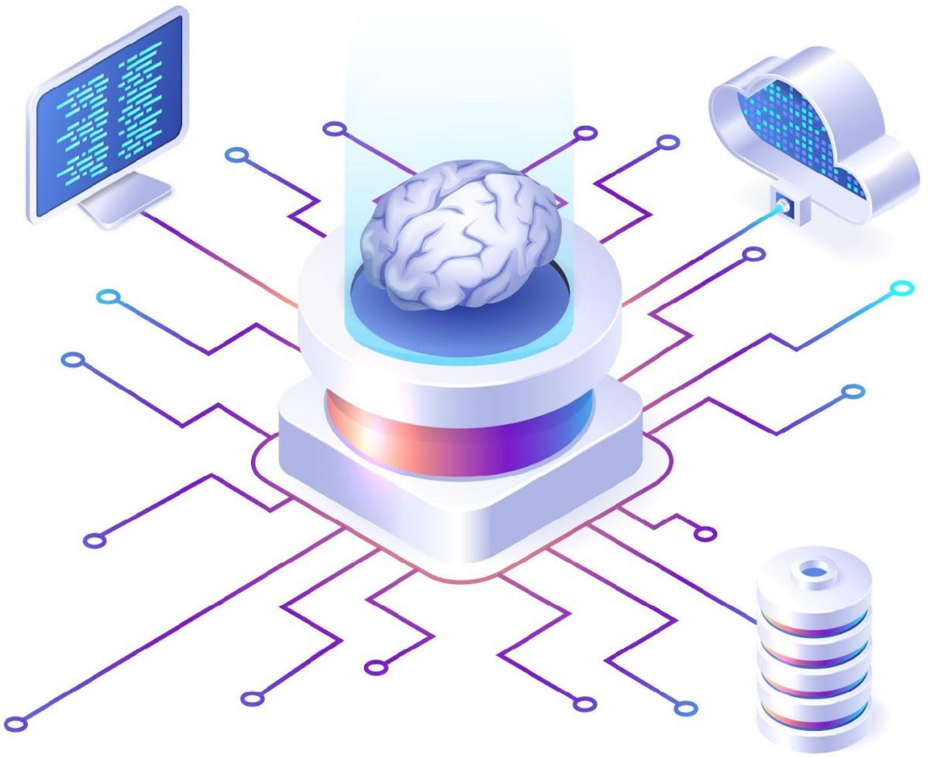
핵심 키워드 추출
(Keyword Extraction)

