Few algorithms for ascertaining merit of a document and their applications

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Motivation

- Is prestige based ranking perfect?
- Are there alternatives?
- Two judging traditions – majority voting and interactive – which is right? Subjective or objective?
- Can a document be analyzed independently to get its quality?

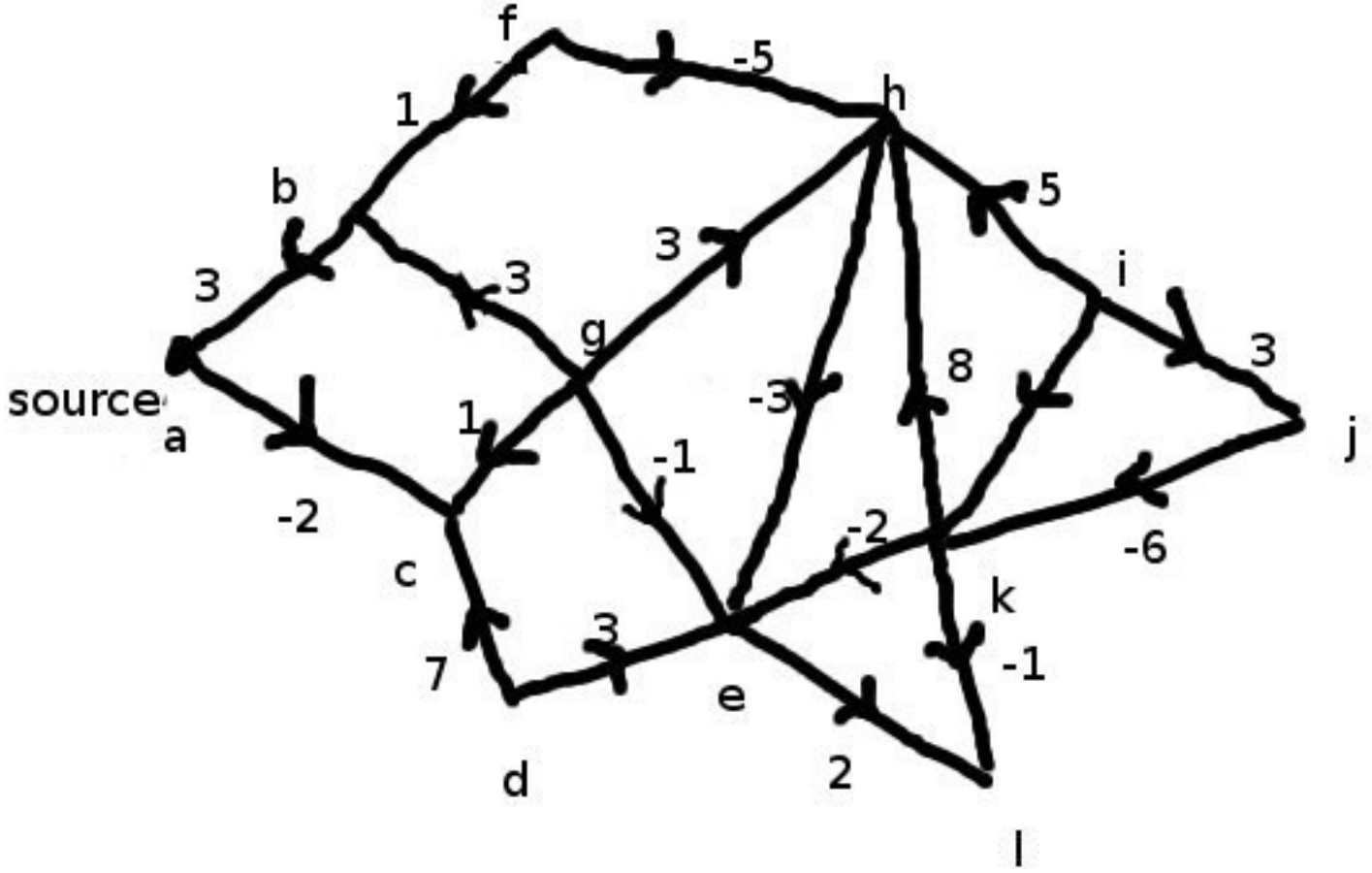
Three Algorithms ...

