A Semantic QA-Based Approach for Text Summarization Evaluation

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Abstract
Many Natural Language Processing and Computational Linguistics applications involves the generation of new texts based on some existing texts, such as summarization, text simplification and machine translation. However, there has been a serious problem haunting these applications for decades, that is, how to automatically and accurately assess quality of these applications. In this paper, we will present some preliminary results on one especially useful and challenging problem in NLP system evaluation – how to semantically compare the content of two text passages (especially for large passages such as articles and books). Our idea is intuitive and very different from existing approaches. We treat one text passage as a small knowledge base, and ask it a large number of questions to exhaustively identify all content points in it. By comparing the correctly answered questions from two text passages, we will be able to compare their content precisely. The experiment using 2007 DUC summarization corpus clearly shows promising results.

1 Introduction
Technologies spawned from Natural Language Processing (NLP) and Computational Linguistics (CL) have fundamentally changed how we process, share, and access information, e.g., search engines, and question answering systems. However, there has been a serious problem haunting many NLP applications, that is, how to automatically and accurately assess the quality of these applications. In some case, evaluation of a NLP task itself has become an active research area itself, such as text summarization evaluation. The main difficulty for developing such evaluation comes from the diversity of the NLP domain, and our insufficient understanding of natural languages and human intelligence in general. In this paper, we focus on one especially useful and challenging area in NLP evaluation – how to semantically compare the content of two text passages (e.g., paragraphs, articles, or even large corpora). Pinpointing content differences among texts is critical to evaluation of many important NLP applications, such as summarization, text categorization, text simplification, and machine translation. Not surprisingly, many evaluation methods have been proposed, but the quality of existing methods themselves is hard to assess. In many cases, human evaluation must be adopted, which is often slow, subjective, and expensive. In this paper we present an intuitive and innovative idea completely different from existing methods: 

If we treat one text passage as a small knowledge base, can we ask it a large number of questions to exhaustively identify all content points in it?

By comparing the correctly answered questions from two text passages, we can compare their content precisely. This idea may seem confusing as “circling around the target” instead of “directly hitting the target”. However, Our Question Answering (QA)-based content evaluation is intuitive and supported by the following insights:

1) When we assess someone’s understanding on a subject, we do not ask him to write down all he knows about the subject. Instead, a list of questions will be asked, and accurate and objective assessment can be achieved by counting the number of correct answers. During this question answering process, we can also identify which areas he needs to improve.
2) Practical operability. When assessing the similarity of two texts, direct comparison may look natural. However, with current methods (no matter supervised or rule-based) this direct approach becomes increasingly difficult as we move to larger text passages. For example, comparing two articles needs to answer the following
questions: how to align sentences, how to semantically represent a sentence, how to generate similarity scores without annotated samples (or as few as possible to minimize cost), how to interpret and evaluate these scores, how to find the content differences of two texts, etc.

3) Easy to interpret. Many existing methods only generate a single score, which illustrates little detail as how an assessment measure is generated and offers no help for system improvement. On the other hand, our QA-based approach requires minimum manual efforts, clearly shows how a measure is calculated, and pinpoints exactly the content differences of two text passages.

In next section we will discuss some existing work. Section 3 will show the architecture for our QA-based evaluation approach, and experiment results will be presented in section 4.

2 Related Work

Although our evaluation method applies to any application where semantic comparison of texts is needed, our current experiments focus on text summarization evaluation. In this section, we will only discuss the existing work on summarization evaluation.

Automatic text summarization is the process to find the most important content from a document and create a summary. How to automatically evaluate summaries remains a challenging problem [Jones 1995, Jing 1998, Steinberger 2012]. [Donaway 2000] introduced content-based measure: comparing the term frequency (tf) vectors of machine summary with the tf vectors of the full text or human summary. The score is computed based on “bag of words” or “tf-idf” model using cosine similarity. However, it is likely the summary vector is sparse compared with the document vector, and a summary may use terms that are not frequently used in the full document. An alternative is to use Latent Semantic Indexing (LSI) to capture semantic topics [Steinberger 2012]. Unfortunately, LSI is expensive to compute, and suffers from the polysemy problem. Other content-based measures include Longest Common Subsequence, Unit Overlap [Radev 2002], Pyramid [Nenkova 2004], Basic Elements [Hovy 2006], and Compression Dissimilarity [Wang 2016].

ROUGE (Recall-Oriented Understudy for Gisting Evaluation) is perhaps the most widely adopted automatic summarization evaluation tool. It determines the quality of a summary by comparing it with human summaries using N-grams, word sequences, and word pairs [Lin 2004]. Its output correlates very well with human judgements. But ROUGE is unsuitable to evaluate abstractive summarization, or summaries with a significant amount of paraphrasing. [Ng 2015] incorporates word embeddings into ROUGE. There have been other efforts to improve automatic summarization evaluation measures, such as the Automatically Evaluating Summaries of Peers task in TAC. The major problem of these methods is the requirement of “gold standard” summaries, and usually only a single score is generated, which is hard to interpret and does not provide any clue as how a summarization system can be improved.

3 A QA-Based method for semantic comparison of texts

Our automated evaluation method will leverage two NLP fields: Question Generation (QG), and Question Answering (QA). Its architecture is illustrated in Error! Reference source not found.. The main idea is first to generate a large number of questions from an original text passage to exhaustively cover its content. To evaluate the content of a newly-generated text passage (e.g., a summary, a simplified version, or a translation to another language), a QA system will use the new passage as the only knowledge source to answer these questions. If a question is correctly answered, it means that this new text passage contains this piece of information. By examining all correct answers, we can have an accurate measure of information contained in the new passage. By comparing the questions that can be answered by original text passage but can not be answered by new passage, we can pinpoint exactly the content differences between these two text passages.

