Beyond Single-Page Web Search Results

Ramakrishna Varadarajan, Vagelis Hristidis, and Tao Li

Abstract—Given a user keyword query, current Web search engines return a list of individual Web pages ranked by their "goodness" with respect to the query. Thus, the basic unit for search and retrieval is an individual page, even though information on a topic is often spread across multiple pages. This degrades the quality of search results, especially for long or uncorrelated (multitopic) queries (in which individual keywords rarely occur together in the same document), where a single page is unlikely to satisfy the user's information need. We propose a technique that, given a keyword query, on the fly generates new pages, called *composed pages*, which contain all query keywords. The composed pages are generated by extracting and stitching together relevant pieces from hyperlinked Web pages and retaining links to the original Web pages. To rank the composed pages, we consider both the hyperlink structure of the original pages and the associations between the keywords within each page. Furthermore, we present and experimentally evaluate heuristic algorithms to efficiently generate the top composed pages. The quality of our method is compared to current approaches by using user surveys. Finally, we also show how our techniques can be used to perform *query-specific* summarization of Web pages.

Index Terms—Internet search, search process, Web search.

1 Introduction

Given a user keyword query, current Web search engines return a list of pages ranked by their "goodness" with respect to the query. However, the information for a topic, especially for long or uncorrelated (multitopic) queries (in which individual query keywords occur relatively frequently in the document collection but rarely occur together in the same document), is often distributed among multiple physical pages connected via hyperlinks [26]. It is often the case that no single page contains all query keywords. Li et al. [26] make a first step toward this problem by returning a tree of hyperlinked pages that collectively contain all query keywords. The limitation of this approach is that it operates at the page level, which ignores the specific context where the keywords are found in the pages. More importantly, it is cumbersome for the user to locate the most desirable tree of pages due to the amount of data in each page and the large number of page trees.

We propose a technique that, given a keyword query, on the fly generates new pages, called *composed pages*, which contain all query keywords. A preliminary version of this work was presented as a poster paper in the 2006 ACM SIGIR [39]. The composed pages are generated by stitching together appropriate pieces from hyperlinked Web pages (hyperlinks to the original Web pages are also displayed). To rank the composed pages, we consider both the hyperlink structure of the original (source) pages and the associations between the keywords within each page.

Our technique has the following key steps: During the preprocessing stage, for each Web page, we create a labeled weighted graph, called the *page graph*, by splitting the page to a set of *text fragments* (graph nodes) and computing the semantic associations between them (graph edges). Then, at query time, given a set of keywords, we first find a tree, called *Web spanning tree*, of hyperlinked pages that collectively contain all the query keywords. Then, we perform a keyword proximity search on the each page's page graph to discover how the keywords contained in the page are associated with each other. For each page in the Web spanning tree, we extract a *page spanning tree* that contains a subset of the query keywords. The page spanning trees of the pages of the Web spanning tree are appropriately combined into a composed page, which is returned to the user. As we will explain later, smaller Web spanning trees are preferable and, hence, single-page results, as created by current Web search engines for AND semantics, are ranked higher.

Note that a key assumption that we make in this paper is that hyperlinked pages are associated with each other. This is a reasonable assumption. Furthermore, each result should be composed of pages associated to each other to have a cohesive meaning. Hence, we only consider hyperlinked pages in building a Web spanning tree.

Example 1. Fig. 1 shows a Web graph extracted from the www.fiu.edu Web site. The hyperlinks between pages are depicted in the Web graph as edges. The nodes in the graph represent the Web pages. Fig. 2 shows the page graph of page 1 in Fig. 1. As denoted in Fig. 1, page 1 is split into seven text fragments $v1, \ldots, v7$, using the newline delimiter, and each one is represented by a node in the page graph. The edges denote semantic associations. Table 1 shows the top-3 search results (composed pages) for the query "Graduate Research Scholarships." We represent the nodes of a Web spanning tree by using rectangles and the nodes of a page spanning tree by using circles. Hyperlinks are solid lines, whereas the semantic links within a page graph are dotted lines. The page spanning trees represent the most "relevant pieces" of each page.

Query-specific summarization. The extraction of the most relevant pieces of information from a Web page using the notion of the page spanning tree has another application

• *The authors are with the School of Computing and Information Sciences, Florida International University, University Park, 11200 S.W. 8th Street, Miami, FL 33199. E-mail: {ramakrishna, vagelis, taoli}@cis.fiu.edu.*

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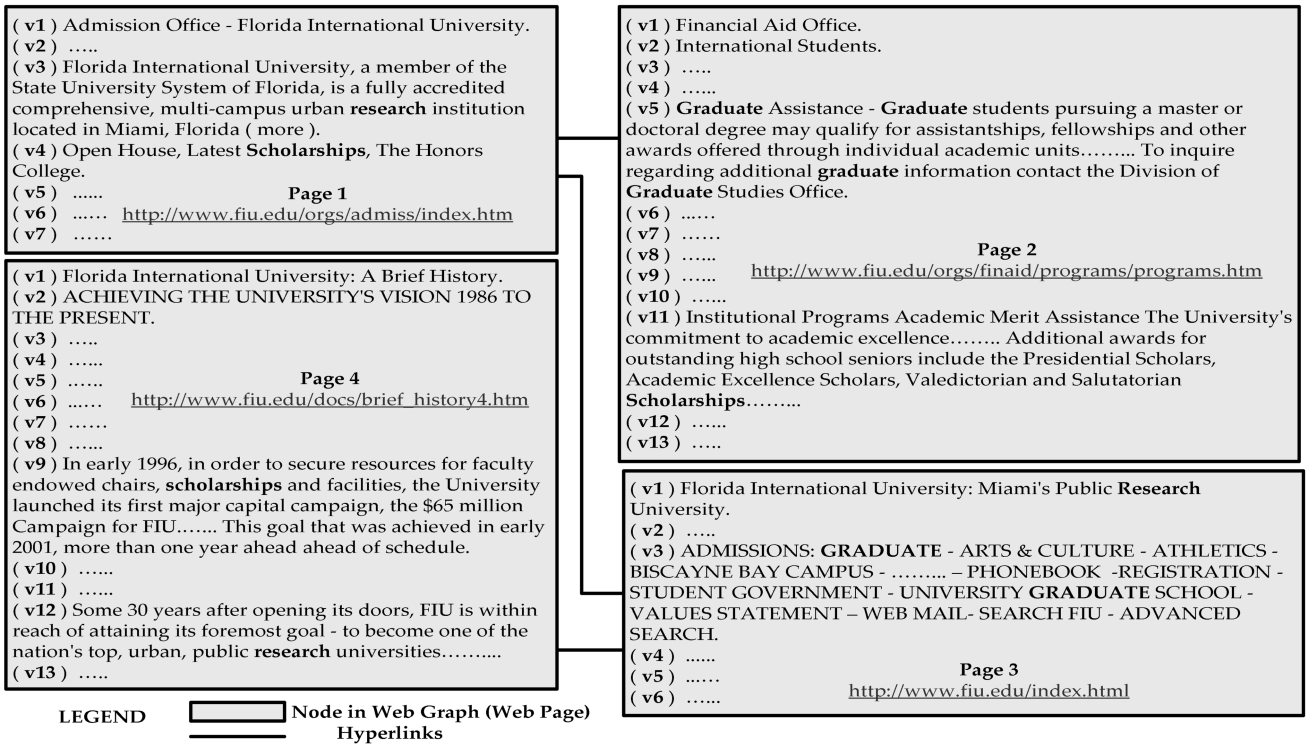


Fig. 1. Sample Web pages from www.fiu.edu.

(by-product), in addition to being a component in creating composed pages. In particular, it is used to perform *query-specific summarization* of Web pages. The most popular use of query-specific summarization today is the snippets displayed for each of the page results of Web search engines. We show how the query-specific summaries corresponding to page spanning trees have better quality than current approaches.

Example 1 (continued). For Web page 1 of Fig. 1 and the keyword query "Research Scholarships," the top summary $v3$-$v4$ is shown in Fig. 3. The top summary is the top spanning tree of the page graph of page 1 shown in Fig. 2. Nodes $v3$ and $v4$ are associated, because they are adjacent in the text (stronger associations are assigned when the nodes have common words, as explained in the following).