- **Citation Graph Maxflow and Path Lengths**
- **Definition Graph Convergence (or) Generalized Recursive Gloss Overlap**
- **Interview algorithm**
- Application to Update summarization
- Application to Topic Detection and Tracking
- Application to Sentiment Analysis

Part I - Directed Graph of Citations

- Merit = influence on future documents = citations
- Construct a directed graph of citations
- Weight of an edge (u,v) = No. Of citations of u by v (is this only way to weight?)
- Polarity of (u,v) = Sentiment Analysis of Citation Context – Positive or Negative
- Number of nodes in all paths of fixed length from source s is a measure of merit (might mislead)

Citation digraph - How it looks



Mincut/Maxflow of Citation DiGraph

- Get Maxflow/Mincut from Ford-Fulkerson algorithm with each distinct vertex pair as (source, sink)

- Mincut of citation graph carries Maximum Flow of the concept from source document s - “most influenced by the source document s”

- Average Maxflow out of a source s, is thus a measure of merit of s (= (∑mxf(s,t)) / (|V|-1))

Part II – Definition Graphs

- “Fruit”

- Evocative - What do we get reminded of after reading the above? *(plant, tree, sweet, taste, food, juice, result ...?)*

- Evocation WordNet

Human thought process and Definition Graphs

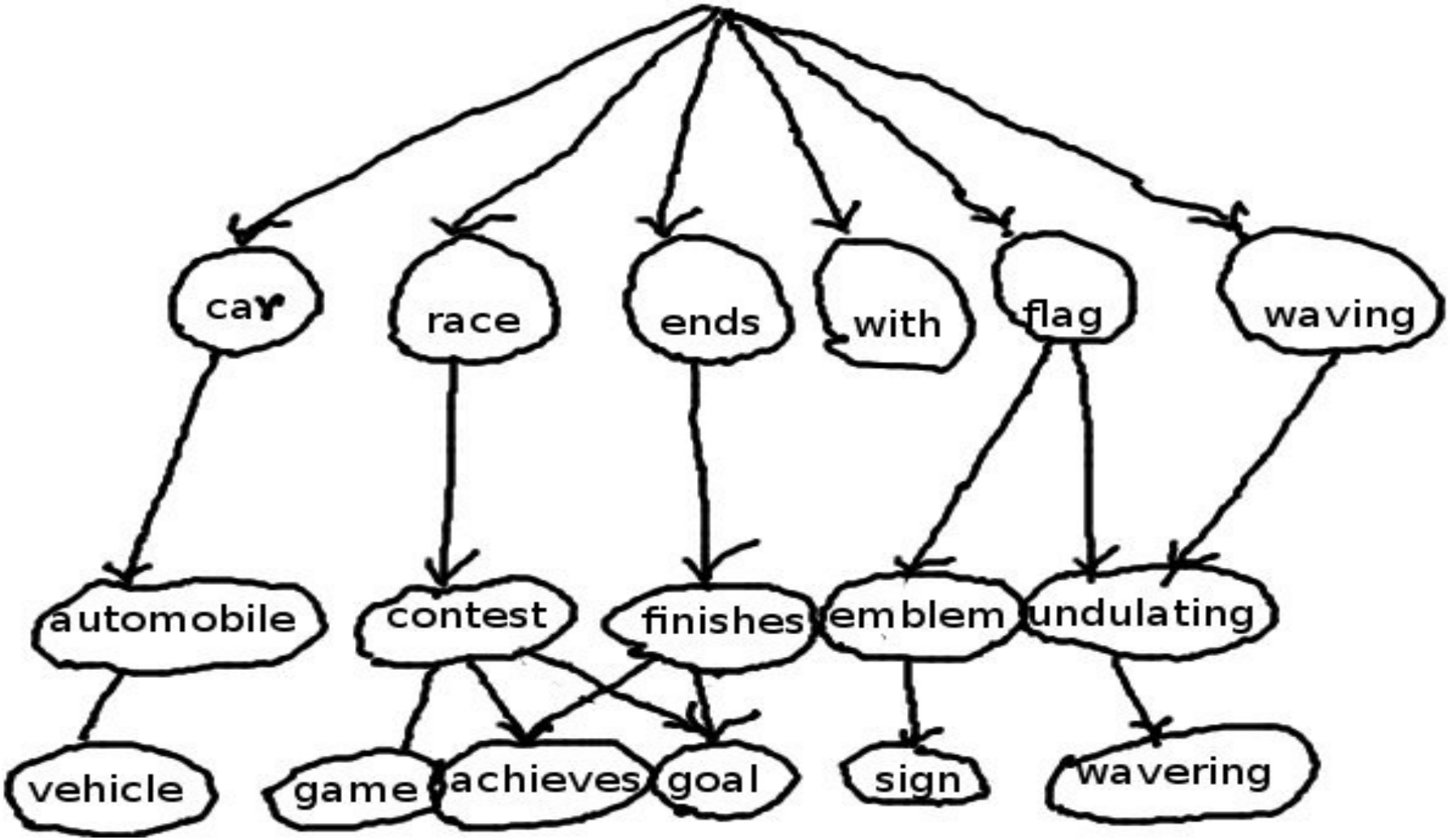
- Humans scan through the natural language text
- Relate the keywords – motivation behind WordNet
- **What distinguishes the merit of 2 documents X and Y? Grammatical correctness? *No*. Both X and Y written equally grammatically. Content and Complexity? *Yes*. How to measure?**

