

Semantic Web Project Report on

AUTOSUMMARIZATION OF TECHNICAL PAPER USING GRAMMATICAL RULE INFERENCE

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Date of Submission: 8th May, 2015

in partial fulfillment for the award of the degree of

Bachelor of Technology

In

Information Technology At



Department of Information Technology

National Institute of Technology Karnataka, Surathkal

April 2015

Department of Information Technology, NITK Surathkal
Semantic Web Technology Project
End Semester Evaluation Report (April 2015)

Course Code : IT 412

Course Title: Semantic Web Technology

Project Title: *Autosummarization of Technical Paper using Grammatical Rule Inference*

Project Group:

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Abstract

Over the years, the amount of information available electronically has grown manifold. There is an increasing demand for automatic methods for text summarization. Domain independent techniques for automatic summarization by paragraph extraction have been proposed in many papers [3, 4]. In this paper, we attempt to summarize a technical paper written in html using grammatical rule inference technique so that it becomes easier for us humans to compare between many technical papers just by reading their summary.

Keywords: *Auto summarization, Grammar Rule Inference Technique, Semantic Web*

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1 Introduction

Nowadays the Web has proved to be as a rich and extraordinary data source of information, here multiple domains can be accessed and mined. Mining Web data is referred as Web Mining. Some of the objectives of mining web data include finding relevant information discovering new knowledge from web personalized, web synthesis and learning about individual users. Amongst these the most common use is finding relevant information. We simply specify a set of keywords or query as a request or a reference and we get a list of pages, ranked as per similarity of query.

Currently searching web face with one problem that many times outcome is not satisfactory because of irrelevance of the information. Searching the exact information from such a huge repository [2] of unstructured web data is still main area of research interest. One solution to this problem is Semantic Web. The Semantic Web is an extension of current Web in which information is given as well defined meaning, hence enabling computers and people to work with better coordination. By using the existing web semantically new semantically structure can be exploited, and then the results of web mining can be improved, thereby building semantic Web [1].

Automatic summarization is the process of reducing a text document with a computer program in order to create a summary that retains the most important points of the original document. As the problem of information overload has grown, and as the quantity of data has increased, so has interest in automatic summarization. Technologies that can make a coherent summary take into account variables such as length, writing style and syntax

Generally, there are two approaches to automatic summarization: extraction and abstraction. Extractive methods work by selecting a subset of existing words, phrases, or sentences in the original text to form the summary. In contrast, abstractive methods build an internal semantic representation and then use natural language generation techniques to create a summary that is closer to what a human might generate. Such a summary might contain words not explicitly present in the original. Research into abstractive methods is an increasingly important and active research area, however due to complexity constraints, research to date has focused primarily on extractive methods.

1.1 ***Motivation***

Current automatic summarizers usually rely on sentence extraction to produce summaries. Human professionals also often reuse the input documents to generate summaries; however, rather than simply extracting sentences and stringing them together, as most current summarizers do, humans often "edit" the extracted sentences in some way so that the resulting summary is concise and coherent.

2 Literature Survey

Currently works have been done in two common approaches to summarisation. The first approach comprises of analysis of text, and rewriting or rephrasing it in a short way. Until today this approach hasn't achieved any substantial results. The second approach, which is similar to algorithm used in this project, tries to extract the key sentences from the text, and then tries to put them together properly. One famous algorithm that implements this approach is TextRank [5].

TextRank is a general purpose graph-based ranking algorithm for NLP. Essentially, it runs PageRank on a graph specially designed for a particular NLP task. For keyphrase extraction, it builds a graph using some set of text units as vertices. Edges are based on some measure of semantic or lexical similarity between the text unit vertices. Unlike PageRank, the edges are typically undirected and can be weighted to reflect a degree of similarity. Once the graph is constructed, it is used to form a stochastic matrix, combined with a damping factor (as in the "random surfer model"), and the ranking over vertices is obtained by finding the eigenvector corresponding to eigenvalue 1 (i.e., the stationary distribution of the random walk on the graph).