In summary, this work has the following contributions:

- We introduce the notion of composed pages to improve the quality of Web search. Composed pages are created on the fly by combining appropriate content from other pages.
- We show how the most relevant information is extracted from a page by viewing a page as a page graph and computing a query-specific page spanning tree. This has applications to query-specific summarization, in addition to the generation of composed pages.
- We propose efficient heuristic algorithms to compute the top composed pages and query-specific summaries. The efficiency of the algorithms is evaluated experimentally.
- We show through user surveys that the inclusion of composed pages in the search results increases the user satisfaction. Furthermore, we show that by using the idea of the page spanning tree, we produce query-specific summaries that are superior to current approaches.
- We have developed prototypes of the Composed Pages system, available at http://dbir.cs.fiu.edu/ComposedPages, and the summarization system, available at http://dbir.cs.fiu.edu/summarization.

The rest of this paper is organized as follows: Section 2 describes the framework used in our paper. Section 3 describes how page graphs are built. Section 4 describes the

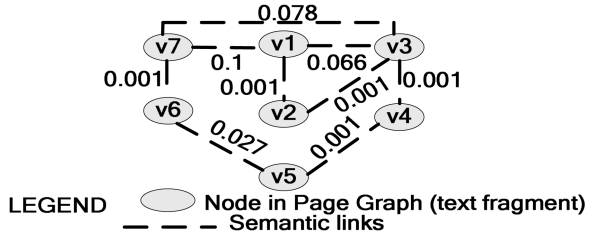


Fig. 2. A page graph of page 1 in Fig. 1.

TABLE 1
Top-3 Search Results for the Query "Graduate Research Scholarships"

Rank	Score	Search Results
1	12.50	1 v3 – v4 — 2 v5
2	101.60	3 v3 – v1 — 1 v4
3	209.89	3 v3 – v1 — 4 v9

Florida International University, a member of the State University System of Florida, is a fully accredited comprehensive, multi-campus urban **research** institution located in Miami, Florida (more)
└Open House, Latest **Scholarships**, Honors College

Fig. 3. Top summary of Web page 1 of Fig. 1 for the query "Research Scholarships".

idea of query-specific document summarization. Section 5 introduces the idea of searching the Web using composed pages. Section 6 presents the algorithms used in our system. Sections 7 and 8 present the quality and performance experiments, respectively. Section 9 describes the related work and, finally, in Section 10, we present our conclusions.

2 Framework

2.1 Data Model

Web graph. Let $D = d_1, d_2, \ldots, d_n$ be a set of Web pages $d_1, d_2, \ldots, d_n$. In addition, let $size(d_i)$ be the length of d_i, in numbers of words. The term frequency $tf(d, w)$ of term (word) w in a Web page d is the number of occurrences of w in d. Inverse document frequency $idf(w, D)$ is the inverse of the number of Web pages containing term w in them.

The *Web graph* $G_W(V_W, E_W)$ of a set of Web pages $d_1, d_2, \ldots, d_n$ is defined as follows:

- A node $v_i \in V_W$ is created for each Web page d_i in D.
- An (undirected) edge $e(u, v) \in E_W$ is added between nodes u, $v \in V_W$, if there is a hyperlink between u and v.

An example of a Web graph is shown in Fig. 1. We view the Web graph as undirected, since an association between pages occurs along both directions of a hyperlink.

Page graph. In contrast to previous work in Web search [25], [26], [31], we go beyond the page granularity. To do so, we view each page as a set of text fragments connected through semantic associations.

A key component of our work is the *page graph* $G_d(V_d, E_d)$ of a Web page d, which is defined as follows:

- d is split into a set of nonoverlapping text fragments, and each fragment is represented by a node $v \in V_d$. A text fragment corresponding to a node v is denoted as $t(v)$.
- An undirected weighted edge $e(u, v) \in E_d$ is added between nodes u, $v \in V_d$, if there is an association (further discussed in Section 3) between $t(u)$ and $t(v)$ in d.

Fig. 2 shows the page graph of page 1 in Fig. 1. The process of building page graphs is explained in Section 3. The page graph is equivalent to the document graph in [38]. Notice that there are many ways of defining the page graph for a Web page. In this work, we exploit the HTML tags to split the page into text fragments, and edges are added when the text fragments are associated through common (or related) words, as we will explain in Section 3. The semantic association between the nodes is used to compute the edge weights (query independent), whereas the relevance of a node to the query is used to define the node weight (query dependent). Note that the Web graph now becomes a graph of page graphs.

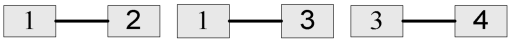


Fig. 4. The minimal total Web spanning trees of the Web graph in Fig. 1 for the query "Graduate Research Scholarships."

Search result. A keyword query Q is a set of keywords $Q = \{w_1, \ldots, w_m\}$. Before defining the result of a keyword query, we need a few more definitions.

Definition 1 (Minimal Total Web Spanning Tree). *Given a Web graph $G_W(V_W, E_W)$, the minimal total Web spanning tree of G_W with respect to a keyword query $Q = \{w_1, \ldots, w_m\}$ is a subtree T of G_W that is both*

- *Total: every keyword $w \in Q$ is contained in at least one node (page) of T, and*
- *Minimal: we cannot remove any node from T and still have a total subtree.*

Fig. 4 shows the minimal total spanning trees for the query "Graduate Research Scholarships" on the Web graph in Fig. 1. The result of a keyword query Q at the page granularity is the minimal total Web spanning tree T. We go one step further in order to improve the user's experience and locate the specific parts of each Web page in T that are relevant to Q. For that, we need the following definition.

Definition 2 (Minimal Total Page Spanning Tree). *Given a page graph $G_d(V_d, E_d)$ for a Web page d and a set of keywords $Q_i \subseteq Q$ ($Q_i = Q$ for query-specific summarization), the minimal total page spanning tree p of G_d is a subtree of G_d that is both*

- *Total: every keyword $w \in Q_i$ is contained in at least one node of p, and*
- *Minimal: we cannot remove any node from p and still have a total subtree.*

Fig. 5 shows two minimal page spanning trees for Pages 2 and 4, respectively, for the query "Graduate Research Scholarships." In both cases, $v2$ is a Steiner node; that is, it does not contain any query keyword in it but is helpful in forming the minimal total spanning tree for the pages, as it has semantic links to the nodes that contain the keywords.

There is a subtle difference in the page spanning tree computation for our two different applications searching using composed pages and query-specific summarization. For the query-specific summarization of a Web page, we compute the page spanning tree that contains all of the keywords in Q. For the composed pages application, for single-page results, we compute the page spanning tree for Q, whereas for multipage results, we compute them for subsets of Q (see Definition 3). Note that for Steiner nodes, Q_i is empty. In this case, p is an empty tree, which we

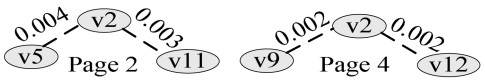


Fig. 5. The minimal total page spanning trees of pages 2 and 4 in Fig. 1 for the query "Graduate Research Scholarships."

represent by just displaying the *title* of the page in our system.

The minimal total Web spanning tree T is "refined" by finding the minimal total page spanning tree p for each of the Web pages $d \in T$, as formally explained in Definition 3. Henceforth, we omit the words "minimal total" for brevity if it is clear from the context when referring to the minimal total Web spanning trees or page spanning trees. The size of a Web or page spanning tree is the number of edges that it contains.

Definition 3 (Search Result). *Given a Web graph $G_W(V_W, E_W)$, page graphs for each Web page in G_W, and keyword query $Q = \{w_1, \ldots, w_m\}$, the search result R is the minimal total Web spanning tree T with nodes (pages) $d_1, .., d_z$, along with the minimal total page spanning tree for each d_i with respect to a subset Q_i of Q. Each page d_i is assigned a subset Q_i of Q (d_i must contain all keywords in Q_i, although it may contain more keywords of Q than Q_i) such that $Q_i \cap Q_j = \emptyset$ for every $i \neq j$, and $Q_1 \cup \ldots \cup Q_z = Q$.*

For example, Table 1 shows the top-3 search results for the query "Graduate Research Scholarships." The Web spanning tree 3-1 gives rise to two search results. Page 3 contains the keywords "graduate" and "research," and page 1 contains "research" and "scholarships," that is, the keyword "research" appears in both pages. One search result is computed with subsets $Q_1 = \{\text{graduate, research}\}$ for page 3 and $Q_2 = \{\text{scholarships}\}$ for page 1, whereas the other is computed with $Q_1 = \{\text{graduate}\}$ for page 3 and $Q_2 = \{\text{research, scholarships}\}$ for page 1. We only return the best (see Section 5.1 for ranking) search result for each Web spanning tree to the user, as shown in Table 1.

