

# **A Framework for Summarization of Multi-topic Web Sites**

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# A Framework for Summarization of Multi-topic Web Sites

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## Abstract

Web site summarization, which identifies the essential content covered in a given Web site, plays an important role in Web information management. However, straightforward summarization of an entire Web site with diverse content may lead to a summary heavily biased to the dominant topics covered in the target Web site. In this paper, we propose a two-stage framework for effective summarization of multi-topic Web sites. The first stage identifies the main topics covered in a Web site and the second stage summarizes each topic separately.

In order to identify the different topics covered in a Web site, we perform coupled text- and link-based clustering. In text-based clustering, we investigate the impact of document representation and feature selection on the clustering quality. In link-based clustering, we study co-citation and bibliographic coupling. We demonstrate that text-based clustering based on the selection of features with high variance over Web pages is reliable and that outgoing links can be used to improve the clustering quality if a rich set of cross links is available.

Each individual cluster computed above is summarized using an extraction-based summarization system, which extracts key phrases and key sentences from source documents to generate a summary. We design and develop a classification approach in the cluster summarization stage. The classifier uses statistical and linguistic features to determine the topical significance of each sentence.

Finally, we evaluate the proposed system via a user study. We demonstrate that the proposed clustering summarization approach significantly outperforms the single-topic summarization approach.

## 1 Introduction

In this section, we briefly describe the research problem, the motivation, and the approach. We aim to address the following two questions:

1. Why is Web site summarization important?
2. How to summarize a Web site with multiple topics?

### 1.1 Why Summarization

In recent years, the World Wide Web (WWW) has experienced a tremendous explosion of online information, which poses a great challenge for Web users to take full advantage of the huge information repository. Hence, effective management of online information becomes more and more critical.

Web information management involves the design of processes for effective management of semi-structured data, meta-data, multimedia information, and multi-dimensional Web databases in order for Web users to precisely and quickly retrieve, locate, navigate, and visualize Web contents. Information management in the WWW context requires a set of tools, as shown in Figure 1. For example, Web Indexing and Retrieval is important for information seeking. Web users are often unable to obtain the information they want without the help of search engines (e.g. Google<sup>1</sup>), which have been gaining more popularity. Web document categorization aims to provide a directory with hierarchical categories (e.g. Yahoo! Directory<sup>2</sup>) which helps Web users locate a particular kind of Web sites more quickly and effectively.

In this paper, we focus on the summarization approach. Text summarization is the process of generating a concise yet meaningful summary which highlights the core contents of source documents. Web document summarization, which is derived from traditional text summarization, is of particular interest in Web information management. It can be categorized as single Web document summarization and multiple Web document summarization.

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<sup>1</sup><http://www.google.com>

<sup>2</sup><http://dir.yahoo.com>

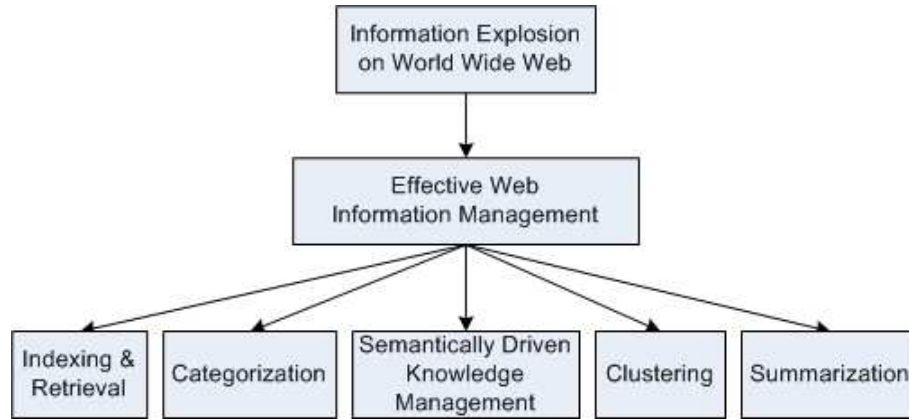


Figure 1: Typical approaches to information management on the World Wide Web.

### 1.1.1 Single Web Document Summarization

Single Web document summarization is the process of summarizing a given Web page by analyzing its textual content and/or contextual knowledge such as anchor text. It has the following main applications:

- Display on hand-held devices [8]. As hand-held devices (e.g. PDA) become increasingly popular, there is increasing demand for display of Web pages on them. However, hand-held devices often have limited memory and computational power, and more importantly, limited screen real estate. Thus, display of complex Web pages is a problem. Also it is very expensive to design small Web pages that are specifically fit on these devices. It turns out that a short and meaningful summary of these conventional Web pages is a good alternative for display on hand-held devices.
- Query formation and expansion. When Web users come to search engines, they often have difficulty forming an accurate query to fulfill their information seeking goals. One common reason is that they cannot find or think of all proper keywords that should be used to form a good query. If each result page of the initial query has a corresponding summary, which contains a few key phrases and key sentences, then Web users will obtain clues from the summary to re-formulate or expand their initial queries. The new queries are often more accurate and can achieve better search results. The process can be repeated and it serves as a feedback system.
- Web document indexing. When search engines display the search results of a particular query, they present a snippet of each result document, which consists of a few sentences extracted from the document in which the query keywords appear. In fact, a Web document can be summarized and stored during the crawling stage. The summary can then be presented as an alternative to the conventional snippet. The concise summary will provide a more comprehensive overview of the document than the conventional snippets and help Web users more easily decide whether the document is what they are looking for.
- Document relevance ranking. Web search engines often return too many matching documents for a search query. Hence, an estimate of the relevance of the documents to the query should be provided such that more relevant documents show up near the top of the result list. A Web document summary can be used to improve the relevance ranking function. The query terms can be matched with the summary to obtain the popularity statistics (e.g. number of query terms that appear in the key phrase list and the key sentence list, positions of query terms in the summary). The obtained statistics can then be used to favor some Web documents over others.

### 1.1.2 Multiple Web Document Summarization

Multiple Web document summarization is an extension to the single Web document summarization task. It has been approached by using statistical and linguistic methods to create a summary which highlights the main contents covered in a Web document corpus. It has the following typical applications:

- Understanding a Web site. A Web site summary can be used to represent the target site: a concise, informative, and meaningful summary can help Web users understand the essential topics in the Web site quickly without browsing [71].

- Organization of search engine results. Search engines often return hundreds of documents for a search query. It is difficult and time-consuming for Web users to browse even the top 10 result documents. It is much more user friendly to present a summary of the search results to the Web users.
- Organization of product reviews. As online shopping becomes more and more popular, shoppers tend to do more shopping research before making a purchase. Review sites (e.g. <http://reviews.cnet.com>), which either provide professional product reviews or allow Web users to write their own opinions and reviews, are gaining more and more traffic. It would be useful to summarize all reviews of a particular product to show the main theme of these reviews, such as pros/cons, in addition to presenting all individual reviews.
- Web directory construction. DMOZ<sup>3</sup> and Yahoo! directories provide a hierarchy of categories, to which millions of Web sites are categorized. Each listed site has a concise human-written summary that highlights the essential content. It is very expensive to manually author such a summary for each Web site. Alternatively, the concise summary can be obtained by summarizing a given site automatically.

## 1.2 How to Summarize

In this paper, we focus on the Web site summarization task in the context of Web information management. Automatically generating coherent summaries as good as human-authored summaries is a challenging task since Web sites often contain diverse topics and heterogeneous contents. The size, diversity, and complexity of Web sites are continuing to grow at a fast rate.

In **single-topic summarization** (e.g. [71]), all Web pages in a given Web site are assumed to be in the same topic group (which is often inaccurate) and therefore are summarized directly. Such a **straightforward summarization** of the entire Web site often yields an incoherent summary or a summary that is heavily biased towards a subset of the topics included in the Web site.

Our main objective is to propose a system which can effectively summarize Web sites with multiple topics and heterogeneous contents to facilitate Web information management. In order to achieve this, we need the ability to first detect what the important topics are in a given Web site. It would be greatly helpful if we could detect the topical relationship between Web pages and group them accordingly. Site maps and index pages help a lot, but they do not always exist and are not always topically grouped.

We propose in this paper a framework for effective summarization of multi-topic Web sites. The system first crawls a given Web site using the breadth-first search algorithm to build a link hierarchy. Each node in the link hierarchy represents a unique Web page collected in the Web site traversal. Then  $K$ -means or  $X$ -means clustering using coupled text- and link-based features is applied to identify the main topics included in the target Web site. Next, each individual cluster is separately summarized by our previous extraction-based summarization system [71]. Finally, the Web site summary consists of a few concise cluster summaries. The overview of this framework is shown in Figure 2.

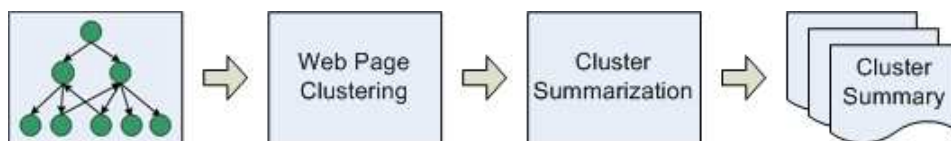


Figure 2: A framework for summarization of multi-topic Web sites.

The main objective of the Web Page Clustering component is to group documents into clusters where documents within the same cluster are related to each other whereas documents between different clusters are not related. We aim to investigate whether basic clustering algorithms such as  $K$ -means and  $X$ -means can find topic groups effectively. Critical evaluation of various clustering algorithms to find the best one in this task is a topic for future research.

Clustering approaches have been mostly text-based. Link analysis has been widely studied in many research areas such as Web document ranking [6, 30], Web document classification [21], topic distillation [10], document similarity analysis [40], Web structure mining [9], site map construction [35], and Web community identification [18]. In this work, we aim to utilize both text- and link-based features. In text-based clustering, we investigate the impact of document representation and feature selection on the clustering quality. In link-based clustering, we employ co-citation and bibliographic coupling. We use entropy and accuracy to evaluate the clustering quality.

<sup>3</sup><http://www.dmoz.org>

Summarization of an individual cluster is a multi-stage process following our previous single-topic summarization system [71]. The process involves five steps. First, plain text is extracted from the HTML source of Web pages. Second, text classification is performed to extract the narrative text<sup>4</sup> for more effective summarization. Third, key phrases are extracted from the narrative text in consideration. Fourth, key sentences are extracted from the narrative text based on the density of key phrases. Finally, a cluster summary is created consisting of both key phrases and key sentences. The cluster summarization process is shown in Figure 3.

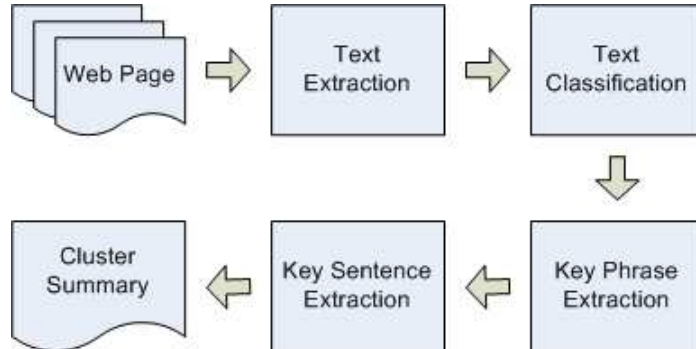


Figure 3: Typical approach to summarization of an Web document corpus.

The cluster summarization described above relies on the extraction of the most significant sentences from the target cluster based on the density of a list of key phrases that best describe the entire cluster. The performance of such an extraction-based approach heavily depends on its underlying key phrase extraction method. Therefore, it is critical to investigate alternative key phrase extraction methods in order to choose the best one. In [70], we benchmark five key phrase extraction methods that can be used in the key phrase extraction stage. The five methods are Term Frequency Inverse Document Frequency (TFIDF) [53], Automatic Keyphrase Extraction (KEA) [67], Keyword (KWD) [71], C-value/NC-value (CNC) [20], and Mixture (MIX), as shown in Figure 4.

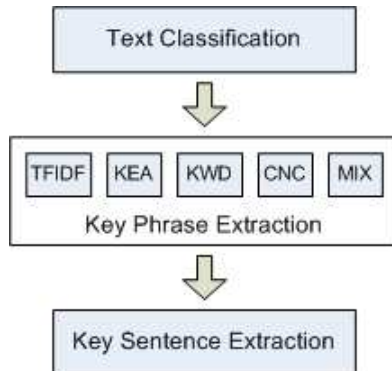


Figure 4: Five methods used in the key phrase extraction stage.

We investigate how well each key phrase extraction method performs in the automatic Web site summarization task via a formal user study, i.e., we learn which method yields summaries with the best quality. In our study, human subjects are asked to read the summaries generated based on different key phrase extraction methods. Then they rate each summary element using a 1-to-5 scale. The quality of each summary is calculated using both the *acceptable percentage* measure and the *quality value* measure. Acceptable percentage is the ratio of summary elements that receive a score of 3, 4 or 5. Quality value is the average score of a summary element. The quality of each type of summaries is compared with each other. One-Way Fully Repeated Measures ANOVA is used to conduct the statistical analysis. We demonstrate that CNC is the best key phrase extraction method [70].

Once the key phrases are identified for each cluster, key sentences can be retrieved from the narrative text. Traditionally, the key sentences are extracted based on the density of key phrases. In this paper, we choose the best

<sup>4</sup>Narrative text is the text paragraphs that are often more structured, informative and coherent than non-narrative text. Here is an example of a narrative paragraph: *The Software Engineering Process Group (SEPGSM) Conference is the leading international conference and exhibit showcase for software process improvement (SPI).* In contrast, a non-narrative paragraph often consists of short phrases or bullets, e.g. *First created on 10 May 2000. Last Modified on 22 July 2003. Copyright ©2000-2003 Software Archive Foundation. All rights reserved.*

key phrase extraction method CNC, which is identified in the comparative study of key phrase extraction methods. Furthermore, we propose a classification approach to key sentence extraction in the cluster summarization stage. The classifier uses statistical and linguistic features to determine the topical significance of each sentence.

To investigate whether the clustering-summarization framework summarizes Web sites better than the single-topic summarization system, we also conduct a formal user study where human subjects are asked to read *the short cluster summaries* generated by our clustering-summarization framework, and *the single long summary* created by our previous summarization system based on the best key phrase extraction method. Then they rate each summary element using a 1-to-5 scale. Again, the quality of the short cluster summaries is calculated using both the acceptable percentage measure and the quality value measure.

The summarization framework proposed above consists of several key components, including feature selection and link analysis in Web page clustering, key phrase extraction and key sentence extraction in cluster summarization. More specifically, link analysis takes into account incoming and outgoing links when measuring the similarity of two Web documents. Key phrase extraction takes advantage of Web-based features in the following ways: 1) features in anchor text and special text are treated separately; 2) a KEA model for key term extraction is trained using Web documents; and 3) Web-specific stop words are used. Furthermore, key sentence classification uses the depth level of web pages in a web site. The contribution of this work is in aggregating these individual components and applying them to the Web site summarization problem.

The rest of the paper is organized as follows: Section 2 reviews literature on Web document summarization. In Section 3, we discuss how to perform coupled text- and link-based clustering. Then Section 4 describes the summarization of resulting clusters and presents the evaluation results. Finally Section 5 concludes our work and describes future work.

## 2 Literature Review

This section reviews literature in text summarization and Web document summarization.

### 2.1 Automatic Text Summarization

Research in automatic text summarization dates back at least to 1958, when Luhn [41] proposed a simple approach which extracts significant sentences to form a summary based on features such as average term frequency and sentence location. Existing text summarization systems generate summaries automatically either by *extraction* or *abstraction*.

The goal of abstraction [3] is to understand the text using knowledge-based methods and compose a coherent summary comparable to a human authored summary. This is very difficult to achieve with current natural language processing techniques [22].

An easier alternative, extraction, has been the focus of automatic text summarization research in recent years [24, 28]. Extraction-based systems [11, 16, 23, 62] analyze source documents using techniques derived from information retrieval (e.g. frequency analysis and keyword identification) to determine the most significant sentences that constitute the summary. The significance of a sentence is determined by features such as the density of keywords [71] and rhetorical relations [44] in the context.

Kupiec et al. [32] build a statistical classification model based on training documents with hand-selected extracts. The model estimates the probability that a given sentence is included in an extract based on a set of heuristic features. Summary generation for new documents proceeds with ranking sentences according to this probability.

Chuang and Yang [11] propose an approach which generates a summary automatically. First, sentences are broken into segments by special cue phrases. Next, each segment is represented by using a set of pre-defined features, both unstructured (e.g. title words) and structured (e.g. rhetorical relations). Finally, machine learning algorithms are applied to the feature set to extract the most important sentence segments for summary inclusion.

Post-processing of the extracted sentences has been used to produce succinct summaries without redundant information. For example, clustering has been applied to find clusters of closely related sentences, and only “core” sentences from all the clusters are used to form the output summary [26]. As a second example, the identification of named entities can help the system rephrase the pronouns used in order to create a meaningful summary [45].

Evaluation of automatically generated summaries can proceed in either of two different modes, *intrinsic* and *extrinsic*. Intrinsic evaluation compares automatically generated summaries against a gold standard (ideal summaries), which is very hard to construct. Extrinsic evaluation measures the utility of automatically generated summaries in performing a particular task (e.g. classification) [43, 58]. Extrinsic evaluation is also called task-based evaluation and it has become increasingly popular recently [52].

### 2.1.1 Multi-document Summarization

Multi-document summarization (MDS) is an extension of single-document summarization into a collection of documents [42]. Multi-document summaries can save users significant time in reading relevant text documents or browsing Web sites. Many of the single-document summarization techniques can also be used in multi-document summarization. However, issues such as *anti-redundancy* and *cohesion and coherence* become critical in MDS [23, 36]. Moreover, multi-document summarization lacks standard procedures and methodologies for evaluation, in contrast to the single-document summarization task [55].

The National Institute of Standards and Technology (NIST) sponsored the Document Understanding Conference<sup>5</sup> starting in 2001, which aims towards providing standard training and test document collections (mostly news articles) which can be shared among the research community, as well as evaluations in single- and multi-document summarization for the conference participants [36].

Current MDS systems often apply a two-phase process, i.e., *topic identification* and *summary generation*. In the first phase, main topics (or events) covered in the multiple source documents are identified. Documents regarding the same topic (or event) with variations in presentation are put into the same set. Then each set of closely related documents is used to produce representative passages for the final summary by extraction or by reformulation [26, 60].

Radev et al. [52] present a MDS system called MEAD<sup>6</sup>, which first uses modified TF-IDF measure to form clusters of documents on the same topic, and then uses centroids of the clusters to identify which sentences are most likely to be relevant to the cluster topic, rather than individual articles. Evaluation demonstrates that summaries generated by MEAD are as good as human created summaries.

Stein et al. [60] propose a different approach which first summarizes single documents and groups summaries in clusters, then selects representative passages from clusters, and finally organizes passages into a coherent summary.

McKeown et al. [45] introduce a system which first identifies the type of document sets, i.e. single-event, person-centered (or biographical), or multi-event, and then summarizes them accordingly.

One research area that is closely related to MDS is called topic hierarchy construction, where a hierarchy of topics represented by key terms is constructed. Sanderson and Croft [54] use a term association method to build a term hierarchy for a set of retrieved documents, with an ordering from general terms to more specific, i.e., the parent concept subsumes the child concept. Lawrie et al. [33] apply the Dominating Set algorithm to present a probabilistic language model for automatic topic hierarchy construction. Terms are efficiently chosen from a retrieved set and form a hierarchy serving as a multi-document summary. Lawrie and Croft [34] build statistical language models to recursively identify the most topical and predicative terms for hierarchy creation. Documents are attached to the hierarchy if they include topic terms. However, these approaches only work well on a small set of related documents. As for summarization, they do not provide key sentences, which is a normal experience in multi-document summarization.

## 2.2 Web Document Summarization

Web document summarization is derived from traditional plain text summarization techniques [71]. To the best of our knowledge, research in Web document summarization has been primarily focused on summarization of a single Web page.