실무형 인공지능 자연어처리

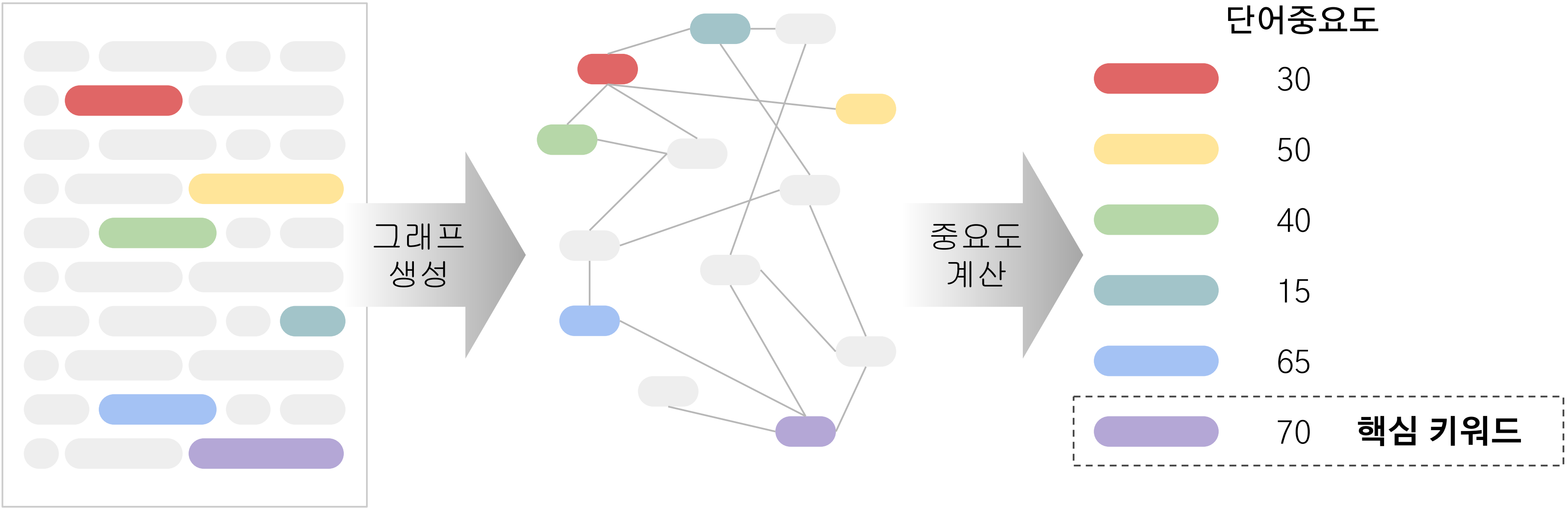


2 TextRank 활용 핵심 키워드 추출

단어의 중요도 판단

TextRank

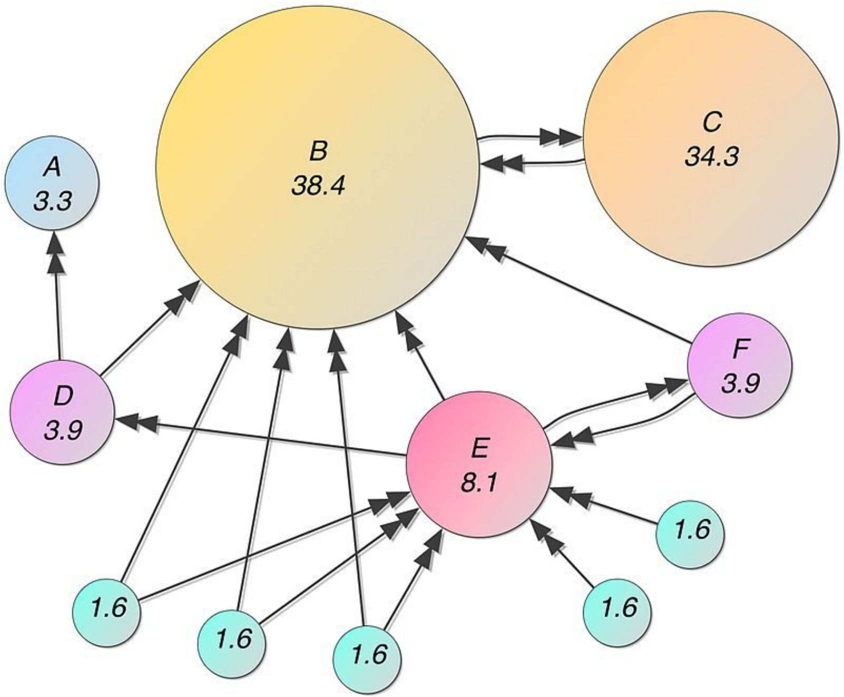
TextRank



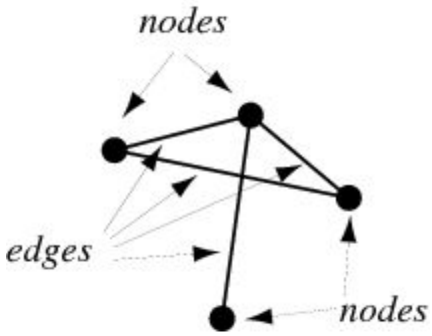
Google PageRank

Google

Google PageRank



그래프



출처 : https://en.wikipedia.org/wiki/PageRank

Google PageRank

$$PR(A) = (1-d) + d\,(PR(T_1)/C(T_1) + \cdots + PR(T_n)/C(T_n))$$

A : PageRank 점수를 계산할 웹페이지(노드)

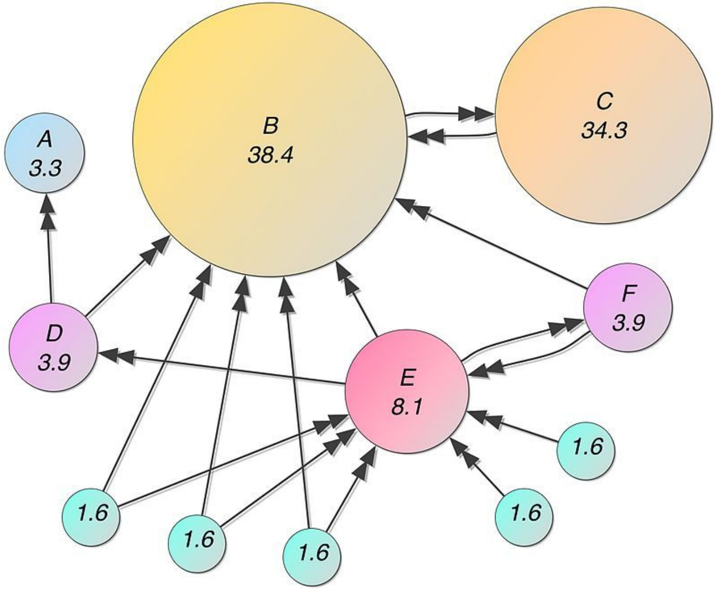
T : A를 링크하고 있는 웹페이지(노드)

