Entity Linking - Part II

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Week 10, Lecture 2

Keyphraseness and Commonness: Always the best decision?

Depth-first search

From Wikipedia, the free encyclopedia

Depth-first search (DFS) is an algorithm for traversing or searching a tree tree structure or graph. One starts at the root (selecting some node as the root in the graph case) and explores as far as possible along each branch before backtracking.

Formally, DFS is an uninformed search that progresses by expanding the first child node of the search tree that appears and thus going deeper and deeper until a goal node is found, or until it hits a node that has no children. Then the search backtracks, returning to the most recent node it hadn't finished exploring. In a non-recursive implementation, all freshly expanded nodes are added to a LIFO stack for exploration.

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	Tree	92.82%	15.97%
	Tree (graph theory)	2.94%	59.91%
	Tree (data structure)	2.57%	63.26%
	Tree (set theory)	0.15%	34.04%
	Phylogenetic tree	0.07%	20.33%
	Christmas tree	0.07%	0.0%
	Binary tree	0.04%	62.43%
	Family tree	0.04%	16.31%

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Using Relatedness: Basic Idea

- In a sufficiently long text, one finds terms that do not require disambiguation at all.
- Use every unambiguous link in the document as context to disambiguate ambiguous ones.

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How to give different weights to the context terms?

 link probability: Use the ones that are almost always used as a link within the articles where they are found, and always link to the same destination

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These two variables - link probability and relatedness - are averaged to provide a weight for each context.

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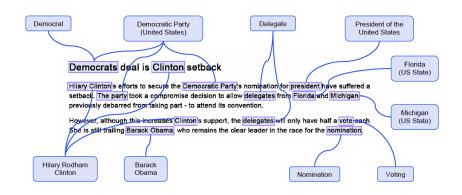
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Can you use this to learn – which concepts should be linked?

Example



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- The automatically identified Wikipedia articles provide training instances for a classifier.
- Positive examples are the articles that were manually linked to, while negative ones are those that were not.
- Features of these articles and the places where they were mentioned are used to inform the classifier about which topics should and should not be linked.

What are the features?

- Link Probability: Average as well as maximum of link probability of the link locations – (e.g. Hillary Clinton and Clinton)
- Relatedness: Topics which relate to the central thread of the document are more likely to be linked
- Disambiguation Confidence: The confidence score of the classifier for disambiguation
- Generality: Defined as the minimum depth at which it is located in Wikipedia's category tree. More useful for the readers to provide links for specific topics.
- Location and Spread: Where are these mentioned? First occurrence, last occurrence and the spread.

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