### 2.2.1 Web Page Summarization

Web page summarization has been either *context-based* or *content-based*. Context-based systems [2, 14] analyze and summarize the context of a Web document (e.g. brief content descriptions from search engine results) instead of its contents. Content-based systems [3, 8] derive from traditional text summarization techniques. The great challenge in Web page summarization is the diversity of contents and the frequent lack of a well-defined discourse structure compared to traditional text [3]. Approaches based on implicit document association (rhetorical relation) analysis [44] are difficult to apply to Web page summarization.

Amitay and Paris [2] propose an approach, which relies on the hypertext structure and the way information is described using it. Instead of analyzing the Web page itself, this approach collects the context of the document by tracing back-links, a service offered by search engines like Google. Text units which contain the link to the target Web page are then extracted. Finally, an automatic filter is used to select the best description for the Web page. Single-sentence sized coherent textual snippets are generated and presented to the user together with results from

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<sup>5</sup><http://duc.nist.gov>

<sup>6</sup><http://www.summarization.com/mead/>

search engines Google and AltaVista<sup>7</sup>. The experiments show that on average users prefer the system to search engines.

Delort et al. [14] address three important issues, *contextualization*, *partiality*, and *topicality* faced by any context-based summarizer and propose two algorithms whose efficiency depends on the size of the text contents and the context of the target Web page.

The drawback of the systems that rely on context analysis is that context information of target pages is not always available and accessible. Consequently, approaches which analyze source contents have been gaining more popularity. However, they rely on the underlying key phrase extraction method to generate key phrases in order to further identify key sentences.

Berger and Mittal [3] propose a system called OCELOT, which applies standard statistical models (in particular, the Expectation Maximization (EM) algorithm) to select and order words into a “gist”, which serves as the summary of a Web document.

Buyukkokten et al. [8] compare alternative methods for summarizing Web pages for display on handheld devices. The *Keyword* method extracts keywords from the text units, and the *Summary* method identifies the most significant sentence of each text unit as a summary for the unit. They test the performance of these methods by asking human subjects to perform specific tasks using each method, and conclude that the combined *Keyword/Summary* method provides the best performance in terms of access times and number of pen actions on the hand held devices.

### 2.2.2 Web Site Summarization

In our previous work [71], we extended single Web document summarization to the summarization of complete Web sites. The “Keyword/Summary” idea of [8] was adopted, and the methodology was substantially enhanced and extended to Web sites as follows:

1. **Web Page URL Crawling** In order to summarize a given Web site, a certain number of Web pages within a short distance from the root (home page) of the target site, which are assumed to describe the main contents of the site in general terms, are collected by a specific Web crawler via the breadth-first search starting at the home page.
2. **Plain Text Extraction** After the Web pages have been collected, plain text is extracted from these Web pages and segmented into text paragraphs by the text browser *Lynx*<sup>8</sup>, which is found to outperform several alternative text extraction tools such as *HTML2TXT*<sup>9</sup> and *html2txt*<sup>10</sup>, in terms of more effective selection of plain text.
3. **Narrative Text Classification** Since Web documents are often not well-structured and include diverse contents such as tables of contents and link lists, it is important to determine which text paragraphs should be considered for summarization. This is achieved in two steps. First, a C5.0<sup>11</sup> classifier *LONGSHORT* is used to filter out *short* text paragraphs. Second, *long* paragraphs are classified into *narrative* or *non-narrative* by another C5.0 classifier *NARRATIVE*, and only narrative paragraphs are used in summary generation. These two classifiers are built based on features (e.g. number of words and part of speech tag) extracted by shallow natural language processing. The cross-validation shows a mean error of 5.9% and 11.3% for *LONGSHORT* and *NARRATIVE*, respectively.
4. **Key Phrase Extraction** Traditionally, key phrases (single keywords or multi-word keyterms) for the entire document corpus are extracted in order to generate a summary. Based on such key phrases, the most significant sentences, which best describe the source documents, can be retrieved. Key phrase extraction from a body of text relies on an evaluation of the importance of each candidate key phrase [8]. In our previous work [70], we investigated five key phrase extraction methods in the straightforward summarization system and demonstrated that CNC is the best method.
5. **Key Sentence Extraction** Once the key phrases are identified, the most significant sentences for summary generation are retrieved from all narrative paragraphs based on the density of key phrases [11].
6. **Summary Formation** The overall summary is formed by the top 25 key phrases and the top 5 key sentences. These numbers are empirically determined based on the fact that key sentences are more informative than key phrases, and the whole summary should fit in a single page.

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<sup>7</sup><http://www.altavista.com>

<sup>8</sup><http://lynx.isc.org>

<sup>9</sup><http://user.tninet.se/~jyc891w/software/html2txt>

<sup>10</sup><http://cgi.w3.org/cgi-bin/html2txt>

<sup>11</sup><http://www.rulequest.com/see5-unix.html>



### 3 Web Page Clustering

In this section, we investigate the clustering problem in our clustering-summarization framework. We use both text- and link-based features to find in a given Web site the most essential topics, which will be further summarized using the CNC-based summarization system to create multiple short cluster summaries.

Text clustering has been extensively researched in many applications. It plays an important role in organizing large document collections into a small number of meaningful topic groups [56]. A variety of approaches (e.g. [4, 15, 27, 61]) to text clustering have been developed. Typically clustering approaches can be categorized as *agglomerative* or *partitional* based on the underlying methodology of the algorithm, or as *hierarchical* or *flat* (non-hierarchical) based on the structure of the final solution [73].

In general, text clustering involves constructing a vector space model and representing documents by feature vectors. First, a set of features is properly selected from the document corpus. Second, each document is represented by a feature vector, which consists of the weights of all chosen features. Finally, clustering proceeds by measuring the similarity (e.g. a function of Euclidean distance) between documents and assigning documents to appropriate clusters.

Web page clustering, which has recently been of significant interest in Web content mining [37], is a useful tool for summarization, organization and navigation of semi-structured Web documents [65]. For instance, an effective clustering system can help greatly improve the organization and presentation of search engine results.

Approaches to Web page clustering have been either *text-based* or *link-based*. Text-based approaches [7, 12] use a set of common terms shared among documents as features. Due to the large number of words in the vocabulary, this approach typically results in a very high dimensional document representation. On the other hand, link-based approaches [13, 64] analyze the hyperlinks between Web documents for feature selection. The feasibility of such approaches depends on availability of a rich set of hyperlinks. Some Web page clustering systems [49, 65] use a combination of the above two.

In this paper, we investigate the problem of Web page clustering in the context of Web site summarization. In order to effectively summarize an entire multi-topic Web site, we need to find the essential topics in a given Web site. Thus, we perform coupled text- and link-based clustering on Web pages from the target Web site to find meaningful topic groups, which can further be individually summarized by a summarization system [71].

However, in text-based clustering where the bag-of-words representation is used, a very high dimensional feature space is often required. These features may not be equally useful. Noise words may not contribute to or even degrade the clustering process. Thus, selecting the “best” feature subset, known as Feature Selection (FS), is an important task<sup>12</sup>.

Feature selection has been well studied in text categorization [68] and text clustering [39] tasks (a review of the literature can be found in [38]). Since Web pages often contain more “utility text” (e.g. navigational menu) than traditional plain text, it is important to perform proper feature selection on the text part. Note that we always extract text using Lynx, so Javascript and HTML tags have already been removed. In this paper, we investigate whether standard feature selection methods, including document frequency, term variance, information gain, mutual information, and  $\chi^2$  statistic, can improve the quality of text-based Web page clustering. For the link-based clustering, we apply co-citation and bibliographic coupling to learn whether linkage information can improve the clustering quality.

More specifically, we apply  $K$ -means and  $X$ -means [50] (an extension of  $K$ -means that identifies the optimal number of clusters within a given range) algorithms to perform clustering on a set of Web pages from a given Web site. The clustering quality is evaluated using entropy and accuracy.

#### 3.1 Web Page Corpora

In order to perform Web page clustering experiments we choose two test Web sites, the Software Engineering Institute (SEI) Web site<sup>13</sup>, and the Air Canada (AC) Web site<sup>14</sup>. The two Web sites have been extensively used in our previous Web-based research [71, 69, 72]. They are well designed for our purpose in that most of the Web pages are static HTML files. More importantly, each Web page can be easily labelled into one of a set of topics, which are defined by the Web site designers. The topic information will be used for clustering evaluation purposes. In the following subsection, we discuss how we crawl a given Web site and collect various features of Web pages for the clustering purpose.

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<sup>12</sup>Note that feature selection is different from feature extraction in the sense that the former chooses an optimal subset of features while the latter often introduces a new and smaller feature space via projection or mapping.

<sup>13</sup><http://www.sei.cmu.edu>, last crawled on November 15, 2005.

<sup>14</sup><http://www.aircanada.ca>, English version, last crawled on November 15, 2005.

### 3.1.1 Web Site Traversal

Intuitively, Web site designers often construct a Web site and organize its contents in a hierarchical manner. In a given Web site, each Web page is uniquely identified by its Uniform Resource Locator (URL). The home page often contains a general introduction to the entity behind the Web site. All Web pages, which are pointed to by the home page, often cover main topics of the Web site. If we go deeper into the Web site, then pages tend to discuss specific topics with more details.

**Breadth-first Search** In order to effectively summarize a given Web site, we need to crawl the site and obtain its link structure. The breadth-first search algorithm is often used for this purpose. The algorithm has two auxiliary lists. One is  $Q$ , a queue of pages to be visited from the front end one by one. Initially,  $Q$  has only one node, which is the home page. The other is  $V$ , a list of pages that are already visited. At each level of the breadth-first traversal, each Web page will be tested whether it has been visited and various features will be updated accordingly. The search process continues until no more new Web pages can be found, or a desired number of pages or depth levels has been visited. The pseudo code of the algorithm is shown in Figure 5.

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*Input:* URL of the home page of a given Web site.

*Output:* A link hierarchy of the target Web site.

*Initialization:* Mark all nodes unvisited.

```

begin
  put home page into  $Q$ 
  while  $Q$  is not empty
     $u$  = front element of  $Q$ 
    remove  $u$  from  $Q$  and add  $u$  to  $V$ 
    visit  $u$ 
  end while
end

```

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Figure 5: Algorithm of breadth-first Web site traversal.

When a Web page is visited in the Web site traversal, various features are dynamically updated. In our work, we look at both text- and link-based features. The former contains the plain text extracted from the HTML source of a Web page, while the latter consists of incoming and outgoing links of the current page. The features that we aim to investigate for each individual Web page are summarized in Table 1.

Table 1: Feature list of a Web page.

Notation	Feature	Meaning
$u$	URL	Uniform Resource Locator of a Web page
$d$	depth	depth level in the breadth-first traversal
$t$	plain text	plain text extracted from the HTML source
$I$	incoming links	set of incoming links
$O$	outgoing links	set of outgoing links

The feature extraction process consists of items such as calculating the depth level of an unvisited page, updating the incoming and outgoing link sets, etc. The pseudo code, which updates the feature list when a Web page is visited, is presented in Figure 6.

For small and medium size Web sites<sup>15</sup>, it is feasible to crawl the entire Web site for complete link hierarchy construction. However, for large Web sites (e.g. <http://www.microsoft.com>), it is very time-intensive to do so. In such cases, the number of levels to crawl should be properly determined in order to construct a link hierarchy which can effectively represent the whole Web site. In our work, site traversal stops when either a total of 1000 Web pages

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<sup>15</sup>By Web site we mean all Web pages that reside in a unique host. Investigation of out-of-host pages is not our focus in this work.

---

*Input:*  $Q$ ,  $V$ , and Web page  $u$ .  
*Output:* Feature list of various Web pages.

```

begin
  parse Web page  $u$  to obtain  $t$  and  $O$ 
  for each  $v \in O$  do
    if  $v \notin V$ , then
      add  $v$  to both  $Q$  and  $V$  and  $d_v = d_u + 1$ 
    endif
    add  $v$  to  $O(u)$  and add  $u$  to  $I(v)$ 
  end for
end

```

---

Figure 6: Algorithm of Web page feature update.

have been crawled, or the crawler has finished crawling the fourth depth level, whichever comes first. The maximum values 1000 and 4 are empirical numbers set in [71].

**Link Hierarchy** The resulting link structure from the breadth-first traversal forms a directed Web graph, as shown in Figure 7. Each node in the link hierarchy represents a Web page, which is uniquely identified by its URL. An arrow indicates that there is a hyperlink pointing from one page to another page. Pages at top levels tend to describe general topics, while pages at bottom levels more often discuss details of these topics.

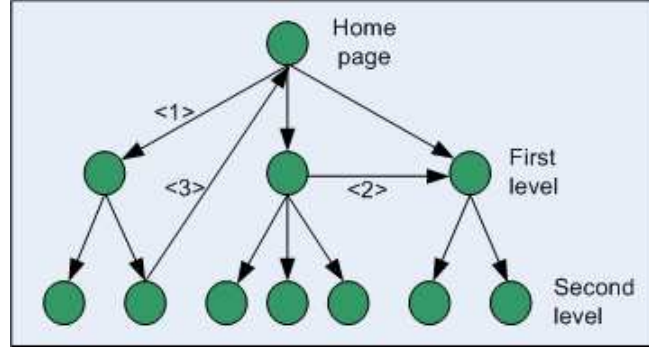


Figure 7: Hierarchical link structure of a Web site.

In such a link hierarchy, we distinguish three types of links.

- **Forward link:** a hyperlink in one Web page pointing to another Web page at a lower layer, labelled  $< 1 >$  in Figure 7.
- **Cross link:** a hyperlink in one Web page pointing to another Web page at the same layer, labelled  $< 2 >$  in Figure 7.
- **Back link:** a hyperlink in one Web page pointing to another Web page at a higher layer, labelled  $< 3 >$  in Figure 7.

These three types of links form the link hierarchy of a given Web site. It is observed that forward-links are of the majority. We aim to investigate the significance of these links in the Web site summarization framework.

In our work, only pages within the target host are collected. Investigation of out-of-host pages is a future research direction. Also only Web pages of the **text/html** content type are kept and all other application files (e.g. .jpg, .gif, and .doc) are removed for simplifying text processing. More details are available in Appendix A.

The above crawling process leads to a smaller set of 927 Web pages for the SEI site and 627 for the AC site. Each remaining Web page is manually visited and a topic label is assigned to it. The Web site designers have already provided a topic for each Web page, which we review. If we do not agree with the Web site designers, we correct it

based on the text and additional information such as the “Keywords” and “Metadata” fields embedded in the HTML code. We observe that more than 95% of the times we agree with the Web site designers about the topic assignment. Only the primary topic is assigned to a Web page when there are multiple topics available. Finally, plain text from all Web pages is extracted by the text browser Lynx.

### 3.1.2 SEI and AC Corpora

The final SEI corpus after preprocessing is summarized in Table 2, where  $i$  is the topic index and  $|T_i|$  is the number of Web pages in each topic  $T_i$ . The topics are presented in the order of first appearance in the site traversal.

Table 2: Topic distribution for the Software Engineering Institute Web site.

$i$	Topic $T_i$	$ T_i $
1	About SEI	180
2	Software Management	115
3	Software Engineering	141
4	Software Acquisition	32
5	Work With Us	90
6	Software Products	225
7	Publications	92
8	News	52

The most populated topic is *Software Products* with 225 documents while the least populated topic is *Software Acquisition* with only 32 documents, as shown in Table 2.

The final AC corpus after preprocessing is summarized in Table 3, where  $i$  is the topic index and  $|T_i|$  is the number of Web pages in each topic  $T_i$ . Again, the topics are presented in the order of first appearance in the site traversal.

Table 3: Topic distribution of the Air Canada Web site.

$i$	Topic $T_i$	$ T_i $
1	About Air Canada	96
2	News and Media	174
3	Flights	135
4	Hotels	36
5	Cars	30
6	Vacation	75
7	Investor	21
8	Career	39
9	Aeroplan	21

The most populated topic is *News and Media* with 174 documents while the least populated topics are *Investor* and *Aeroplan* with only 21 documents, as shown in Table 3.

We observe that both corpora have an imbalanced topic distribution, i.e., a large number of documents are from few topic groups. This may affect feature selection in text-based clustering, i.e., the topic distribution imbalance may favor methods that do not rely on a labelled document set such as Term Variance while worsening the performance of methods that require a labelled document set such as Information Gain and Mutual Information.

## 3.2 Clustering Algorithms

In this work, we experiment with both  $K$ -means and  $X$ -means algorithms.  $X$ -means is an extension of the conventional  $K$ -means algorithm. Our goal is to investigate whether basic clustering algorithms can effectively detect topic groups for further summarization. Investigation of advanced clustering techniques is one of the future research directions.

### 3.2.1 *K*-means

The conventional *K*-means algorithm has been widely used in document clustering tasks due to its implementation simplicity and low computational complexity. This non-hierarchical method first selects *K* data points using a random seed. The data points are used as the initial centroids for the *K* clusters, one for each cluster. Second, all data points are assigned to the cluster whose centroid is the closest (e.g. in terms of Euclidean distance). Third, the centroid of each cluster is recalculated based on the points assigned to it. Steps two and three are repeated until the centroids do not change [61].

### 3.2.2 *X*-means

One major shortcoming of *K*-means is that the number of clusters, *K*, has to be provided beforehand, which is often difficult to decide without any prior topical knowledge of a given document corpus. *X*-means [50], an extension to the standard *K*-means, has the advantage of estimating the optimal number of clusters within a given range. This is useful in finding topic groups in a given Web site.

*X*-means is a variation of the *K*-means algorithm. After each run of *K*-means, it computes the Bayesian Information Criterion [50] to decide which subset of the current centers should be further split in order to better fit the data.

In this work, we experiment with both *K*-means and *X*-means to perform Web page clustering. The implementations of *K*-means and *X*-means are from the WEKA<sup>16</sup> software package and the authors of the *X*-means algorithm<sup>17</sup>, respectively. Both implementations use the Euclidean distance to measure the similarity between two documents, i.e., the smaller the distance is, the more similar they are.

## 3.3 Document Representation

One important task in the clustering process is how to represent documents. The Vector Space Model is often used for this purpose. Each document is represented by a vector which consists of a set of features that are properly chosen from the feature space.

In this work, we look at both text- and link-based features. Text-based features include a list of key phrases that are extracted from the text body of Web pages using automatic phrase extraction methods. In this work, we look at three methods, TFIDF, KEA and CNC. Link-based features consist of incoming links and outgoing links, which are inspired by the ideas of co-citation [57] and bibliographic coupling [29] in the scientific literature, respectively.

### 3.3.1 Text-based Features

For each Web page in the above two Web corpora, we obtain its plain text using Lynx. Then we separately apply three key phrase extraction methods, TFIDF, KEA, and CNC to obtain phrases for document representation.

**TFIDF** TFIDF has been widely used as bag-of-words representation in clustering applications. In this work, we use TFIDF as a baseline method. Keyword identification involves in the following steps:

First, a standard list of 425 stopwords [19] is removed from each text file (plain text of a Web page). Second, plain text is tokenized and each unique word is stemmed using the Porter stemmer, and its frequency in the current text file (TF part) and the number of documents where it appears (DF part) are recorded. After all the documents are processed, *tfidf* values of words (more precisely, word stems) in each document are calculated and normalized as in Equations (1) and (2), respectively.

$$w_{i,j} = f_{i,j} \times \log \frac{N}{n}. \quad (1)$$

$$W_{i,j} = \frac{w_{i,j}}{\sqrt{\sum_i w_{i,j}^2}}. \quad (2)$$

where  $w_{i,j}$  is the *tfidf* weight of term  $t_i$  in document  $d_j$ ;  $f_{i,j}$  is the term frequency of term  $t_i$  in document  $d_j$ ;  $N$  is the total number of documents in the collection;  $n$  is the number of documents containing term  $t_i$ ; and  $W_{i,j}$  is the normalized weight of term  $t_i$  in document  $d_j$ .

All the unique terms in the document collection are ranked according to their *df* values. Those terms with a *df* value above a certain threshold form the feature space for document representation.

<sup>16</sup><http://www.cs.waikato.ac.nz/ml/weka>

<sup>17</sup><http://www.cs.cmu.edu/~dpelleg/kmeans.html>

**KEA** Automatic Keyphrase Extraction (KEA) [67] is an efficient and practical algorithm for extracting key phrases from a document corpus. It consists of two stages: training and extraction.