Recursive Understanding - An Example

- *Document: " Car race ends with flag waving"*

- What is "Car"? Car is an automobile
  - What is "automobile"? Fuel driven Machine
    - What is "Fuel"? Petroleum ...
- What is "race"? Race is ethnic group; contest
  - What is "contest"? Game
    - What is "Game" ? Play ...
- What is "end"? ...
- What is "flag"? ...
- What is "waving"? ...

Previous example visualised



Definition Graph Convergence (or) Generalized Recursive Gloss Overlap

- **<u>Meaningfulness:</u> "Meaningful" text has its keywords' Synsets within threshold WordNet distance (e.g Jiang-Conrath)**

- WordNet relates words by relations - "is-a", "has-a" etc., - SYNonymous SETs

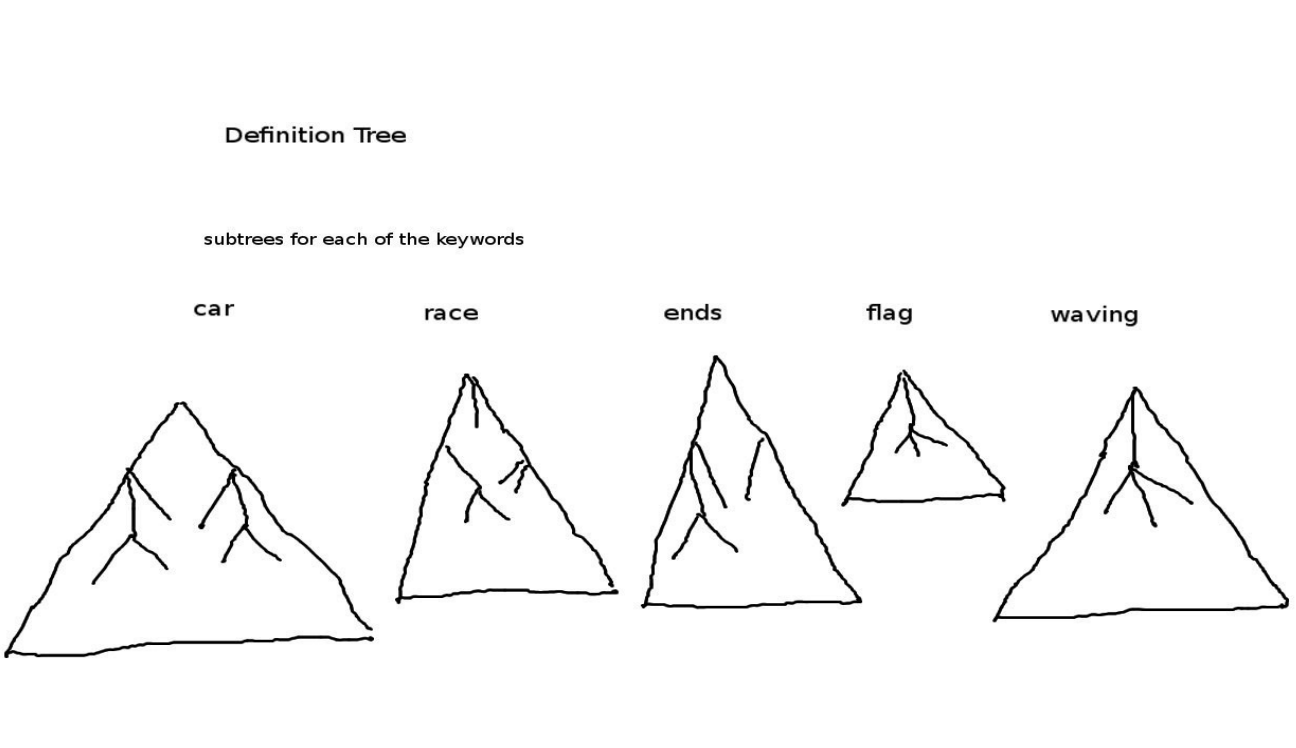
- *Map a document to a **subgraph** of WordNet (Definition Trees/Graphs): F(Document) = G(V,E)*