There also have been works where one can perform a robust decomposition of the text of an article into individual segments that correspond to basic natural parts, such as title, section title, text, etc. This was aimed at automation of the task of building an Ontology of documents. We combine these two approaches for summarisation of a technical papers.

2.1 ***Problem Statement***

"To develop a Travel Route Recommendation System for Indian cities, incorporating user friendly interaction through natural speech dialogues, and natural language processing techniques"

3 Methodology

3.1 *System Architecture*

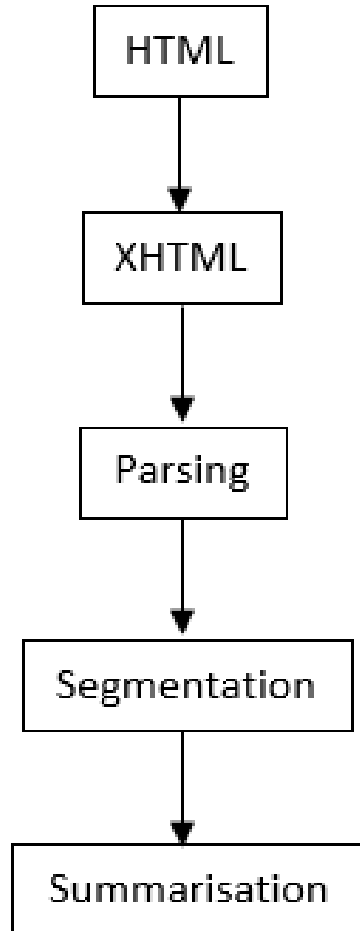


Figure 3.1: System Architecture

3.2 *Different Components of the Project*

1. Preprocessing:

The extraction of information from web pages is the subject matter of the Wrapper Induction work, although their purpose is not the inference of an ontology, but to enable a database like use of that information. In particular, HTML aware wrapper induction approaches bear similarities to the first step of the method developed. In particular, they share the preprocessing of HTML pages with the objective of

cleaning frequent syntax errors and transformation into valid XML syntax (using the XHTML format) to ease further processing.

2. Summarization:

Intersection function: This function receives two sentences, and returns a score for the intersection between them. We just split each sentence into words/tokens, count how many common tokens we have, and then we normalize the result with the average length of the two sentences.

The sentences dictionary: This part is actually the Heart of the algorithm. It receives our text as input, and calculates a score for each sentence. The calculations is composed of two steps: In the first step we split the text into sentences, and store the intersection value between each two sentences in a matrix (two-dimensional array). So values[0][2] will hold the intersection score between sentence 1 and sentence 3.

In fact, we just converted our text into a fully-connected weighted graph! Each sentence is a node in the graph and the two-dimensional array holds the weight of each edge!

In the second step we calculate an individual score for each sentence and store it in a key-value dictionary, where the sentence itself is the key and the value is the total score. We do that just by summing up all its intersections with the other sentences in the text (not including itself).

We calculates the score for each node in our graph. We simply do that by summing all the edges that are connected to the node. Building the summary: Obviously, the final step of our algorithm is generating the final summary. We do that by splitting our text intoparagraphs, and then we choose the best sentence from each paragraph according to our sentences dictionary. The Idea here is that every paragraph in the text represents some logical subset of our graph, so we just pick the most valuable node from each subset!

Why this works: There are two main reasons why this algorithm works: The first reason is that a paragraph is a logical atomic unit of the text. In simple words there is probably a very good reason why the author decided to split his text that way. The second reason is that if two sentences have a good intersection, they probably holds the same information.

So if one sentence has a good intersection with many other sentences, it probably holds some information from each one of them- or in other words, this is probably a key sentence in our text.

4 Work Done

A technical paper in HTML is taken as the input. The HTML code may be having inconsistencies which may lead to problems. Hence the HTML document is standardized by converting it into a XHTML document. This makes the document structured and it get easier for extraction of segments. After converting the HTML document into XHTML we segment the document and extract paragraphs with the help of `<p>`/`</p>` tags that define a paragraph. Once we get the segments (paragraphs), we use our summarization algorithm to summarize each of these paragraphs. We combine the summaries of each paragraphs and create a new document containing the summaries.