In the extraction stage, KEA uses the model to find the best set of (by default 5) key phrases in new documents. More explicitly, KEA chooses a set of candidate key phrases from new documents and calculates their two feature values as above. Then each candidate is assigned a weight, which is the overall probability that this candidate is a key phrase.<sup>18</sup>

We apply the NTXT model built in [70] to the Web pages. All the candidates with a probability above a certain threshold form the feature space for document representation. Their *tfidf* values in each document are calculated and normalized as in Equations (1) and (2), respectively.

**CNC** C-value/NC-value (CNC) [20] is a domain-independent method used to automatically extract multi-word phrases from the whole document corpus.

It consists of linguistic analysis (linguistic filter, part-of-speech tagging [5], and stop-list) followed by statistical analysis (frequency analysis, *C-value*, *NC-value*) to extract and rank a list of multi-word phrases. A linguistic filter is used to extract word sequences likely to be phrases, such as noun phrases and adjective phrases.

C-value is a measure of term likelihood calculated for each candidate term based on its frequency in the corpus and the frequency of its occurrence as nested within longer terms.

NC-value is an extension to the C-value, incorporating information of context words into term likelihood. Context words are those that appear in the vicinity of candidate phrases, i.e., nouns, verbs and adjectives that either precede or follow the candidate phrase.

The final phrase list is ranked by *NC-value*. All phrases above a certain pre-defined threshold form the feature space for document representation. Their *tfidf* values in each document are calculated and normalized as in Equations (1) and (2), respectively.

### 3.3.2 Link-based Features

For the link analysis, incoming and outgoing links of each Web page are recorded during the Web site traversal.

In the scientific literature, co-citation [57] refers to the case that two documents  $d_1$  and  $d_2$  are cited by a third document  $d_3$ . The more co-citations the two documents share, the higher the co-citation strength is. On the other hand, bibliographic coupling [29] occurs when two documents  $d_1$  and  $d_2$  cite a third document  $d_3$ . Similarly, the more citations the two documents have in common, the higher the coupling strength is. Hence, these two measures are widely used to estimate the similarity between two documents in a hypertext context.

In the Web context, co-citation occurs when two Web pages  $p_1$  and  $p_2$  are pointed to by a common third page  $p_3$ , while bibliographic coupling happens when two Web pages  $p_1$  and  $p_2$  both point to a common third page  $p_3$ .

Recall that in the Web site crawling stage, the breadth-first search algorithm is used and only pages within the target host are crawled and collected. Each unique Web page is assigned a *depth* value when it appears in the site traversal for the first time and the home page has a depth of 0. All the crawled pages are sorted in the order of *first appearance* in the site traversal. Those pages whose depth value is lower than a pre-defined threshold form the link-based feature space. The link-based vector for each document consists of binary numbers. If a page in the feature space appears as an incoming or outgoing link of the current document, then the corresponding entry in the link-based vector is 1, otherwise 0.

The above link analysis has been a prominent tool in many fields such as Web information retrieval and Web mining. However, hyperlinks in a Web site are not as “organic” as references between research articles in the scientific literature. Consequently, we may have to rely more heavily on text-based features and investigate whether incorporation of link-based features can improve the clustering quality.

## 3.4 Feature Selection Methods

Clustering of documents often suffers from high dimensionality of the feature space if the bag of words representation is used. For example, when the TFIDF method is used, there are as many as tens of thousands of unique words in the corpus and many of them have no discrimination power against documents. Feature selection involves ranking the feature list and choosing a particular subset of features to represent documents. The subset could be chosen in various ways, for instance, the top  $k$  features, or features with a score of more than a pre-determined threshold.

In this work, we investigate five text-based feature selection methods. They are Document Frequency (DF), Term Variance (TV), Information Gain (IG), Mutual Information (MI), and the  $\chi^2$  statistic (CHI). The first two methods do not need any information about the topic assignment of individual documents, so they are unsupervised

<sup>18</sup>A complete description of how we construct a KEA model and apply it to the Web pages can be found in [70].

methods. In the contrast, the last three methods rely on knowledge of the topic assigned to each document, so they are supervised methods.

In all methods, let  $N$  be the total number of documents in the corpus.

### 3.4.1 Document Frequency

Document frequency is the number of documents in which a term (more precisely, its stem) appears. It is a simple and popular metric to measure a term's popularity of presence in the global corpus. Let  $n$  be the document frequency of a term  $t$ . Hence,  $n \in [1, N]$ .

For each unique term in the corpus, we compute its document frequency and remove all terms whose document frequency is less than a pre-defined threshold. The underlying assumption is that terms that are too rare are not informative and thus could be removed to reduce the feature space [68].

### 3.4.2 Term Variance

Similar to document frequency, term variance [31] is another simple topic-free metric. It measures the variance of a term's frequency of occurrence in all documents. The variance  $V$  of a term  $t$  is formally defined as follows:

$$V(t) = \sum_{i=1}^N f_i^2(t) - \frac{1}{N} \left( \sum_{i=1}^N f_i(t) \right)^2. \quad (3)$$

where  $f_i(t)$  is the number of times that term  $t$  appears in document  $i$ .

For each unique term in the corpus, we compute its term variance and remove all terms whose term variance is less than a pre-defined threshold. The underlying reasoning is that if a term's occurrence is evenly distributed over all documents, then it has little power to discriminate documents. Hence, the quality of a term is proportional to its term variance score, i.e., the higher the  $V(t)$  score, the better the term is.

### 3.4.3 Information Gain

Information gain [68] is a term goodness criterion commonly used in the text categorization task. It measures the number of bits of information obtained for topic prediction given the knowledge of presence and absence of a term in a document. The information gain  $G$  of a term  $t$  is formally defined as follows:

$$\begin{aligned} G(t) = & - \sum_{i=1}^l P(T_i) \log P(T_i) \\ & + P(t) \sum_{i=1}^l P(T_i|t) \log P(T_i|t) \\ & + P(\bar{t}) \sum_{i=1}^l P(T_i|\bar{t}) \log P(T_i|\bar{t}). \end{aligned} \quad (4)$$

where  $l$  is the number of topics in the given corpus;  $P(T_i)$  is the fraction of documents with topic  $T_i$ , i.e.,  $|T_i|/N$ ;  $P(t)$  is the fraction of documents where term  $t$  appears, i.e.,  $n/N$ ;  $P(T_i|t) = m/n$  and  $m$  is the number of documents with topic  $T_i$  where term  $t$  appears;  $P(\bar{t}) = 1 - n/N$ ; and  $P(T_i|\bar{t}) = \frac{|T_i| - m}{N - n}$ .

For each unique term in the corpus, we compute its information gain and remove all terms whose information gain is less than a pre-defined threshold. The underlying reasoning is that terms with high information gain are useful for topic prediction. Hence, the quality of a term is proportional to its information gain score, i.e., the higher the  $G(t)$  score, the better the term is.

### 3.4.4 Mutual Information

Mutual information [68] is a term goodness function often used in statistical language modelling of word associations with topics. Intuitively, it measures the information that a term and the topics share. For example, if term  $t$  and topic  $T_1$  are independent, then the presence or absence of  $t$  does not give any information about  $T_1$  and vice versa. Hence, their mutual information is zero. At the other extreme, if term  $t$  only appears in documents of topic  $T_1$ , and all documents of topic  $T_1$  contain  $t$ , then knowing  $t$  determines  $T_1$  and vice versa. The mutual information  $I$  of a term  $t$  is formally defined as follows:

$$I(t) = \sum_{i=1}^l P(T_i|t) \log \frac{P(t|T_i)}{P(t)}. \quad (5)$$

where  $P(T_i|t) = m/n$ ;  $n$  is the document frequency of term  $t$ ;  $m$  is the number of documents with topic  $T_i$  where term  $t$  appears; and  $P(t|T_i) = m/|T_i|$ .

For each unique term in the corpus, we compute its mutual information with all topics and remove all terms whose mutual information is less than a pre-defined threshold. The underlying reasoning is that terms with high mutual information have more interdependence with topics. Hence, the quality of a term is proportional to its mutual information score, i.e., the higher the  $I(t)$  score, the better the term is.

### 3.4.5 $\chi^2$ Statistic

The  $\chi^2$  statistic [68] can be used as a term goodness function to measure the lack of independence between a term and a topic and can be compared to the  $\chi^2$  distribution with one degree of freedom. The  $\chi^2$  statistic of a term  $t$  can be formally defined as follows:

$$\chi^2(t) = \sum_{i=1}^l P(T_i) \frac{N \cdot (P(t, T_i) \cdot P(\bar{t}, \bar{T}_i) - P(t, \bar{T}_i) \cdot P(\bar{t}, T_i))^2}{P(t) \cdot P(\bar{t}) \cdot P(T_i) \cdot P(\bar{T}_i)}. \quad (6)$$

where:  $P(t, T_i) = m/N$  and  $m$  is the number of documents with topic  $T_i$  where term  $t$  appears;  $P(\bar{t}, \bar{T}_i) = 1 - \frac{n+|T_i|-m}{N}$  and  $n$  is the document frequency of term  $t$ ;  $P(t, \bar{T}_i) = \frac{n-m}{N}$ ; and  $P(\bar{t}, T_i) = \frac{|T_i|-m}{N}$ .

For each unique term in the corpus, we compute its  $\chi^2$  statistic and remove all terms whose  $\chi^2$  statistic is less than a pre-defined threshold. The underlying reasoning is that terms with high  $\chi^2$  statistic have high interdependence with topics. Hence, the quality of a term is proportional to its  $\chi^2$  statistic score.

Document frequency and term variance have a linear computational complexity in terms of number of terms in all documents, while information gain, mutual information, and  $\chi^2$  statistic have a quadratic computational complexity. Moreover, if  $m = 0$ , i.e., term  $t$  and topic  $T_i$  are independent, then the corresponding part in Equations 4, 5, and 6, has a natural value of 0.

In the following subsections we discuss our experiments of text-based, link-based, and coupled text- and link-based clustering. In each part, we show results of clustering experiments and statistical tests. Our main objective is to learn the influence of feature selection on text-based clustering. Additionally, we are interested in learning whether link-based features can improve the clustering quality.

## 3.5 Evaluation Schemes

Evaluation of a particular clustering often uses either *internal quality measure* or *external quality measure*. Internal quality measure maximizes the overall similarity within clusters and dissimilarity between clusters without reference to external topical knowledge. On the other hand, external quality measure such as *entropy* and *F-measure* examines the clustering quality by comparing the resulting clusters to known topic memberships [61].

In this work, we use *entropy* and *accuracy* to evaluate the quality of a particular clustering result  $C = \{C_1, C_2, \dots, C_k\}$  with respect to known topics  $T = \{T_1, T_2, \dots, T_l\}$ . Each cluster  $C_i$  ( $1 \leq i \leq k$ ) or topic  $T_j$  ( $1 \leq j \leq l$ ) represents a set of documents.

### 3.5.1 Entropy

Entropy [48] measures the purity or uniformity of clusters with respect to known topics. It is formally defined as the weighted sum of entropies for all clusters as shown in Equation 7. The smaller the entropy, the better the result.

$$E(C) = - \sum_{i=1}^k \frac{|C_i|}{N} \cdot \sum_{j=1}^l p_{i,j} \log p_{i,j}. \quad (7)$$

where  $p_{i,j}$  is the probability that a document in cluster  $C_i$  is of the topic  $j$ , estimated by  $\frac{|C_i \cap T_j|}{|C_i|}$ .



### 3.5.2 Accuracy

Accuracy (also known as precision) [39] is an intuitive method to calculate the average quality of all clusters. Intuitively the accuracy of a cluster is defined as the fraction of a cluster the dominant topic represents. The overall accuracy of a particular clustering is formally defined as the weighted sum of accuracies for all clusters as shown in Equation 8.

$$A(C) = \sum_{i=1}^k \frac{|C_i|}{N} \cdot \frac{\max_{j=1}^l |C_i \cap T_j|}{|C_i|}. \quad (8)$$

which is equivalent to

$$\frac{1}{N} \sum_{i=1}^k \max_{j=1}^l |C_i \cap T_j|. \quad (9)$$

## 3.6 Text-based Clustering

For text-based clustering, we are interested in finding out whether there is a statistically significant difference between the quality of the following clustering options:

- Clustering methods:  $K$ -means vs.  $X$ -means. In  $K$ -means clustering,  $K$  represents the desired number of clusters and has to be pre-defined. In our case, the topic groups are already known. Hence, we set  $K$  equal to the known number of topics in each Web corpus, i.e., 8 for the SEI corpus and 9 for the AC corpus. For  $X$ -means clustering, we let  $X$ -means determine the optimal number of clusters within the range of  $[1, 20]$ .
- Document representation methods: TFIDF vs. KEA vs. CNC. We separately apply TFIDF, KEA, and CNC to obtain a bag of phrases and define feature sets using the feature selection methods. For example, when the KEA method is used, the sets of phrases from each web page are united and then phrases are ranked by each feature selection method. Thus we have five different feature sets for each type of text-based document representation.
- Feature selection methods: DF vs. TV vs. IG vs. MI vs. CHI. For each document representation used, the five feature selection methods are separately used to define feature sets.
- Dimensionality reduction: we perform clustering in both high and low dimensional space to see if feature selection methods can reduce the dimensionality while maintaining the quality of clusters. The eight different dimensionalities we choose are: 50, 100, 200, 300, 500, 1000, 2000, and 3000. For example, when the dimensionality of 1000 is used, the top 1000 phrases of each feature list will be used to represent all documents using the normalized *tfidf* values of selected phrases.

We enumerate all configurations of the above options to evaluate text-based clustering. This leads to a total of  $2$  (algorithms)  $\times 3$  (document representations)  $\times 5$  (feature selections)  $\times 8$  (dimensionalities) = 240 clustering configurations for each Web corpus. We denote each clustering configuration in the order of *clustering method*, *document representation*, *feature selection*, and finally *dimensionality*. For instance, the configuration of *X-means clustering with 500 KEA phrases ranked by TV* will be denoted as *xm-kea-tv-500*.

For each configuration, the clustering is repeated for 20 times using 20 randomly chosen seeds. The 20 repeated runs produce a list of 20 entropy and 20 accuracy values for each clustering. The mean entropy (denoted as  $\bar{e}$ ), or the mean accuracy (denoted as  $\bar{a}$ ) over all 20 runs is taken as the **quality** of this particular clustering. As an example, Table 4 shows the entropy and accuracy values for configurations *km-kea-tv-500* and *xm-kea-tv-500* on the AC corpus.

As we can see in Table 4,  $K$ -means and  $X$ -means achieve a mean entropy of 0.9396 and 0.7312, respectively, and a mean accuracy of 0.6388, and 0.6983, respectively. This indicates that  $X$ -means algorithm produces a clustering with higher quality than  $K$ -means does.

### 3.6.1 Comparison of All Configurations

We are interested in finding out which clustering configuration can lead to the best clustering quality. For each Web corpus, we sort all the configurations in ascending order of mean entropy over 20 runs (the lower, the better) and in descending order of mean accuracy over 20 runs (the higher, the better), respectively.

Table 4: Entropy and Accuracy values for  $K$ -means and  $X$ -means clustering on the AC corpus using 500 KEA phrases ranked by TV.

Run	Entropy		Accuracy	
	$K$ -Means	$X$ -Means	$K$ -Means	$X$ -Means
1	1.1112	0.7468	0.6029	0.7081
2	0.8396	0.8578	0.6746	0.6699
3	1.0502	0.7873	0.5981	0.6555
4	0.8910	0.9596	0.6364	0.6411
5	0.9587	0.7730	0.6411	0.6746
6	0.9469	0.5581	0.6459	0.7751
7	0.7716	0.6094	0.7129	0.7321
8	1.0240	0.5844	0.6029	0.7656
9	0.7863	0.6070	0.6842	0.7512
10	0.9247	1.0141	0.6077	0.5885
11	0.9947	0.7589	0.5837	0.6890
12	1.0732	0.7789	0.6316	0.7033
13	1.0223	0.8131	0.6220	0.6555
14	0.8415	0.6545	0.6603	0.7129
15	0.7768	0.6314	0.6938	0.7512
16	0.8671	0.6419	0.6651	0.7368
17	0.8886	0.6452	0.6699	0.7033
18	0.8298	0.6425	0.6555	0.7177
19	0.9630	0.7116	0.6172	0.7033
20	1.2316	0.8484	0.5694	0.6316
$\bar{e}/\bar{a}$	0.9396	0.7312	0.6388	0.6983
$s_d$	0.1221	0.1252	0.0385	0.0483

We sort all the configurations of text-based clustering using mean entropy and mean accuracy, respectively. The results of the top 5 configurations on both corpora are summarized in Table 5.

The top configurations are the same with either ranking criterion, mean entropy or mean accuracy, and they are in the same ranking order. The only exception is the fifth configuration on the SEI corpus.

We also observe that the top configurations are dominated by  $X$ -means clustering using CNC document representation, where  $X$ -means algorithm often returns an optimal number of clusters from 8 to 12. This indicates that  $X$ -means clustering is better than  $K$ -means clustering and CNC document representation is better than TFIDF and KEA.

In terms of dimensionality, the top five configurations use a dimensionality between 200 and 500, which indicates feature selection methods can effectively reduce the dimensionality from thousands of features to hundreds.

### 3.6.2 Comparison of $K$ -means and $X$ -means Algorithms

One of our objectives is to compare the clustering quality of  $K$ -means and  $X$ -means algorithms. In order to do this, we pair up clustering configurations such that the only difference between each pair is the clustering method, e.g. *km-cnc-tv-300* vs. *xm-cnc-tv-300*. In this comparison, we use  $K = 8$  for the SEI corpus and  $K = 9$  for the AC corpus.  $X$ -means clustering returns the optimal number of clusters (based on Bayesian Information Criterion [50]), which is between 9 and 12 for the SEI corpus, and between 8 and 12 for the AC corpus.

For each pair of clustering configurations, we have a pair of 20 entropy or accuracy values, on which we apply the two-tail paired  $t$ -test, which generally compares two different methods used for experiments carried out in pairs [17]. It is the difference between each pair of measurements which is of interest.

For example, when comparing *km-cnc-tv-300* and *xm-cnc-tv-300*, we have 20 pairs of entropy values, denoted as  $e_{km_i}$  and  $e_{xm_i}$  ( $i = 1, 2, \dots, 20$ ), which are independent observations from the two samples in  $K$ -means and  $X$ -means clustering, respectively. Then the differences  $d_i = e_{km_i} - e_{xm_i}$  ( $i = 1, 2, \dots, 20$ ) will be a sample of size  $n$  ( $n = 20$ ) from a population with mean zero. Furthermore, if the populations, from which the above two samples are drawn, are approximately normally distributed, then the differences will also be approximately normally distributed. If the

Table 5: The top 5 configurations of text-based clustering, sorted in ascending order of mean entropy  $\bar{e}$  and in descending order of mean accuracy  $\bar{a}$ , respectively.

SEI Corpus				
Rank	$\bar{e}$	Configuration	$\bar{a}$	Configuration
1	0.9227	<i>xm-cnc-tv-300</i>	0.6440	<i>xm-cnc-tv-300</i>
2	1.0005	<i>xm-cnc-chi-300</i>	0.6222	<i>xm-cnc-chi-300</i>
3	1.0201	<i>xm-cnc-tv-500</i>	0.6182	<i>xm-cnc-tv-500</i>
4	1.0314	<i>xm-cnc-chi-500</i>	0.6050	<i>xm-cnc-chi-500</i>
5	1.0444	<i>xm-cnc-mi-500</i>	0.6031	<i>xm-cnc-tv-200</i>
AC Corpus				
Rank	$\bar{e}$	Configuration	$\bar{a}$	Configuration
1	0.6200	<i>xm-cnc-tv-300</i>	0.7502	<i>xm-cnc-tv-300</i>
2	0.6267	<i>xm-cnc-chi-500</i>	0.7426	<i>xm-cnc-chi-500</i>
3	0.6389	<i>xm-cnc-tv-500</i>	0.7347	<i>xm-cnc-tv-500</i>
4	0.6795	<i>xm-kea-tv-300</i>	0.7287	<i>xm-kea-tv-300</i>
5	0.6815	<i>xm-cnc-chi-300</i>	0.7285	<i>xm-cnc-chi-300</i>

observed average difference is denoted by  $\bar{d}$ , the standard deviation of the observed differences by  $s_d$ , and the  $t$ -test statistic by  $t$ , then we have the following equations:

$$\begin{aligned}
\bar{d} &= \frac{\sum_{i=1}^n d_i}{n}, \\
s_d^2 &= \frac{\sum_{i=1}^n (d_i - \bar{d})^2}{n-1}, \\
t &= \frac{\bar{d}}{s_d/\sqrt{n}} \quad (n=20).
\end{aligned} \tag{10}$$

The null hypothesis  $H_0$  and the alternative hypothesis  $H_1$  are given by: 1)  $H_0 : \bar{d} = 0$  ( $K$ -Means clustering and  $X$ -means clustering produce results with the same quality), and 2)  $H_1 : \bar{d} > 0$  ( $X$ -Means clustering is statistically significantly better than  $K$ -Means clustering). If  $H_0$  is true, then the distribution of  $t$  will be a  $t$ -distribution with  $n-1$  degrees of freedom, as the estimate  $s_d$  is calculated from  $n$  differences.