PR(T) : 웹페이지T의 PageRank 점수

C(T) : 웹페이지T에서 연결된 링크 총 갯수

PR(T)/C(T) : T의 PageRank를 링크수로 나눈값

d : Damping factor



TextRank

TextRank: Bringing Order into Texts

https://web.eecs.umich.edu/~mihalcea/papers/mihalcea.emnlp04.pdf

Abstract

In this paper, we introduce TextRank – a graph-based ranking model for text processing, and show how this model can be successfully used in natural language applications. In particular, we propose two innovative unsupervised methods for keyword and sentence extraction, and show that the results obtained compare favorably with previously published results on established benchmarks.

https://web.eecs.umich.edu/~mihalcea/papers/mihalcea.emnlp04.pdf

- 그래프 기반 Ranking 모델 Textrank
- 키워드와 문장 추출을 위한 비지도 학습 방법을 제안

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1 Introduction

Graph-based ranking algorithms like Kleinberg's HITS algorithm (Kleinberg, 1999) or Google's PageRank (Brin and Page, 1998) have been successfully used in citation analysis, social networks, and the analysis of the link-structure of the World Wide Web. Arguably, these algorithms can be singled out as key elements of the paradigm-shift triggered in the field of Web search technology, by providing a Web page ranking mechanism that relies on the collective knowledge of Web architects rather than individual content analysis of Web pages. In short, a graph-based ranking algorithm is a way of deciding on the importance of a vertex within a graph, by taking into account global information recursively computed from the entire graph, rather than relying only on local vertex-specific information.

- 그래프 기반 랭킹 알고리즘은 구글 PageRank에서 사용됨 (웹 분석에 성공적으로 적용)
- 그래프 기반 랭킹 알고리즘은 그래프의 각 vertex의 중요도를 결정하는 방법

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2 The TextRank Model

Graph-based ranking algorithms are essentially a way of deciding the importance of a vertex within a graph, based on global information recursively drawn from the entire graph. The basic idea implemented by a graph-based ranking model is that of “voting” or “recommendation”. When one vertex links to another one, it is basically casting a vote for that other vertex. The higher the number of votes that are cast for a vertex, the higher the importance of the vertex...

- 그래프 기반 랭킹 알고리즘은 그래프 속 vertex (노드)의 중요도를 결정하는 방법
- 기본 아이디어는 (하나의 vertex가 다른 vertex에 연결되면) “투표" 혹은 “추천"
- 많은 득표를 한 vertex가 중요한 vertex임을 의미

