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Model-Based Classification of Web Documents Represented by Graphs

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WebKDD 2006 Workshop on Knowledge Discovery on the Web, Aug. 20, 2006, at KDD 2006, Philadelphia, PA, USA

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- Introduction and Motivation
- Graph-based Representation of Web Documents
- The Hybrid Methodology for Web Document Representation and Classification
  - The Naïve Approach
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  - The Smart Approach with Fixed Threshold
- Comparative Evaluation
- Conclusions and Future Research

Motivation

- Most of Web document classification algorithms
  - Treat web documents the same way as text documents
    - HTML tags are completely ignored
- The popular Vector-Space model
  - Ignores the word position in the document
  - Ignores the order of words in the document
- Solution – structure-sensitive document representation
  - Graph representation in this research

Text Categorization (TC)

Relevant Definitions

- TC – task of assigning a Boolean {T, F} value to each pair $\langle d_j, c_i \rangle \in D \times C$, where $D = (d_1, \ldots, d_{|D|})$ is domain of documents and $C = (c_1, \ldots, c_{|C|})$ is set of pre-defined categories (classes)

- *Single Label TC* – only one category can be assigned to each document
- *Multi Label TC* – overlapping categories allowed
- *Ranking* categorization
  - Degree of relevance of every document to each category is calculated

Graph Based Document Representation

Example –Source: www.cnn.com, 24/05/2005

Iraq bomb: Four dead, 110 wounded

A car bomb has exploded outside a popular Baghdad restaurant, killing three Iraqis and wounding more than 110 others, police officials said. Earlier an aide to the office of Iraqi Prime Minister Ibrahim al-Jaafari and his driver were killed in a drive-by shooting.

FULL STORY

Graph Based Document Representation - Parsing

title

```
<!DOCTYPE HTML PUBLIC "-//W3C//DTD HTML 4.0 Transitiona
<!-- saved from url=(0023)http://edition.cnn.com/ -->
<HTML lang=en><HEAD><TITLE>CNN.com International</TITLE>
<META http-equiv=content-type content="text/html; charset=iso-8859-1">
<META http-equiv=refresh content=1800><LINK href="/" rel=Start><LINK
```

link

```
<DIV class=cnnSectionT1
style="PADDING-RIGHT: 6px; PADDING-LEFT: 6px; PADDING-BOTTOM: 3px; PADDING-TOP: 3px">
<H2><A style="COLOR: #000"
href="http://edition.cnn.com/2005/WORLD/meast/05/23/iraq.main/index.html">Iraq
bomb: Four dead, 110 wounded</A></H2>
<P>A car bomb has exploded outside a popular Baghdad restaurant, killing
three Iraqis and wounding more than 110 others, police officials said.
Earlier an aide to the office of Iraqi Prime Minister Ibrahim al-Jaafari
and his driver were killed in a drive-by shooting.</P>
<P><A class=cnnt1link
href="http://edition.cnn.com/2005/WORLD/meast/05/23/iraq.main/index.html">FULL
STORY</A></P>
```

text

Graph Based Document Representation - Preprocessing

TITLE

CNN International

Stop word removal

Stemming

Text

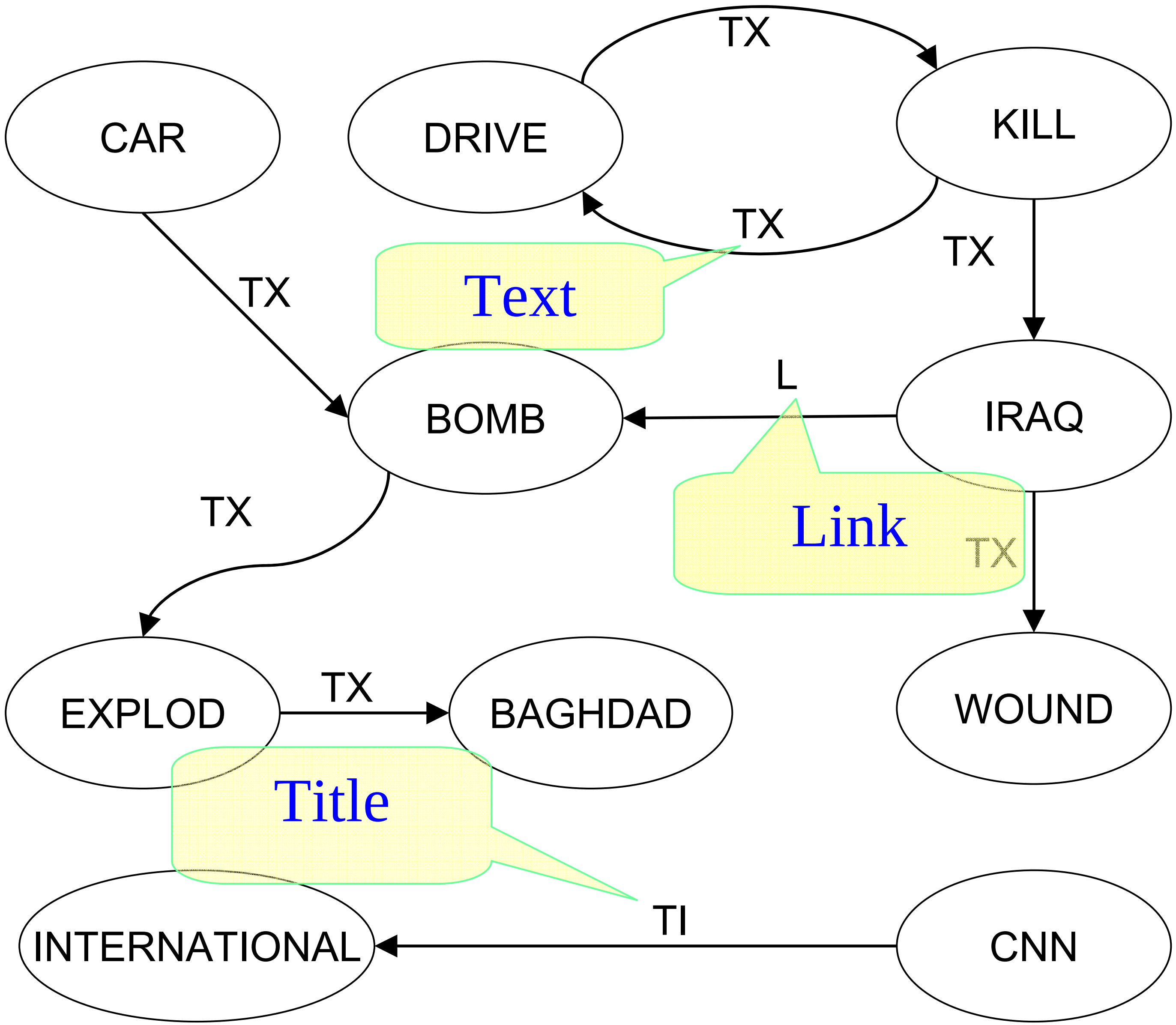
car bomb explod Baghdad restaurant, kill Iraq wound , police official . aide office Iraq Prime Minister Ibrahim al-Jaafari drive kill drive shooting.