5 Results and Analysis

A sample input HTML paper that has been taken as input is shown in the Figure 5.1, Figure 5.2 and Figure 5.3.

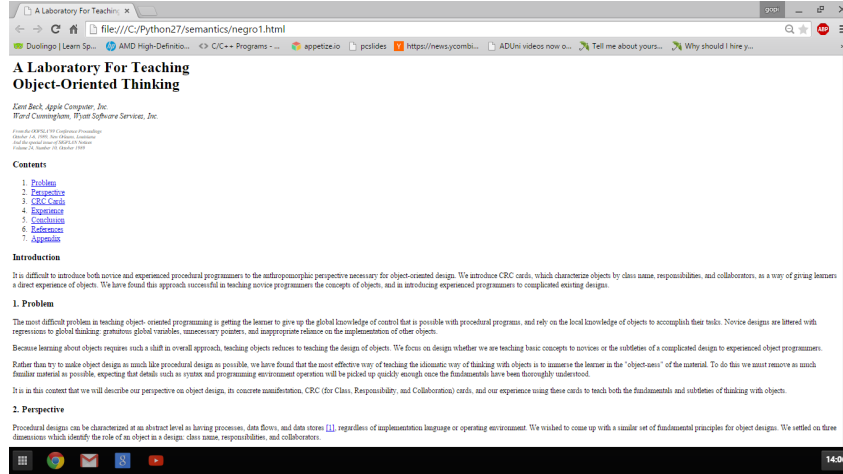


Figure 5.1: Input Data-HTML Page-Part 1

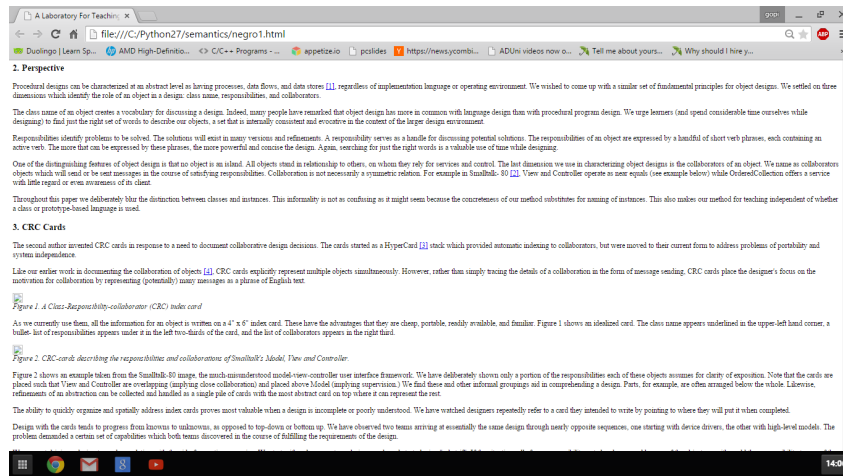


Figure 5.2: Input Data-HTML Page-Part 2

The output, i.e. the summary of the given HTML is shown Figure 5.4 and Figure 5.5.

