Ongoing research on sentence retrieval and novelty detection

Dr. David E. Losada

Grupo de Sistemas Inteligentes

Departamento de Electrónica y Computación

Universidade de Santiago de Compostela (Spain)

http://www-gsi.dec.usc.es/~dlosada

dlosada@dec.usc.es

Outline

- The importance of sentence retrieval & novelty
- Our current research lines
  - Language modeling for sentence retrieval: Multiple-Bernoulli distribution.
  - Hierarchical query-biased summaries
  - Proximity between relevant sentences and query difficulty
  - Language modeling for sentence retrieval: Study of smoothing.

The importance of SR & novelty

- To facilitate effective web information access
- To focus Question Answering processes on a set of well selected sentences
- To assist (query-biased) summarization
- To aid Topic Detection and Tracking methods
- Just to name a few ...

The importance of SR & novelty

Focusing on web retrieval...

[White et al. 2005] *Using top-ranking sentences to facilitate effective information access*. JASIST 56(10), 2005.

- Web searchers typically fail to view results beyond the 1st page
- Doc surrogates can be uninformative and difficult to interpret. Hard to assess the relevance of the returned docs.

The importance of SR & novelty

Focusing on web retrieval...

- Searchers forced to make 2 steps: **1) assess the surrogate.**

  Is this title relevant? Are these terms in the correct context? What comes after the ellipses? Shall I click this title?

  and **2) analyze exhaustively the doc to locate the relevant material**, if any

  [Krish, 2000]: associated cost (time, effort and stress)

The importance of SR & novelty

Focusing on web retrieval...

- Why not to **present directly the document contents**? The required information may be even found directly at the results interface...
- White et al. **shift away from surrogates to actual doc content** (query-relevant top ranking sentences)
- Encourages a **deeper examination of the contents of the doc retrieved set**.
- **Increased contextual coherence** (surrogates are rarely composed of full sentences)
- Highly relevant content from lower ranking docs has now more chance to be viewed.

The importance of SR & novelty

Focusing on web retrieval...

- In [White et al. 2005] user studies for factual searches (e.g. *find a named person's current email address*), decision search (e.g. *choose the best impressionist art museum*) and background searches (e.g. *finding information on dust allegies*).
- Users do not need the top-ranking sentences for the factual queries
- But useful for decision and background searches. A general overview of the topic usually needed to make reasonable search decisions.
  The presentation of top sentences coming from different docs helps to supply the user with a **general view on the query subject**.

USC

The importance of SR & novelty

Focusing on web retrieval...

- Searchers are fully aware of what they are looking for $\Rightarrow$ top ranked sentences not needed
- Searchers are not fully aware of what they are looking for $\Rightarrow$ top ranked sentences useful
- The ranked sentences also encouraged **more page views outside the top 10** docs and a **reduced number of query iterations**.

USC

The importance of SR & novelty

Focusing on web retrieval...

- In [White et al. 2005], they didn't apply any method to filter out redundant sentences

Our research lines

- **Language modeling for sentence retrieval: Multiple-Bernoulli distribution.**
- Hierarchical query-biased summaries
- Proximity between relevant sentences and query difficulty
- Language modeling for sentence retrieval: Study of smoothing.

Motivation

- Multinomial (MN) vs multi-variate Bernoulli (MB) for sr.
- The pioneering LM proposal was based on a query generation process modelled by a MB distribution ([Ponte & Croft, 1998]).
- But, following that, MN models became popular
- In general, there is no good reason for choosing MB (see e.g. [Metzler et.al. 2004]).
- However, the granularity of sr and its particular characteristics could be suitable for a MB approach

Language Modeling

MN and MB can be formally analyzed in the context of Bayesian Statistics:

$$P(\theta_D|D) = \frac{P(D|\theta_D)P(\theta_D)}{P(D)}$$

$P(\theta_D)$: prior belief about the adequacy of the distribution θ_D
$P(D|\theta_D)$: likelihood of the data D under distribution θ_D
$P(\theta_D|D)$ is the posterior distribution.
$P(D)$: prob. of generating the doc. It is independent on θ_D.