We perform two-tail  $t$ -tests at the 5% significance level on all 120 pairs<sup>19</sup> of clustering configurations using both entropy and accuracy on the two Web corpora. We observe that in all 480 comparisons the  $t$ -statistic is greater than  $t_{0.05,19}$ , which is 2.093 from the  $t$ -table. Since  $t > t_{0.05,19}$  ( $P_{value} \leq 0.05$ ), it is reasonable to reject the null hypothesis  $H_0$ , i.e., there is a statistically significant difference between the quality values of  $K$ -means clustering and  $X$ -means clustering. More precisely,  $X$ -means statistically significantly outperforms  $K$ -means in all cases.

In terms of computational performance, we observe that  $X$ -means clustering is generally faster than  $K$ -means clustering since the former applies the *KD-trees* data structure for speedup optimization [50]. Critical evaluation of computational performance of both algorithms is not a main goal of this work and consequently it will be one of the future research directions.

### 3.6.3 Comparison of Document Representation Methods

We are also interested in determining whether document representation has an impact on the quality of Web page clustering. In order to do this, we pair up clustering configurations such that the only difference between each pair is the document representation method, e.g. *xm-kea-tv-300* vs. *xm-cnc-tv-300*. Since  $X$ -means clustering is statistically significantly better than  $K$ -means clustering, we only perform comparisons of document representation methods in  $X$ -means clustering.

We perform  $t$ -tests at the 5% significance level on all 120 pairs<sup>20</sup> of clustering configurations using both entropy and accuracy measures on the two Web corpora. We observe that the  $t$ -test results are consistent when either entropy or accuracy is used on both corpora. The  $t$ -test results of all comparisons are presented in Table 6, where  $<$

<sup>19</sup> $K$ -means vs.  $X$ -means: 3 (document representations)  $\times$  5 (feature selections)  $\times$  8 (dimensionalities) = 120 pairs.

<sup>20</sup>TFIDF vs. KEA vs. CNC:  $C_3^2 \times 5$  (feature selections)  $\times$  8 (dimensionalities) = 120 pairs.

indicates  $P_{value} > 0.05$ , which means no statistically significant difference at the 5% significance level is found, and  $<<$  indicates  $P_{value} \leq 0.05$ , which means a statistically significant difference at the 5% significance level is found.

Table 6: Paired two-tail  $t$ -tests of document representation methods on the SEI and AC corpora using both entropy and accuracy.

Method	SEI Corpus	AC Corpus
TFIDF vs. KEA	$<<$	$<<$
TFIDF vs. CNC	$<<$	$<<$
KEA vs. CNC	$<<$	$<$

Both KEA and CNC are statistically significantly better than TFIDF in  $X$ -means clustering for both entropy and accuracy evaluation, and CNC is statistically significantly better than KEA on the SEI corpus, as shown in Table 6. However, there is no statistically significant difference between KEA and CNC on the AC corpus. This can be explained by the fact that the AC corpus has less narrative text than the SEI corpus and consequently the quality difference between CNC and KEA is smaller on the AC corpus than on the SEI corpus. Overall, CNC is the best document representation method in the Web page clustering task.

### 3.6.4 Comparison of Feature Selection Methods

One of our main objectives is to compare the five feature selection methods in the Web page clustering task. Since IG, MI, and CHI are supervised methods, they are treated as upper bounds on the performance of the unsupervised methods DF and TV. In real world clustering applications where topical knowledge is not available, only DF and TV can be used.

In order to perform the comparisons, we pair up clustering configurations such that the only difference between each pair is the feature selection method, e.g.  $xm-cnc-tv-300$  vs.  $xm-cnc-chi-300$ . Since  $X$ -means clustering is statistically significantly better than  $K$ -means clustering, and CNC is the best document representation method, we only perform comparisons of feature selection methods in  $X$ -means clustering using the CNC document representation.

We perform  $t$ -tests at the 5% significance level on all 80 pairs<sup>21</sup> of clustering configurations using both entropy and accuracy measures on the two Web corpora.

**Results on the SEI Corpus** The  $t$ -test results on the SEI corpus using entropy are presented in Table 7, where  $<$  or  $>$  indicates  $P_{value} > 0.05$ , which means no statistically significant difference at the 5% significance level is found, and  $<<$  or  $>>$  indicates  $P_{value} \leq 0.05$ , which means a statistically significant difference at the 5% significance level is found.

Table 7: Paired two-tail  $t$ -tests of the five feature selection methods on the SEI corpus using entropy.

Method	TV	IG	MI	CHI
DF	$<<$	$<$	$<<$	$<<$
TV		$>>$	$>$	$>$
IG			$<<$	$<<$
MI				$<$

The  $t$ -test results using entropy can be summarized as  $TV > CHI > MI >> IG > DF$  and further grouped as  $\{TV, CHI, MI\} >> \{DF, IG\}$ <sup>22</sup>, as shown in Table 7. When accuracy is used, the  $t$ -test results are similar except that  $CHI >> MI$ . Hence, we can conclude that TV is comparable to the supervised methods CHI and MI, and statistically significantly better than the unsupervised method DF. As a result, TV is the feature selection method of choice on the SEI corpus.

**Results on the AC Corpus** We observe that the  $t$ -test results are consistent when entropy and accuracy are used on the AC corpus, as shown in Table 8.

<sup>21</sup>DF vs. TV vs. IG vs. MI vs. CHI:  $C_5^2 \times 8$  (dimensionalities) = 80 pairs.

<sup>22</sup> $>$  or  $>>$  is not transitive in the mathematical sense.

Table 8: Paired two-tail  $t$ -tests of the five feature selection methods on the AC corpus using both entropy and accuracy.

Method	TV	IG	MI	CHI
DF	<<	<	<<	<<
TV		>>	>>	>
IG			<<	<<
MI				<<

The  $t$ -test results can be summarized as  $TV > CHI >> MI >> IG > DF$  and further grouped as  $\{TV, CHI\} >> \{MI\} >> \{IG, DF\}$ , as shown in Table 8. Again, we can conclude that TV is the feature selection method of choice on the AC corpus.

From the results above, we observe that TV is the feature selection method of choice in the Web page clustering task. In most cases, it statistically significantly outperforms MI, IG, and DF. This can be explained by the fact that the topic distribution is imbalanced so there is not enough data for the supervised methods, i.e., IG, MI and CHI, to perform well. On the other hand, TV can find features with higher variance across documents that have more power to discriminate documents. However, comparing these feature selection methods on more Web sites is highly desired.

### 3.6.5 Comparison of Dimensionalities

We perform text-based clustering in both high and low dimensional space in order to find out if feature selection methods can significantly reduce the dimensionality in text-based clustering. We want to find out what is the proper range of the number of features (instead of a fixed number of features) for each feature selection method such that when these features are used the best clustering quality can be achieved.

Since  $X$ -means clustering is statistically significantly better than  $K$ -means clustering and CNC is the best document representation method, we only perform comparisons of dimensionality in  $X$ -means clustering using CNC document representation. Each feature selection method is separately used to rank the CNC phrases and the top  $n$  ( $n \in \{50, 100, 200, 300, 500, 1000, 2000, 3000\}$ ) phrases are used as features. For each feature selection method, we simply rank the quality of clustering using 8 different dimensionalities according to mean entropy or mean accuracy.

We observe that the results of dimensionality comparisons are consistent when entropy and accuracy are used on both corpora. For each feature selection method on the two corpora, we choose the dimensionality that leads to the lowest entropy and the highest accuracy as the best dimensionality, which is presented in Table 9.

Table 9: Best dimensionality for each feature selection method in CNC-based  $X$ -means clustering on the two corpora using both entropy and accuracy.

Method	DF	TV	IG	MI	CHI
SEI	200	300	100	500	300
AC	300	300	200	500	500

DF and IG tend to suggest a smaller dimensionality than TV, CHI, and MI, as shown in Table 9. Generally speaking, a dimensionality around 300 seems to be a reasonable choice for most feature selection methods. This reduces the high dimensional space of text-based clustering, which is often as high as 3000, by an order of magnitude.

## 3.7 Link-based Clustering

In addition to the conventional text-based clustering, we also investigate the quality of Web page clustering using link-based features, i.e., the incoming and outgoing links. For link-based clustering, we are interested in finding out whether there is a statistically significant difference between the quality of the following clustering options:

- Clustering methods:  $K$ -means vs.  $X$ -means. Same as text-based clustering, we set  $K$  equal to the number of topics in each Web corpus for  $K$ -means clustering, i.e., 8 for the SEI corpus and 9 for the AC corpus. For  $X$ -means clustering, we let  $X$ -means determine the optimal number of clusters within the range of  $[1, 20]$ .

- Document representation: co-citation vs. bibliographic coupling. Web pages whose depth value is less than a pre-defined threshold form the feature space. We separately apply co-citation and bibliographic coupling to represent each Web page using a link-based vector  $V$ , denoted by  $\{w_1, w_2, \dots, w_k\}$  ( $k \leq N$ ), where  $w_i$  equals to 1 if page  $p_i$  (represented by its URL  $u_i$ ) appears as an incoming or outgoing link of the target page, and 0 otherwise.
- Dimensionality: we perform clustering using the top  $k$  pages of the feature space, which consists of all pages whose depth value is less than a pre-defined depth value. The eight different dimensionalities we choose are: 30, 50, 100, 150, 200, 300, 500, and all the pages.

We enumerate all configurations of the above options to evaluate link-based clustering. This leads to a total of  $2$  (algorithms)  $\times 2$  (document representations)  $\times 8$  (dimensionalities) = 32 clustering configurations for each Web corpus. We denote each clustering configuration *clustering\_method-document\_representation-dimensionality*. For instance, the configuration of *K-means clustering using co-citation with the top 200 pages* will be denoted as *km-in-200*, and the configuration of *X-means clustering using bibliographic coupling with the top 300 pages* will be denoted as *xm-out-300*.

For each configuration, the clustering is repeated for 20 times using 20 randomly chosen seeds, which produces a list of 20 entropy and 20 accuracy values. The mean entropy (denoted as  $\bar{e}$ ), or the mean accuracy (denoted as  $\bar{a}$ ) over all 20 runs is taken as the quality of this particular clustering.

### 3.7.1 Comparison of All Configurations

We aim to find out which link-based clustering configuration can lead to the best clustering quality. For each Web corpus, we sort all the configurations in ascending order of mean entropy (the lower, the better) and in descending order of mean accuracy (the higher, the better), respectively.

**Results on the SEI Corpus** We sort all the configurations of link-based clustering on the SEI corpus using mean entropy and mean accuracy. The results of the top 5 configurations are summarized in Table 10.

Table 10: The top 5 configurations of link-based clustering on the SEI corpus, sorted in ascending order of mean entropy  $\bar{e}$  and in descending order of mean accuracy  $\bar{a}$ , respectively.

Rank	$\bar{e}$	Configuration	$\bar{a}$	Configuration
1	0.6296	<i>xm-out-300</i>	0.7605	<i>xm-out-300</i>
2	0.6450	<i>xm-out-200</i>	0.7579	<i>xm-out-200</i>
3	0.8421	<i>xm-out-150</i>	0.6855	<i>xm-out-150</i>
4	0.8628	<i>xm-out-100</i>	0.6628	<i>xm-out-100</i>
5	0.9243	<i>xm-out-500</i>	0.6341	<i>xm-out-500</i>

The top five configurations are the same with either ranking criterion, mean entropy or mean accuracy, and in the same rank order, as shown in Table 10.

We also observe that the top five configurations are dominated by *X-means* clustering using bibliographic coupling. This indicates that *X-means* clustering is better than *K-means* clustering and that bibliographic coupling is better than co-citation. The best clustering configuration using co-citation is *xm-in-200*, which achieves a mean entropy of 1.2964 and a mean accuracy of 0.4983.

In terms of dimensionality, the top five configurations use a dimensionality between 150 and 500, which indicates that link-based clustering only requires a few hundreds of pages as features.

**Results on the AC Corpus** We sort all the configurations of link-based clustering on the AC corpus using mean entropy and mean accuracy, respectively. The results of the top 5 configurations are summarized in Table 11.

Same as link-based clustering on the SEI corpus, the ordering of the top five configurations using mean entropy for ranking is exactly the same as those using mean accuracy for ranking, as shown in Table 11. Moreover, the top five configurations are again dominated by *X-means* clustering using bibliographic coupling. This is a strong indication that *X-means* is better than *K-means* and that bibliographic coupling is better than co-citation in the Web page clustering task. For comparison, the best clustering configuration using co-citation is *xm-in-100*, which achieves a mean entropy of 2.2964 and a mean accuracy of 0.2383.

Table 11: The top 5 configurations of link-based clustering on the AC corpus, sorted in ascending order of mean entropy  $\bar{e}$  and in descending order of mean accuracy  $\bar{a}$ , respectively.

Rank	$\bar{e}$	Configuration	$\bar{a}$	Configuration
1	1.8082	<i>xm-out-200</i>	0.3589	<i>xm-out-200</i>
2	1.8227	<i>xm-out-150</i>	0.3337	<i>xm-out-150</i>
3	1.9028	<i>xm-out-100</i>	0.3048	<i>xm-out-100</i>
4	1.9614	<i>xm-out-300</i>	0.2935	<i>xm-out-300</i>
5	1.9982	<i>xm-out-50</i>	0.2682	<i>xm-out-50</i>

In terms of dimensionality, the top 5 configurations use a dimensionality between 50 and 300, which indicates that link-based clustering only requires a small portion of all pages as features.

### 3.7.2 Comparison of $K$ -means and $X$ -means

Same as the comparison of  $K$ -means and  $X$ -means in text-based clustering, we compare the two methods in link-based clustering. Again, we pair up clustering configurations such that the only difference between each pair is the clustering method, e.g. *km-out-300* vs. *xm-out-300*.

We perform  $t$ -tests at the 5% significance level on all 16 pairs<sup>23</sup> of clustering configurations using both entropy and accuracy on the two Web corpora. We observe that  $X$ -means statistically significantly outperforms  $K$ -means in all 64 comparisons.

### 3.7.3 Comparison of Document Representation

We are interested in learning whether there is a statistically significant difference between link-based clustering using co-citation and bibliographic coupling. In order to do this, we pair up clustering configurations such that the only difference between each pair is the document representation method, e.g. *xm-in-300* vs. *xm-out-300*. Since  $X$ -means clustering is statistically significantly better than  $K$ -means clustering, we only perform comparisons of document representation methods in  $X$ -means clustering.

We perform  $t$ -tests at the 5% significance level on all 8 pairs<sup>24</sup> of clustering configurations using both entropy and accuracy measures on the two Web corpora. We observe that in all 32 comparisons bibliographic coupling is statistically significantly better than co-citation.

### 3.7.4 Comparison of Dimensionalities

We perform link-based clustering in both high and low dimensional space in order to find out what is the proper range of the number of links (instead of a fixed number of links) such that when these links are used the best clustering quality can be achieved.

Since  $X$ -means clustering is statistically significantly better than  $K$ -means clustering and bibliographic coupling statistically significantly outperforms co-citation, we only perform comparisons of dimensionality in  $X$ -means clustering using bibliographic coupling.

For the two Web corpora, we use the top  $k$  ( $k \in \{30, 50, 100, 150, 200, 300, 500, all\}$ ) pages as features. We rank the quality of clustering using 8 different dimensionalities according to mean entropy or mean accuracy.

We observe that the results of dimensionality comparisons are consistent when entropy and accuracy are used on both corpora. The best two dimensionalities for the SEI corpus are 300 and 200, as shown in Table 10. For the the AC corpus, the best two dimensionalities are 200 and 150. Generally speaking, a dimensionality of around 200 seems to be a reasonable choice.

## 3.8 Coupled Clustering

We have presented the results of text-based and link-based clustering, respectively. It is of interest to see whether there is any quality difference between these two approaches and whether combining them can gain more improvement of clustering quality.

<sup>23</sup> $K$ -means vs.  $X$ -means: 2 (document representations)  $\times$  8 (dimensionalities) = 16 pairs.

<sup>24</sup>Co-citation vs. Bibliographic Coupling: one pair for each of 8 dimensionalities.

### 3.8.1 Comparison of Text- and Link-based Clustering

We aim to find out which of the two methods, text-based or link-based clustering, can achieve higher quality on both Web corpora. We perform  $t$ -tests at the 5% significance level on pairs of the top 5 text- and link-based clustering configurations using both entropy and accuracy, where each pair is the  $i^{th}$  best text-based configuration versus the  $i^{th}$  ( $1 \leq i \leq 5$ ) best link-based configuration.

We compare the best five text-based clustering configurations with the best five link-based clustering configurations on both Web corpora (Tables 5, 10 for the SEI corpus, and Tables 5, 11 for the AC corpus), as shown in Table 12. We observe that the results using entropy are the same as those using accuracy.

Table 12: Paired two-tail  $t$ -tests of the best five text-based clustering versus the best five link-based clustering on both Web corpora.

Rank	SEI Corpus	AC Corpus
1	<i>xm-cnc-tv-300</i> << <i>xm-out-300</i>	<i>xm-cnc-tv-300</i> >> <i>xm-out-200</i>
2	<i>xm-cnc-chi-300</i> << <i>xm-out-200</i>	<i>xm-cnc-chi-500</i> >> <i>xm-out-150</i>
3	<i>xm-cnc-tv-500</i> << <i>xm-out-150</i>	<i>xm-cnc-tv-500</i> >> <i>xm-out-100</i>
4	<i>xm-cnc-chi-500</i> << <i>xm-out-100</i>	<i>xm-kea-tv-300</i> >> <i>xm-out-300</i>
5	<i>xm-cnc-mi-500</i> << <i>xm-out-500</i>	<i>xm-cnc-chi-300</i> >> <i>xm-out-50</i>

Link-based clustering is statistically significantly better than text-based clustering on the SEI corpus, as shown in Table 12. However, it is the opposite on the AC corpus, i.e., text-based clustering statistically significantly outperforms link-based clustering. We hypothesize that the effectiveness of link-based clustering depends on the richness of linkage information. The SEI Web site is more of an organically grown Web site with rich cross links, whereas the AC Web site is a corporate hierarchical Web site. To confirm this claim, we take a further look at the outgoing links of both corpora. There is an average of 15.5 outgoing links for a SEI Web page, but only 6.8 outgoing links for an AC Web page. This indicates that only when the linkage information is rich can the link-based clustering achieve high quality.

### 3.8.2 Coupled Text- and Link-based Clustering

We have seen that link-based clustering can be very effective such as on the SEI corpus. We aim to find a measure to detect how rich is the linkage information available in a Web site and how heavily should the linkage information be used to complement text-based clustering.

In order to achieve this, we combine text- and link-based features to perform clustering. Each document will be represented by a single vector, which consists of two sub-vectors, one with text-based features, and the other with link-based features. Based on the evaluation results of text- and link-based clustering, we choose the best text- and link-based clustering configurations, i.e., *xm-cnc-tv-300* and *xm-out-300* on the SEI corpus, and *xm-cnc-tv-300* and *xm-out-200* on the AC corpus, respectively.