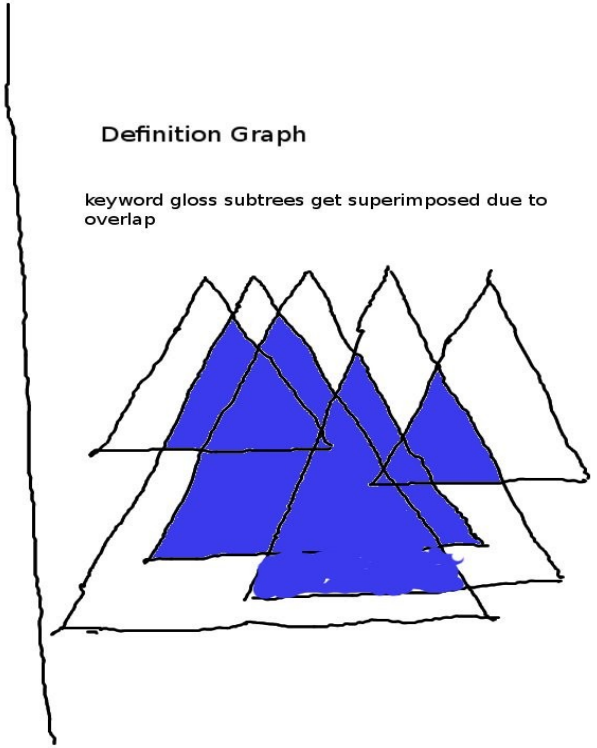
Definition tree and Definition graph

- *DefinitionTree(keyword) = DefinitionTree(gkeyword1) DefinitionTree(gkeyword2)DefinitionTree(gkeyword3) ... DefinitionTree(gkeywordn)* where gkeyword1 through gkeywordn are in the gloss(keyword)

- N subtrees obtained above overlap to form a graph

Definition Tree and Graph - example





Properties of definition graph

- Definition graph is **multipartite**
- Difference in number of vertices in definition tree and definition graph = convergence factor
- Convergence factor is due to gloss overlap - indicator of relatedness
- Relatedness differentiates 2 documents
- We do not consider grammatical structure

