

Enhanced Answer Generation from Web Information

Umesh S. Chaudhari^{1*}, Shivaji B. Patil², Omprakash B. Bhange³ and Amin R. Abbas⁴

^{1,2,3,4}Dept of Computer Engineering, *University of Pune, India*.

www.ijcseonline.org

Received: Feb/24/2015

Revised: Mar/06/2015

Accepted: Mar/22/2015

Published: Mar/31/2015

Abstract – Nowadays Question answering services have gained very popular. It helps all members to post and answer questions as well enables general users to check information from a total set of well answered questions. But, existing QA applications mainly provides only textual answers, which are not enough understandable for many questions. In this paper, we are going to create a scheme that is able to provide textual answers in Question answering with particular media data. This approach get easily checks which type of media information should be added for answers. It then collects data from the web to enrich the answer. This web application type service contain three facts: answer medium selection, query generation for multimedia search, and multimedia data selection and presentation. To answer any query this system process a large set of QA pairs and add them to a pool, it can enable a novel multimedia question answering (MMQA) approach as users can find multimedia answers by matching their questions with those in the pool. There are many different QA research efforts that finds directly answer questions with multimedia data i.e. images and videos, but our approach is created based on community contributed textual question answers and thus it is helps to deal with more day to day needed community complex questions. We have conducted much performances on a multisource QA database's. The results demonstrate the effectiveness of our approach.

Keywords: Web Information, MMQA, QA, Multimedia Search Reranking

1. INTRODUCTION

Multimedia answering is a technique useful for automatically answering a question in a simple language. It is worked on keyword based search systems, user and computer can easily communicate using simple natural language. It avoid extra unwanted information and provide expected result, fully automated QA still faces challenges that such as the deep understanding of complex questions and the syntactic, semantic and contextual processing to obtain final answers. It is found that, in most cases, so automated approach not able to obtain correct results.

Effective Multimedia answer generation overcome this disadvantages Along with the better communication technologies, community QA. It is a best method to acquire information online in which user post their specific questions on any domain and obtain answers provided by other participants. Users are able to get better answers than simply using search engines without any extra effort as in comparison with auto-mated QA systems, community QA usually receives answers with better quality as they are generated based on human intelligence., WikiAnswer is one of the most well-known community QA systems and hosts are more than 15 million answered questions distributed in 6,000 categories.

Despite success, existing of community QA mostly support only textual answers. Textual answers may not

provide sufficient natural and easy to get information. For the questions “what are the preventions about tsunami” and “what are the highlighted areas, the answer of these questions described in very large format. so it will be better if some of information in the form of video's and images that will easily demonstrate the process or the object. Therefore, the textual answers in community QA can be significantly enhanced by adding multimedia contents, and it will provide answer more comprehensive information and better experience.

In fact, users usually post URLs that link to supplementary images or videos in their textual answers. For example:- how to tie a shoeless..? in further questions multimedia answers are also important But existing community QA do not provide adequate support in using media information.

In this paper, we propose a scheme which can fulfill contributed textual answers in community QA with appropriation. following are three main components:

- (1) Answer medium selection:- Given a QA pair, it shows whether the textual answer should be fulfilled with information, and which data should be added. Specifically, we categorize it into one of the four classes: text, text+image, text + image and text + image + video. It means the scheme will automatically generate images, videos or the combination to fulfill the original textual answers.