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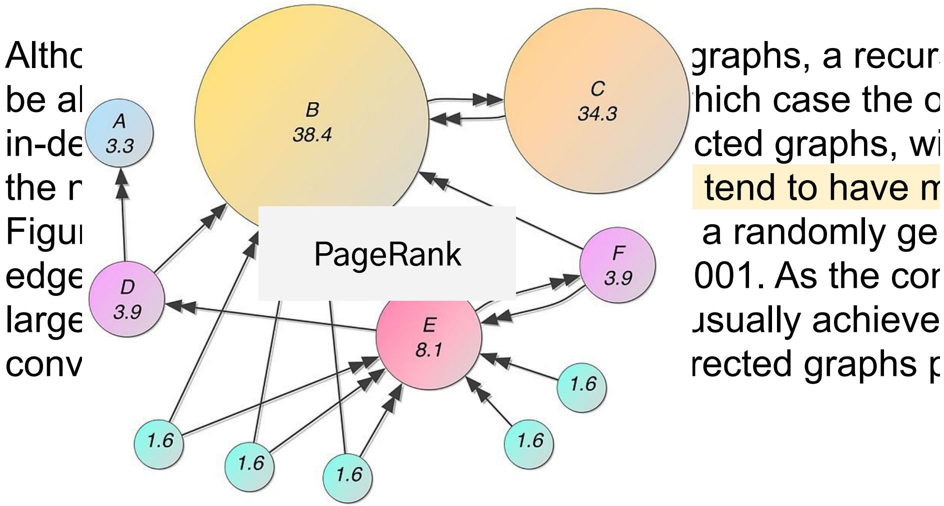
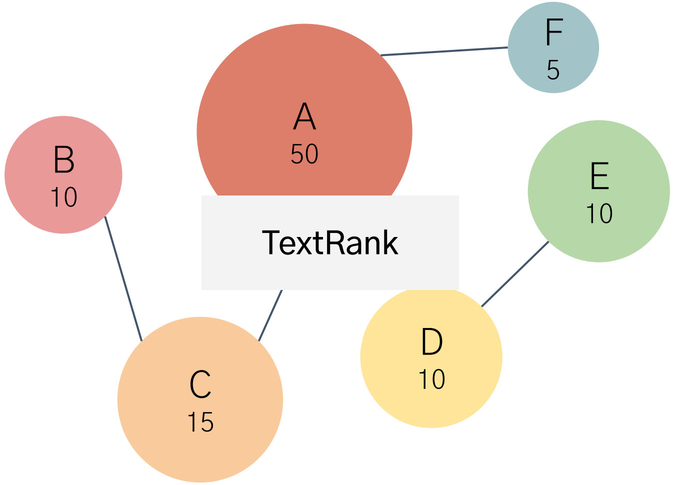
2.1 Undirected Graphs

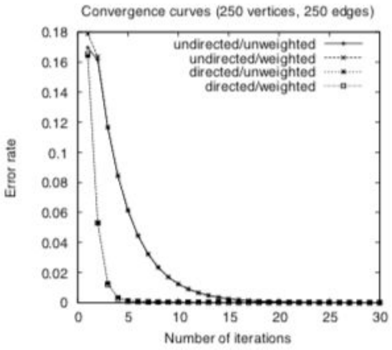




- Undirected 그래프에 경우 더 점진적 수렴 곡선을 가짐 (더 빠르게 수렴한다)

2.2 Weighted Graphs

However, in our model the graphs are build from natural language texts, and may include multiple or partial links between the units (vertices) that are extracted from text. It may be therefore useful to indicate and incorporate into the model the "strength" of the connection between two vertices and as a weight added to the corresponding edge that connects the two vertices...



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

- undirected / weighted graph를 사용시 더 적은 iteration으로 0에 수렴하는 것을 볼 수 있음

2.3 Text as a Graph

1. Identify text units that best define the task at hand, and add them as vertices in the graph.
2. Identify relations that connect such text units, and use these relations to draw edges between vertices in the graph. Edges can be directed or undirected, weighted or unweighted.
3. Iterate the graph-based ranking algorithm until convergence.
4. Sort vertices based on their final score. Use the values attached to each vertex for ranking/selection decisions.

In the following, we investigate and evaluate the application of TextRank to two natural language processing tasks involving ranking of text units: (1) A keyword extraction task, consisting of the selection of keyphrases representative for a given text; and (2) A sentence extraction task, consisting of the identification of the most "important" sentences in a text, which can be used to build extractive summaries.

- 주어진 텍스트의 핵심 키워드를 추출할 수 있음
- 주어진 텍스트의 핵심 문장을 식별할 수 있음

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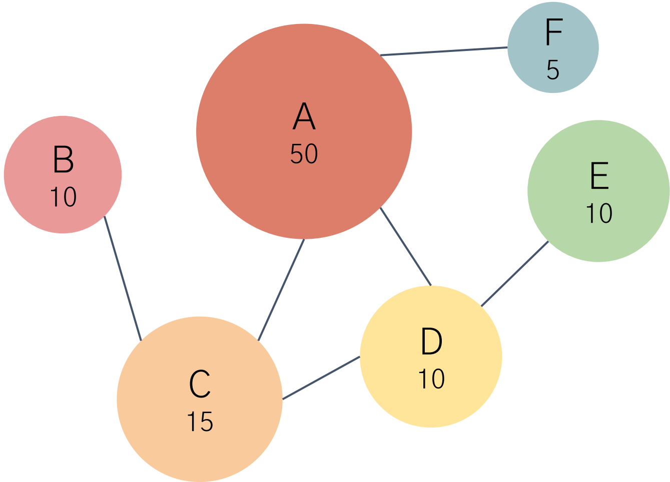
2 The TextRank Model