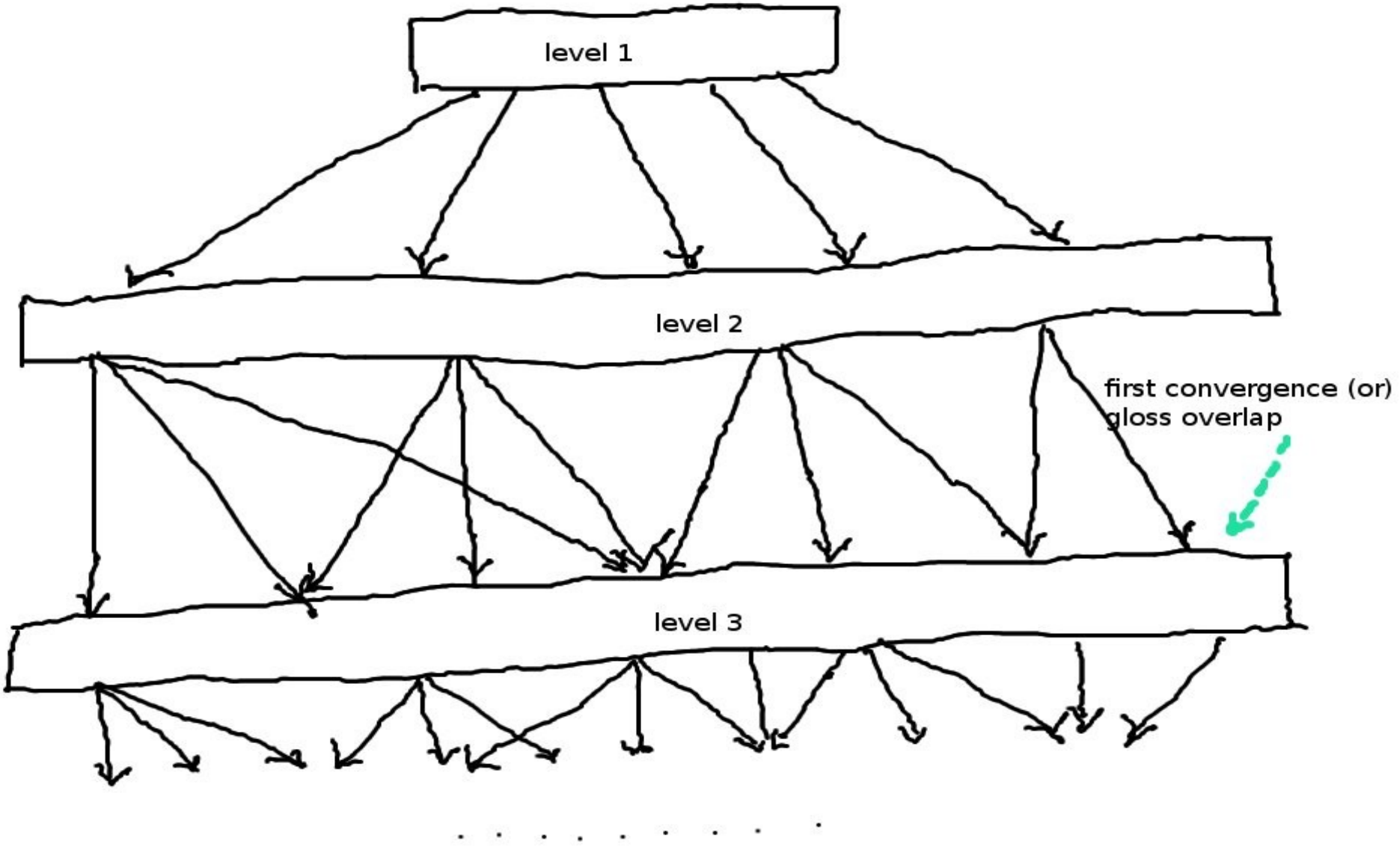
Properties of Definition Graph(contd...)

- Multipartiteness - vertices are partitioned into sets; edges only amongst the sets – useful for preserving recursion level and multipartite-cliques

- Degrees of vertices can be thought of as “votes” for a “theme” keyword – unsupervised text classifier

- Context-sensitiveness still present - Word Sense Disambiguation is done during graph construction

Definition Multipartite Graph Visualised



Recursive Gloss Overlap algorithm

1) Get the document as input

2) keywordsatthislevel = {keywords from the document through tf-idf filter (implementation uses 0.02)}

3) While (current_level < depth_required) {

- For each keyword from keywordsatthislevel lookup the **best matching definition(WSD) for the keyword** and add to a set of tokens in next level

Recursive Gloss Overlap algorithm(contd...)