Problem Definitions. We are now ready to formally define the two problems addressed in this work. The scoring of search results and summary trees is presented in Sections 5.1 and 3.1, respectively. Smaller scores correspond to higher ranking.

Problem 1 (Top-k Search Results). *Given a Web graph G_W, the page graphs for all pages in G_W, and a keyword query Q, find the k search results R with minimum $Score(R)$.*

Problem 2 (Query-Specific Summarization). *Given a document $d \in D$ and its page graph G_d, as well as a keyword query Q, find the best summary, that is, the minimal total spanning tree with minimum score.*

Notice that typically, a single summary per page is required and, hence, problem 2 is a top-1 problem. Notice that the totality property implies that we use *conjunctive* query semantics (AND). Applying OR semantics to Problem 2 is straightforward, as we just replace Q by Q', where Q' is the set of query keywords contained in the page. Applying OR semantics to Problem 1 is unintuitive, since the primary purpose of the composed pages approach is to produce complete (total) answers to the user.

3 Building Page Graphs

The page graph $G_d(V_d, E_d)$ of a page $d \in D$ is constructed as follows: First, we parse d and split it into text fragments by using parsing delimiters (for example, $< \text{p} >$ and $< \text{br} >$ tags). Each text fragment becomes a node in the page graph. A weighted undirected edge is added to the page graph between two nodes if they either correspond to adjacent text fragments in the text or they are semantically associated. The weight of an edge denotes the association degree of the association.

There are many possible ways of defining the association degree between two text fragments. In this work, we consider two fragments to be associated if they share common words (excluding stop words), and the degree of association is calculated by an adaptation of traditional IR term weighting formulas [35], as described in the following. We also consider a thesaurus to enhance the word-matching capability of the system. In future versions of our system, we will consider using WordNet and Latent Semantic Indexing (LSI) techniques to improve the quality of the edge weights. To avoid dealing with a highly interconnected graph, which would lead to slower execution times and higher maintenance cost, we only add edges with weights above a threshold. In addition, notice that the edge weights are query independent, so they can be precomputed. Q is only used in assigning weights to the nodes of G_d.

The following input parameters are required during the precomputation stage to construct the page graph:

1. *Threshold for edge weights*. Only edges with weights not below a *threshold* will be created in the page graph. The choice of the threshold is a trade-off between performance and quality, since a zero threshold would build a dense graph, which would increase the processing time, whereas a higher threshold would decrease the quality of results by not including enough edges.
2. *Parsing delimiters*. Parsing delimiters are used to split the Web page into text fragments. Typical choices are the $< \text{p} >$ (paragraph) tag (each text fragment corresponds to a paragraph) or the $< \text{br} >$ (each text fragment is a sentence). Other tags that could be surrounding a possible text fragment are the $< \text{table} >$, $< \text{ul} >$, $< \text{ol} >$ tags, and so on. For all of these tags, the text between the opening and closing counterparts constitute a text fragment. This way, we found a set of tags that, when used as delimiters, leads to paragraphs that are typically short and leads to more compact page graphs. For plaintext documents, typical choices are newline characters (each text fragment corresponds to a paragraph) or periods (each text fragment corresponds to a sentence).
3. *Maximum text fragment size*. This is used in cases where a fragment is too long, which would lead to large nodes (text fragments) and, hence, large summaries. Users typically desire concise and short summaries.

After parsing the page and creating the graph nodes (text fragments), for each pair of nodes u, v, we compute the association degree between them, that is, the score (weight) $EScore(e)$ of the edge $e(u, v)$. If $EScore(e) \geq threshold$, then e is added to E_d. The score of edge $e(u, v)$, where nodes u and v have text fragments $t(u)$ and $t(v)$, respectively, is

$$EScore(e) = \frac{\sum_{w \in (t(u) \cap t(v))} \left((tf(t(u), w) + tf(t(v), w)) \cdot idf(w) \right)}{size(t(u)) + size(t(v))}, \quad (1)$$

where $tf(d, w)$ is the number of occurrences of w in d, $idf(w, D)$ is the inverse of the number of pages containing w,

and $size(d)$ is the size of the page (in numbers of words). That is, for every word w appearing in both text fragments, we add a quantity proportional to the $tf \cdot idf$ score of w. Notice that stop words are ignored. Furthermore, we use a thesaurus and stemmer (we rely on Oracle interMedia [30], as explained in Section 8) to match words that are related. The sum is divided by the sum of the lengths of the text fragments in the same way as the document length (dl) is used in traditional IR formulas.

Edges between adjacent fragments. We consider adjacent fragment edges as a special case, because two adjacent fragments are semantically related because of their close proximity. Furthermore, linking the adjacent nodes ensures the connectivity of the page graph. We use the following formula, which ensures that there is always an edge between nodes with adjacent text fragments:

$$EScore(e) = max(EScore(e), threshold). \quad (2)$$

The calculation of the edge weights concludes the query-independent part of the page graph creation. Next, when a query Q arrives, the nodes in V_d are assigned query-dependent weights according to their relevance to Q. In particular, we assign to each node v corresponding to a text fragment $t(v)$ node score $NScore(v)$ defined by the Okapi formula [35] and, in order to accelerate this step of assigning node scores, we build a full-text index on the set D of pages (the details of this index are out of the scope of this paper):

$$\sum_{t \in Q,d} \ln \frac{N - df + 0.5}{df + 0.5} \cdot \frac{(k_1 + 1)tf}{(k_1(1-b) + b\frac{dl}{avdl}) + tf} \cdot \frac{(k_3 + 1)qtf}{k_3 + qtf}, \quad (3)$$

where tf is the term's frequency in the document (page), qtf is the term's frequency in the query, N is the total number of documents in the collection, df is the number of documents that contain the term, dl is the document length (in words), $avdl$ is the average document length, and $k1$ (between 1.0 and 2.0), b (usually 0.75), and $k3$ (between 0 and 1,000) are constants.

3.1 Ranking of Page Spanning Trees

In this section, we present our ranking framework for page spanning trees. Recall that the top page spanning tree is the query-specific summary for Problem 2 (Section 2.1). Given the page graph G_d of page d and a query Q, a page spanning tree p is assigned a score $Score(p)$ by combining the scores of the nodes $v \in p$ and the edges $e \in p$:

$$Score(p) = a \sum_{edgee \in p} \frac{1}{EScore(e)} + b \frac{1}{\sum_{nodev \in p} NScore(v)}, \quad (4)$$

where a and b are constants, as discussed in the following. $EScore(e)$ is the score of edge e by using (1), and $NScore(v)$ is the score of node v by using (3).

Intuitively, if p is larger (has more edges), then its score should degrade (increase), since larger trees denote looser semantic connections [2], [7], [21], [22]. The reason is that we take the sum of the inverse of the edge scores in (4). Furthermore, if more nodes of p are relevant to Q, the score should be improved (decreased). Hence, we take the inverse of the sum of the node scores.

(v0) Brain chip offers hope for paralyzed
(v1) A team of neuroscientists have successfully implanted a **chip** into the **brain** of a quadriplegic man, allowing him to control a computer.
(v2)……...
(v3) The **chip**, called BrainGate, is being developed by Massachusetts-based neurotechnology company Cyberkinetics, following **research** undertaken at Brown University, Rhode Island.
(v4) Results of the pilot clinical study will be presented to the Society for Neuroscience annual conference in San Diego, California, on Sunday. Up to five more patients are to be recruited for further **research** into the safety and potential utility of the device.
(v5)……..
(v6)……..
(v7) John Donoghue, professor of neuroscience at Brown and a co-founder of Cyberkinetics in 2001, said that BrainGate could help paralyzed peopled control wheelchairs and communicate using email and Internet-based phone systems.
(v8) ……...
(v9) ……...
(v10) Donoghue's initial **research**, published in the science journal Nature in 2002, consisted of attaching an implant to a monkey's **brain** that enabled it to play a simple pinball computer game remotely.
(v11) The four-millimeter square **chip**, which is placed on the surface of the motor cortex area of the **brain**, contains 100 electrodes each thinner than a hair which detect neural electrical activity. The sensor is then connected to a computer via a small wire attached to a pedestal mounted on the skull.
(v12) ……...
(v13) ……...
(v14) Surgeon Gerhard Friehs, associate professor of clinical neurosciences at Brown Medical School, who implanted the device, described the results as "spectacular" and "almost unbelievable."
(v15) "Here we have a **research** participant who is capable of controlling his environment by thought alone -- something we have only found in science fiction so far," said Friehs.
(v16) …….