Links

Iraq bomb: dead, wound .
FULL STORY.

Graph Based Document Representation – Graph Construction

Word	Frequency
Iraq	3
Kill	2
Bomb	2
Wound	2
Drive	2
Explod	1
Baghdad	1
International	1
CNN	1
Car	1



Web Document Classification with Graph-Based Models

- Advantages (Schenker *et al*., 2004)
  - Keep HTML structure information
  - Retain original order of words
- Limitation
  - Can work only with "lazy" classifiers, which have a very low classification speed
    - Example: k-Nearest Neighbors classifier
- Conclusion
  - Graph models cannot be used directly for <u>model-based</u> classification of web documents
- Solution
  - The **hybrid approach**: represent a document as a <u>vector of sub-graphs</u>

Graph Based Document Representation – Subgraphs Extraction

- ***Naïve Method***
  - Input:
    - ***G*** - Training set of directed, unique nodes graphs
    - t_{min} – Threshold (minimum sub-graph frequency)
  - Output:
    - Set of classification-relevant sub-graphs
  - Process:
    - For each class find frequent sub-graphs $\boldsymbol{SCF} > \boldsymbol{t}_{min}$
    - Combine all sub-graphs into one set

Subgraph Class Frequency

- **Classification-Relevant Sub-Graphs** are frequent in a specific category

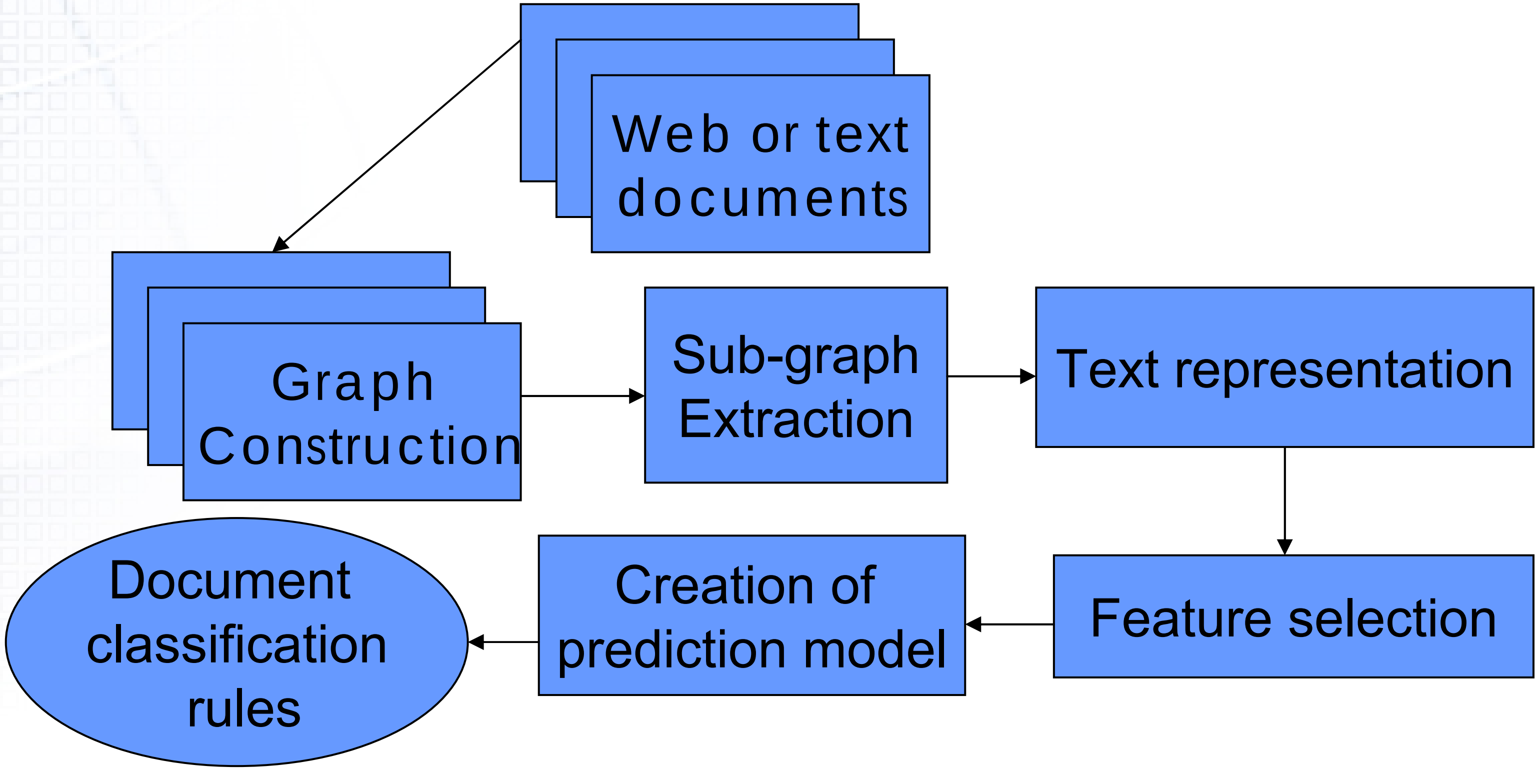
Graph Based Document Representation – Subgraphs Extraction

