The Anatomy of a Large-Scale Hypertextual Web Search Engine

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TextRank: Bringing Order into Texts

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First Presentation

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September 15, 2016

Old Dominion University
Intro to Information Retrieval
CS734/834

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Introduction

Pre-Google WWW

Figure 1: Chaotic Earth

Source: apod.nasa.gov - Sakurajima Volcano with Lightning

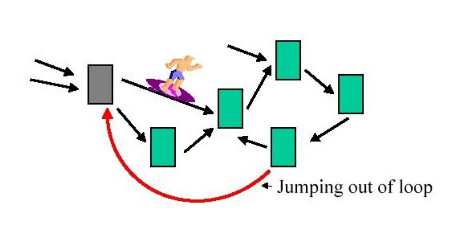
Pre-Google WWW

In the beginning there was the World Wide Web; and the traffic of knowledge kept increasing, so the number of irrelevant documents recall. Then Google was born introducing PageRank to bring order to the **Web**.

Google PageRanking

Random Surfer Model

Figure 2: Random Surfer



Source: http://slideplayer.com/slide/5996837/ slide 26

PageRank Calculation Cont.

Internet consisting of only 3 pages.

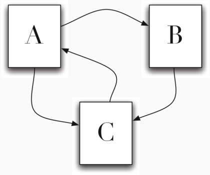


Figure 3: Three Web-pages

Since we do not know any of the pages ranking, we will assume that:

$$PR(A) = PR(B) = PR(C) = \frac{1}{3} \approx 0.33$$

Graph and example taken from textbook[4] chapter 4

PageRank Calculation Cont.

First iteration:

$$PR(C) = \frac{PR(A)}{2} + \frac{PR(B)}{1} = \frac{0.33}{2} + \frac{0.33}{1} = 0.5$$

$$PR(A) = \frac{PR(C)}{1} = \frac{0.33}{1} \approx 0.33$$

$$PR(B) = \frac{PR(A)}{2} = \frac{0.33}{2} \approx 0.17$$

Second iteration:

$$PR(C) = \frac{PR(A)}{2} + \frac{PR(B)}{1} = \frac{0.33}{2} + \frac{0.17}{1} \approx 0.33$$

$$PR(A) = \frac{PR(C)}{1} = \frac{0.5}{1} = 0.5$$

$$PR(B) = \frac{PR(A)}{2} = \frac{0.33}{2} \approx 0.17$$

PageRank Calculation Cont.

Third iteration:

$$PR(C) = \frac{PR(A)}{2} + \frac{PR(B)}{1} = \frac{0.5}{2} + \frac{0.17}{1} \approx 0.42$$
$$PR(A) = \frac{PR(C)}{1} = \frac{0.33}{1} \approx 0.33$$
$$PR(B) = \frac{PR(A)}{2} = \frac{0.5}{2} = 0.25$$

After few more iterations:

$$PR(C) = \frac{PR(A)}{2} + \frac{PR(B)}{1} \approx 0.4$$
$$PR(A) = \frac{PR(C)}{1} \approx 0.4$$
$$PR(B) = \frac{PR(A)}{2} \approx 0.2$$

See Table 1 for full iteration calculation.

PageRank Calculation

$$PR(A) = (1-d) + d\left(\frac{PR(T_1)}{C(T_1)} + \cdots + \frac{PR(T_n)}{C(T_n)}\right) [1]$$

$$S(V_i) = (1-d) + d * \sum_{j \in In(V_i)} \frac{1}{|Out(V_j)|} S(V_j) [3]$$

TextRank

TextRank Benefits

A graph-based ranking algorithm of natural language texts with the purpose of:

- Keyword Extraction

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- Sentence Extraction

TextRank Work Comparison

Although TextRank work is based on equation (2) taken from Google PageRank equation (1), its research innovation is in great deal related to A. Hulth [2] “Improved automatic keyword extraction given more linguistic knowledge”.

TextRank vs Hulth-2003

Comparison between TextRank and Hulth-2003 algorithms:

TextRank	Hulth-2003
Application	**Application**
Keyword Extraction Sentence Extraction	Keyword Extraction Sentence Extraction
Approach	**Approach**
Unsupervised	Supervised

TextRank Keyword Extraction Example

Given a text

Compatibility of systems of linear constraints over the set of natural numbers. Criteria of compatibility of a system of linear Diophantine equations, strict inequations, and nonstrict inequations are considered. Upper bounds for components of a minimal set of solutions and algorithms of construction of minimal generating sets of solutions for all types of systems are given. These criteria and the corresponding algorithms for constructing a minimal supporting set of solutions can be used in solving all the considered types systems and systems of mixed types.

