otherwise} \end{cases}$$

Custom Shortest Path Kernel

Given the Floyd-transformed graphs $C_1 = (V_1, E_1)$ and $C_2 = (V_2, E_2)$ of G_1 and G_2 , the shortest path kernel is defined as:

$$k(G_1, G_2) = \frac{\sum_{v_1 \in V_1, v_2 \in V_2} k_{node}(v_1, v_2) + \sum_{e_1 \in E_1, e_2 \in E_2} k_{walk}^{(1)}(e_1, e_2)}{norm}$$

where k_{node} is a kernel for comparing two vertices, $k_{walk}^{(1)}$ a kernel on edge walks of length 1 and $norm$ a normalization factor. Specifically:

$$\mathbf{M}_1 = \mathbf{A}_1 + \mathbf{D}_1$$

$$\mathbf{M}_2 = \mathbf{A}_2 + \mathbf{D}_2$$

$$norm = \|\mathbf{M}_1\|_F \times \|\mathbf{M}_2\|_F$$

where $\mathbf{A}_1, \mathbf{A}_2$ are the adjacency matrices of the Floyd-transformed graphs, $\mathbf{D}_1, \mathbf{D}_2$ diagonal matrices with diagonal entries set to 1 if the corresponding term exists in the corresponding document and $\|\cdot\|_F$ is the Frobenius norm for matrices

Run Time Complexity

Standard kernel computation:

- All shortest paths from root: $\mathcal{O}(b^d)$ time (average branching factor b with breadth-first search)
- All shortest paths for n nodes: $\mathcal{O}(nb^d)$ time
- Compare all pairs of shortest paths from C_1 and C_2 : $\mathcal{O}(n^4)$
- However, since each node has a unique label, we have to consider n^2 pairs of edges
- Hence, total complexity: $\mathcal{O}(n^2 + nb^d)$

Special case for $d = 1$:

$$k(d_1, d_2) = \frac{\sum \mathbf{M}_1 \circ \mathbf{M}_2}{\|\mathbf{M}_1\|_F \times \|\mathbf{M}_2\|_F}$$

$\mathcal{O}(n + m)$ time in the worst case scenario

Evaluation

Document classification

- Goal: classify documents in a predefined set of categories
- Compute kernel matrix for all pairs of documents
- Support Vector Machine Model using the kernel matrices
- Compute Accuracy and F1 score

Link Detection

- Goal: find if two documents are linked
- Compute kernel distances for all pairs of documents
- Calculate Detection and Miss probabilities for every possible detection threshold (DET curve)

Dataset		WebKB		News		Subjectivity		Amazon		Polarity	
Method		Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score	Accuracy	F1-score
Dot product	$n = 1$	0.9026	0.8923	0.8110	0.7764	0.8992	0.8992	0.9188	0.9188	0.7627	0.7626
	$n = 2$	0.9047	0.8950	0.8091	0.7732	0.9101	0.9101	0.9200	0.9202	0.7746	0.7745
	$n = 3$	0.9026	0.8917	0.8072	0.7710	0.9090	0.9090	0.9181	0.9185	0.7741	0.7740
	$n = 4$	0.8940	0.8813	0.8031	0.7651	0.9039	0.9039	0.9131	0.9133	0.7719	0.7718
Cosine	$n = 1$	0.9248	0.9188	0.8117	0.7766	0.9003	0.9002	0.9400	0.9400	0.7670	0.7669
	$n = 2$	0.9305	0.9275	0.8149	0.7797	0.9094	0.9094	0.9413	0.9413	0.7756	0.7756
	$n = 3$	0.9298	0.9259	0.8097	0.7738	0.9099	0.9099	0.9419	0.9418	0.7765	0.7765
	$n = 4$	0.9248	0.9208	0.8076	0.7709	0.9076	0.9075	0.9413	0.9413	0.7753	0.7753
Tanimoto	$n = 1$	0.9062	0.8983	0.8155	0.7815	0.9094	0.9093	0.9225	0.9226	0.7749	0.7748
	$n = 2$	0.9040	0.8945	0.8075	0.7700	0.9061	0.9060	0.9181	0.9185	0.7735	0.7735
	$n = 3$	0.9241	0.9180	0.7980	0.7575	0.9021	0.9020	0.9344	0.9347	0.7648	0.7648
	$n = 4$	0.9176	0.9084	0.7899	0.7483	0.8953	0.8952	0.9300	0.9300	0.7586	0.7586
DCNN		0.8918	0.8799	0.7991	0.7615	0.9026	0.9026	0.9181	0.9181	0.7326	0.7326
CNN	static,rand	> 1 day		0.7757	0.7337	0.8716	0.8715	0.8881	0.8882	0.7150	0.7150
	non-static,rand	> 1 day		0.8113	0.7749	0.8961	0.8960	0.9356	0.9356	0.7654	0.7653
SPGK	$d = 1$	0.9327	0.9278	0.8104	0.7749	0.9148	0.9148	0.9400	0.9401	0.7776	0.7775
	$d = 2$	0.9370	0.9336	0.8089	0.7729	0.9146	0.9146	0.9413	0.9413	0.7789	0.7788
	$d = 3$	0.9291	0.9233	0.8078	0.7703	0.9137	0.9137	0.9444	0.9444	0.7761	0.7760
	$d = 4$	0.9291	0.9223	0.8097	0.7730	0.9118	0.9118	0.9463	0.9463	0.7780	0.7780

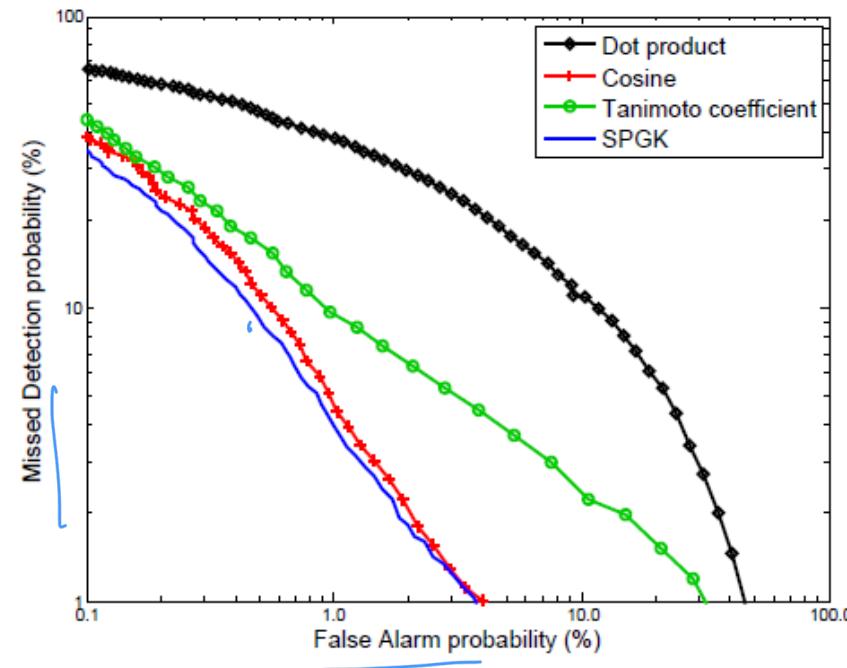
- On 4/5 datasets, SPGK outperforms the other three similarity measures and the NN architectures

Story Link Detection

(DL + graphs) (Tenn)

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