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AUTOMATIC TEXT SUMMARIZATION

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Abstract - The advent of WWW has created a large reservoir of data. There is an enormous amount of textual material, and it is only growing every single day. The data is unstructured and the best that we can do to navigate it is to use search and skim the results. A short summary, which conveys the essence of the document, helps in finding relevant information quickly. Automatic summarization is the process of shortening a text document with software, in order to create a summary with the major points of the original document. This method uses Natural Language Processing (NLP) Techniques to summarize a given text document.

Keywords - Natural Language Processing (NLP), Extractive Summarization and Abstractive summarization, Entity Recognition, Relationship Extraction, Template Design, Summary Generation

I. INTRODUCTION

With the rapid growth of the Internet, people are overwhelmed by the tremendous amount of online information and documents [1]. There are mainly 6 reasons why Automatic Text Summarization is needed: [2]

- Summaries reduce reading time.
- When researching documents, summaries make the selection process easier.
- Automatic summarization improves the effectiveness of indexing.
- Automatic summarization algorithms are less biased than human summarizers.
- Personalized summaries are useful in question-answering systems as they provide personalized information.
- Using automatic or semi-automatic summarization systems enables commercial abstract services to increase the number of texts they are able to process.

Natural Language Processing (NLP) is all about interpreting human language from one structure to another. In NLP, Summarization is one of the research work which focuses on providing relevant summary using various Natural Language Processing tools and techniques [3]. To deal with the massive information across the digital world, there is a need to have an automatic summarization method. Basically, Summarization is categorized into two types - Extractive and Abstractive [4][5]. Extractive methods work by selecting a subset of existing words, phrases, or sentences in the original text to form the summary. Examples of this include key phrase extraction and document extraction, where the goal of the former is to select individual words to "tag" a document. The goal of this method is to select whole sentences (without modifying them) to create a short paragraph summary.

Abstractive text summarization involves generating entirely new phrases and sentences to capture the meaning of the source document. This is a more challenging approach, but is also the approach ultimately used by humans. Classical methods operate by selecting and compressing content from the source document.

II. EXISTING MODEL

When we want to shorten a text document with software in order to create a summary with the major points of the original document, there are mainly 4 phases – Entity Recognition, Relationship Extraction , Subgraph Construction, Template Design and finally Summary generation.

A. *Entity Recognition:*

It is a sub-task of information extraction that seeks to locate and classify the text into pre-defined categories such as the names of persons, organizations, locations, quantities, monetary values, percentages etc., where each of it becomes an entity.

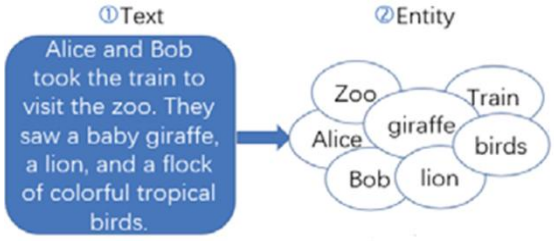
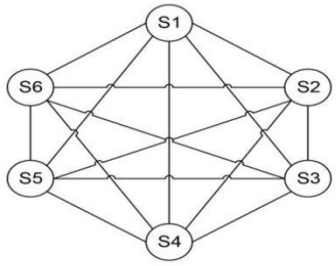


Fig 2.1:Entities extracted from a document

B. *Subgraph Construction:*

After the entities are extracted through First stage method the document should be computed to extract key sentences, which are still in the original document order. To handle the problem of key sentence extraction, we utilizes a graph model. A subgraph is built from a single document, or we can

build subgraph from multiple documents. Therefore, the use of knowledge-based graphs can be a good way to complete the task of multi-text summary.



- Node -> Sentence
- Edge -> Similarity between 2 sentences

Fig 2.2: A general notation of a subgraph

C. *Template Design:*

The extraction summary template we propose is accomplished by combining different SPARQL query languages for knowledge graph [23]. Among them, the simplest template traverses all the directional triplets of the document subgraph into the syntactic structure of the subject-predicate-object, and simply combines these sentences to form a summary. The so called complex template is adding the tasks of knowledge inference and aggregation of the subgraph, and accomplishes similar human reasoning. Table 2.3 shows the difference between the simple and complex templates.

Simple Template	Alice see animals. Bob see animals
Complex Template	Alice and Bob visit the zoo and see animals and birds.

Table 2.3: Examples of choosing a simple and a complex template

D. *Summary Generation:*

Since the information extracted from the text is the structure of the graph, the abstract of the text can be extracted by asking questions.

Question	Who visited zoo? What did they see?
Summary	Alice and Bob. They saw animals.

Table 2.4: Choosing a query template

III. PROPOSED SYSTEM

In the existing system, after the generation of a summary for a document of say about 1000 words, the summary is cut down to almost about 800 words. To further shorten the summary and to acquire more precision, the proposed model includes another phase other than the 4 main phases. This phase is known as the Relationship Extraction Phase.

We establish a candidate relationship set between the existing entities. Then, the relationship of the subject-predicate-object structure is determined by the syntactic dependency tree, and the relationship pair with the highest probability is chosen. Words like located in, employed by, part of, married to etc all represent relationship among entities. Based on the availability of training data and annotated text we can perform relation extraction in 5 methods:-a. Hand-built patterns, b. Bootstrapping methods, c. Supervised methods, d. Distant supervision, e. Unsupervised methods.