Source: [3]

TextRank Steps

1. Text is tokenized

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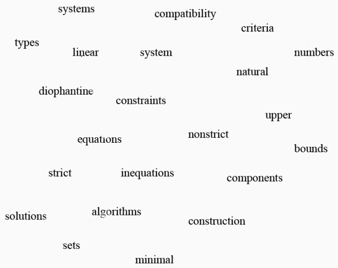
1. Text is tokenized
2. Edge is added between lexical units
3. Each vertex is set to initial value of 1
4. TextRank algorithm runs until it converges

Tokenize Text

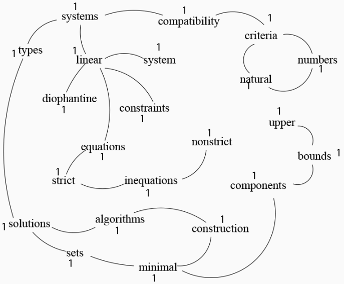
Figure 4: Tokenize Text



Vertices added to the graph can be restricted with syntactic filters. [3] best results were observed for nouns and adjectives only.

Adding Edges

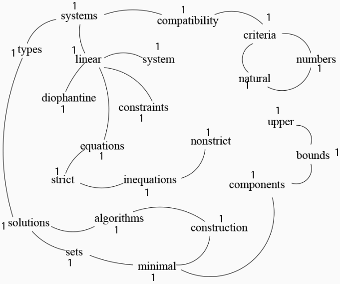
Figure 5: Create Relationship Among Vertices



Co-occurrence within a window of *N* words. Set in [3] to two, three, five, or ten words. See table **??** for results obtained by TextRank

Set Vertex Initial Value

Figure 6: Set Vertex Initial Value to 1



Co-occurrence within a window of N words.

TextRank Equation

TextRank modified Google PageRank "random surfer model" equation:

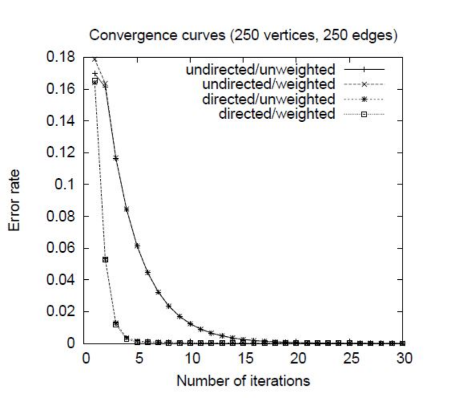
$$S(V_i) = (1 - d) + d * \sum_{j \in In(V_i)} \frac{1}{|Out(V_j)|} S(V_j) \tag{1}$$

Taking into account edge weights to compute the score associated with a vertex in the graph:

$$WS(V_i) = (1 - d) + d * \sum_{V_j \in In(V_i)} \frac{w_{ji}}{\sum_{V_k \in Out(V_j)} w_{jk}} WS(V_j) \tag{2}$$

Convergence Comparison

Figure 7: Convergence Graph

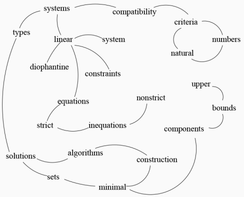


Source: [3] page 405

TextRank Keyword Extraction Example

Figure 8: Keywords Extraction Graph Example

Compatibility of systems of linear constraints over the set of natural numbers. Criteria of compatibility of a system of linear Diophantine equations, strict inequations, and nonstrict inequations are considered. Upper bounds for components of a minimal set of solutions and algorithms of construction of minimal generating sets of solutions for all types of systems are given. These criteria and the corresponding algorithms for constructing a minimal supporting set of solutions can be used in solving all the considered types systems and systems of mixed types.



Keywords assigned by TextRank:
linear constraints; linear diophantine equations; natural numbers; nonstrict inequations; strict inequations; upper bounds

Keywords assigned by human annotators:
linear constraints; linear diophantine equations; minimal generating sets; non–strict inequations; set of natural numbers; strict inequations; upper bounds

Sample graph built for keyphrase extraction from an Inspec abstract.