Language Modeling

- Applying MAP ...
  - $P(D|\theta_D)$ (MN) and $P(\theta_D)$ (Dirichlet) leads to a posterior distribution which is also Dirichlet and...

$$\widehat{\theta_i} = P(w_i|\widehat{\theta_D}) = \frac{tf_{i,D} + \alpha_i - 1}{|D| + \sum_{i=1}^{|V|} \alpha_i - |V|}$$

  - $P(D|\theta_D)$ (MB) and $P(\theta_D)$ (Multiple Beta) leads to a posterior distribution which is also Multiple Beta and...

$$\widehat{\theta_i} = P(w_i|\widehat{\theta_D}) = \frac{\delta_{i,D} + \alpha_i - 1}{\alpha_i + \beta_i - 1}$$

Query likelihoods

- Standard unigram LM

$$P(Q|\widehat{\theta_D}) = \prod_{w_i \in Q} P(w_i|\widehat{\theta_D})^{qtf(w_i)}$$

- MB likelihood

$$P(Q|\widehat{\theta_D}) = \prod_{w_i \in Q} P(w_i|\widehat{\theta_D}) \prod_{w_i \notin Q} (1 - P(w_i|\widehat{\theta_D}))$$

Different space of events (binary vectors, such as in BIM)
Product across non query terms. Kind of off-topic correction.

Sentence retrieval

- Lack of a non-binary tf component in MB seems less important
- MB takes into account the non-query terms:
  - the terms in the sentence (especially those ones having $P(w_i|\widehat{\theta_S})$ high) which are missing in the query text $\Rightarrow$ penalty in the retrieval score.
  - Intuition: The sentence will probably deviate from the query topic.

Sentence retrieval

- But MB is not efficient for doc retrieval, why?
  - Docs are usually multi-topic whereas sentences deal with a single topic.
  - MB selects sentences very focused on query topics.
  - In doc retrieval, most relevant docs will mention many non-query terms
  - The lack of non-binary tf is undoubtedly an issue for doc retrieval

Experiments

(More details can be found in [Losada 05])
Main findings...

- MB was always better than (or at least as good as) MN
- MB is more stable w.r.t the smoothing levels
- In most of the cases the MB performance was significantly better than the MN performance (> 10%)

Our research lines

- Language modeling for sentence retrieval: Multiple-Bernoulli distribution.
- **Hierarchical query-biased summaries**
- Proximity between relevant sentences and query difficulty
- Language modeling for sentence retrieval: Study of smoothing.

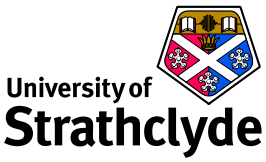
Hierarchical query-biased summaries

- Joint collaboration

University of Santiago de Compostela

Grupo de Sistemas Inteligentes

University of Strathclyde



Information Access lab

Fabio Crestani
& Simon Sweeney

Hierarchical query-biased summaries

- Summarization with novelty detection
- Two basic aims:
  - Incremental length summaries vs fixed length summaries
    (interesting e.g. in WAP mobile phones)
  - Incorporating novelty detection does really help?

Hierarchical query-biased summaries

- Whilst summarisation paired with novelty detection is not a new concept, we are concerned with the mechanism of delivery.
- Is there an optimal strategy for showing summaries in response to the request to 'show me more'?
- In previous work we took 'more' to mean an increase in summary length.
- An intuitive approach 'more' as a function of the summary length and information content.

Hierarchical query-biased summaries

- Compare user groups performance with both systems (increasing vs constant length), and baseline systems that do not use novelty.