Let  $V$  denote a document vector,  $V_{text}$  the text-based sub-vector, and  $V_{link}$  the link-based sub-vector, respectively. We combine text- and link-based sub-vectors using a linear model, i.e.,  $V = \{\lambda \cdot V_{text}, (1 - \lambda) \cdot V_{link}\}$  ( $\lambda \in [0, 1]$ ). The key is to determine  $\lambda$ , i.e., how much weight we should give to each of the two sub-vectors.

Finding the best  $\lambda$  is a one-dimension optimal search problem. To simplify the problem, we choose  $\lambda$  from 0 to 1 in increasing steps of 0.1 to perform  $X$ -means clustering using the combined features. Entropy and accuracy values are calculated the same as before. The mean entropy and accuracy values for each coupled clustering (a different  $\lambda$ ) are summarized in Table 13.

The best  $\lambda$  for the coupled clustering on the SEI corpus is 0.4, as shown in Table 13. This means combining text- and link-based features achieves better clustering quality than using either text- or link-based features alone. However, on the AC corpus, incorporating link-based features always decreases the clustering quality, which means link-based features are useless.

The above results indicate that text is more consistently reliable for Web page clustering than link knowledge. For some Web sites (e.g. SEI), linkage information is helpful. For other sites (e.g. AC), it might be harmful (at least no benefit is gained). The link structure of a Web site is more like a “tree” with back links<sup>25</sup> and cross links<sup>26</sup> [59].

<sup>25</sup>A back link is a hyperlink from a lower depth level Web page pointing to a higher depth level Web page, where levels are determined in the breadth-first site traversal.

<sup>26</sup>A cross link is a hyperlink between two Web pages, which are at the same depth level of the breadth-first site traversal.



Table 13: Mean entropy and mean accuracy values for coupled text- and link-based clustering on the SEI and AC corpora.

$\lambda$	SEI Corpus		AC Corpus	
	$\bar{e}$	$\bar{a}$	$\bar{e}$	$\bar{a}$
0.0	0.6296	0.7605	1.8082	0.3589
0.1	0.6268	0.7641	1.7235	0.4386
0.2	0.6209	0.7687	1.5923	0.4716
0.3	0.6152	0.7696	1.5085	0.5186
0.4	0.6098	0.7757	1.4393	0.5537
0.5	0.6342	0.7586	1.3187	0.5969
0.6	0.6937	0.7239	1.2234	0.6573
0.7	0.7561	0.7015	0.9127	0.6858
0.8	0.8123	0.6890	0.7239	0.7012
0.9	0.8639	0.6803	0.6456	0.7149
1.0	0.9227	0.6440	0.6200	0.7502

It is different from the Web graph, where link structure has already been shown to be useful in various Web-based applications.

We observe that the average number of cross links (or the ratio of cross links in outgoing links) of a Web page is an indicator of whether the linkage information should be incorporated into clustering. If the cross link information is rich (e.g. more than 50% of outgoing links are cross links), then giving higher weight to link-based features will achieve better clustering quality.

This makes sense because intuitively commercial Web sites (e.g. AC) are more likely to be designed and constructed by a person or a team using Web site design tools and methodologies. Consequently they are more likely to be hierarchical (a tree with branches and some back links). In contrast, academic Web sites (e.g. SEI) are often built and connected by many individuals. Moreover, they tend to grow organically and have more cross links between nodes.

Precisely measuring the richness of cross link information is a future research direction.

### 3.9 Summary

In this paper, we investigate  $K$ -means and  $X$ -means clustering using both text- and link-based features. In text-based clustering, we study document representation methods and feature selection methods for dimensionality reduction. In the link-based clustering, we study co-citation and bibliographic coupling. We evaluate the clustering quality using both entropy and accuracy, which are found to be consistent. Our main contribution consists of the following findings:

- $X$ -means algorithm is statistically significantly better than  $K$ -means algorithm in the Web page clustering task.
- CNC is a better text-based document representation method than TFIDF and KEA.
- Term Variance is the best text-based feature selection method, which can reduce the dimensionality by an order of magnitude if CNC is used.
- Bibliographic coupling is statistically significantly better than co-citation in the link-based clustering.
- Combining text- and link-based features can improve the clustering quality over the use of either type of features alone if the cross link information is rich.

## 4 Cluster Summarization

In the previous section, we discussed how to conduct coupled text and link-based clustering to obtain significant topic groups of a given Web site. In this section, we discuss how to separately summarize each individual cluster. We also present summaries of test Web sites, experimental methodology, and evaluation results.

Automatic summarization of an individual cluster is a multi-step process adapted from our previous work [71]. It consists of the following steps.

1. First, key phrases are extracted from the narrative text of Web pages. The key phrase extraction tool we use in this work is the C-value/NC-value (CNC) [20] method, which has been found to outperform alternative key phrase extraction methods in [70].
2. Second, key sentences are extracted from the narrative text of all Web pages. In this work, we propose a classification method where linguistic and lexical features are used to build a classifier that can be used to classify a sentence into key-sentence or non-key-sentence automatically.
3. Third, a short summary is generated for each cluster. The cluster summary consists of the top  $n_1$  key phrases and the top  $n_2$  key sentences. The parameters  $n_1$  and  $n_2$  are heuristically determined by both the informativeness of the key phrases and the key sentences and the size of the cluster summaries.

## 4.1 Key Sentence Extraction

Traditionally, in an extraction-based summarization system, once the key phrases are identified, the most significant sentences can be retrieved based on the density of key phrases present in them [11]. The significance of a sentence is measured by calculating an importance value, which is the maximum of weights of all *word clusters* within the sentence. A word cluster is defined as a sequence of words which starts and ends with a key phrase and at most 2 non-key-phrases must separate any two neighboring key phrases [8]. The weight of a word cluster is computed by adding the weights of all key phrases within the word cluster, and dividing this sum by the total number of key phrases [71]. The maximum weight of word clusters is taken as the *sentence weight*. All sentences in narrative text paragraphs are ranked by *sentence weight* and the top sentences are the key sentences to be included in the summary.

The traditional key phrase extraction method above looks for sentences with high key phrase density intuitively. Consequently, the key sentences extracted are often dominated by a few key phrases. In this paper, we propose a machine learning approach to key phrase extraction. It looks at linguistic and lexical features beyond key phrase density and builds a model for key sentence classification.

Intuitively, whether a sentence is a key sentence is determined by its coherence and topicality (relatedness to the main topic of the target Web site). The coherence is reflected by the part-of-speech patterns, which have proved to be effective in several Web-based applications such as query ambiguity reduction [1] and question answering [51]. The topicality has strong connection with features such as the depth level of the Web page where a sentence appears, as well as its weight calculated above. We hypothesize that these linguistic and lexical features contain sufficient information to determine whether a sentence is a key sentence. We apply the classification approach to test this hypothesis.

### 4.1.1 Key Sentence Classification

In order to build *KeySentence*, a classifier that is able to classify a sentence as key-sentence or non-key-sentence, a training set is needed. In our previous study [71], we created a collection of 3242 paragraphs for learning the NARRATIVE classifier, which classifies a text paragraph into narrative or non-narrative. From the paragraphs labelled narrative, we randomly select 1328 sentences. Then, the part-of-speech tags for all words in these sentences are computed using a rule-based part-of-speech tagger [5]. A total of 32 part-of-speech tags are found and summarized in Table 14.

Each part-of-speech tag is quantified by its frequency of occurrence in a paragraph. Let  $n_i$  ( $i = 1, 2, \dots, 32$ ) be the number of times the  $i^{th}$  tag appears in the paragraph. Then  $P_i$ , the fraction of the total number of all 32 tags (i.e., words) that  $n_i$  represents, is represented by Equation 11.

$$P_i = \frac{n_i}{\sum_{i=1}^{32} n_i} \quad (11)$$

Eight more attributes are added to this feature set for building the KeySentence classifier. All the 40 features and their meanings for a sentence are summarized in Table 15. Next, each sentence is manually labelled as key-sentence or non-key-sentence. The criterion to determine if a sentence is a key sentence or not is that a key sentence must provide important topical information about the Web site. Thus, we obtain a data set of 1328 sentences for building the KeySentence classifier.

We use the machine learning tool C5.0 to train a decision tree for key sentence classification. The 10-fold cross-validation shows a mean error rate of 9.5%, which is summarized in Table 16.

Table 14: A list of 32 part-of-speech tags used in part-of-speech tagging.

Tag	Meaning & Example	Tag	Meaning & Example
CC	conjunction (and, or)	RBR	adverb, comparative (faster)
CD	number (four, fourth)	RBS	adverb, superlative (fastest)
DT	determiner, general (a, the)	RB	adverb, general (fast)
EX	existential (there)	SYM	symbol or formula (US\$500)
FW	foreign word (ante, de)	TO	infinitive marker (to)
IN	preposition (on, of)	UH	interjection (oh, yes, no)
JJR	adjective, comparative (lower)	VBD	verb, past tense (went)
JJS	adjective, superlative (lowest)	VBG	verb, -ing (going)
JJ	adjective, general (near)	VCN	verb, past participle (gone)
MD	modal auxiliary (might, will)	VBP	verb, (am, are)
NNPS	noun, proper plural (Americas)	VBZ	verb, -s (goes, is)
NNP	noun, proper singular (America)	VB	verb, base (go, be)
NNS	noun, common plural (cars)	WDT	det, wh- (what, which)
NN	noun, common singular (car)	WP\$	pronoun, possessive (whose)
PRP\$	pronoun, possessive (my, his)	WP	pronoun (who)
PRP	pronoun, personal (I, he)	WRB	adv, wh- (when, where, why)

Table 15: List of the 40 features used in learning the KeySentence classifier.

Feature	Meaning
$P_i$	percentage of each of 32 part-of-speech tags
$length$	number of words in a sentence
$depth$	depth level of the Web page
$distance_d$	number of words from the beginning of document
$distance_p$	number of words from the beginning of paragraph
$phrase$	number of key phrases
$frequency$	sum of number of occurrences of all key phrases
$cluster$	number of word clusters
$weight$	sentence weight

The decision tree generated by the C5.0 program and its evaluation are presented in Figure 8. The tree has 11 leaf nodes. Among the total 1328 cases, 116 cases are misclassified, leading to an error of 8.7%. In the decision tree, about 29.5% of cases are following this rule: if the percentage of general determiners is not greater than 3.125%, and the percentage of proper singular nouns is greater than 12.1212%, then the sentence is not a key sentence.

A total of seven features play an important role in this decision tree, i.e.,  $P_{DT}$ ,  $P_{NNP}$ ,  $P_{CC}$ ,  $distance_d$ ,  $length$ ,  $depth$ , and  $frequency$ , as shown in Figure 8. This confirms our hypothesis that linguistic and lexical features play an important role in determining the coherence and topical significance of a sentence.

We apply the KeySentence classifier on all sentences from the narrative paragraphs of an individual cluster. The key sentences are then sorted in descending order of their significance weight.

Once the key phrases and key sentences for a given cluster are extracted, it is straightforward to generate a short cluster summary, which consists of the top  $n_1$  key phrases and the top  $n_2$  key sentences. The parameters  $n_1$  and  $n_2$  are heuristically determined by both the informativeness of the key phrases and the key sentences and the size of the cluster summaries. In this work, we set  $n_1 = 5$  and  $n_2 = 5$ .

In the following subsections, we show how summaries of test Web sites are generated, describe the methodology of our user study, and present the evaluation results.

## 4.2 Summaries of Test Web Sites

In this work, we choose six Web sites from the DMOZ directory. The URLs are listed in Table 17.

The six sites have been widely tested in our previous summarization research [71, 69, 72]. The first three sites are

Table 16: Cross-validation of the KeySentence classifier.

Fold	1	2	3	4	5	6	7	8	9	10	Mean
Size	11	12	12	13	10	11	13	12	11	10	11.5
Error(%)	9.5	10.2	10.3	9.7	8.9	11.2	9.6	8.3	8.5	9.0	9.5

---

$P_{DT} \leq 0.03125 :$   
 $P_{NNP} \leq 0.121212 : y$  (68/12)  
 $P_{NNP} > 0.121212 : n$  (392/16)  
 $P_{DT} > 0.03125 :$   
 $P_{NNP} > 0.538462 :$   
 $distance_d \leq 0.127796 : y$  (16)  
 $distance_d > 0.127796 : n$  (76/12)  
 $P_{NNP} \leq 0.538642 :$   
 $length \leq 11 :$   
 $distance_d \leq 0.308824 : y$  (16/4)  
 $distance_d > 0.308824 : n$  (20)  
 $length > 11 :$   
 $P_{CC} > 0.045455 : y$  (256/12)  
 $P_{CC} \leq 0.045455 :$   
 $P_{DT} > 0.125 : y$  (252/20)  
 $P_{DT} \leq 0.125$   
 $depth > 3 : y$  (172/36)  
 $depth \leq 3$   
 $frequency \leq 3 : n$  (40/4)  
 $frequency > 3 : y$  (20)

(y)	(n)	← classified as
716	32	(y): class <i>key-sentence</i>
84	496	(n): class <i>non-key-sentence</i>

---

Figure 8: Decision tree of the KeySentence classifier.

academic Web sites regarding software engineering and artificial intelligence, while the last three sites are commercial airlines and network product/service providers.

For each test Web site, we apply the clustering approach to obtain the main topics. Some clusters have too few documents for summarization. Consequently, we sort all resulting clusters according to the number of documents in each cluster. The top five clusters are summarized using the CNC key phrase extraction method and the KeySentence classifier introduced above. Each cluster summary consists of 5 key phrases and 5 key sentences. These five short summaries represent the most important topics covered in the given Web site, and they will be compared with a single long summary, which is generated using the CNC-based summarization system and consists of 25 key phrases and 25 key sentences.

A full list of all short cluster summaries and single long summaries are presented in Appendix C.

### 4.3 Evaluation Methodology

Evaluation of automatically generated summaries proceeds in *intrinsic* mode, where summaries are compared against a gold standard, or in *extrinsic* mode, which measures the utility of summaries in performing a particular task (e.g. site browsing).

In this work, we aim to investigate how well different types of summaries reveal the main contents of a given Web

Table 17: URLs of the six test Web sites chosen from the DMOZ directory.

Index	Site	URL
1	SEI	<a href="http://www.sei.cmu.edu">http://www.sei.cmu.edu</a>
2	AIAI	<a href="http://www.aiai.ed.ac.uk">http://www.aiai.ed.ac.uk</a>
3	AI	<a href="http://www.ai.uga.edu">http://www.ai.uga.edu</a>
4	AC	<a href="http://www.aircanada.ca">http://www.aircanada.ca</a>
5	Nortel	<a href="http://www.nortel.com">http://www.nortel.com</a>
6	Oracle	<a href="http://www.oracle.com">http://www.oracle.com</a>

site<sup>27</sup>. In other words, we are interested in the correctness and completeness of the long single summary and the five short cluster summaries of a given Web site. Our assumption is that the subjects can define the most essential topic of a given Web site well enough for the most essential topic to be used as gold standard. To do so, we conducted a user study where summaries are judged by subjects using a golden standard of their own.

#### 4.3.1 Study Design

We conduct a user study in a “within-subjects” fashion where human subjects read and rate both types of summaries of a given Web site (in sheets of paper) based on their understanding of how these summaries relate to the most essential topic of the target Web site. Our study is close to the intrinsic evaluation in the sense that human subjects rate the summaries against a hypothetical gold standard of their own. The study makes sense in that Web site summaries are expected to reveal the main contents of Web sites. Similar studies in which human subjects rate documents or phrases have been reported in [30, 40, 47, 63].

In our study, we focus on the “method” factor only. Other factors such as “subject” (inter-rater reliability) and “Web site” (e.g. academic vs. commercial) might also play a role in this learning task. Inter-rater reliability measures the rating agreement between subjects in a user study. It is based on a score of how much consensus there is in the ratings given by subjects. There are a number of statistics that can be used to determine the inter-rater reliability. For example, the *joint-probability of agreement* is a simple measure, which takes the number of times each rating (e.g. 1, 2, ..., 5) is given by each subject and then divides this number by the total number of ratings [66]. Investigation of these factors is a topic of future research.

For each given Web site, human subjects are asked to execute the following steps:

1. Browse the Web site and subjectively define *the most essential topic*, which is defined as *the entity behind the Web site and its main activity*. The most essential topic serves as a representation of the core contents of the target Web site. For example, the most essential topic for the SEI Web site could be defined as “Software Engineering Institute at CMU for improvement of software engineering management and practice”.
2. Read two types of automatically generated summaries: a) a single long summary, which is obtained by summarizing an entire Web site directly, consisting of 25 key phrases and 25 key sentences; and b) the top five cluster summaries, which are obtained by summarizing the five largest clusters after clustering Web pages in the given site, each consisting of 5 key phrases and 5 key sentences, and then decide their informativeness.
3. Rate each summary element (key phrase or key sentence) based on the extent to which it is related to the most essential topic, using a 1-to-5 scale (1 = not related, 2 = poorly related, 3 = fairly related, 4 = well related, and 5 = strongly related).
4. Complete a short survey, which is designed to get feedback on improving our summarization systems.

#### 4.3.2 Study Recruitment

To decide on the number of human subjects, we consulted related studies in the literature. A related research reported in [8] asks 15 subjects to evaluate five summarization methods by collecting data such as number of pen movements in the task of browsing Web pages using handheld devices.

<sup>27</sup>We acknowledge that there are other critical factors in multi-document summarization such as coherence, redundancy deduction, and compression rate, which we leave for future research.

In another study [30], 37 subjects are asked to rate Web pages, which are returned by three different search engines, into “bad”, “fair”, “good”, and “excellent” in terms of their utility in learning about the search topic. However, no specific statistical analysis methods are reported in these two studies.

In [46], 45 subjects are divided into four groups to perform task-based evaluation of multi-document summaries in order to determine whether multi-document summaries measurably improve user performance when using online news browsing systems for directed research.

A size of 20 subjects is sufficient for our study. Each subject was asked to review all the six Web sites. This means that for each type of summary, we have a sample size of 120 with replication. Participants are graduate students in computer science with strong reading comprehension and significant Web browsing experience.

Participants are graduate students in computer science with strong reading comprehension skills and Web browsing experiences. They are recruited because of the technical nature of the Web sites being summarized. Human subjects are provided with a computer with Internet access and summaries in hard copies. They are also given instructions on how to conduct the user study, including 1) a summary rating example, which is designed to help them become familiar with the evaluation process; and 2) a short survey, which is designed to provide feedback on improving our summarization systems. The summary rating example and the short survey are presented in Appendix B. They are required to finish the study in a session of two hours.

## 4.4 Summary Evaluation

In this subsection, we explain how to measure the quality of the single long summary and the top five short cluster summaries, respectively. We also present the statistical analysis of rating data collected in the user study. Our main objective is to investigate which type of summary captures better the topics and contents covered in a Web site.

### 4.4.1 Evaluation Measures

For each type of summary, we have a sample size of 120 (6 Web sites, and 20 subjects for each site) with replication. Let  $n_1, n_2, n_3, n_4$ , and  $n_5$  be the number of summary elements (key phrases or key sentences) that receive a score of 1, 2, 3, 4, and 5, respectively. Hence for each summary,  $\sum_{i=1}^5 n_i$  will be 25 for either key phrases or key sentences.

We are interested in the distribution of users’ rating scores. The percentage of numbers of times each score is given for both types of summaries are shown in Table 18. As we can see, the individual cluster summaries have a higher concentration of scores of 4 and 5 over the single summary of the overall Web site and close to each other for the score of 3.

Table 18: Distribution of users’ rating scores for two types of summaries.

	Key Phrases					Key Sentences				
Score	5	4	3	2	1	5	4	3	2	1
Single (%)	16.9	25.9	26.9	17.4	13.0	12.2	25.9	28.0	23.8	10.1
Cluster (%)	24.8	32.9	23.7	12.8	5.9	19.2	30.3	27.5	15.4	7.6

We aim to formally evaluate and compare the five key phrase extraction methods by an analysis of both *acceptable percentage* and *quality value*, which are both calculated based on the rating data obtained in the user study.

