

OPINIONS on **OPINOSIS**

OPINOSIS - A Graph-Based Approach to Abstractive Summarization of Highly Redundant Opinions

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Presentation's structure

Background

- The GZH's paper in a nutshell.
- OPINOSIS
- My Opinions

Text summarization

- Automatic creation of a shortened version of a text maintaining its most important points
- Coherent and correctly-developed summaries
- A possible approach to Information overload
- Useful summary : concise, readable, and fairly well-formed

Text summarization

Types of summaries:

- Purpose (Indicative, informative, and critical)
- Form

Extractive (salient paragraphs, sentences, phrases) Abstractive(concise summary of the central subject)

- Dimensions (Single-document vs. multi-document)
- Context (Query-specific vs. query-independent)

Information organized around the key aspects to represent a wider diversity of views on the topic.

- Centroid-based, sentence utility MEAD (Radev et al. 00)
- Reformulation

(McKeown et al. 99, McKeown et al. 02)

Generation by Selection and Repair
 (DiMarco et al. 97)



- Implements extractive summarization: selects a subset of highly relevant sentences from the cluster's overall set of sentences.
- Deep NLP and machine learning techniques.
 - Decision-tree, trained on a manually annotated corpus for CST relationships
 - CST (Cross-document Structure Theory) relationships: subsumption, identity, paraphrase, elaboration/refinement, etc.



For each sentence computes:

- centroid score (a measure of the centrality of a sentence to the overall topic of a cluster)
- position score (decreases linearly as the sentence gets farther from the beginning of a document)
- overlap-with-first score (the inner product of the weighted vector representation of the sentence and the first sentence (or title, if there is one)
- Produces a cluster centroid, consisting of words which are central to all of the documents in the cluster.
- Ranks sentences on their distance to the centroid.

Natural Language Processing (NLP)

- Shallow NLP: mixing simple syntactic feature (word order or location and similarity) with domain-specific interpretation.
- Deep NLP: Sophisticated syntactic, semantic and contextual processing: named-entity recognition, relation detection, coreference resolution, syntactic alternations, word sense disambiguation, logic form transformation, logical inferences (abduction) and commonsense reasoning, temporal or spatial reasoning, etc.

http://opennlp.sourceforge.net./

POS Tag	Meaning	Example
CC	coordinating conjunction	and
dt	determiner	the
nn	noun, singular	table
vb	verb, base form	take
jj	adjective	red
rb	adverb	however, here, good
in	preposition	in, of, like
to	ТО	to go, to him

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GZH's Paper Summary

- A framework for summarizing highly redundant opinions
- Use graph representation to generate concise abstractive summaries
- Any corpus with high redundancies (Twitter comments, Blog comments, etc)

GZH's Approach Schema



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OPINOSIS-Graph

- Each sentence \rightarrow sequence of word units
- Word unit : pair (word, POSannotation)
- Word units \rightarrow **nodes** of OPINOSIS-Graph
- Directed edges: (v, w) iff v and w are successive word units in the same sentence
- $v \text{-} node \leftarrow PRI_v$ Positional Reference Information
- PRI_v list of pairs (SID_v, PID_v)

- $SID_v = i$ iff v is a unit word in sentence i
- $PID_v=j$ iff position of v in sentence SID_v is j
- Algorithm 1: OpinosisGraph(Z)
- Input : Topic related sentences to be summarized: $Z = \{z_i\}_{i=1}^n$
- **•** Output: G = (V, E)

OpinosisGraph(Z)

for i = 1 to n do {

 $w \leftarrow Tokenize(z_i); sent_size \leftarrow SizeOf(w)$ for j = 1 to $sent_size$ do { $LABEL \leftarrow w_i; SID \leftarrow i; PID \leftarrow j$ if ExistsNode(G, LABEL) then { $v_i \leftarrow GetExistingNode(G, LABEL)$ $PRI_{v_i} \leftarrow PRI_{v_i} \cup (SID; PID) \}$ else { $v_i \leftarrow CreateNewNode(G, LABEL)$ $PRI_{v_i} \leftarrow (SID; PID) \}$

if j > 1 and not $ExistsEdge(v_{j-1} \rightarrow v_j, G)$ then $AddEdge(v_{j-1} \rightarrow v_j, G)$

Remarks on OPINOSIS-Graph

- Property 1. (Redundancy Capture) Highly redundant discussions are naturally captured by subgraphs.
- Property 2. (Gapped Subsequence Capture) Existing sentence structures introduce lexical links that facilitate the discovery of new sentences or reinforce existing ones.
- Property 3. (Collapsible Structures) Nodes that resemble hubs are possibly collapsible.