A. *Hand-built patterns:*

Hand built rule-based systems have a naive approach towards relation extraction task. They come up with the relations between entities by analyzing set of sample examples and writing a possible set of rules which obey it. For example, Agar is a substance prepared from a mixture of red algae, such as Gonidium, for laboratory or industrial use. While reading this sentence human can predict, there is a hyponym relation between red algae and Gonidium. We predict this by observing the connecting words 'such as' between these two words. For identifying relations such as hyponyms we can use this technique.

B. *Bootstrapping Method:*

If we don't have enough annotated data to train and lots and lots of unannotated text for relation extraction then, we will not get a good result. The solution for this approach is bootstrapping technique. In this approach, we have some seed instances, which is manually tagged data used for the first phase of training called the seed instances. We train with seed instances and learn the classifier, and test with the classifier, and get more train examples by adding the test results to the training set. Thus, the training set will grow up to a sufficient amount. This approach can be called as a semi-supervised model. [6]

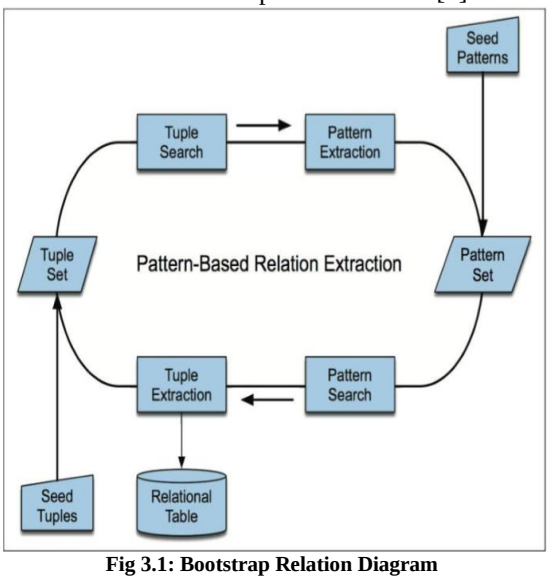


Fig 3.1: Bootstrap Relation Diagram

C. Supervised Methods:

Supervised systems are the state-of-the-art system for many natural language processing tasks. The supervised system will learn from the already tagged corpus with the help of features or learn by the systems. The key idea for the supervised learning is to model the relation extraction task as a classification problem (Binary, or multi-class) and train the classifier with different techniques for prediction of new relations. We take help from various available machine learning algorithm for designing the classification problem. For the sake of simplicity
and clarity, we restrict our discussion to binary relations between two entities. Given a sentence
S = w1, w2, .., e1.., wj , ..e2, .., wn,
where e1 and e2 are the entities, then a mapping function f (.) can be given as:

$$f_R(T(S)) = \begin{cases} \text{True}, & \text{if } e_1 \text{ and } e_2 \text{ are related according to relation } R \\ \text{False}, & \text{Otherwise.} \end{cases}$$

Where T(S) are the features extracted from the sentence S. The mapping function f(.) defines whether there exists a relation between these entities. [6]

D. Distant Supervision:

Modern models of relation extractions are based on supervised learning of relations from small hand-labeled corpora. An alternative paradigm that does not require labeled corpora, and allowing the use of corpora of any size is distant Supervision which combines both supervised and unsupervised training techniques. This uses Freebase, a large semantic database of several thousand relations. For each pair of entities that appears in some Freebase relation, we find all sentences containing those entities in a large unlabeled corpus and extract textual features to train a relation classifier.[7]

E. Unsupervised Methods:

Unsupervised information extraction, extracts strings of words between entities in large amounts of text, and clusters and simplifies these word strings to produce relation-strings. Unsupervised approaches can use very large amounts of data and extract very large numbers of relations, but the resulting relations may not be easy to map to relations needed for a particular knowledge base.[7]

IV. METHODOLOGY

This model builds named entity recognizer with NLTK(Natural Language Tool Kit) and SpaCy, to identify the names of things, such as persons, organizations, or locations in the raw text. When assigning weights forwords, we can think of binary (0 or 1) or real-value (continuous) weights and decide which words are more correlated to the topic. The two most common techniques in this category are: Word Probability and TFIDF (Term Frequency Inverse Document Frequency).

4.1 Word Probability: The simplest method is to use frequency of words as indicators of importance. This is word probability. The probability of a word is determined as the number of occurrences of the word, f (w), divided by the number of all words in the input (which can be a single document or multiple documents):

$$P(w) = \frac{f(w)}{N}$$

4.2 TFIDF (Term Frequency Inverse Document Frequency): Since word probability techniques depend on a stop word list in order to not consider them in the summary and because deciding which words to put in the stop list is not very straight forward, there is a need for more advanced techniques. One of the more advanced and very typical methods to give weight to words is TFIDF. This weighting technique assesses the importance of words and identifies very common words (that should be omitted from consideration) in the document by giving low weights to words appearing in most documents. The weight of each word w in document d is computed as follows:

$$q(w) = f_d(w) * log\frac{|D|}{f_D(w)}$$

where fd(w) is term frequency of word w in the document d, fD(w) is the number of documents that contain word w and |D| is the number of documents in the collection D.

V. CONCLUSION

Generating abstractive summary is becoming a necessity in this large digital world where huge amount of information is available to get a concise and short summary. It is difficult for humans to summarize large amounts of text. In this paper, we emphasized various extractive and abstractive approaches for single and multi-document summarization. We have described some of the most extensively used methods such as Bootstrapping, supervised and unsupervised methods. Although it is not feasible to explain all diverse algorithms and approaches comprehensively in this paper, we think it provides a good insight into recent trends and progresses in automatic summarization methods and describes the state of the art in this research area.

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