

Extraction and Clustering of Keywords for Documents

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Abstract: In this topic there are large numbers of documents which are cover more information about any topic. We are extracting one keyword from that document, when we are extracting this keyword can easily retrieve whole document. However, even a small piece contains a variety of words, which are potentially related to several topics; more- over, using an automatic speech recognition (ASR) system introduce errors among them. There for, it is difficult to infer precisely the in sequence requirements of the discussion participants. We first propose an algorithm to extract keywords from the output of an ASR system which makes use of topic modeling techniques and of a sub modular reward function which favors range in the keyword set, to match the possible range of topics and reduce ASR noise. This method is to derive many topically divided queries starting this keyword set, in organize to take full advantage of the probability of making at least one related reference when with these queries to search over the English Wikipedia. Examples like Fisher, AMI, and ELEA conversational corpora.

Keywords: Document recommendation, information retrieval, keyword extraction, meeting analysis, topic modeling.

I. INTRODUCTION

Data mining is the procedure that attempts to find out patterns in large data sets. It utilizes methods at the intersection of fake aptitude, machine learning, statistics, and database systems. The overall goal of the data mining procedure is to remove in sequence from a data set and transform it into an understandable structure for further use.

Data is accessible in the form of databases, ID & multimedia resources. Access to this information is conditioned by the availability of suitable search engines. But even these are available users can not search particular information because they are not aware that relevant information is available. Just-in-time-retrieval system which is observes the current activities of users & provides relevant information. A just-in-time information retrieval agent is software that proactively retrieves and presents in sequence based on a person's local situation in an easily accessible yet nonintrusive manner. They continuously watch a person's environment and present information that may be useful without requiring any action on the part of the user.

Automatic speech recognition is the process by which a computer maps an acoustic speech indication to passage. Automatic speech appreciative is the process by which the computer maps an acoustic speech signal to some form of abstract meaning of the speech. A new method for keyword extraction from conversations is introduced, which preserves the diversity of topics.

Topic based clustering that aims only to solve the problem of grouping together articles of similar topic. News organization would like to be able to access related document with minimum effort. The topic based clustering decreases the probability of including ASR errors into the queries, and the diversity of keywords increases the probability that at least single of the recommended papers answers a need for information, or can main to a useful

text when following its hyperlinks. Relevance and diversity can be enforced at three stages: when extracting the keywords; when structure one or some implicit queries; or when re-ranking their results.

The center of this paper is on figuring verifiable questions to a without a moment to spare recovery framework for utilization in meeting rooms. Conversely to unequivocal talked inquiries that can be made in business Web crawlers, our in the nick of time recovery framework must develop certain questions from conversational information, which contains a much bigger number of words than a question. For example, in the illustration examined in Section V-B underneath, in which four individuals set up together a rundown of things to help them get by in the mountains, a short piece of 120 seconds contains approximately 250 words, connecting to a assorted bag of areas, for example, 'chocolate', 'gun', or 'lighter'. What might then be the most supportive 3-5 Wikipedia pages to prescribe, and how might a framework focus them?

II. IMPLEMENTATION

- i. State of the art: just-in-time retrieval and keyword extraction
- ii. Formulation of implicit queries from conversations
- iii. Data and evaluation methods

i. State of the art: just-in-time retrieval and keyword extraction

Such frames persistently screen clients' workouts to separate data needs, and intellect effectively recovers applicable data. To complete this, the frames by and large focus certain questions (not indicated to clients) from the words that are composed or talked by clients amid their workouts. In this part, we study existing without a instant to replacement recovery frames and sequences utilized by

them for analysis detailing. Definitely, we will contemporary our Automatic Content Linking Device (ACLD) a without a moment to replacement record suggestion frame for assemblies, for which the sequencessuggested in this paper are expected. In II-B, we talk about past necessary word mining actions from a transcription or content.

a. Query Formulation in Just-in-Time Retrieval Systems

One of the initial systems for paper authorization, denoted to as query-free examine, was the Fixit system, an associated to an knowledgeable analytic system for the producers of a particular company (fax machines and copiers). Fixit monitored the state of the user's interface with the diagnostic system, in terms of the positions in a belief network built from the relations among indications and errors, and ran background searches on a databank of preservation guides to provide extra support data correlated to the current state. The Recollection Agent, another quick in the nick of time recovery frame, is closer in idea to the frame considered in this paper. The Recollection Agent was integrated into the Emacs content tool, and ran looks at normal time intervals (like clockwork) utilizing a question that was in light of the most current words wrote by the user, for example using a structure of 20–500 words positioned by repetition. The Recollection Agent was got out to a multimodal setting under the name of Jimminy, a wearable right hand that helped users with taking records and getting to data when they couldn't use a standard PC console, e.g. while conversation about with someone else. Consuming TFIDF for significant word abstraction, Jimminy enlarged these watchwords with features from different modalities, for instance the user's position and the name of their converser(s).