- **●** Valid Start Node VSN: v s.t. $Average(PID_v) \le \sigma_{vsn}$
- Valid End Node VEN: v is a punctuation (period, comma), or any coordinating conjunction (but, yet).
- Valid Path : A path connecting a VSN to a VEN satisfying a set of well-formedness POS constraints.
- Regular-expression POS constraints:

 (/nn) + .(/vb) + .*(/jj) + .*
 (/jj) + .(/to) + .*(/vb).*
 (/rb).*(/jj) + .*(/nn) + .*
 (/rb) + .(/in) + .*(/nn) + .*

Redundancy and Gap

Path Scoring

Favor a valid path with a high redundancy score, to represent well most of the redundant opinions.

- $W = \{v_1, v_2 \dots, v_s\}$ a "path" in the Opinosis-Graph.
- Sentence z_i cover W if $\forall j \in \{1, \dots, s-1\}$ $\exists (i, p) \in PRI_{v_j} \text{ and } \exists (i, p') \in PRI_{v_{j+1}} \text{ such}$ that $p' - p \leq \sigma_{gap}$.
- Path redundancy of the path W: $r(W) = |\{z_i | z_i \text{ cover } W\}|.$

Redundancy and Gap



 $\sigma_{gap} = 1 \Rightarrow r(W) = 0$ $\sigma_{gap} = 2 \Rightarrow r(W) = 2$ $\sigma_{gap} = 4 \Rightarrow r(W) = 3$

Redundancy and Gap

Scores

$$W = \{v_1, v_2 \dots, v_s\}; |W| = \text{length of } W;$$

 $W_{i,j} = \text{the subpath } \{v_i, \dots, v_j\} \ (1 \le i < j \le s)$

•
$$S_{basic}(W) = \frac{1}{|W|} \sum_{k=1,s} r(W_{1,k})$$

• $S_{wt_len}(W) = \frac{1}{|W|} \sum_{k=1,s} r(W_{1,k}) \cdot |W_{1,k}|$
• $S_{wt_loglen}(W) = \frac{1}{|W|} \left[r(W_{1,2}) + \sum_{k=2,s} r(W_{1,k}) \cdot \log |W_{1,k}| \right]$

Path Composition

- Collapsible Node: node v_c with POS = vb
- Collapsed candidates: Remaining path after a candidate node v_c :



 $CC(v_c) = \bigcup_{P \text{ anchor}} \{P' | P' \text{ collapsed candidate for } P\}.$

Stitched sentence: Logical sentence obtained from an anchor and its collapsed candidates.

- Collapsible node: v_c anchor of v_c : P
- Collapsed candidates for $P: \{P_1, \ldots, P_{k-1}, P_k\}$
- Stitched sentence $(k \ge 2)$: $PP_1 \operatorname{comma} P_2 \operatorname{comma} \dots \operatorname{comma} P_{k-1} \operatorname{cc} P_k$. Examples:

The paper is nice, deep and useful for summarization. The paper is nice, interesting but not useful.

• coordinating conjunction cc: from all parents u in G of the first node v of P_k , having POS=cc, select $\operatorname{argmax}_{u:POS(u)=cc}r(\{u,v\}).$

System's parameters

- σ_{gap} controls the maximum allowed gaps in discovering redundancies.
- σ_{vsn} qualify nodes that tend to occur early on in a sentence.
- σ_{ss} controls the maximum number of paths to be chosen (summary size).
- σ_r a redundancy score threshold, to prune non-promising paths.

Empirically set.

Summarization

- Algorithm 2: OpinosisSummarization(Z)
- **Input** : Topic related sentences to be summarized:

 $Z = \{z_i\}_{i=1}^n$

• **Output:** $\mathcal{O} = \{Opinosis Summaries\}$

OpinosisSummarization(Z)

 $q \leftarrow OpinosisGraph(Z)$ $node_size \leftarrow SizeOf(g)$ for j = 1 to $node_size$ do { if $VSN(v_i)$ then { $pathLen \leftarrow 1; score \leftarrow 0$ $cList \leftarrow CreateNewList()$ $\mathbf{Traverse}(cList, v_j, score, PRI_{v_i}, label_{v_i}, pathLen)$ $candidates \leftarrow \{candidates \cup cList\}$ } $\mathcal{C} \leftarrow EliminateDuplicates(candidates)$ $\mathcal{C} \leftarrow SortByPathScore(\mathcal{C})$ for i=1 to $\sigma_{s,s}$ do $\mathcal{O} = \mathcal{O} \cup PickNextBestCandidate(\mathcal{C})$