V_i로 들어오는(In)
Edge 가중치의 합산

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

TextRank

Factor

V_i의 인접 Vertex에서 나오는
(out) edge의 가중치

$$PR(A) = (1-d) + d\,(PR(T_1)/C(T_1) + \cdots + PR(T_n)/C(T_n))$$

PageRank

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3 Keyword Extraction

The task of a keyword extraction application is to automatically identify in a text a set of terms that best describe the document. Such keywords may constitute useful entries for building an automatic index for a document collection, can be used to classify a text, or may serve as a concise summary for a given document. Moreover, a system for automatic identification of important terms in a text can be used for the problem of terminology extraction, and construction of domain-specific dictionaries… The simplest possible approach is perhaps to use a frequency criterion to select the "important" key words in a document.

- 키워드 추출은 문서를 대변할 수 있는 단어 집합을 자동으로 식별하는 것

3.1 TextRank for Keyword Extraction

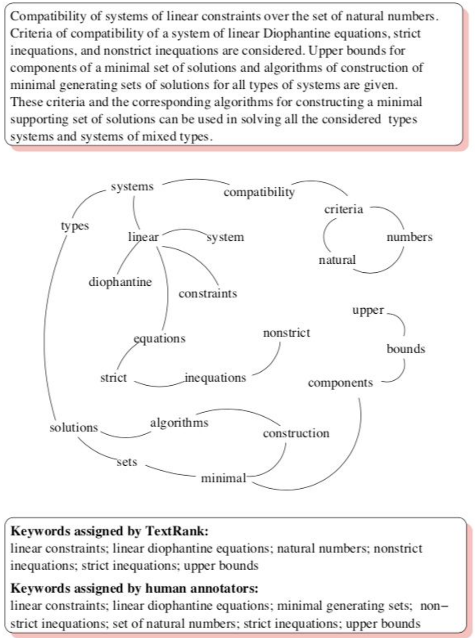

Figure 2: Sample graph build for keyphrase extraction from an *Inspec* abstract

The TextRank keyword extraction algorithm is fully unsupervised, and proceeds as follows. First,the text is tokenized, and annotated with part of speech tags – a preprocessing step required to enable the application of syntactic filters… Next, all lexical units that pass the syntactic filter are added to the graph, and an edge is added between those lexical units that co-occur within a window of words. After the graph is constructed (undirected unweighted graph), the score associated with each vertex is set to an initial value of 1, and the ranking algorithm described in section 2 is run on the graph for several iterations until it converges– usually for 20-30 iterations, at a threshold of 0.0001.… For this example, the lexical units found to have higher “importance” by the TextRank algorithm are (with the TextRank score indicated in parenthesis): numbers (1.46), inequations (1.45), linear (1.29), dio phantine (1.28), upper (0.99), bounds (0.99), strict (0.77)

- 1단계 : 텍스트는 품사가 태깅되어 토큰화 됨
- 2단계 : 단어 윈도(window of words)에 동시 등장한 토큰 사이는 엣지를 추가하여 그래프를 생성
- 3단계 : 0.0001을 threshold로 20-30회 반복

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3.2 Evaluation

Method	Assigned Total	Assigned Mean	Correct Total	Correct 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

Table 1: Results for automatic keyword extraction using TextRank or supervised learning (Hulth, 2003)

- Textrank 방식이 정밀도(Precision)와 F-measure 에서 가장 높지만 재현율(Recall)은 지도학습 방법에 비해 높지 않음
- 그리고 windows가 클수록 정확도는 낮아짐 (= 멀리 떨어져 있는 단어가 관계를 정의할 만큼 강력하지 않음)

5 Why TextRank Works

Intuitively, TextRank works well because it does not only rely on the local context of a text unit (vertex), but rather it takes into account information recursively drawn from the entire text (graph) … The sentences that are highly recommended by other sentences in the text are likely to be more informative for the given text, and will be therefore given a higher score… Through its iterative mechanism, TextRank goes beyond simple graph connectivity, and it is able to score text units based also on the "importance" of other text units they link to. The text units selected by TextRank for a given application are the ones most recommended by related text units in the text, with preference given to the recommendations made by most influential ones, i.e. the ones that are in turn highly recommended by other related units. The underlying hypothesis is that in a cohesive text fragment, related text units tend to form a "Web" of connections that approximates the model humans build about a given context in the process of discourse understanding.