- ***Smart Method***
  - Input
    - ***G*** – training set of directed, unique nodes graphs
    - CR_{min} - Minimum Classification Rate
  - Output
    - Set of classification-relevant sub-graphs
  - Process:
    - For each class find sub-graphs $\boldsymbol{CR} > \boldsymbol{CR}_{min}$
    - Combine all sub-graphs into one set
- **Classification-Relevant Sub-Graphs** are more frequent in a specific category than in other categories

Graph Based Document Representation – Subgraphs Extraction

- ***Smart with Fixed Threshold Method***
  - Input
    - ***G*** – training set of directed, unique nodes graphs
    - t_{min} – Threshold (minimum sub-graph frequency)
    - CR_{min} - Minimum Classification Rate
  - Output
    - Set of classification-relevant sub-graphs
  - Process:
    - For each class find sub-graphs $\boldsymbol{SCF > t_{min}}$ and $\boldsymbol{CR > CR_{min}}$
    - Combine all sub-graphs into one set
- **Classification-Relevant Sub-Graphs** are frequent in a specific category *and* not frequent in other categories

Predictive Model Induction with Hybrid Representation



Frequent Subgraphs Extraction: Notations

Notation	Description
G	Set of document graphs
t_{min}	Subgraph frequency threshold
K	Number of edges in the graph
G	Single graph
sg	Single subgraph
sg^k	Subgraph with k edges
F^k	Set of frequent subgraphs with k edges
E^k	Set of extension subgraphs with k edges
C^k	Set of candidate subgraphs with k edges

Frequent Subgraphs Extraction: Algorithm

(based on the FSG algorithm by Kuramochi and Karypis, 2004)

$F^0 \leftarrow$ Detect all frequent 1 node subgraphs (nodes) in G
$k \leftarrow 1$
While $F^{k-1} \neq \emptyset$ **Do**
  For Each subgraph $sg^{k-1} \in F^{k-1}$ **Do**
    For Each graph $g \in G$ **Do**
      If sg^{k-1} is subgraph of g **Then**
        $E^k \leftarrow$ Detect all possible k edge extensions of sg^{k-1} in g
  For Each subgraph $sg^k \in E^k$ **Do**
    If sg^k already a member of C^k **Then**
      $\{sg^k \in C^k\}.Count{+}{+}$
    Else
      $sg^k.Count \leftarrow 1$
      $C^k \leftarrow sg^k$
  $F^k \leftarrow \{sg^k \text{ in } C^k \mid sg^k.Count > t_{min} * |G|\}$
  $k{+}{+}$
Return $F^1, F^2, \ldots F^{k-2}$

Frequent Subgraphs Extraction: Complexity

Subgraph isomorphism

Isomorphism between graph $G_1=(V_1,E_1,\alpha_1,\beta_1)$ and part of graph $G_2=(V_2,E_2,\alpha_2,\beta_2)$ can be found by two simple actions:

1. Determine that $V_1 \subseteq V_2$ - $O(|V_1|*|V_2|)$
2. Determine that $E_1 \subseteq E_2$ – $O(|V_1|^2)$

Total complexity:

$O(|V_1|*|V_2| + |V_1|^2) \leq O(|V_2|^2)$

Graph isomorphism

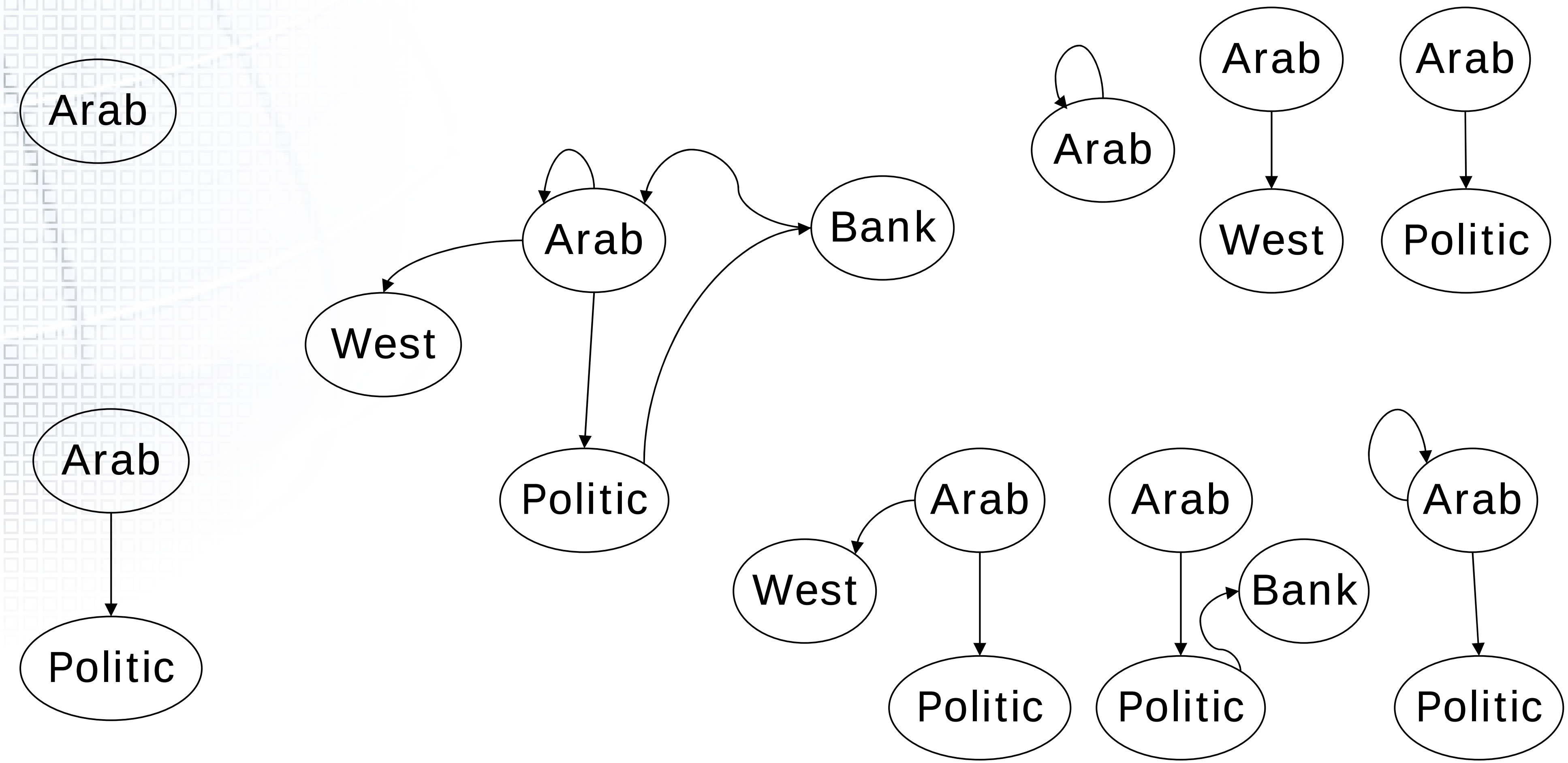
Isomorphism between graphs $G_1=(V_1,E_1,\alpha_1,\beta_1)$ and $G_2=(V_2,E_2,\alpha_2,\beta_2)$ can be found by two simple actions:

1. Determine $G_1 \subseteq G_2$ - $O(|V^2|)$
2. Determine $G_2 \subseteq G_1$ - $O(|V^2|)$

Total complexity: $O(|V^2|)$

Frequent Subgraph Extraction Example

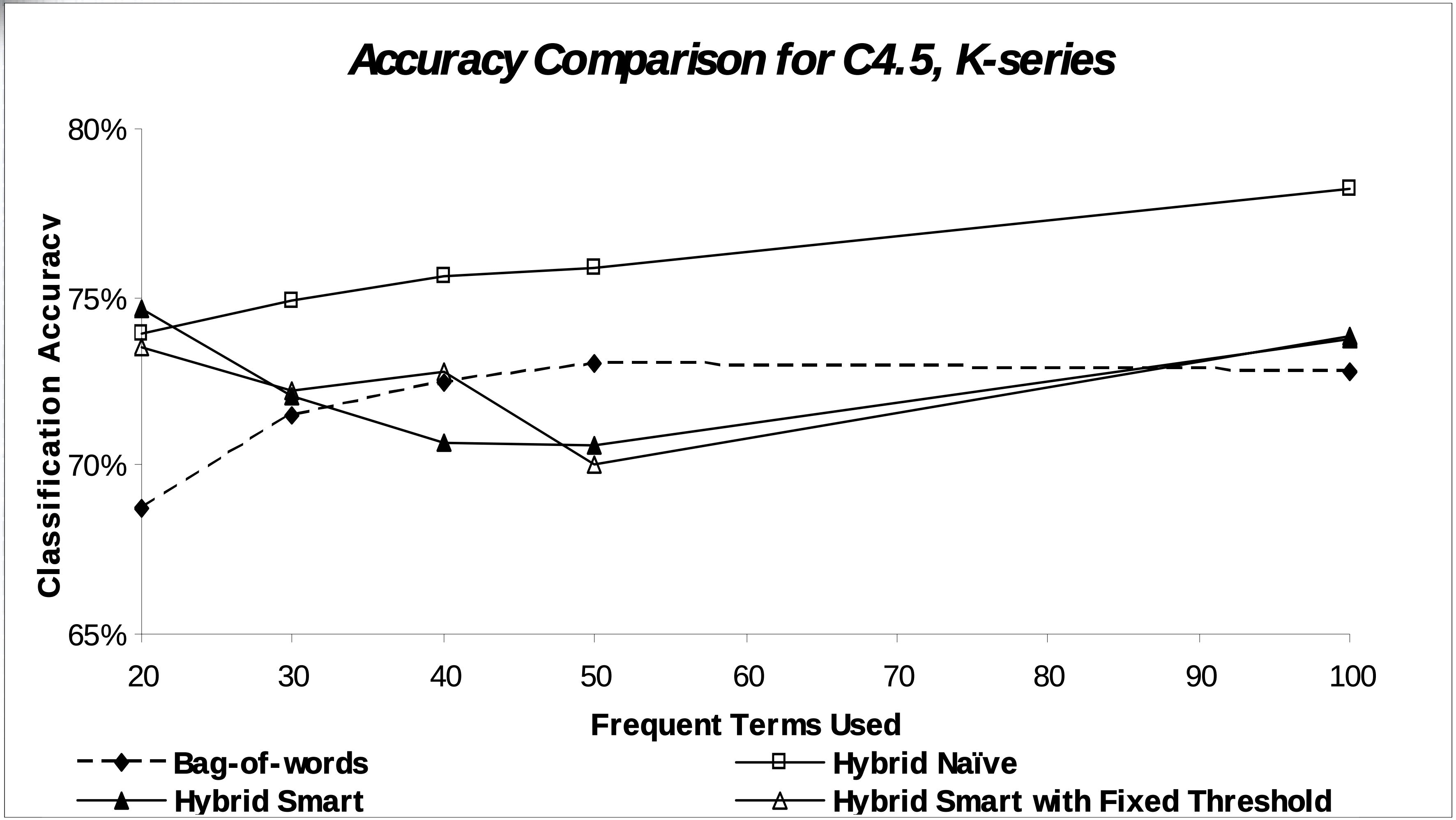
Subgraphs **Document Graph** **Extensions**