Comments on Traverse

- Traverse is a recursive Depth First Search to find valid paths (σ_r used to avoid unuseful paths)
- The PRI overlap information, path length, summary sentence and path score are maintained during recursion
 - when v, the node visited, is collapsible, corresponding collapsed candidates are composed with the current path to v
 - the stitched sentence and its final score are added to the list of candidate summaries

Evaluation techniques

- Strong focus on evaluation : BLEU, ROUGE...
- ROUGE metric (Recall-Oriented Understudy for Gisting Evaluation)
 - 1. Calculates n-gram overlaps between system generated summaries and model summaries (human made)
 - 2. A high level of overlap should indicate a high level of shared concepts between the two summaries.
 - 3. Unable to provide any feedback on a summary's coherence

Evaluation techniques

	Relevant	Non-relevant
System relevant	A	В
System non-relevant	С	D

• Precision
$$P = \frac{A}{A+B}$$

• Recall
$$R = \frac{A}{A+C}$$

• F-score
$$F = \frac{2PR}{P+R}$$

Experimental Setup

- Reviews from Tripadvisor.com, Amazon.com and Edmunds.com
 - 51 review documents each about an entity
 E and a topic *X*
 - 100 sentencens per review document
 - best 4 reference (human) summaries for each review document
- Performance comparison between humans,
 Opinosis and the baseline method Mead

Experimental Setup

- For each reference summary compute ROUGE scores over the remaining 4-1=3 reference summaries
- Method MEAD selects 2 most representative sentences as summaries
- Readability test: are Opinosis summaries are readable ?
 - Mix N sentences from system summary and M sentences from human summary
 - Ask a human assessor to pick at most N sentences that are least readable

Experimental Setup

Readability test:

$$readability(\mathcal{O}) = 1 - \frac{\#CorrectPick}{N}$$

- Opinosis parameters: $\sigma_{ss} = 2$; $\sigma_{vsn} = 15$
- Opinosis_{best}: $\sigma_{gap} = 4$; $\sigma_r = 2$; S_{wt_loglen}
- ROUGE scores reported with the use of stemming and stopword removal

Performance comparison

Human vs. Opinosis vs. MEAD



Performance comparison



very high recall scores (explanation: extractive)

 extremely low precision scores (explanation: sentence extraction)

humans

Mead :

- reasonable agreement amongst themselves
- better than Opinosis
- comparable to Mead

Performance comparison

Opinosis :



- closer in performance to humans than to Mead
- recall scores slightly lower than that achieved by humans
- improvement of precision by Opinosis over that of humans is more significant than the decrease of recall (Wilcoxon test)

Gap setting

Effect of Gap Threshold (σgap)



 $\sigma_{gap} = 1$: low performance; redundancies veiled. $\sigma_{gap} = 2$: big jump in performance $\sigma_{gap} > 2$: slow improving peformance

Comparison of scoring functions

Compare: Scoring Functions



S_{wt_loglen} is the winner !

The effect of heavily favoring redundant subgraphs (S_{basic}) over longer but reasonably redundant ones $(S_{wt_loglen}, S_{wt_len})$ is not sound.

Readability test

- Human assessor picked the least 2 readable from 565 sentences (102 were Opinosis generated).
- Out of these 102, the human assessor picked only 34, resulting in an average readability score of 0.67.
- . 34 sentences with problems:
 - 11 contained no information, incomprehensible
 - 12 were incomplete (false positives of validity check)
 - 8 had conflicting information (e.g. "the hotel room is clean and dirty").
 - 3 considered "poor grammar"

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Positive Opinions

- Nice, interesting and simple approach.
- Carrying ideas from sequential data mining.
- Professional evaluation
- Path-aggregation building of a network !
- Adding OPINOSIS to conference management software systems (e.g. EasyChair)?

My Opinions

Not quite positive Opinions:

- Gap could change an opinion (Not not).
- Emphasizes too much on the surface order of words (not quite abstractive).
- Shallow NLP must be reward by learning.
- Mathematical inaccuracies in the text.
- Algorithms not optimized for huge corpus.







Thanks !