**Acceptable Percentage** Related research in [63] defines acceptable key phrases as those that are rated good or fair by human subjects. In our work, acceptable key phrases and key sentences are those that receive a score of 3, 4, or 5. These summary elements are reasonably related to the most essential topic of a given Web site. In other words, they correctly and completely capture the main contents of the target Web site. The percentage,  $P$ , is then formally defined as:

$$P = \frac{n_3 + n_4 + n_5}{\sum_{i=1}^5 n_i}. \quad (12)$$

For each type of summary (either the single long summary or the top five cluster summaries), let  $P_{kp}$  be the acceptable percentages of key phrases and  $P_{ks}$  be the acceptable percentage of key sentences, respectively. Then the final score of a summary, denoted as  $P_s$ , is a linear combination of  $P_{kp}$  and  $P_{ks}$ , i.e.,  $P_s = \lambda \cdot P_{kp} + (1 - \lambda) \cdot P_{ks}$ ,  $\lambda \in (0, 1)$ . The  $\lambda$  is empirically set to 0.5 based on users’ preference in a simple survey conducted in the key phrase extraction research [70].

**Quality Value** In addition to the acceptable percentage measure, we also aim to compare the two types of summaries using the *quality value* measure, which calculates the average correctness score of summary elements. The average quality,  $Q$ , is the average score achieved by the elements of the summary, formally defined in Equation 13.

$$Q = \frac{\sum_{i=1}^5 n_i \times i}{\sum_{i=1}^5 n_i}. \quad (13)$$

The higher the quality value, the more accurately the summary captures the main contents of a site.

For each type of summary (either the single long summary or the top five cluster summaries), let  $Q_{kp}$  be the average quality of key phrases and  $Q_{ks}$  be the acceptable percentage of key sentences, respectively. Then the final quality of a summary, denoted as  $Q_s$ , is a linear combination of  $Q_{kp}$  and  $Q_{ks}$ , i.e.,  $Q_s = \lambda \cdot Q_{kp} + (1 - \lambda) \cdot Q_{ks}$ ,  $\lambda \in (0, 1)$ . Again, the  $\lambda$  is empirically set to 0.5.

#### 4.4.2 Evaluation Results

The results of acceptable percentage values for both types of summaries of the six test Web sites are presented in Table 19.

Table 19: Summary of acceptable percentage for both types of summaries of the six test Web sites.

	Single summary			Cluster summaries		
Site	$P_{kp}$	$P_{ks}$	$P_s$	$P_{kp}$	$P_{ks}$	$P_s$
SEI	0.82	0.87	0.85	0.89	0.95	0.92
AIAI	0.63	0.61	0.62	0.75	0.68	0.71
AI	0.70	0.81	0.75	0.82	0.83	0.82
AC	0.52	0.54	0.53	0.68	0.51	0.60
Nortel	0.71	0.58	0.65	0.84	0.82	0.83
Oracle	0.79	0.56	0.68	0.90	0.83	0.87
Average	0.70	0.66	0.68	0.81	0.77	0.79

The acceptable percentage of the summaries of top five clusters is higher than that of the single long summary for each test Web site, as shown in Table 19. We apply the One-Way Fully Repeated Measures ANOVA on the acceptable percentage data and a statistically significant difference between the two types of summaries ( $P_{value} = 4.92065E^{-06}$ ) is found at the 5% significance level. This indicates that the top five cluster summaries statistically significantly outperform the single long summary in capturing the essential topics and main contents covered in a Web site.

We are generous in the sense that we take summary elements of score 3 as acceptable. If we are stricter and take only summary elements of scores 4 and 5 as acceptable, then the acceptable percentage difference between two types of summaries will be even bigger, as can be seen in Table 18.

The results of average quality values for both types of summaries of the six test Web sites are presented in Table 20.

Table 20: Summary of average quality for both types of summaries of the six test Web sites.

	Single summary			Cluster summaries		
Site	$Q_{kp}$	$Q_{ks}$	$Q_s$	$Q_{kp}$	$Q_{ks}$	$Q_s$
SEI	3.36	3.60	3.48	3.78	4.07	3.92
AIAI	2.97	2.93	2.95	3.31	3.07	3.19
AI	3.12	3.28	3.20	3.62	3.45	3.54
AC	2.81	2.79	2.80	3.34	2.77	3.05
Nortel	3.19	2.88	3.03	3.52	3.39	3.45
Oracle	3.52	2.91	3.21	3.91	3.57	3.74
Average	3.16	3.06	3.11	3.58	3.39	3.48

The average quality of the summaries of the top five clusters is higher than that of the single long summary for each test Web site, as shown in Table 20. We apply the One-Way Fully Repeated Measures ANOVA on the quality

value data and a statistically significant difference between the two types of summaries ( $P_{value} = 7.81804E^{-08}$ ) is found at the 5% significance level.

The acceptable percentage measure and the quality value measure lead to the same evaluation results, i.e., the top five clusters summaries are statistically significantly better than the single long summary. This can be explained by the fact that the acceptable percentage and the average quality are intrinsically related as they are both based on users' ratings. The only difference is that the former gives equal weight to (a summation of) the number of summary elements with scores 3, 4, and 5, while the latter gives different weight to summary elements with different scores (number of such elements times the score they receive).

#### 4.4.3 Analysis of a Survey

We have demonstrated that the top five cluster summaries are statistically significantly better than the single long summary in the multi-topic Web site summarization task. Moreover, we aim to present the results of the short survey completed by the study participants.

- Survey Question 1. *Overall, which type of summary do you like better, the single long summary or the top five short cluster summaries?*

A total of 17 subjects vote for the top five short clusters summaries and the other three favor the single long summary, which has been shown to be comparable to human authored summaries [71]. People seem to prefer the cluster summaries because of the following reasons:

- The cluster summaries often reveal the main topics on a web site.
- The cluster summaries are shorter and more representative of the main topics.
- The cluster summaries are more comprehensive and comprehensible.

- Survey Question 2. *If the answer to Question 1 is the latter, how many cluster summaries do you prefer?*

The 17 subjects, who like the cluster summaries better, prefer the number of cluster summaries to be between 3 and 6. The average of their preferred numbers is 4.9, which is very close to the number we choose, i.e., 5. The standard deviation is 0.8.

- Survey Question 3. *For the single long summary, what is the ideal number of key phrases in your opinion? And key sentences?*

The ideal number of key phrases given by human subjects varies from 5 to 15, with an average of 9.8 and a standard deviation of 2.7. The ideal number of key sentences varies from 5 to 10, with an average of 7.1 and a standard deviation of 1.6. This indicates that 10 and 7 might be reasonable numbers for key phrases and key sentences, respectively.

- Survey Question 4. *For each cluster summary, do the same as in Question 3.*

The ideal number of key phrases in each cluster summary is suggested to be between 3 and 6, leading to an average of 4.7 and a standard deviation of 0.9. The ideal number of key sentences suggested varies from 2 to 5, leading to an average of 3.3 and a standard deviation of 1.2. This indicates that for each cluster summary, 5 key phrases and 3 key sentences are acceptable.

- Survey Question 5. *The summary consists of two parts, key phrases and key sentences. Which part do you think is more important? Suppose there are 10 points of importance for the whole summary. How many points should be assigned to each part (e.g. 4 to key phrases and 6 to key sentences), respectively?*

The points given by subjects vary from 3:7 (meaning 3 for key phrases and 7 for key sentences) to 6:4, leading to an average of 5:5. The standard deviation is 1.5 and 1.6 for key phrases and key sentences, respectively. This indicates that key phrases are as important as key sentences.

- Survey Question 6. *Overall, how would you rate the clustering method in terms of effectively finding distinct main topics of a given Web site? Please give a 1-to-5 score.*

The overall score of the clustering-summarization framework varies from 3 to 5, leading to an average of 4.1 and a standard deviation of 0.6. This indicates that the summarization framework achieves a reasonable score of 4.1 out of a possible 5.



- Survey Question 7. *What else do you think can be done to improve the summarization system? Any comments, suggestions are more than welcome.*

Subjects also provide useful comments and feedback from the users' perspective. The following is a list of quotes from the users.

1. The clustering-summarization approach is much better because it provides more context and is easier to digest. The readers are able to get an idea of what one cluster is about. In contrast, the long summary is too confusing in terms of presenting diverse topics.
2. In the clustering-summarization approach, some of the phrases and sentences seem to be more relevant to the essential topic because they are grouped into one cluster so they seem to make more sense than in a single long summary.
3. It seems that the number of cluster summaries depends on the target Web site and its main topics. For example, the Air Canada Web site can be summarized using less clusters because its scope is smaller than that of the Oracle Web site.
4. It will be better to highlight the main topics if there are more clusters and less elements in each cluster summary.
5. It will be nice to include a heading for each cluster summary so that one knows what that cluster is about.
6. It will be much better to replace personal pronoun (e.g. he) in a key sentence with the real name.
7. It will be better to eliminate service-related pages during the crawling stage. such as copyright pages, which can be long and complicated, but are not very useful for summarizing the main topics.
8. The single long summary takes too much time to comprehend. Thus, it does not seem to be very useful.
9. It is interesting to learn if different clustering methods will lead to different cluster summaries.
10. It is interesting to conduct a study to measure the relatedness of key phrases and key sentences in a cluster summary to topic that the cluster represents.

## 5 Conclusion

In this paper, we propose a framework for summarization of multi-topic Web sites. The system first applies coupled text- and link-based  $X$ -means clustering to find the most significant topics covered in a given site, and then summarizes each individual cluster using an extraction-based summarization approach. Each cluster summary consists of key phrases and key sentences. We conducted a user study to evaluate how well cluster summaries capture the main topics of a given Web site, compared with a single long summary, which is generated using our previous single-topic summarization of an entire Web site. Our user study demonstrates that the clustering-summarization approach statistically significantly outperforms the straightforward summarization approach in the multi-topic Web site summarization task.

The main contribution of this work is a framework for clustering and summarization of multi-topic Web sites.

- We demonstrate that text-based  $X$ -means clustering with Term Variance feature selection statistically significantly outperforms other clustering configurations in terms of effectively finding the essential topics of a Web site. Moreover, outgoing links can be used to enhance the clustering quality if cross links, as determined by the breadth-first site traversal, are sufficiently rich.
- We propose a classification approach for finding the key sentences in the cluster summarization task. The classifier uses statistical and linguistic features to determine the topical significance of a sentence in addition to the traditional method, where sentences are extracted based on the density of key phrases.
- Intrinsic evaluation is performed on the cluster summaries. Subjects judge how effectively the cluster summaries capture the essential topics of a Web site.

The proposed summarization framework has many potential applications, such as effective organization of search engine results and faceted browsing of large Web sites.

Future research issues include the following:

- Investigation of whether anchor text can be helpful in the Web page clustering task.
- Evaluation of clustering using more advanced measures [25].

- Investigation of the subject learning factor to determine whether there is a statistically significant difference within human subjects.
- Evaluation of other factors in multi-document summarization such as coherence, completeness, redundancy, and compression rate.
- Investigation of more advanced learning algorithms such as Support Vector Machines in the key sentence classification task.
- Hierarchical summarization of a Web site to construct a concept hierarchy, which can be obtained by first creating a link hierarchy of the target Web site, and then identifying concept groups of related documents that are further summarized using a coupled content-link summarization system.
- Investigation of applications of our clustering-summarization framework, for example integration with Web site content management systems.
- Experimental comparison of our framework with existing multi-document summarization systems such as MEAD [52].

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## A Web Page Parsing

In this section, we discuss how to process a Web page URL when the page is parsed. During the parsing process, the following tasks will be performed: link filtering, link resolution, link validation, link pruning, and file truncation.

### A.1 Link Filtering

We aim to focus on static Web pages only and filter out noisy URLs. Link filtering does the following:

- Remove all query terms in a URL because we focus on static pages, not dynamic pages. For instance, `http://www.dal.ca/search.html?Computer+Science` will be truncated into `http://www.dal.ca/search.html`
- Remove the fragment (also known as reference) part, which is indicated by the sharp sign character “#”, because a fragment only indicates that after the specified resource is retrieved, the application is specifically interested in that part of the document. For example, `http://www.cs.dal.ca/grad.html#Resources` will be truncated into `http://www.cs.dal.ca/grad.html`.
- Discard a URL if it contains one or more of the following punctuation marks, i.e., ‘! @ \$ ^ & \* ( ) = [ ] { } — \ ; ’ < > , and blank space.

### A.2 Link Resolution

Convert a relative URL against the base URL into an absolute URL. For example, `/course` against the FCS home page `http://www.cs.dal.ca/` yields `http://www.cs.dal.ca/course`.

### A.3 Link Validation

We aim to focus on Web pages of the **text/html** content type from the same host. Link validation does the following:

- A URL is tested whether it has the same host as the homepage. We only look at in-host Web pages and investigation of out-host pages is a future research direction.
- Test whether there are connection and access problems such as the “Page not found 404” error.
- For URLs with new port numbers, we treat them as external URLs from other hosts and discard them accordingly. For example, when traversing `http://www.cs.dal.ca` (default port: 80), we find a URL `http://www.cs.dal.ca:6000`, which is treated as a out-host page. Consequently this page will not be further visited and parsed.
- For URLs of usernames such as `http://www.cs.dal.ca/~user`, they are not added into Q (queue of pages to visit), which means that they will not be further visited and parsed. However, these pages are still part of the set of outgoing links of the target page and they are treated as leaves in the final link hierarchy.
- In order to avoid parsing either a known binary file (for example, .jpg, .bmp, .doc and .dat), or a file whose file type is non-obvious or unfamiliar to us, we only deal with Web pages with the **text/html** content type. All Web pages of other file types will be treated as binary files. They are added into the link hierarchy but not Q, the queue of pages to visit. Again, these pages are only part of outgoing links of a particular page and treated as leaf nodes in the link hierarchy.

Conversion of .pdf files into pure text for text analysis is a future research direction because .pdf files are mostly documentation records or forms and therefore they are too specific for summary generation. Omitting them should not have a big effect on quality of summarization.

### A.4 Link Pruning

For each page, the set of its outgoing links will be examined in order to select only a proper subset of links. For example, when parsing the page `http://www.cs.dal.ca/news`, we find many links of specific news such as `http://www.cs.dal.ca/news/2005-03-01.shtml`. These pages very likely are leaves in the link hierarchy. If the number of such links is too big, say 500, then most probably inclusion of all these pages does not benefit the summarization. Thus, we select only the first 10 representatives of such pages. Of course, links with further paths such as `http://www.cs.dal.ca/news/archive/` are added to the link hierarchy.

## A.5 File Truncation

For each URL found in a page, we check the size of the page represented by this URL. If it is greater than 50K, we truncate it to that size. The reason is that some documents such as privacy statements contain too much text information and use of their full text does not benefit summarization at all.

## B User Study Instructions

This chapter presents the instructions on how to conduct the user study. It includes a summary rating example and a short survey.

### B.1 A Summary Rating Example

Each user is provided with a summary rating example, which is designed to help them be familiar with the evaluation process. A snippet of the summary rating example is shown in Figure 9.

A Summary Rating Example for SEI: <http://www.sei.cmu.edu>

Ranking scales  
5: strongly related; 4: well related; 3: fairly related; 2: poorly related; 1: not related.

The most essential topic extracted  
Software Engineering Institute at CMU for improvement of software engineering management and practice.

<u>Top 25 key phrases</u>	<u>Ratings</u>
1) software engineering institute	5
2) engineering institute	2
3) software engineering	5
4) carnegie mellon university	4
5) carnegie mellon	2
.....	

<u>Top 25 key sentences</u>	<u>Ratings</u>
1) The Software Engineering Institute (SEI) sponsors, co-sponsors, and is otherwise involved in many events throughout the year.	4
2) The Software Engineering Institute offers a number of courses and training opportunities.	4
3) Information contained on the Software Engineering Institute Web site is published in the interest of scientific and technical information exchange.	3
4) The Software Engineering Institute is a federally funded research and development center sponsored by the U.S. Department of Defense and operated by Carnegie Mellon University.	5
5) As CEO and director, Nielsen's responsibilities will include setting a technical and business strategy for the Software Engineering Institute.	3
.....	

Figure 9: Snippet of a summary rating example.

### B.2 A Short Survey

At the end of the user study, users have to complete a short survey, which is designed to get feedback on improving our summarization systems. There are seven survey questions as follows:



1. Overall, which type of summary do you like better, the single long summary or the top five short cluster summaries?
2. If the answer to Question 1 is the latter, how many cluster summaries do you prefer?
3. For the single long summary, what is the ideal number of key phrases in your opinion? And key sentences?
4. For each cluster summary, do the same as in Question 3.
5. The summary consists of two parts, key phrases and key sentences. Which part do you think is more important? Suppose there are 10 points of importance for the whole summary. How many points should be assigned to each part (e.g. 4 to key phrases and 6 to key sentences), respectively?
6. Overall, how would you rate the clustering method in terms of effectively finding distinct main topics of a given Web site? Please give a 1-to-5 score.
7. What else do you think can be done to improve the summarization system? Any comments, suggestions are more than welcome.

## C A Full List of Summaries

This chapter presents both the single long summary and the top five short cluster summaries for each of the six test Web sites.

1. <http://www.sei.cmu.edu>

### • A Single Long Summary

#### Part I. Top 25 Key Phrases

- software engineering institute
- engineering institute
- software engineering
- carnegie mellon university
- carnegie mellon
- mellon university
- carnegie mellon university term
- capability maturity model
- capability maturity model integration
- capability maturity
- maturity model
- maturity model integration
- software process
- software engineering institute partner
- model integration
- product line
- engineering institute partner
- team software process
- institute partner
- software architecture
- personal software process
- general navigation button
- process improvement
- topic navigation button

- team software

## Part II. Top 25 Key Sentences

- The Software Engineering Institute (SEI) sponsors, co-sponsors, and is otherwise involved in many events throughout the year.
- The Software Engineering Institute offers a number of courses and training opportunities.
- Information contained on the Software Engineering Institute Web site is published in the interest of scientific and technical information exchange.
- The Software Engineering Institute is a federally funded research and development center sponsored by the U.S. Department of Defense and operated by Carnegie Mellon University.
- As CEO and director, Nielsen’s responsibilities will include setting a technical and business strategy for the Software Engineering Institute.
- The Software Engineering Institute recently provided the Internal Revenue Service with an independent report on the IRS’s delayed, over-cost modernization effort.
- Nielsen will take over as CEO and director of the Software Engineering Institute on August 1.
- IEEE Spectrum: Why Software Fails September 2005 Article about the Capability Maturity Model (CMM) created by the Software Engineering Institute to help organizations assess and analyze their software development practices.
- Nielsen is selected as CEO and director of the Software Engineering Institute.
- Len Bass is a Senior Member of the Technical Staff at the Software Engineering Institute (SEI) and participates in the High Dependability Computing Program.
- Peter is a senior member of the technical staff member at the Software Engineering Institute (SEI).
- Jorgen Hansson is a senior member of the technical staff at the Software Engineering Institute (SEI).
- Thomas Longstaff is the Deputy Director for Technology in the Networked Systems Survivability (NSS) Program at the Software Engineering Institute (SEI).
- Prior to coming to the Software Engineering Institute, Longstaff was the technical director at the Computer Incident Advisory Capability (CIAC) at Lawrence Livermore National Laboratory in Livermore, California.
- Mead is a senior member of the technical staff in the Networked Systems Survivability Program at the Software Engineering Institute (SEI).
- Shimeall is a Senior Member of the Technical Staff with the Networked Systems Survivability Program at the Software Engineering Institute (SEI).
- At the Software Engineering Institute (SEI), we have been working in open systems since 1993, developing courses, related products, and other sources of open systems information.
- news@sei is a quarterly hardcopy newsletter published by the Software Engineering Institute that gives readers an overview of SEI work, events and publications.
- Paul Clements is a Senior Member of the Technical Staff, Software Engineering Institute.
- The Product Line Systems Program of the Software Engineering Institute is proud to be represented by the following books.
- The Software Engineering Institute has established a software architecture curriculum.
- A 1996 technical report [1] from the Software Engineering Institute, in its introduction points out that software architecture is still a relatively immature area from both research and practice perspectives.
- Video lectures for this course include resident experts at the Software Engineering Institute and recognized leaders from industry and academia.
- Humphrey describes a software process improvement strategy based on the software process maturity model developed at the Software Engineering Institute.
- This report presents the interim results of work done by members of the Networked Systems Survivability Program at the Software Engineering Institute in exploring these issues.