Fig. 6. Sample news page from www.cnn.com.

Constants a and b are used to calibrate the importance of the size of the summary (in numbers of edges) versus the amount of relevant information contained. In particular, higher a values boost the score of smaller and tightly connected summaries, whereas higher b values benefit summaries with more relevant content (that is, containing nodes with a high score with respect to the query). Notice that a and b can also be viewed as adjusting parameters for the query-independent and query-dependent parts of the scoring function, respectively. We use $a = 1$ and $b = 0.5$ in our system, which we have found to produce high-quality answers.

4 Query-Specific Summarization

This section tackles Problem 2 of Section 2.1. Given a query Q and a page graph G_d for a page d, the query-specific summary is the page spanning tree p of the G_d with minimum $Score(p)$, according to (4).

Example 2. Fig. 7 shows the page graph for the page in Fig. 6. The page is first split into text fragments $v0, \ldots, v16$, which correspond to its paragraphs (the newline delimiter was used). Notice that the edge between nodes $v8$ and $v7$ has the highest weight, because there are many infrequent (hence with high idf value) words that are common between them, like "Donoghue" and "BrainGate."

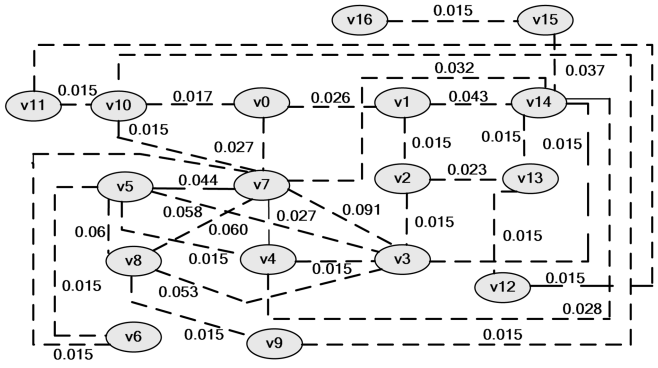


Fig. 7. Page graph of the sample page in Fig. 6.

Table 2 shows the top-ranked spanning trees for the page graph in Fig. 7 for the query "Brain Chip Research." The values shown above the nodes in Table 2 indicate the node scores with respect to the query, as computed by (3). The top result (whose textual representation is shown in Fig. 8) is the best summary for this query. Intuitively, this result is the best, because it contains the minimum possible number of nodes, and the edge that connects the two nodes is strong. In addition, observe that result 4 is ranked lower than result 3, even though it has fewer nodes. The reason is that the nodes of result 4 are connected through very commonly occurring words like "computer" and "brain," whereas in result 3, they are connected through infrequent words like "Friehs."

5 Search Using Composed Pages

This section tackles Problem 1 in Section 2.1. In Section 5.1, we explain how a search result (Definition 3) is ranked, whereas Section 5.2 discusses how a composed page is constructed for a search result.

5.1 Ranking Search Results

Recall that a *search result* R is a Web spanning tree T, where each page d in T is represented by its page spanning tree p. Clearly, there is no optimal ranking function, since it is possible to come up with different ranking functions for different domains or specific queries. In this work, we adopt principles that are well accepted in previous work on ranking Web pages [25], [26], [31] and trees of data [2], [7], [14], [17], [21], [38].

The *first ranking principle* that we adopt [26] is that search results involving fewer pages are ranked higher. Intuitively, if a search result is larger (has more edges), then its score should degrade (increase), since larger trees denote looser semantic connections. Hence, search results are primarily ranked by the (inverse of the) size of their Web spanning tree. Recall that by Definition 3, all search results contain all query keywords.

Within search results with the same size of the Web spanning tree, we rank according to the scores of the involved page spanning trees, as computed by (4). Note that the first ranking principle also applies in ranking individual page spanning trees as expressed in (4); that is, page spanning trees with smaller size are ranked higher.

What is left is defining how the scores of the constituting page spanning trees computed by (4) are combined to compute the overall score of a search result. Again, we do not claim that we have the optimal combining function, but we rely on previous work to define the next principle. The *second ranking principle* is that the scores of the page spanning trees are combined using a monotone combining function to compute the score of the search result. Notice that we have already used another variant of this principle in (4), where the scores of the nodes and edges are combined using a monotone function.

To incorporate the global importance of the pages used in constructing a search result, we use their PageRank [31] values. The score of a search result R is computed as follows, given the scores of its page spanning trees p, where we chose summation as our monotone combining function:

$$Score(R) = \sum_{p \in R} \frac{Score(p)}{PR(p)}, \quad (5)$$

where $PR(p)$ is the PageRank score of page d that contains the page spanning tree p.

TABLE 2
Top Summaries for the Query "Brain Chip Research"

Rank	Score	Summary
1	67.74	0.046 v0 — 0.017 — 0.008 v10
2	84.77	0.046 v0 — 0.027 — 0.0 v7 — 0.027 — 0.0003 v4
3	87.64	0.012 v1 — 0.043 — 0.0 v14 — 0.037 — 0.0005 v15
4	103.77	0.008 v10 — 0.015 — 0.005 v11
5	167.41	0.046 v0 — 0.027 — 0.0 v7 — 0.032 — 0.0 v14 — 0.037 — 0.0005 v15

5.2 Composed Pages

A composed page is a dynamic page created on the fly by stitching together pieces from other pages. Given a query Q, a composed page is a representation of a search result, as defined in Definition 3, in a Web page format. The score of a composed page is the score of the corresponding search result defined by (5).

The key requirements in constructing a composed page are the following: First, display the tree-structured (more specifically tree of trees) search result in a page format. Second, allow users to easily navigate to the original pages that were used to construct the composed page. Fig. 9 shows the composed page constructed for search result 1 in Table 1. A composed page for a search result is constructed

Brain chip offers hope for paralyzed.

Donoghue's initial **research** published in the science journal Nature in 2002 consisted of attaching an implant to a monkey's **brain** that enabled it to play a simple pinball computer game remotely.

Fig. 8. Top summary for the document in Fig. 6 for the query "Brain Chip Research."

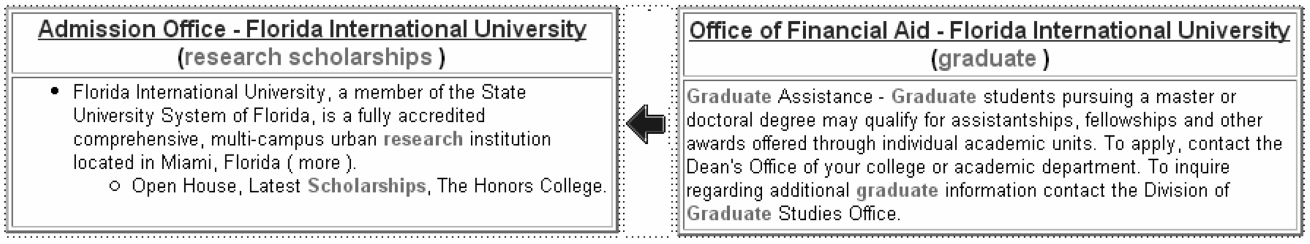


Fig. 9. Composed page for search result 1 for the query "Graduate Research Scholarships."

by displaying links to all pages in its Web spanning tree, along with the text fragments of the page spanning trees. The page spanning trees are displayed in an unordered list format that depicts their structure. A subbulleted list denotes the parent-child relationship in the page spanning tree of text fragments.

6 Algorithms

In this section, we present various algorithms used in our system. Note that the algorithms used in the query-specific summarization problem are also used as a component of the composed-pages problem. The precomputation requirements are also the same. Section 6.1 presents the algorithm for preprocessing the Web pages and creating a database of *page graphs*. Section 6.2 presents algorithms for solving the query-specific summarization problem (Problem 2), which are adopted in Section 6.3 to solve the top-k search results problem (Problem 1).