Source: [3]

Conclusion

Summary

"The Anatomy of a Large-Scale Hypertextual Web Search Engine" has at this point over 15,000 citations. PageRank has truly contributed to bring order to the Web in the Information Retrieval arena. This is manifested on how TextRank used the same principles of Google to outperform without any supervised approach algorithms to automatically identify a keyword or a sentence that best describes a text.

Questions?

Tables

Table 1: PageRank Iteration Calculation for Figure 3

Iteration	A	B	C	A-Error	B-Error	C-Error
0	0.333333	0.333333	0.333333	-	-	-
1	0.333333	0.500000	0.166667	0.0000	0.1667	0.1667
2	0.500000	0.333333	0.166667	0.1667	0.1667	0.0000
3	0.333333	0.416667	0.250000	0.1667	0.0833	0.0833
4	0.416667	0.416667	0.166667	0.0833	0.0000	0.0833
5	0.416667	0.375000	0.208333	0.0000	0.0417	0.0417
6	0.375000	0.416667	0.208333	0.0417	0.0417	0.0000
7	0.416667	0.395833	0.187500	0.0417	0.0208	0.0208
8	0.395833	0.395833	0.208333	0.0208	0.0000	0.0208
9	0.395833	0.406250	0.197917	0.0000	0.0104	0.0104
10	0.406250	0.395833	0.197917	0.0104	0.0104	0.0000
11	0.395833	0.401042	0.203125	0.0104	0.0052	0.0052
12	0.401042	0.401042	0.197917	0.0052	0.0000	0.0052
13	0.401042	0.398438	0.200521	0.0000	0.0026	0.0026
14	0.398438	0.401042	0.200521	0.0026	0.0026	0.0000
15	0.401042	0.399740	0.199219	0.0026	0.0013	0.0013
16	0.399740	0.399740	0.200521	0.0013	0.0000	0.0013
17	0.399740	0.400391	0.199870	0.0000	0.0007	0.0007
18	0.400391	0.399740	0.199870	0.0007	0.0007	0.0000
19	0.399740	0.400065	0.200195	0.0007	0.0003	0.0003
20	0.400065	0.400065	0.199870	0.0003	0.0000	0.0003
21	0.400065	0.399902	0.200033	0.0000	0.0002	0.0002
22	0.399902	0.400065	0.200033	0.0002	0.0002	0.0000
23	0.400065	0.399984	0.199951	0.0002	0.0001	0.0001
24	0.399984	0.399984	0.200033	0.0001	0.0000	0.0001

Final result is shown on page 7

Keyword Extraction Results

Table 2: Results for automatic keyword extraction using TextRank or supervised learning (Hulth, 2003)

	Assigned		Correct				
Method	Total	Mean	Total	Mean	Precision	Recall	F-measure
TextRank							
Undirected, Co-occ.window=2	6,784	13.7	2,116	4.2	***31.2***	43.1	***36.2***
Undirected, Co-occ.window=3	6,715	13.4	1,897	3.8	28.2	38.6	32.6
Undirected, Co-occ.window=5	6,558	13.1	1,851	3.7	28.2	37.7	32.2
Undirected, Co-occ.window=10	6,570	13.1	1,846	3.7	28.1	37.6	32.2
Directed, forward, Co-occ.window=2	6,662	13.3	2,081	4.1	31.2	42.3	35.9
Directed, backward, Co-occ.window=2	6,636	13.3	2,082	4.1	31.2	42.3	35.9
Hulth (2003)							
Ngram with tag	7,815	15.6	1,973	3.9	25.2	***51.7***	33.9
NP-chunks with tag	4,788	9.6	1,421	2.8	29.7	37.2	33.0
Pattern with tag	7,012	14.0	1,523	3.1	21.7	39.9	28.1

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- S. Brin and L. Page, *The anatomy of a large-scale hypertextual web search engine*, Computer Networks and ISDN Systems, 30 (1998), pp. 107––117.
- A. Hulth, *Improved automatic keyword extraction given more linguistic knowledge*, in Proceedings of the 2003 conference on Empirical methods in natural language processing, Association for Computational Linguistics, 2003, pp. 216–223.
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