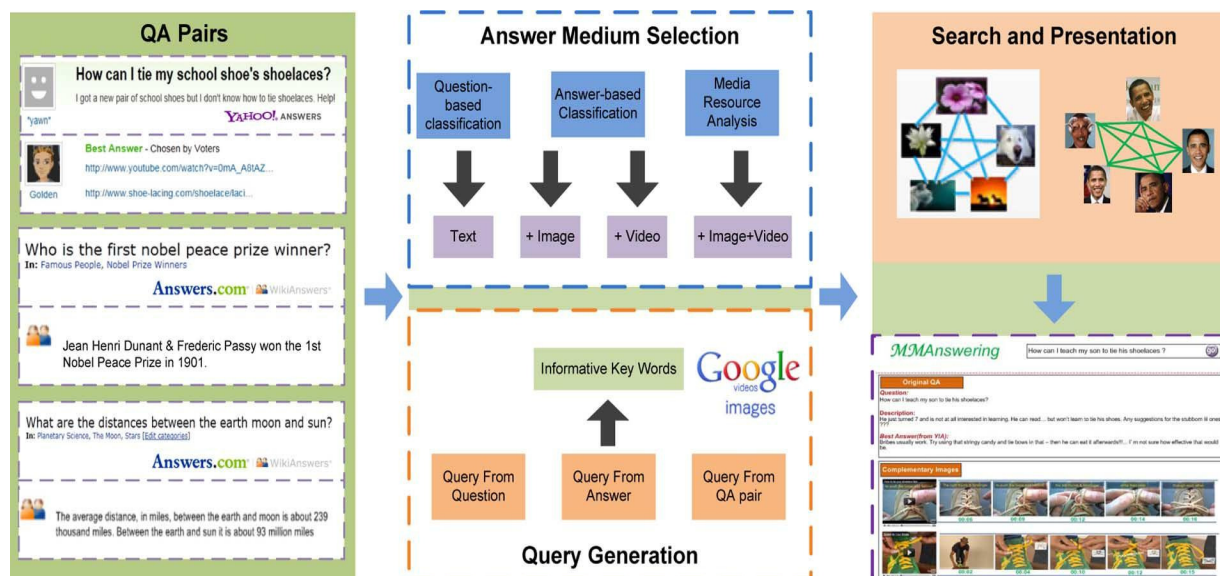


Fig: The Schematic illustration of the proposed system

- (2) Query generation for multimedia search:-To collect the multimedia data, we need to generate queries. Given a QA pair, this extracts three queries from the question, the answer, and the QA pair, respectively. The most informative query will be selected in three-class classification model.
- (3) Multimedia data selection and presentation:- this is Based on the queries which is generated, in this we randomly collect image and video data with multimedia search engines. Then we perform rearranging and duplicate removal to obtain accurate images or videos to fulfill the textual answers.

There are already some several re-search efforts related to automatically answering questions with multimedia data, so it is known Multimedia Question Answering (MMQA). For example, Yang *et al.* proposed a technology that supports factoid QA in news video. Yeh *et al.* presented a photo-based QA system for finding information about physical objects. Li *et al.* proposed an approach that leverages YouTube video collections as a source to automatically find videos to describe cooking techniques. But these approaches usually work on certain narrow domains and can hardly be generalized to handle questions in broad do-mains. This is due to the fact that, in order to achieve automatic MMQA, we need to understand the questions, which is not an easy work. Our approach in this task does not aim to directly answer of the questions, we

fulfill the community-contributed answers with multimedia contents. Our strategy breaks the gap between question and multimedia answer into two gaps i.e., the gap between question and textual answer and the gap between textual answer and multimedia answer. In this the first gap is worked by the crowd-sourcing intelligence of community members so we can focus on second gap. Therefore, this work can also be taken as an approach that achieves the MMQA problem by jointly exploring human and computer.

II. RELATED WORK

A. From Textual QA to Multimedia QA

The investigation of QA systems started from 1960s and mainly focused on expert systems in specific domains. Text-based QA has gained its research popularity since the establishment of a QA. Automatic QA still has difficulties in answering complex questions. Along with the blooming of Web 2.0, community QA becomes an alternative approach. It is a large and diverse question-answer forum, acting as not only a corpus for sharing technical knowledge but also a place here one can seek advice and opinions. However, nearly all of the existing cQA systems, such as Yahoo! Answers, Wiki Answers and Ask Metafilter, only support pure text-based answers, which may not provide intuitive and sufficient information.

An early system named Video QA extends the text-based QA technology to support factoid QA by

leveraging the visual contents of news video as well as the text transcripts.

B. Multimedia Search

Generally, multimedia search efforts can be categorized into two categories: text-based search and content-based search. The text-based search approaches use textual queries, a term-based specification of the desired media entities, to search for media data by matching them with the surrounding textual descriptions. To boost the performance of text-based search, some machine learning techniques that aim to automatically annotate media entities have been proposed in the multimedia community. Further, several social media websites, such as Flickr and Facebook, have emerged to accumulate manually annotated media entities by exploring the grass root Internet users, which also facilitates the text-based search. However, user-provided text descriptions for media data are often biased towards personal perspectives and content cues, and thus there is a gap between these tags and the content of the media entities that common users are interested in. To tackle this issue, content-based media retrieval performs search by analyzing the contents of media data rather than the metadata.

C. Multimedia Search Reranking

The text information usually does not accurately describe the content of the images and videos, and this fact can severely degrade search performance [32]. Reranking is a technique that improves search relevance by mining the visual information of images and videos. Existing reranking algorithms can mainly be categorized into two approaches, one is pseudo relevance feedback and the other is graph-based reranking.

III. ANSWER MEDIUM SELECTION

Answer media selection is a key concept of this project & this is a major component of our scheme. The textual question has to reach the proper answer in proper medium. It determines whether we need to and which type of medium we should add to get final answer. For some questions, such as "what was the first name of India, required answer should be in textual format is sufficient. But some questions require some additional information, such as image, audio, video,

For example, for the question "where is the oldest temple of India", this question needs some extra information to provide

proper image or video view, so it is better to add images with textual answer, we also add videos for answering the question. Depend upon the types of question we have to differentiate the answer medium.