- 텍스트 단위(버텍스)의 로컬 컨텍스트를 고려할뿐만 아니라, 전체 텍스트(그래프)에서 재귀적으로 정보를 고려하기 때문에 Textrank가 잘 작동
- 링크하는 다른 텍스트 단위의 "중요성"을 바탕으로 텍스트 단위를 평가

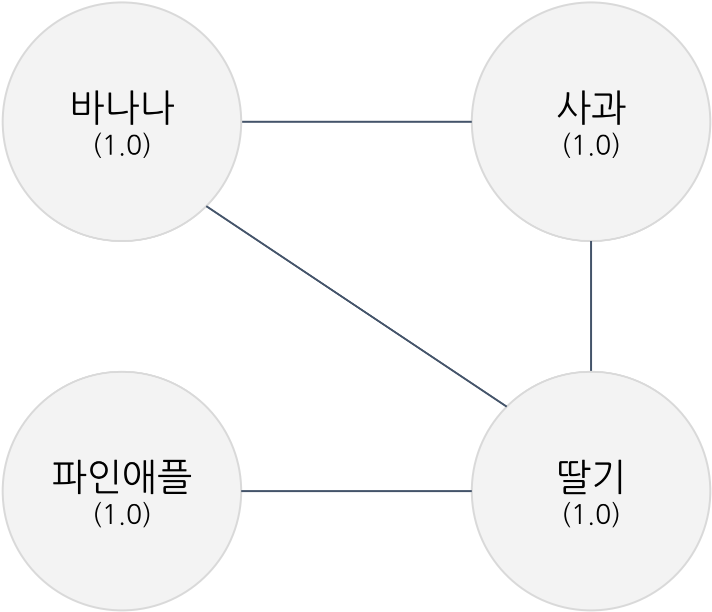
6 Conclusions

In this paper, we introduced TextRank – a graph- based ranking model for text processing, and show how it can be successfully used for natural language applications. In particular, we proposed and evaluated two innovative unsupervised approaches for keyword and sentence extraction, and showed that the accuracy achieved by TextRank in these applications is competitive with that of previously proposed state-of-the-art algorithms. An important aspect of TextRank is that it does not require deep linguistic knowledge, nor domain or language specific annotated corpora, which makes it highly portable to other domains, genres, or languages.

- Textrank는 깊은 언어지식이나 도메인 별 corpora를 필요로 하지 않고, 다른 도메인, 장르, 언어에 적용할 수 있음

Textrank 과정 : 그래프 생성

딸기	바나나	사과	딸기	파인애플



2 The TextRank Model

계산할 단어 노드의
TextRank 스코어

V_i로 들어오는(In)
엣지 가중치 합산

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

Damping Factor

V_i의 인접 노드에서 나오는
(out) 엣지 가중치

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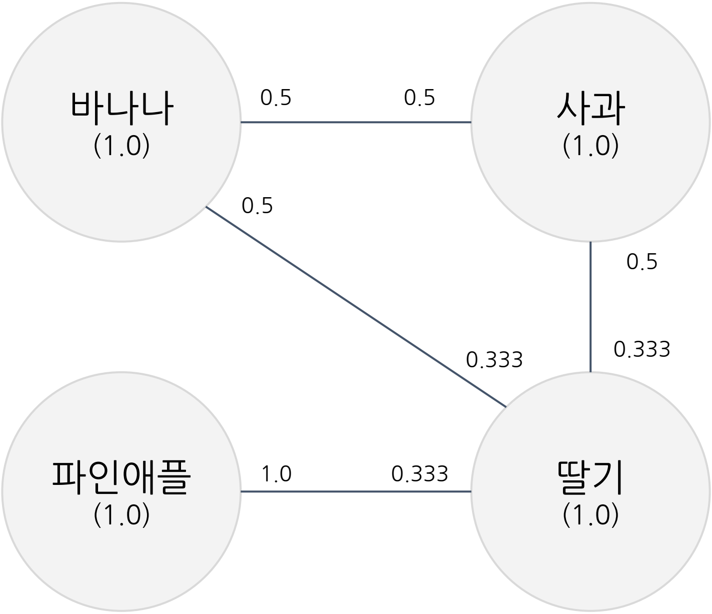
Textrank 과정 : 행렬로 계산하기

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



노드	스코어
바나나	1.0
사과	1.0
파인애플	1.0
딸기	1.0

	바나나	사과	파인애플	딸기
바나나	0	0.5	0	0.5
사과	0.5	0	0	0.5
파인애플	0	0	0	1.0
딸기	0.333	0.333	0.333	0
	0.858	0.858	0.433	1.85