- **Top 5 Short Cluster Summaries**

Cluster I. Software Architecture

- software architecture
- software engineering
- software architecture professional
- architecture professional
- professional certificate
- SEI architecture experts provide technical assistance and coaching in software architecture requirements, software architecture design, software architecture documentation, and architecture-centric life-cycle practices.
- He is a co-author of Applied Software Architecture and Documenting Software Architectures: Views and Beyond, published by Addison-Wesley and lectures on architecture-centric approaches.
- The significance of the program family concept to software architecture is that software architecture embodies those decisions at or near the top of Parnas' program family decision tree.
- Raghuraman Ramasubbu(Senior Software Engineer, Mastech Corporation): Software architecture is a framework that provides the basis for manifestation of all software objects within an enterprise.
- Human Aspects of Software Engineering details software engineering from the perspective of those involved in the software development process: individuals, team, customers, and the organization.

Cluster II. Open System

- open system
- process research
- process improvement
- software process
- software engineering research
- This tutorial covers key open system concepts and definitions, an open system engineering process, open system policy, conformance management, today's transition environment, and an open system transition process.
- The IPRC is not trying to solve a particular business problem, but to chart potential directions for the future of software process research.
- We are sponsoring the IPRC as a focal point for top researchers and forward-thinking organizations investigating the latest in software process research.
- We are part of a world recognized center of excellence for software engineering research, the Software Engineering Institute, which serves as a trusted broker among industry, government, and academia.
- If the Engineering Process group is new to process improvement, members should consider taking the Defining Software Processes or Mastering Process Improvement courses.

Cluster III. Risk Management

- risk management
- software engineering
- continuous risk
- continuous risk management
- software engineering institute
- Customers/collaborators are welcomed for work that will further refine the areas of Software Risk Evaluation, Continuous Risk Management (CRM), Team Risk Management, and Risk Process Checks.
- The Team Risk Management Service extends Continuous Risk Management overview to all organizations in a program, tailoring methods and tools to the joint management of program risks.

- The Continuous Risk Management Guidebook was developed to help a project or organization establish continuous risk management as a routine practice and then continue to improve this process.
- The SEI's products for Continuous Risk Management are completely consistent with the requirements of RSKM.
- Successful team risk management depends upon having implemented, or partially implemented, Continuous Risk Management within the program's organizations.

#### Cluster IV. Product Line

- product line
- software product line
- software product
- line practice
- product line practice
- Initiating and operating a software product line organization is a low-risk, predictable process that results in little or no organizational upheaval.
- Third-party vendors provide tools and services that support software product lines.
- Influential industry analysts promote software product lines as a critical technology.
- Government acquisition managers are well educated about software product lines.
- The organizational interest in software product line has grown tremendously over the last five years.

#### Cluster V. People CMM

- people cmm
- software engineering institute
- capability maturity model
- maturity model
- capability maturity
- This course is a prerequisite for the Intermediate Concepts of the People CMM course, People CMM Assessment Team Training, and People CMM Lead Appraiser Training.
- The People Capability Maturity Model (People CMM) is a framework that helps organizations successfully address their critical people issues.
- Gans work at the SEI includes assisting organizations in successfully addressing their critical human capital issues through the use of the SEI's People Capability Maturity Model (People CMM).
- The People Capability Maturity Model (People CMM) is a framework that guides organizations in improving their processes for managing and developing their workforces.
- Systems integrators worldwide are adopting the Software Engineering Institute's Capability Maturity Model Integration, a technology that is replacing the traditional Capability Maturity Model.

## 2. <http://www.aiai.ed.ac.uk>

### • A Single Long Summary

#### Part I. Top 25 Key Phrases

- artificial intelligence applications institute
- artificial intelligence application
- version date source
- artificial intelligence
- intelligence application
- version date
- plan representation

- knowledge acquisition
- process interchange format
- knowledge based system
- activity representation
- ai planning
- core group
- process specification language
- nist process specification language
- knowledge management
- planning process
- core plan representation
- case based reasoning
- spar core group
- specification language
- knowledge representation
- process interchange
- air force
- activity specification

## Part II. Top 25 Key Sentences

- Back to Home page Artificial Intelligence Applications Institute School of Informatics, The University of Edinburgh.
- IM-PACs is be based on I-X, a key research orientated asset of the Artificial Intelligence Applications Institute (AIAI) at the University of Edinburgh.
- Dr Stuart Aitken Artificial Intelligence Applications Institute The University of Edinburgh Edinburgh EH8 9LE Email: stuart@aiai.ed.ac.uk
- WxCLIPS was started in 1992 by Julian Smart at the Artificial Intelligence Applications Institute, part of the University of Edinburgh.
- I-X is a valuable asset of the Artificial Intelligence Applications Institute and must not be used without the prior permission of a rights holder.
- O-Plan is a valuable asset of the Artificial Intelligence Applications Institute and must not be used without the prior permission of a rights holder.
- Professor Austin Tate, Artificial Intelligence Applications Institute, Division of Informatics, University of Edinburgh.
- Artificial Intelligence Applications Institute, University of Edinburgh.
- Process Steps, Process Products and System Capabilities, Artificial Intelligence Applications Institute, University of Edinburgh, Technical Report ISAT-AIAI/TR/4 Version 2, April 14, 1997.
- Rob was a pioneer of artificial intelligence applications, creating a successful company based in Livingston.
- Rob Milne was perhaps the best-known and most successful person in Europe who has produced and promoted artificial intelligence applications.
- Analysis of Candidate PSL Process/Plan Representations, Artificial Intelligence Applications Institute, AIAI-PR-66, Edinburgh, Scotland.
- EXPECT: Explicit Representations for Flexible Acquisition In Proceedings of the Ninth Knowledge Acquisition for Knowledge-Based Systems Workshop, February 26-March 3, 1995.
- For example, SPAR has been a contributing source towards the development of the Core Plan Representation (CPR) [Pease & Carrico, 1997].
- As an example of the level at which the Reference Object Model for SPAR will be described, the OMWG Core Plan Representation [Pease & Carrico, 1997] Object Model is shown here.

- As an example of the level at which the Reference Object Model will be provided, see the current OMWG Core Plan Representation Request For Comment document [Pease & Carrico, 1997].
- The working group members represent some of the most experienced people worldwide who have been involved in creating shared plan, process and activity representations or standards for some years.
- The paper provides a comprehensive bibliography and related world wide web resources for work in the area of plan, process and activity representation.
- AIAI is a collaborator on the National Institute for Standards and Technology (NIST) Process Specification Language (PSL) project.
- The work on SPAR has been conducted alongside the development of the National Institute of Standards and Technology Process Specification Language (NIST PSL).
- Advanced Knowledge Technologies Rapid Knowledge Formation Case-based Reasoning Case-based Reasoning has been successfully applied to fraud detection in the finance industry.

## • Top 5 Short Cluster Summaries

### Cluster I. Intelligence Application

- intelligence application
- artificial intelligence applications institute
- intelligence applications institute
- artificial intelligence application
- applications institute
- IM-PACs is based on I-X, a key research orientated asset of the Artificial Intelligence Applications Institute (AIAI) at the University of Edinburgh.
- Rob was a pioneer of artificial intelligence applications, creating a successful company based in Livingston.
- WxCLIPS was started in 1992 by Julian Smart at the Artificial Intelligence Applications Institute, part of the University of Edinburgh.
- I-X is a valuable asset of the Artificial Intelligence Applications Institute and must not be used without the prior permission of a rights holder.
- O-Plan is a valuable asset of the Artificial Intelligence Applications Institute and must not be used without the prior permission of a rights holder.

### Cluster II. Knowledge Based System

- knowledge based system
- knowledge base
- knowledge acquisition
- knowledge engineering
- knowledge modelling
- Areas of expertise include the use of methodologies for knowledge engineering, knowledge acquisition techniques, and in programming knowledge-based software systems.
- The fundamental training strategy behind this “journeyman” scheme is the building of a fully documented knowledge based system with supervision from AIAI staff.
- Increasingly, belief network techniques are being employed to deliver advanced knowledge based systems to solve real world problems.
- The approach was tested and refined through the development of a knowledge-based system for the support of planning for search and rescue.
- Edinburgh have developed the Enterprise ontology for representing an organization and its activities, as well as having considerable experience in applying knowledge modelling to the knowledge engineering process.

### Cluster III. Intelligent System

- intelligent system
- case based reasoning
- intelligent systems creation
- system development
- system development process
- (2006) The Helpful Environment, Special Issue on Next 50 Years of Intelligent Systems, IEEE Intelligent Systems.
- Advanced Knowledge Technologies Rapid Knowledge Formation Case-based Reasoning Case-based Reasoning has been successfully applied to fraud detection in the finance industry.
- AIAI can play a role in Intelligent System development projects during any of these phases, but most typically would be involved during the earlier stages of analysis, modelling and design, and proof-of-concept implementation where AIAI's experience of working with specifically AI concepts and technologies will be most telling.
- Systems Integration - A broad vision of an open architecture for intelligent systems creation for synthesis tasks (such as planning, design and configuration) based on the handling of “issues” and the management or maintenance of the constraints describing the product of the process.
- During the first year of AUSA, AIAI will develop a generic framework for modelling the system development process.

#### Cluster IV.

- ai planning
- planning system
- ai planning system
- plan representation
- plan ontology
- Responsive Planning and Scheduling Using AI Planning Techniques - Optimum-AIV - Austin Tate - in “Trends & Controversies - AI Planning Systems in the Real World”, IEEE Expert: Intelligent Systems & their Applications, Vol. 11 No. 6, pp. 4-12, December 1996
- Dr John Levine is an Informatics Research Fellow working on evolutionary computation and AI planning systems.
- The Nonlin hierarchical partial-order AI planning system, developed by Austin Tate at the University of Edinburgh, is available in a browsable and downloadable form here:

#### Cluster V.

- air force
- air force research
- air force research laboratory
- force research laboratory
- research laboratory
- This work is sponsored by the Defense Advanced Research Projects Agency (DARPA) and the Air Force Research Laboratory (Rome), Air Force Materiel Command, USAF, under grant numbers F30602-95-1-0022 and F30602-97-C-0275.
- AIAI is part of the DARPA/Air Force Research Laboratory (Rome) Planning Initiative (ARPI) Initiative Support and ACP Testbed (ISAT) Project, working as a subcontractor to ISX Corporation.
- Supported by The Technical Cooperation Program, United States Air Force Research Laboratory/Information Directorate, Rome Research Site, Defense Advanced Research Projects Agency, UK Defence Science and Technology Laboratory, and Defence Science and Technology Organisation, Australia.

- From 1998 to 2000, the O-Plan project was supported by the the US Planning Initiative/Planning and Decision Aids Program (ARPI/PDA), the US Army Small Unit Operations Program (SUO), and the Cooperating Agent Based Systems Program (CoABS) - with funding through the Defense Advanced Research Projects Agency (DARPA) and the Air Force Research Laboratory (AFRL) by contract number F30602-99-1-0024 monitored by Wayne Bosco at AFRL.
- In August 1997, DARPA and the Air Force Research Laboratory (Rome) Planning Initiative (ARPI) Program Managers proposed an effort to build on the accumulated expertise from past DARPA and ARPI sponsored research in order to create a shared plan representation suitable for use in ARPI and on applied research programmes in their communities.

### 3. <http://www.ai.uga.edu>

#### • A Single Long Summary

##### Part I. Top 25 Key Phrases

- artificial intelligence
- artificial intelligence center
- ai center
- university system
- intelligence center
- natural language
- programming language
- baud rate
- natural language processing
- assembly language
- c compiler
- program memory
- neural network
- operating system
- degree program
- development tool
- external memory
- embedded processor
- embedded controller
- model snake
- independent study
- von neuman architecture
- serial port
- sample code
- sparse ii

##### Part II. Top 25 Key Sentences

- The Artificial Intelligence Center is an interdepartmental research and instructional center within the Franklin College of Arts and Sciences of the University of Georgia.
- It was officially established as the Artificial Intelligence Center in 1995.
- Located in the same building as the Artificial Intelligence Center, the library has millions of books and bound periodicals and also provides online access to many indexes and journals.
- The Master of Science in Artificial Intelligence (M.S.A.I.) degree program is offered by the interdisciplinary Artificial Intelligence Center.



- Artificial Intelligence Center The University of Georgia 111 Boyd GSRC Athens, Georgia 30606-7415 U.S.A.
- The workshop, hosted by the Artificial Intelligence Center of the University of Georgia will be held April 16, 2004 at the Georgia Center for Continuing Education.
- To see if the author of a package is still at The University of Georgia, use the University’s online directory, and if unsuccessful, contact the Artificial Intelligence Center.
- Covington % Artificial Intelligence Center % The University of Georgia % Athens, Georgia 30602-7415 % July 28, 1994
- Opened in June 1999, this is a small electronics laboratory established within the Artificial Intelligence Center to enable faculty and students to participate in research programs involving microelectronics.
- Although the Artificial Intelligence Center does not teach electrical engineering, many students arrive with an electrical engineering background, and this laboratory helps them put it to good use.
- The Artificial Intelligence Center has an Industrial Partners Program giving corporations access to our research and our graduates entering the job market.
- The Artificial Intelligence Center houses two degree programs, the Master of Science program in Artificial Intelligence and the bachelor’s degree program in Cognitive Science.
- The AI Center currently offers a two-year interdisciplinary masters degree program in Artificial Intelligence and houses the undergraduate Cognitive Science program for UGA.
- The following is a list of the various anonymous ftp sites that have 8051 source code and programming languages.
- The following is a list of the anonymous ftp sites that have source code and programming languages for various microcontrollers.
- The masters program includes a comprehensive study of AI, with strengths on logic programming, expert systems, neural networks, genetic algorithms, and natural language processing.
- Areas of specialization include automated reasoning, cognitive modeling, neural networks, genetic algorithms, expert databases, expert systems, knowledge representation, logic programming, and natural-language processing.
- Natural Language Processing for Prolog Programmers, by Covington, is being “printed on demand” by Prentice Hall.
- You must do library research to determine how your work fits into the existing science and technology of natural language processing.
- It provides a true introduction to Natural Language Processing without requiring familiarity with Lisp or Prolog.
- Applied Natural Language Processing NOTE: Future plans for LING 6570 are unclear.
- This compiler recognizes a subset of the BASIC programming language and generates assembly language sources files.
- Has a unique architecture with three memory spaces: program memory, data memory, and a CPU register file.
- Program: 8051.zip Description: Many development tools including: debugger, monitor, LCD and stepper moter driver, communications, host client, and much more.

## • Top 5 Short Cluster Summaries

### Cluster I.

- computer science
- artificial intelligence
- ai center
- artificial intelligence center
- intelligence center

- Areas of specialization include automated reasoning, cognitive modeling, neural networks, genetic algorithms, expert databases, expert systems, knowledge representation, logic programming, and natural-language processing.
- The Artificial Intelligence Center is an interdepartmental research and instructional center within the Franklin College of Arts and Sciences of the University of Georgia.
- The Artificial Intelligence Center houses two degree programs, the Master of Science program in Artificial Intelligence and the bachelor's degree program in Cognitive Science.
- It was officially established as the Artificial Intelligence Center in 1995.
- Located in the same building as the Artificial Intelligence Center, the library has millions of books and bound periodicals and also provides online access to many indexes and journals.

#### Cluster II.

- neural network
- fuzzy logic
- fuzzy logic software
- genetic algorithm
- neural network technology
- Fuzzy Logic and neural networks are two design methods that are coming into favor in embedded systems.
- The masters program includes a comprehensive study of AI, with strengths on logic programming, expert systems, neural networks, genetic algorithms, and natural language processing.
- Areas of specialization include automated reasoning, cognitive modeling, neural networks, genetic algorithms, expert databases, expert systems, knowledge representation, logic programming, and natural-language processing.
- This is the step where neural networks technology can be helpful to the fuzzy-logic designer.
- In an effort to change fuzzy logic from a “buzzword” (as it is in most parts of the world) to a well established design method (as it is in Japan), most manufacturers of microcontrollers have introduced fuzzy logic software.

#### Cluster III.

- natural language
- language processing
- natural language processing
- artificial intelligence
- programming language
- The masters program includes a comprehensive study of AI, with strengths on logic programming, expert systems, neural networks, genetic algorithms, and natural language processing.
- Areas of specialization include automated reasoning, cognitive modeling, neural networks, genetic algorithms, expert databases, expert systems, knowledge representation, logic programming, and natural-language processing.
- Natural Language Processing for Prolog Programmers, by Covington, is being “printed on demand” by Prentice Hall.
- You must do library research to determine how your work fits into the existing science and technology of natural language processing.
- It provides a true introduction to Natural Language Processing without requiring familiarity with Lisp or Prolog.

#### Cluster IV.

- embedded system
- embedded systems programming

- embedded system software
- embedded processor
- embedded controller
- Embedded Systems Programming - programming and systems design articles - Miller Freeman Publications - 500 Howard St., San Francisco, CA 94105 - (415) 397-1881
- Embedded Systems Programming in C and Assembler - John Forrest Brown - Van Nostrand Reinhold, 1994 - 304 pages, \$49.95 - ISBN 0-442-01817-7 - covers Motorola and Intel processors - includes diskette with code from the book - book review in Dr.
- Based on the article "A Portable Real Time Kernel in C" in Embedded Systems Programming (Part 1: vol 5 no 5 May 1992, Part 2: vol 5 no 6 June 1992)
- Embedded Systems Programming Periodical, focus on embedded system software issues.
- Is a microcontroller an embedded processor? Is an embedded processor a microcontroller? What's the difference between an embedded processor and a microcontroller? Well, today - not much.

#### Cluster V.

- baud rate
- baud rate generator
- Automatic baud rate detection
- serial port
- operating system
- A2: When Timer 1 is used as the baud rate generator, the baud rates in Modes 1 and 3 are determined by the Timer 1 overflow rate and the value of SMOD (PCON.7 - double speed baud rates) as follows:
- Timer 1 defaults to the baud rate generation for the console port except during execution of any commands that send output to the list port and during the execution of the PWM statement.
- It is interesting to note that the run command leaves timer #1 in auto-baud rate generation mode.
- A typical 8051 contains: - CPU with boolean processor - 5 or 6 interrupts: 2 are external 2 priority levels - 2 or 3 16-bit timer/counters - programmable full-duplex serial port (baud rate provided by one of the timers) - 32 I/O lines (four 8-bit ports) - RAM - ROM/EPROM in some models
- It also has a host of onboard support devices, some members have all of them while others have a subset, the peripherals include: RAM, ROM (mask, OTP, or EEPROM), 2 timers (configurable as timers / counters / comparators / PWM output), watchdog timer, SCI (synchronous serial port), SPI (asynchronous serial port), A/D (8 bit, 8 channel), interrupts.

#### 4. <http://www.aircanada.ca>

##### • A Single Long Summary

##### Part I. Top 25 Key Phrases

- air canada
- return date
- departure date
- news release
- star alliance
- air canada fleet
- fleet fin number
- fleet air canada
- fleet air
- flight attendant
- canada jazz

- air canada jazz
- travel agent
- executive biography
- technical service
- annual information form
- air canada technical service
- air canada technical
- canada technical
- canada technical service
- canada cargo
- air canada cargo
- canada vacation
- air canada vacation
- canada jetz

## Part II. Top 25 Key Sentences

- Or, if you wish, you may forward your request and any original unused Air Canada ticket to Air Canada by mail.
- Departure Date and Return Date: A date in the past was chosen.
- Departure Date and Return Date: A Saturday night stay is required and the dates chosen do not meet this condition.
- Departure Date and Return Date: The dates chosen do not meet the minimum stay requirements.
- Departure Date and Return Date: The dates chosen do not meet the maximum stay requirements.
- Departure Date and Return Date: Your date selection does not meet this offers Advance Purchase requirement.
- Brewer acted as a key negotiator in the founding of Star Alliance, of which Air Canada was also a founding member.
- This is the average age of the Air Canada fleet as of this month.
- Air Canada Flight Attendants are ambassadors of the customer experience onboard each and every Air Canada flight.
- Roles of an Air Canada Flight Attendant include Safety professional, caregiver and service provider.
- Air Canada's Flight Attendants make an immediate and lasting positive impression.
- Whether flying on domestic, transborder, or international routes, your child receives extra-special care from Air Canada agents and flight attendants.
- Each year, Air Canada, including Air Canada Jazz, receives thousands of requests for support.
- First among these sub-brands is Air Canada Jazz, Air Canada's primary source for feeder traffic and one of the top four regional carriers in the world.
- Air Canada will allow unaccompanied minors to travel on any itinerary involving Air Canada, Air Canada Jazz and Tier 3 flights.
- It is as easy as asking for an Electronic ticket next time you book a flight with Air Canada or your travel agent.
- If you need any additional information, or have any questions about how to plan for a child travelling on their own, please contact your travel agent or Air Canada.
- Next / we have Air Canada's Technical Services group, which is responsible for the maintenance, repair and overhaul of aircraft.
- Air Canada Jetz is a jet charter service by Air Canada offering premium business service to satisfy the travel needs of corporate clients and professional sports teams.