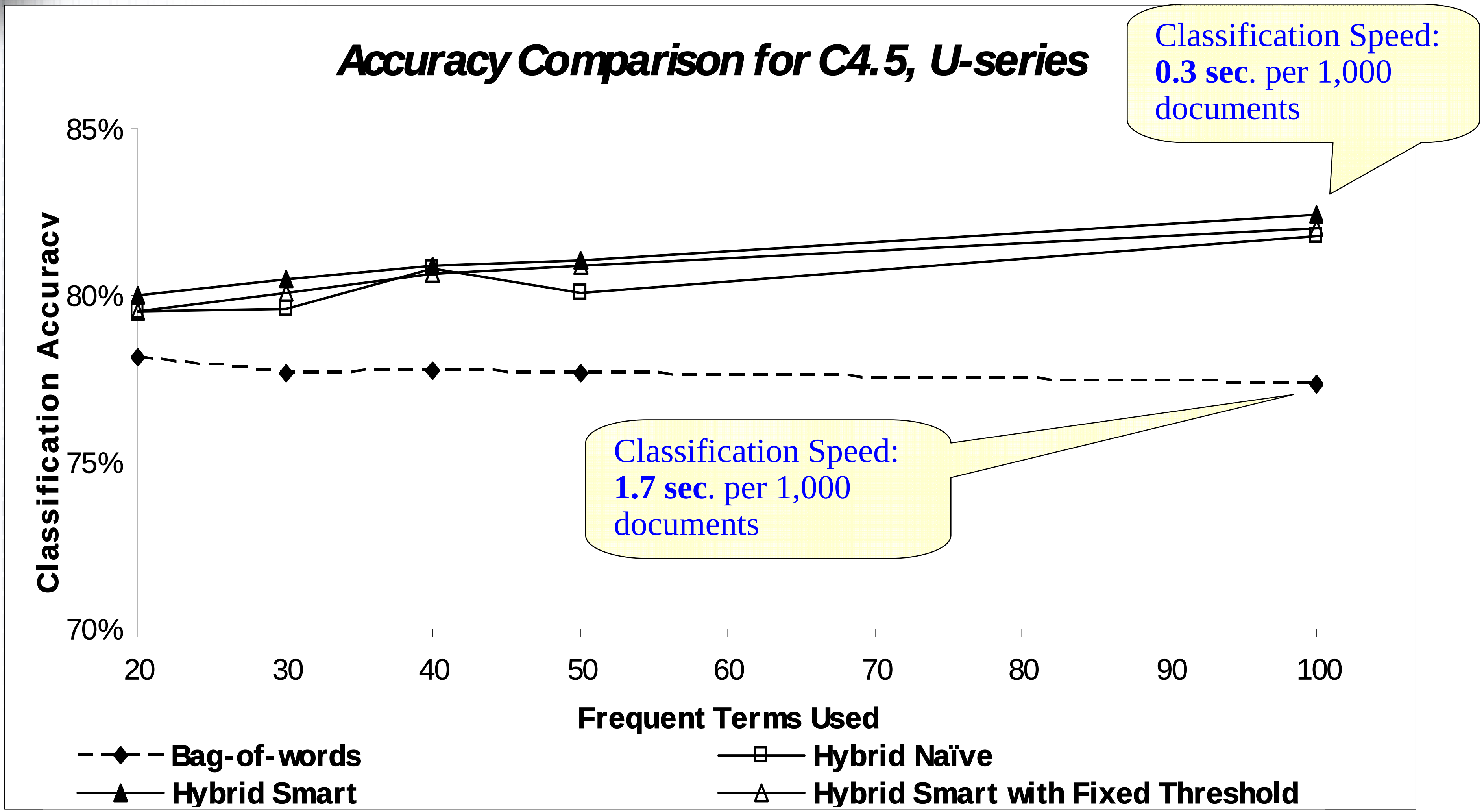
Comparative Evaluation

- Benchmark Data Sets
  - K-series
    - 2,340 documents and 20 categories
    - Documents in those collections were originally news pages hosted at Yahoo
  - U-series
    - 4167 documents taken from the computer science department of four different universities: Cornell, Texas, Washington, and Wisconsin
    - 7 major categories: course, faculty, students, project, staff, department and other
- Dictionary construction
  - *N* most frequent words in each document were taken for vector / graph construction, that is, exactly the same words in each document were used for both the graph-based and the bag-of-words representations

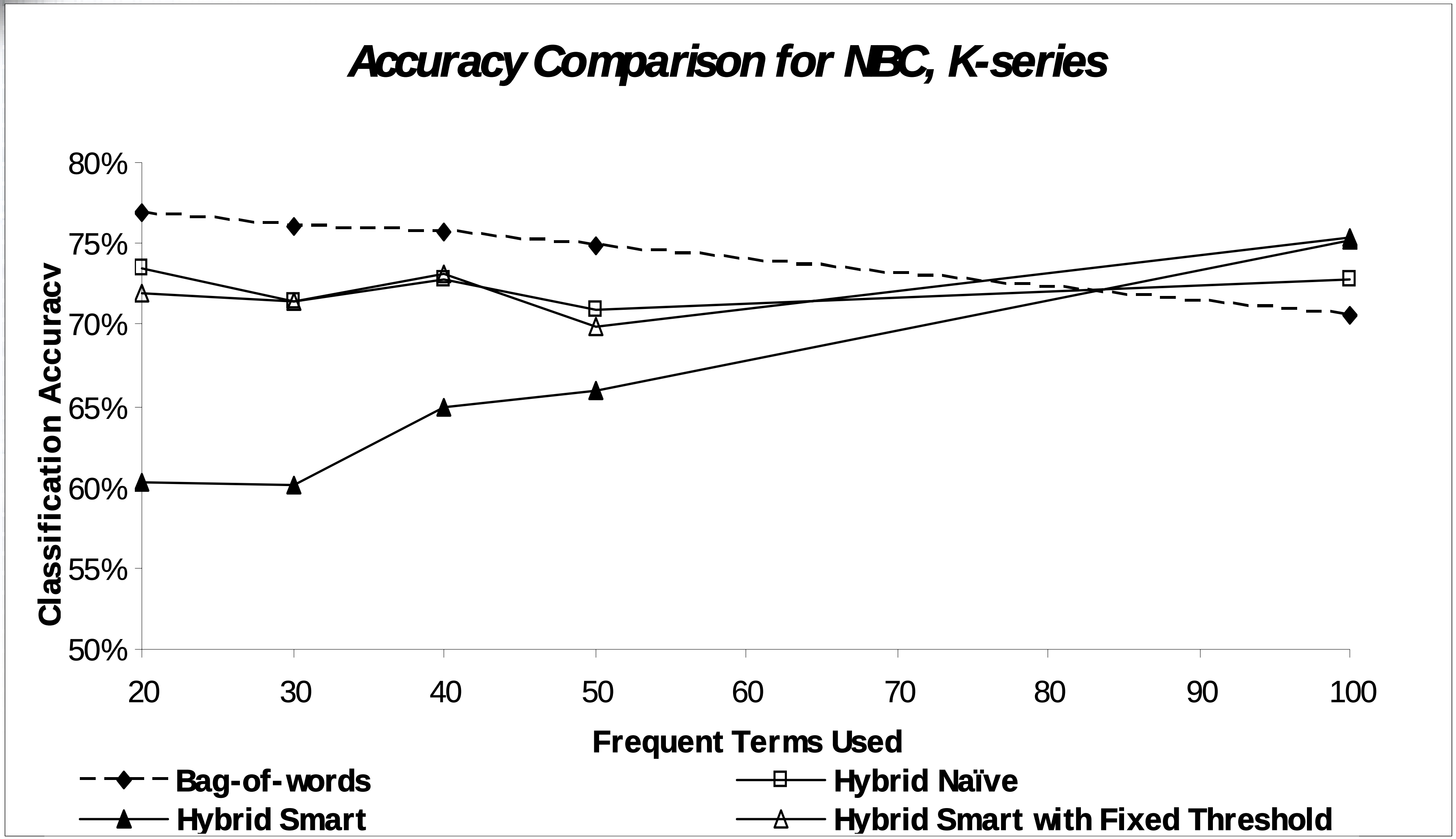
Classification Results with C4.5– K series data set