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Textrank 과정 : 행렬로 계산하기

노드별 스코어

index	노드	스코어
0	바나나	1.0
1	사과	1.0
2	파인애플	1.0
3	딸기	1.0

노드간 엣지 가중치 행렬(그래프)

노드id	바나나(0)	사과(1)	파인애플(2)	딸기(3)
바나나(0)	0	0.5	0	0.5
사과(1)	0.5	0	0	0.5
파인애플(2)	0	0	0	1.0
딸기(3)	0.333	0.333	0.333	0

Textrank 과정 : 행렬로 계산하기

노드간 엣지 가중치 행렬(그래프)

노드id	바나나(0)	사과(1)	파인애플(2)	딸기(3)
바나나(0)	0	0.5	0	0.5
사과(1)	0.5	0	0	0.5
파인애플(2)	0	0	0	1.0
딸기(3)	0.333	0.333	0.333	0

스코어 계산

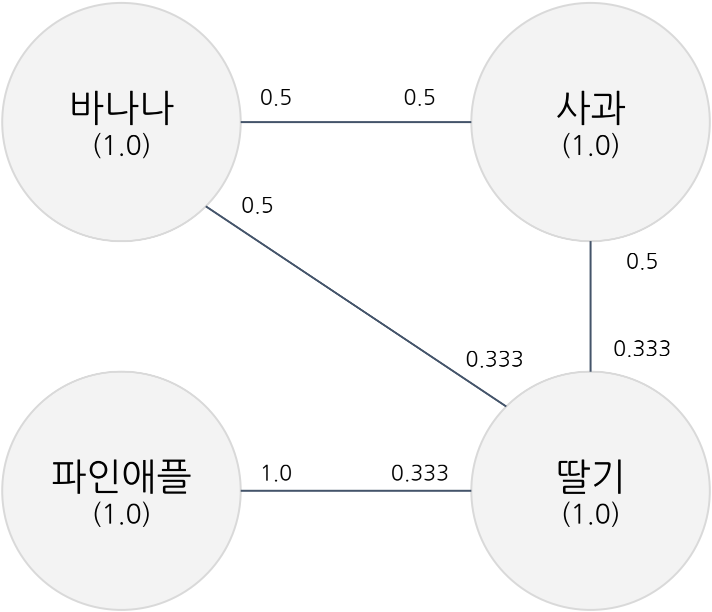
S(바나나) = (1−0.85) + 0.85 x (0.5 + 0.333) = **0.858**

S(사과) = (1−0.85) + 0.85 x (0.5 + 0.333) = **0.858**

S(파인애플) = (1−0.85) + 0.85 x (0.333) = **0.433**

S(딸기) = (1−0.85) + 0.85 x (0.5 + 0.5 + 1) = **1.85**

Textrank 과정 : 행렬로 계산하기



노드	스코어
바나나	1.0
사과	1.0
파인애플	1.0
딸기	1.0

S(바나나) = (1−0.85) + 0.85 x (0.5 + 0.333) = **0.858**

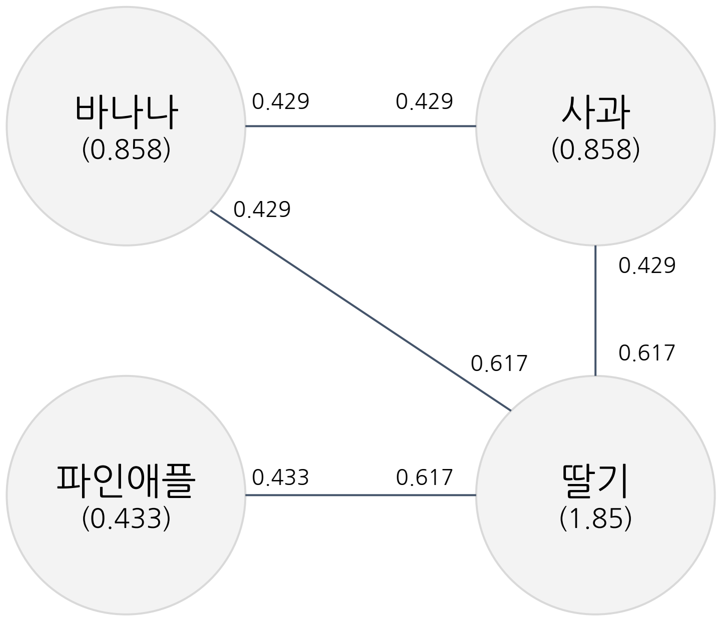
S(사과) = (1−0.85) + 0.85 x (0.5 + 0.333) = **0.858**