Preprocess (Web Graph G_w, Parsing Delimiters P, Threshold τ, Maximum Fragment size sz)

1. For each web page (node) d in G_w do {
/* create and store page graph G_d for d*/
2. Parse d and split it into text fragments with maximum size sz using the delimiters in P;
3. Create a node for each text fragment and add it to the page graph, G_d of d;
4. For every pair of nodes in G_d find if they are semantically related by calculating the edge weight using Equation 1 and add it to G_d if the edge weight $\geq \tau$;
5. For every pair of adjacent nodes, build an edge e with weight equivalent to $max(Escore(e), \tau)$ according to Equation 2;/*in close proximity as explained*/
6. Find All-pairs shortest path using Floyd Warshall's algorithm using the inverse of each edge's weight;}
7. Compute and store the PageRank values of all pages (nodes) in G_w; /* compute PageRank values; build full-text index*/
8. For each keyword w locate and store all pages in D that contain w; /*Stemming is used in this step. Stop words are ignored*/

Fig. 10. Preprocessing algorithm.

6.1 Preprocessing Algorithm

Fig. 10 describes the preprocessing algorithm. Before any query arrives, we precompute and store the following:

- *The page graph for each page*. In particular, we parse the HTML documents based on the tags, as described in Section 3, and compute the edge weights. The parameters described in Section 3 are taken as input, and page graphs are built accordingly.
- *The PageRank values of each page*. These are obtained by executing the PageRank algorithm [31].
- *A full-text index*. This is used to efficiently locate the pages, specifically the text fragments that contain the keywords, and to calculate their query-specific score.
- *The all-pairs shortest paths*. In order to boost the performance of the algorithms, we use the all-pairs shortest paths between the nodes of the page graph G_d of every page d. Note that the inverse of the edge weights is used, since larger edge weights denote tighter association in our setting.

6.2 Compute the Top-1 Page Spanning Trees (Query-Specific Summaries)

For both Problems 1 or 2, we need to solve a variant of the Group Steiner Tree problem, which is referred to as the keyword proximity search problem [7], [14] and is defined as follows:

Given a weighted data graph $G(V, E)$, a keyword query Q, which is a set of keywords, and an integer k, find the k minimum-weight subtrees of G such that every keyword in Q is contained in at least one vertex of the subtree, and we cannot remove any node from it and still have a tree.

When $k = 1$, the keyword proximity search problem has been shown to be equivalent to the Group Steiner problem, which is NP-complete. The keyword proximity search problem is slightly more complex, since the groups of nodes are not disjoint, in contrast to the Group Steiner Problem, which is defined as follows:

Given an undirected, connected, and weighted graph $G = (V, E)$ and a family $R = \{R_1, \ldots . R_k\}$ of disjoint groups of vertices, where R_i is a subset of V, find a minimum-cost tree T that contains at least one vertex from each group R_i. Since the weights of the graph are nonnegative, the solution is a tree structure.

This section presents two algorithms adopted from BANKS [7] to compute the top query-specific summary: the enumeration and the expanding search algorithms. The algorithms return a top-1 summary for a Web page d, given its page graph G_d and a query Q. The reason that we employ top-1 summary algorithms is that typically, the user only requests a single summary for a document, as in the case of snippets in Web search engine results.

```
Top-1-MTPST-Enumeration (Page Graph Gd, Query Q,
Quality parameter ω)
1. Results ←∅; /*stores summaries*/
2. Find all nodes in Gd that contain some keyword
   of Q; /*use full-text index*/
3. Find all minimal combinations of nodes that
   collectively contain all keywords in Q;
4. For each minimal node combination C do {
5.      Create closure graph Gc that contains only
        the nodes in C;
6.      Find all possible spanning trees S of Gc;
7.      Calculate the score of each spanning tree
        in S using Equation 4 by using shortest
        path weights between any two nodes;
8.      Pick the spanning tree p with the minimum
        score;
9.      Replace the edges u~v in p with their
        precomputed shortest paths u~u1~…~uk~v; /*
        i.e., we are adding the Steiner nodes.*/
10.     Trim p to make it a minimal total span
        ning tree;
11.     Recalculate the score of p using Equation
        4 and add p to Results;
12.     ω--;
13.     If(ω==0) Return the top ranked summary in
        Results; }
```

Fig. 11. Top-1 enumeration algorithm.

Top-1 Enumeration Algorithm. This algorithm Top-1-Minimal-TotalPageSpanningTree-Enumeration (*Top-1-MTPST-Enumeration*) is shown in Fig. 11. First, we find all combinations of nodes in G_d that are minimal (no node is redundant) and total (collectively contain all keywords in Q). Then, for each combination, we create a complete graph G_c (called *closure graph*) that contains all nodes in the combination and all pairs of edges between them, with their weight equal to their precomputed shortest path distance. We then calculate all possible spanning trees in G_c, compute their scores by using (4), and so on (see Fig. 11 for more details). This algorithm accepts a quality parameter ω. Higher values of ω yield higher quality results. Intuitively, this parameter decides the number of different summaries that are considered before we pick the best one, given that this is an NP-complete problem.

Example 2 (continued). Consider the page graph in Fig. 7 and the query "Brain Chip Research." The nodes that contain the keywords are $v0$, $v1$, $v3$, $v4$, $v10$, $v11$, and $v15$. We then find all minimal and total node combinations, which are $\{v0, v10\}$, $\{v15, v0\}$, $\{v0, v3\}$, $\{v4, v0\}$, and so on. For each combination, we create a closure graph. For example, the closure graph for the second combination is $v15 \sim v0$ with edge weight 88.74 (which is the length of the shortest path from $v15$ to $v0$). We then find all possible spanning trees of this graph, which is just $v15 \sim v0$, for the above closure graph. Then, we replace the edge between $v15$ and $v0$ with the shortest path between them, which is $v15 \sim v14 \sim v1 \sim v0$. This tree is not minimal and, hence, we trim it to get the minimal result $v15 \sim v14 \sim v1$ and output this result, along with its score.

```
Top-1-MTPST-ExpandingSearch(Page graph Gd, Query
Q, Quality parameter ω)
1. Results ←∅;  /*stores summaries*/
2. Find all nodes N={N1,…,Nm} that contain the
   keywords in Q and create expanding areas for
   each; /*Ni has the nodes that contain wi*/
3. Repeat until each expanding area spans the
   entire graph G {
4.   For each node v in N do {
5.      Add to the expanding area of v the mini-
        mum-score adjacent edge from the (pre-
        computed) shortest paths starting at v
        and ending at a node in N not containing
        the same keywords as v;
6.      Check for new results (summaries);
        /*i.e., trees that contain a node from
        each of N1,…,Nm */
7.      Trim summaries to make them minimal;
8.      Calculate the score of each summary p
        using Equation 4 and store in Results;
9.      ω--;
10.     If(ω==0) Return the top ranked summary
        in Results;}}
```

Fig. 12. Top-1 expanding search algorithm.

Top-1 Expanding Search Algorithm. The basic idea is that an expanding area is created for each keyword node (a node that contains a query keyword) of G_d, and we start from the nodes that contain the query keywords and progressively expand them according to a shortest path algorithm until we find all minimal total spanning trees. In particular, the algorithm (Fig. 12) finds (using the precomputed full-text index) all the nodes that match some keywords in the query and starts expanding them incrementally. We call the subgraph created from each keyword node v the expanding area of v. At each iteration, we expand each expanding area in parallel by adding all adjacent edges (later, we will discuss heuristics of expansion) to the expanding area of the previous iteration. A result (summary) is generated when a set of expanding areas meet at a common point (node) and form the minimal total page spanning tree for Q.

We use the precomputed all-pairs shortest paths data to efficiently grow the expanding area. That is, we only consider the edges that are contained in the shortest path from the current node v to any other node u that contains additional query keywords than v. When two or more expanding areas meet, we check for possible new summaries. If a summary is found, it is trimmed to become minimal, and its score is calculated using (4).