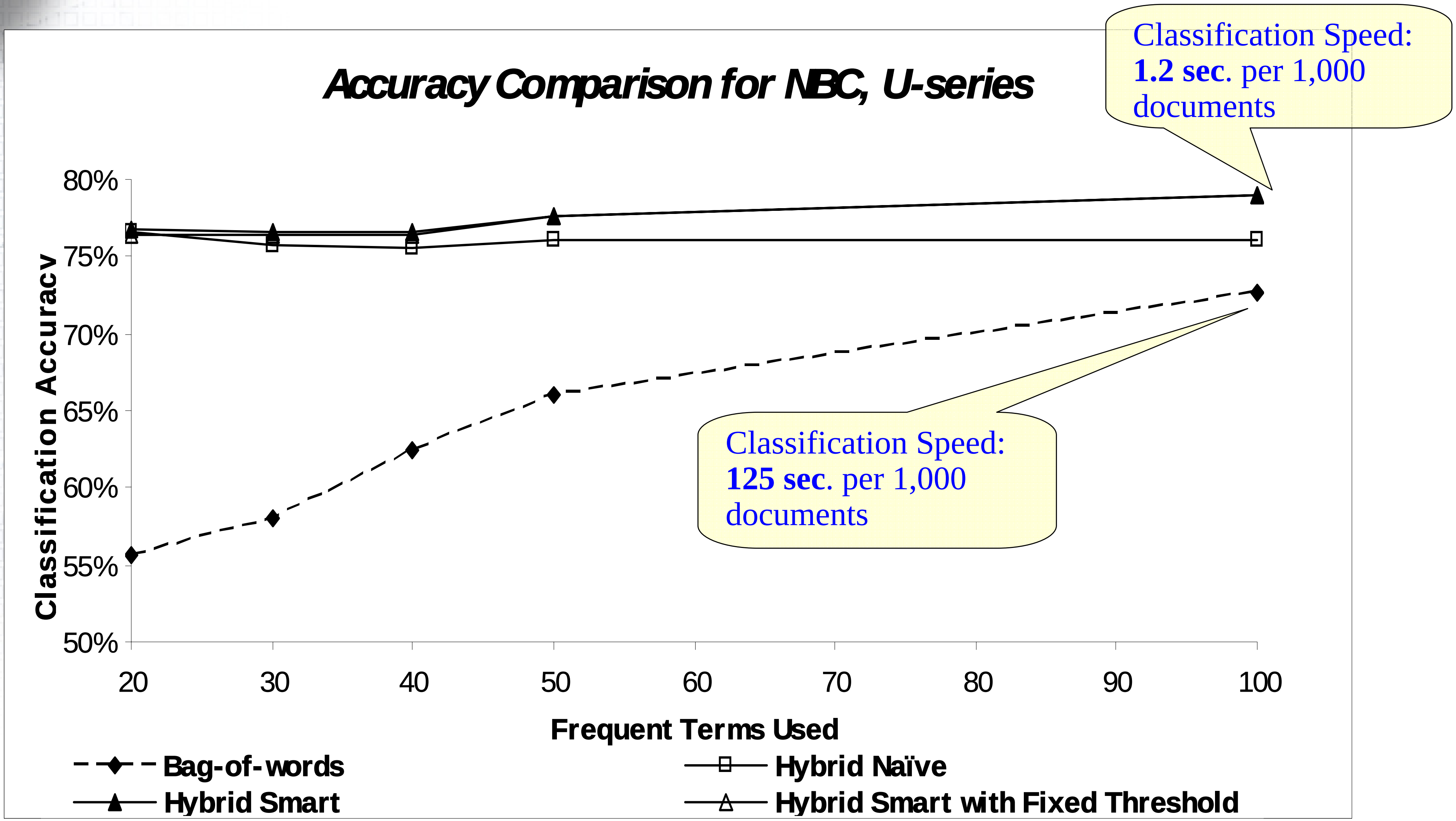
Classification Results with C4.5– U series data set



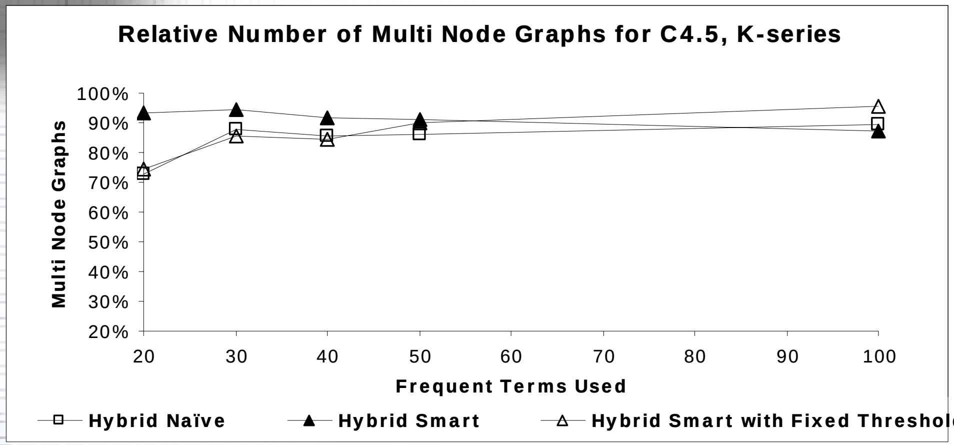
Classification Results with Naïve Bayes – K series data set