S(파인애플) = (1−0.85) + 0.85 x (0.333) = **0.433**

S(딸기) = (1−0.85) + 0.85 x (0.5 + 0.5 + 1) = **1.85**

	바나나	사과	파인애플	딸기
바나나	0	0.5	0	0.5
사과	0.5	0	0	0.5
파인애플	0	0	0	1.0
딸기	0.333	0.333	0.333	0

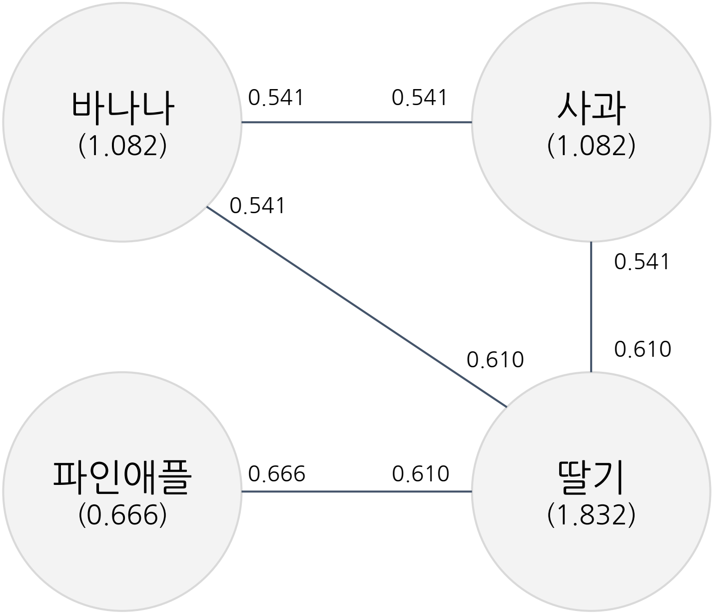
Textrank 과정 : 행렬로 계산하기



노드	이전 스코어	현 스코어
바나나	0.858	1.039
사과	0.858	1.039
파인애플	0.433	0.674
딸기	1.85	1.248

	바나나	사과	파인애플	딸기
바나나	0	0.429	0	0.429
사과	0.429	0	0	0.429
파인애플	0	0	0	0.433
딸기	0.617	0.617	0.617	0

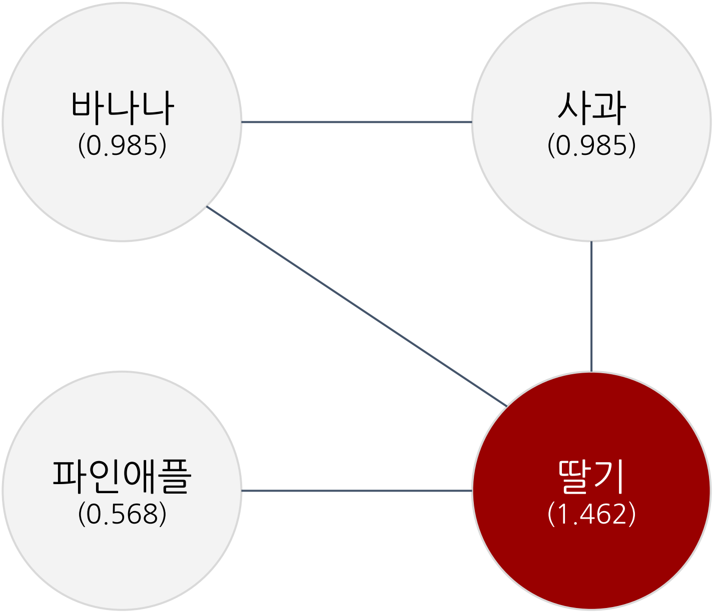
Textrank 과정 : 행렬로 계산하기



노드	이전 스코어	현 스코어
바나나	1.039	0.945
사과	1.039	0.945
파인애플	0.674	0.504
딸기	1.248	1.606

	바나나	사과	파인애플	딸기
바나나	0	0.519	0	0.519
사과	0.519	0	0	0.519
파인애플	0	0	0	0.674
딸기	0.416	0.416	0.416	0

Textrank 과정 : 계산 완료



감사합니다.

daniel@fins.ai