- Air Canada Jetz is a jet charter service offering a premium business service for corporate groups or sports teams or rock bands.
- Randell is the President and CEO of Air Canada Jazz, which was formed in 2001 with the consolidation of AirBC, Air Ontario, Air Nova and Canadian Regional Airlines.
- Air Canada's regional airline, Air Canada Jazz, a wholly-owned subsidiary of ACE Aviation Holdings Inc., and its commercial partners serve an additional 48 Canadian and 18 U.S. cities.
- The regional market remains even more bleak with no sign of recovery and Air Canada Jazz recorded an unsustainable operating loss of almost \$90 million in the past year.
- We are also moving ahead with the conversion of Air Canada Cargo to a stand-alone subsidiary.
- Starting with the ancillary, non-passenger transportation side of the business, we have Air Canada Cargo.

## • Top 5 Short Cluster Summaries

### Cluster I.

- air canada
- flight attendant
- travel agent
- canada jazz
- air canada jazz
- Air Canada Flight Attendants are ambassadors of the customer experience onboard each and every Air Canada flight.
- Roles of an Air Canada Flight Attendant include Safety professional, caregiver and service provider.
- Air Canada's Flight Attendants make an immediate and lasting positive impression.
- Whether flying on domestic, transborder, or international routes, your child receives extra-special care from Air Canada agents and flight attendants.
- It is as easy as asking for an Electronic ticket next time you book a flight with Air Canada or your travel agent.

### Cluster II.

- air canada
- star alliance
- canada jazz
- air canada jazz
- air canada jetz
- Brewer acted as a key negotiator in the founding of Star Alliance, of which Air Canada was also a founding member.
- Each year, Air Canada, including Air Canada Jazz, receives thousands of requests for support.
- First among these sub-brands is Air Canada Jazz, Air Canada's primary source for feeder traffic and one of the top four regional carriers in the world.
- Randell is the President and CEO of Air Canada Jazz, which was formed in 2001 with the consolidation of AirBC, Air Ontario, Air Nova and Canadian Regional Airlines.
- As at December 31, 2004, Air Canada employed approximately 32,000 people worldwide including 3,500 at Air Canada Jazz.

### Cluster III.

- technical service
- air canada technical service
- air canada technical
- canada technical

- canada technical service
- Air Canada Technical Services, a wholly-owned subsidiary of ACE Aviation Holdings Inc., offers customers worldwide diverse range of technical expertise in the maintenance, repair and overhaul of aircraft, engines, components and various ground and test equipment.
- Air Canada Technical Services also sells ground-handling services to airlines and other customers, as well as training services for mechanics, flight attendants and pilots.
- In March 2003, he assumed the role of President & CEO, Air Canada Technical Services in addition to his responsibilities as Vice President, System Operations Control.
- That includes the possible sale of a significant interest in Air Canada Technical Services and the creation of an Airport Ground Handling Services subsidiary.
- We see these businesses - like Aeroplan and Air Canada Technical Services - as undervalued assets with lots of potential.

#### Cluster IV.

- air canada vacation
- perfect vacation package
- air canada
- holiday package
- vacation package
- Next is Air Canada Vacations, one of Canada's largest tour operators.
- Find the perfect vacation package to Antigua and book an Air Canada Vacations package today!
- Find the perfect all-inclusive vacation package to Puerto Plata and book an Air Canada Vacations package today!
- Find the perfect vacation package to Aruba and book an Air Canada Vacations package today!
- Find the perfect all-inclusive vacation package to Punta Cana and book an Air Canada Vacations package today!

#### Cluster V.

- air canada
- canada cargo
- air canada cargo
- canada air
- air canada fleet
- Claude Morin was appointed President & CEO, Air Canada Cargo, a separate limited partnership of ACE Aviation Holdings Inc, in December 2004.
- We are also moving ahead with the conversion of Air Canada Cargo to a stand-alone subsidiary.
- Starting with the ancillary, non-passenger transportation side of the business, we have Air Canada Cargo.
- This is the average age of the Air Canada fleet as of this month.

#### 5. <http://www.cisco.com>

##### • A Single Long Summary

##### Part I. Top 25 Key Phrases

- nortel networks
- nortel networks limited
- service provider
- code division multiple access
- internet protocol

- division multiple access
- local area network
- wireless local area network
- nortel networks common share
- multiple access
- wireless local area
- code division
- wireless mesh
- forward looking statement
- wireless mesh network
- networks common share
- universal mobile telecommunications system
- wireless mesh network solution
- session initiation protocol
- high speed downlink packet
- network solution
- internet protocol multimedia subsystem
- mesh network
- high performance internet
- internet protocol multimedia

## Part II. Top 25 Key Sentences

- Nortel Networks, the Nortel Networks logo and the Globemark are trademarks of Nortel Networks.
- How would you describe the working environment at Nortel Networks? Nortel Networks is an open and transparent company.
- Nortel Networks, the Nortel Networks logo, the Globemark and Business Without Boundaries are trademarks of Nortel Networks.
- About Nortel Networks Nortel Networks is an industry leader and innovator focused on transforming how the world communicates and exchanges information.
- Nortel Networks, the Nortel Networks logo, the Globemark, Business Without Boundaries, Symposium, Alteon and BayStack are trademarks of Nortel Networks.
- The financial results of Nortel Networks Limited (“NNL”), Nortel Networks Corporation’s principal operating subsidiary, are fully consolidated into Nortel Networks results.
- General “Associated Companies” means any parent, subsidiary company or affiliate of Nortel Networks Limited.
- We would like to acknowledge the years of contribution and service to the Company and Nortel Networks Limited by Messrs.
- Currie has also been appointed chief financial officer and Sledge, interim controller, of Nortel Networks Limited, the Company’s principal operating subsidiary.
- Nortel Networks Limited The financial results of NNL are consolidated into the Company’s results.
- Xros’ revolutionary technology will play a key role in our strategy to deliver an all-optical Internet, said Clarence Chandran, president, Nortel Networks Service Provider and Carrier Group.
- The Qtera technology brings Nortel Networks solutions closer than ever to the all-optical Internet.
- The Nortel Networks solution will save us \$300,000 per year in operational expenses while enabling the entire voice-and-data network to be managed by one person,” Adams says.
- Built with a communications infrastructure that features Nortel Networks solutions to support services from the SBC Communications Inc.

- The PacketHop-Nortel Networks solution combines both fixed and mobile Wireless LAN mesh technologies to deliver broadband wireless infrastructure and applications that are highly scalable, survivable and secure.
- As a result of the merger, each outstanding share of Alteon WebSystems common stock was converted into a right to receive 1.83148 Nortel Networks common shares.
- Under terms of the agreement, Alteon WebSystems shareholders will receive a fixed exchange ratio of 1.83148 Nortel Networks common shares for each share of Alteon WebSystems common stock.
- Of the purchase price, an estimated US\$705 million will be paid in Nortel Networks common shares at closing on a fully diluted basis.
- As a result of the merger, each outstanding share of Clarify common stock was converted into a right to receive 1.3 Nortel Networks common shares.
- Under the terms of the agreement, Clarify shareholders will receive a fixed exchange ratio of 1.3 Nortel Networks common shares for each share of Clarify common stock.
- Nortel Networks’ common shares are listed on the New York, Toronto, Montreal and London stock exchanges.
- As a result, all Nortel Networks common shares will be owned by New Nortel.
- The share exchange will not be taxable to Canadian or United States Nortel Networks common shareholders who hold their shares as capital property.
- A wireless local area network (WLAN) supports remote access to a variety of mobile devices for WakeMed’s healthcare professionals - mobile VoIP phones, PDA’s, laptops and tablet PCs.
- Nortel’s wireless local area networks (LAN) 2200 series portfolio won the security category for its class at SuperComm 2003.

## • Top 5 Short Cluster Summaries

### Cluster I.

- nortel networks
- nortel networks limited
- service provider
- bay networks
- networks common share
- Nortel Networks, the Nortel Networks logo and the Globemark are trademarks of Nortel Networks.
- How would you describe the working environment at Nortel Networks? Nortel Networks is an open and transparent company.
- About Nortel Networks Nortel Networks is an industry leader and innovator focused on transforming how the world communicates and exchanges information.
- The financial results of Nortel Networks Limited (“NNL”), Nortel Networks Corporation’s principal operating subsidiary, are fully consolidated into Nortel Networks results.
- Nortel Networks’ common shares are listed on the New York, Toronto, Montreal and London stock exchanges.

### Cluster II.

- wireless networks
- wireless mesh
- wireless solution
- network management
- wireless mesh network
- MeshPlanner is a precise, intuitive planning tool that optimizes wireless mesh network design to reduce planning and implementation cost.



- Nortel sees its Wireless Mesh Network solutions being applied wherever there is a need for communication networks.
- Nortel's Wireless Mesh Network solution is a very versatile technology that fills a special market niche for serving the increasing demand for anywhere, anytime mobile, broadband access.
- Nortel's Wireless Mesh Networks solution introduces the concept of a peer-to-peer mesh topology, with wireless communication between access points.
- Nortel is breaking new ground and leading the wireless broadband evolution by providing our customers and allies with innovative wireless mesh network technology.

#### Cluster III.

- internet protocol
- local area network
- wireless local area network
- internet protocol multimedia subsystem
- internet protocol multimedia
- A wireless local area network (WLAN) supports remote access to a variety of mobile devices for WakeMed's healthcare professionals - mobile VoIP phones, PDA's, laptops and tablet PCs.
- Nortel's wireless local area networks (LAN) 2200 series portfolio won the security category for its class at SuperComm 2003.
- Wi-Fi - short for wireless fidelity - is the popular term for a high-frequency wireless local area network (WLAN).
- Nortel and Research In Motion announced a joint initiative aimed at delivering secure, full-featured, Session Initiation Protocol-enabled business communications over wireless local area networks.
- Nortel solutions for Internet Protocol (IP) telephony and secure wireless local area networks (LANs) are helping maximize efficiency of communications and collaboration at the Michigan Information Technology Center (MITC), which also serves as Internet2's headquarters.

#### Cluster IV.

- nortel networks
- network management
- data network
- mesh network
- network solution
- The CDMA2000 1X Wireless Data Network, deployed by Nortel Networks, will enable Multi-Links to significantly boost network capacity to accommodate a greater number of voice calls.
- The Qtera technology brings Nortel Networks solutions closer than ever to the all-optical Internet.
- The Nortel Networks solution will save us \$300,000 per year in operational expenses while enabling the entire voice-and-data network to be managed by one person," Adams says.
- Built with a communications infrastructure that features Nortel Networks solutions to support services from the SBC Communications Inc.
- The PacketHop-Nortel Networks solution combines both fixed and mobile Wireless LAN mesh technologies to deliver broadband wireless infrastructure and applications that are highly scalable, survivable and secure.

#### Cluster V.

- optical networks
- optical networks solutions
- large-scale optical networks
- optical internet

- internet service
- Negative developments associated with Nortel’s supply contracts and contract manufacturing agreements, including as a result of using a sole supplier for a key component of certain optical networks solutions
- Xros’ revolutionary silicon-based micro-mirror technology will allow data to be switched through large-scale optical networks entirely in the form of light.
- StorageXtend was tested over WilTel’s nationwide SONET network to ensure interoperability with EMC and Nortel Networks Business Continuity Over Optical Networks solution.
- With a clear recognition of growing customer need for more cost-effective and simplified MAN and WAN networking options, Nortel and EMC have jointly developed a set of Business Continuity over Optical Networks solutions, to enable enterprise customers to easily deploy high availability data replication for their storage area network.

## 6. <http://www.oracle.com>

### • A Single Long Summary

#### Part I. Top 25 Key Phrases

- service oriented architecture windows
- security service oriented architecture
- architecture windows server
- applications technology product
- management applications technology
- management application
- windows server system
- management applications technology product
- architecture windows server system
- enterprise management application
- applications technology
- enterprise management applications technology
- peoplesoft enterprise
- technology products a z
- enterprise management
- technology product
- e business suite
- tools enterprise management
- oracle e business suite
- windows server system technologies
- jd edwards
- oracle aces techblast newsletter
- developer tools enterprise management
- products a z
- tools enterprise management application

#### Part II. Top 25 Key Sentences

- PeopleSoft Enterprise HelpDesk PeopleSoft Enterprise HelpDesk enhances the overall speed and quality of internal support operations by optimizing the efforts of your help desk staff and providing comprehensive process automation.

- Oracle Enterprise Manager Oracle Enterprise Manager with Oracle Grid Control provides a single, integrated interface for administering and monitoring applications and systems in an Oracle Grid.
- We will still continue to deliver tax, legal, and regulatory updates for six-years for the PeopleSoft Enterprise and JD Edwards EnterpriseOne applications.
- JD Edwards World belongs to the Oracle Applications product line, which also includes PeopleSoft Enterprise, JD Edwards EnterpriseOne, and the Oracle E-Business Suite.
- Oracle E-Business Suite On Demand Oracle’s end-to-end business applications for CRM, ERP, SCM, and more, without the demands of monitoring and maintenance.
- Oracle E-Business Suite is a fully integrated, comprehensive suite of business applications for the enterprise.
- Oracle E-Business Suite provides businesses the functional best practices and industry-specific capabilities they need to adapt to change and compete more effectively.
- The Oracle E-Business Suite family of Marketing Applications provides true information-driven marketing, enabling you to plan, execute, and analyze marketing campaigns and complex trade promotions.
- Implement one or several application families – or implement the complete Oracle E-Business Suite for the fastest way to high-quality enterprise information.
- Oracle E-Business Suite family of Order Management applications streamline and automate the entire sales order management process, from order promising and order capture to transportation and shipment.
- Implement one or several application families–or implement the complete Oracle E-Business Suite for the fastest way to high-quality enterprise information.
- Oracle Advanced Procurement is a key component of the Oracle E-Business Suite.
- Oracle’s solution includes a Compliance package, an RFID pilot kit, and integrated support in Oracle E-Business Suite and Oracle Application Server.
- Oracle cMRO touches 22 applications in the Oracle E-Business Suite to provide a comprehensive air transportation maintenance and A&D MRO service solution.
- 7-Eleven “We bought the entire Oracle E-Business Suite because it was pre-integrated, pre-tested, and pre-defined.
- In fact Oracle builds security into all of its products–not just into Oracle Database but also Oracle Application Server, Oracle Collaboration Suite, and Oracle E-Business Suite.
- These are a few examples of the advanced support technologies available to Oracle E-Business Suite and Oracle technology customers.
- Oracle E-Business Suite Customers Applications Customers [spacer.gif] [spacer.gif] Oracle E-Business Suite offers a complete set of applications capable of automating any daily business process.
- We also chose Oracle Fusion Middleware and the BPEL Process Manager in order to deploy and extend our next generation of Oracle E-Business Suite Applications.”
- Plugged In [See a sample] News, events, and support information for E-Business Suite, PeopleSoft Enterprise, JD Edwards EnterpriseOne, JD Edwards World, and Siebel customers.
- Oracle Applications Oracle Applications, including the Oracle E-Business Suite, PeopleSoft Enterprise, JD Edwards EnterpriseOne and JD Edwards World, enable information-driven business processes that connect and automate an organization.
- Oracle’s certification of PeopleSoft, Oracle E-Business Suite and JD Edwards EnterpriseOne applications with Oracle Fusion Middleware is expected to benefit customers both immediately and in the long-term.
- JD Edwards EnterpriseOne and JD Edwards World On Demand High availability and continuous availability solutions specifically designed to support the JD Edwards product family.

## • Top 5 Short Cluster Summaries

### Cluster I.

- collaboration suite
- oracle collaboration
- oracle collaboration suite

- oracle application
- oracle product
- About Oracle Collaboration Suite Oracle Collaboration Suite is the first enterprise-class collaboration product built on the right architecture: Oracle Database and Oracle Application Server.
- Especially attractive to us is Oracle Collaboration Suite’s ease of use and the security offered by Oracle applications and database products.
- Oracle Collaboration Suite 10g Content Services is a robust platform priced and designed for enterprise-wide records management, business process automation and integrated file and document management.
- Oracle Collaboration Suite On Demand is a complete management service for messaging, calendaring, file sharing, and real-time communications.
- Oracle Database, Oracle Application Server, and Oracle Collaboration Suite address all your information integration needs so you can make better business decisions faster.

#### Cluster II.

- oracle fusion
- fusion middleware
- oracle fusion middleware
- oracle application
- application server
- Oracle Fusion Middleware has a range of interoperability with Microsoft .Net and Office.
- Oracle Fusion Middleware is built on the industry’s most complete, J2EE and open-standards-based integration infrastructure.
- Oracle Portal is a member of the Oracle Fusion Middleware family of products, which bring greater agility, better decision-making, and reduced cost and risk to diverse IT environments today.
- Oracle Fusion Middleware is a family of standards-based, customer-proven products that includes Oracle Application Server and related tools and options, Oracle Collaboration Suite, and Oracle Data Hubs.
- The underlying information infrastructure of Oracle Fusion Middleware maximizes the benefits of information-driven applications through the combination of the Oracle Database and Oracle Applications.

#### Cluster III.

- application server
- oracle database
- oracle application
- oracle application server
- oracle product
- Oracle Database, Oracle Application Server, and Oracle Collaboration Suite address all your information integration needs so you can make better business decisions faster.
- Oracle offers the only complete, integrated software stack—Oracle Database 10g and Oracle Application Server 10g—engineered to work together to enable grid computing.
- In fact Oracle builds security into all of its products—not just into Oracle Database but also Oracle Application Server, Oracle Collaboration Suite, and Oracle E-Business Suite.
- Finally, Oracle technology, including Oracle Database and Oracle Application Server, integrates all your employee information for an accurate view of training levels, benefits, and status across your organization.
- The portal architecture is provided through Oracle Application Server 10g and includes the maximum set of functionality, including Oracle Discoverer, Reports, and Forms.

#### Cluster IV.

- e business suite

- oracle e business
- oracle e business suite
- business process
- business intelligence
- Oracle E-Business Suite On Demand Oracle's end-to-end business applications for CRM, ERP, SCM, and more, without the demands of monitoring and maintenance.
- Oracle E-Business Suite is a fully integrated, comprehensive suite of business applications for the enterprise.
- Oracle E-Business Suite provides businesses the functional best practices and industry-specific capabilities they need to adapt to change and compete more effectively.
- The Oracle E-Business Suite family of Marketing Applications provides true information-driven marketing, enabling you to plan, execute, and analyze marketing campaigns and complex trade promotions.
- Oracle Advanced Procurement is a key component of the Oracle E-Business Suite.

#### Cluster V.

- management service
- customer relationship
- relationship management
- customer relationship management
- management solution
- All Campus Solutions Product Modules Customer Relationship Management Increase revenues and drive customer satisfaction and loyalty through Sales, Marketing, and Service effectiveness.
- Oracle's PeopleSoft Customer Relationship Management (CRM) Warehouse captures all customer-related data into a single repository and combines it with complex analysis of your sales, marketing, and service initiatives.
- Customer Relationship Management Metrics and KPIs PeopleSoft Customer Scorecard provides more than 25 predefined metrics and KPIs that provide quick and simplified views into the complete customer lifecycle.