Example 2 (continued). For the page graph in Fig. 7 and the query "Brain Chip Research," we grow the expanding area of $v0$ to $v0 \sim v10$, which is the first precomputed shortest path of source $v0$, and check for possible summaries. $v0 \sim v10$ is total and minimal and, hence, we add it to the set of results. We continue growing each expanding area by using its precomputed shortest paths. Then, we grow $v1$ to $v1 \sim v2$, $v3$ to $v3 \sim v2$, $v4$ to $v4 \sim v3$, $v10$ to $v10 \sim v9$, and $v11$ to $v11 \sim v10$, and once we

```
Heuristic-Top-k-Expanding-Search(Web graph Gw,Page graphs PG ={Gd1, Gd2 … Gdn},Keyword query Q = {w1,…,wm})
1.   Results ← 0; /* result count */
2.   Find all keyword nodes KN in Gw using the full text index; /*nodes that match some keyword in Q*/
3.   Let Zj be the set of nodes of Gw that contain wj;
4.   Let Lj be the set of expanding areas corresponding to the root nodes in Zj;
5.   Let buffer(i) be an array ordered by score to buffer search results containing i pages;
6.   For each node(page)d contained in Z1∩Z2∩…∩Zm do {/*single-page search results*/
7.      TSR ← getTopSearchResult(d,{Gd},Q);
8.     Insert TSR into buffer(1);/* Insert TSR into the ordered buffer of single page search results */
9.     Results++;}
10.   While (Results < k) {
11.    For j in 1...m do {
12.    For each expanding area L in Lj do {
13.       Expand the expanding area L, with a node v having the maximum HeuristicWeight; /* Equation 6*/
14.       Join v to all previously expanded nodes u generated by the expanding areas Ls, s≠j;
          /* By "join" we mean find all instances of v as an end node in the already expanded nodes. */
15.       For each web spanning tree WST generated by the join {
16.          Trim useless leaves to make it minimal;
17.          TSR ← getTopSearchResult(WST,{Gd1, Gd2… Gdz}, Q);
18.          Insert TSR in to buffer(length(TSR)); / * length(TSR) equals number of pages in TSR */
19.          Results++; If(Results = k){ Output results in buffer and return; }}}}}
MODULE: getTopSearchResult(Web spanning tree WST, Page graphs WPG = {Gd1, Gd2 … Gdz} of WST, Keyword query
Q = {w1,…,wm})
1.   SearchResults ←∅; /*stores search results*/
2.   Find the set of possible partitions PQ of Q as per Definition 3;
3.   For each partition {Q1,…,Qz} of the keywords in PQ do{
4.     For each page di in WST do {
5.       PSPi←ϕ;
6.       If(Qi≠ϕ){
7.             PSPi ← Top-1-MTPST-ExpandingSearch(Gdi,Qi,ω); }} /* Qi is the subset of Q assigned to page
               di, ω is the quality factor*/
8.             Create a search result R with each PSPi and WST;/*if PSPi = ϕ we use the title of page di
               (this corresponds to the Steiner node which has no keywords in it)*/
9.             Compute Score(R) using Equation 5 and add R to SearchResults;}
10.  Return the top ranked search result in SearchResults;
```

Fig. 13. The heuristic top-k expanding search algorithm.

expand $v11$, we have another summary $v11 \sim v10$ that is total and minimal.

6.3 Computing the Top-k Search Results

This algorithm is an adaptation of the top-1 expanding search algorithm in Section 6.2. It also uses the *Top-1-MTPST-ExpandingSearch* method as a subroutine to compute the page spanning trees of the pages in a Web spanning tree. We adopt expanding search and not the naive enumeration algorithm, since the former is shown to perform better in Section 8. The key differences from the algorithm in Fig. 12 are the following. First, *Heuristic-Top-k-Expanding-Search* (Fig. 13) operates on Web graphs, instead of page graphs and, hence, produces Web spanning trees instead of page spanning trees. Second, we introduce the following heuristic based on (5), which is our ranking function. In particular, we first expand toward pages d with the highest *HeuristicWeight* value as defined by

$$HeuristicWeight(d) = PR(d) * IRScore(d), \qquad (6)$$

where d is a Web page, PR is its PageRank value, and $IRScore(d)$ is its Information Retrieval score for Q. The $PR(d)$ component of (6) is intuitive, since it also appears in the ranking equation (5). The $IRScore(d)$ component is a heuristic estimate of the $Score(p)$ component of (5), where p is the page spanning tree for page d. The intuition is that a page with high IR score for Q is also expected to have page spanning trees with high score for Q. We use the full-text indexer to compute $IRScore(d)$. Finally, notice that the *Heuristic-Top-k-Expanding-Search* algorithm has two steps. First it computes the Web spanning trees, and for each of them, it computes the top search results by computing the corresponding page spanning trees for its pages (the *getTopSearchResult* method). The following are the key steps of the algorithm involved in computing the top-k search results for a query Q:

- Compute the minimal total Web spanning tree WST, given the Web graph G_w and query Q.
- Then, compute the best search result for WST, given the page graphs of each page in WST and the query Q, by considering all possible combinations of keyword assignments to the pages of WST, according to the constraints of Definition 3.

The above steps are repeated until k search results are computed. The *getTopSearchResult* method takes as input a

TABLE 3
Real and Synthetic Data Sets

Name	#*nodes* (Web pages)	#*edges* (Hyperlinks)	*Size (MB)*
FIU1	25,108	137,929	4564
FIU2	6,054	45,405	115

Web spanning tree and the page graphs of the constituent pages and returns the best search result after evaluating all possible search results. It uses the *Top-1-MTPST-Expanding-Search* method to compute the top page spanning trees corresponding to the query.

7 Quality Experiments

To evaluate the quality of the results of our approach for Problems 1 and 2, we conducted three surveys: one for Problem 1 and two for Problem 2. The subjects of the survey are 20 students (of all levels and various majors) from Florida International University (FIU), who were not involved in the project. In these surveys, the users were asked to evaluate the results based on their quality. Sections 7.1 and 7.2 present the results for Problems 1 and 2, respectively.

Data sets. We use two real data sets (Table 3). FIU1 is a hyperlinked set of 25,108 Web pages (nodes) crawled from the fiu.edu domain, connected through 137,929 hyperlinks (edges) used for performance evaluation. FIU2 is a subset of the Web pages available at the fiu.edu domain used for quality evaluation, which offers faster response times and more focused results that are easier to compare.

7.1 Composed Pages

We used FIU2 for our user surveys. The participants were asked to evaluate the quality of the search results with respect to 10 queries. We chose both long-sized and medium-sized queries. For each query, users were asked to rate their satisfaction for the top-5 search results produced from the Heuristic Top-k Expanding Search algorithm in Fig. 13 and for the results produced by Google. We chose the first five results from Google that are included in the subset of crawled FIU Web pages. The Google query was constrained to pages using the "site: fiu.edu" condition. Each participant was asked to assign a score between 1 and 5 to each alternative query answer, where 5 denotes the highest user satisfaction. The results of the survey prove the superiority of our approach, as shown in Table 4.

7.2 Query-Specific Summarization

To evaluate the quality of our query-specific summaries, we created two user surveys on a DUC and a Web data set, as explained in the following. The size of a result was also taken into consideration by the participants: A longer result carries more information but is less desirable. Each participant was asked to compare the summaries and rank them, assigning a score of 1 to 5, according to their quality for the corresponding query. A rank of 5 (1) represents a summary that is most (least) descriptive.

7.2.1 Comparison with the DUC Data Set

The data set used in this survey consists of 20 documents and four queries taken from the DUC 2005 data set [10], as shown in Table 6. We compare our summaries with the DUC Peer summaries for quality. The DUC peers are human and automatic summaries used in quality evaluation. We compared our summaries against the DUC peers with the highest linguistic quality. Unfortunately, most of the summaries in the DUC data sets are query independent, and the few query-dependent ones are multidocument. Hence, in order to compare our work to that of DUC, we used the following method to extract single-document summaries from query-dependent multidocument summaries for a set of 20 documents over four topics. The sentences that have been extracted from a document d to construct the multidocument summary are viewed as d's single-document summary for the query/topic. Notice that the DUC summaries are created by extracting whole sentences from documents.

The results of the survey prove the superiority of our approach, as shown in Table 6. Our method of combining extracted sentences using semantic connections in the form of Steiner trees leads to higher user satisfaction than the traditional sentence extraction methods. In particular, the Steiner sentences in summaries provide coherency in the aggregation of the keyword-containing sentences.