- Remove common tokens with previous levels - an optimization

- Update the number of vertices*(unique tokens)*, edges*((x,y)='y is in definition of x')* and relatedness *(linear overlap or quadratic overlap)*

- Update keywordsatthislevel

Recursive Gloss Overlap algorithm(contd...)

} //end while

5) Output the ***Intrinsic merit score = |vertices|*|edges|*|relatedness| / first_convergence_level***

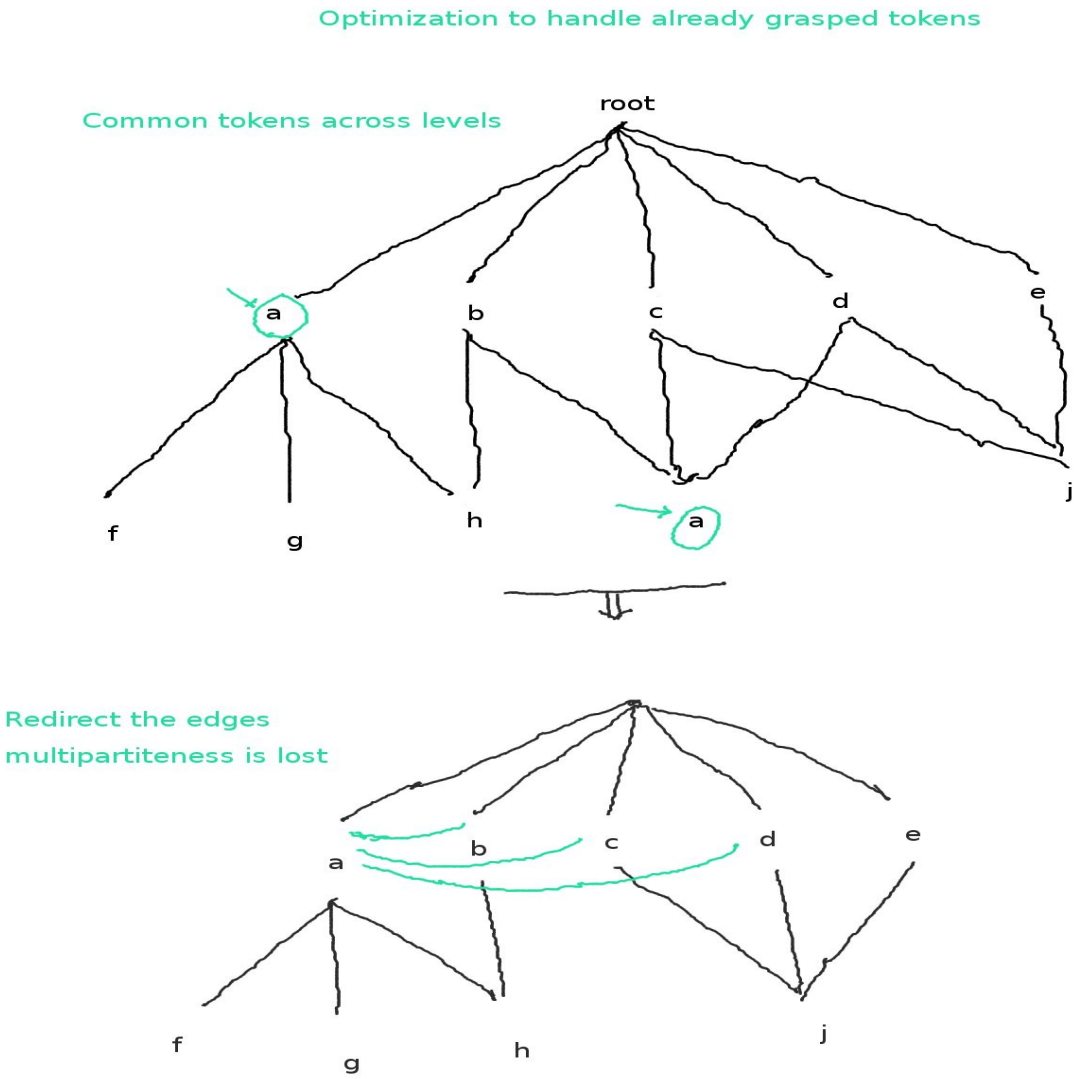
Where

*a) Relatedness = **number of overlaps** (linear, also called as convergence factor) (or)*