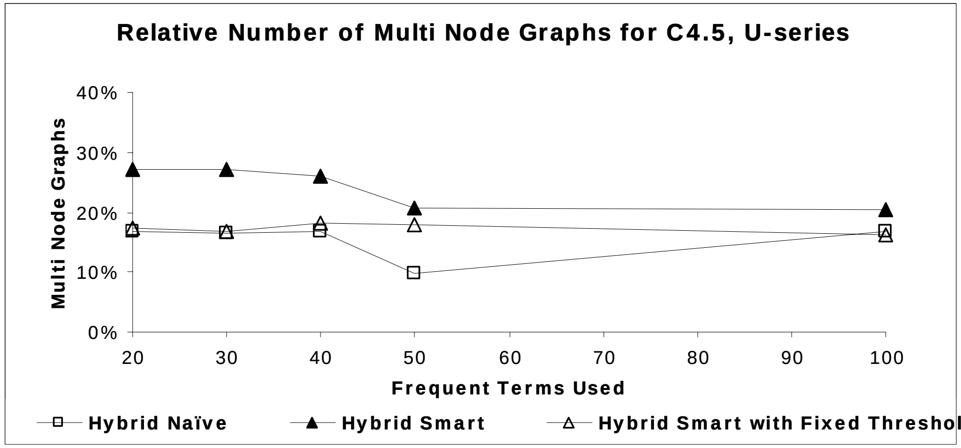


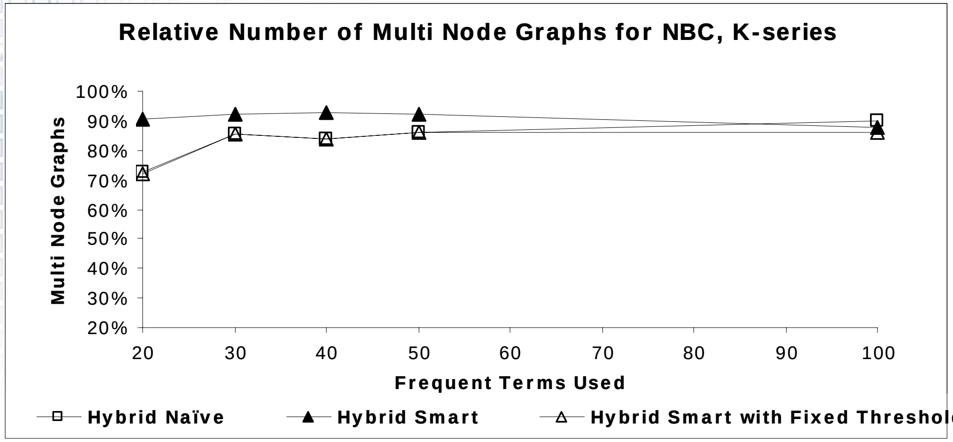
Classification Results with Naïve Bayes – U series data set

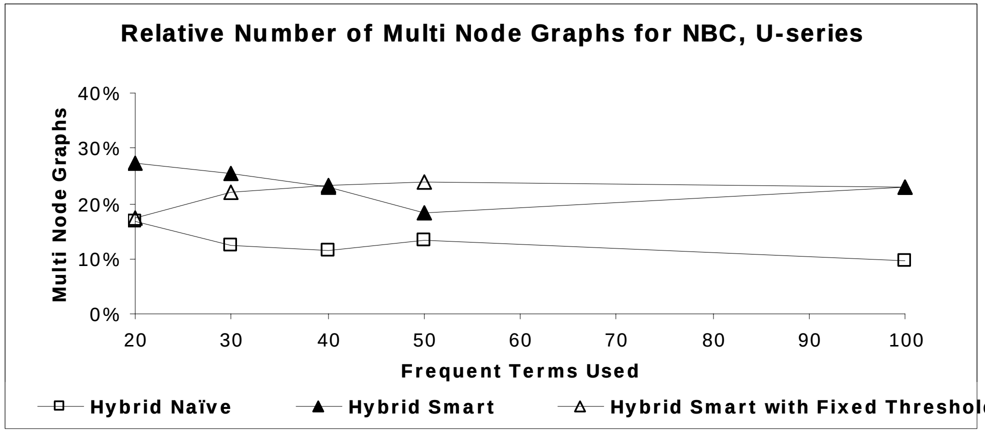


Percentage of Multi-node Subgraphs









Summary

- Different document representations were empirically compared in terms of classification accuracy and execution time
- The proposed hybrid methods were found to be more accurate in most cases and generally much faster than their vector-space and graph-based counterparts

Future research

- Finding optimal parameters for sub-graph extraction:
  - Graph size *N*
  - t_{min} for Naïve extraction
  - CR_{min} for Smart extraction
- Applying the hybrid methodology to additional classifiers
- Applying the hybrid methodology to unsupervised learning (clustering)

Thank you!

Selected References

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