7.2.2 Comparison with the Google and MSN Desktop

The data set used in this survey consists of seven news documents taken from the technology section of cnn.com. The participants were asked to evaluate the quality of the summaries of the seven documents with respect to five queries each (35 queries in total). We chose queries where keywords appear both close and far from each other. For each query-document pair, three summaries are displayed, corresponding to 1) the result of the top-1 expanding search

TABLE 4
Average Top-5 Search Result Ratings for 10 Queries

Keyword Queries	Google Search	Heuristic Expanding Search	Keyword Queries	Google Search	Heuristic Expanding Search
Undergraduate Housing safety	2.06	3.41	*Undergraduate Summer athletics accomplishments*	2.25	4.5
Graduate financial aid regulations	2.41	3.59	*Physics alumni achievements*	3.25	3.00
Computer Science Internship opportunities	2.88	3.65	*Electrical transfer student eligibility*	2.66	4.66
Campus Safety requirement regulations	2.24	3.35	*Freshman internship opportunities*	1.66	4.66
Biomedical Research fellowship eligibility	1.24	3.35	*Mechanical Graduate admission policies*	1.66	4.66
Average Rating	2.16	3.47	Average Rating	2.29	4.29

TABLE 5
Average Summary Ratings for Documents

Documents	Keyword Queries														
	Google Desktop Summary					MSN Desktop Summary					Top-1 Expanding Summary				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
D1	2.33	2.00	3.00	1.67	2.00	2.33	2.00	0.67	1.67	3.00	4.87	4.33	4.93	4.67	4.00
D2	3.67	3.33	2.67	2.67	1.67	3.67	3.00	3.00	3.00	1.00	3.67	3.33	4.00	4.00	3.67
D3	1.60	1.60	2.00	1.60	2.00	1.60	1.00	1.80	2.20	1.20	4.00	4.20	4.00	3.60	3.40
D4	1.00	1.33	0.66	1.33	2.33	2.66	2.00	1.33	1.66	1.33	3.66	3.66	4.00	4.00	3.33
D5	2.50	3.00	2.50	1.00	3.00	1.50	1.50	1.50	2.00	3.50	4.00	3.50	4.00	4.00	3.50
D6	1.00	1.50	1.50	2.50	1.00	2.00	2.50	1.50	3.50	2.00	4.00	4.50	4.00	2.50	4.00
D7	3.00	1.00	3.00	1.00	1.00	1.50	2.50	1.50	2.50	2.00	3.00	4.00	3.00	4.50	4.50
Average Rating	1.97					2.00					3.89				

TABLE 6
Average Summary Ratings for the DUC Topics

Query 1 (*International Organized Crime*) DUC Topic ID: d301i			Query 2 (*Women in Parliaments*) DUC Topic ID: d321f			Query 3 (*Drugs Mental Illness*) DUC Topic ID: d383j			Query 4 (*Stolen Art Recovered*) DUC Topic ID: d422c		
Doc. ID	DUC Peer	Top-1 Expanding	Doc. ID	DUC Peer	Top-1 Expanding	Doc. ID	DUC Peer	Top-1 Expanding	Doc. ID	DUC Peer	Top-1 Expanding
FT941-3237	2.33	4.66	FT921-7786	4.00	2.50	FT933-4868	2.00	4.33	LA051889-0110	4.00	3.00
FT944-8297	2.50	3.33	FT922-190	2.00	4.00	FT942-16465	1.00	5.00	FT911-5359	2.00	3.00
FT931-3563	2.83	3.00	FT921-937	2.00	4.33	LA090389-0060	1.66	4.33	LA070990-0048	2.33	4.33
FT943-16477	4.00	4.17	FT922-13353	2.83	4.17	FT922-715	1.00	4.33	LA032090-0091	3.00	3.66
FT943-16238	3.67	3.67	FT921-74	2.33	3.67	LA111290-0137	1.66	4.33	FT923-1946	4.33	3.00
Average	3.06	3.77	Average	2.63	3.73	Average	1.46	4.46	Average	3.13	3.40

algorithm, 2) Google Desktop's summary, and 3) MSN Desktop's summary. Summaries 2 and 3 were created by indexing the two documents in our desktop and then submitting the five queries to the Desktop engines.

The summaries are the snippets output for these documents. In order to compare apples to apples, we chose queries for which the length of the summaries produced by all three methods are similar, since clearly, it is not fair to compare summaries of different lengths, as some people favor conciseness, whereas others the amount of information.

In this survey, we set constant a to 1 and b to 0.5 in (4), which we found to produce higher quality summaries. Notice that by increasing the value of constant a, we favor short results, whereas by increasing constant b, we favor longer and more informative results. Hence, by setting a to 1 and b to 0.5, we favor shorter summaries, which have similar size to the ones produced by the Google and MSN Desktop. This makes their comparison fairer.

The results of the survey, which show the superiority of our approach, are presented in Table 5, whereas the queries are shown in Table 7 (only 10 queries are shown, whereas the remaining 25 are omitted due to space constraints). Notice that Google and MSN Desktop systems do not always include all keywords in the summary when they are more than two and have big distances between them. In contrast, our approach always finds a meaningful way to connect them.

8 Performance Experiments

We evaluate the performance of the algorithms presented in Section 6. Section 8.1 shows our results for Problem 2, whereas Section 8.2 is for Problem 1. We used a Linux machine with Power $4 + 1.7$-GHz processor and 3.7 Gbytes of RAM. The algorithms were implemented in Java. To build the full-text index, we used Oracle interMedia [30] and stored the documents in the database. JDBC was used to connect to the database system. We used the precomputation technique described in Section 6.1. We used FIU1

TABLE 7
Queries Used for Documents

Query #	Document *D1*	Document *D2*
1	*Microsoft worm protection*	*IT Research awards*
2	*Anti-virus protection*	*Algorithms development Research*
3	*Recovering worm deleted files*	*Software projects*
4	*Worm affected agencies*	*Large research grants*
5	*Deleted computer software*	*Computer network security project*

TABLE 8
Average Times for Calculating Node Weights

Number of keywords	2	3	4	5
Time (msec)	5.31	9.37	11.50	17.33

(described in Section 7) for performance evaluation, as FIU2 is a very small data set for this purpose.

8.1 Query-Specific Summarization

First, we compare the performance of the two algorithms in Section 6.2 for summarizing keyword queries of various lengths. The execution time consists of two parts: 1) the computation of the scores of the nodes of the page graph (remember that this is query specific and cannot be precomputed) and 2) the generation of the top summaries (minimal total page spanning trees) in the page graph. The first part is handled by Oracle interMedia [30], and the average time for a single page for various-length queries is shown in Table 8. The second part of the execution is handled separately by the two algorithms, and the results are shown in Fig. 14. In particular, Fig. 14 compares the performance of the Top-1 Enumeration and Top-1 Expanding search algorithms.

We observe that the expanding search algorithms are faster than the enumeration ones, especially for long queries. Notice that we do not compare the performance of our algorithms to BANKS, since our Top-1 algorithms are adaptations of the BANKS algorithms to our problem. In particular, we use the precomputed all-pairs shortest paths data to efficiently grow the expanding area in the Top-1 Expanding search algorithm and efficiently construct the page spanning tree from the spanning trees of the closure graph in the Top-1 Enumeration algorithm.

Finally, we measure the accuracy of the Top-1 algorithms. In order to have a yardstick to compare the Top-1 algorithm results, we first perform an exhaustive search to find all summaries, along with their optimal scores. In particular, we measure (see Table 9) the average rank of the summary of the Top-1 algorithms in the optimal list of summaries. We observe that the Top-1 expanding algorithm better approximates the Top summary in the optimal list of summaries when compared to the Top-1 enumeration algorithm, as shown in Table 9.

8.2 Searching Using Composed Pages

First, we measure the quality of the *Heuristic-Top-k-Expanding-Search* algorithm as follows: In order to have a yardstick to compare our results, we first perform an exhaustive search to find all search results, along with their optimal scores. Then, we measure the quality of the heuristic top-k algorithm by comparing its top-k search results produced with the optimal top-k search results. We compare two top-k lists by using Spearman's rho metric:

$$\rho(\sigma_1, \sigma_2) = \left(\sum_{i=1}^{K} |\sigma_1(i) - \sigma_2(i)|^2 \right)^{1/2}, \quad (7)$$

where ρ is Spearman's rho metric, σ_1 and σ_2 are two top-k lists, and $\sigma_1(i)$ and $\sigma_2(i)$ are the ranks of the ith search result in each of the top-k lists. Fig. 16 shows the average quality of the results (over 50 queries) of our heuristic search and the *Nonheuristic* expanding search (where a random page is chosen for expansion at every step) compared to the optimal exhaustive search. Fig. 16a shows the quality of the Heuristic and Nonheuristic Top k for fixed $m = 2$ (two keyword queries) and varying number k of requested results. Fig. 16b shows the quality for a fixed number $k = 25$ of requested results and varying the query length. As shown in Fig. 16, the expansion based on the *Heuristic-Weight* (6) yields better Top-k results.