The following categorization of answer medium selection as a QA classification task. It contains four classes: (1) only text: - that means we require to provide only text format answer, which contains only text format (2) Text+image: - which means we have to add image and we have to also provide text information (c) text+video: - that means that only video information needs to be added with text information; and (d) text+image+video: - that means we have to add both image and video information.

A. Question-Based Classification

Since many questions contain multiple sentences and some of the sentences are uninformative, we first employ the method in to extract the core sentence from each question.

The classification is accomplished with two steps. First, we categorize questions based on interrogatives, and in this way we can directly find questions that should be answered with text. Second, for the rest questions, we perform a classification using a naive Bayes classifier.

Questions can mainly be categorized into the following classes based on interrogative words: yes/no class, choice class, quantity class, enumeration class, and description class.

TABLE II
REPRESENTATIVE CLASS-SPECIFIC RELATED WORDS

Categories	Class-Specific Related Word List
Text	name, population, period, times, country, height, website, birthday, age, date, rate, distance, speed, religions, number, etc
Text+Image	colour, pet, clothes, look like, who, image, pictures, appearance, largest, band, photo, surface, capital, figure, what is a, symbol, whom, logo, place, etc.
Text+Video	How to, how do, how can, invented, story, film, tell, songs, music, recipe, differences, ways, steps, dance, first, said, etc.
Text+Image+Video	president, king, prime minister, kill, issue, nuclear, earthquake, singer, battle, event, war, happened, etc.

B. Answer-Based Classification

Besides question, answer can also be an important information clue. For answer classification, we extract bigram text features and verbs. The verbs in an answer will

be useful for judging whether the answer can be fulfilled with video content.

However, if a textual answer contains many complex verbs, it is more likely to describe a dynamic process and thus it has high probability to be well answered by videos. So, verb can be an important clue.

C. Media Resource Analysis

It will be beneficial to take into account the search performance of different medium types. Here we only introduce our method for search performance prediction. We predict search performance based on the fact that, most frequently, search results are good if the top results are quite coherent.

D. Medium Selection Based on Multiple Evidences

We perform medium selection by learning a four-class classification model based on the results of question-based classification, answer-based classification, and media resource analysis. For question-based classification, we have four scores, i.e., the confidence scores that the question should be answered by “text”, text + image, text + video, text + image + video.

IV. QUERY GENERATION FOR MULTIMEDIA SEARCH

To collect relevant image and video data from the web, we need to generate appropriate queries from text QA pairs before performing search on multimedia search engines. We accomplish the task with two steps. The first step is query extraction. Textual questions and answers are usually complex sentences. But frequently search engines do not work well for queries that are long and verbose.

Therefore, we need to extract a set of informative keywords from questions and answers for querying. The second step is query selection. This is because we can generate different queries: one from question, one from answer, and one from the combination of question and answer. Which one is the most informative depends on the QA pairs.

V. MULTIMEDIA DATA SELECTION AND PRESENTATION

We perform search using the generated queries to collect

image and video data with Google image and video search engines respectively. However, as mentioned above, most of the current commercial search engines are built upon text-based indexing and usually return a lot of irrelevant results. There-fore, reranking by exploring visual information is essential to reorder the initial text-based search results.

VI. ACKNOWLEDGMENT

We feel great pleasure in submitting the paper on “Enhanced Multimedia Answer Generation from Web Information”. We sincerely thanks the inspiration; support and guidance of all those people who have been instrumental in making this project a success.

In addition, a thank to Professor “**Mr. Rajesh Bharati**”, who introduced us to the Methodology of work, and whose passion for the “underlying structures” had lasting effect. We also thank the University of Pune for consent to include copyrighted pictures as a part of our paper.

Many people, especially our classmates and team members itself, have made valuable comment suggestions on this proposal which gave us an inspiration to improve our assignment. We thank all the people for their help directly and indirectly to complete our assignment.

VII. REFERENCES

- [1]. Liqiang Nie ,meng Wang,Zheng jun Zha,Yue Gao IEEE members”Beyond Text QA:Multimedia Answer Generation by Harvesting Web Information-2013”
- [2]. S. A Quarteroni and S. Manandhar, “Designing an interactive open domain question answering system,” J. Natural Lang. Eng., vol. 15, no. 1, pp. 73–95, 2008.
- [3]. L. A. Adamic, J. Zhang, E. Bakshy, and M. S. Ackerman, “Knowledge sharing and Yahoo answers: Everyone knows something,” in Proc. Int. World Wide Web Conf., 2008.
- [4]. G. Zoltan, K. Georgia, P. Jan, and G.-M. Hector, Questioning Yahoo! Answers, Stanford InfoLab, 2007, Tech. Rep.
- [5]. H. Yang, T.-S. Chua, S. Wang, and C.-K. Koh, “Structured use of external knowledge for event-based open domain question answering,” in Proc. ACM Int. SIGIR Conf., 2003.
- [6]. Trec: The Text Retrieval Conf. [Online]. Available: <http://trec.nist.gov/>.