*Relatedness = **number of overlapping parents * number of overlaps**2** (quadratic)*

b) First_convergence_level = level of first gloss overlap

Snapshot of Definition graph

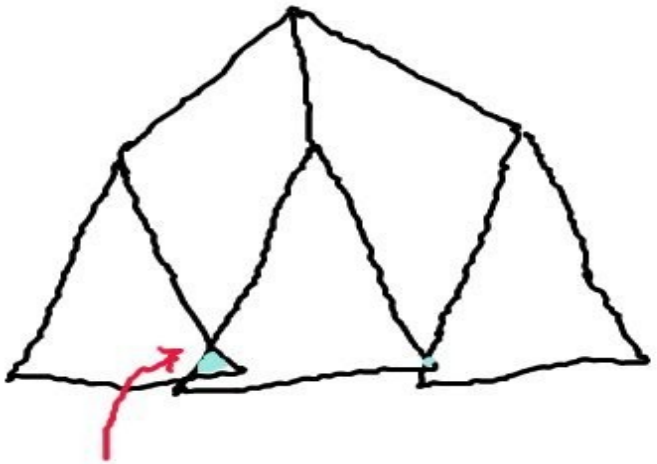


Intuition behind the intrinsic merit score

- vertices ~ knowledge represented by document
- edges ~ relationship among keywords (relation: 'x is in definition of y')
- relatedness ~ complexity quantified by overlap
- first_convergence_level ~ Mingling of definition subtrees
- Above suffice to quantify “meaningfulness” defined earlier *(proportional to V*E*R/ f)*

Comparing two documents for merit

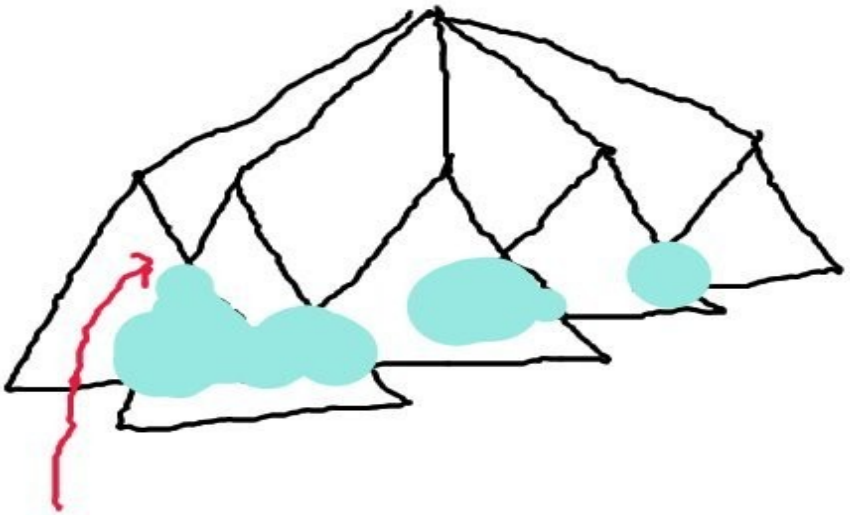
Document1 has less overlap



first convergence level = 5

Example: Car plies on sky

Document2 has more overlap



first convergence level = 2

Example: Cars and buses ply on road

BFS/DFS of definition graph

- Visiting all nodes of definition graph – O(V+E)
- But this does not take into account the relatedness
- Worst case complexity of constructing definition graph is O(x^d) *(where x is the average size of a keyword definition and d is the depth)*
- For a meaningful document, overlaps bring down this to great extent – no exponential blowup- O(V)

Pros and Cons

- No False negatives – more meaningful content will have greater intrinsic merit score than less meaningful document

- False positives exist – two documents with same keywords ignoring grammar will have same merit score.