Question generation (QG) has been widely used in many fields. In a document retrieval system, a QG system can be used to construct well-formed questions [Hasan 2012]. Current QG methods are designed to generate questions with some focus, e.g. a query in an IR system, main topic in a tutoring system [Le 2014]. Usually questions are formed by exploiting named-entity information and predicate-argument structures of sentences. Then a QG system ranks the questions in two aspects. One is the question’s relevance to the topic and the subtopics of the original passage; and the other is the syntactic similarity of each question with the original passage. As a re-
The system outputs questions with high relevance to the topic of original text passage. For our evaluation system, we want to generate not only the questions that closely relate to the topic, but also the questions covering even minor content points. Current QG systems can not always generate well-structured high quality questions.

For our evaluation system an alternative is available. We can first apply a Named Entity Recognition method to identify named entities (e.g., person name, time) from a text passage. For each identified named entity, we will generate a set of questions according to predefined question templates. For example, there is one text passage:

“...... Born in Hodgenville, Kentucky, Lincoln grew up on the western frontier in Kentucky and Indiana......”

If “Lincoln” is recognized as a person, questions will be automatically generated, e.g.,

- Who is Lincoln?
- When was Lincoln born?
- Where was Lincoln born?
- When did Lincoln die?
- Where did Lincoln die?

These questions are generated without considering specific text passages, so it is possible some answers cannot be found in the original text passage. In this case, all questions are still asked to an original text passage and to a generated (e.g., summarized, simplified, translated) text passage. The difference of the two answer sets will show the content difference of two texts. The advantage of this approach is that we do not have to rely on the quality of questions from a QG system. As long as the predefined question template is carefully constructed, we can obtain questions with good coverage (over-coverage does not matter) and high quality.

After a large set of questions is generated from original text, we need a QA system to see how many questions can be correctly answered using the content from a single text. A typical QA system usually includes an information-retrieval component to return a large set of ranked documents that may contain the answer. Figure 1 shows the architecture of a customized QA system that will satisfy the needs of this evaluation project. After the question processing step, our QA system component doesn’t pass formulated queries to a passage-retrieval component. Instead, it uses the queries to search for relevant sentences within a document, from which the system will extract answers. The change in structure increases the difficulties in the question-processing step, and the answer-processing step, of the QA system.

4 Experiment

To test our idea, we built a proof-of-concept system using some existing QG and QA systems. For the QG component, we adapted the system developed in [Heilman 2011]. For the QA component, we adapted an open source QA framework, OpenEphyra, by replacing the Passage Retrieval component with a text searching component, which searches only within one document.

We used the Document Understanding Conference (DUC) 2007 corpus, which contains 2 sets of text passages. The first set is the original documents divided into 45 topics. Each topic consists of 25 original documents. The second set of texts is the summaries of each topic. The summaries were generated by 2 baseline summar-
rization systems, 30 participating summarization systems, and 4 human summarizers. All of these summaries have been evaluated by human assessors, and have been given scores on their content responsiveness and linguistic quality. Due to time constraints, we chose to compare the performance of 10 summarization systems with system ID 4, 9, 10, 14, 16, 17, 22, 25, 26, and 30. These systems are evenly distributed performance-wise as evaluated by human assessors.

In the QG phase, the QG component generates a large set of questions for each topic. The number of generated questions ranges from a few hundred to a few thousand, and varies from topic to topic depending on the document length.

In the QA phase, for each topic we use the set of questions corresponding to this topic as input to the QA system. To make sure the answers generated by the QA system are mostly correct, we set the confidence score of the answers to a very high value (0.8 or 0.9 as shown in Table 1). In other words, if the QA system is not highly positive about the answer to a question, it will not answer that question. For each summarization system, we calculate the percentage of answered questions among the total questions and normalized it to [1, 5], matching scores of human assessors. Finally, we compare the content scores given by human assessors and our scores by computing their Pearson’s correlation. As shown in Table 1, in general our scores and human scores correlate very well. The longer questions can generally more difficult for a QA system and sometimes results in lower performance. Since summarization tends to keep most important information, not all questions are of the same importance. Questions covering important information should be given higher priority. By question filtering, we applied LDA to identify topic words of documents, and filtered out the questions that do not contain these topic words. Performance gets better since a summarization system will not be penalized by not covering unimportant information. While the correlation we obtained is lower than ROGUE, we are confident that our performance can be significantly improved with better QG and QA components.

| Confidence | Question Length | Question Filtering | Correlation |
|------------|----------------|--------------------|-------------|
| 0.8        | 20             | No                 | 0.6120      |
| 0.9        | 20             | No                 | 0.6379      |
| 0.8        | 20             | Yes                | 0.7725      |
| 0.9        | 20             | Yes                | **0.8363**  |
| 0.8        | 30             | No                 | 0.6373      |
| 0.9        | 30             | No                 | 0.5092      |
| 0.8        | 30             | Yes                | 0.6310      |
| 0.9        | 30             | Yes                | 0.5462      |
|            |                |                    | **ROUGE SU4** | 0.8827 |
|            |                |                    | **ROUGE 2** | 0.9281 |

Table 1 Experiment Results

5 Conclusion

In this paper we present an innovative semantic evaluation method for various NLP applications by leveraging QG and QA fields. Our method requires no manual efforts, is easy to interpret, illustrates details about NLP systems being evaluated. Initial experiments on text summarization evaluation showed promising results.
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