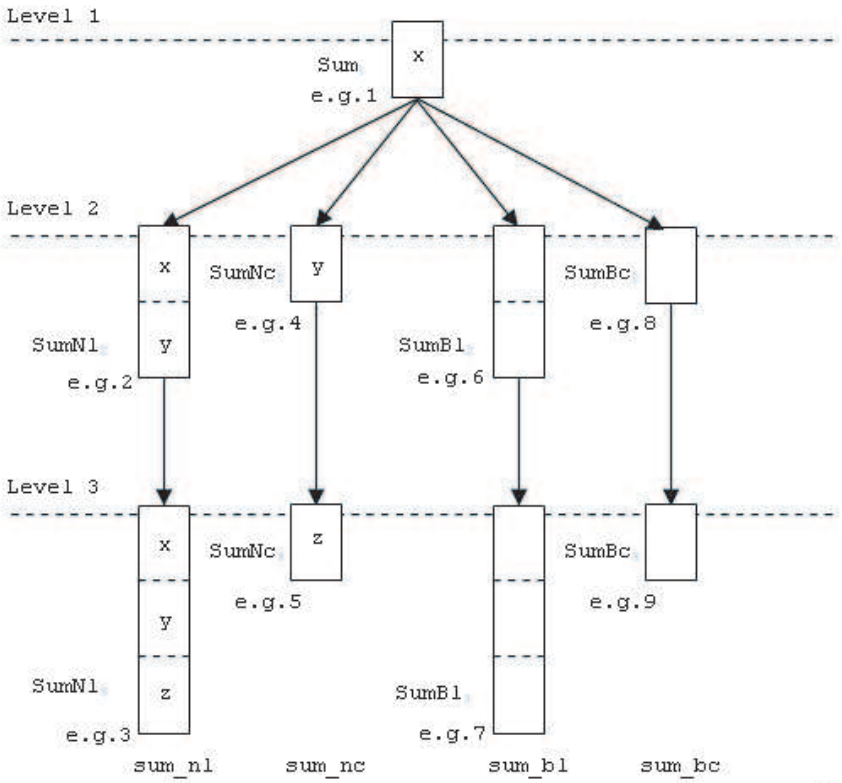
Hierarchical query-biased summaries

- Research questions...
  - Do query-biased summaries that take account of novelty (SumN) perform better or worse than those without novelty (SumB)?
  - Do query-biased summaries that have a fixed, or constant length (Sumc) perform better or worse than those with an increasing length (Suml)?
  - Which of the summary configurations (SumNl, SumNc, SumBl, SumBc) achieves the highest level of performance?

Hierarchical query-biased summaries

1. Start from a rank of sentences in decreasing similarity to the query
   (e.g. [Tombros & Sanderson 98])
2. Top X sentences produce the 1st level summary
   (re-ordered as they appear in the doc)
3. If the user wants to see more...

Hierarchical query-biased summaries



Hierarchical query-biased summaries

- User studies ongoing to test the 4 alternatives.
- Given the summaries test the ability to identify correctly relevant documents
- User groups are shown summaries 2 out of the 4 configurations.
- The first summary shown (at level 1) is generic, and the same for all users.

Hierarchical query-biased summaries

- To generate the novel summaries...
  - Sentences have a relevance score (e.g. [Tombros & Sanderson 98]) and a novelty score
  - Novelty score measures how novel they are with respect to the previously seen summaries (e.g. wordsSeen)

Our research lines

- Language modeling for sentence retrieval: Multiple-Bernoulli distribution.
- Hierarchical query-biased summaries
- **Proximity between relevant sentences and query difficulty**
- Language modeling for sentence retrieval: Study of smoothing.

Proximity and query difficulty

Many questions but very few answers...

- How to retrieve relevant sentences from a set of top retrieved docs?
- Many different methods tried out in the context of the TREC novelty tracks (2002, 2003, 2004). VSP, LMs (2-stage, KLD, ...)
- A regular tf/idf technique works consistently better than any other approach [Allan et al 03].

Proximity and query difficulty

- Some recent (tiny) improvements for sentence retrieval using named entities, phrases and combinations of query words [Li & Croft 05]
- Hence, it is a challenging problem and an effective solution is still to come.

Proximity and query difficulty

- There is some evidence that users tend to locate relevant sentences in close proximity one to each other [collins-thompson et al 02] (CMU)
- CMU applied a window of nearby sentences (2-3 sentences before and 2-3 sentences after) to adjust the tf/idf score of a sentence.
- It didn't improve sentence retrieval

Proximity and query difficulty

Anyway, there is a lack of exhaustive reports addressing this issue...