- Other ranking schemes can be derived from definition graph – based on graph connectedness, completeness etc.,

Application of Recursive gloss overlap to sentiment analysis

- Needed - SentiWordNet - gloss with quantified positivity/negativity score for a keyword

- Example: *"That movie was fantastic. Graphics was awesome"*

- Def Graph level 1: {movie:*motion picture;+0.1*, fantastic:*great;+0.7*, graphics:*software technique; +0.05*, awesome:*great;+0.7*}

- Polarity of Overlap – {great} with positivity score +0.7

Parallelizability of Recursive Gloss Overlap

- Def Graph construction parallelizable - set of tokens of each level broken into subsets
- Assign each subset to a processor (Map)
- Get the results of gloss lookup for subsets and merge them (Reduce)
- To do – Apply MapReduce framework to Recursive Gloss Overlap – E.g Needs a Hadoop cluster

Part III – Interview Algorithm

- Reference "interviews" the candidate – both are documents

- Candidate is inducted into reference if the interview score is above threshold

- Interview is less invasive compared to definition graph construction

- Tree/Graph of interviews can be built (transitive) –e.g x interviews (y,z), y interviews w, z interviews p

Interview Algorithm (contd...)

- Intrinsic merit of candidate measured by either a) Citation Digraph or b) Recursive gloss overlap algorithms

- Interview - a) **supervised** (reference Q&A available) or b) **unsupervised** (reference Q&A are computed from reference – 'Q's are keywords / 'A's are contexts)

- Interview is the set of tuples = {t(1), t(2), ...,t(n)}
  t(i) = (question,answer,expected_answer,score)

Interview Algorithm (contd...)

- Total interview score = ∑(t(i).score) ***(where t(i).score = |shingles(answer) ∩ shingles(expected_answer)| / |shingles(answer) U shingles(expected_answer)|***

- Value addition = edit distance of DefGraph(Reference) and DefGraph(Candidate) ***(where EditDistance(G,H) = |edges added| + |edges removed| to transform G into H)***

- Final score = ***w1 * intrinsic_merit + w2 * interview_Q&A_score + w3 * value_addition, where w1,w2 and w3 are weights***

Application to Update summarization

- Fix a news summary as reference which has to be updated
- Fix the candidate news items
- Go through the Interview algorithm and get scores for candidates
- Choose the best candidate and update the summary after sentence scoring

Application to Topic Detection and Tracking

1)Interview score(n1,n2) decreases and editdistance(n1,n2) increases as n2 becomes more irrelevant to n1. We have **link detection** - (Do two news stories discuss same topic?)

2)definition graph edit distance score for all possible pairs (Nx, Ny) in a topic and choose Ny with maximum pairwise distance(outlier). - **topic detection** (Does this story exist in correct topic?).

3)**Topic tracking** can be done by periodically constructing definition graph and finding vertices with high number of indegree. These keywords are voted high and point to the topic of the news story **(unsupervised text classifier)**.

Test Results – Spearman Coeff Ranking for RGO Intrinsic Merit

- Spearman coefficient, correlations between Google ranking and Recursive Gloss Overlap IM score(quadratic overlap) are **73%, 4%, 9% and 25% for few Google queries**

- Spearman coefficient correlations between human ranking and Recursive Gloss Overlap IM score(quadratic overlap) are **38% and 90% for 2 judges and 1 judge respectively**

Test Result – Citation Graph Maxflow

- Link graph with 7 html files with some product review comments
- Average concept maxflow out of each page:
  - 'file2.html': 3.7142857142857144
  - 'file4.html': 3.2857142857142856
  - 'file5.html': 2.0
  - 'file3.html': 3.4285714285714284
  - 'file7.html': 0.0
  - 'file1.html': 3.4285714285714284
  - 'file6.html': 0.0
- File2 has greater average maxflow – implies that concept flowing out of file2 is maximum