Next, we compare the execution time of the algorithms, which consists of two parts: 1) the computation of the Web spanning trees in the Web graph and 2) the generation of the top-k search results. Fig. 15 shows the execution time of the different algorithms for computing the Top-k search results (Definition 3). As before, we measure the performance with changing k and fixed $m = 2$ (Fig. 15a) and changing m with fixed $k = 25$ (Fig. 15b). Notice that Fig. 15 shows the total execution time of the *Heuristic-Top-k-Expanding-Search* algorithm and its Nonheuristic and Optimal counterparts. The Heuristic algorithm has longer execution time when compared to the Nonheuristic algorithm, because during each expansion step, it has to select among the available neighbors the one with the highest *HeuristicWeight* (6), whereas the Nonheuristic algorithm selects a random page for expansion.

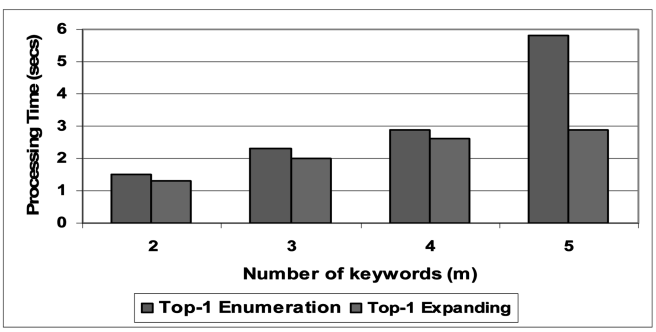


Fig. 14. Processing time of Top-1 algorithms.

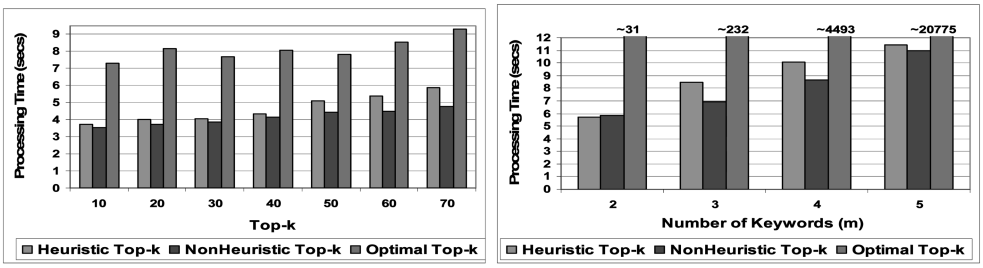
TABLE 9
Average Ranks of Top-1 Algorithms with Respect to the Optimal List of Summaries

Number of keywords	2	3	4	5
Top-1 Enumeration	1.4	1.8	2.1	2.78
Top-1 Expanding Search	1.1	1.3	1.4	1.8

9 Related Work

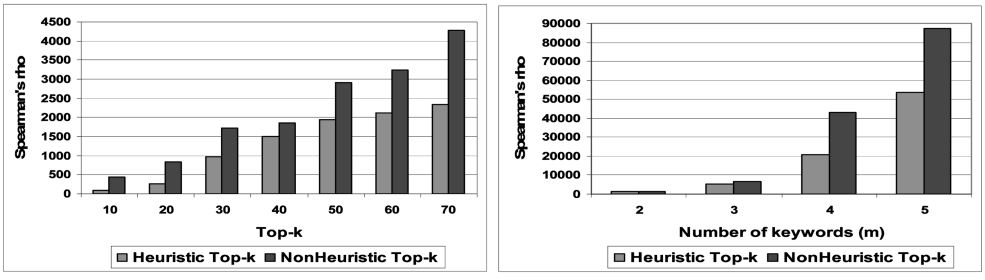
Document Summarization. A large corpus of work has focused on generating query-independent summaries [3], [5], [6], [15]. The OCELOT system [6] provides the summary of a Web page by selecting and arranging the most (query-independent) "important" words of the page. Amitay and Paris [3] propose a new fully automatic pseudosummarization technique for Web pages, where the anchor text of hyperlinked pages is used to construct summaries. Barzilay and Elhadad [5] use lexical chains for text summarization.

The majority of systems participating in the previous Document Understanding Conference [10] (a large-scale summarization evaluation effort sponsored by the US Government) and the Text Summarization Challenge [13]



(a) (b)

Fig. 15. Execution time for the top-k search results. (a) Performance with changing k (with $m = 2$). (b) Performance with changing m (with $k = 25$).



(a) (b)

Fig. 16. Quality of algorithms. (a) Spearman's rho versus Top k (with $m = 2$). (b) Spearman's rho versus query size (with $k = 25$).

are extraction based. Extraction-based automatic text summarization systems extract parts of original documents and output the results as summaries [9], [11], [15], [19]. Other systems based on information extraction [32] and discourse analysis [27] also exist, but they are not yet usable for general-domain summarization. However, they do not exploit the inherent structure of the document and mostly focus on query-independent summaries. In this work (as in [38]), we also show the semantic connections between the extracted fragments, which improve the quality, as shown in Section 7.2.

White et al. [40], Tombros and Sanderson [37], and Goldstein et al. [15] create query-dependent summaries by using a sentence extraction model, in which the documents (Web pages) are broken up into their component sentences and are scored according to factors such as their position. A number of the highest scoring sentences are then chosen as the summary. Abracos and Pereira-Lopes [1], Hearst [18], and Salton et al. [34] select the best passage of a document as its summary. However, these works ignore possible semantic connections between the sentences or the possibility that linking a relevant set of text fragments will provide a better summary. Radev et al. [33] provide a technique for multi-document summarization used to cluster the results of a Web keyword query. Erakan and Radev [12] and Mihalcea and Tarau [28] provide a technique to rank sentences based on their similarity with other sentences across multiple documents and then provide a summary with the top-ranked sentences. However, their methods are query independent in contrast to our work.

The idea of splitting a Web page to fragments has been used by Cai et al. [8] and Song et al. [36], where they extract query-independent rankings for the fragments, for the purpose of improving the performance of Web search. Cai et al. [8] partition a Web page into blocks by using the vision-based page segmentation algorithm. Song et al. [36] provide learning algorithms for block importance.

Finally, all major Web search engines generate query-specific snippets of the returned results. Although their algorithms are not published, we observed that they simply extract some of the query keywords and their surrounding words. Recently, some of these companies have made available tools to provide the same search and snippet functionality on a user's desktop [16], [29].

Keyword search in data graphs. For both Problems 1 and 2, when the page graphs are already created and a query arrives, the system searches the page graphs (also the Web graph) for subtrees that contain all (or a subset of) query keywords. This problem has been studied by the database and graph algorithm communities. In particular, recent work [2], [7], [14], [17], [20], [21], [23], [24] has addressed the problem of free-form keyword search on structured and semistructured data. Li et al. [26] tackle the problem of proximity search on the Web, which is viewed as a graph of hyperlinked pages.

10 Conclusions

In this paper, we describe a technique to improve the quality of Web search results by on the fly creating and ranking composed pages. This technique is particularly successful for long or multitopic queries, where single-page results unlikely satisfy the user's information need. We also describe a technique for query-specific Web page summarization, which, in addition to having its own merit, is used for computing the top-k composed pages. We have presented and evaluated efficient algorithms for both problems. We also conducted user surveys to measure user satisfaction.

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Ramakrishna Varadarajan received the BE degree in computer science and engineering from the University of Madras, India, in 2004 and the MS degree in computer science from Florida International University, Miami, in 2006. He is currently working towards the PhD degree in the School of Computing and Information Sciences, Florida International University, Miami. His research interests include Web search, ranked keyword search in graph databases, and various domains like biological and clinical databases.

Vagelis Hristidis received the BS degree in electrical and computer engineering from the National Technical University Athens and the MS and PhD degrees in computer science from the University of California, San Diego, in 2004, under the supervision of Yannis Papakonstantinou. He is an assistant professor in the School of Computing and Information Sciences, Florida International University, Miami. His main research work addresses the problem of bridging the gap between databases and information retrieval.

Tao Li received the PhD degree in computer science from the University of Rochester in 2004. He is currently an assistant professor in the School of Computing and Information Sciences, Florida International University, Miami. His research interests include data mining, machine learning, information retrieval, and bioinformatics.