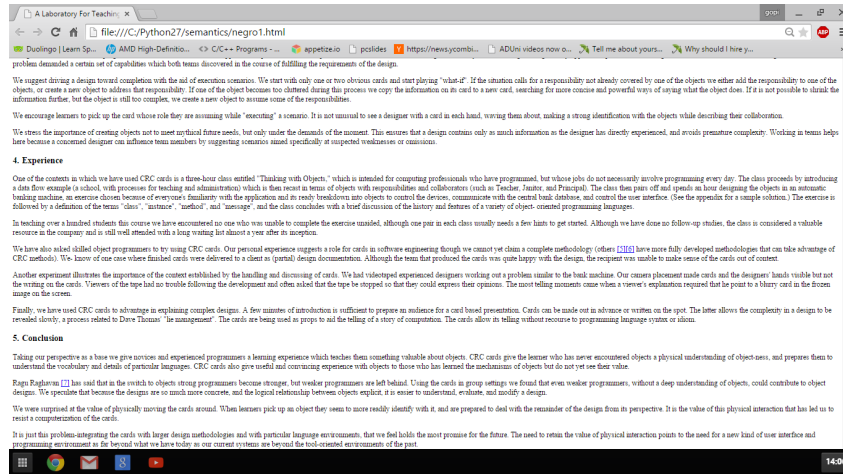


Figure 5.3: Input Data-HTML Page-Part 3

```

1
2
3   October 1-6, 1989, New Orleans, Louisiana.
4
5   We have found this approach successful in teaching novice programmers the concepts of objects, and in introducing experienced programmers to
6   complicated existing designs..
7   The most difficult problem in teaching object- oriented programming is getting the learner to give up the global knowledge of control that is possible
8   with procedural programs, and rely on the local knowledge of objects to accomplish their tasks.
9
10  Because learning about objects requires such a shift in overall approach, teaching objects reduces to teaching the design of objects.
11
12  Rather than try to make object design as much like procedural design as possible, we have found that the most effective way of teaching the idiomatic
13  way of thinking with objects is to immerse the learner in the "object-speak" of the material.
14
15  Procedural designs can be characterized at an abstract level as having processes, data flows, and data stores
16
17  We settled on three dimensions which identify the role of an object in a design: class name, responsibilities, and collaborators..
18
19  The class name of an object creates a vocabulary for discussing a design.
20
21  The more that can be expressed by these phrases, the more powerful and concise the design.
22
23  For example in Smalltalk- 80
24  , View and Controller operate as near equals (see example below) while OrderedCollection offers a service with little regard or even awareness of its
25  client..
26
27  This informality is not as confusing as it might seem because the concreteness of our method substitutes for naming of instances.
28
29  The cards started as a HyperCard
30  stack which provided automatic indexing to collaborators, but were moved to their current form to address problems of portability and system
31  independence..
32
33  However, rather than simply tracing the details of a collaboration in the form of message sending, CRC cards place the designer's focus on the
34  motivation for collaboration by representing (potentially) many messages as a phrase of English text..
35

```

Figure 5.4: Output - Summary of the Technical Paper - Part 1

6 Conclusion & Future Work

An application has been created using which a user can get the summary of any technical paper written in HTML so that it becomes easy for the user to compare between many such papers for similarities.

6.1 Future Work

Future work includes functionalities that can compare the summaries of any two technical papers automatically and tell the user whether those two papers are similar or not.

```

31 As we currently use them, all the information for an object is written on a 4" x 6" index card.
32
33 We have deliberately shown only a portion of the responsibilities each of these objects assumes for clarity of exposition.
34
35 The ability to quickly organize and spatially address index cards proves most valuable when a design is incomplete or poorly understood.
36
37 We have observed two teams arriving at essentially the same design through nearly opposite sequences, one starting with device drivers, the other with
38 high-level models.
39
40 If the situation calls for a responsibility not already covered by one of the objects we either add the responsibility to one of the objects, or create
41 a new object to address that responsibility.
42
43 We encourage learners to pick up the card whose role they are assuming while "executing" a scenario.
44
45 This ensures that a design contains only as much information as the designer has directly experienced, and avoids premature complexity.
46
47 The class proceeds by introducing a data flow example (a school, with processes for teaching and administration) which is then recast in terms of
48 objects with responsibilities and collaborators (such as Teacher, Janitor, and Principal).
49
50 In teaching over a hundred students this course we have encountered no one who was unable to complete the exercise unaided, although one pair in each
51 class usually needs a few hints to get started.
52
53 Our personal experience suggests a role for cards in software engineering though we cannot yet claim a complete methodology (others
54 have more fully developed methodologies that can take advantage of CRC methods).
55
56 Another experiment illustrates the importance of the context established by the handling and discussing of cards.
57
58 The cards are being used as props to aid the telling of a story of computation.
59
60 CRC cards give the learner who has never encountered objects a physical understanding of object-ness, and prepares them to understand the vocabulary
61 and details of particular languages.
62
63 has said that in the switch to objects strong programmers become stronger, but weaker programmers are left behind.
64
65 It is the value of this physical interaction that has led us to resist a computerization of the cards..
66

```

Figure 5.5: Output - Summary of the Technical Paper - Part 2

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