b. Keyword Extraction Methods

Different schemes have been suggested to subsequently eliminate key words from a content, and are related also to interpreted discussions. The most punctual processes have used word frequencies and TFIDF qualities to rank words for abstraction. On the further side, words have been located by checking pairwise word co-event frequencies. These methods don't reflect word significance, so they may overlook low-recurrence words which together demonstrate an extremely notable subject. Semantic relations between terms can be developed from a really developed dictionary, for example, Word Net, or from Wikipedia, or from a logically gathered dictionary developing idle issues schemes, for example, LSA, PLSA, or LDA. Hazen also useful issue modeling techniques to audio records. In alternative learning, he used PLSA to build a dictionary, which was then used to grade the terms of a discussion text with respect to each topic using a weighted point-wise common data counting purpose.

ii. Formulation of Implicit Queries from conversations

We advise a two-phase technique to the formulation of implicit queries. The first phase is the extraction of keywords from the record of a discussion part for which documents must be suggested, as provided by an ASR

system. These keywords should cover as much as possible the areas noticed in the discussion, and if potential keep away from words that are clearly ASR errors. The second stage is the clustering of the keyword set in the form of some topically-disjoint queries

a. Diverse Keyword Extraction

We advise to take advantage of topic modeling techniques to build a topical representation of a discussion part, and then select content words as keywords by using relevant relationship, while also fulfilling the reporting of a various range of subjects, motivated by recent summarization methods. The benefit of diverse keyword extraction is that the coverage of the main subjects of the discussion part is maximized.

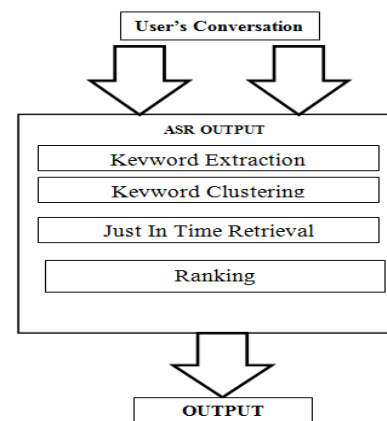


Fig. 1 The three steps of the proposed keyword extraction method

Additionally, in order to cover more subjects, the suggested algorithm will choose a smaller number of keywords from each subject. This is required for two reasons. This will lead to more different implicit queries, thus increasing the multiplicity of recovered documents. and, if words which are in actuality ASR noise can create a main topic in the fragment, then the algorithm will choose a smaller number of these noisy keywords compared to algorithms which overlook mixture.

Algorithm 1: Diverse keyword extraction.

Input: a given text t , a set of topics Z , the number of keywords k

Output: a set of keywords S

$S \leftarrow \emptyset$

While $|S| \leq k$ **do**

$S \leftarrow S \cup \{ \text{argmax}_{w \in t \setminus S} (h(w, S)) \}$ where
 $h(w, S) = \sum_{z \in Z} \beta_z [p(z|w) + r_{S,z}]^\lambda;$

end

return S

The benefit of diverse keyword extraction is that the coverage of the main topics of the conversation fragments is

maximized. The future method for diverse keyword extraction proceeds in three steps,

1. Used to represent the division of the abstract subject for each word.
2. These topic models are used to determine weights for the abstract topics in each conversation fragment represented by β_z
3. the keywordlist $W = \{w_1, w_2, \dots, w_k\}$. which covers a maximum number of the most important topics are preferred by rewarding range, using an unique algorithm introduced in this part.

Selection of Configurations: Using the rank biased overlap (RBO) as a similarity metric, based on the fraction of keywords overlapping at different ranks.

$$RBO(S, T) = \frac{1}{\sum_{d=1}^D (\frac{1}{2})^{d-1}} \sum_{d=1}^D (\frac{1}{2})^{d-1} \frac{|S_{1:d} \cap T_{1:d}|}{|S_{1:d} \cup T_{1:d}|}$$

Where, RBO = rank biased overlap S and T be two ranked lists, and S_i be the keyword at rank i in S . The set of the keywords upto rank d in S is $\{S_i : i : \leq d\}$. noted as $S_{1:d}$. RBO is calculated as above Equ.

a. Keyword Clustering

The different set of extracted keywords is measured to denote the possible information needs of the applicants to a discussion, in terms of the ideas and topics that are declared in the discussion. To maintain the variety of topics alive in the keyword set, and to decrease the noisy result of each data need on the others, this set must be divided into several topically-disjoint subsets. Each subset corresponds to an implicit query that will be sent to a document recovery system. These subsets are obtained by clustering topically-similar keywords, as follows.