- Aim: test different operators to check whether or not a combination with nearby sentences is good.
- For each sentence, we only consider the sentence before and the sentence after.
- Regular tf/idf as a baseline and proximity method for re-ranking the sentences.

Proximity and query difficulty

- We first conducted some preliminar analytical study to check the working hypothesis (relevant sentences are in close proximity one to each other).
- Very different datasets: TREC-2002 (old TREC topics, very few relevant sentences), TREC-2003/4 (new topics, AQUAINT collection). But...

Proximity and query difficulty

	$P(R)$	$P(R\|prev\ is\ rel)$	$P(R\|next\ is\ rel)$	$P(R\|prev\ \&\ next\ are\ rel)$
2002	0.024	0.285	0.281	0.660
2003	0.391	0.802	0.790	0.928
2004	0.159	0.572	0.561	0.766

- Relevant sentences tend to occur nearby.
- But how to come out with an effective sentence retrieval method able to handle proximity?

Proximity and query difficulty

So far, we tried out...

1. $rsv(s_i) = \lambda sim(s_i) + (1-\lambda)\frac{sim(s_{i-1})+sim(s_{i+1})}{2}$
2. $rsv(s_i) = \lambda sim(s_i) + (1-\lambda)\frac{sim(s_{i-1})+sim(s_{i+1})}{2}$ (only sims<>0 are considered)
3. $rsv(s_i) = \lambda sim(s_i) + (1-\lambda)max(sim(s_{i-1}), sim(s_{i+1}))$
4. $rsv(s_i) = min(sim(s_i), \lambda sim(s_i) + (1-\lambda)\frac{sim(s_{i-1})+sim(s_{i+1})}{2})$
5. $rsv(s_i) = min(sim(s_i), \lambda sim(s_i) + (1-\lambda)max(sim(s_{i-1}), sim(s_{i+1})))$

- Last two methods to avoid that a sentence with high initial score gets significantly penalized when there are low score surrounding sentences.

Proximity and query difficulty

- Evaluated for both long and short queries
- Main evaluation ratios: F measure (std metric in the novelty track), P@10 and P@5
- No major difference among proximity methods
- Small average improvements in performance (but most of them are not stat. significant).
- Anyway, in most of the cases, the number of queries whose performance is improved w.r.t the baseline is larger than the number of queries whose performance is decreased

Proximity and query difficulty

- Is there any query feature that helps to adjust the proximity-based methods?
- Correlation between sentence retrieval performance and query difficulty measures?
  [He & Ounis, 04]
  - Average inverse collection term frequency (ICTF)
  - Query scope
- Suitable for predicting trends in sentence retrieval?
- Adequate for adjusting the proximity-based approach?

Proximity and query difficulty

- No correlations were found between F and ICTF/Query scope (still need to check P@5 and P@10)
- Proximity methods tend to work better when the avg rsv of the retrieved set of sentences is high
- Conclusion: Rel sens tend to be close to each other but an effective proximity-based SR method is still to come

Our research lines

- Language modeling for sentence retrieval: Multiple-Bernoulli distribution.
- Hierarchical query-biased summaries
- Proximity between relevant sentences and query difficulty
- **Language modeling for sentence retrieval: Study of smoothing.**

Smoothing for SR

- Joint collaboration

University of Santiago de Compostela	University of A Coruña
Grupo de Sistemas Inteligentes	IRLab

- Research project ***Retrieval of relevant and novel sentences using IR models and techniques*** (2005-2008), funded by Ministerio de Educación y Ciencia. TIN2005-08521-C02-01.

Smoothing for SR

- C. Zhai, J. Lafferty. *A study of smoothing methods for language models applied to adhoc IR*, SIGIR-01 (ACM TOIS 2004).
- Re-examine smoothing strategies in the context of a sentence retrieval problem.

Conclusions

- Multiple-Bernoulli LMs look promising for sentence retrieval
- Effective novelty techniques at the sentence level are promising for improving current doc summarization methods
- Relevant sentences tend to be close one to each other but still don't know how to effectively model this fact