Clusters of keywords are constructed by ranking keywords for each main topic of the fragment. The keywords are ordered for each topic by decreasing values of $\beta \cdot p(z|w)$. Moreover, in each cluster, only the keywords with a $\beta \cdot p(z|w)$ value higher than a threshold are kept for each topic z .

b. From Keywords to Document Recommendations

As a first impression, one implicit query can be arranged for each discussion part by using as a query all keywords special by the various keyword removal technique. However, to improve the retrieval results, multiple implicit queries can be formulated for each discussion part, with the keywords of each cluster from the before fragment. In tests with only one implicit query per discussion fragment, the document results parallel to each discussion fragment were arranged by selecting the first document retrieval results of the implicit query.

iii. Data and evaluation methods

Our proposals were tested on three conversational corpora, the Fisher Corpus, the AMI Meeting Corpus, and the ELEA Corpus. The significance of the keywords was assessed by designing association task and averaging some judgments obtained by crowdsourcing this assignment through the Amazon Mechanical Turk (AMT) stage. In addition, the $-NDCG$ measure was used to determine topic

range in the catalog of keywords. Afterward, the quality of implicit queries was assessed by estimating (again with human judges recruited via AMT) the significance of the papers that were retrieved when submitting these queries to the Lucene search engine over the English Wikipedia and merging the results as explained above. Here, the conversational data came only from the ELEA Corpus, which offers clearer criteria for assessing the significance of references than the Fisher and AMI Corpora. We now describe the three corpora and the data extracted from them, as well as the evaluation methods for each task.

a. Conversational Corpora Used for Experiments

The Fisher Corpus contains about 11,000 topic-labeled telephone conversations, on 40 pre-selected topics (one per conversation).

In our experiments, we used the manual suggestion transcripts available with the corpus. We created a topic model using the Mallet implementation of LDA, over two thirds of the Fisher Corpus, given the enough number of single-topic documents, fixing the number of abstract topics at 40. The remaining data was used to build 11 fake discussion fragments for testing, by concatenate 11 times three remains about three dissimilar topics. The AMI Meeting Corpus contains discussion on manipulative remote controls, in sequence of four scenario-based meetings each, for a total of 171 meetings. Speakers were not constrained to talk about a single topic throughout a meeting, hence these transcripts are multi-topic. Since the number of meetings in the AMI Corpus is not large enough for building topic models with LDA, we used a subset of the English Wikipedia with 124,684 articles. Following several previous studies, we fixed the number of topics at 100. We chosen for trying 8 conversation fragments, each 2–3 minutes long, from the AMI Corpus. We used both manual and ASR transcripts of these fragments. The ASR transcripts were generated by the AMI real-time ASR system for meetings, with an average word error rate (WER) of 36%.

b. Evaluation Protocol and Metrics

We designed comparison tasks to evaluate the relevance of extracted keywords and of recommended documents with respect to each discussion fragment. For the former evaluation, we compared the relevance (or representativeness) of two lists of keywords extracted from the same conversation fragment by two different extraction methods. We displayed the transcript of the fragment to a human subject in a web browser, followed below it by several control questions about its content, and then by two lists of keywords (typically, nine keywords in our experiments). The subjects had to read the conversation transcript, answer the control questions, and then decide which keyword cloud better represented the content of the discussion fragment. Without the control questions or the discussion transcript. A similar method was applied to compare recommended documents, except that two lists of retrieved documents (typically, with seven items each) are shown instead of word clouds, and their potential utility as recommendations to the discussion participants is compared.

III. CONCLUSION

We have considered a particular form of just-in-time retrieval systems intended for conversational environments, in which they recommend to users documents that are relevant to their information needs. We focused on modeling the users information needs by deriving implicit queries from short discussion fragments. These queries are based on sets of keywords extracted from the conversation. We have proposed a novel diverse keyword extraction technique which covers the maximal number of important topics in a part. Then, to reduction the loud effect on queries of the mixture of topics in a keyword set, we proposed a clustering technique to divide the set of keywords into smaller topically-independent subsets constituting implicit queries.

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